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Abstract

Technology hardware and deployment processes ('soft technology') seem fundamentally different, but little work examines the nature of this difference and its implications for technology improvement. Here we present a model to study the roles of hardware and soft technology in cost evolution and apply it to solar photovoltaic (PV) systems. Differing properties of hardware and soft technology help explain PV's cost decline. Rapid improvements in hardware affected globally traded components that lowered both hardware and soft costs. Improvements in soft technology occurred more slowly, were not shared as readily across locations, and only affected soft costs, ultimately contributing less than previously estimated. As a result, initial differences in soft technology across countries persisted and the share of soft costs rose. In general, we show the usefulness of modelling dependencies between technology costs and features to understand past drivers of cost change and inform future technology development.

Keywords: technology evolution, photovoltaics, cost modelling, balance-of-system costs, solar energy

1 Introduction

Technologies exhibit a range of cost trajectories [1–3], from the rapidly-falling costs of integrated circuits and photovoltaic (PV) systems [4, 5] to the rising costs of nuclear power plants [6, 7]. Across technologies cost declines are often slowed by 'soft costs', the costs of processes and services that are needed to design and deploy hardware. Solar photovoltaics (PV) and wind soft costs have fallen slowly, while the soft costs of nuclear and geothermal power have risen (Fig. 1), and in general the share of soft costs has increased. For example, in the U.S., while the total costs of PV systems have fallen precipitously, the share of soft costs has risen (see Fig. 1) to 35-64% of the total costs [8]. Soft costs also contribute to large cost differences across locations. Utility-scale solar PV plants in Japan and the U.S. cost twice as much as in Germany and Italy, and wind farms are 1.5 times as costly in South America as in China [9].

The soft costs of technologies are commonly added to hardware costs to determine total costs. However, the costs of a technology are ultimately affected by underlying features—the amounts of materials used, the duration of labor-intensive activities—that do not always contribute additively to the total [10]. Here we advance a method to analyze the cost evolution of a technology in terms of these features and we apply this method to PV systems to better understand the differing roles of hardware and soft technology features in driving PV's cost evolution

This work contributes to a large literature on technology cost evolution. One line of work uses phenomenological models that take cost to be a function of an independent variable, such as time or cumulative production [1]. A particularly well-known of these models is Wright's Law, which takes the cost C of one unit of a technology (e.g., an airplane, a wind turbine, etc.) to be a power law in the cumulative production y of these units [16, 17], $C \sim y^{-\alpha}$, where the exponent α varies across technologies [1] or categories of cost components (e.g., PV modules, balance-of-systems costs [18]). Studies of this kind can characterize rates of change [19] and inform cost forecasts when combined with an appropriate error model [1, 20]. However, these methods are limited in what they can reveal about how these rates depend on technology characteristics and human efforts [5, 10].

Another approach is to divide total cost into additive, hardware or non-hardware related components, and then discuss hardware or soft technology (i.e. non-hardware) improvements affecting these components, such as—in the case of PV—gains in installer experience affecting soft cost components [21, 22]. Studies using this approach have found that module costs fell faster than non-module costs, and have discussed the potential dependence of soft costs on

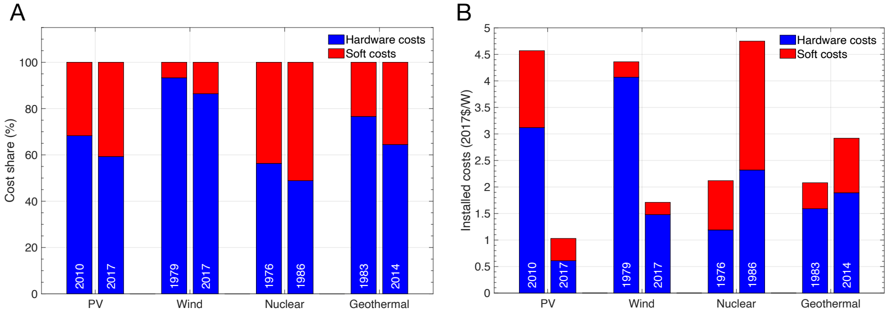

Fig. 1: **Soft costs of several energy technologies.** Rising share of soft costs (A) and absolute soft costs (B) in utility-scale PV systems, large-scale wind turbines, nuclear power plants, and geothermal power plants. Data for PV systems (estimate from this paper) and wind turbines represents installed costs ($/W) in the U.S. [11]. Data for nuclear lightwater reactors [12, 13] and geothermal power plants [14, 15] represents overnight construction costs, also in units of $/W. Absolute costs have decreased by 77% and 61% for PV systems and wind, respectively, and increased by 124% and 40% for nuclear and geothermal power plants over the respective time periods shown in the plot.

hardware features (e.g., [23, 24]). But a formal model like the one we advance is required to identify the large set of dependencies between technology costs and features and to quantify their effects on cost change.

A third strategy has been to search for factors correlated with low hardware and soft costs. Reductions in hardware costs are often associated with global knowledge exchange through supply chains and standardization [25, 26]. In contrast, soft costs are often tied to regional factors, and the co-evolution of competencies by installers, financiers, and PV system operators (e.g., [27]). Analyses of U.S. data have found that lower soft costs are more common in areas with greater installer density and experience, for example [28, 29].

The strategy we use combines elements of the second and third approaches. Some recent studies have examined technology cost change in a bottom-up framework that emphasizes the contributions of particular variables, each representing a technology feature that can change over time [2, 5, 7, 10]. However, this approach has not yet been applied to PV systems. Importantly, it has not yet been directed at understanding what caused the contrasting roles of hardware and soft technology in the evolution of PV costs.

Here we pursue these goals, presenting a conceptual and quantitative framework to decompose cost declines in technologies into the contributions of changing hardware and soft technology features. We apply this framework to understand cost declines in residential and utility-scale PV systems over several decades within large PV markets. A key finding is the degree to which hardware features dominate past declines in total costs, which is not captured in previous work emphasizing the influence of cost shares rather than that of features (e.g., [23, 30, 31]). We also study countries' cost trajectories, to better understand how today's cost differences were generated. We find that countries with lower soft costs today already had lower soft costs decades earlier. The persistence of these cross-location differences stem from slow improvement rates in soft technology features across the board, while soft cost reductions arose primarily from improvements to the features of globally traded hardware. Our method and findings can inform country-specific and global efforts to improve hardware and soft technology features in PV and other technologies.

2 Conceptual and quantitative framework

We develop a cost model that accounts for the materials and task inputs needed to manufacture and deploy a PV system (see Methods 8.1 and equation (1)). We group these inputs according to a standard distinction between the costs of physical equipment ('hardware costs') and deployment processes ('soft costs'). As shown in Figure 2, we also classify the technology features ('variables') that affect these cost components as either hardware or soft technology variables. Hardware variables, such as module efficiency, describe features of physical equipment. Soft technology variables, such as the durations of installation tasks, describe features of processes and services that are not embodied in hardware (see Methods 8.2).

The dependencies of cost components on variables can be viewed as a bipartite network (Fig. 2D) that captures how each technology feature influences different components of costs. A notable pattern is that hardware variables (e.g., inverter efficiency or module efficiency) tend to affect many cost components, including soft cost components, while soft technology variables (e.g., mechanical installation time) tend to affect just a few. This is one of several differences between hardware and soft technology, as defined in our model (Fig. 2). Another is that changes in hardware variables can affect soft costs per watt in two different ways— through quality improvements (e.g., improving module efficiency) and design changes (e.g., automation) (Fig. 2C)—while changes in soft technology variables do not alter hardware costs per watt. In addition, hardware variables derive from characteristics of a technology's design that often endure over time and can be exploited in any location deploying the hardware. Soft technology variables have tended to differ across locations and fluctuate over time.

As discussed in the following sections, the differing properties of hardware and soft technology can help explain PV's global cost dynamics. To estimate how much each hardware and soft technology variable reduced PV system costs in the past, we use a recently developed method [10] that decomposes the total cost change into contributions from each variable (see Methods section 8.4 and equation (5)). Because of the network structure of dependencies, different variables have different influences over total cost. To quantify this, we develop a measure of the total cost influence that each variable has (Eq. (4)). Besides the structural influence of each variable on costs, an important factor is how quickly different variables improved with time. We compare actual cost change contributions with expected contributions based on each variable's influence, observing which variables out-performed or under-performed the expectation because of how quickly they improved through innovation. Together, these steps provide a view of cost change based on technology variables that differs from ones based on categories of additive cost components. Next, we apply our framework to understanding the drivers of PV's cost decline in the U.S. and other major PV markets.

