System Price Dynamics for Battery Storage

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Abstract

While steep learning curves have been documented for lithium-ion battery packs, little evidence exists on whether total system prices for end-users reflect this decline. We use project-level data from California to estimate system price dynamics and experience rates for battery storage systems. We document low experience rates of about 1.3%, i.e., with every doubling in cumulative projects, system prices fall by 1.3%. Larger systems show higher experience rates of up to 11%, while smaller systems show slightly negative experience rates. We find that limited competition among installers is restraining price declines for small systems. Moreover, learning is driven by industry (rather than firm) experience and is significantly lower for balance-of-system costs. In sum, our results suggest that price dynamics relevant to end-users fall behind the pace of reported cost declines for battery packs, and warrant policy focus on installer competition and balance-of-system costs.

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Introduction

Battery storage is a key ingredient for decarbonized energy systems (Arbabzadeh et al., 2019). When widely distributed across the system, battery storage facilitates the growth of wind and solar energy (Zerrahn et al., 2018; Schill, 2020; Tong et al., 2021), provides grid stabilization services (Davies et al., 2019), and supports off-grid electricity provision (Jaiswal, 2017; Lee and Callaway, 2018).

The growing relevance of battery storage coincides with a massive increase in R&D and patenting, aiming to reduce battery costs (IEA, 2020, 2022). However, the economics of battery storage remain challenging for end-users and often dependent on subsidies (Comello and Reichelstein, 2019). As a consequence, understanding learning and potential price reductions for battery storage is important for predicting future market shares and for designing effective support policies.

To analyze and forecast learning and cost reductions, previous studies estimate learning or experience rates for battery storage. Typically, learning rates indicate the change in technology costs associated with a doubling of experience, where experience is measured as cumulative installed capacity. The literature finds learning or experience rates for batteries mostly between 12% and 30% (Kittner et al., 2017; Schmidt et al., 2017; Hsieh et al., 2019; Kittner et al., 2020; Ziegler and Trancik, 2021). Yet, while these results are largely confined to analyzing global averages of scarce annual data for battery cells and packs, less is known on the dynamics of *total system prices* for distributed storage systems, i.e. what drives prices relevant to end-users. Importantly, although evidence for solar photovoltaics (PV) shows that market structure matters (Gillingham et al., 2016), there are no documented experience rates for local battery storage markets that take into account the degree of installer competition. A further consequence of scarce data is that little attention has so far been paid to estimating the price dynamics for the different applications of distributed battery storage (e.g. for small residential and larger non-residential systems) as well as its different cost components, such as balance-of-system (BOS) costs.

In this article, we provide several contributions to the literature on learning by doing and technological progress of battery storage. First, we use rich project-level data from California to provide an empirical analysis of total system price dynamics in battery storage markets. We estimate experience rates of about 1.3%, implying that, on average, experience rates for system prices fall behind the majority of reported experience and learning rates for battery packs and cells (Kittner et al., 2017; Schmidt et al., 2017; Ziegler and Trancik, 2021). Second, we document substantial heterogeneity in total system prices and show that experience rates for larger systems are significantly higher than for smaller residential systems (11% vs. -2%). Third, we show that besides experience and system size, market structure matters. In particular for small storage systems, we find that less competition among installer firms is associated with lower experience rates and thus, on average, higher system prices. Fourth, we report that non battery-related costs, i.e. BOS costs, show lower experience rates than total prices. Lastly, we explore experience spillover effects and find a price-reducing effect of industry-wide experience. In contrast, we find that firm-specific experience does not explain observed reductions in system prices.

Overall, our analysis reveals that total price dynamics and specifically BOS costs do not match the pace of cost reductions for battery packs. Learning effects play a minor role especially for small system prices, which are rather driven by the economics of installer firms and the degree of competition among them. Because we find marked differences in learning for small residential and larger systems, the results of this article further highlight the relevance of tailoring support policies for battery storage to the different use cases. In addition, our findings stress the policy potential for reducing BOS costs and increasing installer competition to further accelerate investment in distributed storage.

