The Economics of Solar Electricity

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Keywords

Abstract

The benefits and costs of increasing solar electricity generation depend on the scale of the increase and on the time frame over which it occurs. Short-run analyses focus on the cost-effectiveness of incremental increases in solar capacity, holding the rest of the power system fixed. Solar's variability adds value if its power occurs at high-demand times and displaces relatively carbon-intensive generation. Medium-run analyses consider the implications of nonincremental changes in solar capacity. The cost of each installation may fall through experience effects, but the cost of grid integration increases when solar requires ancillary services and fails to displace investment in other types of generation. Long-run analyses consider the role of solar in reaching twenty-first-century carbon targets. Solar's contribution depends on the representation of grid integration costs, on the availability of other low-carbon technologies, and on the potential for technological advances. By surveying analyses for different time horizons, this article begins to connect and integrate a fairly disjointed literature on the economics of solar energy.

1. INTRODUCTION

Recent trends in the economics of solar energy are striking. Global installations of solar photo-voltaic (PV) technology, which converts sunlight directly to electricity, increased from 26 mega-watts (MW) direct current (dc) in 2000 to an estimated 21,000 MW in 2011. This rapid increase in installations has been driven by steep declines in cost and by policies favoring renewable energy. In the United States, the capacity-weighted average installed costs of the technology fell by an estimated 17% between 2009 and 2010 (Barbose et al. 2012). Policy interventions also continue apace, with property tax assessment programs and clean energy standards recently joining feed-in tariffs, renewable portfolio standards (RPS), and carbon pricing.

Despite these recent increases in solar resource deployment and industry prominence, solar energy still contributes a very small share of total electricity generation. In fact, it provides less than half a percent of the United States' electricity. The relatively high cost of solar technology has been a major impediment to further market penetration. The recent decline in installation costs not-withstanding, standard measures of the costs of solar energy production still exceed the costs of more conventional generation by a significant margin. However, these standard measures fail to account for important public benefits such as reductions in greenhouse gas (GhG) emissions.

Economic analyses of solar PV must take into account several features that distinguish solar PV from more conventional thermal generation. First, the fuel (sunlight) is free. Consequently, vari-able costs associated with solar power generation are close to zero. Second, increasing the level of grid-connected solar capacity typically displaces fossil fuel generation and thereby reduces op-erating costs, GhG emissions, and other pollutants as well. The marginal economic and envi-ronmental benefits associated with additional solar thus depend on the operating characteristics and emission intensities of the units displaced on either the operating or the build margin. Third, solar electricity generation is nondispatchable: It cannot be turned on and off when needed but works precisely when the sun is shining. Nondispatchability engenders two issues: Solar generation is variable, with predictable changes over diurnal and seasonal cycles, and intermittent, with un-predictable changes due to cloud cover. Given nondispatchability, the variability can be advantageous insofar as solar resources are most productive during high-demand hours when energy's value is greatest. However, intermittency of a solar resource can add to system costs, as additional system reserves and backup generation may be required to maintain system reliability.

The value of a solar resource and the methods used to assess it depend on the time horizon over which benefits are realized and measured. This article assesses the market and nonmarket values of solar power across a range of timescales.[1] At one extreme, short-run analyses examine incremental increases in solar capacity within the existing electricity system. Both the cost of installing solar technology and the set of generators available to the grid are taken as given. The benefits are the operating costs and emissions avoided by displacing conventional generation.

Medium-run analyses typically feature nonincremental increases in solar penetration and al-low for more flexibility or malleability in the larger power system. The increased penetration of

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[1]We focus on public benefits and costs in our analysis, as opposed to private benefits and costs, which may include transfers from other agents and/or involve externalities on others. Thus, we ignore subsidies offered by government agencies when calculating economic value, as these represent a transfer of public funds to private entities. Borenstein (2012) points out that this distinction between public and private benefits/costs for renewable energy may be quite important because different types of economic actors (e.g., residential homeowners, city council members, federal agency policy makers) may have very different perspectives on benefits and costs. In a similar vein, we also ignore any impacts on green job creation. Policies promoting the manufacturing and deployment of new solar resources may generate new employment opportunities, and employment effects may be substantial in some geographic areas. However, public and private investments in solar power are likely offset by reduced spending on other economic activities, and the net impact of investments in solar on national employment is likely to be small.

solar has two competing impacts on costs. On the one hand, the cost of installing solar PV may fall with cumulative installations. On the other hand, the costs associated with intermittency may increase with higher penetration, although they can be attenuated when system operators alter system infrastructure, demand-side management programs, and the operating capabilities of conventional generation to better accommodate higher levels of solar penetration.

At the other extreme timescale, large-scale integrated assessment models (IAMs) consider the evolution of the global energy system over the next century and its interaction with climate goals. Over this long timescale, the electric grid passes through several generations of infrastructure. Furthermore, solar technology itself can evolve due to purposeful research and development (R&D) efforts. Although installation costs make it difficult for solar to compete with more conventional generation sources in the short run, this need not be the case in the long run. In multidecadal IAMs, solar's long-term role is determined primarily by the strength of climate policy and by the ability to integrate additional solar capacity into the grid once it has already reached high levels of penetration.

In principle, analyses conducted at different timescales should be viewed as complements. Short-run analyses are useful for evaluating the impacts of existing subsidies and incremental installation decisions. Medium-run analyses can inform grid planning and nonincremental policies such as an RPS. Long-run analyses consider the ultimate costs of climate targets and how to lower those costs by scaling policy interventions over time. By surveying the core analytics and estimates associated with analysis conducted over different time horizons, we aim to connect and integrate a fairly disjoint literature on the economics of solar power.

We begin by briefly introducing solar electricity–generating technologies and the challenge posed by intermittency. Section 3 covers the core analytics of short-run costs and benefits, with an emphasis on incremental increases in solar power production. The medium-run perspective in Section 4 considers the benefits from learning by doing (LBD) and the costs of grid integration. Section 5 examines solar's implementation in long-run IAMs, highlighting their treatment of solar's intermittency and their representations of technological change. Section 6 concludes with opportunities to progress by linking timescales.

2. SOLAR PHOTOVOLTAICS: TECHNOLOGICAL ALTERNATIVES AND DEFINING CHARACTERISTICS

Whereas most energy sources can be traced back to the energy of the sun, PVs are unique in that they directly convert the energy of the sun into electricity. The photons in sunlight can free an electron from its bonds and cause it to conduct electricity. Whereas other energy sources use photosynthesis (biofuels and fossil fuels) or convective heating (wind) as a middleman between solar energy and power production, solar PV eliminates the middleman by directly generating electricity from sunlight. The apparent efficiency of directly generating electricity is a conceptually appealing aspect of solar PV. In reality, however, it has proven difficult to find cost-effective ways to exploit this potential.

In this section, we first discuss some challenges to cost-effective grid integration of solar resources. We then provide an overview of commercially viable PV technologies.

2.1. Variability and Intermittency

One challenge to the widespread adoption of solar PV is the difficulty of integrating large quantities of solar generation into the electric grid. This difficulty arises because, as discussed above, the solar resource is both variable, exhibiting daily and seasonal patterns that are largely predictable, and intermittent, exhibiting short-term variation that is largely unpredictable. This variability and intermittency of the solar resource directly translate into solar generation because PV is

nondispatchable: Its output is driven by solar insolation and cannot be intentionally adjusted up or down. Diurnal variation and seasonal variation in solar generation require a system operator to have energy storage resources and/or to maintain other sources of generation for use during periods when solar output is low. The intermittency of solar PV generation requires a system operator to hold dispatchable generation in reserve to either fill in unanticipated drops in solar PV output or reduce output when solar PV output is unexpectedly high. Whereas the key technological challenges in the cost of solar relate to materials and PV efficiency, the key technological challenges in grid integration relate to improvements in storage and grid controls.

Several studies assess the intermittency of solar PV generation. A common metric is the delta: the change in the insolation index from one time interval to the next, measured as a fraction of maximum sunlight. Using solar insolation data from 23 instrument sites in Kansas and Oklahoma, Mills & Wiser (2010) observe that deltas greater than ± 0.6 occur for timescales ranging from one minute to one hour. The standard deviation of deltas grows slightly as the length of the interval increases. Using actual generation data from a 5 MW solar PV installation in Arizona, Hansen (2007) finds similarly high levels of intermittency.

Because the electric grid matches aggregate generation to aggregate load, intermittency presents less of a problem as PV sites become more geographically dispersed. Mills & Wiser (2010) find that the correlation between deltas for pairs of sites decreases in the distance between sites and increases in the length of the timescale. The correlations between deltas are nearly zero for one-minute and five-minute timescales for all site pairs. Furthermore, the standard deviation of deltas for insolation data aggregated from multiple sites is much less than that for a single site. Similarly, the model in Hoff & Perez (2010) predicts that the standard deviation of deltas would decrease by a factor of 20 if a 5 MW installation were instead spread among 1,000 5 kW sites.

The ability to forecast generation has emerged as a significant issue for grid integration of wind resources (e.g., GE Energy 2008). This is also true of solar. Less work has been done on solar forecasting than on wind forecasting, but an emerging literature should be useful for managing system operations as solar penetration increases (e.g., Lorenz et al. 2011, Marquez & Coimbra 2011, Mathiesen & Kleissl 2011, Perez et al. 2010). For longer intervals such as 30 min, changes in solar PV output from one interval to the next would have fairly minor effects on grid operations if the changes could be accurately forecast several hours in advance: Generators would simply be dispatched with output rates set to compensate for the forecast changes in solar PV output. However, even perfectly forecasted changes in solar PV output for very short timescales would require setting some units aside so that their output rate could be adjusted quickly up or down to compensate for rapid PV output changes. Finally, if the standard deviation of solar PV forecast errors from one interval to the next is large, then a system operator may need to hold large amounts of capacity in reserve. We further discuss this challenge in Section 4.1.2.

Energy storage is often proposed as the solution to solar's variability and intermittency. Storage could smooth out intermittent generation and permit shifting of energy to periods with high demand but low insolation. Research and experimentation are under way for large-scale energy storage technologies such as fly-wheel systems, compressed air energy storage, pumped hydro, and various advanced battery technologies.[2] Pumped hydro storage is the most widely used technology, accounting for 4.3% and 2.1% of total generating capacity in the European Union and United States, respectively (Deane et al. 2010). Most existing pumped hydro facilities were constructed to shift low-cost, off-peak energy from coal or nuclear plants to peak periods. A number of utilities in the United States are exploring how existing and planned pumped hydro facilities could be used to manage

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[2]Dunn et al. (2011) review the potential for several battery technologies to provide large-scale energy storage for the grid.

renewables' variability and intermittency.[3] Yet energy storage systems are currently quite costly, and there is relatively little practical experience with using large-scale storage to manage renewable sources' variability and intermittency.[4] We therefore do not consider storage when reviewing the economics of solar PV in the short to medium term (Sections 3 and 4). Instead, we examine ways in which a system operator can address intermittency via scheduling dispatchable generators and demand-side management. In Section 5, we discuss the role that energy storage plays in conjunction with renewable penetration in IAMs of long-run economic growth and climate change.

2.2. Technology Overview

Commercially viable PV technologies fall into one of three categories: thick-film silicon, thin-film, and third-generation technologies. The following discussion of these technologies emphasizes cost comparisons. The cost of a PV system is made up of two parts: the module cost and the balance-of-system (BOS) cost. BOS costs typically include inverters, mounting hardware, and labor, but they may also be broadly defined to include permitting and fees, shipping, overhead, and installer profit. For residential and commercial PV, BOS costs have historically accounted for approximately 50% of the total installed cost. With the recent drop in the cost of modules, BOS costs are now approaching two-thirds of system costs. When PV technologies are compared, costs are often presented in $/$W_p$, or the cost per watt peak of dc power of a module or installed system. This number accounts for both the cost of manufacturing the module and the efficiency of the solar cell.

2.2.1. Thick-film crystalline silicon technologies. Until recently, solar PV was dominated by the most mature module technology: thick-film silicon. These modules use mono- or polycrystalline silicon. Crystalline silicon has a low absorption coefficient, which measures how well a material absorbs a given wavelength. This type of module therefore needs to be relatively thick (at least 100 μm thick) to absorb a sufficient part of the solar spectrum.

Thick-film PV technology is relatively inexpensive and reliable compared with other PV technologies. In the late 1990s, module costs averaged approximately $4.8/$W_p$ (Barbose et al. 2011). In recent years, these costs have fallen precipitously: Barbose et al. (2012) estimate that modules cost $2.4/$W_p$ in 2010. Much of this drop occurred between 2008 and 2010, and this trend continued through 2011.[5] Recent drops in module costs were accompanied by decreasing BOS costs that were estimated to be $3.8/$W_p$ in 2010. These figures are for typical residential rooftop systems. There are significant economies of scale in solar PV installations. Barbose et al. (2012) report that large commercial rooftop systems (greater than 1 MW) cost 42% less than residential rooftop systems on average, and utility-scale systems cost even less.

2.2.2. Thin-film technologies. In principle, thin-film technologies have cost advantages over thick-film technologies because thin films require fewer materials and can potentially be produced by using innovative, relatively low cost techniques such as screen printing. In practice, however, there are critical technical issues related to module efficiency, manufacturing scale-up, yield, throughput, and reliability (Surek 2003). As of 2007, thin films had captured approximately 6.5%

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[3]Sioshansi et al. (2012) note that the majority of recent preliminary permits for new pumped hydro facilities issued by the Federal Energy Regulatory Commission are for western US states with high RPS.

[4]In addition to barriers to storage deployment such as cost and lack of system efficiency, Deane et al. (2010) describe other barriers due to regulatory treatment of storage investments and incomplete markets for services provided by storage systems.