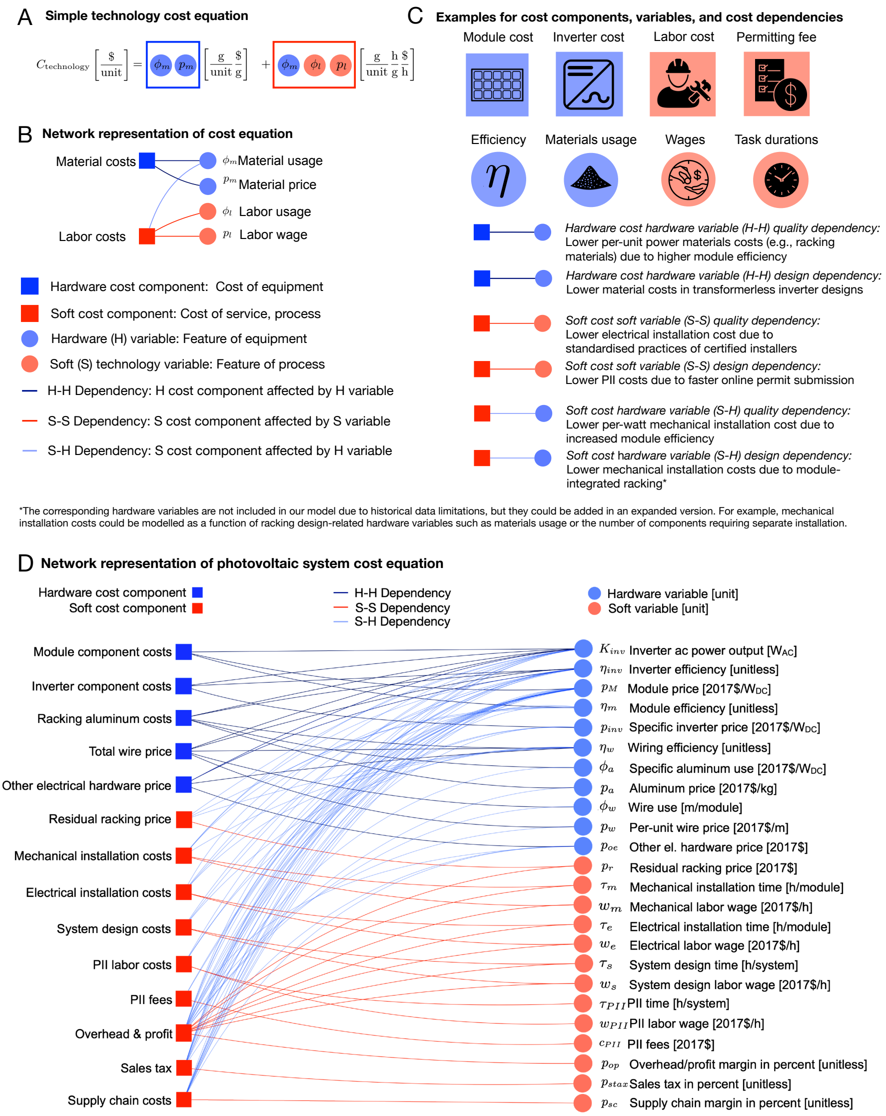

Fig. 2: See next page for figure caption.

Fig. 2: **Conceptual framework for cost modelling.** Importantly, 'costs' here refer to the costs per unit service, and 'unit' refers to the unit service. In this study, the unit of service is the power capacity of the installed PV system. (A) A simple cost model containing two cost components and four variables, which are defined in (B). (B) Graphical representation of cost model as a bipartite network of cost dependencies on hardware and soft technology variables. In this example, hardware cost components are dependent on hardware features (H-H dependencies), while soft cost components are dependent on both hardware and soft features (S-S and S-H dependencies). S-H dependencies will be present whenever per-unit material usage rates affect per-unit labor costs, as is the case for PV systems. Dependencies arise either from changes in the performance of hardware and infrastructure delivery processes ('quality dependency'), or from larger changes that alter the design of physical equipment or installation processes ('design dependency'). (C) Examples and terminology for cost dependencies. (D) Relationships between cost components (squares) and variables (circles) in residential PV systems. A line from a cost component to a variable indicates that the variable appears in the expression for the cost component in equation (1). Light lines indicate that soft cost components were influenced by hardware variables ('S-H dependencies'). Dark lines indicate that a cost component of one type (hardware or soft) was influenced by a variable of the same type (H-H and S-S dependency). Cost components that include a manufacturer margin are listed as prices. Icon credits: Maurizio Fusillo under a Creative Commons licence CC BY-SA 3.0 .

3 Cost change in U.S. residential-scale systems

A pervasive theme of our results in the U.S. and in other countries is that a substantial amount of cost reduction derived from changes in hardware variables. Over the period 1980-2017, PV costs fell significantly, with BOS costs (in \$/W) falling by 94% and PV system costs by 96%. Of these changes, hardware variables caused approximately 80% of the reduction in total BOS costs (Fig. 3A), and 90% of the reduction in total PV system costs (Fig. 3B).

Tellingly, in the category of soft costs (a subset of BOS costs) hardware variables contributed 77% of the change over 1980-2017. As noted earlier Figure 2D shows that hardware variables have a large number of linkages to soft costs, suggesting the potential for hardware variables to strongly influence soft costs. Taking actual historical changes of variables into account, we find that hardware variables indeed caused the majority of reductions in soft costs. As a result, soft costs declined at rates that were slower but still approaching that of hardware (-98% overall for hardware costs, and -94% for soft costs) over the 1980-2017 period.

Many of these soft cost reductions were achieved through hardware quality improvements. More efficient and less materials intensive modules reduced installation and supply chain costs, while the design of PV systems and ancillary equipment remained fundamentally the same. Past soft cost reductions

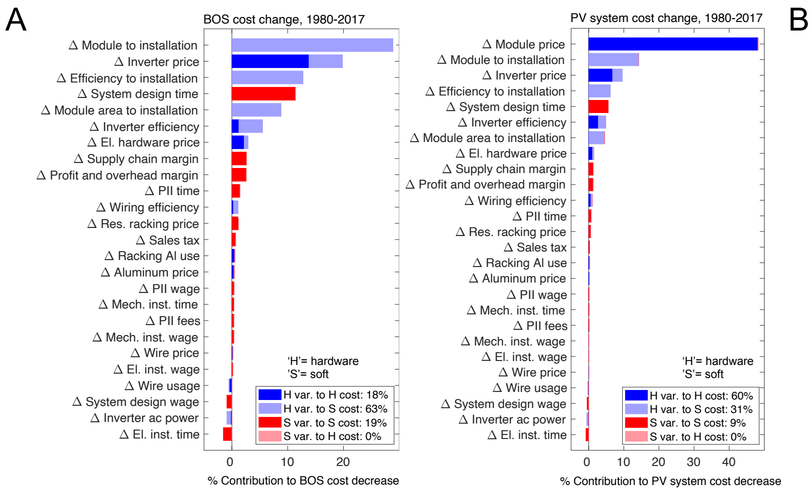

Fig. 3: **Estimated contributions to cost reduction in residential PV systems in the U.S. over the 1980-2017 period.** Results are shown for a 5kW system. Bars extending to the right (left) show cost-reducing (cost-increasing) contributions. (A) shows contributions to BOS cost change, and (B) shows contributions to PV system cost change. In both (A) and (B), the bar labeled 'Δ Module to installation' shows the contributions of module price variables (Eq. 2) to soft cost change, except for the contributions of module efficiency and area, which are shown separately. Note that 'installation' here refers to all non-module costs of the installation process in accordance with the chosen system boundary (Eq. 1), including design costs, supply chain costs, mechanical and electrical installation costs, and other soft costs. In (B), the bar labeled 'Δ Module price' shows the contributions of changing module variables to module manufacturing price change (see Eq. 2). Percentages give the fraction of the net cost change over the 1980-2017 period (see Table 1) that was caused by each low-level mechanism. Contributions are negative when they act in the opposite direction to the net cost change over a period. In all periods above, the net change cost was negative, therefore positive contributions correspond to cost-reducing effects. Cost change contributions in absolute terms are given in Supplementary Table 7.

therefore represent primarily one of two avenues for hardware-driven soft cost declines, namely hardware quality improvements rather than hardware design improvements (Fig. 2C).