Battery storage trends in California

To analyze technological progress and its determinants, we require detailed data on the total prices of individual storage systems. To this end, we conduct our analysis using the case of California and rich project-level data provided by the California Public Utilities Commission (CPUC). More specifically, the data are from the CPUC's Self Generation Incentive Program (SGIP), which administers the vast majority of subsidized battery storage systems in California. SGIP data include, amongst others, information on location, involved firms, system size, and "total eligible costs", i.e. total system prices.

Although other states in the US have started to promote battery storage, California represents the vast majority of distributed storage capacity (82% in 2019 for systems below 1 MW) in the US (EIA, 2021). The SGIP data hence offer a well representative sample. Moreover, cost and growth dynamics are comparable to markets outside the US, e.g. to the German market (Figgener et al., 2021, 2022).

Figure 1 shows the growth of SGIP supported storage projects over time. The program has supported about 8,000 systems (panel a) or about 250 MWh of storage capacity (panel b) annually over the recent years. In total, the program supports almost 1.1 GWh of cumulative storage capacity until 2021. The SGIP data, i.e. our sample, starts in 2008 and ends in December 2021 (because there are very few observations in the early years, Figure 1 shows data beginning in 2014).

As further shown in Figure 1, the bulk of capacity additions until 2017 came from larger systems (above 10kW). From 2017 onward, the number of small systems (below 10kW) surged to several thousand new installations per year. In parallel, this increase led to a rising share of residential storage capacity, which in 2021 represents more than 50% of total interconnected capacity. Among the reasons for this strong uptake of residential storage are wildfire-related power shutoffs, a gradual phase-out of net metering policies, new product

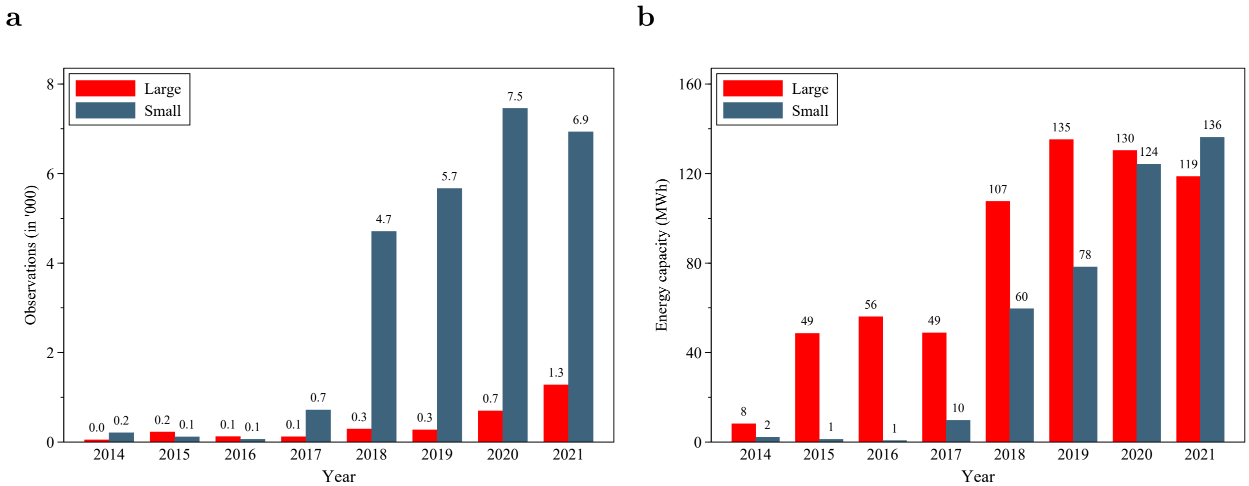

Figure 1: SGIP battery systems and installed capacity by size segment. a, number of subsidized storage systems. **b,** installed storage capacities. Data as of February 2022.

launches, and government subsidies for adopters (Barbose et al., 2021).

Similar to distributed solar generation (Gillingham et al., 2016), battery storage prices vary substantially across regions. Figure 2 illustrates this price dispersion for battery storage by county for large (panel a) and small systems (panel b). As can be seen, prices differ considerably by county, ranging from about 900 to 2800 USD per kWh.