[5]Processing silicon wafers requires technology from the semiconductor industry (Halme 2002). The process constitutes approximately 50% of the total direct module manufacturing cost (Goetzberger & Hebling 2000). The cost of silicon wafers has been an important driver of cost reductions over the period 1975–2001 (Nemet 2006).

of the PV market. Their share peaked in 2009 at 18% before falling to approximately 10–11% by 2011.[6] Until the recent run-up, one technology, amorphous silicon, had made up 64% of the thin-film market, mostly in consumer electronic devices such as calculators (van Sarka et al. 2007). However, its low efficiency and light-induced degradation have prevented further penetration. Other thin-film technologies (particularly cadmium telluride and copper indium gallium selenide) have potential for higher efficiencies but have problems related to scarcity and toxicity of materials. Semiorganic and purely organic cells are also promising but have issues with stability in an outdoor environment and with their realized energy conversion efficiency (Green et al. 2001).

2.2.3. Third-generation technologies. In contrast to thin-film technologies, so-called third-generation technologies have very high efficiencies but are very expensive to manufacture. These technologies are qualitatively different from thick- and thin-film technologies. For example, quantum dots consist of tiny crystals of semiconductors just a few nanometers thick, and multijunction cells optimize layers of materials for the full spectrum of light. Both concepts can theoretically generate higher efficiencies due to their ability to produce multiple excitons for each photon received.

These technologies still face technical challenges. For example, the laboratory efficiency of quantum dots is approximately 2%, whereas the theoretical maximum is 42%. Manufacturing costs could also be a challenge, as quantum dots, for example, require unusually precise placement of the semiconductor crystals.

2.2.4. Concentrating solar power. A technology that is commonly compared with PV is concentrating solar power (CSP). CSP uses sunlight to heat up a liquid, which is then used to turn a turbine that generates electricity. The thermal mass of the working fluid reduces the intermittency of generation and can even smooth its diurnal profile. We generally do not discuss CSP in this review, but in Section 5 we describe how it competes with PV in long-run models.

2.2.5. Technological change in solar cells. There is great potential for improvements in solar PV. The two primary avenues for reducing cells' cost are reducing manufacturing costs and increasing cells' conversion efficiency. For organic solar cells, a third challenge is to increase their lifetime. The cost of manufacturing the cells can be reduced through lower material costs and through improved production techniques. Efficiency and lifetime are important not just for the cost of a given cell but also because higher efficiencies reduce land requirements and longer lifetimes reduce the frequency of replacement. We discuss avenues for technological change in more detail in Sections 4.2 and 5.1.2.

3. THE SHORT RUN: INCREMENTAL CHANGES TO THE EXISTING GRID

In this section, we consider the costs and benefits that accrue in the short run from an incremental increase in PV capacity. The defining feature of the short run is that all costs and benefits are evaluated conditional on the existing state of the technology and the power system to which the solar technology is connected. In other words, the costs of solar technologies, the operating characteristics of incumbent generators, and the infrastructure of the electric power system are taken as given.

This discussion begins by reviewing standard approaches to measuring short-run costs. We then introduce a conceptual framework for valuing the short-run benefits of solar capacity. To make this discussion more concrete, we use the framework to estimate the short-run net benefits of

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[6]See Shiao (2012).

incremental PV capacity additions at four sites across the country. This exercise is intended to illustrate how regional and temporal variation in the solar resource interacts with preexisting power system operating characteristics to determine the short-run value of incremental increases in PV penetration.

3.1. Short-Run Costs

The levelized cost of electricity (LCOE) generation is a common benchmarking tool used to compare costs across different energy technologies. Conceptually, it measures the constant (in real terms) price per unit of electricity generated that would equate the net present value of revenue from the plant's output with the net present value of the cost of production:

$$\text{LCOE} = \frac{\sum_{t=0}^{L} \dfrac{C_t}{(1+i)^t}}{\sum_{t=1}^{L} \dfrac{E_t}{(1+i)^t}}. \tag{1}$$

The numerator in Equation 1 measures the net present value of the costs incurred to construct and operate the generation technology. The life span of the technology is L. The discount rate is i. C_t captures the installation and operating costs incurred in time period t. These costs are dominated by the up-front module installation and BOS costs incurred in $t = 0$. Ongoing operation and maintenance (O&M) costs (including the costs of periodically replacing the inverter) are also incurred over the life of the project.

As noted above, the intermittent nature of solar generation has potentially significant implications for the economic value of a solar resource. For small changes in PV penetration, however, the intermittency of the solar resource does not impose significant costs. Our discussion of short-run cost considerations therefore focuses exclusively on module and BOS costs.

Energy output in period t is E_t. The quantity of electrical energy produced by a grid-connected PV panel in a given hour depends on a host of factors, including latitude, weather and cloud cover, the time of year, the installed capacity of the system (measured in power), and the orientation and tilt of the panels. Section 3.3 includes a detailed discussion of how site-specific solar energy production potential can be estimated or forecast.

Table 1 summarizes module costs for commercial and near-commercial PV technologies. We present high and low module costs for each technology, along with an estimated lifetime. Several low values come from recent news reports. The high values come from older, peer-reviewed papers. We include both because there is some question about whether the current low prices reflect fundamentals or whether they reflect a glut in the market and possible dumping. We provide the LCOE of the module by itself and that of the module with BOS costs. The BOS costs are derived from Goodrich et al. (2012). These costs are adjusted to reflect the fact that lower efficiencies require panels to cover a greater area to provide a given quantity of power, which leads to higher BOS costs. The low values for the BOS costs are based on utility-scale installations; the high values are based on residential installations. We show the LCOE under two assumptions about interest rates: 3% to represent the social costs of investment and 15% to represent the costs to investors. For this simple calculation, we ignore O&M costs. To estimate energy output, we assume a capacity factor of 18.3% (Nemet & Baker 2009). In Section 3.3, we use a more sophisticated approach to estimate energy generated by a thick-film silicon technology.

The LCOE estimates reported in **Table 1** are often compared with those of conventional generating sources. For example, LCOE estimates for natural gas or coal-fired generation are typically in the range of $0.07–$0.09 per kilowatt hour (kWh) (EIA 2010), whereas the lowest estimate in **Table 1** is only $0.10/kWh. However, comparisons based on LCOE alone are

Table 1 Module costs for commercial and near-commercial photovoltaic technologies

Technology	Module cost ($/W$_p$)	Lifetime (years)	LCOE module ($/kWh)		Efficiency[j] (used for BOS estimate)	BOS[k] ($/W)	LCOE total ($/kWh)	
			$i = 3\%$	$i = 15\%$			$i = 3\%$	$i = 15\%$
Thick-film silicon: low	0.70[a]	30[g]	0.02	0.07	14.5%	2.32	0.10	0.29
Thick-film silicon: high	1.78[b]	30	0.06	0.17	14.5%	3.25	0.16	0.48
Thin-film inorganic: low	0.76[c]	20[h]	0.03	0.08	14.0%	2.40	0.13	0.31
Thin-film inorganic: high	1.65[d]	20	0.07	0.16	6.0%	7.87	0.40	0.95
Thin-film organic: low	0.75[e]	5[i]	0.10	0.14	11.0%	3.06	0.52	0.71
Thin-film organic: high	3.22[f]	5	0.44	0.60	5.0%	9.44	1.72	2.36

[a]From Green Tech Media (2012); [b]from Little & Nowlan (1997); [c]from Osborne (2010); [d]from Zweibel (1999); [e]from Smestad (1994); [f]from Meyer (1996); [g]from Branker et al. (2011); [h]typical warranty period; [i]from Kalowekamo & Baker (2009); [j]from DOE (2012); [k]calculated on the basis of values in Goodrich et al. (2012) (low values were based on utility, and high values were based on residential).

problematic because the economic value of a unit of energy depends on the conditions of the power market at the time the energy is generated (Joskow 2011). The value of energy can vary by orders of magnitude across hours. In what follows, we demonstrate the importance of accounting for differences in value depending on when energy is generated.

3.2. Short-Run Benefits: Displaced Generation and Emissions

The short-run benefits associated with incremental increases in PV capacity manifest indirectly as reductions in the operating costs and emissions of the marginal, dispatchable generating units on the system.[7] To frame our discussion of these benefits, we modify and extend a model developed by Lamont (2008). **Table 2** introduces notation and defines the main components of the framework.

The short-run value (or benefit) per year of installed solar capacity K is defined to be the system operating costs and emission costs that would manifest if there were no installed solar capacity on the system less the system operating costs and emission cost given solar capacity K:

$$V(K) = \sum_{b=1}^{H}\big[C(y_b) + \tau EM(y_b)\big] - \sum_{b=1}^{H}\big[C(y_b - s_b K) + \tau EM(y_b - s_b K)\big]. \qquad (2)$$

Because the variable operating costs of solar generation are very low, it is standard to assume that a grid-connected solar-generating unit will be dispatched to the full capacity available in any

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[7]In this short-run analysis, we do not explicitly account for any reductions in the need to build additional generation capacity in the future. By focusing on the operating margin, rather than on the build margin, we implicitly assume that the power system is in long-run equilibrium.

Table 2 Components of short-run analysis

h	Indexes hours over a year time horizon: $h = 1, \ldots, H$
y_h	Load in hour h
s_h	Solar output in hour h per unit of capacity (production factor)
K	Total installed solar generation capacity
CF	Capacity factor, equal to average solar output per unit of capacity
$y_h - s_h K$	Net load in hour h
τ	Monetized damages per ton of CO_2 equivalent (CO_2e)
$C(x)$	Operating costs of dispatchable generation given output x
$\lambda = C'(x)$	Marginal cost of dispatchable generation given output x
$EM(x)$	Emissions released given dispatchable generation at level x
$\phi = EM'(x)$	Marginal operating emission rate given dispatchable generation at level x

given hour ($s_h K$). Subtracting this hourly solar generation from the corresponding hourly load yields a measure of net load.[8] Equation 2 implicitly assumes that an incremental increase in solar production will decrease electricity production at dispatchable units by an equal increment.[9] We assume that solar's productivity s_h is independent of K. This assumption is likely to hold for small changes in K.[10]

Variable operating costs $C(x)$ capture the fuel and operations costs incurred by dispatchable generating units. Social costs include not just the private costs in $C(x)$ but also the external costs of emissions. These are the product of the marginal damage τ from emissions and total emissions $EM(x)$. In this short-run formulation, both operating costs and emissions vary with the level of output x, but the operating characteristics of the dispatchable generators are fixed.

Differentiating Equation 2, we obtain an intuitive expression for the short-run marginal value of solar capacity:

$$V'(K) = \sum_{h=1}^{H} (s_h \lambda_h + \tau s_h \phi_h) \tag{3a}$$

$$= H\left(\overline{\lambda} CF + \text{Cov}(\lambda, s)\right) \tag{3b}$$

$$+ H\tau\left(\overline{\phi} CF + \text{Cov}(\phi, s)\right), \tag{3c}$$

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[8]In systems supplied by hydro and/or wind, the y variable should be reinterpreted as load minus wind and hydro. Similarly, net load should be interpreted as load net of solar, wind, and hydro.

[9]This assumption simplifies the exposition but, as we discuss below, ignores differences in transmission and distribution line losses.

[10]Large increases in K may affect s_h in at least two ways. First, as solar is installed at progressively lower quality sites, the average value of s_h may fall. Second, due to weak correlation of PV output across sites, the overall variance of s_h will fall as penetration increases (Mills & Wiser 2010).

where $\overline{\lambda}$ and $\overline{\phi}$ refer to averages over all hours and $\text{Cov}(\cdot,\cdot)$ is the population covariance. Solar's capacity factor CF is the average value of s_h over all hours. The key thing to note is that it is not enough to consider only the mean values: Because solar energy covaries with demand, it is crucial to consider covariance as well. Subequation 3b captures the short-run economic value of the electricity generated by an incremental unit of solar capacity. As a point of departure, we interpret λ to measure the marginal cost of electricity produced by dispatchable generators on the system. In the power systems engineering literature, the system lambda parameter is derived from an economic least-cost dispatch model and represents the cost of the last kilowatt produced by dispatchable units over a particular hour (excluding transmission losses).

If solar output s is uncorrelated with λ, the expected value of avoided fuel costs in any given hour is simply the average system lambda (averaged across hours) multiplied by the solar capacity factor. However, solar power is generally available during the times of day when the marginal cost of supplying load is high. As we show below, this positive correlation can significantly influence the marginal economic value of PV resources.[11]

Subequation 3c captures the monetized value of the emissions offset by solar electricity generation. The change in system-wide emissions that is associated with an incremental change in net load is summarized by the marginal operating emission rate (MOER) ϕ. The quantity of emissions released per unit of electricity generated varies significantly across dispatchable units according to fuel type (e.g., nuclear versus coal fired), plant vintage, and plant efficiency. In systems in which base load generating units are more emission intensive than marginal generators in peak hours, the covariance term in Subequation 3c is negative.

3.3. Short-Run Costs and Benefits of a Solar Resource: Application

A simple application of the valuation framework introduced above illustrates how temporal and spatial variations in solar resource potential, marginal economic costs, and marginal emission profiles play a role in determining the short-run benefits of incremental increases in PV penetration. We estimate the market and nonmarket values of the electricity generated by a single grid-connected 5 kW (dc) fixed PV array.[12] We compare these benefits with the costs of installing and maintaining a state-of-the-art system. We consider four sites spread across the country: Boston, Massachusetts; San Francisco, California; Trenton, New Jersey; and Tucson, Arizona.

3.3.1. Measuring site-specific energy production potential.
As a first step, we characterize the solar resource potential at our four sites. The most straightforward approach to measuring solar power potential involves metering actual electricity production at a PV panel installed at the sites of interest (see, for example, Gowrisankaran et al. 2013). However, these data are available for a very limited number of sites. In the analysis summarized below, we use an alternative, simulation-based approach.

