

# Evaluating the causes of cost reduction in photovoltaic modules

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## Abstract

Photovoltaics (PV) module costs have declined rapidly over forty years but the reasons remain elusive. We advance a conceptual framework and quantitative method for quantifying the causes of cost changes in a technology, and apply it to PV modules. Our method begins with a cost model that breaks down cost into variables that changed over time. Cost change equations are then derived to quantify each variable's contribution. We distinguish between changes observed in variables of the cost model – which we term low-level mechanisms of cost reduction – and R&D, learning-by-doing, and scale economies, which we refer to as high-level mechanisms. Increased module efficiency was the leading low-level cause of cost reduction in 1980-2012, contributing almost 25% of the decline. Government-funded and private R&D was the most important high-level mechanism over this period. After 2001, however, scale economies became a more significant cause of cost reduction, approaching R&D in importance. Policies that stimulate market growth have played a key role in enabling PV's cost reduction, through privately-funded R&D and scale economies, and to a lesser extent learning-by-doing. The method presented here can be adapted to retrospectively or prospectively study many technologies, and performance metrics besides cost.

**Keywords**— Photovoltaics (PV), solar energy, PV modules, cost model, technological change

## Highlights

- We model technology improvement to identify causes of photovoltaics (PV) cost decline.
- Improvements to module efficiency and materials costs were important.
- Since 2001, increasing plant size enabled economies of scale to reduce costs.
- Market-stimulating policies were responsible for a large share of PV's cost decline.
- Modeling cost reduction mechanisms can reveal further cost reduction opportunities.

## 1 Introduction

Photovoltaics (PV) have exhibited the most rapid cost decline among energy technologies (Trancik and Cross-Call, 2013) (Fig. 1.) In parallel with cost declines and performance improvement, global PV deployment has grown rapidly (Trancik, 2014). Continued PV deployment could help reduce greenhouse gas emissions and other pollution from energy systems (Hertwich et al., 2015), and contribute to climate change mitigation (Trancik and Cross-Call, 2013). For PV deployment to

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experience sustained growth in the future, however, particularly when considering the additional costs of addressing solar intermittency (Braff et al., 2016), further cost declines are likely needed (U.S. Department of Energy, 2012). This paper aims to identify the causes of PV's rapid cost declines in the past and gain insight into maintaining the pace of improvement in the future. More fundamentally, we aim to advance a model for understanding the mechanisms of technology improvement at multiple levels, from human efforts to devices, that can be applied to many technologies and measures of performance.

Improvement trends in PV and other technologies have been studied by various research communities. Correlational analysis is a common approach in these studies, often focusing on cost (or other measure of performance) and production or research investment levels (Nagy et al., 2013). One of the most widely-used models is the experience curve, which relates a technology's cost to cumulative production as a power law. Using this relationship as an explanatory or predictive tool, studies have estimated the rates of performance improvement for a range of technologies (Grubler et al., 1999; Koh and Magee, 2008; Nagy et al., 2013; Rubin et al., 2015; Zheng and Kammen, 2014). For example, PV module costs fell by about 20% with every doubling of cumulative capacity since the 1970s (McDonald and Schrattenholzer, 2001; Nemet, 2006). Several explanations for this cost decline have been proposed, such as public research and development efforts and various consequences of market growth (Bettencourt et al., 2013), including learning-by-doing, economies of scale, and private research and development efforts (Funk, 2013; McDonald and Schrattenholzer, 2001; Sagar and van der Zwaan, 2006; van der Zwaan and Rabl, 2004; Yu et al., 2011; Pillai, 2015). These studies share an approach to examining technology cost evolution where important high-level drivers of cost reduction are assumed and their influence on cost is inferred based on correlation. Technologies are treated as black boxes and the causes of cost reduction within technology are not modeled mechanistically.

Another group of studies uses detailed, device-level cost models, to understand how features of a technology or manufacturing process contribute to costs at one or more snapshots in time. Several such studies exist for PV, and they provide information on how individual cost components contribute to total costs, while taking into account the physics of PV technologies (Goodrich et al., 2013a; Powell et al., 2012, 2013; Woodhouse et al., 2013a,b). They also propose avenues for future technical improvement at the device or manufacturing level, and estimate cost reductions that might be achieved in the future (Jones-Albertus et al., 2016). Missing from these studies, however, is a method of accurately quantifying how each change to a feature of the technology or manufacturing process contributes to cost reductions, when many changes occur simultaneously. This knowledge is needed to understand the mechanisms of cost reduction but requires further modeling advances.

Pursuing both dynamic and detailed, device-level models is critical for identifying the causes of improvement in PV and other technologies. This combined approach would address inherent limitations in using correlational analyses to identify causal effects, especially in the case where data is limited, as is often the case in technology evolution research. This approach would also address the lack of dynamics in device-level studies. A few past studies have begun to develop such a methodology by decomposing technology costs over time (McNerney et al., 2011; Nemet, 2006). A study of the drivers of PV module cost changes from the 1970s to the early 2000s (Nemet, 2006) pioneered a bridge of this kind, and found that learning-by-doing had a limited effect on cost reductions.

In this paper we propose a new conceptual framework and dynamic-yet-detailed quantitative model for analyzing PV's (or any technology's) cost evolution. We start with a cost equation that computes costs from a set of variables, such as module efficiency, wafer area, and manufacturing plant size. From this we derive cost change equations that estimate the contribution of each variable to cost changes. Multiple simultaneous changes to variables have different impacts on cost than

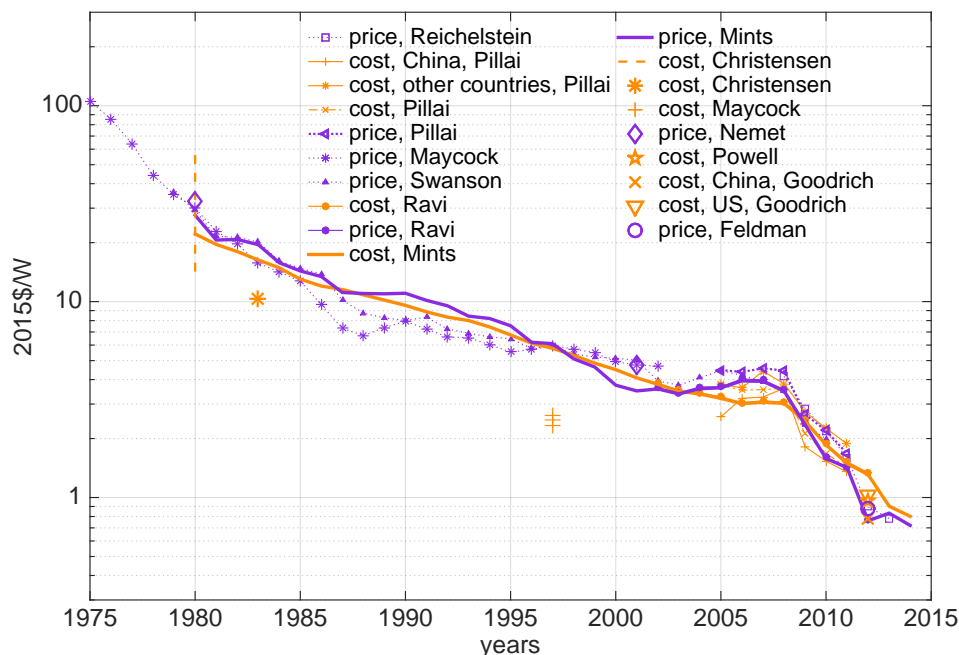


Figure 1: Module costs and prices since 1975. Costs are shown in orange, and prices are shown in purple. References: (Reichelstein and Sahoo, 2014); (Pillai and Cruz, 2013); Maycock price data from (Nemet, 2006) and cost data from (Maycock, 1997); (Swanson, 2011); (Ravi, 2013); (Mints, 2015); (Christensen, 1985); (Nemet, 2006); (Powell et al., 2013); (Goodrich et al., 2013b); (Feldman et al., 2014). Values are averages across different crystalline silicon PV technologies except for those in (Powell et al., 2013) (multicrystalline silicon) and (Goodrich et al., 2013b) (monocrystalline silicon).

individual changes summed together, and this must be accounted for in attributing cost changes to individual variables. Our method of estimating variable contributions is derived from adapting the total differential of cost (which decomposes infinitesimal cost changes) to finite changes.

In attributing PV's cost decline to particular causes, we draw a distinction between low-level causes (or mechanisms) and high-level causes (or mechanisms). Low-level mechanisms explain cost reduction in terms of changes to variables of a cost model. High-level mechanisms explain cost reduction in terms of processes like R&D, learning-by-doing, and scale economies that subsume low-level cost reductions. Both low- and high-level mechanisms can simultaneously provide explanations for a technology's cost change. For example, suppose a technology realizes an improvement to yield from learning-by-doing on the factory floor. The resulting cost reduction can be explained in two ways. One way is to say that yield increased; the other way is to say that learning-by-doing drove down costs. Both explanations are correct, and emphasize different views of the process of improvement. The explanation based on yield improvement (a low-level mechanism) ties the cost reduction to the detailed, device-level cost model of this technology. The explanation based on learning-by-doing (a high-level mechanism) ties the cost reduction to a general improvement mechanism that is discussed widely in studies of historical technology evolution. Here we consider both levels, and thus bridge bottom-up and top-down approaches to understanding technology cost evolution.

By considering both the low-level and high-level causes of PV's improvement we uncover lessons

that are useful for a variety of decision-makers. These may include engineers who design and manufacture PV modules, or firm managers and government policy-makers who develop strategy to support technological development. For example, our findings contribute to a long-standing debate concerning the effect of public investments in R&D versus market-expansion policies (Duke and Kammen, 1999; Hoppmann et al., 2013; Zheng and Kammen, 2014).

We focus on crystalline silicon PV modules because of their long history and dominant market share among PV technologies (Fraunhofer Institute, 2017). A key goal of our analysis is to understand the mechanisms of PV technology improvement and cost reduction over time, making it essential to study costs over a long time period. Since the 1950s, this technology has improved steadily due to R&D and manufacturing efforts (Powell et al., 2012). We analyze the costs starting in 1980, when space applications of PV were overtaken by terrestrial applications, which did not require as high quality and reliability (Candelise et al., 2013; Green, 2005; Nemet, 2006). We look at typical costs globally, since PV modules are manufactured and traded globally. We focus on costs rather than prices because mechanisms of technology improvement are reflected directly in costs, while prices also include mark-ups that are influenced by other factors, such as market competition (Pillai and McLaughlin, 2013). The method we develop can be adapted to study PV systems as a whole (including non-module cost components that show significant potential for cost reduction (Fraunhofer Institute, 2015; Trancik et al., 2015)), and a wide range of other technologies and measures of performance other than cost (Carbajales-Dale et al., 2014; Hertwich et al., 2015; Needell et al., 2016). The method might also prove a useful quantitative framework for eliciting high-quality input from experts on the prospects for future technological improvements (Morgan, 2014).

This paper is organized as follows: Section 2 provides a detailed explanation of the cost model. Section 3 explains the method of attributing cost changes to variables. Section 4 shows the results of our analysis and the connection between low-level and high-level mechanisms. In Section 5 we discuss the implications for future developments in PV and conclude.

## 2 Cost model

### 2.1 Cost decomposition strategy

We first develop a cost model for PV modules. The cost components are calculated based on quantities (or usage ratios)  $\phi$  and prices of inputs  $p$  used in manufacturing.

$$C_m \left( \frac{\$}{\text{module}} \right) = \underbrace{\frac{1}{y_m} \sum_{i \neq c, w} \phi_{mi} p_i}_{\text{non-cell module costs}} + \underbrace{\frac{n_{mc}}{y_m y_c} \sum_{i \neq w} \phi_{ci} p_i}_{\text{non-wafer cell costs}} + \underbrace{\frac{n_{mc} n_{cw}}{y_m y_c y_w} \sum_i \phi_{wi} p_i}_{\text{wafer costs}}, \quad (1)$$

where

$y_m$	yield at module manufacturing
$y_c$	yield at cell manufacturing
$y_w$	yield at wafer manufacturing
$\phi_{mi}$	quantity of input $i$ per module
$\phi_{ci}$	quantity of input $i$ per cell
$\phi_{wi}$	quantity of input $i$ per wafer
$p_i$	price of input $i$
$n_{mc}$	number of cells per module
$n_{cw}$	number of wafers per cell.

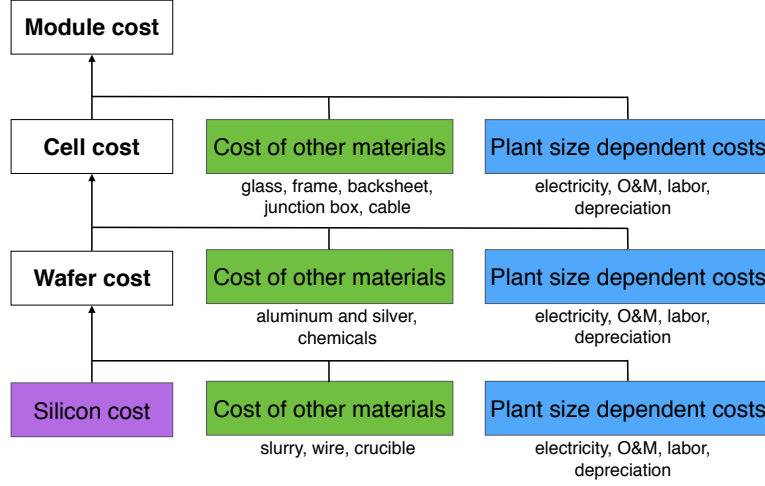


Figure 2: Cost components for wafer, cell and module levels (vertical disaggregation) and different input types (horizontal disaggregation).

While this equation has been written to represent wafer, cell, and module costs, which is a decomposition scheme specific to PV, the formulation of costs in terms of usage ratios ( $\phi$ ) and input prices ( $p$ ) is a general one that can describe any technology.  $\phi$  variables generally change as the result of engineering efforts to improve efficiency and materials utilization, while  $p$  variables change due to bulk purchasing, scarcity or other market effects (Kavak et al., 2015), or input substitutions.

At each of the three levels of PV manufacturing costs – wafer production, cell production, and module production (vertical levels in Fig. 2) – there are costs for materials, labor, operation & maintenance, electricity, and depreciation of plant and equipment. Decomposing by vertical level disaggregates the production process for PV modules, but creates challenges here for estimating the sources of cost reduction over time. A consistent categorization of costs is needed for every time period of interest starting with 1980, but such early cost data is scarce. Instead we accomplish this consistency over time by decomposing module production costs into three components by input type: silicon costs, non-silicon material costs, and plant-size dependent costs (horizontal categories in Fig. 2). These components are further modeled as described below.

## 2.2 Silicon costs

Historical prices of silicon (i.e. polysilicon) can be obtained from the literature (de La Tour et al., 2013; Nemet, 2006; Yu et al., 2011) or from industry sources (Mints, 2015). The amount of silicon used per wafer is a function of wafer area, silicon density, silicon layer thickness, and silicon utilization (the fraction of the silicon ingot used in the wafer after accounting for losses). Multiplying by the number of cells and the price of silicon, total silicon cost for the module can be expressed as

$$\text{Si cost} = n_{mc} \frac{Ah\rho}{U} p_s = n_{mc} Av\rho p_s. \quad (2)$$

Here  $n_{mc}$  is the number of cells per module,  $A$  is wafer area,  $h$  is wafer thickness,  $\rho = 2.33 \text{ g/cm}^3$  is wafer density,  $U$  is silicon utilization, and  $p_s$  is the price of polysilicon. We define the combination  $v \equiv h/U$ , which we refer to as ‘silicon usage’ for simplicity. The data for these variables are provided in Table 1.