Finally, as shown in panel c of Figure 2, average storage prices decline significantly especially in the early years of our sample, with a parallel decline in variance. The strong decline for small systems in 2017 coincides with the launch of a new and aggressively priced product from Tesla, a firm that acts both as installer and battery technology provider. While average prices of small systems tend to slightly adjust upwards thereafter, this price decline suggests to include the role of competition, amongst other drivers, to explain the heterogeneity and dynamics in system prices as observed in Figure 2.

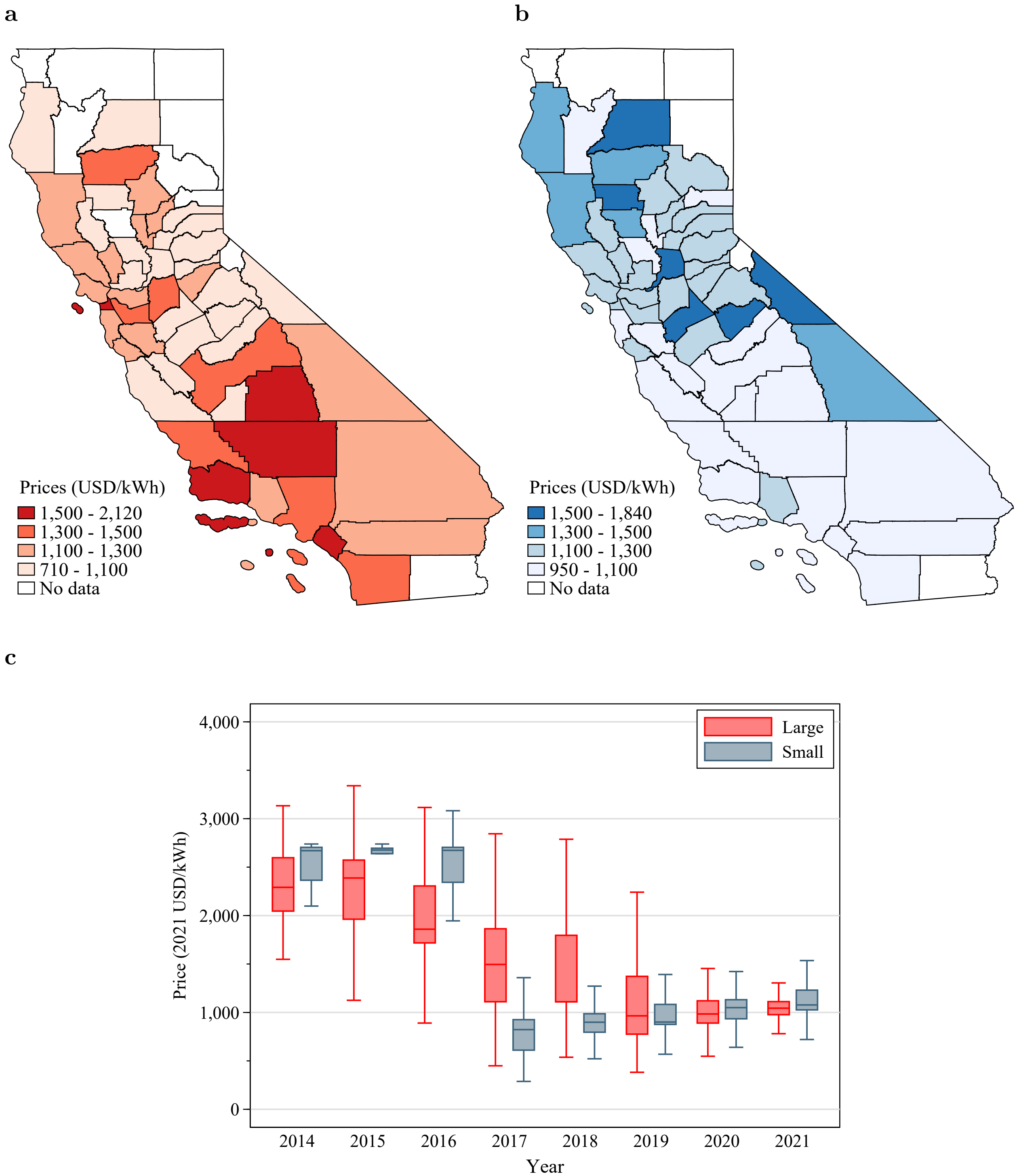

Figure 2: System prices. a, mean prices for large systems by county, number of counties in parentheses. **b,** mean prices for small systems by county. **c,** by size segment and year.