The relative share of hardware and soft costs in PV has changed since 1980, which might at first suggest that different variables may be more influential in 2017 than they were in 1980. Yet even though the hardware cost share has fallen from 59% to 34%, hardware variables have an influence on costs in 2017 (75%) that is almost as large as that in 1980 (81%) (Fig. 4A). As discussed earlier, this happens because hardware variables affect many soft cost

Table 1. Change in PV system hardware costs, soft costs, and total installed costs, and comparison of total installed costs computed here (using Eq. 1) to estimates from the literature. In the absence of a nationally averaged cost benchmark like the one provided by NREL for 2012 and 2017 we give a range of empirical prices (low and high end from [40]) and cost estimates (values in between from [41, 42]) for the year 1980. ΔC_H refers to the cost change driven by hardware variables, and $\Delta C_H/\Delta C$ gives the fraction of cost change caused by hardware variables. Note that this number is higher than the contribution from changing hardware cost components to total system costs (60%), as it accounts for the contribution of hardware features to soft cost declines.

Costs ($/W)	C (1980)	C (2001)	C (2012)	C (2017)	ΔC (1980 -2017)	ΔC_H (1980 -2017)	$\Delta C_H/\Delta C$
Hardware costs	47.0	8.2	1.6	1.0	-46.0	-46.0	1
Soft costs	33.1	7.4	2.0	1.9	-31.2	-23.8	0.77
Total costs							
This paper	80.1	15.6	3.6	2.9	-77.2	-69.8	0.91
Other sources	41.58 [40–42] -115.83	11.80 [43]	4.5 [23]	2.4 [23]			n/a

components (Fig. 2D), but soft technology variables do not affect hardware cost components.

Another important factor is how quickly different variables improve with time. While Figure 4A shows that hardware variables in principle have greater leverage over costs than soft technology variables do, the actual cost reductions they drive will depend on how much these underlying variables change. To probe this we compare the actual cost reductions of variables to their influence shares (Fig. 4B).

First, we see that actual cost reductions contributed by different variables correlate with the cost reductions we would have expected based on the influence of these variables in PV's dependency structure alone (Fig. 2D). This lends further support to using these dependencies to assess opportunities for further cost reduction.

Second, historical changes in hardware variables resulted in even greater cost reduction than would have been expected on the basis of their initial influence shares in 1980 alone (Fig. 4B). In principle, soft technology variables could have improved so rapidly that they overcame their weaker influence on costs. But evidently, the reverse is true in this case: Not only do hardware variables have a greater leverage on costs, but historically they were more amenable to change than soft technology variables, with hardware variables overshooting their expected cost change contribution. Even during a more recent time period (2017-2021, see Supplementary Note 9) characterized by

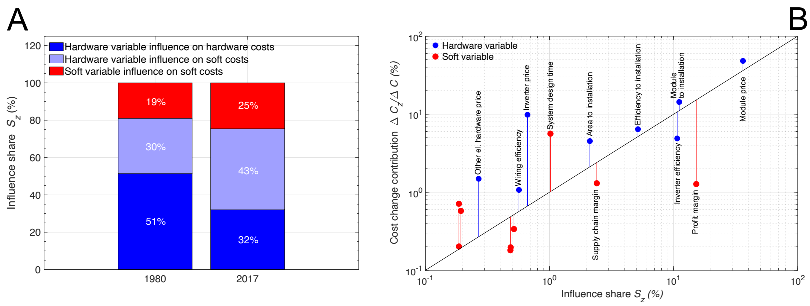

Fig. 4: **Cost influence of individual variables and comparison to their cost change contribution.** (A) Influence share by variable and cost component type (hardware or soft) in 1980 and 2017 (see equation (4)). (B) Comparison of variables' influence shares in 1980 and their contributions to PV system cost change over the 1980-2017 period (as shown in Fig. 4B). Many hardware variables (blue circles) have contributed more to cost reductions than expected based on their influence shares in 1980, while many soft technology variables (red circles) contributed less.

mature and standardized PV equipment, hardware variables have continued to improve and contribute substantially to soft cost reductions.

Cost change contributions are listed individually for all variables in Supplementary Table 7. Two hardware components, the module and the inverter, were responsible for over 85% of PV system cost change. Of this, approximately one third came from reductions to soft costs (light blue bars in Fig. 3). An example of these hardware-driven soft cost reductions is increased module area, which reduced installation cost because every installed module represented a larger deployment of capacity. Reductions in the price of modules contributed over 70% of PV system cost change, with 25% coming from the effect on installation costs.

For BOS, the majority of cost decline over the 1980-2017 period was driven by hardware variables affecting soft cost components (63%), not directly through changing hardware cost components (18%). Although BOS hardware is physically distinct from modules, many BOS soft cost components are functions of hardware module variables including module area, efficiency, silicon usage, and non-silicon materials costs. Three of the five most influential BOS cost change mechanisms are therefore module variables (Table 1).

In contrast, soft technology variables were much less influential, causing about one fifth of BOS cost reductions since the 1980s, and only about one tenth of PV system cost reductions. These contributions came primarily from reductions in system design time. System design benefitted from R&D efforts to develop circuit and system design guidelines and performance simulation tools. Such materials and tools began to be published in the mid-1970s (e.g., [32, 33]), and later informed the development of standardized design software. Efforts to improve other soft technology variables (e.g., to reduce installation time) occurred later, though many inventions to date have not been widely adopted. Examples include PV-integrated roofing materials (e.g., [34]), and automated module deployment (e.g., [35]).

After soft cost reductions driven by improving module features, the most important driver of BOS cost decline was reductions in inverter price. This hardware variable was responsible for 20% of overall BOS cost change between 1980 and 2017. Improved circuit designs and advanced power electronics for switching reduced material usage in inductive components and heat sinks, leading to higher inverter power density and conversion efficiency. As a result, specific inverter weight (kg/W) in 2014 was less than 10% of that in 1995 [36]. Typical inverter efficiencies are 98% in the U.S. today, compared with 80% in the 1980s [23, 37]. Increasing integration of subcomponents and modular designs, which reduced component counts and simplified manufacturing processes, were also important [37]. Simultaneously, inverter factories reached gigawatt-levels of output in the late 2000s, reducing manufacturing costs through scale economies [38, 39].

We also perform a higher-resolution analysis of how specific module-related variables, including changes to module efficiency and the costs of module manufacturing, affected PV system installation costs (Extended Data Fig. 1). Module efficiency alone, which increased from 8% in 1980 to 16% in 2017, contributed 17% to PV system cost change. Most immediately, a higher efficiency leads to a lower dollar-per-watt cost for modules. Critically, it also causes any cost that scales with module count to have lower dollar-per-watt cost. In particular, we estimate that approximately 40% of the total cost change arising from improvements to module efficiency can be attributed to soft cost reductions.

Additional analyses and robustness tests are included in Supplementary Information. (See Supplementary Notes 2-5 for details on the main dataset and a discussion of data uncertainties, Supplementary Note 6 for a decomposition of cost change into shorter time intervals, and Supplementary Note 7 for a sensitivity analysis.)

4 High-level mechanisms of cost reduction

We now consider how cost variable changes were driven by various kinds of human efforts and emergent phenomena such as economies of scale. Extending the framework in [10], we consider how cost-determining variables for residential PV systems were affected by five high-level mechanisms: research and development (R&D), learning-by-doing (LBD), economies of scale (EOS), financial incentives, and pricing strategy.

To link variables to high-level mechanisms, we consider what aspects of PV technology were amenable to which mechanisms, based on engineering knowledge of PV and empirical accounts of improvement efforts in the academic and grey literature (see Supplementary Note 11 and [10]). Variables such as module efficiency, which describes an engineering property and requires laboratory and non-routine alterations to manufacturing processes to change, are assigned to R&D. Variables that incrementally improved from repeated practice were assigned to learning-by-doing. Variables that improved through higher production output or bulk purchasing discounts were assigned to economies of scale. We include pricing strategy as a high-level mechanism to capture strategic price reductions by companies as they responded to market pressures, such as the increased imports of PV modules and inverters from China. A complete list of high-level mechanisms and assignments is given in Supplementary Table 10.

This approach lets us observe an interesting aspect of how the drivers above likely achieved cost reductions in PV systems. With hardware variables accounting for most cost reduction, the mechanisms largely driving them—R&D and scale economies—unsurprisingly played a dominant role (Extended Data Fig. 2). Less obviously, a large portion of these cost reductions were realized in soft cost components. This is especially pronounced in BOS costs—here, we see that *most* of the benefits of R&D and scale economies were realized by the lowering of soft cost components, rather than the lowering of hardware costs. However, we note that rough classifications of this kind cannot yield sharp quantitative estimates, and therefore our conclusions focus on low-level drivers and their differences across countries (see next section).