Factor	Unit	1980	2001	2012	References and notes
Plant size ( $K$ )	MW/yr	1	13.3	1000	1980: (Swanson, 2006), (Mints, 2015). 2001: (Mitchell et al., 2002), (Mints, 2015). 2012: (Pillai, 2015), (Powell et al., 2012), (Mints, 2015). modules/yr 1.72x10 <sup>4</sup> 8.09x10 <sup>4</sup> 3.35x10 <sup>6</sup> Calculated by dividing the plant size in MW/yr by module power output in each year. We use the modules/year values to populate the plant size variable in our model.
Module efficiency ( $\eta$ )	unitless	8%	13%	15.2%	1980: (Christensen, 1985), (Mints, 2015), (Maycock, 1995). 2001: (Rohatgi, 2003), (Symko-Davies et al., 2000), (Mints, 2015). 2012: (Powell et al., 2012), (Mints, 2015).
Polysilicon price ( $p_s$ )	2015\$/kg	126	36	26	1980: (Mints, 2015), (Williams, 1980), (Costello and Rappaport, 1980), (Christensen, 1985). 2001: (Mints, 2015), (Swanson, 2006). 2012: (Mints, 2015), (Powell et al., 2013).
Wafer area ( $A$ )	cm <sup>2</sup>	90	156	243	1980: (Christensen, 1985), (Mints, 2015). 2001: (Mints, 2015), (Swanson, 2006). 2012: (Powell et al., 2012), (Mints, 2015).
Silicon thickness ( $t$ )	$\mu$ m	500	300	180	1980: (Swanson, 2006), (Fraunhofer Institute, 2017). 2001: (Swanson, 2006), (Sarti and Einhaus, 2002), (Green, 2005), (Fraunhofer Institute, 2017). 2012: (Applied Materials, 2011), (Fraunhofer Institute, 2017), (Goodrich et al., 2013a).
Silicon utilization ( $U$ )	unitless	0.20	0.36	0.45	1980: (Hammond, 1977). 2001: (Sarti and Einhaus, 2002). 2012: (Centrotherm Photovoltaics, 2010).
Silicon usage ( $v$ ) $\equiv t/U$	cm	0.25	0.083	0.04	See the references for $t$ and $U$ .
Yield ( $y$ )	unitless	75%	86%	95%	1980: (Mints, 2015). 2001: (Rohatgi, 2003), (Mints, 2015), (Sarti and Einhaus, 2002), (Little and Nowlan, 1997). 2012: (Applied Materials, 2011), (ITRPV, 2012), (Mints, 2015).
Share of materials costs ( $\theta$ )	unitless	0.69	0.43	0.65	1980: (Williams, 1980). 2001: (Maycock, 1997). 2012: (Powell et al., 2013).
Scaling factor ( $b$ )	unitless	0.27	0.27	0.27	(Maycock, 1997).
Module cost	2015\$/W	29.07	4.08	1.08	1980: (Mints, 2015), (Christensen, 1985). 2001: (Mints, 2015). 2012: (Mints, 2015), (Goodrich et al., 2013b), (Powell et al., 2013), (Ravi, 2013).

Table 1: Data used to calculate module cost components. Table S1 provides the individual data collected from the references above and the approach for obtaining the central estimate of each variable.

### 2.3 Non-silicon materials costs

Non-silicon materials include the crucible used to produce silicon ingots; slurry and wire used for wafer-sawing; aluminum and silver pastes, chemicals and screens used in cell manufacturing; and glass, frame, backsheet, encapsulant, ribbon, junction box and cable used in the module (Powell et al., 2013). To a first-approximation, the usage of these materials can be categorized as proportional to wafer area (e.g. aluminum pastes), proportional to module area (e.g. glass), proportional to module perimeter (e.g. frame), or neither (e.g. junction box), so that costs would take the form

$$\begin{array}{l} \text{non-Si} \\ \text{materials costs} \end{array} = c_0 + n_{mc}c_1A + c_2A_m + c_3P \quad (3)$$

with  $A$  representing wafer area,  $A_m$  the module area,  $P$  the module perimeter, and the  $c_i$  various constants. Because of data limitations, and since most materials costs depend on area, we ignore the fixed and perimeter dependent categories in this expression. Since the late 1970s wafer area  $A$  and module area  $A_m$  have increased proportionally,<sup>1</sup>  $A \propto A_m$ . Thus we simplify Eq. (3) to

$$\text{non-Si materials costs} = n_{mc}cA, \quad (4)$$

<sup>1</sup>The relationship between wafer area and module area is given by

$$A_{\text{module}} = \frac{n_{mc}A}{\alpha}$$

where  $n_{mc}$  is the number of cells per module and  $\alpha$  is the area utilization, the fraction of module area used by cells. Both wafer area and module area increased about three-fold in the last twenty years, while  $\alpha$  and  $n_{mc}$  have stayed almost constant in a typical module (Christensen, 1985; Powell et al., 2013).

where  $c$  is the per-area cost of all non-silicon materials and  $A$  is wafer area. Here the non-Si materials costs account for the costs at all of the wafer, cell and module levels. We derive the value of  $c$  from estimated materials costs in the three time periods. Based on the literature, the share of materials costs in PV modules varied between 43-69% (Williams, 1980; Maycock, 1997; Powell et al., 2013). We calculate the materials costs using the total module cost and the fraction due to materials, subtract the cost of silicon, and divide out the wafer area to obtain  $c$ .

## 2.4 Plant size-dependent costs

We model electricity, labor, maintenance and depreciation costs per wafer as a group of costs that are expected to experience scale economies with increases in PV plant scale (Maycock, 1997). In many manufacturing processes it is common for both capital and operating costs to rise less-than-proportionately with plant output. Plant-size dependent scale economies occur for many reasons, including greater amortization of fixed costs and machine scaling effects (Silberston, 1972). Production efficiencies may also occur, such as with labor tasks that become more specialized in larger plants, leading to more efficient workers (Silberston, 1972). In practice it is difficult to separate these many effects, and here we capture them as a whole using a power-law model based on PV plant scale,

$$\text{plant size-dependent costs} = n_{mc}p_0 \left( \frac{K}{K_0} \right)^{-b}, \quad (5)$$

where  $K_0$  is a reference plant size,  $p_0$  represents the total of these costs for a plant with the reference size, and  $b$  is the scaling factor. For convenience we take  $K_0$  as the number of modules manufactured in a year in a 1000 MW plant (the typical plant size value for 2012), though this choice is just a convention since the effects of a different choice of  $K_0$  would be absorbed into a different value for  $p_0$ . We use  $b = 0.27$  as the scaling factor (Maycock, 1997). We obtain this value by computing the change in labor, capital, utilities and overhead costs between plants of two sizes described in Maycock (1997). We obtain  $p_0$  for 2012 from Powell (2013). For 1980 and 2001 we compute  $p_0$  by computing non-materials costs and dividing out the factor  $(K/K_0)^{-b}$ .

## 2.5 Final cost equation

The power output of a module  $M$  is given by

$$M = \frac{\sigma n_{mc} A \eta}{\alpha} \quad (6)$$

where  $\sigma = 0.1 \text{ W/cm}^2$  is the solar constant,  $n_{mc}$  is the number of cells per module,  $A$  is wafer area,  $\eta$  is module efficiency, and  $\alpha$  is module area utilization. We assume a constant value of  $n_{mc} = 72$ . Some wafers, cells, and modules created during production are faulty and must be discarded, leading to waste and additional costs. To account for this we include the production yield  $y$ .<sup>2</sup> Summing the three components of module costs, and dividing by module capacity, total costs are

$$C \left( \frac{\$}{W} \right) = \frac{\alpha}{\sigma A \eta y} \left[ A v \rho p_s + c A + p_0 \left( \frac{K}{K_0} \right)^{-b} \right]. \quad (7)$$

<sup>2</sup>Wafer, cell and module production each have individual process yields, though for simplicity we represent overall yield with one value.

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Developing the cost model means choosing a set of variables to include, and the level of detail to expose about PV modules. The choice of variables used here reflects data availability, as well as what aspects of PV modules have received focus by researchers and industry. In principle, variables in the model above could be decomposed further to produce a model with additional detail. For example, module efficiency could be disaggregated into other variables, such as open circuit voltage, short-circuit current, and fill factor, which in turn could be further disaggregated. Efficiency, however, is a major cost-determining variable, and its cost contributions are important regardless of whether they came through open circuit voltage, fill factor, or another variable. Also, theoretically one could model all of the cost components including the materials, electricity, labor and so on as dependent on both plant size and wafer area. However, the data to populate such a sophisticated model is not available. Therefore we make a compromise and model the electricity, labor, maintenance and depreciation costs as scaling with plant size, while we model materials costs as dependent on wafer area.

We populate Eq. (7) with historical data from three snapshots in time (1980, 2001 and 2012) (Table 1) and obtain the three cost components for 1980, 2001 and 2012. The cost components are illustrated in Fig. 2 and their values are shown in Table 2. While all of the cost components have gone down in units of \$/W, their shares of total cost have varied. In particular silicon has become a smaller fraction of total cost over time, while non-silicon materials have become a larger fraction. The share of the plant-size dependent costs increased between 1980 and 2001 and then decreased after 2001.

Our decomposition variables are similar to Nemet (2006) (and one of the time periods we consider (1980-2001) is the same as in Nemet (2006)), though there are a few important differences which are summarized here. We include the contribution of non-silicon material costs, which are not considered in Nemet (2006). To avoid double-counting the reductions from efficiency improvements, we model silicon usage in units of g/module instead of g/W. Similarly we model plant output in units of modules/year instead of W/year. The share of costs that we find to be plant size-dependent and area-dependent are different. In Nemet (2006), all costs are modeled as being plant-size dependent while we model only non-materials costs as plant-size-dependent, based on Maycock (1997). Also based on Maycock (1997) we use a higher exponent for scale-dependent costs,  $b = 0.27$  versus  $b = 0.18$  in Nemet (2006). Therefore, compared with Nemet (2006) our plant scale variable affects a smaller fraction of total module costs, while influencing this fraction more strongly. We similarly model all materials costs as area-dependent, and all non-materials costs as non-area-dependent. As a result a much larger fraction of costs are independent of wafer area in our model, 31-57% depending on the period versus 4% in Nemet (2006). Other differences in the modeling approach used here and in Nemet (2006) are discussed at the end of Section 3.

Our approach also differs from the one taken in Pillai (2015), which uses a cost model that directly incorporates both low-level technical variables (e.g. module efficiency) and high-level effects (e.g. industry investment). First, we include the effects of other materials costs in addition to silicon in our model. More fundamentally, our cost model focuses on mechanistic relationships between cost components and variables, captured in detailed, device-level cost models, in order to study variables with a direct effect on cost components. For many technologies, there are known engineering relationships that provide substantial information about the causes of cost change. These relationships constrain what variables enter the cost model and the functional forms they appear in. For high-level mechanisms such as R&D investment to drive down costs, they must affect one or more of these underlying variables. Separating low and high in our analysis thus allows mechanisms at different levels to be non-competing explanations of cost reduction. For example, industry R&D investment and lower silicon usage may be simultaneously correct explanations for some portion of cost reduction, to the extent that the R&D is what led to lower silicon usage.



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Cost component	1980		2001		2012	
	\$/W	%	\$/W	%	\$/W	%
Silicon cost	10.88	37%	0.56	14%	0.14	14%
Non-silicon materials cost	9.17	32%	1.19	29%	0.56	51%
Plant size-dependent cost	9.01	31%	2.33	57%	0.38	35%
Total module cost	29.07	100%	4.08	100%	1.08	100%

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Table 2: Cost components in 1980, 2001 and 2012. Costs are in 2015 US dollars.

Moreover, the low-level mechanisms identified in our study provide useful insight on how high-level mechanisms affect cost. For example, knowing that R&D led to cost reduction through a particular set of low-level mechanisms (e.g. conversion efficiency and others) can help with identifying potential future constraints or opportunities for R&D policy.

### 3 Attributing cost changes to variables

How much of the cost reduction in PV modules came from each of the variables in Eq. (7)? While it is simple to compute how much Eq. (7) changes when its variables change, it is more difficult to say what any individual variable contributed. Here we describe a general method for decomposing cost changes into contributions from individual variables. We outline the approach here and give the full derivation in Supporting Information Section S2. For any function  $C(r_1, r_2, \dots)$ , an infinitesimal change  $dC$  can be straightforwardly split into contributions from individual variables using the total differential,

$$dC = \sum_z \frac{\partial C}{\partial r_z} dr_z = \sum_z dC_r. \quad (8)$$

Here a summation term  $dC_r = (\partial C / \partial r_z) dr_z$  accounts for the impact on  $C$  of a small change in variable  $r_z$ . Over a period of time  $t_1$  to  $t_2$ , this term contributes a finite change to  $C$  given by the integral

$$\Delta C_z(t_1, t_2) = \int_{t_1}^{t_2} \left( \frac{\partial C}{\partial r_z} \right) \frac{dr_z}{ds} ds. \quad (9)$$

Eq. (9) gives the contribution of variable  $z$  to changes in  $C$  between  $t_1$  and  $t_2$ . Summing over the contributions from all variables then recovers the total change,  $\Delta C(t_1, t_2)$ .

The challenge is to approximate this integral in a practical setting, where data about the technology's cost and variables have been sampled at discrete times. To do this, we first note that a cost can always be decomposed into a sum over cost components  $i$ ,  $C(\mathbf{r}) = \sum_i C_i(\mathbf{r})$ , which typically account for different categories of inputs. In addition, the cost components are often (as in Eq. (7)) products of functions of variables,

$$C_i(\mathbf{r}) = C_i^0 \prod_z g_{iz}(r_z), \quad (10)$$

where  $C_i^0$  is a constant and each function  $g_{iz}(\cdot)$  gives the dependence of cost component  $i$  on variable  $z$ . Then approximating the integral Eq. (11), it can be shown that the contribution of the  $z$ th

variable to the change in total cost from time  $t_1$  to time  $t_2$  is

$$\Delta C_z(t_1, t_2) \approx \sum_i \tilde{C}_i \ln \left( \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)} \right), \quad (11)$$

where  $r_z^1$  and  $r_z^2$  are the values of  $r_z$  at  $t_1$  and  $t_2$ , and  $\tilde{C}_i$  is a representative value of cost component  $i$  during the period. There are several ways the representative value  $\tilde{C}_i$  could be computed; in the SI, we show that a particularly good choice is given by  $\tilde{C}_i = (C_i^2 - C_i^1)/(\ln C_i^2 - \ln C_i^1)$ , where  $C_i^1$  and  $C_i^2$  are the values of cost component  $i$  at  $t_1$  and  $t_2$ .<sup>3</sup> With this choice the variable contributions computed using Eq. (11) sum to the total change in the cost of the technology,  $\Delta C = \sum_z \Delta C_z$ . Eq. (11) thus produces a decomposition of  $\Delta C$ , adapting the decomposition of  $dC$  in Eq. (8) to finite changes in cost. The method here is then a two-step procedure. First, one writes down (through knowledge of a technology) an equation for cost  $C$  as a function of a set of variables  $\mathbf{r}$ . Then, between two times for which one has data on the variables, one computes Eq. (11) for each variable.

In our case, the variables are  $\mathbf{r} = (A, \eta, y, K, p_s, v, c, p_0)$ . The three cost components in Eq. (7) can be written in the form of Eq. (10) as

$$C_1(\mathbf{r}) = \left( \frac{\alpha \rho}{\sigma} \right) v p_s \eta^{-1} y^{-1} \quad (12)$$

$$C_2(\mathbf{r}) = \left( \frac{\alpha}{\sigma} \right) c \eta^{-1} y^{-1} \quad (13)$$

$$C_3(\mathbf{r}) = \left( \frac{\alpha}{\sigma K_0^{-b}} \right) p_0 K^{-b} A^{-1} \eta^{-1} y^{-1}, \quad (14)$$

which from top to bottom are silicon costs, non-silicon materials costs, and plant-dependent costs. Each cost component is a constant pre-factor multiplied by a product of functions of the variables. Eq. (11) can then be computed to give estimates for individual variables. For example, the cost change due to a change in efficiency is

$$\Delta C_\eta = \sum_{i=1}^3 \tilde{C}_i \ln \left( \frac{(\eta^2)^{-1}}{(\eta^1)^{-1}} \right) = - \sum_{i=1}^3 \tilde{C}_i \ln \left( \frac{\eta^2}{\eta^1} \right). \quad (15)$$

The values of  $\tilde{C}_i$  can be computed from the cost components at the beginning and end of each period being studied. As an example, cost component 1 changed from 10.88 \$/W in 1980 to 0.56 \$/W in 2001 (Table 2), leading to a value for  $\tilde{C}_1$  of 3.48 \$/W.