Estimating experience rates for battery storage

A well-established approach to measuring technological progress is to use learning rates, that indicate percentage changes in technology costs associated with a doubling of experience (Wright, 1936; Arrow, 1962). While experience is measured differently in the literature, a common approach is to proxy experience with cumulative installed capacity, namely cumulative kilowatt-hours (kWh) in the case of energy storage (Schmidt et al., 2017). Similar to other energy technologies, such as wind power (Schauf and Schwenen, 2021), lithium-ion battery learning and experience rates as reported in the literature differ substantially, depending on the technology variant, definition of experience, model specification, and the sample period. Reported experience rates for electric vehicle battery packs are between 6% and 21% (Nykvist and Nilsson, 2015; Schmidt et al., 2017; Hsieh et al., 2019; Kittner et al., 2020). Experience rates for batteries range from 15% to 30% (Kittner et al., 2017; Schmidt et al., 2017; Kittner et al., 2020; Ziegler and Trancik, 2021), or even higher when accounting for performance improvements beyond cost declines (Ziegler and Trancik, 2021).

Our methodological approach relies on one-factor experience curves (Schmidt et al., 2017). In particular, we use SGIP data and predict total prices per kWh for battery storage systems (in logs) with experience (measured as cumulative projects, likewise in logs). Since learning on total system prices typically does not depend on the energy storage capacity of the system, we use the natural log of cumulative projects to proxy for experience. In additional analyses, we validate our results using cumulative capacity in kWh. We use least squares regression with standard errors clustered at the county level. Additional information and summary statistics for the underlying data are presented in the Methods section and in the Supplementary Information (Tables 1 to 3).

Table 1 reports the estimated coefficients and corresponding experience rates. We compute the experience rates as $1 - 2^{\beta}$, where β is the estimated coefficient for experience. As shown in column (1), a doubling of experience, when measured as the cumulative number of projects, is associated with a decline in system prices of 1.29%. In column (2), we proxy experience by cumulative installed capacity and find slightly higher experience rates of about 3.33%. These estimates for project-level data are significantly below the previously reported experience rates (Schmidt et al., 2017; Hsieh et al., 2019; Kittner et al., 2020; Ziegler and Trancik, 2021).

Table 1: Estimated experience rates

Dependent variable: Price in 2021 USD/kWh	All observations	
	(1)	(2)
EXP #	-0.019^{*}	
	(0.011)	
EXP kWh		-0.049^{***}
		(0.015)
Experience rate %	1.29	3.33
Adjusted R^2	0.003	0.01
N	28,299	28,299

All variables are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Scale and installer competition

To further probe into the markedly low experience rates for system prices, we explore whether learning effects differ when splitting the sample according to different storage applications. We split the sample in residential (i.e. small, 10 kW or less) and non-residential (i.e. larger, above 10 kW) systems. This scale threshold is consistent with the definition of the CPUC (CPUC, 2016).

Table 2 presents the results for small and large storage systems. As shown in column (1), large systems show experience rates of about 11.11%. In column (2), we control for the market concentration in each county, as measured by the county-specific Herfindahl-Hirschman Index (HHI), which impacts prices with marginal significance. The specification in column (2) further controls for system size in kWh and duration in hours. We add these controls to account for installation-related economies of scale within CPUC's classification of large and small segments. In this specification, we also control for unobserved, time-invariant county and installer firm heterogeneity by including corresponding fixed effects. We find an experience rate of 8.44%. In sum, the experience rates for large systems are much higher than for the sample including all systems and closer to the experience rates as reported in previous studies.