5 Cost change in U.S. utility-scale systems

In the case of utility scale systems, hardware variables were also influential in reducing both hardware and soft costs in (Fig. 5B). Hardware variables influenced overall costs through hardware cost reductions (dark blue bar, Fig. 5B) more than through soft cost reductions (light blue bar), as was the case for residential systems but to a lesser degree.

One distinction between utility-scale and residential PV systems is that utility-scale systems are built by engineering, procurement and construction (EPC) firms and sold by developers, while for many residential systems, both steps are completed by one installer firm. The involvement of two companies affects the soft cost structure. We study a more recent period (2015-2021) where soft cost data reflects this structure and is available in a consistent format (see Supplementary Note 10). (Note that improved data availability allows us to distinguish between overhead and profit margin, while these two variables are combined into one (‘p_{op}’) for residential PV systems.)

During the 2015-2021 period, hardware variables contributed 88% to cost reductions in utility-scale systems, primarily by reducing module costs (49%), electrical and structural BOS costs (14 and 11%, respectively), and inverter costs (11%). For soft cost reductions, the most influential change was a reduction in the margin charged to cover developer overhead costs, possibly due to the increasing size of developers or increased competition and associated efficiency gains. Compared to residential systems and utility-scale systems over the 2010-2017 period (Fig.5B), these results show that systematic organizational changes such as new business models, which is an example of a soft technology change, can become a leading cause of soft cost reductions, contrary to the past where the majority of soft cost change was driven by hardware improvements. As we show in Supplementary Fig. 3, design choices such as trackers also affect the cost change ranking.

6 Cost change in other countries over time

We now consider mechanisms of cost change in other countries. As estimated above, much of the cost decline in U.S. residential and utility-scale systems can be attributed to changes in hardware variables. Most hardware is traded globally, consistent with the fact that hardware costs differ less across countries than soft costs do (Fig. 6), and suggesting that hardware variables would have been similarly influential in other countries.

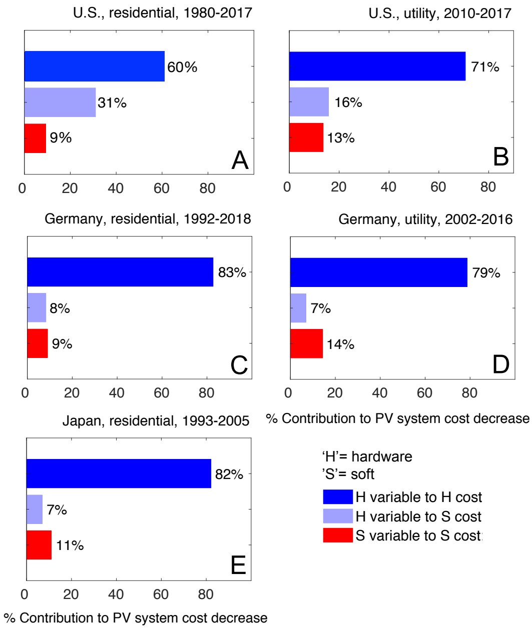

Fig. 5: **Estimated contributions to PV system cost reduction over different time periods in the U.S., Germany, and Japan.** (A) U.S. residential-scale. (B) U.S. utility-scale. (C) Germany residential-scale. (D) Germany utility-scale. (E) Japan residential-scale (no data available for utility-scale). Hardware variables contribute 80-90% to overall PV system cost change in different countries. Soft technology variables contribute 9-20%. (Detailed cost change breakdowns are given in Supplementary Fig. 36. We discuss data uncertainties and comparisons to reported prices in Supplementary Notes 3-5.)

Was this the case? And for soft costs, how did countries with currently lower levels of cost reach them? To study this we perform a similar cost change decomposition on data from residential and utility systems in Germany and Japan, countries that played major roles in the expansion of PV in the 1990s and 2000s. Japan led the market from 1992-2003 with residential deployment growth, while Germany became the primary driver from 2004 to 2012 [44]. PV-focused policies in each country (the 1000-roofs program in Germany, the SunShine program in Japan) resulted in data collection efforts over several decades [45–47] that produced data that we use here. (See Supplementary Notes 3-5 for a discussion of data uncertainties.)

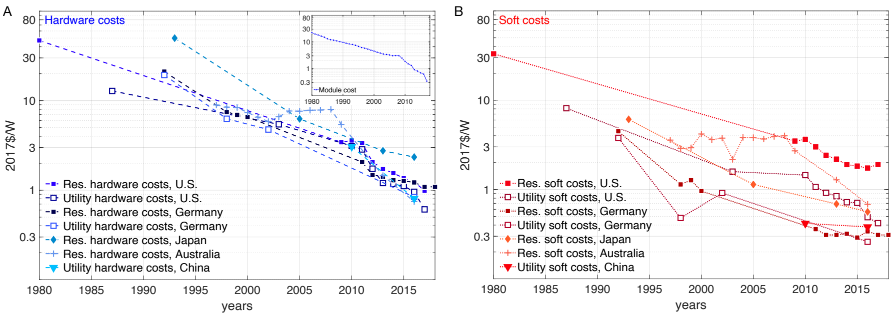

Fig. 6: **Evolution of PV system costs during the 1980-2018 period.** (A) Evolution of total PV hardware costs, (A, inset) module costs, and (B) total PV soft costs. Total PV hardware costs include modules, inverters, and other electrical hardware. Soft costs include all non-hardware PV system costs. Dashed and dotted lines are guides to the eye. Hardware costs are similar across countries. Soft costs diverge but have trended downwards at similar rates in all major PV markets (Germany, Italy, Japan, U.S., Australia), likely driven by improvement in globally traded PV hardware (see near-parallel lines in right panel). Countries with comparatively low soft costs today already started out at lower soft cost levels (e.g, Germany, China). The Japanese PV market is characterized by a dominance of domestic brands and a supply chain with high margins [48], which explains the comparatively higher hardware costs in Japan (where part of the difference stems from soft costs but isn't separated out due to data limitations). Time series data was compiled from journal papers, national lab reports, as well as international organizations and country-level solar PV associations. Modules: [10, 23]; U.S.: This paper, [23] (residential); [23, 49, 50] (utility); Japan: [45, 48]; Germany: [9, 46, 47, 51] (utility); [46, 51–53] (residential); Australia: [54–56] (residential). China: [9, 57].

As expected, changes in hardware variables were critical to cost reduction in Germany and Japan, as they were the U.S. (Fig. 5). About 60-80% of net cost change in Germany 1992-2018 and Japan 1993-2005 came from reductions in hardware costs. However, as in our U.S. estimates, this already high figure underestimates the contributions of hardware variables, as roughly half of all reductions in soft costs (e.g., Figs 5CE) originated in hardware variables.

As a result, hardware *variables* caused around 90% of the net cost change in residential PV systems. (Supplementary Note 12 provides a discussion of uncertainties and effects of alternate data sources, which we find to be small.)

The results suggest that a main reason why hardware and soft costs fell at similar rates across countries was that changes in both cost categories were driven by improved, globally traded hardware. Notably, countries in our data set that started with high soft costs rarely reached comparatively low soft costs. Achieving this transition would have needed additional contributions from soft technology variables to soft cost change. Relatedly, countries with low soft costs did not reach current costs primarily through rapidly evolving soft technologies, but instead had lower soft costs to begin with.

In Supplementary Note 13, we examine how consistent these results are with the drivers of cost differences across countries today. Given that countries with lower soft costs today already had lower soft costs to begin with, and further soft cost reductions were driven primarily by globally traded hardware affecting hardware and soft costs everywhere, cost differences should still be driven by soft technology variables. We find that this is the case, and that longer mechanical installation times are most influential, causing 20-30% of these cost differences. Installation times are also longer in several developing countries (China, India) but are offset by lower wages (Supplementary Fig. 41). In the SI we also study the contributions of high-level mechanisms (Supplementary Fig. 38) to cost differences across countries to suggest possible ways to reduce these differences.

7 Conclusions

The case of PV systems offers insights into how a technology's cost changes over time and varies between places. A key finding is the very limited extent to which soft technology improvements contributed to cost change or, relatedly, the very large extent to which improvements in the physical features ('hardware variables') of this technology not only lowered hardware costs but also explain changes in soft costs. Across major markets, we estimate that hardware features were responsible for 85-90% of PV system cost change. In contrast, features of processes and services to deploy PV systems, 'soft technology variables', contributed only the remaining 10-15%.