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[11]For example, using data on solar PV production and wholesale electricity prices in California, Borenstein (2008) finds that the favorable timing of solar PV generation increases its economic value by 0–20% relative to a valuation based on a flat, average cost of electricity generation.

[12]The median size of residential PV systems installed in the United States in 2011 is 5 kW.

The National Renewable Energy Laboratory (NREL) has developed a simulation tool (PVWATTS v. 2) that uses typical meteorological year weather data (TMY2), together with a PV performance model, to simulate hour-by-hour, site-specific energy production over a typical year for thousands of sites. We simulate the performance of a 5 kW (dc) fixed PV array, assuming that the tilt angle is set equal to the latitude of the location (this normally maximizes annual energy production).[13] We simulate production by assuming both a south-facing configuration and a west-facing configuration.[14]

The first to third rows in **Table 3** report simulated ac electricity generation summed over the course of a typical year at each site. **Figure 1** plots simulated electricity generation by hour averaged across summer hours (May to September). Of the four sites, the installation in Tucson has the greatest electricity-generating potential over the course of the year. However, in the summer months between the hours of 11 A.M. and 4 P.M., the San Francisco site has the highest average hourly output (when demand and prices are high). This is likely due to the relatively moderate summer temperatures in San Francisco.[15]

3.3.2. Measuring site-specific costs.
The primary cost consideration in this short-run analysis is the up-front installation cost. To estimate site-specific system costs, we use the median reported price (measured in 2011 $/W) of customer-owned systems with capacity below 10 kW installed in 2011 (Barbose et al. 2012). These costs are reported in the first row of **Table 3**. We assume that the inverter is replaced every 10 years (Navigant Consulting 2006). We assume a current inverter cost of $3,000 (Barbose et al. 2012). Following Borenstein (2008), we further assume that these costs decline at 2% annually in real terms.

We assume a project life of 30 years (Branker et al. 2011). To account for the fact that energy output tends to decline over time as panels degrade, we assume a degradation rate of 0.5% per year (Skoczek et al. 2008). Finally, we assume a real discount rate of 3%. This rate is appropriate for public policy analysis but is lower than the rates that private buyers or investors would face.

The third row of **Table 3** reports the LCOE for each site (measured in $/kWh). We observe substantial variation in LCOE, both across sites and within sites across panel orientations. Because the installed cost per watt is quite similar across locations, the lowest LCOE estimates are associated with the highest energy production potential.

3.3.3. Measuring the short-run economic value of solar energy production.
Having constructed site-specific cost estimates, we are interested in assessing whether the short-run benefits justify these costs. An important component of these benefits is the economic costs avoided when marginal units reduce production in hours with solar electricity generation. Our approach to measuring short-run marginal economic costs varies with the structure of the electricity market in which the solar resource is located.

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[13]This is a standard system design assumption. Increasing (decreasing) the tilt angle favors energy production in the winter (summer). So setting the tilt angle equal to latitude will not necessarily maximize the economic value in systems in which prices are systematically higher in the summer or winter.

[14]We assume a standard dc-to-ac derate factor of 0.77. Borenstein (2008) notes that production from west-facing panels can be better synchronized with system load (potentially increasing economic value on average).

[15]High temperatures decrease PV module efficiency.

Table 3 Short-run analysis of solar photovoltaics at four sites

Location	Boston, MA		Trenton, NJ		Tucson, AZ		San Francisco, CA	
Panel orientation	South	West	South	West	South	West	South	West
Cost per W_p	$6.10		$5.90		$5.20		$6.40	
ac energy per year (kWh)	6,219	4,479	6,030	4,560	8,314	6,529	7,220	5,839
Levelized cost ($/kWh)	$0.290	$0.400	$0.290	$0.390	$0.190	$0.240	$0.260	$0.320
Average λ ($/kWh)	$0.068		$0.055		$0.061		$0.051	
Weighted average λ ($/kWh)	$0.076	$0.078	$0.074	$0.077	$0.063	$0.061	$0.055	$0.055
Percent increase in economic value	13%	15%	21%	24%	3%	7%	10%	12%
Average ϕ (lb CO_2/kWh)	1.21		1.70		1.26		1.09	
Emission displacement rate (lb CO_2/kWh)	1.24	1.25	1.65	1.64	1.18	1.19	1.11	1.12
Percent increase in emissions displaced	3%	3%	−3%	−4%	−1%	−3%	3%	2%
Net cost	$0.20	$0.31	$0.20	$0.30	$0.12	$0.17	$0.19	$0.25
Break-even cost per W_p (social cost of carbon = $21/tCO_2$)	$1.45	$0.92	$1.44	$1.00	$1.72	$1.18	$1.19	$0.85

In regions of the country where the electricity sector has not been subject to wholesale market restructuring, local control areas compute and report hourly system lambdas that can be used to value electricity produced by a solar resource.[16] These lambda parameters are derived from the economic dispatch that minimizes the operating cost of meeting system load. They represent the shadow value of the constraint that supply equal demand. Our Tucson site is the only one in a region subject to traditional regulation. We use the system lambdas reported by Tucson Electric Power over the period 2004–2007 to value the electricity production potential.

In restructured wholesale electricity markets, control areas do not report system lambdas. Instead, real-time locational marginal prices (LMPs) can be used to value the electricity generated by a renewable resource supplying a restructured electricity market. These prices reflect the marginal cost of supplying (at least cost) the next increment of electricity to a particular location given the supply and demand bids submitted by market participants and the physical constraints on the system. We collect LMPs over a four-year period (2004–2007) from the California, New England, and PJM electricity markets that correspond to the San Francisco, Boston, and New Jersey sites, respectively.

Figure 1 illustrates the positive correlation between solar power production and the marginal economic cost of electricity production. The figure also demonstrates how orienting solar panels west versus south reduces total electricity production but strengthens the correlation between electricity production and the marginal economic value.

The fourth through sixth rows of **Table 3** report both the average marginal economic value (averaged across all hours over the period 2004–2007) and a weighted average value (weighted by PV production potential). Intuitively, accounting for the temporal coincidence between solar resource

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[16]These parameters are computed by local control areas where demand following is performed primarily by thermal dispatch and reported to the Federal Energy Regulatory Commission (FERC).
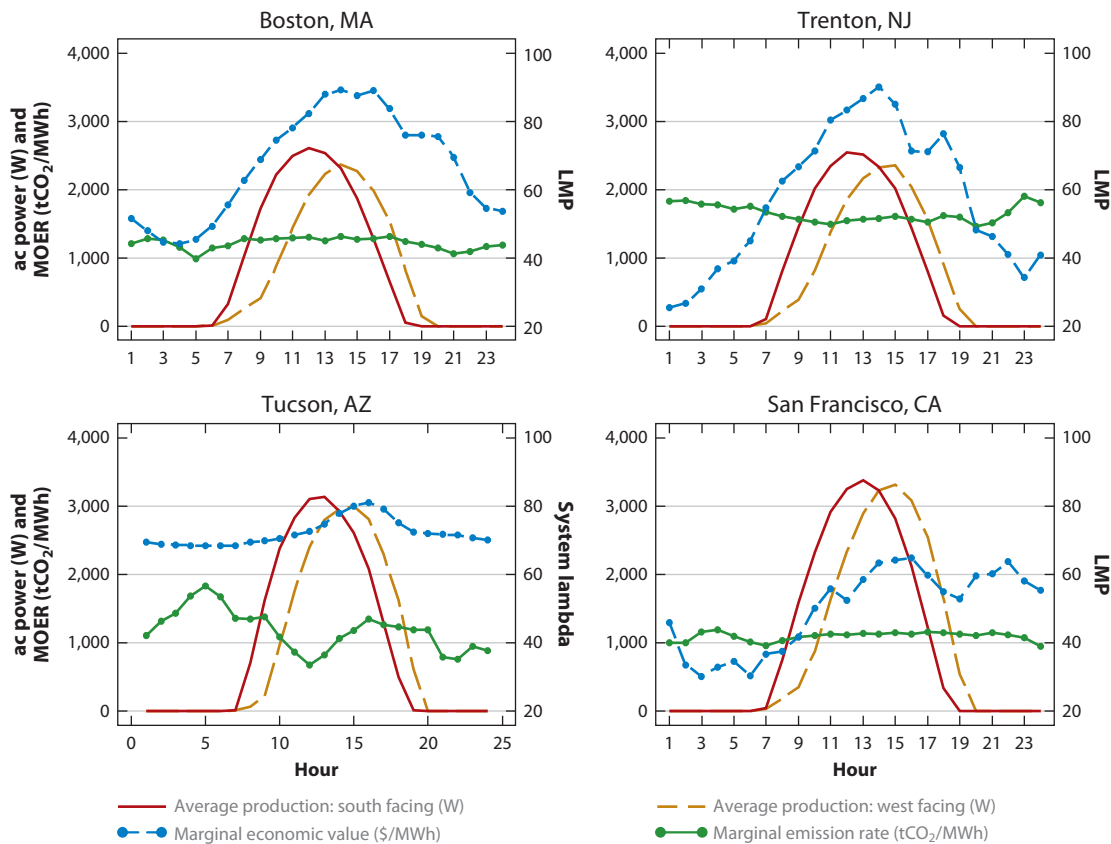
Figure 1

Daily profiles for simulated electricity generation, emission displacement, and economic value at the four sites shown. The red lines denote the south-facing arrays, and the yellow lines denote the west-facing arrays. Locational marginal prices (LMPs) (or system lambda in the case of Arizona) are measured on the right vertical axis. The blue lines plot these marginal economic values (averaged across hours in May–September) by hour. The green lines plot these region-specific MOER (marginal operating emission rate) point estimates (corresponding to summer hours in 2004–2007).

availability and marginal economic value increases the net present value of the electricity generated by solar PV. To highlight this point, we calculate the net present value using both the average marginal economic value and the hour-specific values. Across all sites and panel orientations, accounting for the temporal correlation between resource potential and our measure of marginal economic value increases the annual value estimate.[17] The stronger the positive correlation between regional load profiles and solar resource profiles, the larger is this percentage increase (see **Table 3**).

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[17]All the systems we consider are summer peaking. Hours of high demand (and high prices) are therefore associated with above-average solar PV production. Because the PV production data are simulated and derived separately from the LMP/system lambda data, the positive correlation between solar output and our hourly measures of marginal economic value generally underestimates the true correlation. However, Borenstein (2008) finds that the bias introduced by a failure to account for the unobserved correlation is likely small.

In **Table 3**, we observe variation in marginal economic values across sites. Interpreting this variation is complicated by several factors.

First, the system lambda reported to the Federal Energy Regulatory Commission (FERC) by local control areas and the LMP prices determined in restructured electricity markets are not directly comparable. Whereas hourly system lambdas capture variable electricity production costs (i.e., fuel and variable O&M), LMP prices are composed of an energy cost component, a transmission congestion component, and a marginal line loss component. Thus, in some sense, the LMP is a preferable measure of the value of solar power generation in a particular location because it captures not only the energy component, but also the marginal value of reduced congestion and line losses.

In contrast, because bids to supply are affected not only by fuel and operating costs, but also by the market structure and associated incentives that govern the bidding behavior of the market, the energy cost component of an LMP need not equal the marginal operating costs of suppliers in the market. Differences we observe in average marginal economic value across markets are likely due in part to differences in market structure. Importantly, if there are distortions or imperfections in the market that drive a wedge between the marginal economic cost and the marginal bid, the LMP may be an imperfect measure of the economic value of solar power generation.[18]

3.3.4. Measuring the short-run environmental benefits of solar energy production.
Conceptually, the quantification of marginal emission impacts is very similar to that of the marginal economic impacts discussed above. To estimate the emissions displaced by a new PV installation, we need to identify the emission intensity of the marginal units displaced. However, whereas system lambda and LMPs provide a readily observable measure of the short-run marginal economic costs of electricity production, marginal emission rates pose more of a challenge.

Methods to quantify the impact of increasing renewables penetration on emissions have advanced in recent years (see, for example, Broekhoff 2007, Gil & Joos 2007). The simplest approach assumes that the system average emission rate (easily calculated by dividing total system emissions by total system generation) can be used to estimate the emission intensity of the marginal generator in all hours. However, this assumption is unlikely to hold in practice, particularly in regions where the emission rates of base load generation differ markedly from the emission profiles of marginal units. Several recent papers use plausibly exogenous variation in wind power production, together with rich hourly data tracking system demand and plant-level operations, to identify the effect of marginal increases in wind electricity generation on system-wide emissions (Cullen 2012, Kaffine et al. 2013, Novan 2012).[19]

Callaway et al. (2013) take a somewhat different approach. Focusing on those regions and markets in which demand following is performed primarily by thermal-generating units, they estimate hour-specific average effects of hour-to-hour changes in thermal generation on hour-to-hour changes in system-wide emissions (controlling for hour-of-day-by-season fixed effects). Conditional on the assumptions that the marginal units in any given hour are thermal units, and that incremental increases in intermittent renewable electricity generation will have the same impact on system operations (and emissions) as observable fluctuations in fossil generation, these

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[18]For example, if a price cap binds in high-demand hours, the LMP will underestimate the true value. If the electricity market is imperfectly competitive, the LMP will overestimate the true value in hours during which prices reflect the exercise of market power.

[19]Much of this analysis focuses on Texas, where relatively high levels of wind penetration generate the variation required to clearly identify the impact of wind generation on emissions. These studies document significant variation in emission displacement across hours of the day.

MOER estimates can be used to estimate the emissions displaced by an incremental increase in renewable resource capacity.