Table 2: Regression results by segment

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.170^{***}	-0.127^{***}	0.028^{*}	0.021^{***}
	(0.008)	(0.017)	(0.014)	(0.007)
HHI		0.148^{*}		0.577^{***}
		(0.088)		(0.107)
Size kWh		-0.039^{**}		-0.173^{***}
		(0.019)		(0.013)
Duration		-0.123^{*}		-0.426^{***}
		(0.072)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.11	8.44	−1.93	−1.49
Adjusted R^2	0.39	0.66	0.01	0.67
N	2,957	2,957	25,331	25,331

All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Column (3) of Table 2 shows results for the sample of small systems, which are in stark contrast to the results for larger systems. Learning for small systems is close to zero with an estimated negative experience rate of approximately 2%. In addition, the relatively good model fit (adjusted R^2) of the one-factor model for large systems does not apply to small systems.

We again extend the basic model to control for the county-level HHI, for scale effects, and for county and installer firm heterogeneity. The results for this specification are shown in column (4) and indicate that scale effects play a significant role for small systems, too. For instance, an increase of a small storage system's capacity by ten percent associates with a decrease in system price per kWh of about 1.7%.

Importantly, we find that also the level of installer competition significantly determines the system price. Specifically, a more concentrated installer market (a higher HHI) is associated with higher prices. In other words, an increase in the HHI by 0.12 (one standard deviation) is associated with an increase in system prices by 5.3%. Notably, the model in column (4) that accounts for the HHI and system scale characteristics explains a relevant part of the variation in system prices (as shown by the relatively high R^2).

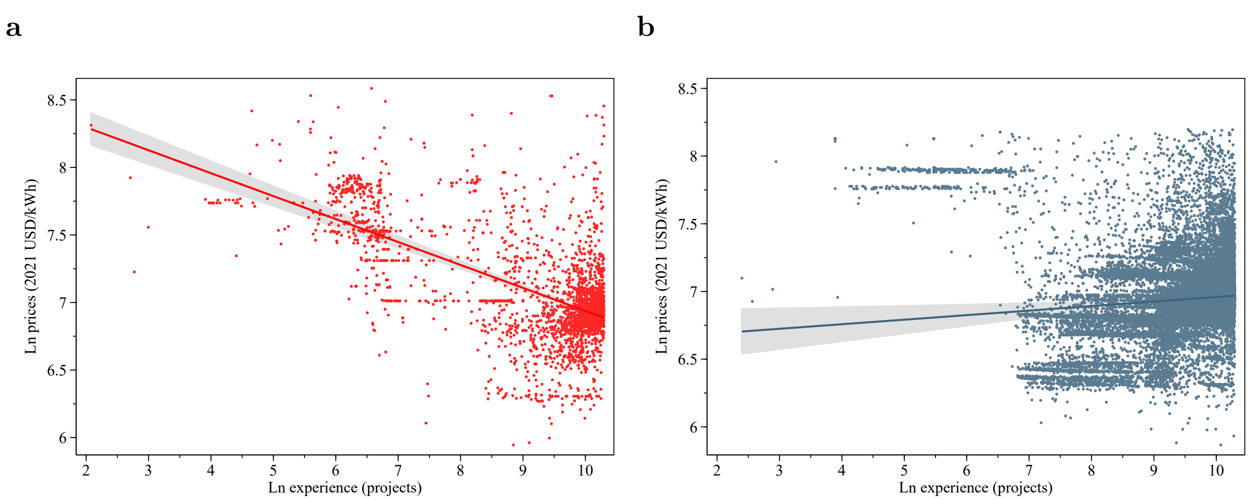

Figure 3: Experience curves. **a,** for large systems above 10 kW. **b,** for small systems below 10 kW. 95% confidence intervals are shown in grey.

Figure 3 illustrates the experience curves for small and large systems graphically. Panel a of Figure 3 shows the experience curve for larger systems as estimated in column (1) of Table

2. In line with the relatively high R^2 for larger systems, the model describes the data well. In contrast, panel b of Figure 3 shows the experience curve for smaller systems (that correspond to the estimates in column (3) of Table 2). As can be seen, there is significant heterogeneity in system prices for small systems. The above findings indicate that, first, learning follows strongly different magnitudes for large and small systems, and second, experience alone does not describe the data well, especially for smaller storage systems. As we have shown in our regression results above, further factors such as market concentration, system size, and duration play a significant role for total system prices, and in particular for small storage systems.