An important departure from the method of Nemet (2006) is that we start with a cost equation first rather than beginning directly with cost change equations. This two-step approach has significant advantages. It ensures that our cost change equations are consistent with a realizable cost model, whose values can be directly compared with actual costs. A cost model shows explicitly how variables jointly determine total cost, making it easier to see what modeling assumptions are being made. It also helps to avoid double-counting or undercounting the effects of variables on costs, because the dependence of cost on each variable has been fully accounted for in the cost model.<sup>4</sup>

<sup>3</sup>In the SI we also show several other properties of  $\tilde{C}_i$ . It is related to and larger than the geometric mean of cost component  $i$  in the two periods,  $C^{geo} = \sqrt{C_i^1 C_i^2}$ , and a good approximation in practice is a value about 1/3 of the way from the geometric mean to the arithmetic mean,  $\tilde{C} = \frac{1}{2}(C_i^1 + C_i^2)$ .

<sup>4</sup>As an example of how double-counting can occur, silicon usage in PV modules is sometimes expressed in units of grams per watt. However, silicon usage per watt can decrease either because of a reduced silicon need per wafer, or because of an efficiency improvement. Efficiency of PV modules improved at the same time that silicon needs per

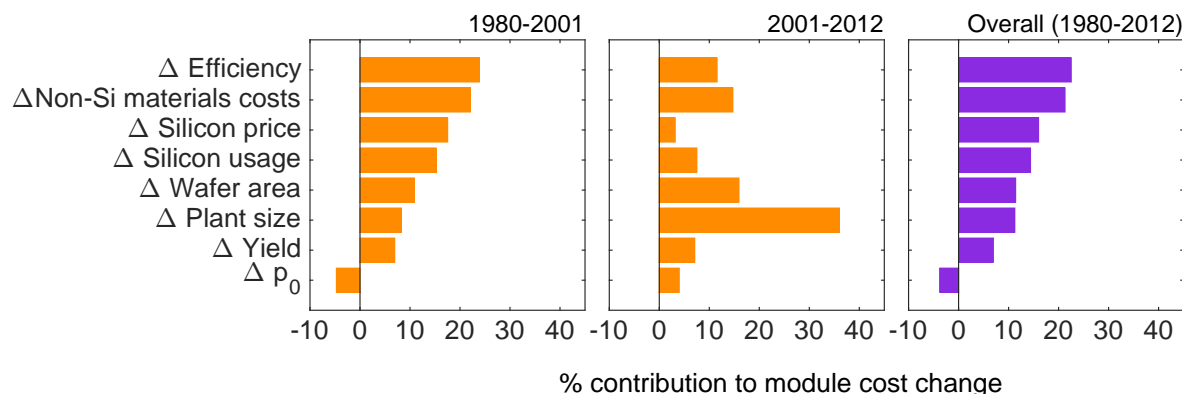


Figure 3: Contribution of the low-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). Mechanisms are listed in the order of decreasing contribution for the 1980-2001 period.

## 4 Results and discussion

In this section we first discuss the *low-level mechanisms* of module cost reduction, which refer to changes to variables in the cost equation. We then relate the low-level mechanisms to *high-level mechanisms* of cost reduction, which refer to strategies (e.g. R&D investment) or emergent effects (e.g. learning-by-doing, economies of scale) that drive down costs by affecting one or more low-level mechanisms.

### 4.1 Low-level mechanisms of cost reduction

Figure 3 and Table 3 show the changes in module cost due to each variable in the two periods, 1980-2001 and 2001-2012, and the entire period, 1980-2012. Improving efficiency was the largest contributor in the first period, responsible for 24% of the cost reduction. In the second period, module efficiency was only the fourth most significant factor, and its contribution dropped to 12%. Efficiency increased at the wafer and cell levels through many improvements, such as surface passivation (Green, 2005), anti-reflective coating (Goetzberger et al., 2003), and texturing of the wafers (Bruton, 2002; Rohatgi, 2003), and at the module level with improvements such as a glass structural layer laminated design (Green, 2005).

The second most significant factor in 1980-2001 was lower per wafer area costs of non-silicon materials, contributing 22% of the cost decline. The contribution of this factor in 2001-2012 was 14%. Non-silicon materials include substances such as as glass, laminate, and metal paste that become embedded in the module as well as slurry and wire used during production. The cost of these materials has been reduced by various process and module design improvements. For example, the cost of slurry used in wafer cutting may be reduced by recycling, with recycling rates up to 80% reported (Applied Materials, 2011).

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wafer decreased. As a result, silicon usage per watt has changed more than silicon usage per wafer has. If the full cost reduction benefit of higher efficiency were already counted elsewhere, then the silicon-usage benefit of higher efficiency will be double-counted.

Double-counting is less likely to occur if the analysis of cost changes starts with an equation for cost. In constructing this equation, the grams-per-watt units of silicon usage would have to be reconciled with the watts units of efficiency  $\times$  wafer area  $\times$  the solar constant to recover the correct units for cost. Once this reconciling of units is done, the cost change equations that are derived from the cost equation will automatically avoid double-counting as well.

Cost change due to:	1980-2001		2001-2012		1980-2012	
	$\Delta\$/W$	%	$\Delta\$/W$	%	$\Delta\$/W$	%
$\Delta$ Efficiency	-5.96	24%	-0.35	12%	-6.30	23%
$\Delta$ Non-Si materials costs	-5.51	22%	-0.44	14%	-5.95	21%
$\Delta$ Silicon price	-4.38	18%	-0.10	3%	-4.47	16%
$\Delta$ Silicon usage	-3.80	15%	-0.23	8%	-4.02	14%
$\Delta$ Wafer area	-2.71	11%	-0.48	16%	-3.19	11%
$\Delta$ Plant size	-2.07	8%	-1.08	36%	-3.15	11%
$\Delta$ Yield	-1.73	7%	-0.21	7%	-1.95	7%
$\Delta p_0$	1.18	-5%	-0.12	4%	1.06	-4%
Change in module cost	-24.99	100%	-3.00	100%	-27.99	100%

Table 3: Contribution of the low-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). Mechanisms are listed in the order of decreasing contribution for the 1980-2001 period. Costs are in 2015 USD.

Changes in polysilicon price contributed about 18% and 3% of the module cost decline in 1980-2001 and 2001-2012, respectively. The endpoints of our analysis lie on either side of a temporary period of silicon shortage in 2005-2008, during which polysilicon prices surged. Before this period, most polysilicon was used by the semiconductor industry. The PV industry used wafers rejected by the semiconductor industries, which has higher purity requirements (Sarti and Einhaus, 2002). Around 2006 polysilicon demand by the PV industry surpassed that of the semiconductor industry and polysilicon producers responded by increasing capacity. While more than 80% of the global polysilicon production was consumed by the semiconductor industry before 2000 (Fu et al., 2015), about 90% went to manufacturing PV cells as of 2012 (U.S. Geological Survey, 2012).

Decreasing silicon usage contributed 15% to module cost reduction in 1980-2001 and 8% in 2001-2012. Silicon usage depends on wafer thickness  $h$  and silicon utilization  $U$ . To study the total cost reduction from both variables, we define the combination  $v \equiv h/U$ . In 1980-2001 wafer thickness decreased from about 500  $\mu\text{m}$  to 300  $\mu\text{m}$  while silicon utilization increased from about 20% to 35%. Reduced thickness and higher utilization contributed about equally to the silicon cost reduction in this period. Silicon usage continued to decrease in 2001-2012, though it had a less significant cost impact. The industry developed thinner wafers both to reduce the cost of silicon and to increase conversion efficiency (Goetzberger et al., 2003). Silicon utilization also increased, though losses remain high, with about 50% of entering silicon lost during slicing of wafers from silicon ingots. Decreasing thickness contributed about 70% of silicon cost reduction in this period while utilization contributed the remaining 30%.

Increasing wafer area also contributed to module cost reduction, increasing from 90  $\text{cm}^2$  to 156  $\text{cm}^2$  in 1980-2001, and growing significantly again to about 240  $\text{cm}^2$  by 2012. Increasing wafer area, given a fixed number of cells per module, means that each module assembled produces twice as much power. Material costs are mostly proportional to area, but other assembly costs are insensitive to area (Ghannam et al., 1997; Nemet, 2006), so that larger wafer area yields cost savings.

Process improvements led to increasing yields in wafer, cell and module production. Overall yield increased from 75% in 1980 to 95% in 2012. The change in yield contributed about 7% to the module cost decline in both 1980-2001 and 2001-2012. Reduced handling of wafers, cells and modules due to automation, and improvements in processes such as wafering, help to increase yield (Applied Materials, 2011). We note that other improvements (such as larger wafer sizes) can decrease yields (Bruton, 2002), so that yield considerations can be a limiting factor for otherwise

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cost-saving practices.

The pre-factor  $p_0$  in Eq. (5) provides the level of plant-size dependent costs for a plant of a fixed size  $K_0$ , thus accounting for the overall level of electricity, labor, capital and depreciation costs at each time. The change in  $p_0$  was estimated to have increased cost in the 1980-2001 period and decreased cost in the 2001-2012 period. As described in Section 2 we calibrate  $p_0$  in 1980 and 2001 by requiring non-material costs in our cost model to match values from our data. We regard the variable with caution since changes are difficult to interpret and it is likely to propagate uncertainty in the data. However, its effects are among the smallest in both periods.

Finally, increasing manufacturing plant sizes resulted in scale economies through shared infrastructure, reduced labor requirements, higher yield, and better quality control (del Canizo et al., 2009). Typical plant sizes have scaled up with the industry, starting from 1 MW in 1980 and growing to about 13 MW in 2001 and to 1000 MW in 2012. Plant size became an especially significant factor in the more recent period, contributing almost 40% of the decline in module cost.

In Section S3 of the Supporting Information we estimate the sensitivity of our results to the uncertainty in the input variables shown in Table 1. We conclude that overall our results are robust to changes in the variables.

Our findings show some similarities to earlier reported results, as well as some differences. Similar to Nemet (2006) we find that increasing module efficiency was the largest contribution to cost reduction in 1980-2001. While Nemet (2006) finds the sources of cost declines to be heavily concentrated in plant size and module efficiency changes, we find cost-reducing effects were spread across a number of variables. In Nemet (2006) the costs of non-silicon materials are not considered, though we find that non-silicon material costs contributed almost as much to cost reduction as silicon did in this period. We obtain a lower estimate for the contribution of plant size in this period (8% versus 46%), and larger contributions for wafer area (11% versus 3%), silicon consumption (15% versus 3%), yield (7% versus 2%) and silicon price (18% versus 12%). Comparing our results from the 2001-2012 period with Pillai (2015), which looks at the period 2005-2012, we find a similar contribution by efficiency increases, and a smaller contribution by silicon price and silicon usage reductions, with plant size instead making the single largest contribution.

## 4.2 High-level mechanisms of cost reduction

Low-level cost reductions can be attributed to various ‘high-level’ mechanisms such as research and development, learning-by-doing, and economies of scale. Estimating the contributions of these mechanisms is useful because they align more closely with the policy levers often used to drive down cost. To estimate how much each contributed to cost reduction in PV modules (Fig. 4), we categorize each low-level mechanism according to the high-level mechanisms responsible for it. In Section S4 of the Supporting Information we perform a sensitivity analysis to test the effect of these assumptions. Our conclusions about the relative importance of different high-level mechanisms are robust to various schemes for relating low-level and high-level mechanisms (see Fig. S20).

Changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) are labeled as being caused by research and development (R&D) (Pisano, 1996; Rosenberg, 1982). R&D can result in improvements to either the manufacturing process or the technology being produced. We consider an improvement to have been made by learning-by-doing (LBD) if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature (Pisano, 1996). Cost changes that result from increases to the module manufacturing plant scale, and from volume purchases of materials or scale economies in materials supplier industries, we categorize as economies of scale (EOS).

Based on this we categorize improvements to module efficiency, wafer area and silicon usage

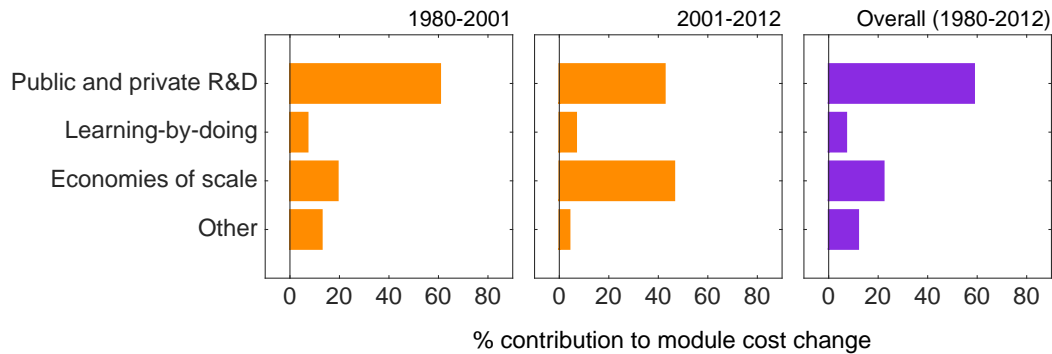


Figure 4: Percentage contribution of the high-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). We categorize the changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) as being caused by research and development (Pisano, 1996; Rosenberg, 1982). We consider an improvement to have been made by learning-by-doing if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature (Pisano, 1996). We categorize the changes that result from increases to the scale of the module manufacturing plant as economies of scale.

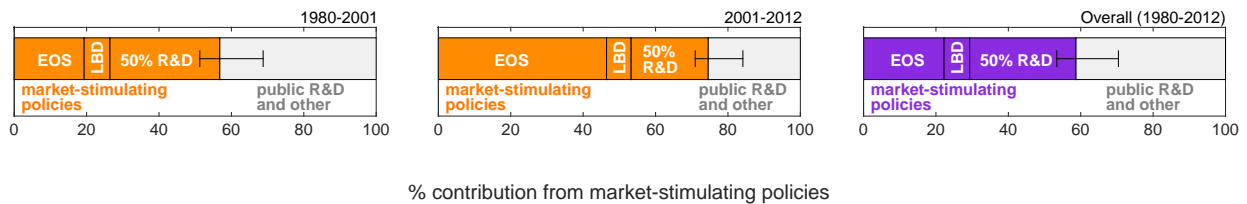


Figure 5: Percent contribution of market-stimulating policies (e.g. feed-in-tariffs, renewable portfolio standards) to module cost reduction in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers. Scale economies, learning-by-doing, and private R&D were all catalyzed by market-stimulating policies. Our data does not let us separate the effects of private and public R&D. To accommodate this, we add 50% of total R&D contributions to the contributions of scale economies and learning-by-doing. This effectively assumes that 50% of R&D improvements came from private R&D (roughly commensurate with the share of R&D expenditures in clean energy (McCrone et al., 2016, 2017; Nemet and Kammen, 2007)). (See Section S5 for the approach used to obtain this estimate.) Uncertainty bars show the total contribution from market-stimulating policies that would result under the alternate assignments of low-level mechanisms to high-level mechanisms shown in Fig. S20 without accounting for uncertainty in the private R&D estimate.

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under R&D. Improvements to cell efficiency were largely achieved by R&D done at national labs, universities and companies (National Renewable Energy Laboratory, 2018; Green, 2005; Goetzberger et al., 2003; Bruton, 2002; Rohatgi, 2003). Closing the gap between cell and module efficiencies also required R&D to improve module assembly processes such as encapsulation and interconnections (Green, 2005). Larger wafer area was achieved through R&D on single crystal growing and multicrystalline ingot casting (Christensen, 1985). Wafer thickness and silicon utilization improved through manufacturing techniques such as wire-sawing that were improved through R&D (Luque, 1987; Green, 2000; Kazmerski, 2006; Goetzberger et al., 2003). LBD may have been an additional driver of wafer area and silicon usage, which are affected by the efficiency of the manufacturing process.

Yield likely improved mainly through LBD, as advances in quality control of wafers and cells reduced rejects and increased automation reduced excess handling (Swanson, 2006). R&D may have played a role, though we expect that improving yield mainly involved repeated routine manufacturing activity.