This difference derives from the structural influence of hardware variables on both soft cost components and hardware cost components. Our findings add insight to previous studies (e.g., [31]) that focus on the contributions of changes in categories of additive cost components, rather than changes in underlying features determining cost, and associate larger shares of historical cost reductions to soft cost change than the 10-15% result reported here for soft technology. Looking across locations, we find that technology features that improved slowly in the past also tend to be the ones that sustain cost differences between countries today.

Our results suggest that a technology's network of dependencies between soft technology and hardware features, along with its initial cost structure, may help determine its rate of cost improvement. PV technology has had a rapid rate of improvement among energy technologies, with PV system costs falling 97% in the 37 years from 1980 to 2017. The early cost structure of PV emphasized hardware costs (60% in 1980), creating a fertile ground for the hardware-driven cost reductions that came from improvement efforts targeted at hardware features. Due to the many dependencies of soft costs on hardware variables (Fig. 2D), improved hardware simultaneously reduced soft costs, and the same dependencies suggest additional potential for hardware-driven soft cost reductions (Fig. 4A).

However this does not mean that cost trends are necessarily determined by a technology's nature. Nurture can also play an important role [58]. Our approach suggests there are essentially two broad strategies for lowering PV soft costs further. One is to develop engineering design solutions that improve soft costs (and hardware costs) through hardware improvements–i.e., replicating the mechanisms that successfully reduced PV costs in the past. A clear example of this strategy is to further increase the efficiency of modules. Another is to introduce hardware innovations that weaken the dependence of soft costs on soft technology variables and instead make them more reliant on hardware, e.g., robotic construction systems. Similarly, adopting simpler, more standardized PV equipment could reduce on-site customization tasks (for example, plug-and-play PV systems). Although these design strategies originate in hardware changes, they will likely affect both hardware and soft technology variables.

A second strategy is to target soft technology features directly. Examples of the second strategy include process simulation tools to develop high-productivity workflows for installation, and monitoring deployment activities to track inefficiencies and find solutions such as standardized checklists, engineering review software, and automated permitting platforms. Since all hardware, not just PV hardware, needs delivery and installation processes to become functional, the strategies above may characterize the main strategies for innovation available generally. The framework we use can be applied to other technologies to explore this, by mapping the structure of dependencies between costs and technology variables, and examining the changes to these variables and their effects on costs, retrospectively and prospectively.

The limited role of soft technology change in PV could be a feature of other clean energy technologies as well. The cost of wind, nuclear, and PV-plus-storage energy systems is now determined to a substantial degree by soft costs [7, 59, 60]. Rapid adoption of low-carbon energy systems will likely require soft costs to fall more quickly going forward than they have in the past. To achieve this, R&D to advance soft technology may require more location-specific and comparative studies, and more focus on conceptualizing the desired end result. For example, most hardware can be separated into components that are either identical across build sites (e.g., PV module, fission reactor) or readily adjustable (e.g., mounting systems, seismic isolation). But it is less clear how to achieve similar packagability for soft technologies, such as business models, supply chain management techniques, and permitting practices. Some parts of soft technology may be more easily codified and deployed in a consistent form across locations through software development and training programs, for example, while others may inherently require tailored approaches. An approach like the one here could be used to investigate this question. Future work could also build on our approach to further decompose individual hardware and soft technology variables, potentially revealing important micro-level drivers of cost change not identifiable at higher levels of aggregation (e.g., the role of surface passivation in module efficiency gains).

Another promising area for future work is to study the cost improvement potential of technologies across locations using similar hardware. Combining cost change modelling with expert assessments of variables' improvement potential is one approach to estimating, for example, the rate of soft technology improvement required for a given cost target and expected rate of improvement in hardware features. Expert input could also be used to model dependencies between technology variables themselves, expanding the focus beyond the direct dependencies of cost components on variables captured here. Overall, a focus on technology features, rather than the cost components that emerge from combinations of those features, may be an effective way to inform forecasts of technology improvement, because features may better match the aspects of technology decision-makers have agency over (e.g., the number of permits required, installation task durations).

8 Methods

8.1 Cost equations

As with any good, the cost of a PV system is the total cost of its inputs, both physical and non-physical. A PV system consists of an array of PV modules, each attached to a support structure and interconnected with each other and with an inverter through wires and cables. The inverter converts direct-current electricity generated by the modules into alternating-current electricity that can be used on-site or transmitted elsewhere. The total cost of a PV system is the cost of these pieces of physical hardware (hardware costs) plus the costs of labor, fees, and other services needed for system design, construction and grid interconnection (soft costs).

Our topmost grouping divides PV system costs into the costs of modules and balance-of-systems (BOS) costs, which capture all costs incurred by the installer other than the purchase price of the module. For modules we use the model developed in [10]. For BOS costs we use a model that accounts for other materials and task inputs needed to deploy a PV system. Tasks completed for each module, such as electrical and mechanical installation, scale with the number of modules, while other tasks such as design and permitting are completed only once per system (under average conditions as reported here [23]). Although design drawings were completed by hand in the 1980s, suggesting a dependency of total design costs on the module count, historical sources indicate that detailed drawings on how to fix individual modules on roofs were completed only once per system [61]. Our model does not account for subsidies and therefore represents the unsubsidized PV system cost to the owner. The full list of variables in our model is given in Figure 2, and a full description of our model and data are given in Methods and Supplementary Notes 1-3. The final model of system cost per AC watt generated is:

$$
\begin{aligned}
C_{sys} = \frac{1+p_{op}}{K_{inv}\eta_{inv}} \Bigg[& \underbrace{p_M K_s}_{\text{Module component costs}} + \underbrace{p_{inv} K_s}_{\text{Inverter component costs}} + \frac{1}{\eta_w} \\
& \Bigg(\underbrace{K_s \phi_a p_a}_{\text{racking aluminum costs}} + \underbrace{\frac{K_s \alpha}{A \eta_m n_{mc} \sigma} \phi_w p_w}_{\text{total wire price}} + \underbrace{\tau_s w_s}_{\text{system design costs}} \\
& + \underbrace{\frac{K_s \alpha}{A \eta_m n_{mc} \sigma} \sum_{i=1}^{2} \tau_i w_i}_{\text{mechanical and electrical installation costs}} + \underbrace{\tau_{PII} w_{PII}}_{\text{PII labor costs}} \\
& + \underbrace{p_r}_{\text{residual racking price}} + \underbrace{p_{oe}}_{\text{other el. hardware price}} \Bigg) \Bigg] \\
& + \frac{1}{K_{inv}\eta_{inv}} \Bigg(\underbrace{c_{PII}}_{\text{PII fees}} + \underbrace{c_{sc}}_{\text{supply chain costs}} + \underbrace{c_{stax}}_{\text{sales tax expenses}} \Bigg). \qquad (1)
\end{aligned}
$$

Here, C_{sys} is the PV system's price as offered by the installer, which at the same time is a cost to the consumer (e.g., a household or utility). (Note that the cost components we identify with brackets in equation (1) are defined by the pre-factor denominator as well as the variables listed directly above the brackets.) The product $(K_s\alpha)/(A\eta_m n_{mc}\sigma)$ is the number of modules per system of capacity K_s, and its presence in three of the terms above reflects the fact that these cost components scale with the number of modules deployed. The number of modules per system is multiplied by τ_i (per-module task durations) and w_i (task-specific wages) to give total labor costs (see Fig. 2). Note that the variable p_{op} accounts for both installer profit and overhead expenses. We combine these two factors here due to historical data limitations. We separate them in our analysis of cost change in utility-scale systems (see section 5 in the main article and Supplementary Fig. 3), which covers a more recent time period.

In a separate analysis, we decompose module cost further. The module price p_M, in units of dollars per DC watt, is modeled as the sum of silicon costs, non-silicon material costs, and plant-size dependent costs (see Table 2, based on [10]), plus a margin charged by the manufacturer:

$$p_M = \frac{\alpha}{\sigma A \eta_m y} \left[Av\rho p_s + cA + p_0 \left(\frac{K}{K_0} \right)^{-b} \right] + p_{mf}. \tag{2}$$

We compute the factory margin p_{mf} as the difference between the first three cost components above and module factory-gate prices in each year (see Supplementary Table 6).

Table 2. Module cost equation variables and cost components. (Note that A_m, the module area, is computed as $n_{mc}A/\alpha$.)