In our illustrative exercise, we focus exclusively on GhG emission impacts. Fossil fuel combustion also emits harmful local and regional pollutants. However, those pollutants that cause the largest damages are subject to emission trading programs during the time period we consider.[20] If we assume that the prevailing permit prices adequately capture marginal damages from emissions, then the social cost of the damages caused by emissions at marginal plants should already be reflected in our measures of marginal economic operating costs.[21] In contrast, damages from GhG emissions were not internalized over the time period we consider. We use the MOER estimates for carbon dioxide (CO_2) generated by Callaway et al. (2013) to capture these emission impacts. **Figure 1** plots these region-specific MOER point estimates (corresponding to summer hours in 2004–2007).

The seventh to ninth rows of **Table 3** report the average MOER by region and a weighted average (weighted by hourly solar electricity generation). Accounting for the temporal correlation between solar electricity generation and marginal emission displacement rates does not strongly affect estimates of total emission displacement. Because the emission intensity of marginal producers is highest in New Jersey, our estimate of emissions displaced per unit of electricity generated is highest for the installation in Trenton. In fact, the New Jersey installation displaces more emissions than does the Arizona installation, even though potential solar electricity generation is much higher in Arizona.

3.3.5. Regional variation in the short-run net benefits of solar energy production.
Ultimately, we are interested in integrating short-run cost and benefit estimates to evaluate the net returns to incremental investment in PV capacity. One approach to integrating emission displacement estimates into the larger valuation exercise involves assigning a dollar value to each ton of CO_2 (tCO_2) emissions avoided (i.e., the social cost of carbon). We assume a value of $21/t$CO_2$, which is the central value from Greenstone et al. (2011). The tenth and eleventh rows of **Table 3** subtract the weighted average marginal economic value (per kWh of electricity generated) and the monetized value of the emissions displaced (per kWh) from the corresponding levelized-cost estimate to come up with an estimate of net cost per kWh.

An alternative approach involves calculating the installation cost (measured in $/W$_p$) that equates the net present value of costs with the net present value of benefits. The last row of **Table 3** reports this break-even cost for a social cost of carbon of $21/t$CO_2$. **Figure 2** plots break-even costs for a range of social costs of carbon, including the range of $5–$65 per tCO_2 from Greenstone et al. (2011).

A striking result illustrated by both **Table 3** and **Figure 2** is that the PV installations located in the colder locations with relatively low solar resource potential (i.e., New Jersey and Massachusetts) are more cost effective than the installation in relatively sunny California. Specifically, the break-even cost per W$_p$ in San Francisco is below the break-even costs at the two installations in the northeast. The northeast's advantage is due to emission-intensive generating units on the margin, greater marginal economic operating costs, and the stronger correlation between solar resource profiles and marginal economic cost profiles.

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[20]Sulfur dioxide emissions are subject to a nationwide cap-and-trade program. Nitrogen oxide emissions are subject to regional emission trading programs in regions of the country where these emissions cause the most damage.

[21]The increase in PV capacity we consider would have no noticeable effect on equilibrium permit prices or on associated operating costs.
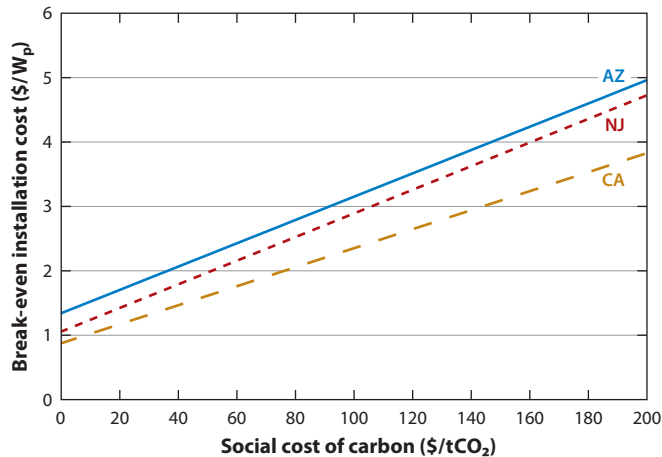
Figure 2

Break-even installation costs corresponding to each social cost of carbon. All calculations are for south-facing panels.

Figure 2 illustrates how, at current technology costs, solar electricity generation is cost effective only if we assume a very high social cost of carbon. At a value of $21 per tCO_2, PV installation costs would need to drop below $1.50/$W_p$ to be cost effective at the sites in New Jersey and Massachusetts. The most optimistic numbers from **Table 1** imply a total installed cost of approximately $3/$W_p$. At this cost, even our most promising installation (in Tucson) would become cost effective only if the social cost of carbon were at least $90 per tCO_2.

3.4. Summary: The Short Run

In sum, the economics of solar energy do not look very good in the short run. However, short-run valuation imposes several restrictions and assumptions. By focusing on the operating margin, we do not explicitly consider a capacity credit, or capacity value. This leads us to undervalue benefits at some sites.[22] However, this short-run analysis of an incremental increase in PV capacity ignores any costs associated with intermittency. Moreover, recent work shows how the marginal economic value of new PV generation can fall as the degree of penetration increases (Mills & Wiser 2012a). Medium-run analyses, the focus of the following section, are better equipped to consider the economics of nonincremental changes in PV penetration.

4. THE MEDIUM RUN: NONINCREMENTAL CHANGES IN CAPACITY AND INCREMENTAL CHANGES IN TECHNOLOGY

In the medium to longer term, much higher levels of solar penetration than those seen to date may occur. Over these longer time horizons, the structure of the power system can adjust to accommodate greater penetration by renewables. Moreover, increased adoption of solar technologies

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[22]Our approach to valuing economic benefits should implicitly capture capacity value in restructured energy-only markets such as Texas, but not in markets in which producers are compensated for capacity value outside the hourly wholesale market.

can reduce costs through learning effects in production or installation. We discuss the consequences of integrating nonincremental additions of solar capacity into the electric grid. We then discuss the impact of nonincremental changes in solar capacity on costs by surveying the empirical literature on learning effects.

4.1. Increasing Costs: Grid Integration

Electricity systems operate under a variety of constraints. Transmission lines have capacity constraints that limit movement of energy across the grid. Generators have minimum and maximum generation rates, ramping constraints that limit the rate at which output can be changed, and start-up costs that are incurred whenever a unit is turned on. There are also constraints on system operations imposed by reliability considerations. The system operator must match energy demand and supply in real time so as to maintain system frequency within narrow tolerances. This requires holding some generation in reserve so that energy supply can be adjusted up or down to offset variations in demand and supply.

The various operating constraints associated with existing transmission and generation can add significant costs to integrating large-scale solar. For example, Denholm & Margolis (2007) consider how large-scale deployment of PV would interact with the existing infrastructure in the Electric Reliability Council of Texas system. With solar generation at 20% of load, they find that operating constraints for base load generation units (mainly nuclear and coal) would cause substantial amounts of solar generation to be wasted, thereby increasing the net cost of usable solar energy.[23] However, over time, investments in generation and transmission can be made in response to demand changes and penetration of renewables. These investments have the potential to provide more flexibility in managing the grid for renewable generation.

4.1.1. Adjusting for solar's variability. Several studies examine how the amounts and types of conventional generation capacity should adjust for increasing solar penetration. Capacity planning for dispatchable generation technologies is often based on a screening curve methodology (Shaalan 2003, Stoft 2002). The amounts of each type of capacity (e.g., base load, midmerit, and peaking) are chosen to minimize total cost (including investment, operating, and maintenance costs) while meeting system load in each hour. In this type of optimization, system loads are typically characterized by a load duration curve that represents the cumulative distribution of hourly loads during the year.

One approach for examining how large-scale solar impacts the grid is to modify the standard screening curve methodology by treating intermittent renewable generation as negative load: The generation from a given amount of intermittent capacity is subtracted from load in each hour to obtain the residual (or net) load in each hour. The screening curve analysis may be applied to the load duration curve for residual loads to find optimal capacities for dispatchable technologies, given a fixed amount of intermittent capacity (Kelly & Weinberg 1993). This modified screening curve methodology can provide insight into the impact of large-scale solar penetration on the rest of the grid, but it is not directly informative about the value of solar power.

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[23]By contrast, Rothleder et al. (2011) estimate that less than 0.02% of total renewable generation would be wasted in California under a 20% RPS; generation from solar PV is projected to compose a fairly small fraction of renewable generation in California.

Lamont (2008) extends the standard screening curve method to consider cost-minimizing investment and production decisions for both dispatchable and intermittent renewable technologies. This approach allows him to characterize the marginal value of capacity for a renewable technology, given optimal capacity levels for all technologies. Lamont's expression for marginal value is essentially identical to Subequation 3b above. That is, the marginal value of renewable capacity is the product of its capacity factor times the average marginal cost of the dispatchable generation it displaces (average system lambda), plus a term reflecting the covariance of lambda and renewable generation.

In spite of the similarity of Lamont's (2008) marginal value term to Subequation 3b, there are important differences between short-term valuation and longer-term valuation. In Lamont's formulation, solar (and other renewables) can penetrate at a large scale, and the amounts and types of conventional generation capacities change in response to market incentives. Rather than taking the distribution of λs (or of wholesale spot prices) as given, as in a short-run analysis, Lamont recomputes the cost-minimizing conventional generation profile conditional on levels of renewable capacity. On the basis of this cost-minimizing solution, the new joint distribution of system lambdas and solar output can be derived and the marginal value of solar computed. Lamont's approach computes the marginal value of renewable capacity on the basis of long-run equilibrium levels of alternative types of generation capacity. By contrast, the marginal value of renewable capacity derived by using the short-run model we outline in Section 3 is based on displaced generation for the current state of the power system. The short-run derivation of marginal value captures the full marginal benefits of displaced generation if the current system is in long-run equilibrium, but not otherwise.

Lamont (2008) applies his methods to the 2001 California electric grid. As expected, the covariance term is negative for wind energy and positive for solar PV. The positive covariance of solar PV and λ raises the marginal value of solar by 20%; this estimate is at the high end of the range of short-term timing premia estimates for solar from Borenstein (2008).[24] As solar costs fall and solar penetration increases, the optimal mix of conventional generation shifts away from base load investment and generation and toward intermediate (e.g., combined-cycle natural gas) investment and generation; these impacts of increasing solar penetration are also what would be predicted by a screening curve analysis using net load. Solar PV capacity displaces a small percentage of dispatchable capacity. Penetration of solar PV capacity to 30% of peak load displaces dispatchable capacity amounting to approximately 5% of peak load.

Over the medium and long run, adjustments to the grid infrastructure made in response to large-scale renewable penetration can reduce investment and operating costs for dispatchable generation, thereby offsetting some of the investment cost of renewables. We now address the system reliability issues associated with large-scale solar penetration.

4.1.2. Intermittency and system reliability. The above discussion accounts for how the predictable variability of the solar resource affects grid investments. However, as discussed in Section 2.1, solar's intermittency challenges grid reliability: Unexpected short-term changes in solar generation require additional backup capacity to avoid temporary mismatches between supply and demand.

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[24]Borenstein (2008) uses California wholesale prices, which were constrained by a regulated price cap, to estimate the marginal value of solar. Lamont (2008) simulates wholesale prices in the absence of a cap, which would lead to a higher estimate. However, Lamont's analysis is based on solar penetration levels of 10–20%, whereas Borenstein's analysis considers a marginal change in solar capacity. Because higher solar penetration tends to reduce wholesale prices during periods of high solar insolation, Lamont's higher penetration tends to reduce his estimate of solar's marginal value.

Mismatches of long enough duration impact resource adequacy: the availability of sufficient generation, transmission, and distribution resources to consistently serve loads.[25] Mismatches of very short duration impact system security, which refers to the fluctuations in system frequency due to real-time mismatches. To maintain system frequency within a narrow tolerance, the system operator requires generators to be available on a standby basis so that customers can continue to be served in the event that one or more generators fails or that load or renewable generation deviates from forecasted levels (Stoft 2002). Spinning reserves are available on a very short term basis (typically within 30 min or less), whereas nonspinning reserves allow for a longer response time (30 min to 2 h).

PV generation is commonly adjusted for impacts on resource adequacy by estimating its capacity credit (or capacity value). Roughly speaking, the capacity credit indicates the amount by which load could increase after solar PV capacity is added while the level of system reliability is kept the same as it was before PV capacity was added or load was increased.[26] Because solar generation's intermittency can increase the risk of a system interruption and loss of load event, the requirement to maintain system reliability is important. To fix ideas, consider a specific system reliability index and two measures of capacity credit. A commonly used reliability index is the loss of load expectation (LOLE): the expected number of outages over some time horizon. LOLE can be expressed as the expected number of hours of outages in a system per year. One measure of the capacity credit is effective load carrying capacity (ELCC). The ELCC of a generator is defined as the amount by which adding a generator to the system enables load to increase while the same LOLE is maintained. An alternative measure of the capacity credit is equivalent conventional power (ECP). The ECP of a generator is equal to the amount of capacity from an alternative technology (e.g., natural gas turbine) that would be needed to replace that generator while the same LOLE was maintained.

Estimated capacity credits for solar PV range from 10% to 95% (Hoff et al. 2008, Perez et al. 2006). This wide range is due to differences in physical setting (which influence the timing and variability of solar generation and its correlation with load) and to differences in estimation methods. Madaeni et al. (2012) review capacity credit estimation methods and apply them to 14 solar PV locations in the western United States. Their analysis uses predicted solar PV generation from NREL's Solar Advisor Model and data on loads and conventional generators from the entire Western Electricity Coordinating Council interconnection. Madaeni et al.'s ECP estimates for solar PV range from 56% to 75% across the sites, and their ELCC estimates range from 52% to 70%. Their assumptions of a very broad geographic area for loads and generators and no transmission constraints yield a very flexible electric system; these assumptions likely contribute to estimated capacity credits for PV that are much higher than PV capacity factors. Also, the Madaeni et al. capacity credit estimates are for a marginal increase in PV capacity. Estimated PV capacity credits are decreasing in the projected level of PV penetration (Mills & Wiser 2012b). Studies that are based on higher PV penetration, a smaller geographic area, and more detailed models of conventional generation tend to yield lower capacity credit estimates. For example, the capacity credit implied by Lamont (2008) for large-scale PV in California is 17%. Capacity credit estimates implied by computations in Gowrisankaran et al. (2013) (see below) for large-scale PV in Arizona range from 17% to 35%.