The increasing size of module plants brought about economies of scale (EOS), as manufacturers simultaneously prepared for higher demand (Nemet, 2006) and looked for better access to capital (Goodrich et al., 2013b). Larger plants realized cost savings from spreading out the costs of shared infrastructure across greater output and from physical or geometric scaling relationships (Bruni, 1964; Silberston, 1972). In our model we assume all non-material costs realize scale benefits so that increasing plant sizes lowers the cost per watt of labor, capital equipment, and electricity.

Silicon prices were driven by different developments over time. Until the mid-2000s, demand for silicon wafers by the PV industry was met mainly with wafers rejected by the semiconductor industry (Woditsch and Koch, 2002; Sarti and Einhaus, 2002). The availability of silicon was mainly a positive externality of semiconductor production. In this period knowledge spillover was important (Swanson, 2006). The semiconductor industry developed know-how for producing single crystal silicon ingots and slicing wafers that benefited the PV industry. We therefore categorize silicon price's high-level mechanism as 'other' for 1980-2001. The PV industry surpassed the semiconductor industry in silicon demand around 2006 (Fisher et al., 2012), leading to a price spike and supply shortage. To meet the demand, polysilicon producers rapidly scaled up their capacities (Fu et al., 2015). For 2001-2012 we therefore choose EOS as the main high-level mechanism for decreasing silicon price.

Decreases to non-silicon materials costs were important sources of cost reduction in both time periods. Non-silicon materials costs can be decomposed into material usage (mass/area) times material price (dollars/mass). We propose that R&D helped reduce materials usage through new module designs (Green, 2005; ITRPV, 2018), while EOS led to the decreasing prices due to volume purchases or scale economies in materials supplier industries (Silberston, 1972; Goodrich et al., 2013b). We assign decreases in non-silicon materials costs equally to R&D and EOS, and explore the effect of other assignments in Fig. S20.

Finally we choose 'other' as the high-level mechanism for the change in  $p_0$ .  $p_0$  includes different types of costs (electricity, labor, capital and depreciation) and multiple high-level mechanisms can affect it. For example, the labor costs component of  $p_0$  can be reduced through LBD. We do not have the information to break down  $p_0$ , and therefore cannot quantify the high-level mechanisms governing it. However, this issue does not affect the results much since the module cost change due to the change in  $p_0$  has been small.

Adding the effects of low-level mechanisms, we estimate the percent changes in module cost due to R&D, LBD, and EOS in the two time periods (Fig. 4). In the Supporting Information, we consider other plausible categorizations of low-level mechanisms and show the maximum and minimum values achieved with these alternate categorizations. Fig. S20 shows two alternative cases

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that include recategorizing  $c$ ,  $A$  and  $v$ . These two alternative categorizations are meant to reflect the lowest and highest values R&D, EOS and LBD can take, so that robust conclusions can be drawn.

Our estimates show a strong impact from R&D. R&D played a dominant role in the first period, improving multiple cost equation variables that reduced cost significantly. (Table 3.) R&D's impact is high in the second period as well. LBD is estimated to have had a small impact, though we show in Fig. S20 that LBD's impact could be higher to the extent that it contributed to improvements in wafer area and silicon usage.

Scale economies changed from being a minor contributor in the first period to a significant one in the second. In the first period, though the change in plant size was responsible for significant cost reductions in absolute terms, cost reductions overall were dominated by R&D-driven efficiency and material usage improvements. These improvements slowed down and plant size grew more in percentage terms in the second period (Table 1), permitting EOS to contribute a larger share.

Private R&D, learning-by-doing and scale economies were all catalyzed by market-stimulating policies (e.g. through feed-in-tariffs, renewable portfolio standards). It is challenging to separate the effects of private and public R&D, though data suggests that private and public R&D expenditures have been similar in magnitude (McCrone et al., 2016, 2017; Nemet and Kammen, 2007). (See Section S5.) As a rough estimate, if 50% of R&D expenditures were from private R&D, and if private R&D expenditures have the same tendency to reduce cost as public R&D expenditures, then market-stimulating policies would have contributed about 60% of cost reduction over both periods. These results are shown in Fig. 5, where uncertainty bars reflect the range in contribution from market-stimulating policies that would result under the alternate assignments of low-level mechanisms to high-level mechanisms given in Fig. S20. Even without relying on funding levels as a proxy, there is evidence of private R&D's impact on variables such as efficiency, wafer area, silicon and non-silicon materials usage, all of which developed in conjunction with changes to the manufacturing process (National Renewable Energy Laboratory, 2018; Green, 2005; Goetzberger et al., 2003; Christensen, 1985; Kazmerski, 2006; Bruton, 2002; Rohatgi, 2003; ITRPV, 2018). Moreover, if we consider the unlikely scenario in which private R&D is assumed to have no effect on cost at all, market-stimulating policies would still be estimated to contribute roughly a third of the cost decline through EOS and LBD (Fig. 3). These results demonstrate that PV is an example of a technology where market-stimulating policies played a significant role in encouraging innovative activity and driving down costs (Bettencourt et al., 2013; Huenteler et al., 2016).

Some cost reductions came from improvements made outside of the PV industry, and were not stimulated by PV market expansion. We make a rough estimate of the upper bound on these effects using the variables that were affected by outside developments.  $p_0$  includes equipment costs in module manufacturing, and some equipment improvements (e.g. wire-sawing) took place in other industries and were transmitted to module manufacturing as knowledge spillovers. The change in wafer area may have come from improvements in the semiconductor industry. As noted earlier the price of silicon was also affected by developments in the semiconductor industry. Summing the cost reductions from these three variables would give us an estimate of 23% of PV's cost reduction coming from developments outside the PV industry in 1980-2012.

### 4.3 Prospective cost reductions

Considering the various low-level and high-level causes of historical cost declines, how effective would different strategies be at reducing module costs going forward? To gain insight we perform two simple analyses to assess how influential each low-level and high-level mechanism is for reducing costs under our model. In the first analysis, each cost equation variable is changed one-at-a-time,



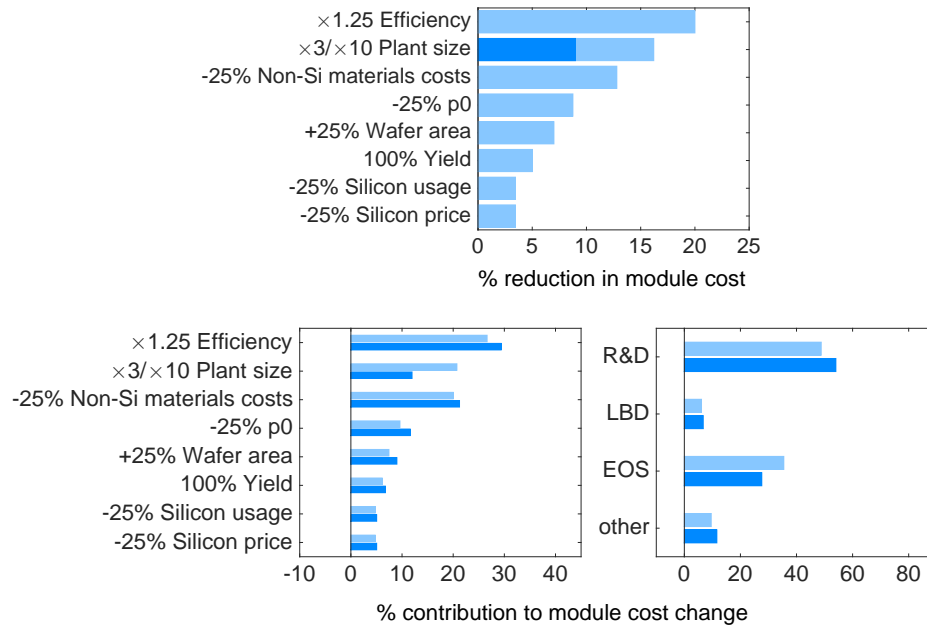


Figure 6: Prospective cost reductions. Top: Module cost reductions from one-at-a-time changes to cost equation variables. The reduction in module cost below the 2012 value is shown for each one-at-a-time variable change. Most variables are adjusted up or down by 25%, in a direction that reduces cost. Yield was changed from 95% to 100%. Plant size is increased by a factor of 3 (dark blue) and a factor of 10 (light blue). Bottom: Percent contributions of low-level mechanisms (left) and high-level mechanisms (right) to module cost reduction below the 2012 value in a scenario where several cost equation variables are changed simultaneously by the amounts shown. Separate bars are shown for the cases where plant size increases by a factor of 3 (dark blue) and a factor of 10 (light blue). R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers.

starting from its 2012 value, in a direction that reduces cost. With the exceptions of yield and plant size we change each variable by the same percentage of  $\pm 25\%$  to see how much cost reduction results. While different variables are not equally likely to realize a given percentage improvement, this approach lets us see how strongly each variable influences cost. To avoid using an unphysical yield above 100% instead of raising it by 25% we set yield equal to 100%. Plant size historically grew by very large factors far exceeding 25% – 13-fold in 1981-2001, and 75-fold in 2001-2012, and a 25% increase would not be expected to achieve much cost reduction. Instead we consider a 3-fold and a 10-fold increase in plant size. A 3-fold increase would result in plant sizes of about 3 GW/year, slightly larger than the size of the largest plants in China currently (Pillai, 2015). The results are shown in the top panel of Fig. 6. The most influential variables are efficiency, plant size, and non-silicon materials costs. Plant-size contributes substantially, though as plants become larger it may become more difficult to increase plant sizes by factors large enough to realize significant further gains.

High-level mechanisms often encompass improvements in several variables at the same time, and therefore we also model the simultaneous occurrence of multiple low-level mechanisms. To assess the cost change contribution of each low-level mechanism, we need to use the cost change equations developed in Section 3. (This is in contrast to the one-at-a-time changes to variables described above, whose contributions to cost change can be computed by comparing total costs at each snapshot in time.) In this second analysis we alter all variables simultaneously by the amounts given above. We then group the cost changes from these variables by high-level mechanism in the same way as in the second period of our historical analysis. The results<sup>5</sup> are shown in the bottom row of Fig. 6. Changing all variables at once, with a 10-fold increase in plant size, module costs decline to 44% of the 2012 value. As was observed historically, combined public and private R&D accounts for most of the decline in this scenario.

Our model can be used as a tool to perform prospective analyses to guide future engineering and policy efforts. The above analysis shows one scenario in which high-level mechanisms drive several low-level mechanisms. In this scenario, summing the percent contributions of learning-by-doing and scale economies, in the case of a 10X plant size increase, about 40% of total cost reduction results from mechanisms related to market-expansion (or roughly 65% if we assign 50% of future R&D-related improvements to the private sector, commensurate with the past share of private R&D funding (McCrone et al., 2016, 2017; Nemet and Kammen, 2007) as explained in Section S5).

Several scenarios could be developed to prospectively investigate the effects of low-level mechanisms, public R&D funding strategies, market-stimulating policies, private R&D, and other firm-level strategy. Expert elicitation could be used to assess the potential for changing variables in the cost equation. (The quantitative framework can enable the elicitation to focus on detailed variables that technical experts are familiar with, and may therefore help to elicit more reliable information from experts than has traditionally been achieved (Hultman and Koomey, 2007; Morgan, 2014).) Using this information, an exploration of the effects of different combinations of high- and low-level mechanisms could inform decisions in the public and private sectors. This approach could be applied not only to PV modules, but PV systems, energy storage, and other technologies, as well as performance metrics other than cost.

<sup>5</sup>In the 10X plant size case, plant size and non-Si materials costs swap places in the ranking of their effects. This can happen since changing all variables at once has different effects on cost than changing variables one-at-a-time and then aggregating their effects.

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## 5 Conclusions and policy implications

PV module costs declined dramatically in the last forty years. To identify the reasons, we advance an analysis method that bridges top-down, high-level analyses of technology cost evolution with bottom-up engineering models. The method begins with a cost equation relating a technology's costs to a set of underlying variables, e.g. technical performance characteristics such as efficiency or material usage. Cost change equations are then derived to estimate each variable's contribution. These variables explain cost changes 'at a low-level', and we term changes to these variables low-level mechanisms of cost reduction. Other processes like R&D, learning-by-doing, and scale economies may encompass several low-level mechanisms and drive down costs as a whole. We term these high-level causes of cost reduction.

We find that cost reductions in PV modules were fairly evenly distributed across a number of low-level mechanisms, which may help explain why this technology experienced relatively steady cost reductions over the past three decades. We estimate that changes to efficiency contributed 23% to the cost reduction from 1980-2012, non-silicon materials costs 21%, silicon price 16%, silicon usage 14%, wafer area 11%, plant size 11%, and yield 7%.

Several high-level mechanisms were important. These include public and private R&D and economies of scale, which contributed an estimated 59% and 22%, respectively, of the cost decline between 1980 and 2012. Learning-by-doing, defined here as incremental and resulting from a repeated, routine manufacturing process (e.g. not requiring an experimental production line), contributed 7% of the cost decline during this period.

Looking across both the 1980-2001 and the 2001-2012 periods, our findings suggest that the key drivers of decreasing costs have been changing over time. Economies of scale in particular have had a greater impact more recently, and likely offer an avenue for further cost reductions. Notably, the typical 2012 plant size in our data set has been surpassed by several new Chinese plants with typical sizes of 1-2 GW/year (Goodrich et al., 2013b). However there may be a limit to how much plant sizes will grow, and savings from economies of scale may be exhausted over time.

R&D, both public and private, was a key driver of module cost reduction historically and can be valuable going forward in improving module efficiency and reducing materials use. Improvements to module efficiency in particular would help cut the per-watt cost of all cost components of PV modules (as well as PV systems). Variables that might face limitations in the short term are manufacturing yield, which is already close to 100%, and wafer area, which is constrained by yield considerations.

Market-stimulating policies have played a central role in driving down the costs of PV modules, with private R&D, economies of scale, and learning-by-doing together contributing an estimated 60% of the cost decline in PV modules between 1980 and 2012. This finding contributes to an ongoing debate on the effectiveness of market-expansion policies, as complements to publicly-funded R&D (Hoppmann et al., 2013). In the case of PV, our analysis shows that private sector activity, which was incentivized by government policies in various nations (Trancik et al., 2015), was critically important for driving down costs. Additionally, our findings support the importance of public R&D to complement private sector activity, which may focus more on refinements to technology and manufacturing rather than the more major innovations needed as the limits to incremental improvements are reached (Hoppmann et al., 2013; Zheng and Kammen, 2014). These results add insight to earlier findings from correlational analyses on the importance of market expansion in driving energy patenting (as a proxy for innovative activity) in recent years (Bettencourt et al., 2013), with public R&D having played the dominant role in the 70s and 80s.

Looking forward, market-stimulating policies can continue to support cost declines, through a virtuous, mutually-reinforcing cycle of technology improvement and emissions reductions (Trancik

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et al., 2015). However, our results suggest that these policies should be complemented by public R&D to reduce the risks of exhausting the improvement potential of current-generation, silicon-based module technology, by exploring devices based on other abundant semiconductor materials with the potential for lower processing costs (Kavlak et al., 2015).

In this work we provide a reconstruction of trends in PV modules across time using three representative points in time, drawing from a variety of sources. It is important to note that the data used in this work has uncertainties, for example due to the incomplete sampling of firms. Nevertheless we provide a framework for modeling costs and cost changes that can be populated with the best available data.

This analysis can be helpful in guiding engineering efforts, the formulation of energy and climate policy, and research investments by government and the private sector. The method outlined here can be applied to many technologies to understand the reasons for past changes in cost or other performance, and to explore promising opportunities for future improvement.