Symbol	Meaning	Unit
Module		
α	Area utilization	unitless
σ	Solar constant	W_{dc}/m^2
A	Wafer area	m^2
η_m	Module efficiency	unitless
y	Yield	unitless
v	Silicon usage	m
ρ	Wafer density	g/cm^3
p_s	Polysilicon price	2017$/kg
c	Non-Si materials cost	2017$/$m^2$
K	Module manufacturing plant size	MW/year
K_0	Reference plant size (2012)	MW/year
b	Scaling factor	unitless
p_{mf}	Module factory margin	2017$/$W_{dc}$
n_{mc}	Number of cells per module	unitless

8.2 Classification of technology features

Like cost components, variables can be classified as either hardware or soft technology variables. Hardware variables, such as module efficiency, describe features of physical equipment and production inputs such as materials (see Fig. 2). When these variables are improved, for example by implementing a new design, the improvement is embodied in the physical technology. In the case of PV, these physical technology improvements have happened in markets that are globally integrated. In contrast, soft technology variables, such as the durations of installation tasks, describe features of processes and services. Traditionally, soft technology improvements (with the exception of some software advances) have not been as widely shared across locations, and have not necessarily persisted over time. For example, how quickly a PV module is mounted on a rooftop often depends on location-specific levels of installer experience, and can vary for the same installer crew from one site to another.

Soft technology variables can be defined for all processes affecting technology unit cost, including project management, system design, manufacturing, shipping, installation, operation, and end-of-life management. The specific set of hardware and soft technology variables included in a model will depend on the chosen system boundary. The system boundary reflects the perspective of a technology developer involved in the delivery of a particular technology service, e.g. the construction of new power capacity or the delivery of electricity. Technology characteristics that are embodied in the physical resources (e.g., machines or materials) used during production within the boundary are classified as hardware features. Technology characteristics that are contained in non-physical resources used within the boundary (human and computer-based knowledge and routines, e.g. installation practices and software) are classified as soft features.

In this paper we draw the system boundary around the PV installation project. Soft costs account for the soft technologies, services and processes, used inside this system boundary to grow the business, and design and install the PV system, and hardware costs account for the physical equipment that is purchased from the suppliers that make this equipment. Based on this boundary choice, all module and inverter variables are classified as hardware variables. This perspective matches that of installers, who source modules and inverters that arrive as pieces of hardware with fixed features. We note that with a different system boundary, module (or inverter) manufacturing would involve soft technology, e.g., labor processes that evolved with time and contributed to changing costs. However, here we focus on installation soft costs, which have been shown to have considerably slowed overall PV cost declines [22, 24, 31, 66]. Additionally, we explore the effects of expanding the boundary to include module manufacturing soft costs in a sensitivity analysis (see Supplementary Note 8).

The relationships in equation (1) can be viewed as a bipartite network (Fig. 2D) connecting technology variables to the cost components that they affect. The details of this network are specific to the technology involved and capture the structure of variables' influence on costs. A notable pattern, far more apparent in Fig. 2D than in equation (1), is that hardware variables (e.g., inverter efficiency or module efficiency) tend to affect many cost components, including soft cost components, while soft technology variables (e.g., mechanical installation time) tend to affect just a few.

Changes in hardware variables can affect soft costs per watt either through quality improvements realized without large changes in physical design (e.g., higher efficiency modules reducing area-dependent labor costs, see 'Hardware quality dependency' in Fig. 2), or through design changes that alter how installation tasks are performed or make them more efficient (e.g., module-integrated racking). In contrast, changes in soft technology variables do not alter hardware costs per watt. For example, an installation task may take less time as an installer crew becomes more experienced, but this improvement does not change the equipment used.

8.3 Cost influence shares

The fact that any given variable can influence multiple cost components is important, and in a variable-based understanding of cost reductions it is useful to have a metric of the total cost influence that a variable has. A natural measure of the zth' variable's influence is based on the sum of all cost components that r_z influences in equation (1),

$$I_z = \sum_i C_i(\frac{\partial \ln C_i}{\partial \ln r_z}). \tag{3}$$

In Figure 4, we normalize these raw influences and look at variables' *influence shares*

$$S_z = I_z / \sum_{z'} I_{z'}, \tag{4}$$

showing how these influence shares changed over the period 1980-2017 for different variables, and how the influence shares of variables compare with actual cost reductions they contributed based on cost change equations (see next section).

8.4 Cost change equations

Having defined a cost model, we now consider how much each variable reduced PV system costs in the past. Using a recently developed method [10], we decompose the total cost change into contributions from each variable. The total cost C of a technology is given as a sum of *cost components* C_i, which are functions of a vector $\vec{r}^t = (r_1^t, r_2^t, \ldots)$ of explanatory variables at time t: $C(\vec{r}^t) = \sum_i C_i(\vec{r}^t)$. Often, as in our PV cost model, the cost components are products of functions of the explanatory variables, $C_i(\vec{r}^t) = C_{i0} \prod_j g_{ij}(r_j^t)$. For this class of cost equations it can be shown that the change in the total cost between two times, t_1 and t_2, due to a change in variable r_z is

$$\Delta C_z \approx \sum_i \tilde{C}_i \ \ln \frac{g_{iz}(r_z^2)}{g_{iz}(r_z^1)}, \tag{5}$$

where r_z^1 and r_z^2 are the values of r_z at times t_1 and t_2, and $\tilde{C}_i$ is a representative value of the cost component i over the time interval. It can be shown that $\tilde{C}_i = (C_i^2 - C_i^1)/(\ln C_i^2 - \ln C_i^1)$ is a particularly good choice [10], where C_i^1 and C_i^2 are the values of the cost components at the beginning and end of the interval. With this choice total cost change equals the sum of the estimated contributions from individual variables, $\Delta C = \sum_z \Delta C_z$. Supplementary Note 1 contains further discussion of this method, including example cost change equations for PV systems.

More conceptually, cost change equations lead to a variable-based decomposition rather than one based on categories of additive cost components. Note that the percent change in total cost C that occurs after a 1% change in cost component C_i is just C_i's cost share, $\theta_i = C_i/C$:

$$\frac{\partial \ln C}{\partial \ln C_i} = \theta_i. \tag{6}$$

This fact agrees with the intuition that larger categories of cost components present proportionally greater opportunity for cost reduction. On the other hand, the variables (i.e., the technology features) that a given policy intervention might act on do not always align in obvious ways with cost components. Given this, consider the corresponding expression for the percent change in cost from a 1% change in a variable r_z:

$$\frac{\partial \ln C}{\partial \ln r_z} = \sum_i \theta_i \frac{\partial \ln C_i}{\partial \ln r_z}. \tag{7}$$

Wherever there is a dependency of cost component C_i on variable r_z the partial derivatives $\partial \ln C_i/\partial \ln r_z$ are non-zero. Such dependencies are represented as links in Fig. 2D. Equation (7) could also be expressed as $dC_z = \sum_i C_i(\partial \ln C_i/\partial \ln r_z) d\ln r_z$, showing that it is the infinitesimal counterpart to the cost change equation, equation (5). While equation (7) captures these dependencies in theoretical terms, equation (5) gives a practical way to account for them using a technology cost model and data.

9 Data

We populate the cost equation with data from the years 1980, 2001, 2012, and 2017, supplemented by inflation-adjusted data from nearby years where necessary. The year 1980 was chosen because this was when space applications of PV were overtaken by terrestrial applications, which had lower quality and reliability requirements [5, 27, 67]. The years 2001 and 2012 were selected to match previous work on PV module costs [10], and 2017 was selected to cover recent developments. While these years make cost change analyses possible for each of the intervals 1980-2001, 2001-2012, and 2012-2017, our conclusions focus on the full interval 1980-2017, and we discuss the recent time period 2017-2021 in Supplementary Note 9. Off-grid systems with batteries were prevalent in the 1980s, but for consistency we focus on grid-connected residential systems, which also existed [68]. Details on cost data are given in Supplementary Notes 2 and 3.

We focus on changes to a representative PV system characterizing the state of PV technology in each period, drawing on reference PV system designs prepared for DOE and NASA [69], Sandia National Laboratory [70], and NREL [21, 23], as well as on installer surveys [48, 53]. These sources directly incorporate empirical data (see Supplementary Note 3 and Supplementary Table 4). To help validate our model we cross-check its output with prices reported from alternate sources. We conduct sensitivity analyses in cases where differences between reported prices and bottom-up estimates are large (Supplementary Note 4). As often the case in historical technology studies, individual data points have significant uncertainty. To understand how this impacts our results we perform extensive sensitivity analyses (Supplementary Notes 5 and 7), which our findings take into account. After making cost change estimates at the fine levels of individual variables, cost components, and years, we developed our main findings based on aggregations across these inputs (as shown below), taking care to draw conclusions that held despite the variations across different data source. In this way we ensured that the conclusions drawn were robust to data uncertainty.