Balance-of-system costs

So far, our results point to significant learning in total system prices of larger battery storage systems but not for small systems. Next, we explore which cost components are driving these results. In particular, we investigate whether observed price declines can be attributed to the cost of battery packs or rather to non-battery, i.e. BOS costs.

Whereas battery packs are arguably a globally traded commodity, BOS costs primarily encompass components with mostly local learning, such as installation, permitting, customer acquisition, and mark-ups. In addition to these "soft" cost components (O'Shaughnessy et al., 2019), BOS costs also entail inverters and other auxiliary hardware like cables.

Specifically, we proxy BOS costs by deducting battery pack prices from total system prices. Since the SGIP data only provides system prices, we use yearly averages for battery pack prices from Bloomberg's battery price survey to compute BOS costs. This approach is consistent with earlier studies in the context of solar PV, that examine learning in non-module (i.e. BOS) or soft costs after subtracting module (and inverter) costs (Shum and Watanabe, 2008; Strupeit and Neij, 2017). Hence, our BOS measure includes the potentially missing ability of installer firms to purchase battery packs at prices published by Bloomberg, e.g. because of low order volumes or a lack of trading networks.

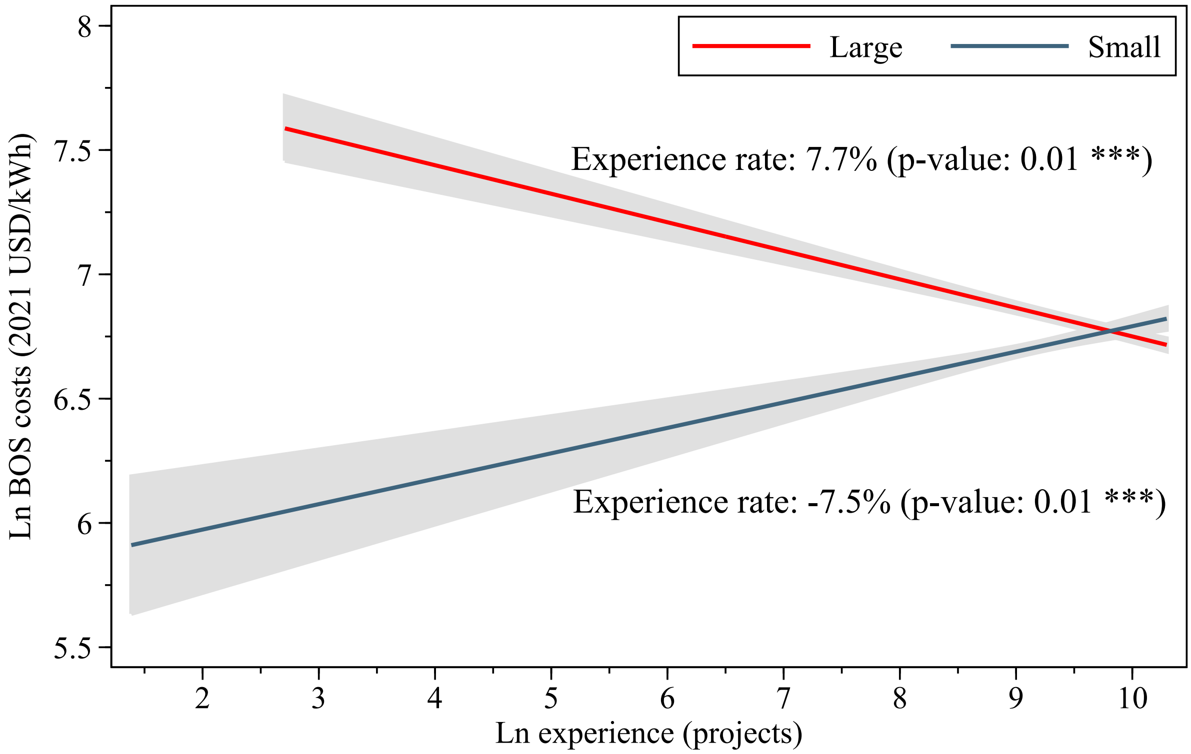

Figure 4: BOS cost learning curves, with 95% confidence intervals in grey.