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# Supporting Information

## S1 Data table

Factor	Unit	1980	2001	2012
Plant size ( $K$ )	MW/yr	a) 1 MW/yr (global average) (Mints, 2015) b) 1 MW/yr (Swanson, 2006): "A large PV plant in 1980 had a capacity of 1 MW/year in 1980." – Central value used in analysis: 1 MW/yr	a) 14 MW/yr (13 manufacturers with active production lines in the PVMaT program add up to 176 MW cell and/or module production capacity. The average is 14 MW.) (Mitchell et al., 2002) b) 12.5 MW/yr (global average) (Mints, 2015) – Central value used in analysis: mean (12.5, 14) = 13.25 MW/yr	a) 1115 MW (average based on eleven companies from several countries, where the range is 438 to 2400 and standard deviation is 542 (Pillai, 2015)) b) (Side note: For U.S. only, 400 MW based on two vertically integrated U.S. firms (Powell et al., 2012)) c) 400 MW (global average) (Mints, 2015) – Central value used in analysis: 1000 MW/yr, which is a round number based on Pillai's data (Pillai, 2015).
Module efficiency ( $\eta$ )	unitless	a) 8% (average efficiency of modules using monocrystalline Si cells based on surveys of manufacturers (Mints, 2015) b) Efficiencies of eight Block IV generation modules in the Flat-Plate Solar Array Project were 9.6%, 10.1%, 9.6%, 8.8%, 7.2%, 11.4%, 8.2%, 8.1%. The first six modules listed use monocrystalline Si cells, and the last two use multicrystalline Si cells. (Christensen, 1985) c) (Side note: In 1990, 11% for multi, 12% for monocrystalline silicon modules (Maycock, 1995)) – Central value used in analysis: 8%. This is a round number that reflects more or less the characteristics of the representative module we use (a Solarex module from Block IV generation, which has 72 multicrystalline cells, each of which is 95x95 mm, and an area utilization of about 0.9, in (Christensen, 1985).	a) 13.5% for multicrystalline Si cells (Rohatgi, 2003) b) 12.7% for modules with monocrystalline Si cells in 2000 (Symko-Davies et al., 2000) c) 13.6% for modules with monocrystalline Si and 12.1% with multicrystalline Si cells (Mints, 2015) – Central value used in analysis: mean(13.5%, 12.7%, 13.6%, 12.1%) = 13.0%	a) 14.5% for modules with multicrystalline Si cells (Powell et al., 2012) b) 14% and 17% for modules with multicrystalline monocrystalline Si cells, respectively (Mints, 2015) – Central value used in analysis: mean(14.5%, 14%, 17%) = 15.2%
Polysilicon price ( $p_s$ )	2015\$/kg (All prices converted to 2015\$ using U.S. GDP deflator.)	a) 66 \$/kg (Mints, 2015) b) 150 \$/kg (Williams, 1980) c) 162 \$/kg (Costello and Rapaport, 1980) d) (Side note: In 1975, it was greater than \$97/kg (Christensen, 1985)) – Central value used in analysis: mean(66, 150, 162) = 126 \$/kg	a) 32 \$/kg (Mints, 2015) b) 39 \$/kg in 2002 (Swanson, 2006) – Central value used in analysis: mean(32,39) = 35.5 \$/kg	a) 21 \$/kg (Mints, 2015) b) 31 \$/kg (Powell et al., 2013) – Central value used in analysis: mean(21, 31) = 26 \$/kg

Factor	Unit	1980	2001	2012
Wafer area (A)	cm <sup>2</sup>	<p>a) Wafer areas of eight Block IV generation modules in the Flat-Plate Solar Array Project were 83, 45, 79, 45 cm<sup>2</sup> for round wafers; and 100, 90, 90, 41 cm<sup>2</sup> for square or quasquare wafers (Christensen, 1985)</p> <p>b) 80 cm<sup>2</sup> (Mints, 2015): “1980 was a breakthrough year with wafer diameter sizes moving from 3 inches to 4 inches”, which means from 45 to 80 cm<sup>2</sup>.</p> <p>c) (Side note: Later in the 1981-1984 period, 100 cm<sup>2</sup> was typical (Christensen, 1985))</p> <p>– Central value used in analysis: 90 cm<sup>2</sup> to reflect the characteristics of the representative module we use (a Solarex module from Block IV generation, which has 72 multicrystalline cells, each of which is 95x95 mm, and an area utilization of about 0.9, in (Christensen, 1985))</p>	<p>a) 156 cm<sup>2</sup> (Mints, 2015)</p> <p>b) 156 cm<sup>2</sup> (125x125 mm) (Swanson, 2006)</p> <p>– Central value used in analysis: 156 cm<sup>2</sup></p>	<p>a) 243 cm<sup>2</sup> (156x156 mm) (Powell et al., 2012)</p> <p>b) 243 cm<sup>2</sup> (156x156 mm) (Mints, 2015)</p> <p>– Central value used in analysis: 243 cm<sup>2</sup></p>
Silicon thickness (t)	μm	<p>a) 500 μm (Swanson, 2006)</p> <p>b) (Side note: In 1990, it was 400 μm (Fraunhofer Institute, 2017))</p> <p>– Central value used in analysis: 500 μm</p>	<p>a) 300 μm in 2002 (Swanson, 2006)</p> <p>b) State-of-the-art wafers are in the 250-350 μm range (Sarti and Einhaus, 2002)</p> <p>c) (Side note: In 2004, thickness was around 260 μm for both mono and multicrystalline Si wafers (Green, 2005))</p> <p>d) (Side note: In 2006, thickness was around 200 μm (Fraunhofer Institute, 2017))</p> <p>– Central value used in analysis: mean(300, mean(250,350)) = 300 μm</p>	<p>a) 180 μm (Applied Materials, 2011)</p> <p>b) 180 μm (Fraunhofer Institute, 2017)</p> <p>c) 180 μm (Goodrich et al., 2013a)</p> <p>– Central value used in analysis: 180 μm</p>
Silicon utilization (U)	unitless	0.20 in 1977 (“About 80% of the purified silicon is left as scrap in the crucibles used to grow large cylinders of the material in crystalline form, or ends up as sawdust when the thin wafers used to make cells are cut from the cylinder.”) (Hammond, 1977)	0.36 (30% of the incoming silicon mass is wasted during ingot-to-brick process, and 34% of the incoming silicon mass is wasted during brick-to-wafer process. Utilization is 1 - (0.30 + 0.34) = 0.36) (Sarti and Einhaus, 2002)	0.45 (estimation based on 124 million 170 μm wafers or 107 million 180 μm wafers being obtained from a 2700 ton ingot) (Centrotherm Photovoltaics, 2010)
Silicon usage ( $v \equiv t/U$ )	cm	0.25	0.083	0.04

Factor	Unit	1980	2001	2012
Yield ( <i>y</i> )	unitless	a) 75% (includes yield at wafer, cell and module manufacturing) (Mints, 2015) – Central value used in analysis: 75%	a) 86% (obtained by multiplying the wafering yield of 0.92, cell yield of 0.98, and module yield of 0.95) (Rohatgi, 2003) b) 88% (includes yield at wafer, cell and module manufacturing) (Mints, 2015) c) 85% (Sarti and Einhaus, 2002) d) (Side note: In 1997, yield was reported as 84% (Little and Nowlan, 1997)) – Central value used in analysis: mean(86%, 88%, 85%) = 86.3%.	a) 94.5% (obtained by multiplying the wafering yield of 97.5% (Applied Materials, 2011), cell yield of 98.5% (ITRPV, 2012), and module yield of 99% (ITRPV, 2012)). Note that wafering yield is reported as “>95%” in (Applied Materials, 2011), which implies a value in the 95%-100% range. The average of this range is 97.5%, assuming a uniform (i.e. maximally uncertain) distribution between 95% and 100%. b) 95% (includes yield at wafer, cell and module manufacturing) (Mints, 2015) – Central value used in analysis: 95%
Share of materials costs ( <i>θ</i> )	unitless	0.69 (Williams, 1980)	0.43 for 1997 (Maycock, 1997)	0.65 (Powell et al., 2013)
Scaling factor ( <i>b</i> )	unitless	a) 0.27 (Maycock, 1997): Average of the range [0.14, 0.41] calculated based on different assumptions when comparing a 10 MW and a potential 100 MW plant, by scaling only the non-materials costs. b) (Side note: 0.10 (Rohatgi, 2003): Calculated based on 1.06\$/W cost for 25 MW plant versus 0.79\$/W for a 500 MW plant.) c) (Side note: 0.20 (Ghannam et al., 1997): Calculated based on 3.6\$/W cost for 2 MW plant versus 1.2\$/W for a 500 MW plant.) – Central value used in analysis: 0.27 because this value is obtained by scaling only the non-materials costs with plant size, as we do in our model. The values in (b) and (c) scale the total costs with plant size, therefore we do not use these.		
Module cost	2015\$/W (All cost and price data converted to 2015\$ using U.S. GDP deflator.)	a) cost: 22.13 (average for multi and monocrystalline Si modules globally) (Mints, 2015) b) cost: 36 (average cost of the Block IV generation modules in the Flat-Plate Solar Array Project, which had a cost range between 14 and 56 2015\$/W) (Christensen, 1985)  Price data for comparison: a) price: 33 (Nemet, 2006) b) price: 28 (Mints, 2015) c) price: 30 (Nemet, 2006)  – Central value used in analysis: mean of the cost data, which is mean(22.13, 36) = 29.07 \$/W	a) cost: 4.08 (average for multi and monocrystalline Si modules globally) (Mints, 2015)  Price data for comparison: a) price: 4.8 (Nemet, 2006) b) price: 3.5 (Mints, 2015) c) price: 5.0 (Swanson, 2011)  – Central value used in analysis: 4.08 \$/W	a) cost: 1.31 (average for multi and monocrystalline Si modules globally) (Mints, 2015) b) cost: 0.78 (monocrystalline Si modules made in China) (Goodrich et al., 2013b) c) cost: 1.03 (monocrystalline Si modules made in the U.S.) (Goodrich et al., 2013b) d) cost: 0.96 (multicrystalline Si modules made in the U.S.) (Powell et al., 2013) e) cost: 1.34 (average cost for crystalline Si modules, cites SPV Market Research) (Ravi, 2013)  Price data for comparison: a) price: 0.77 (Ravi, 2013) b) price: 0.88 (Feldman et al., 2014) c) price: 0.76 (Mints, 2015)  – Central value used in analysis: mean of the cost data, which is mean(1.31, 0.78, 1.03, 0.96, 1.34) = 1.08 \$/W

Notes:

- Side notes in parentheses show additional data that we found. These are not used to determine the central values of variables but are included here for completeness.
- In most cases, the references shown in the table do not cite any other source for their data. We treat these references as the primary sources. In a small number of cases (e.g. 2012 module cost from (Ravi, 2013)) a secondary source cites a primary source that we were unable to access directly. In these cases, we cite both the secondary source and the primary source.

Table S1: Data used to populate the cost model.

## S2 Derivation of Eq. 11

Here we derive Eq. 11 from the main paper, which we use to estimate the contributions of individual cost equation variables to the change in cost of a technology. Let  $C(\mathbf{r})$  be an equation for cost as a function of a vector of variables  $\mathbf{r} = (r_1, r_2, \dots)$ . Changes in  $\mathbf{r}$  lead to changes in  $C$ , and we would like to know how much of the change in  $C$  we should ascribe to an individual variable  $r_z$ . For infinitesimal changes to  $C$ , decomposing the change is straightforward. The total differential of  $C$  is  $dC = \sum_z \frac{\partial C}{\partial r_z} dr_z$ , in which the  $z$ th term  $\frac{\partial C}{\partial r_z} dr_z$  gives the contribution of variable  $z$  to  $dC$ . For finite changes in cost, one may integrate  $dC$  over a time period of interest. Let  $t_1$  and  $t_2$  denote the beginning and end of this period. The change in cost over the period is

$$\Delta C(t_1, t_2) = \sum_z \int_{t_1}^{t_2} \left( \frac{\partial C}{\partial r_z} \right) \frac{dr_z}{ds} ds, \quad (16)$$

where the  $z$ th term gives the contribution of variable  $r_z$  to the total change in cost over the period. We denote this contribution by  $\Delta C_z(t_1, t_2)$ :

$$\Delta C_z(t_1, t_2) \equiv \int_{t_1}^{t_2} \left( \frac{\partial C}{\partial r_z} \right) \frac{dr_z}{ds} ds. \quad (17)$$

Eq. (17) expresses the intuitive idea that the contribution of variable  $z$  depends on how much this variable changes ( $\frac{dr_z}{ds} ds$ ) and how much this change affects cost ( $\frac{\partial C}{\partial r_z}$ ), with the resulting effects summed over the period.

If it were possible to observe the cost model variables  $\mathbf{r}$  in continuous time, Eq. (17) would provide all that is needed to compute the contribution of each variable  $r_z$ . Clearly this is not an option in practice; data about a technology must be sampled at discrete times. The problem is similar to that of constructing economic index numbers (e.g. the consumer price index), where data on prices and quantities of economic goods are gathered at discrete intervals. Several practical index formulas can be understood as discrete-time approximations of the continuous-time Divisia index, which involves an integral over price and quantity changes in a basket of goods. Similarly, we consider here how to approximate the integral Eq. (17) using data for the cost equation variables  $\mathbf{r}$  observed at discrete times. First, suppose the variables  $\mathbf{r}$  are known at a set of times  $t_a, t_b$ , etc. between  $t_1$  and  $t_2$ . Then one can break up the integral from  $t_1$  to  $t_2$  into integrals over shorter periods,

$$\begin{aligned} \Delta C_z(t_1, t_2) &= \int_{t_1}^{t_2} dC_z \\ &= \int_{t_1}^{t_a} dC_z + \int_{t_a}^{t_b} dC_z + \dots + \int_{t_z}^{t_2} dC_z, \end{aligned} \quad (18)$$

where  $dC_z$  is the integrand in Eq. (17). Breaking up the original integral from  $t_1$  to  $t_2$  as much as possible, eventually there will be no more data from intermediate times to exploit. At this point each integral in Eq. (18) will have the form of Eq. (17), with values of  $\mathbf{r}$  known only at the beginning and end of the period that the integral spans. Thus, we should ask how to approximate Eq. (17) in the situation where the cost equation variables are known only at the end points  $t_1$  and  $t_2$ .

To develop an approximation, note that the cost of any good can be broken out into a sum over a set of cost components,  $C = \sum_i C_i$  (e.g. representing different production inputs or categories of cost). In addition, for many cost equations of interest (including our PV cost equation), the cost components  $C_i$  are multiplicatively separable functions of the variables,  $C_i(\mathbf{r}) = C_i^0 \prod_w g_{iw}(r_w)$ ,

where  $C_i^0$  is a constant and the function  $g_{iw}(\cdot)$  gives the dependence of  $i$ th cost component on the  $w$ th variable. Thus the function  $C(\mathbf{r})$  takes the form

$$C(\mathbf{r}) = \sum_i C_i^0 \prod_w g_{iw}(r_w). \quad (19)$$

The partial derivative  $\partial C / \partial r_z$  in Eq. (17) then becomes

$$\frac{\partial C}{\partial r_z} = \sum_i \frac{\partial C_i}{\partial r_z} = \sum_i C_i \frac{\partial \ln C_i}{\partial r_z} = \sum_i C_i \frac{d \ln g_{iz}}{dr_z}, \quad (20)$$

and Eq. (17) becomes

$$\Delta C_z(t_1, t_2) = \sum_i \int_{t_1}^{t_2} C_i(s) \frac{d \ln g_{iz}}{dr_z} \frac{dr_z}{ds} ds, \quad (21)$$

where  $C_i(s)$  denotes  $C_i(\mathbf{r}(s))$ . Eq. (21) then enables the following approximation. We approximate the time-evolving cost component  $C_i(s)$  by a representative constant  $\tilde{C}_i$  characterizing cost component  $i$  during the period  $t_1$  to  $t_2$ . We discuss how to compute  $\tilde{C}_i$  momentarily. Then  $\tilde{C}_i$  may be taken out of the integral, which can be integrated to give Eq. 11 from the main paper,

$$\Delta C_z(t_1, t_2) \approx \sum_i \tilde{C}_i \ln \left( \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)} \right), \quad (22)$$

where  $r_z^1 = r_z(t_1)$  and  $r_z^2 = r_z(t_2)$  are the values of  $r_z$  at times  $t_1$  and  $t_2$ . As required, Eq. (22) needs only the values of cost equation variables at the start and end of the period. Intuitively, Eq. (22) can be understood as multiplying the representative value of cost component  $i$  from the period,  $\tilde{C}_i$ , by the factor change induced in  $C_i$  by changes in  $r_z$ , and then summing  $r_z$ 's effects across all cost components to get its contribution to the change in total cost.