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[25]See Bushnell (2005) for a discussion of resource adequacy issues.

[26]Capacity credit is distinct from capacity factor. The capacity credit of a PV installation may be either higher or lower than its average output (capacity factor), depending on the distribution of PV generation and on how this distribution matches up with system loads and with the availability of dispatchable generators.

Capacity credits reflect resource adequacy, but solar PV intermittency also influences system security. Greater solar PV penetration increases the variability of supply and therefore requires more ancillary services to maintain reliability. A greater need for ancillary services can raise costs both through requiring more generation capacity to provide these services and through the direct costs of maintaining reserves. These direct costs include the fuel costs for spinning reserves, the increase in energy costs from running some units out of merit order, and the additional maintenance costs imposed by more frequent starts and stops.

Mills & Wiser (2010) use their solar insolation data (described in Section 2.1) to estimate the cost of the reserves required to maintain system security. They calculate the standard deviation of solar generation deltas for three timescales: 1 min, 10 min, and 1 h. They assign sufficient operating reserves so that the likelihood of reserves being insufficient is less than 0.3% for each timescale, and they estimate a cost of reserves that has both a fixed component and a variable component. For 10% PV penetration at a utility in the midwestern United States, their estimated additional cost of reserves ranges from $0.039/kWh of solar generation (if the PV installation is at a single site) to $0.0027/kWh of solar generation (if the PV installation is dispersed across 25 sites).

A complete analysis should include both resource adequacy and system security costs of solar's intermittency. Furthermore, adjusting the grid for resource adequacy also affects system security, and adjusting the grid for system security also affects resource adequacy. Gowrisankaran et al. (2013) combine both reliability measures in an empirical approach to estimating the equilibrium value of renewable energy. Their approach is based on a welfare-maximizing system operator who chooses generation capacity investments, generator dispatch, operating reserves, and demand curtailment. This approach addresses the system security aspect of reliability by explicitly considering how solar's intermittency influences costs via its effect on operating reserve decisions, and it also addresses the resource adequacy aspect of reliability by examining optimal investment in conventional generation. Instead of using a fixed, exogenous level of reliability as a constraint, Gowrisankaran et al. allow the level of system reliability to emerge endogenously via welfare optimization. This approach also overlaps with Lamont's (2008) analysis in that conventional generation capacity and output decisions are made within an optimizing framework. Gowrisankaran et al. extend Lamont's approach to consider a forecasting model of demand and solar output, operating reserve decisions, and demand-side management via curtailment decisions.

Using this empirical approach, Gowrisankaran et al. (2013) analyze the impact of a state-mandated renewable portfolio standard (RPS) on the Tucson Electric Power utility service area in southeastern Arizona. They assume that the RPS will be met entirely via solar PV investments and that solar PV capacity costs are $4.14/W$_p$ (dc).[27] As a reference point, they observe that the LCOE PV is $0.117/kWh higher than for a combined-cycle natural gas generator. Their estimated welfare cost for PV is slightly higher than the levelized-cost gap: from $0.004/kWh to $0.012/kWh higher as the RPS ranges from 10% to 25%. The cost increases associated with system security are minor: Unforecastable solar intermittency is estimated to add only $0.004/kWh.[28] The bulk of the estimated welfare costs are associated with the high installed cost of PV and the relatively small amount of conventional generation capacity that is displaced (i.e., low implied capacity credit). An important finding is that Gowrisankaran et al.'s estimated welfare costs are based on reoptimizing

[27]This is a weighted average of utility-scale and residential costs of installed PV, based on data in Barbose et al. (2012).

[28]The estimated costs associated with grid integration of solar are embedded in their overall welfare cost estimates, so it is difficult to break out grid integration costs separately. On the basis of the reported welfare results, we can infer that grid integration costs rise by $0.011/kWh as the RPS goes from 10% to 25%. The $0.011/kWh figure does not include integration costs associated with going from very low solar penetration to 10% penetration.

decisions regarding generation investment, operating reserves, and demand curtailment by the system operator in response to changes in solar PV penetration. Gowrisankaran et al. estimate that welfare costs would be approximately six times higher if, instead, the system operator followed rule-of-thumb policies. These welfare costs do not account for reduced CO_2 emissions. If CO_2 reductions are valued at \$21/tCO_2 (Greenstone et al. 2011), then solar contributes another \$0.014/kWh to welfare. The net welfare cost for PV then ranges from slightly smaller than the levelized-cost gap (for low RPS requirements) to approximately the size of the gap (for larger RPS requirements). A 20% RPS would be welfare neutral with a solar capacity cost of \$1.63/W.

Tucson is one of the locations used in the short-run analysis of Section 3. By recalculating the results for Tucson in **Table 3** so that the assumptions match those used in Gowrisankaran et al. (2013), we can compare the results based on a short-run analysis to those based on a medium-run analysis. The LCOE for south-facing solar PV in Tucson is \$0.193/kWh, roughly equal to the corresponding figure in **Table 3**.[29] The short-run approach estimates a net welfare cost of \$0.119/kWh, whereas Gowrisankaran et al. estimate that a 15% RPS met entirely with solar PV has a net welfare cost of \$0.108/kWh. The medium-run analysis estimates that welfare costs are approximately one cent per kWh lower than the short-run estimate. This is a surprising comparison because the medium-run analysis includes grid integration costs associated with system security and resource adequacy that are not part of the short-run estimate. The difference between short-run and medium-run welfare cost estimates is likely due to differences in approach and data. The short-run analysis uses system lambda data from FERC to estimate the value of displacing generation. In contrast, the medium-run analysis uses a model based on generator characteristics, fuel costs, and optimal dispatch to estimate the value of displaced generation. The medium-run analysis also explicitly takes into account savings associated with reduced investment in fossil fuel units.[30] Estimates based on system lambda may miss some of the energy cost savings and some of the capacity investment savings. Also, the implied estimate of marginal emission displacement from Gowrisankaran et al. is slightly higher than the estimate from the short-run approach.

Finally, Lew & Piwko (2010) examine the impact of renewable energy targets on the portion of the western US grid served by the WestConnect group of transmission providers. Their analysis uses components similar to those of the Rothleder et al. (2011) study, including a production module based on the GE Multi-Area Production Simulation Software for simulation. They conclude that it would be feasible to meet a 30% wind target and a 5% solar target, provided that several changes are made to current practices and resources. Their recommended changes include modifying current practices to increase (*a*) coordination of generation scheduling across balancing areas, (*b*) utilization of existing transmission links, (*c*) operating reserves (in particular, wind plants should provide some down reserves), (*d*) use of state-of-the-art wind and solar forecasts for dispatch decisions, and (*e*) demand-side management practices. In addition, dispatchable generation should be made more flexible as new units replace old generation capacity. These qualitative findings of Lew & Piwko (2010) are in the spirit of the quantitative results from Gowrisankaran et al. (2013), who estimate dramatically higher costs associated with solar PV penetration when the system operator fails to adjust operating policies.

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[29]The effects of assuming lower installed cost per watt peak capacity coupled with slightly greater PV output roughly offset the effects of assuming a higher discount rate and shorter panel life.

[30]Gowrisankaran et al. (2013) assume no imports or exports, so all generation is done by the utility. This assumption biases the estimated value of energy savings upward relative to the short-run approach. Also, although the medium-run analysis takes into account additional reliability costs associated with system security, these costs were estimated to be quite low.

4.2. Decreasing Costs: Experience Effects

Most installation cost estimates in **Table 1** are for current costs. Yet, we expect the cost and performance parameters of solar technologies to change through time, both through (*a*) advances discovered and perfected through R&D expenditures and (*b*) production or experience effects such as LBD and economies of scale. Technological change resulting from production effects tends to be incremental. R&D, in contrast, can lead to nonincremental improvements in technology (see Section 5.1.2). The two avenues of technical change are not independent and often interact. Policy can potentially play a large role in each of these effects, and understanding the potential evolution of solar costs and the degree of knowledge spillovers can in turn impact optimal policy.

A traditional distinction is between technology-push policies, such as R&D investment (Hoffert et al. 2002, Nemet & Kammen 2007, Prins & Rayner 2007), and demand-pull policies, such as a carbon price or an adoption subsidy (O'Neill et al. 2003, Pacala & Socolow 2004, Yang & Oppenheimer 2007). The first set of policies aims for the development of new technologies and nonincremental improvements in current technologies; the second set of policies aims to induce production effects by increasing demand. Although the literature argues about the relative benefits of the two directions, the consensus is that both have an important role to play and should exist simultaneously (Grübler et al. 1999, Horbach 2007, Mowery & Rosenberg 1979, Norberg-Bohm 1999, Requate 2005). More specifically, technology-push policies tend to dominate the early stages of the innovation process, whereas demand-pull policies become more important in the later stages (Dosi 1988, Freeman & Perez 1988). Finally, Taylor (2008) argues for a third category of technology policy, which she terms "interface improvement ... government actions which share a focus on improving the boundary-space between innovators and technology consumers." This third category has proven to be particularly important in the case of solar, in which the system installers play an important role in the cost of PV and as a conduit for knowledge to flow backward to the technology producers and developers.

4.2.1. Learning by doing.
Increased production has been noted to decrease production costs. Experience effects have been noted empirically in services since Bryan & Harter (1899) and in manufacturing since Wright (1936). First, it was qualitatively observed that workers became more efficient as they produced more units. Second, it was observed that unit costs decrease with accumulated production experience. Arrow (1962) went on to formalize the concept of LBD in his seminal paper, focusing mainly on labor costs.

Experience curves are a common way to capture LBD. In particular, LBD has most commonly been represented as a power function due to simplicity and as a generally good fit to observations. Measures of fit for energy technologies are often well above 0.90 (McDonald & Schrattenholzer 2001). Let c_t be the time t cost measure of interest (say cost per watt peak or the LCOE). Then the power function for LBD is

$$c_t = c_{t-1}\left(\frac{X_t}{X_{t-1}}\right)^{-b}, \tag{4}$$

where X_t is the experience at time t. Experience is measured as cumulative capacity in the appropriate metric: total watts of solar cells produced if cost per watt peak is measured or total energy produced by solar if LCOE is measured. The exponent b measures the strength of the learning effect. Estimates of the learning effect are often presented as the learning rate: the rate at which unit costs decrease for each doubling of the cumulative capacity. The learning rate is given by $1 - 2^{-b}$. Numerous studies estimate this value for solar PV; most estimates lie between 0.17 and 0.22 (Harmon 2000, Jamasb & Kohler 2007, McDonald & Schrattenholzer 2001,

Miketa & Schrattenholzer 2004, Nagy et al. 2012, Neij 1997, OECD/IEA 2000, van der Zwaan & Rabl 2004, Williams & Terzian 1993). However, a few studies estimate higher learning rates of 0.28–0.35 (Jamasb & Kohler 2007, McDonald & Schrattenholzer 2001, Nagy et al. 2012). An important, but oft-overlooked, question is the degree to which learning effects are appropriable to the firm. Policy intervention is generally warranted only if the learning effects are nonappropriable.

Although most estimated learning rates focus on the PV cells themselves and use global cumulative capacity, a few papers consider LBD in BOS. Schaeffer et al. (2004) find learning rates for BOS in Germany and the Netherlands of 0.22 and 0.20, respectively. Bollinger & Gillingham (2012) study the California market and find that there is highly nonappropriable contractor LBD at the regional level. This finding is relevant because van Benthem et al. (2008) find that solar subsidies are warranted if, and only if, there is LBD in BOS.

4.2.2. Criticisms and alternatives.
Several studies criticize the attribution of cost reductions to LBD (e.g., Dutton & Thomas 1984). Argote & Epple (1990) propose four alternative hypotheses for the observed technical improvements: economies of scale, knowledge spillovers, organizational forgetting, and employee turnover. Knowledge spillovers are especially important in firm-level analyses of technical change. The latter two categories are typically addressed by depreciating the value of experience over time (Thompson 2007).

Nemet (2006) uses a decomposition model to gauge the effect of different factors on aspects of solar cells. He finds that three key factors explained much of the reduction in cost: solar manufacturing plant size, module efficiency, and the cost of silicon. (BOS is not included in this study.) From 1980 to 2001, plant size accounted for 43% of the cost reduction. The increase in manufacturing plant size produced economies of scale. This channel is different from LBD and traditional experience curves because the scale of the plants depends on current and forecasted demand rather than on cumulative demand. The cost of silicon is exogenous to the PV market: It is driven primarily by events in the semiconductor market. Although module efficiency may have increased due to learning effects, it also appears to have had a strong relationship to R&D: Nemet finds that of 16 key advances, 6 were made by firms and 10 by universities or other research organizations. Another cost-lowering factor was changing the main application for PV from space to the terrestrial market in the late 1970s. The terrestrial market allowed for lower quality, greater competition, standardization, and lower manufacturers' margins due to greater price elasticity of demand.

4.3. Summary: The Medium Run

In the medium run, there are costs associated with maintaining system reliability as solar penetration rises. There are additional system security costs associated with solar intermittency and capital costs for backup generation to address solar variability. The magnitude of system integration costs depends on a multitude of factors: the degree of solar penetration, energy and capital costs for dispatchable generators, correlation of solar output and load, weather, and more. The results reviewed in Section 4.1.2 suggest that grid integration costs would be in the range of $0.005/kWh to $0.02/kWh of solar generation for penetration in the 10–20% range (assuming multiple, dispersed solar sites). Integration costs would raise the installed cost of solar by $0.15 to $0.60/$W_p$. These estimates assume an optimized electricity system; integration costs could be much higher under inefficient grid management and incentives.