Data availability. The data used to populate the cost and cost change equations (1-5) along with references are provided with this paper (Supplementary Tables 1-3 and 9). Source data are available from IRENA (https://www.irena.org/publications/) and NREL (https://www.nrel.gov/research/publications.html, [23]) for free and from the German Solar Association (https://www.solarwirtschaft.de/en/press/market-data/) at cost.

Code availability. All steps in this analysis are described in Methods equations (1-5). The code is available upon request.

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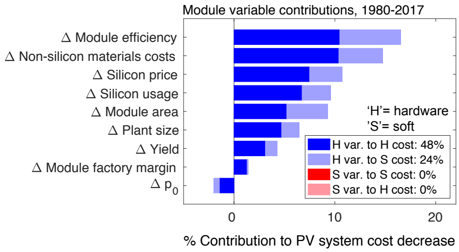
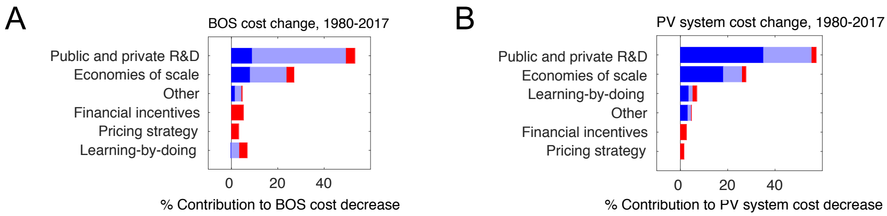
Author contributions. M.M.K., J.E.T., G.K., and J.M. conceptualized the study and developed the methodology. M.M.K. built the model. M.M.K., J.E.T, J.M., and G.K., analyzed the results and wrote the paper. J.E.T. led the research team.

Competing interests. The authors declare no competing interests.



Extended Data Figure 1. Estimated contributions from module price variables (Eq. 2) to cost reduction in residential PV systems in the U.S. Results are shown for the 1980-2017 period and a 5kW system. Note that contrary to Fig. 3, module price variable contributions sum up to less than 100% (see legend box) because they represent the contributions of one technology component to total system cost change. In all panels, percentages give the fraction of the net cost change over the 1980-2017 period that was caused by each variable. Cost change contributions in absolute terms (in 2017 $\$/W_{ac}$) are given in Supplementary Table 8.



Extended Data Figure 2. Estimated contributions from high-level mechanisms to PV system cost reduction. Percentages give the estimated fraction of the net cost change over the 1980-2017 period (see Table 1) that was caused by each high-level mechanism for the chosen assignment between low- and high-level mechanisms (see Supplementary Table 10). Contributions are negative when they act in the opposite direction to the net cost change over a period. In all periods above, the net change cost was negative, therefore positive contributions correspond to cost-reducing effects and negative contributions to cost-raising effects. Note that assignments of low-level mechanisms to high-level are based on a combination of quantitative modelling results and qualitative accounts in the literature. Due to data limitations, the decomposition for some cost components (i.e., the decomposition of module mechanisms in Extended Data Fig. 1) is more fine-grained than for others; applying the same level of decomposition across all cost components may alter the results.

References

[1] Nagy, B., Farmer, J.D., Bui, Q.M., Trancik, J.E.: Statistical basis for predicting technological progress. PLoS ONE **8**, 52669 (2013)

[2] McNerney, J., Farmer, J.D., Trancik, J.E.: Historical costs of coal-fired electricity and implications for the future. Energy Policy **39**(6), 3042–3054 (2011)

[3] McNerney, J., Farmer, J.D., Redner, S., Trancik, J.E.: Role of design complexity in technology improvement. Procceedings of the National Acaedmy of Sciences **108**(22), 9008–9013 (2011)

[4] Moore, G.: Cramming more components onto integrated circuits. Electronics 38 (8): 114–117 (1965)

[5] Nemet, G.F.: Beyond the learning curve: factors influencing cost reductions in photovoltaics. Energy Policy **34**(17), 3218–3232 (2006). https://doi.org/10.1016/j.enpol.2005.06.020

[6] Grubler, A.: The costs of the french nuclear scale-up: A case of negative learning by doing. Energy Policy **38**(9), 5174–5188 (2010)

[7] Eash-Gates, P., Klemun, M.M., Kavlak, G., McNerney, J., Buongiorno, J., Trancik, J.E.: Sources of cost overrun in nuclear power plant construction call for a new approach to engineering design. Joule **4**(11), 2348–2373 (2020)

[8] Feldman, D., Ramasamy, V., Fu, R., Ramdas, A., Desai, J., Margolis, R.: Us solar photovoltaic system and energy storage cost benchmark: Q1 2020. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States) (2021)

[9] IRENA: Renewable power generation costs in 2017. Technical report, International Renewable Energy Agency (2018)

[10] Kavlak, G., McNerney, J., Trancik, J.E.: Evaluating the causes of cost reduction in photovoltaic modules. Energy Policy **123**, 700–710 (2018)

[11] Christmas, S., Berliner, D., Brown, K., Costello, D., Fellhauer, C., Flaim, S., Heiferling, P., Lavender, J., Nasr, L., Taylor, R., Watkins, J., Withholder, R.: Solar cost databank. Technical report, Solar Energy Research Institute (1979)

[12] United Engineers & Constructors: Capital Cost: Pressurized Water Reactor Plant. Technical report, Nuclear Regulatory Commission & Energy Research and Development Administration (1977). https://doi.org/10.2172/6033498

[13] United Engineers & Constructors: Energy Economic Data Base (EEDB) Program: Phase VIII. Technical report, U.S. Department of Energy (1986)

[14] Popat, L.V.: The economics of geothermal power. Engineering Costs and Production Economics **7**(2), 159–170 (1983)

[15] Agency, I.R.E.: Geothermal power: Technology brief. Technical report, IRENA (2017)

[16] Wright, T.P.: Factors affecting the cost of airplanes. Journal of aeronautical sciences **3**(4), 122–128 (1936)

[17] Rubin, E.S., Azevedo, I.M.L., Jaramillo, P., Yeh, S.: A review of learning rates for electricity supply technologies. Energy Policy **86**, 198–218 (2015). https://doi.org/10.1016/j.enpol.2015.06.011

[18] Elshurafa, A.M., Albardi, S.R., Bigerna, S., Bollino, C.A.: Estimating the learning curve of solar pv balance–of–system for over 20 countries: Implications and policy recommendations. Journal of Cleaner Production (2018)

[19] McDonald, A., Schrattenholzer, L.: Learning rates for energy technologies. Energy Policy **29**(4), 255–261 (2001). https://doi.org/10.1016/S0301-4215(00)00122-1

[20] Meng, J., Way, R., Verdolini, E., Anadon, L.D.: Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. Proceedings of the National Academy of Sciences **118**(27) (2021)

[21] Goodrich, A., James, T., Woodhouse, M.: Residential, commercial, and utilityscale photovoltaic (pv) system prices in the united states: current drivers and cost-reduction opportunities. Contract **303**(2012), 275–3000 (2012)

[22] Barbose, G., Darghouth, N., Elmallah, S., Forrester, S., Kristina SH, K., Millstein, D., Rand, J., Cotton, W., Sherwood, S., O'Shaughnessy, E.: Tracking the sun: Pricing and design trends for distributed photovoltaic systems in the united states-2019 edition. Technical report, Lawrence Berkeley National Laboratory (2019)

[23] Fu, R., Feldman, D.J., Margolis, R.M., Woodhouse, M.A., Ardani, K.B.: Us solar photovoltaic system cost benchmark: Q1 2017. Technical report, National Renewable Energy Laboratory (NREL), Golden, CO (United States) (2017)

[24] Solar futures study. Technical report, United States Department of Energy (2021)

[25] Helveston, J.P., He, G., Davidson, M.R.: Quantifying the cost savings of

global solar photovoltaic supply chains. Nature, 1–5 (2022)

[26] Junginger, M., van Sark, W., Faaij, A.: Technological learning in the energy sector: lessons for policy, industry and science. Edward Elgar Publishing (2010)

[27] Candelise, C., Winskel, M., Gross, R.J.: The dynamics of solar pv costs and prices as a challenge for technology forecasting. Renewable and Sustainable Energy Reviews **26**, 96–107 (2013)

[28] Gillingham, K., Deng, H., Wiser, R., Darghouth, N., Nemet, G., Barbose, G., Rai, V., Dong, C., et al.: Deconstructing solar photovoltaic pricing. The Energy Journal **37**(3) (2016)