To determine  $\tilde{C}_i$ , we would like a value that provides a good representation of cost component  $i$  during the time period as it changed from its initial value  $C_i^1 = C_i(t_1)$  to its final value  $C_i^2 = C_i(t_2)$ . One possible choice is the arithmetic mean,  $\bar{C}_i = \frac{1}{2}(C_i^1 + C_i^2)$ , while another is the geometric mean,  $C_i^{geo} = \sqrt{C_i^1 C_i^2}$ . There turns out to be an especially good choice of  $\tilde{C}_i$  that is related to the geometric mean. First, note that the  $z$ th term in the sum Eq. (22) can be understood as the contribution of variable  $r_z$  to the change in cost component  $i$ . We denote this as  $\Delta C_{iz}$ :

$$\Delta C_{iz}(t_1, t_2) \equiv \tilde{C}_i \ln \left( \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)} \right). \quad (23)$$

Summing the  $\Delta C_{iz}$  over all cost components  $i$ , as in Eq. (22), gives the contribution of variable  $z$  to total cost change  $\Delta C_z$ . Alternatively, summing the  $\Delta C_{iz}$  over all variables  $z$  gives the contribution of changes in cost component  $i$  to the change in total cost:  $\Delta C_i(t_1, t_2) = \sum_z \Delta C_{iz}(t_1, t_2)$ . However, unlike  $\Delta C_z$ ,  $\Delta C_i$  is directly computable from data – it is simply the observed change  $C_i^2 - C_i^1$  in the cost component over the period. We can therefore require  $\Delta C_i(t_1, t_2)$  to equal the observed change in cost component  $i$ , choosing a value of  $\tilde{C}_i$  that meets this requirement. Plugging Eq. (23)

into  $\Delta C_i(t_1, t_2) = \sum_z \Delta C_{iz}(t_1, t_2)$  and rearranging, we have

$$\begin{aligned}
\Delta C_i(t_1, t_2) &= \tilde{C}_i(t_1, t_2) \sum_z \ln \left( \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)} \right) \\
&= \tilde{C}_i(t_1, t_2) \ln \left( \prod_z \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)} \right) \\
&= \tilde{C}_i(t_1, t_2) \ln \left( \frac{C_i^0 \prod_z g_{iz}(r_z^2)}{C_i^0 \prod_z g_{iz}(r_z^1)} \right) \\
&= \tilde{C}_i(t_1, t_2) \ln \left( \frac{C_i^2}{C_i^1} \right) \\
&= \tilde{C}_i(t_1, t_2) \Delta \ln C_i(t_1, t_2).
\end{aligned} \tag{24}$$

Solving for  $\tilde{C}_i$  gives

$$\tilde{C}_i = \frac{\Delta C_i}{\Delta \ln C_i}. \tag{25}$$

Eqs. (25) and (22) are the final results. To get a feel for this choice of  $\tilde{C}_i$ , note that it can be written in the form

$$\tilde{C}_i = C_i^{geo} \frac{\sinh f}{f} = C_i^{geo} \left( 1 + \frac{1}{48} f^2 + \dots \right), \tag{26}$$

where  $C_i^{geo} \equiv \sqrt{C_i^1 C_i^2}$  is the geometric mean of cost component  $i$  at times  $t_1$  and  $t_2$ , and  $f \equiv \frac{1}{2} \ln (C_i^2 / C_i^1)$ . Eq. (26) can be obtained from Eq. (25) by rearranging  $\Delta C_i$  as

$$\begin{aligned}
\Delta C_i &= C_i^2 - C_i^1 \\
&= \sqrt{C_i^1 C_i^2} \sqrt{\frac{C_i^2}{C_i^1}} - \sqrt{C_i^1 C_i^2} \sqrt{\frac{C_i^1}{C_i^2}} \\
&= C_i^{geo} \left( \frac{C_i^2}{C_i^1} \right)^{1/2} - C_i^{geo} \left( \frac{C_i^2}{C_i^1} \right)^{-1/2} \\
&= C_i^{geo} \left( e^{\frac{1}{2} \ln(C_i^2 / C_i^1)} - e^{-\frac{1}{2} \ln(C_i^2 / C_i^1)} \right) \\
&= C_i^{geo} \cdot 2 \sinh \left( \frac{1}{2} \ln (C_i^2 / C_i^1) \right).
\end{aligned} \tag{27}$$

$\tilde{C}_i$  is larger than the geometric mean and smaller than the arithmetic mean, and in practice a good approximation is  $\tilde{C}_i \approx \frac{2}{3} C_i^{geo} + \frac{1}{3} \bar{C}_i$ , i.e. the value a third of the way from the geometric to the arithmetic mean. With this choice of  $\tilde{C}_i$  Eq. (22) remains an approximation of the integral Eq. (21), but the choice ensures that the sum of contributions produced by Eq. (22) exactly equals the total change in cost.

We show now an example of the formulas and method above. Consider the cost equation

$$\begin{aligned}
C(r_1, r_2, r_3, r_4) &= C_1(r_1, r_2) + C_2(r_3, r_4) \\
&= r_1 r_2 + r_3 r_4.
\end{aligned} \tag{28}$$

	Quantity	$t_1$	$t_2$	$\tilde{C}_i$	Cost change contribution ( $\Delta C_i$ )	Percent contribution
Costs	$C_1(t)$	50	5	19.54	-45.0	73.8%
	$C_2(t)$	20	4	9.94	-16.0	26.2%
	Sum	70	9	-	-61.0	100.0%
	Quantity	$t_1$	$t_2$	Percent change	Cost change contribution ( $\Delta C_z$ )	Percent contribution
Variables	$r_1(t)$	10	5	-50%	-13.5	22.2%
	$r_2(t)$	5	1	-80%	-31.5	51.6%
	$r_3(t)$	4	2	-50%	-6.9	11.3%
	$r_4(t)$	5	2	-60%	-9.1	14.9%
	Sum	-	-	-	-61.0	100.0%

Table S2: Calculation of cost change contributions in an example with cost equation  $C(\mathbf{r}) = r_1 r_2 + r_3 r_4$ .

An equation with this structure could arise, for example, if  $r_1$  and  $r_3$  were quantities of two production inputs used by a technology and  $r_2$  and  $r_4$  were their prices. Suppose variables  $r_1$  through  $r_4$  are known at two times, with the values given in Table S2. The change in total cost can be decomposed either in terms of changes contributed by particular cost components ( $\Delta C_i$ ), or in terms of changes contributed by particular variables ( $\Delta C_z$ ). As noted earlier, the  $\Delta C_i$  are simple to compute, and are just the observed changes in the cost components. The contributions of each variable may be computed from Eq. (22) using representative values of the cost components  $\tilde{C}_1$  and  $\tilde{C}_2$  during the period. Computing  $\tilde{C}_1$  and  $\tilde{C}_2$  using Eq. (25), the variable contributions will be constrained to reproduce the known cost component changes  $\Delta C_1$  and  $\Delta C_2$ . In this example, where the cost equation is simple, one can directly see the effects of these two constraints on the estimated variable contributions: The contributions from  $r_1$  and  $r_2$  sum to  $\Delta C_1$ , while the contributions from  $r_3$  and  $r_4$  sum to  $\Delta C_2$ . As a consequence, we also have that the sum of all variable contributions equals the change in total cost.

## S3 Sensitivity analysis for low-level mechanisms

### S3.1 Model sensitivity for low-level mechanisms

In this section we explore the sensitivity of our model to the uncertainty in the input variables of Table 1. We vary each variable in each of the three time periods by  $\pm 20\%$ , for a total of eight cases, and recompute the list of cost change contribution in both periods. We take the minimum and maximum of the changes in each variable out of these eight cases to produce error bars.<sup>6</sup> Figure S1 shows how the percent contributions change when silicon usage  $v$  is varied. Since contributions must sum to 100%, changing  $v$  affects the relative contributions of both  $v$  and all other variables to a greater or lesser extent. Figures S2-S9 show the same analysis for other variables, total module cost, and the scaling factor,  $b$ . Figure S10 shows the contributions obtained from all of the individual sensitivity analyses shown in Figures S1-S7. We conclude that the model is most sensitive to module efficiency, wafer area, and the share of materials costs while not as

<sup>6</sup>An exception is yield, which is varied by  $\pm 7\%$ ,  $\pm 4\%$  and  $\pm 4\%$  of its value in 1980, 2001, and 2012, respectively, to ensure that it does not exceed 100%. To prevent efficiency from decreasing over time in our sensitivity tests, we limit the variation of efficiency such that module efficiency is varied by  $\pm 7\%$  of its value in 2001 and 2012.



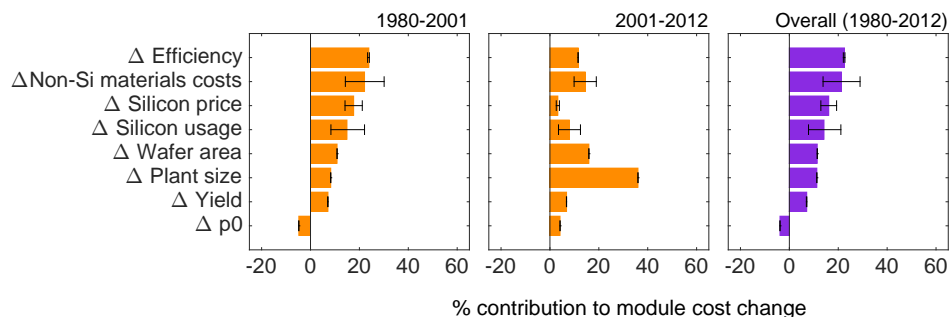


Figure S1: Sensitivity analysis for silicon usage,  $v$ . We vary silicon usage in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

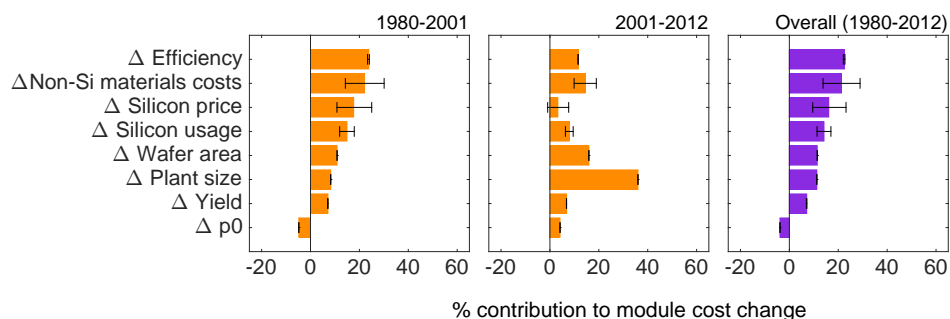


Figure S2: Sensitivity analysis for silicon price,  $p_s$ . We vary silicon price in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

sensitive to changes in other variables and the scaling factor,  $b$ . We find that a smaller change in efficiency during a period is associated with larger changes in non-silicon materials and  $p_0$ , and in some scenarios with more modest assumptions about efficiency improvement, we find that the relative contributions of efficiency and non-silicon materials switch places Figure S3. In these scenarios, both efficiency and non-silicon materials continue to play significant roles in cost reduction. Furthermore, conversion efficiency estimates may be fairly reliable because of standard testing procedures. The share of materials costs ( $\theta$ ) constrains the relative magnitude of the materials costs and plant-size dependent costs. A change in the value of  $\theta$  affects the contribution of the non-Si materials costs ( $c$ ), since  $c$  is fitted based on  $\theta$ , as well as the contributions of variables in the plant-size dependent cost component (wafer area, plant size and  $p_0$ ). Wafer area only affects plant-size dependent costs directly, and therefore a change in the value of wafer area affects the contribution of plant size and  $p_0$  (the other variables in this cost component), as well the contribution of wafer area itself.

### S3.2 Data-informed sensitivity analysis for low-level mechanisms

In this section we estimate the sensitivity of our cost change results to the variation in the historical

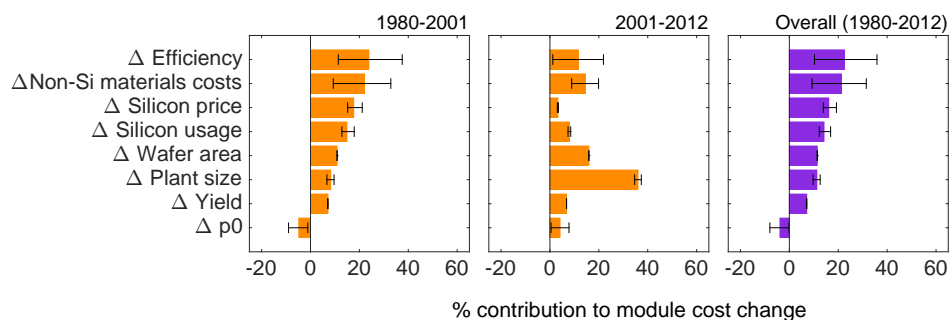


Figure S3: Sensitivity analysis for module efficiency,  $\eta$ . Note that module efficiency in 1980 is varied by  $\pm 20\%$  of its value, while module efficiency in 2001 and 2012 by  $\pm 7\%$  of its value to prevent efficiency from decreasing over time in our sensitivity tests. We recompute the list of cost change contributions of low-level mechanisms in both periods for a total of eight cases. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

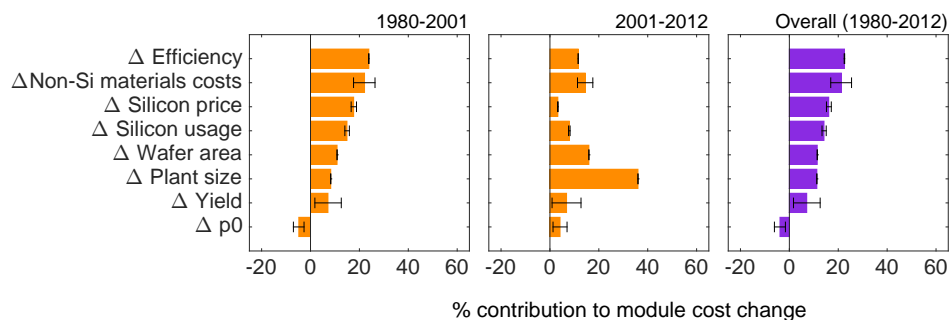


Figure S4: Sensitivity analysis for yield,  $y$ . We vary yield by  $\pm 7\%$ ,  $\pm 4\%$  and  $\pm 4\%$  of its value in 1980, 2001, and 2012, respectively, to ensure that it does not exceed 100%. We recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanism out of these eight cases.