Experience effects are likely to lower costs in the medium run. Policy intervention may be justified, at least for BOS costs, but more research would be valuable. At a 20% penetration rate (as in many of the integration studies above), the estimated learning rates imply that the cost of PV

would fall considerably. For example, if we assume a 1,000-fold increase in installed capacity (from approximately 0.02% of the market to 20% of the market) and use the central learning rate of 0.2, then the total installed costs for thick-film silicon from **Table 1** fall from a range of $3/W_p–$5/W_p to a range of $0.33/W_p–$0.55/W_p. This is a radical change. Even with a more conservative long-run learning rate of 0.1, the costs drop to $1/W_p–$1.75/W_p. These reductions in the installed cost of solar would greatly outweigh the increased costs due to integration in an optimized electricity system.

These medium-run analyses consider the implications of near-term policies to promote solar PV, but policies will increasingly be driven by long-run carbon goals. The next section examines solar's role in achieving these goals.

5. THE LONG RUN: TWENTY-FIRST-CENTURY CLIMATE TARGETS

The need to reduce GhG emissions is increasingly shaping the energy sector. Developed countries have announced goals of reducing emissions by as much as 80% by 2050, which would require the energy sector to decarbonize almost completely. Integrated assessment models (IAMs) analyze this energy transformation by coupling energy, macroeconomic, and emission modules. Whereas the above sections discuss many complexities pertinent to assessing the cost-effectiveness of solar technologies over the next decade or two, IAMs' long time horizons and comprehensive coverage limit such models to more simplified representations. We here discuss how they model the evolution of capital costs, the costs imposed by intermittency, and the interaction between solar and other forms of land use. We also describe general conclusions about solar's role in achieving long-run climate targets. To our knowledge, this is the first survey of a specific technology's implementation in energy-economy IAMs.[31]

Energy-economy IAMs are broadly classified along two dimensions. First, top-down models consist of an aggregated macroeconomic growth model adjusted for energy and pollution stocks, bottom-up models select investments from a suite of detailed technologies to meet current and future demand, and hybrid models link a bottom-up energy sector module to a top-down macroeconomic module (e.g., Hourcade et al. 2006).[32] Top-down models include macroeconomic feedbacks from changing energy prices, but they use highly stylized representations of the energy sector and are not suited for analyzing the evolution of particular technologies. Bottom-up models capture substitution between technologies over time, but they ignore macroeconomic feedbacks, and their substitution possibilities are restricted to the set of modeled technologies. Hybrid models have emerged over the past decade as an attempt to combine the best of both worlds. In reviewing solar electricity implementations, we necessarily focus on bottom-up and hybrid models.

The second dimension for classifying IAMs describes whether they optimize or evaluate policy (e.g., Kolstad 1998). Cost-benefit analyses determine an optimal policy path by trading off the costs and benefits of GhG emissions over time. In policy-optimizing IAMs, climate modules convert emission paths into warming paths, and damage functions translate warming into welfare changes, typically via reductions in economic output. A forward-looking policy maker allocates each period's output to reducing emissions insofar as the future climatic benefits justify the current mitigation costs. The cost of the last unit of optimal abatement indicates that period's social cost of

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[31]Several models lack complete public descriptions. Others have evolved beyond their last public descriptions. We piece this survey together from peer-reviewed publications, reports, websites, and communication with modeling teams. All communication happened by email between June and November of 2012. We refer to models by their standard acronyms.

[32]Macroeconometric models estimate systems of equations from time-series data. In this scheme, they fit somewhere between a top-down model and a hybrid model.

carbon. Historically, policy-optimizing IAMs have tended to be top-down models, but an increasing number of models include both cost-benefit capacity and explicit representations of multiple energy technologies. In contrast, cost-effectiveness analyses find the least-cost investment and deployment path that satisfies exogenously specified emission constraints, warming constraints, or carbon price paths. To conduct policy evaluations, IAMs do not require a damage function to translate warming into welfare, because they do not need to calculate the benefits of climate policy. The value of displaced emissions derives from the shadow value of emissions under the given constraints. Policy evaluation models analyze how the cost of a policy target changes with the level of the target, with coordination among nations, and with the set of energy technologies.

The evolution of a technology-rich IAM's energy sector depends on the evolution of demand and on the relative cost of each supply technology. We begin by describing IAMs' representations of installation costs, including how recent implementations of learning endogenize cost declines and how R&D could further lower costs. We then survey two constraints on solar's long-term evolution: the cost of grid integration and the availability of land for solar installations. We conclude by surveying results about the growth of solar electricity and the role of R&D policies.

5.1. Technology Costs

Models measure the installation costs of solar sources in two ways: (a) dollars per unit of rated or peak power and (b) dollars per unit of energy generated.[33] We begin with the power measure, as it directly reflects the cost of manufacturing and installing solar equipment. **Figure 3** plots installation cost in several models. For reference, we include the cost of concentrating solar power (CSP), as it often competes with PV in these models. The change in installation cost over time reflects exogenous technological change in some cases (AIM, DNE21, GCAM, and MESSAGE) and reflects LBD along a representative installation path in others (ReMIND and IMAGE).

Across these models, the cost of PV in 2005 ranges from $3.50/W to almost $6/W. For comparison, the range of installation costs for thick-film silicon for 2010–2012 from **Table 1** is $3/W to $5/W. CSP is relatively cheap in some models (GCAM and MESSAGE) but much more expensive than PV in others (ReMIND and WITCH). PV's range of costs narrows over time because costs decrease strongly in all models. In fact, PV usually costs less than $2/W in 2050. The results with endogenous costs (ReMIND and IMAGE) demonstrate the importance of technological change: Solar becomes much cheaper in scenarios with stringent GhG targets because it gets used more. In fact, were we to plot the cost evolution under IMAGE's business-as-usual path, we would see almost no cost decline because solar is barely used (D. van Vuuren, personal communication). Finally, adding storage imposes large additional costs in GCAM. The high cost of storage ensures that grid integration is an important constraint on the growth of solar electricity, as we see below.

The second measure of solar's cost, and the one that lends itself to direct comparison with other technologies, is the cost per unit of energy generated. This cost depends on the insolation over the plant's lifetime at the location at which the plant is installed.[34] In terms of **Table 2**, the productivity factor s varies by location. A given PV panel will produce more energy in Arizona or the Sahara than in San Francisco or Germany. Its LCOE will therefore be lower in the sunnier locations. Although some models (e.g., EPPA, MERGE-ETL, and GRAPE) directly specify solar's cost in terms of LCOE, most models specify the cost per unit power and then convert it to LCOE by using other parameters or inputs to the model. In particular, many models use geographic information

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[33]Several models also include small ongoing operations and maintenance costs.

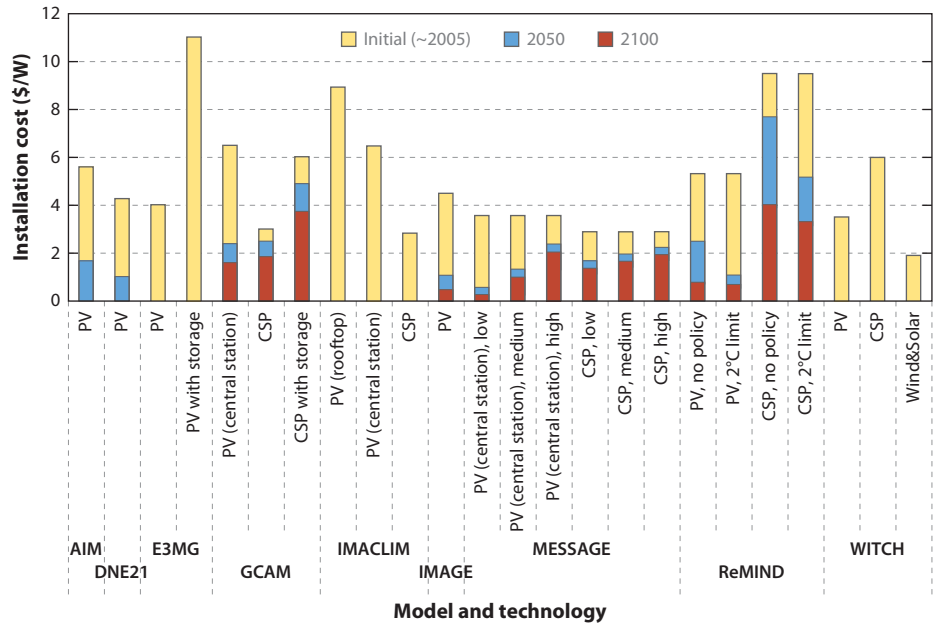[34]These IAMs typically use a plant lifetime of 30–40 years.

Figure 3

Installation costs by model and solar electricity technology. Costs evolve exogenously except in E3MG, IMACLIM, and WITCH (for which only initial costs are plotted) and in ReMIND and IMAGE (in which cost trajectories use representative installation paths). AIM's horizon extends only to 2050. Sources: AIM, O. Akashi (personal communication); DNE21, K. Wada (personal communication); E3MG, Anderson & Winne (2004); GCAM, **http://wiki.umd.edu/gcam/index.php?title=Electricity**; IMACLIM, Bibas & Méjean (2012); IMAGE, D. van Vuuren (personal communication); MESSAGE photovoltaic (PV), V. Krey (personal communication); MESSAGE concentrating solar power (CSP), N. Johnson (personal communication); ReMIND, N. Bauer (personal communication); WITCH PV/CSP, M. Tavoni (personal communication); WITCH Wind&Solar, Bosetti et al. (2009). Plotted MESSAGE costs are for North America, and WITCH Wind&Solar is a global average. As far as can be determined, dollars are constant.

systems (GIS) data to estimate average insolation over predefined regions or grid cells.[35] Another approach, taken by E3MG, directly assumes the capacity factor (Anderson & Winne 2004). In WITCH, capacity factors differ by region (Bosetti et al. 2007) and exogenously increase over time (Bosetti et al. 2009).

Finally, some models further distinguish between resource costs and resource grades for solar. The resource cost is like a supply curve for the land needed for solar installations. In particular, GCAM uses a GIS-based analysis to estimate the maximum resource for each type of solar in each region and, for rooftop PV, to estimate a resource supply curve (**http://wiki.umd.edu/gcam/index. php?title=Electricity**). Models that use resource grades convert variations in insolation and transmission access into a discretized supply curve for that region's insolation (i.e., a discretized plot of the capacity factor against the total solar resource). Examples include AIM (Masui et al. 2010), IMAGE (de Vries et al. 2007), and MESSAGE (V. Krey, personal communication).

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[35]These models include AIM (Masui et al. 2010), GCAM (**http://wiki.umd.edu/gcam/index.php?title=Electricity**), GRAPE (A. Kurosawa, personal communication), IMAGE (de Vries et al. 2007), MESSAGE (V. Krey, personal communication based on Hoogwijk 2004), and ReMIND (Pietzcker et al. 2009).

5.1.1. Learning by doing in integrated assessment models.

The strong cost decreases in **Figure 3** are often exogenous. Aside from developing hybrid IAMs, the major structural advance of the past decade has been endogenizing installation costs.[36] The most common method captures LBD via the traditional experience curve formulation described in Section 4.2. The key parameter is the learning rate. The standard formulation assumes complete spillovers between regions so that each region's costs fall with global installation capacity. Some models extend the basic experience curve to include a floor cost. This floor cost is implemented either as a lower bound on costs or by applying the learning model to the gap between the current cost and the floor cost rather than to the entire current cost.

LBD is thought to be most important for immature technologies like solar.[37] **Figure 4** plots the floor cost against the learning rate. When there are no floor costs, learning rates cluster around 10% (MERGE-ETL and MESSAGE). These rates are lower than the estimated range of 17–22% reported in Section 4.2. When models use higher learning rates, they typically have higher floor costs (E3MG, IMACLIM, ReMIND, and WITCH) or have the learning rate decline exogenously over time toward that same 10% level (IMAGE). All else equal, solar is more attractive in models with higher learning rates and less attractive in models with higher floor costs. It is not clear how these two effects net out in the models with higher learning rates and higher floor costs.

Estimating LBD is challenging because we seek a causal relation, whereas statistical correlations between cost and installed capacity pick up other factors such as exogenous cost declines. Moreover, even if historical learning curves can be confidently identified and estimated, there is no underlying theory that implies they should hold in the future. Nordhaus (2009) emphasizes that learning representations can skew model outcomes: Estimated learning rates are probably biased upward, and a higher learning rate tilts a model toward that technology. This tilt happens because, in a forward-looking model, a higher learning rate produces a shadow benefit to installation by lowering future costs. Magné et al. (2010) find that greater learning rates accelerate deployment in MERGE-ETL but do not strongly affect long-run deployment, which is determined first and foremost by climate goals. However, the model comparisons in Krey & Clarke (2011) suggest that learning rates do strongly affect the long-run mix of technologies used to achieve climate goals. Regardless of whether the mix of technologies is sensitive to the learning rate, Tavoni et al. (2012) show that total mitigation cost is sensitive to learning. In a policy-optimizing model, lower mitigation costs imply lower optimal emissions, and scenarios with lower emissions favor increased solar deployment. Therefore, in a policy-optimizing (or cost-benefit) setting, greater learning rates for solar technologies would increase solar installation not only by raising the shadow benefit of that technology but also by lowering optimal emissions.