[29] Nemet, G.F., O'Shaughnessy, E., Wiser, R., Darghouth, N., Barbose, G., Gillingham, K., Rai, V.: Characteristics of low-priced solar pv systems in the us. Applied Energy **187**, 501–513 (2017)

[30] Ramasamy, V., Feldman, D., Desai, J., Margolis, R.: Us solar photovoltaic system and energy storage cost benchmark: Q1 2021. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States) (2021)

[31] Barbose, G., Darghouth, N.R., Weaver, S., Feldman, D., Margolis, R., Wiser, R.: Tracking us photovoltaic system prices 1998–2012: a rapidly changing market. Progress in Photovoltaics: Research and Applications **23**(6), 692–704 (2015)

[32] Imamura, M., Hulstrom, R., Cookson, C., Waldman, B., Lane, R.: Definition study for photovoltaic residential prototype system (1976)

[33] Kirpich, A.: Conceptual design and systems analysis of photovoltaic systems. volume ii. study results. final report. Technical report, General Electric Co., Philadelphia, Pa.(USA). Space Div. (1977)

[34] Hayter, S.J., Martin, R.L.: Photovoltaics for buildings cutting-edge pv. Technical report, National Renewable Energy Lab., Golden, CO (US) (1998)

[35] Briggs, R., Daniels, A., Greenaway, R., Oster Jr, J., Racki, D., Stoeltzing, R.: Automated installation methods for photovoltaic arrays. Unknown (1982)

[36] Agora Energiewende, F.I.: Current and future costs of photovoltaics: Long-term scenarios for market development, system prices and LCOE of utility-scale systems (2015)

[37] Bower, W.: Inverters—critical photovoltaic balance-of-system components: status, issues, and new-millennium opportunities. Progress in Photovoltaics: Research and Applications **8**(1), 113–126 (2000)

[38] release, A.P.: ABB in India doubles solar inverter manufacturing capacity with a new state-of-the-art factory (2016). http://www.abb.com/cawp/seitp202/dd2d6344a0e0424bc12580220022020d.aspx

[39] Newsroom, S.: World's largest and CO2-neutral inverter factory inaugurated by SMA Technology AG. (2009). https://www.sma.de/en/newsroom/current-news/news-details/news/2189-worlds-largest-and-co2-neutral-inverter-factory-inaugurated-by\-sma-solar-technology-ag.html

[40] Burgess, E., Post, H., Key, T.: Subsystem engineering and development of grid-connected photovoltaic systems. In: Fourth EC Photovoltaic Solar Energy Conference, pp. 238–247 (1982). Springer

[41] Costello, D., Rappaport, P.: The technological and economic development of photovoltaics. Annual Review of Energy **5**(1), 335–356 (1980)

[42] Smith, J.L.: Photovoltaics as a terrestrial energy source. volume 3: An overview. U.S. Department of Energy Photovoltaics Program **DOE/ET-20356-6** (1980)

[43] Feldman, D., Barbose, G., Margolis, R., Wiser, R., Darghouth, N., Goodrich, A.: Photovoltaic (pv) pricing trends: historical, recent, and near-term projections. Technical report, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States) (2012)

[44] Trancik, J.E., Brown, P.R., Jean, J., Kavlak, G., Klemun, M.M., Edwards, M.R., McNerney, J., Miotti, M., Mueller, J.M., Needell, Z.A.: Technology improvement and emissions reductions as mutually reinforcing efforts: Observations from the global development of solar and wind energy. Technical report, Institute for Data, Systems, and Society, MIT (2015)

[45] Kimura, O., Suzuki, T.: 30 years of solar energy development in japan: co-evolution process of technology, policies, and the market. In: Berlin Conference on the Human Dimensions of Global Environmental Change:?Resource Policies: Effectiveness, Efficiency, and Equity, pp. 17–18 (2006)

[46] Wiese, A., Kaltschmitt, M., Fahl, U., Voß, A.: Vergleichende kostenanalyse einer windtechnischen und photovoltaischen stromerzeugung (1992)

[47] Gabler, H., Mohring, H.-D.: Photovoltaische großanlagen–technologie und

realisierung. Forschungsverbund Sonnenenergie Themen, 56–60 (2002)

[48] Friedman, B., Margolis, R., Seel, J.: Comparing photovoltaic (pv) costs and deployment drivers in the japanese and us residential and commercial markets. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States) (2016)

[49] Ahmed, K.: Renewable Energy Technologies: a Review of the Status and Costs of Selected Technologies. The World Bank, (1994)

[50] Moore, L., Post, H., Mysak, T.: Photovoltaic power plant experience at tucson electric power. In: ASME 2005 International Mechanical Engineering Congress and Exposition, pp. 387–394 (2005). American Society of Mechanical Engineers

[51] Fuhs, W.: Photovoltaik–stand und perspektiven. FVS DGS Themen (2000)

[52] Bericht über den stand der markteinführung und der kostenentwicklung von anlagen zur erzeugung von strom aus erneuerbaren energien (erfahrungsbericht zum eeg). Technical report, Bundesministerium für Wirtschaft und Energie (2002)

[53] Research, E.: Photovoltaik-preismonitor deutschland q1 2018. Technical report, Bundesverband Solarwirtschaft (2018)

[54] Watt, M., Passey, R.: National survey report of pv power applications in australia. Technical report, Australian PV Association (2010)

[55] Calhoun, K., Crofton, K., McIntosh, R.M.I. Robert: Lessons from Australia: Reducing Solar PV Costs Through Installation Labor Efficiency. (2014). http://www.rmi.org/Knowledge-Center/Library/2014-11_RMI-AustraliaSIMPLEBoSFinal

[56] Johnston, W., Egan, R.: National survey report of pv power applications in australia 2016. Report, Australian PV Institute (July 2017) (2017)

[57] Lin-Lin, Y.: Economic analysis of solar photovoltaic based on life cycle costing. State Electricity Regulatory Commission **2500**, 3000 (2010)

[58] Fink, T., Reeves, M., Palma, R., Farr, R.: Serendipity and strategy in rapid innovation. Nature communications **8**(1), 2002 (2017)

[59] Agency, I.R.E.: Renewable power generation costs in 2018. Technical report, IRENA (2018)

[60] Fu, R., Remo, T.W., Margolis, R.M.: 2018 us utility-scale photovoltaics-plus-energy storage system costs benchmark. Technical report, National

Renewable Energy Lab.(NREL), Golden, CO (United States) (2018)

[61] Cox III, C.: Residential photovoltaic systems costs. Technical report, Massachusetts Inst. of Tech., Lexington (USA). Lincoln Lab. (1980)

[62] Wiser, R., Bolinger, M., Cappers, P., Margolis, R.: Analyzing historical cost trends in california's market for customer-sited photovoltaics. Progress in Photovoltaics: Research and Applications **15**(1), 69–85 (2006)

[63] Barbose, G.L., Darghouth, N.R., Millstein, D., Spears, M., Wiser, R.H., Buckley, M., Widiss, R., Grue, N.: Tracking the sun viii: the installed price of residential and non-residential photovoltaic systems in the united states. Technical report, Lawrence Berkeley National Laboratory (LBNL), Berkeley, CA (United States) (2015)

[64] Barbose, G.L., Darghouth, N.R., LaCommare, K.H., Millstein, D., Rand, J.: Tracking the sun: Installed price trends for distributed photovoltaic systems in the united states-2018 edition. Technical report, Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States) (2018)

[65] O'Shaughnessy, E., Nemet, G.F., Pless, J., Margolis, R.: Addressing the soft cost challenge in us small-scale solar pv system pricing. Energy Policy **134**, 110956 (2019)

[66] Ardani, K., Seif, D., Margolis, R., Morris, J., Davidson, C., Truitt, S., Torbert, R.: Non-hardware (" soft") cost-reduction roadmap for residential and small commercial solar photovoltaics, 2013-2020. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States) (2013)

[67] Green, M.A.: Silicon photovoltaic modules: a brief history of the first 50 years. Progress in Photovoltaics: Research and Applications **13**(5), 447–455 (2005). https://doi.org/10.1002/pip.612

[68] Watts, R., Smith, S., Dirks, J.: Photovoltaic industry progress through 1984. Technical report, Pacific Northwest Labs., Richland, WA (USA) (1985)

[69] Macomber, H., Ruzek, J.B., Costello, F.A.: Photovoltaic stand alone systems. Monegon, Caithersburg, MD (1981)

[70] Palmer, R., Penasa, D., Thomas, M.: Detailed cost estimate of reference residential photovoltaic designs. Sandia Report **SAND83**, 1–35 (1983)