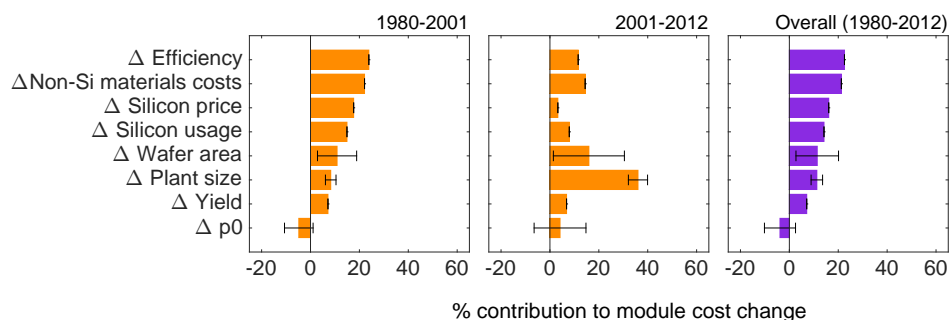


Figure S5: Sensitivity analysis for wafer area,  $A$ . We vary wafer area in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

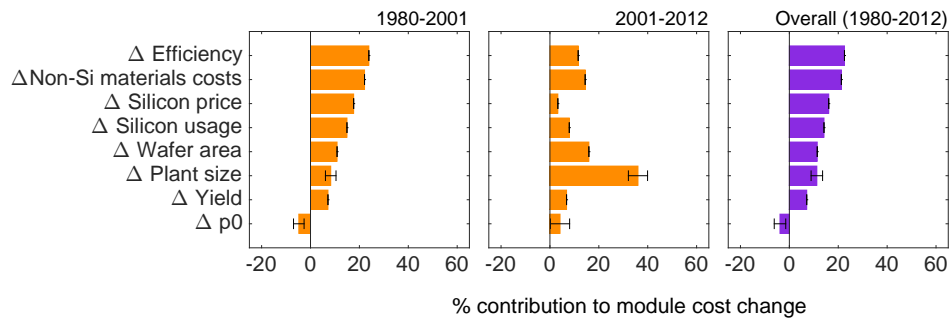


Figure S6: Sensitivity analysis for plant size,  $K$ . We vary plant size in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

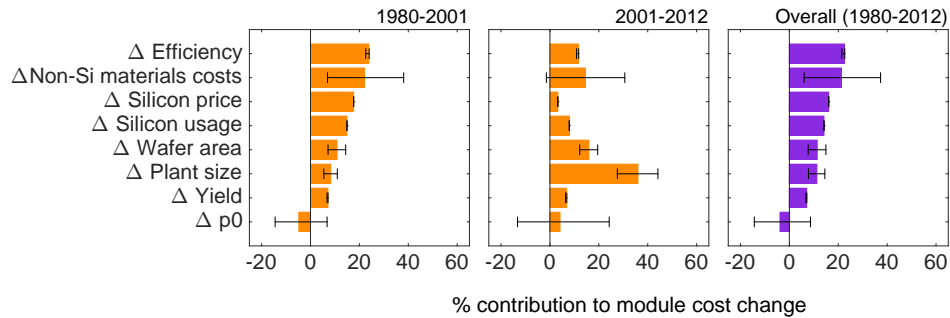


Figure S7: Sensitivity analysis for the share of materials costs,  $\theta$ . We vary the share of materials costs in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

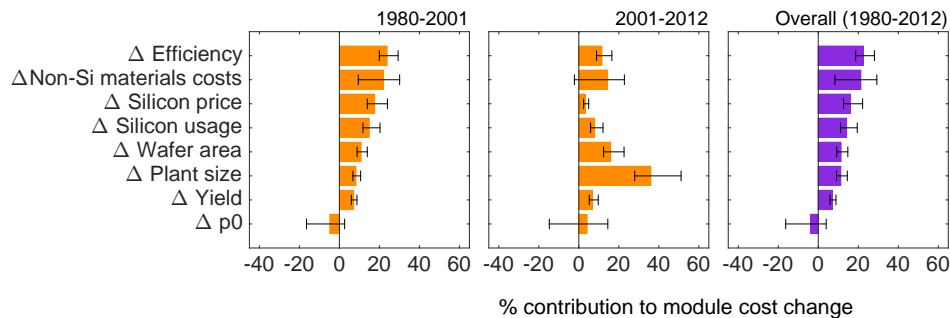


Figure S8: Sensitivity analysis for module cost,  $C$ . We vary module cost in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

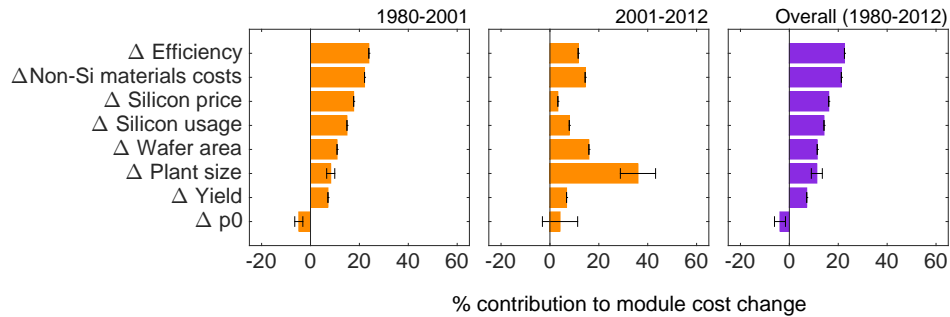


Figure S9: Sensitivity analysis for scaling factor,  $b$ . We vary the scaling factor in 1980, 2001, and 2012 by 20%, for a total of eight cases, and recompute the list of cost change contributions of low-level mechanisms in both periods. The error bars show the minimum and maximum value of the low-level mechanisms out of these eight cases.

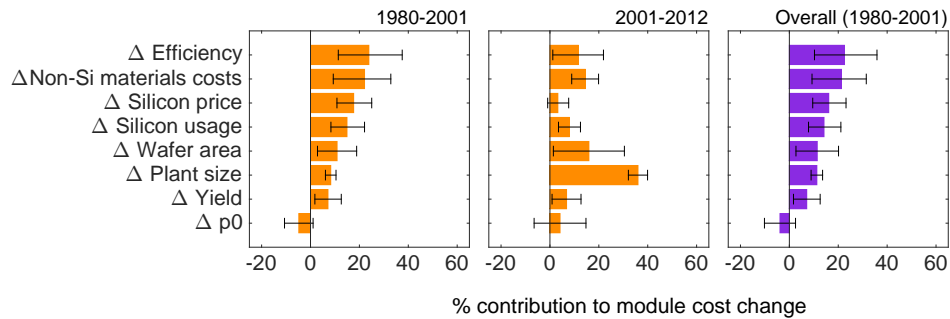


Figure S10: Contributions to cost reduction with error bars representing scenarios in which all variables are varied relative to the central scenario by  $\pm 20\%$ , except for yield, which is varied by  $\pm 7\%$ ,  $\pm 4\%$ ,  $\pm 4\%$  of its value in 1980, 2001, and 2012, respectively, and efficiency, which is varied by  $\pm 7\%$  of its value in 2001 and 2012 to prevent these variables from decreasing over time.

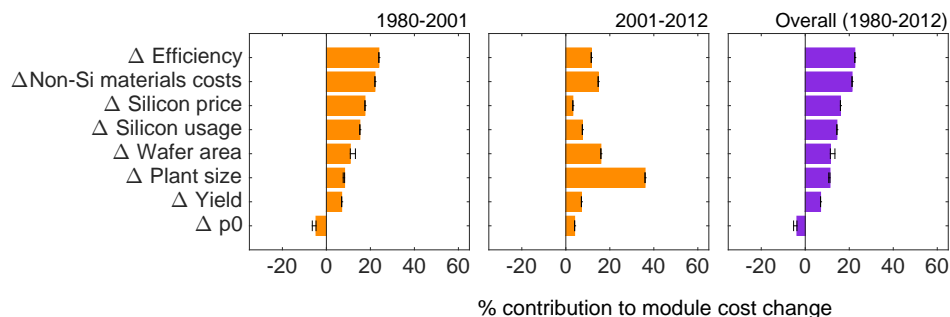


Figure S11: Data-informed sensitivity analysis for wafer area,  $A$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

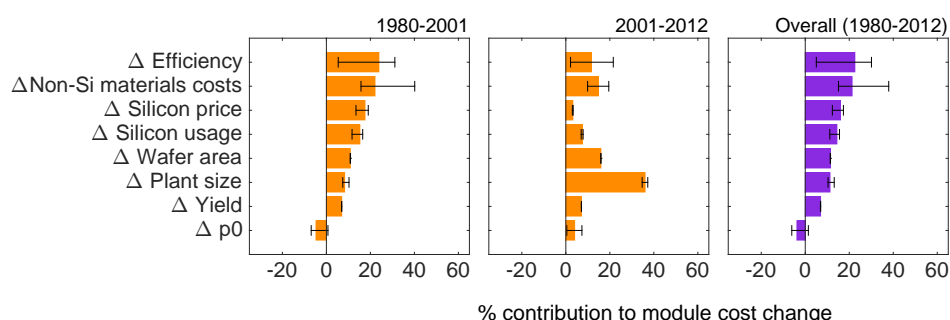


Figure S12: Data-informed sensitivity analysis for module efficiency,  $\eta$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

data shown in Table S1. Where we have multiple data points for a variable, we use these data to inform the lower and upper bounds of the variation in each variable. Figures S11-S16 show how the contributions to cost reduction vary when variables vary between these lower and upper bounds. Figure S17 combines these results from the individual variable analyses. Figure S18 shows the contributions when we vary the module cost based on the historical module cost and module price data. Figure S19 shows the contributions when different values are used for the scaling factor  $b$ . We see that the results are most sensitive to the variation in efficiency and silicon price in 1980. However, note that we use a wide range of efficiency values for 1980 (7.2% to 11%) while the central value we use (8%) is a reliable estimate for our representative module we use for 1980. The estimates for silicon price in 1980 show a wide range. We obtain the central value by averaging the three data points we have in order to deal with the uncertainty in this historical price value. If the lowest end of the variation is used in the analysis, then the contribution of silicon price to cost reduction between 1980 and 2001 is lower. However, if the highest end of the variation is used, then the contribution of silicon price to cost reduction between 1980-2001 might have been higher than the central case. The contribution of non-silicon materials costs ( $c$ ) varies due to the variation in silicon price since these variables are linked (since  $c$  is fitted based on the share of materials prices

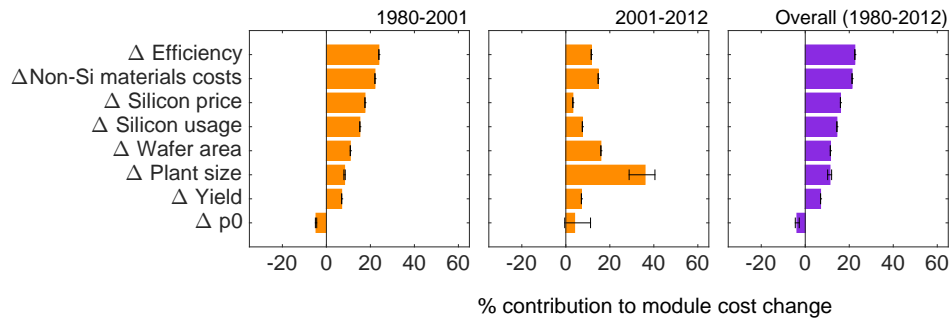


Figure S13: Data-informed sensitivity analysis for plant size,  $K$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

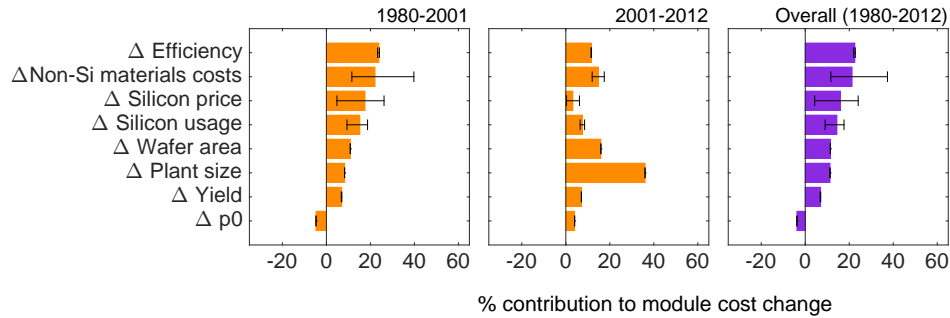


Figure S14: Data-informed sensitivity analysis for silicon price,  $p_s$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

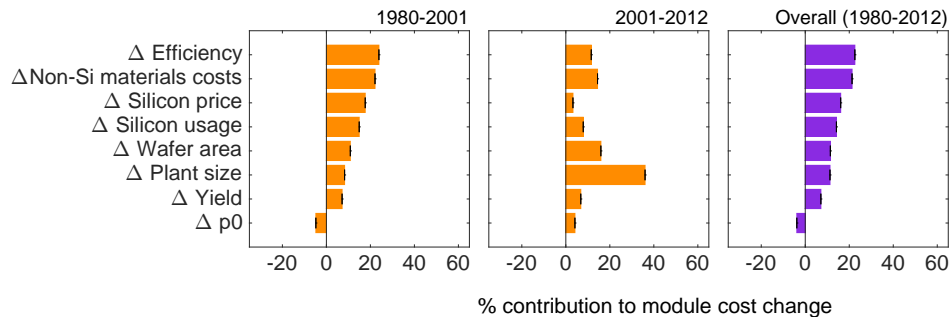


Figure S15: Data-informed sensitivity analysis for silicon usage,  $v$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

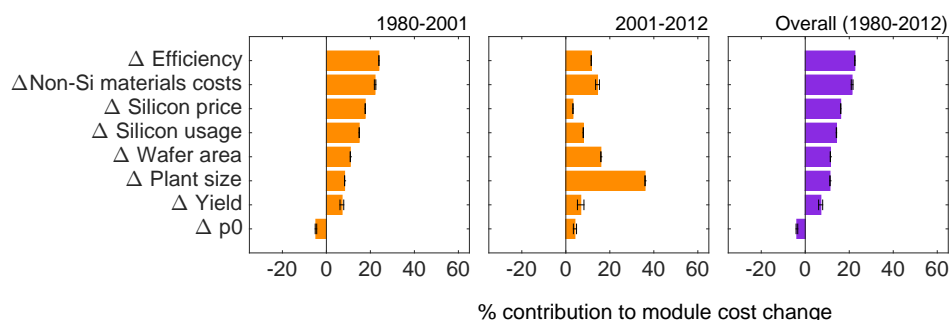


Figure S16: Data-informed sensitivity analysis for yield,  $y$ . Black lines show the contributions to cost reduction when the variable is varied using the range shown in Table S1 for 1980, 2001, and 2012.

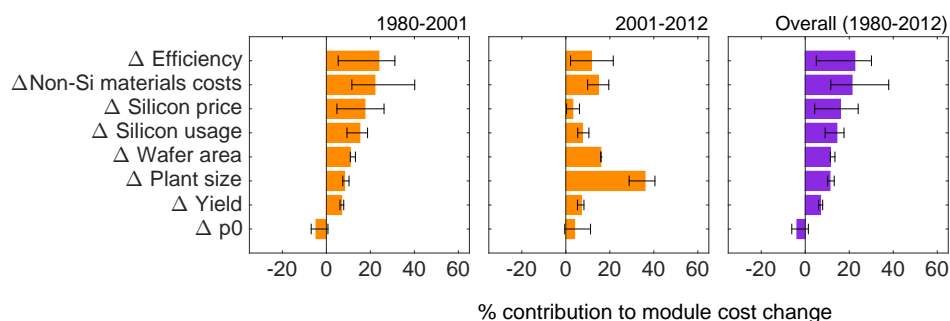


Figure S17: Combined data-informed sensitivity analysis. Black lines show the contributions to cost reduction when the individual data-informed sensitivity analyses (Figures S11 - S16) are combined.

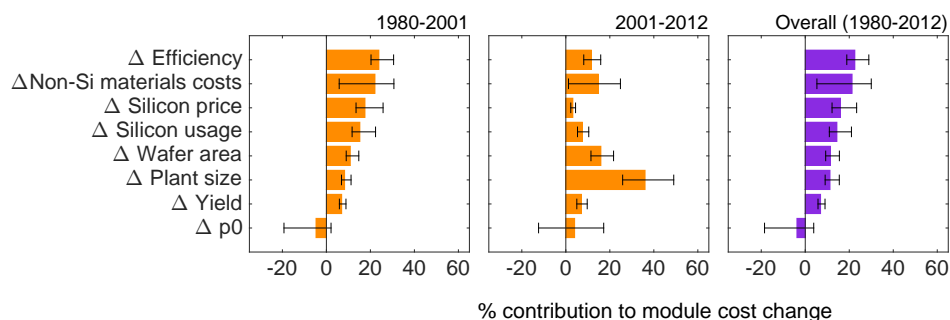


Figure S18: Data-informed sensitivity analysis for module cost,  $C$ . Black lines show the contributions to cost reduction when module cost is varied using the range of module cost and price data shown in Table S1 for 1980, 2001, and 2012.

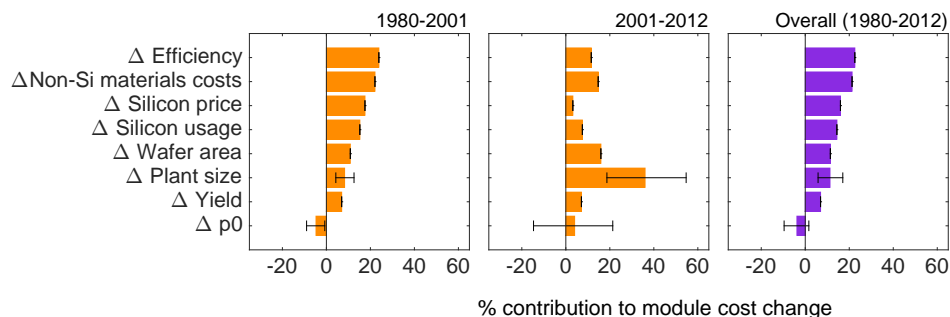


Figure S19: Data-informed sensitivity analysis for scaling factor,  $b$ . Black lines show the contributions to cost reduction when the  $b$  is varied using the range shown in Table S1.

and the cost of silicon). The results are not very sensitive to other variables.