5.1.2. R&D in integrated assessment models.

LBD reflects incremental changes in the cost of solar technology, but R&D is also an important driver of technical change over multidecadal timescales. A few models endogenize technical change by allowing direct investments in R&D: MERGE-ETL allows investment into, among others, solar R&D (Magné et al. 2010), and WITCH has included R&D investments for energy efficiency and innovative low-carbon technologies (Bosetti et al. 2006, 2009). We here describe recent estimates of the effectiveness of future R&D. Section 5.4 surveys model implementations of these estimates.

Each of the PV technologies described in Section 2 could be advanced by targeted R&D funding from private firms or from the government. Data on privately funded R&D are notoriously hard

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[36]Endogenizing some aspects of technological change need not eliminate a role for exogenous technological change, which can still capture spillovers from other technologies or basic science research (Clarke et al. 2006).

[37]For this reason, models typically assume that solar has more scope than wind for technological improvement.
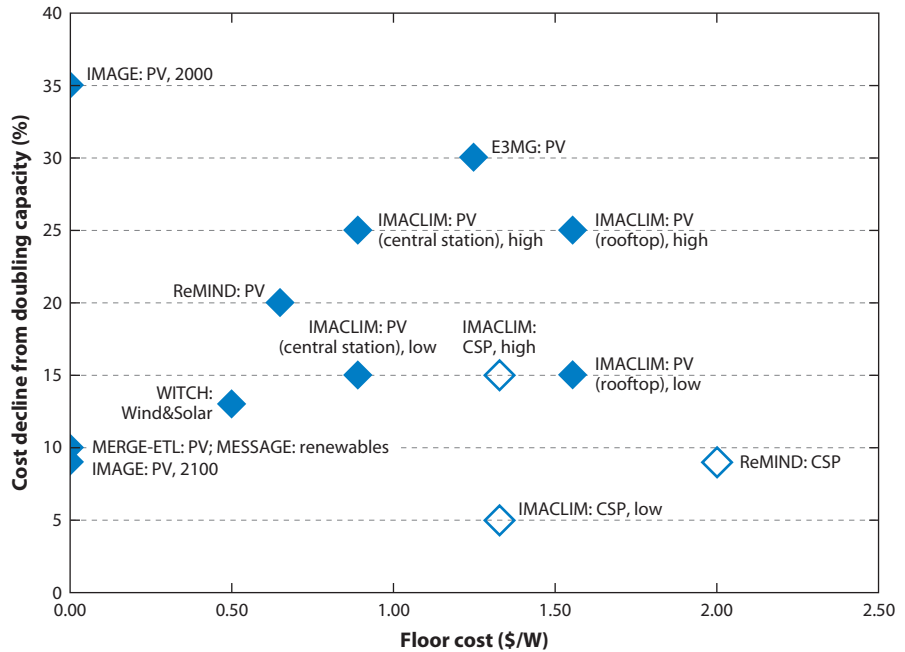
Figure 4

Learning rates and floor costs for models with endogenous technological change in solar electricity generation. Sources: E3MG, Anderson & Winne (2004); IMACLIM, Bibas & Méjean (2012); IMAGE, Edenhofer et al. (2010); MERGE-ETL, Magné et al. (2010); MESSAGE, Riahi et al. (2011); ReMIND, Luderer et al. (2011); WITCH, Bosetti et al. (2006, 2007, 2009) (floor cost from V. Bosetti, personal communication). MESSAGE's plotted rate is constructed for a high-emission scenario. E3MG's floor cost is actually specified in units of energy, but it is based on long-term projections of $1,000–1,500/kW. Abbreviations: CSP, concentrating solar power; PV, photovoltaic.

to obtain. The level of governmental R&D funding is clearer. In 2010 the US Department of Energy spent approximately $175 million on solar PV, system integration, and market development, whereas the US Department of Defense spent $787 million on solar (although much of this was probably due to deployment rather than to R&D specifically) (Anadon et al. 2011). Recently, the European Union has also been spending approximately $163 million per year (Bosetti et al. 2012).

These sums show that governments are spending a significant amount on R&D. There has been recent interest in applying science to science policy. To do this, analysts must estimate the returns to R&D investments. Such estimations are difficult because the outcomes of research are inherently uncertain and difficult to predict given only historical data: One breakthrough does not predict another, nor does a lack of breakthroughs predict future failure.[38]

Given this empirical challenge and the ongoing need to make funding decisions, the National Research Council (2007) recommends that the US Department of Energy use probabilistic assessment based on expert elicitations of R&D programs. Expert elicitation is a formal, structured method for assessing expert judgment (Morgan & Henrion 1990). For solar technologies, one particular goal is to obtain probability distributions for the effectiveness of R&D spending at reducing the cost of solar energy.

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[38]One of the main attempts to estimate the effectiveness of solar R&D was Nemet's (2006) work described in Section 4.2.

A number of recent expert elicitations have been targeted toward solar. **Table 4** summarizes the information about the different studies. Here we present the major findings. Baker et al. (2009) find that a search for new inorganic semiconductors appears promising: A low R&D investment ($15 million per year) was estimated to achieve success by 2050 with a probability of approximately 40%, where success was defined as achieving a cost of $50/m^2 with 15% conversion efficiency and a 20-year lifetime. This success translates into a power cost of approximately $0.38/W or a LCOE of approximately $0.02/kWh, not including BOS costs. Anadon et al. (2011) asked each expert to provide a recommended amount of R&D funding and had each expert assess the technology he or she thought most promising. On average, experts recommended funding of $410 million per year, or approximately four times the current amount. The median estimates of the cost of utility-scale PV in 2030 ranged from $0.35/W to $1.25/W under business-as-usual funding and from $0.30/W to $0.85/W under the recommended funding. Bosetti et al. (2012) focus on European funding and assess mostly European experts. They find that the median estimates for the LCOE in 2030 ranged between $0.075/kWh and $0.145/kWh for the business-as-usual funding trajectory of $163 million per year and between $0.07/kWh and $0.11/kWh when the funding was increased by 50% to $245 million per year. Curtright et al. (2008) assess 26 different technologies and find that only approximately half of the 18 experts felt that there was a "better than even chance of any PV technology achieving US$0.30/W$_p$" in either 2030 or 2050, although a few experts were more optimistic about 2050 than about 2030. The results from the US Department of Energy EERE (Energy Efficiency and Renewable Energy) study have not been made public.

There are two avenues for future research in this direction. One involves updating the studies to take account of the recent drops in the cost of solar. Given a current cost of $0.7/W$_p$ and a learning rate of 20%, a mere tenfold increase in the demand for solar would reduce costs to $0.34/W$_p$. Thus, the numbers from the elicitations appear fairly conservative in comparison with today's prices and potential industry growth. The second avenue for future research is to harmonize these studies by carefully reviewing assumptions so that their numbers are directly comparable.

5.2. Approximating the Costs of Grid Integration

As discussed in Section 4, solar's intermittency can impose additional costs on grid management. These costs become increasingly important as solar reaches high penetration rates. Many IAMs have solar generating a large fraction of electricity in carbon-constrained futures. These high-penetration scenarios make it imperative that IAMs represent the extra costs imposed by intermittency. The challenge is that they must do so without the grid models necessary to calculate the capacity credits and reliability measures described in Section 4.1.

Many IAMs account for intermittency by exogenously adjusting solar's cost to include ancillary costs. These ancillary costs increase with the fraction of solar in a region's grid. A forward-looking policy maker accounts for these future costs when making installation decisions. For instance, GCAM makes the required backup capacity a logistic function of total solar capacity, with each new unit of solar requiring one full unit of backup capacity once solar reaches 20% of grid capacity (**http://wiki.umd.edu/gcam/index.php?title=Electricity**).[39] This is equivalent to assigning solar a capacity credit of zero once it reaches high penetration levels. IMAGE requires

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[39]GCAM also provides the option of building a more capital-intensive plant that has integrated energy storage. These units with storage cost more up front but do not pay the intermittency penalty that otherwise restrains solar at high levels of penetration.

Table 4 Expert elicitations targeted toward the effectiveness of solar R&D[a,b]

Group	End point year(s)	Format	Number of experts	Technology	End points
University of Massachusetts	2050	F2F	3	New inorganic, purely organic, quantum dots and multijunction, CIGS	Manufacturing cost, efficiency, lifetime
Harvard	2030	Survey	11	Residential, commercial, utility PV	Capital cost per W_p, efficiency
FEEM	2030	F2F	16	General	LCOE
Carnegie Mellon	2030, 2050	F2F	18	Twenty six, including C-Si, thin films, concentrator, excitonic, novel high efficiency	Cost per W_p, efficiency
EERE	2030	Survey, follow-up	18	General	Cost per W_p

[a]Abbreviations: CIGS, copper indium gallium selenide; EERE, Office of Energy Efficiency and Renewable Energy (US Department of Energy); F2F, face to face; FEEM, Fondazione Eni Enrico Mattei; LCOE, levelized cost of electricity.
[b]From Curtright et al. (2008), Baker et al. (2009), Anadon et al. (2011), and Bosetti et al. (2012).

both backup capacity and spinning reserves (van Vuuren et al. 2006): Intermittent sources receive reduced capacity credits once they provide greater than 5% of total grid capacity and spinning reserve requirements are 15% of the total intermittent capacity (compared with 3.5% of the capacity for a standard plant). A couple of models exogenously limit the share of solar: GRAPE limits it to 20% (A. Kurosawa, personal communication), and DNE21 limits it to 15%, although PV with storage is allowed to reach 20% (K. Wada, personal communication). Both AIM (O. Akashi, personal communication) and E3MG (Anderson & Winne 2004) require that solar installations pay an additional cost for storage once capacity exceeds 20% of the market.

As an extension of these approaches, ReMIND imposes additional costs depending on the timescales over which a solar technology creates intermittency (Pietzcker et al. 2009). Each type of intermittency requires its own storage technology, and the need for storage increases with penetration. Intermittency on a daily scale requires redox-flow batteries, intermittency on a weekly scale requires hydrogen electrolysis or backup combined-cycle gas turbine capacity, and intermittency on a seasonal scale requires sufficient grid capacity to always meet demand. The storage cost per unit of PV electricity increases linearly with PV penetration, which makes total PV storage cost increase with the square of PV penetration. Importantly, CSP does not need to offset daily intermittency with batteries, because its built-in thermal storage already smooths generation over the daily cycle.[40]

An alternate approach to capturing intermittency is to combine generation types in a production function for electricity. The macroeconometric model E3MG (Anderson & Winne 2004) and the computable general equilibrium model EPPA (Paltsev et al. 2009) make PV an imperfect substitute for fossil-fueled and nuclear electricity in a nested constant elasticity of substitution structure. This imperfect substitutability means that combining one unit of solar electricity with

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[40]See Section 5.3 for how this representation of storage affects technology deployment.

one unit of gas-fired electricity is less useful than combining one unit of coal-fired electricity with one unit of gas-fired electricity. Because additional solar capacity displaces fewer units of fossil-fueled or nuclear electricity as solar's share of generation increases, the effective capacity credit decreases with increasing penetration.[41]

Finally, the MESSAGE team and NREL have moved toward connecting a grid model to a tractable IAM to capture the resource adequacy and system security concerns described in Section 4.1.2 (Sullivan et al. 2013). To represent resource adequacy, they require that firm capacity be a multiple of average load, with the multiplier varying by region. Renewable sources contribute their capacity credits, which decline with penetration. To represent system security concerns, these researchers run a unit-commitment model of a limited grid under a range of penetration scenarios to develop flexibility coefficients for each potential source of electricity.[42] These coefficients define the ability of each source to provide ancillary services. For example, simple-cycle gas turbines and electricity storage receive coefficients of 1, combined-cycle gas turbines have a coefficient of 0.5, a nuclear plant has a coefficient of 0, solar PV has a coefficient of −0.05, and wind has a coefficient of −0.08. When MESSAGE's energy sector is constrained to maintain some minimal degree of flexibility (i.e., some fraction of load must be met by flexible generation), the shadow value on the constraint combines with the flexibility coefficient to yield the cost of solar's intermittency. This approach comes closest to capturing the full range of effects discussed in Section 4. A next step would model each region's grid under a wider range of penetration scenarios and approximate flexibility coefficients as functions of solar's penetration or even of the complete set of generators.

5.3. Land as a Scarce Resource

Although future technologies and ancillary costs will certainly affect future installations, current installation decisions reveal the importance of land. Solar installations generate relatively little energy per unit of land, which can make acquiring land for generation and transmission a particular hurdle for a central station plant. Yet most IAMs account for land only as a potential quantity of sunshine, not as a scarce resource in its own right. This lack of attention to land requirements stands in stark contrast to the careful focus on land in bioenergy modeling. As future generations of models allow for greater resolution and coupling, land use modules should begin to interact with a broader set of energy technologies.[43]

Some models have already taken steps beyond the standard GIS-based assessments of insolation and resource supply curves. First, IMAGE (de Vries et al. 2007) and AIM (Masui et al. 2010, Silva Herran 2012) explicitly adjust insolation for land cover. A given quantity of sunlight has different implications depending on whether it arrives at the desert or at the forest. de Vries et al. (2007) note that land use assumptions matter because renewable sources sometimes compete with each other for land, but in practice they find that PV's role depends more on the technology's development.

In addition to the physical interaction between land cover types and solar arrays, there is also an opportunity cost to using land for solar arrays. This opportunity cost arises when solar arrays

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[41]The hybrid model WITCH also has a nested structure in which aggregated fossil-fueled electricity is combined with nuclear and renewables via an elasticity of substitution (Bosetti et al. 2007). It also has a cost of integrating renewables on the basis of renewables' share of electricity generation (M. Tavoni, personal communication).

[42]Solar PV was actually not included in the unit-commitment model. Its coefficient was presumably estimated by assumptions about how its flexibility compares with that of other sources included in the model.