## S4 Sensitivity analysis for high-level mechanisms

In the main text we propose a primary assignment for each variable. Here we show how the high-level results would change for different assignments of low-level mechanisms to high-level mechanisms. Table S3 shows the alternate assignments that result in the lowest and highest values of R&D, EOS and LBD. Figure S20 shows the results of these assignments.

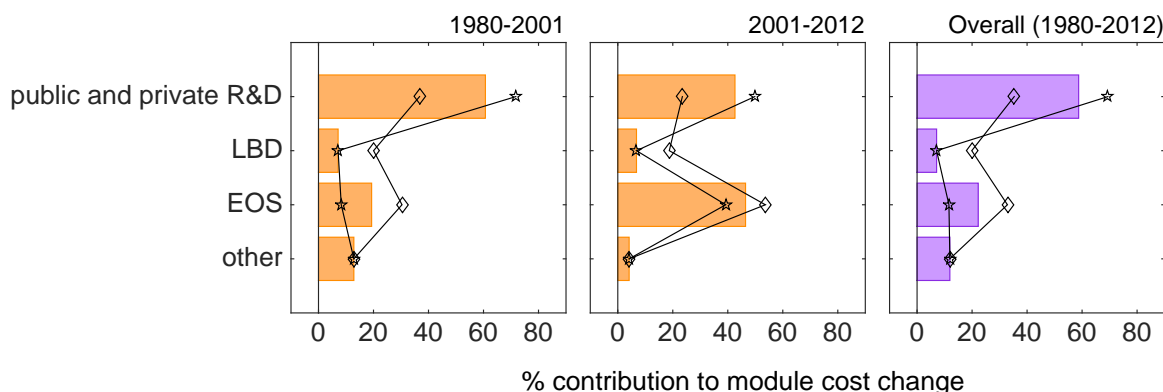


Figure S20: Percentage contribution of the high-level mechanisms to module cost decline in 1980-2001 (left), 2001-2012 (middle), and 1980-2012 (right). R&D = Research and development, LBD = Learning-by-doing, EOS = Economies of scale, Other = other mechanisms such as spillovers. We categorize the changes that require a lab setting or a nonroutine production activity (e.g. experimental production line) as being caused by R&D (Pisano, 1996; Rosenberg, 1982). We consider an improvement to have been made by LBD if it was achieved as a result of repeated routine manufacturing activity and if it was incremental in nature (Pisano, 1996). Changes that result from increases to the scale of the module manufacturing plant we categorize as EOS. Assignments of low-level mechanisms are given in Table S3. Bars show the results under the primary assignment, while the ★ and ◇ cases show the results under alternative assignments.

Figure S21 shows the percentage contribution of all high-level mechanisms when low-level mechanisms are given an alternate assignment one-at-a-time. Wafer area and silicon usage were originally assigned to R&D. Here we assign 50% of these variables to LBD and 50% remains



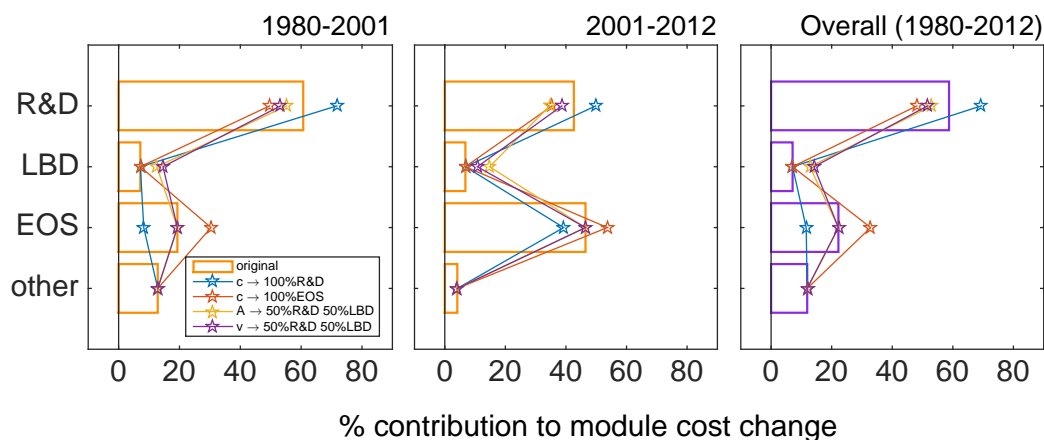


Figure S21: Possible percentage contribution of high-level mechanisms in each period. Lines with markers link high-level contributions under alternate assignments of low-level mechanisms to high-level mechanisms. Reassignments are made one-at-a-time. Non-Si materials costs ( $c$ ) were originally assigned equally to R&D and EOS, and we consider two possible reassignments, to R&D only and to EOS only. Wafer area ( $A$ ) and silicon usage ( $v$ ) were originally assigned to R&D, and here we also consider a case where they are assigned to LBD and R&D equally.

assigned to R&D. Non-Si materials costs were originally assigned equally to R&D and EOS. Here we consider a 100% assignment to R&D and a 100% assignment to EOS. We find that in 1980-2001 and 1980-2012 R&D remains the most important mechanism. LBD gains importance to the extent that wafer area and silicon usage were LBD-driven. EOS and R&D have almost equal contributions in the second period.

Figures S22 - S24 explore high-level contributions when multiple low-level mechanisms may be reassigned as shown in Tables S4-S6. Figure S25 shows the results from all combinations of reassignments. To allow extreme cases to be observed more easily, Figure S22 shows only combinations of reassignments that result in a minimum or maximum contribution for R&D. Figures S23 and S24 do the same for LBD and EOS, respectively. R&D never switches places with any other mechanisms in the first period. It can switch places with EOS in the second period. LBD can switch places with EOS in the first period. It does not switch places with any mechanism in the second period.

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Low-level Mechanisms	High-level Mechanisms		
	Primary Assignment	Case ★	Case ◇
$\Delta$ Efficiency	R&D	R&D	R&D
$\Delta$ Non-Si materials costs	0.5 R&D, 0.5 EOS	R&D	EOS
$\Delta$ Wafer area	R&D	R&D	0.5 R&D, 0.5 LBD
$\Delta$ Silicon usage	R&D	R&D	0.5 R&D, 0.5 LBD
$\Delta$ Plant size	EOS	EOS	EOS
$\Delta$ Yield	LBD	LBD	LBD
$\Delta$ Silicon price	other (1980-2001) EOS (2001-2012)	other (1980-2001) EOS (2001-2012)	other (1980-2001) EOS (2001-2012)
$\Delta p_0$	other	other	other

Table S3: Assignment of low-level mechanisms to high-level mechanisms. The primary assignments lead to the bars given in Figure 4. Alternative assignments (★ and ◇ cases) reflect assignments with the lowest and highest values of R&D, EOS and LBD, and correspond to the star and diamond cases in Figure S20.

Low-level mechanisms	Original	(1)	(2)
$\Delta$ Non-Si materials costs	0.5 R&D 0.5 EOS	R&D	EOS
$\Delta$ Wafer area	R&D	R&D	0.5 R&D 0.5 LBD
$\Delta$ Silicon usage	R&D	R&D	0.5 R&D 0.5 LBD

Table S4: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of R&D. Note that other low-level mechanisms remain in their primary high-level mechanisms. The contributions of the high-level mechanisms in each case are shown in Figure S22

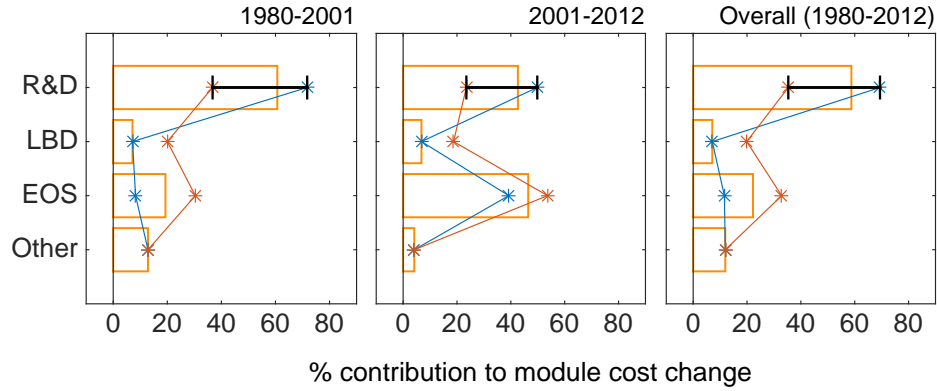


Figure S22: Possible percentage contribution of high-level mechanisms under the highest and lowest cases for R&D. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for R&D is obtained when 50% of both wafer area ( $A$ ) and silicon usage ( $v$ ) is moved to LBD from their original assignment to R&D; and non-Si materials costs ( $c$ ) are assigned to EOS in place of their original assignment to 50% R&D and 50% EOS. The highest case for R&D is obtained when both wafer area ( $A$ ) and silicon usage ( $v$ ) remain in R&D, and non-Si materials costs ( $c$ ) are assigned to R&D only.

Low-level mechanisms	Original	(1)	(2)	(3)	(4)	(5)
$\Delta$ Non-Si materials costs	0.5 R&D 0.5 EOS	0.5 R&D 0.5 EOS	R&D	EOS	R&D	EOS
$\Delta$ Wafer area	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D
$\Delta$ Silicon usage	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D

Table S5: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of LBD. Other low-level mechanisms remain in their primary assignments. High-level contributions for each assignment are shown in Figure S23.

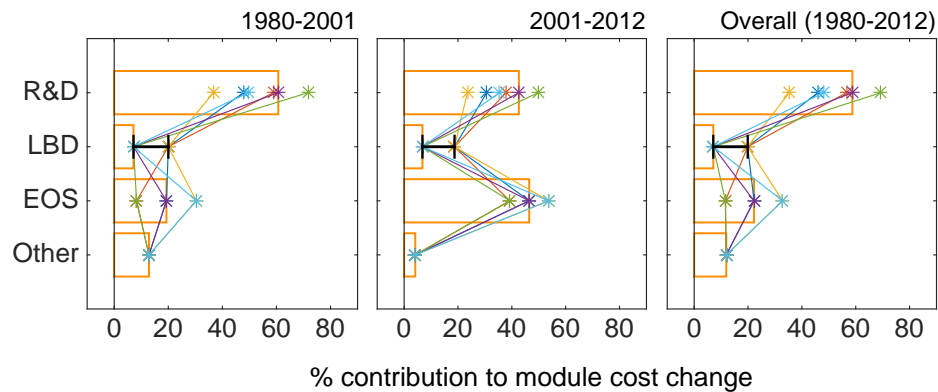


Figure S23: Possible percentage contribution of high-level mechanisms under highest and lowest cases for LBD. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for LBD is obtained when both wafer area ( $A$ ) and silicon usage ( $v$ ) remain in their original assignment to R&D. The highest case for LBD is obtained when 50% of both wafer area ( $A$ ) and silicon usage ( $v$ ) is moved to LBD from their original assignment to R&D.

Low-level mechanisms	Original	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta$ Non-Si materials costs	0.5 R&D 0.5 EOS	EOS	EOS	EOS	EOS	R&D	R&D	R&D	R&D
$\Delta$ Wafer area	R&D	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD	R&D	0.5 R&D 0.5 LBD
$\Delta$ Silicon usage	R&D	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D	R&D	0.5 R&D 0.5 LBD	0.5 R&D 0.5 LBD	R&D

Table S6: Alternate assignments of three low-level mechanisms to high-level mechanisms to achieve the lowest and highest possible contributions of EOS. Other low-level mechanisms remain in their primary assignments. High-level contributions for each assignment are shown in Figure S24.

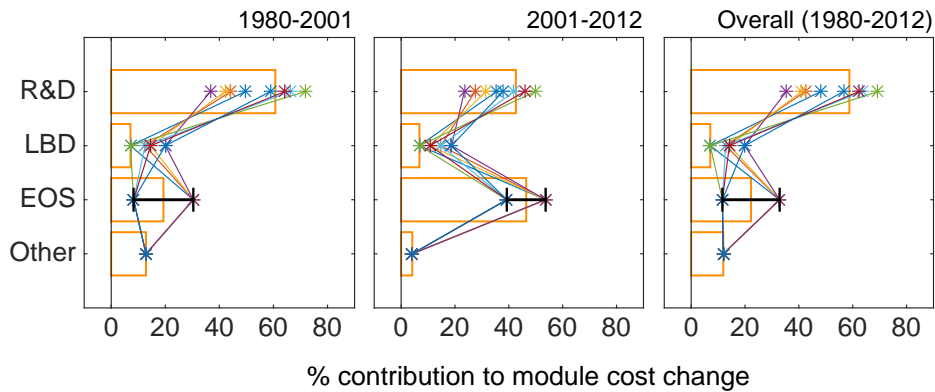


Figure S24: Possible percentage contribution of high-level mechanisms under highest and lowest cases for EOS. Horizontal bars show the contribution of the primary mechanisms. Lines with markers link results under alternate assignments. The lowest case for EOS is obtained when non-Si materials costs ( $c$ ) are assigned to R&D rather than their original assignment of 50% R&D and 50% EOS. The highest case for EOS is obtained when non-Si materials costs ( $c$ ) are assigned to EOS only.

## S5 Data for private and public R&D

We estimate the shares of public vs. private R&D based on R&D investment levels obtained from (McCrone et al., 2016, 2017) and (Nemet and Kammen, 2007) as explained in more detail below. As we note in the main paper 50% is a rough approximation based on the available data. This approximation is reached from looking at PV, renewable, and energy investment data across several data sources. Overall, we think 50% is a good rough approximation, taking into account the different technology coverage and periods spanned:

- McCrone et al. (2016) and McCrone et al. (2017) give shares of public and private R&D investment for different renewable energy technologies in 2015 and 2016. For solar public R&D investments were on average 50% in 2014 and 2015.
- McCrone et al. (2016) also look at global R&D investment in renewable energy generally. They find that public (government) and private (corporate) R&D were almost equal globally between 2004 and 2015.

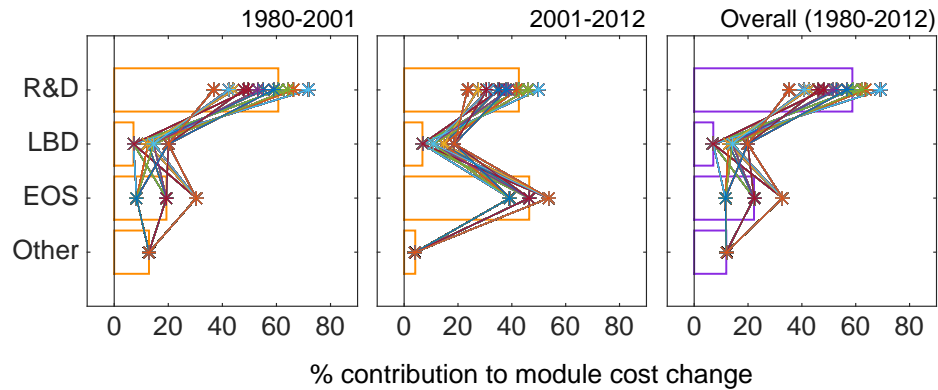


Figure S25: Possible percentage contributions of high-level mechanisms in each period. Contributions here are obtained by reassigning multiple variables at once from primary mechanisms to secondary mechanisms, based on all cases shown in Tables S4-S6, and Figures S22-S24. Horizontal bars show the contribution under the primary assignment used in the main text. Lines with markers link results under alternate assignments.

- Nemet and Kammen (2007) examine total U.S energy R&D investment over a 30-year period. The shares of public and private sectors were roughly equal from 1985 to 1992, and when integrated over time, public R&D has a 57% share between 1980 and 2003.