[43]Solar installations do not affect albedo in any of the surveyed models.

exclude other energy and nonenergy uses. The computable general equilibrium model EPPA represents land's opportunity cost by making land an input to production functions, including the production function for solar electricity (Paltsev et al. 2009). A future advance could combine these GIS-based and general equilibrium approaches by adjusting the land input for its land cover type and by making land an input to ecological services and values.

A third approach to treating land scarcity appears in ReMIND (Pietzcker et al. 2009). Here CSP and PV compete for sites: The total area in a region devoted to CSP and PV must not exceed the total area available for solar installations, as determined from geographical and social restrictions. The opportunity cost of PV is the chance to install CSP. This competition between solar technologies generates interesting dynamics. When CSP is an available technology, it largely crowds out PV and becomes the dominant electricity source in scenarios with a 2°C warming constraint. This occurs despite CSP having higher investment costs per unit of peak power (**Figure 3**) and slower learning rates (**Figure 4**). The reason CSP competes so successfully is that it has greater load hours and lower storage costs.[44] When renewable technologies compete for land, deployment paths become more sensitive to model assumptions that affect their relative costs.

### 5.4. Solar Generation and R&D for Future Climate Targets

Two general conclusions emerge from practically every technology-rich energy-economy IAM: There is no silver bullet, and GhG policy drives the use of solar electricity. To the first point, no one energy technology will solve global warming. Solar, wind, biomass, carbon capture and sequestration, and nuclear all have roles to play in these models' least-cost pathways. To the second point, the no-policy scenario (termed the business-as-usual or reference scenario) typically has solar's share of generation increase as energy demand expands and solar's costs decline, but solar's role remains trivial at a global level without the spur of emission goals. But when GhG emissions are constrained, some models have solar technologies forming the backbone of the energy system by 2050.

Model intercomparisons implement similar scenarios in several models to learn which features are consistent across models and to discover which factors drive interesting differences. For instance, baseline solar use is low across all models in the ADAM intercomparison, but for different reasons (Edenhofer et al. 2010): Solar is simply noncompetitive in MERGE, it is costly to scale up in IMAGE, and POLES constrains rooftop PV by surface space and central station solar by transmission. Baseline solar use is greatest in ReMIND because that model has costs fall quickly with cumulative installation. Krey & Clarke (2011) find that solar energy production increases strongly over time in most model runs, but with patterns that differ by solar technology (**Figure 5**). In the reference scenario, solar PV is almost nonexistent. Although adopting stringent CO_2 targets strongly increases CSP in several models, it more strongly affects PV: The highest values for solar PV far exceed the highest values for the other solar technologies. Care must be taken because different models include different sets of technologies, but these results suggest that solar PV is especially sensitive to model assumptions.

Technological progress is also an important piece of these models. For instance, the RECIPE intercomparison demonstrates that estimates of total mitigation cost are sensitive to the calibration of technological progress (Tavoni et al. 2012). Low rates of LBD strongly increase costs relative to those in the baseline calibrations, and fast learning rates decrease costs. Solar technologies

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[44]Recall that ReMIND requires PV installations to buy battery capacity to offset daily intermittency, whereas CSP uses its built-in thermal storage to counter daily intermittency. In this model, CSP can almost fully compensate for removing PV from the set of available technologies, but PV's storage requirements hinder PV from compensating for CSP.
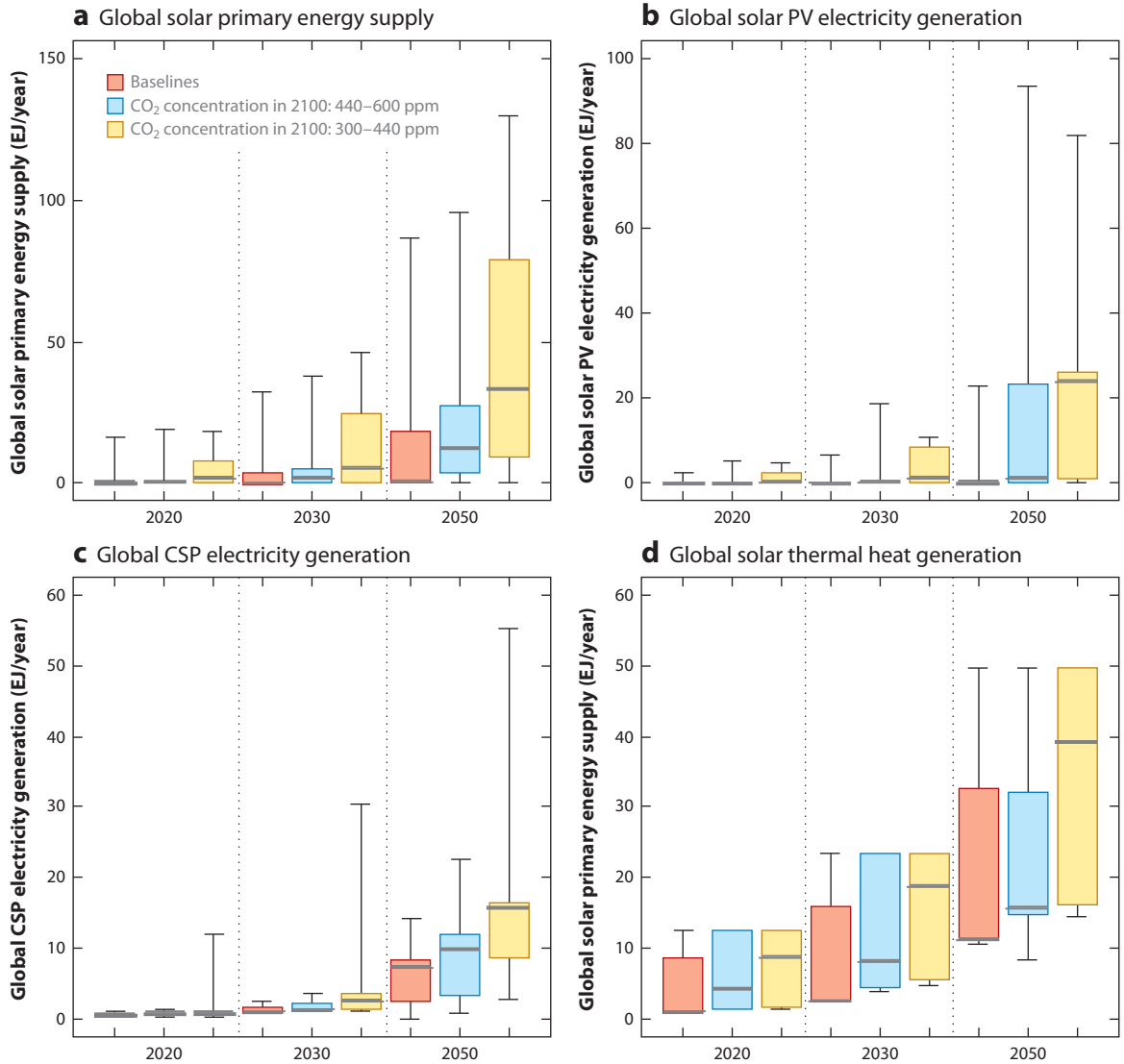
Figure 5

Solar energy across integrated assessment models and scenarios. Scenarios are grouped according to the CO_2 concentration in 2100. The red boxes represent the reference scenario, and the blue and yellow boxes represent progressively more stringent CO_2 targets. The gray lines give the median, the boxes give the interquartile range, and the whiskers give the total range. Solar thermal heat refers to nonelectricity (water-heating) applications. From figure 9 in Krey & Clarke (2011), with permission from Taylor & Francis.

typically have the highest learning rates because they are deemed immature, but they are often not the most crucial technologies for attaining low mitigation costs.[45] McJeon et al. (2011) find that breakthroughs in solar are less valuable than breakthroughs in carbon sequestration or nuclear.

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[45]Removing a technology can radically alter the evolution of the energy sector without strongly affecting total mitigation cost (e.g., Paltsev et al. 2009).

This is in large part because they assume that solar's intermittency limits its potential share of generation. Similarly, Pietzcker et al. (2009) find that solar is less valuable than carbon sequestration and biomass options because both can help decarbonize transportation, whereas the electricity sector has several potential decarbonization pathways beyond solar. The most valuable technologies are those that help in sectors with fewer options, those for which operating costs are independent of scale, and those for which installation costs decrease in scale. Solar meets the third condition through LBD, but it requires electrified vehicles or fuel cell vehicles to meet the first condition and requires cheap electricity storage or hydrogen electrolysis to meet the second condition.

R&D portfolio models have used the elicitation data from Section 5.1.2 to learn about the optimal size and allocation of R&D budgets. Baker & Solak (2011) implement the data from Baker et al. (2009) on solar PV (as well as data on carbon sequestration and nuclear) in a reduced R&D portfolio model. The objective is to minimize the cost of GhG abatement plus climate damages for a given R&D budget constraint. They use GCAM to derive the impact of technical change on the cost of abatement. They find that, for a given budget, the composition of the optimal portfolio is robust to stochasticity in climate damages. Solar PV funding focuses first on new inorganics, then on organics, and finally on other third-generation technologies. However, the optimal amount of R&D funding depends on climate damages. Building on this model, Baker & Solak (2013) implement the same data in a version of the DICE model, which is the benchmark top-down, policy-optimizing IAM. They find that optimal investment searches for new organic and inorganic semiconductors. The optimal portfolio is robust to the policy environment, to damage stochasticity, and to assumptions about the opportunity cost of R&D funding.

In another study building on elicitation data, Anadon et al. (2011) use the elicitation data from one representative expert for each of several technology categories to determine an optimal allocation for different budget levels. They consider multiple goals, including minimizing cost for a given cap on CO_2, minimizing the cost of clean energy credits under a standard, and maximizing consumer surplus. This study relies on the MARKAL-US model to generate the societal impacts of technical change. They find that the optimal investment in solar varies considerably depending on the objective. Solar dominates the energy R&D portfolio when the objective is to minimize the cost of a clean energy standard, it has a more modest role when the objective is to minimize the cost of a cap-and-trade policy, and it plays almost no role when the objective is to maximize consumer surplus. The authors go on to make an overall recommendation, qualitatively combining these different objectives, the range of expert opinion, and the impacts on deployment. In this recommendation, the share of solar energy R&D is approximately the same as it is in the current federal budget (7–8%), but the dollar amount is higher by more than two and a half times. As a comparison, the recommended budget allocation increases the share of electricity storage R&D to 5% from its current share of 1%. This increase presumably occurs because storage is an enabling technology that can "accommodate the variability of solar PV" as well as that of wind.

An important question is how to balance different types of technology policies.[46] Demand-pull policies, such as subsidies and RPS, work directly on production effects such as LBD.

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[46]Lemoine et al. (2012) find that optimal funding for research into "carbon-free" R&D like solar panels is driven primarily by the stringency of long-term climate goals and the corresponding need for high levels of emission reductions. Weakening emission limits or developing cheap negative-emission technologies tilts optimal R&D funding toward "emission intensity" technologies.

Technology-push policies, such as government-funded R&D and R&D tax credits, work directly on innovation. Nemet & Baker (2009) combine the results from an expert elicitation on purely organic solar cells with a bottom-up manufacturing cost model to compare the effects of R&D funding and demand subsidies. They find that R&D funding is more effective than subsidies in reducing the costs of organic PV, but subsidies still have value as a hedge against R&D failure.

5.5. Summary: The Long Run

The results of these technology-rich IAMs and R&D portfolio models suggest that solar electricity has a large role to play in a carbon-constrained future and that near-term R&D funding is crucial to minimizing the cost of carbon constraints. In the IAMs, the cost of grid integration often limits the role of solar, whereas LBD increases solar's role. Many models represent grid integration costs by exogenously limiting solar's share of grid capacity to 15–20% or by imposing significant penalties on solar capacity once solar's share reaches these levels. However, the medium-run analyses in Section 4.1 suggest that the cost of grid integration depends strongly on how the grid is managed. If grid operators follow rule-of-thumb policies, solar's integration costs can be quite large, but if investment, operations, and demand management decisions are properly optimized in light of solar's penetration, then grid integration costs can be relatively small, even when solar's share of capacity reaches 15% or more. Whether IAMs should approximate costs for an optimized grid or for a rule-of-thumb grid depends on their objectives. Future work should explore such models' sensitivity to assumptions about grid integration costs while calibrating approximations to the richer grid that models use in short-run and medium-run analyses. On the technology side, models either use learning rates below those reported in Section 4.2 or apply a floor cost that limits the scope for learning. Future work should clarify the trade-off between floor costs and learning rates, and it should refine models of technological change to combine incremental LBD effects with R&D-assisted step changes in technology.

6. CONCLUSIONS

This review shows that economic analyses of solar electricity have improved understanding of the costs imposed by solar's intermittency, of the emission benefit from increasing solar capacity, of the potential for technological change, and of the key factors influencing solar's role in attaining twenty-first-century climate targets. We also show how analyses focused on different timescales not only answer different questions but take different approaches in doing so. Short-run analyses answer questions about incremental changes in solar capacity by using relatively realistic models of the electric grid. Medium-run analyses answer questions about strong solar policies and high penetration rates by using more simplified models of grid operation while also potentially accounting for incremental changes in technology. Long-run analyses answer questions about the multidecadal evolution of the energy sector by using reduced representations of intermittency and potentially dramatic technology dynamics.

Further progress may come from linking these timescales. How do the short-run costs and benefits of incremental solar capacity change as the energy system changes around it? To what extent do high-penetration scenarios become less costly when grid operators can take advantage of geographic diversity and the full set of solar technologies? How does the additional cost imposed by adjusting for intermittent solar resources change when energy infrastructure is optimized for longer-term climate targets? What short- or medium-run feature should be the key constraint on solar's growth in a long-run model? We hope that this review not only brings these

questions to light but establishes the connections between analytic frameworks that will help answer them.

DISCLOSURE STATEMENT

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