To estimate learning in non-battery pack costs, we rerun our one-factor experience curve model using BOS costs as the dependent variable. Figure 4 depicts the resulting experience rates, again for the small and large segment without further controls. As shown, BOS learning is less strong than total system price learning. This holds for both segments, but in particular for small systems, where we estimate negative BOS learning of about 7.5%. Because BOS learning is slower or negative as compared to total prices, BOS costs make up for an increasing share of total battery system prices.

To illustrate the increasing relevance of non-battery costs, Figure 5 plots the share of BOS costs over time. As shown, at the end of our sample in 2022, BOS costs account for more than 80% of stationary system prices.

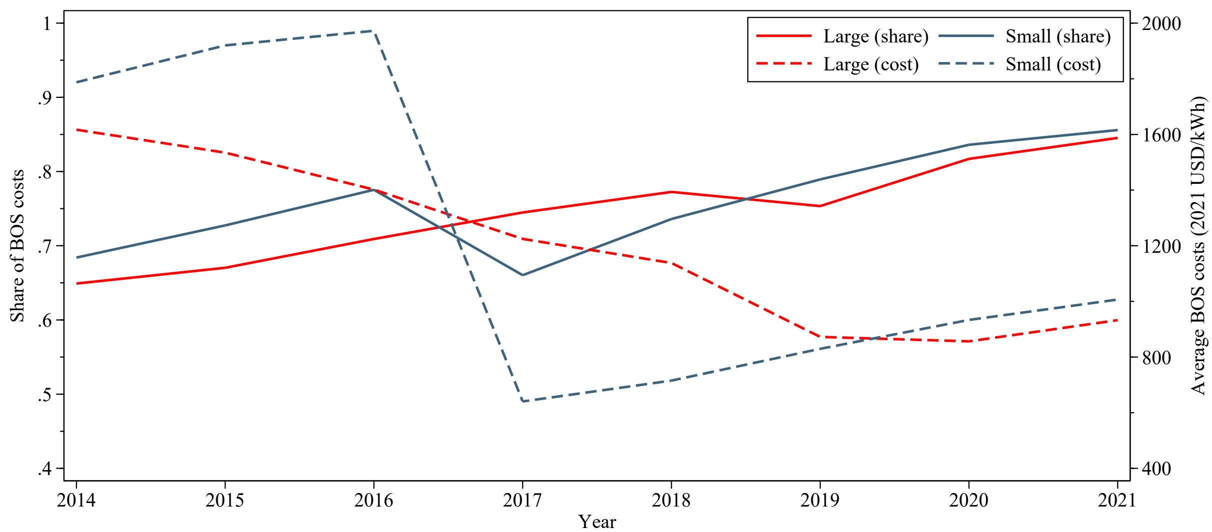

Figure 5: BOS costs and BOS cost percentage of total prices.

Overall, our findings suggest that local BOS cost learning cannot match the pace of upstream battery technology learning. In Supplementary Table 4 we show that our results hold when running the extended model with additional controls, e.g. for HHI.

Separating industry from firm learning

The previous analysis assumes homogeneous experience spillover effects within California, i.e. capacity added by one firm directly factors into the entire experience stock across the industry. This assumption is implicit to the vast majority of experience curve studies, and is impossible to test without project-level and installer firm-level data. In closing, we exploit our data to explicitly investigate the prevalence of spillover effects by separating industry from installer firm learning (Irwin and Klenow, 1994; Bollinger and Gillingham, 2019; Nemet et al., 2020). Because our earlier findings indicate that reductions in total system prices are primarily driven by global progress in battery packs rather than installer-specific BOS costs, we expect industry-wide learning to dominate intra-firm learning. We conduct our analysis by computing separate experience stocks for the industry and installer firms, and include both as explanatory variables (see Methods).

Table 3: Industry versus firm learning by segment

Price in 2021 USD/kWh	Price		BOS	
	(1)	(2)	(3)	(4)
SPILL #	-0.161^{***}	-0.089^{***}	-0.127^{***}	-0.055^{***}
	(0.021)	(0.013)	(0.020)	(0.018)
EXP Firm #	0.035^{***}	0.074^{***}	0.034^{**}	0.085^{***}
	(0.012)	(0.006)	(0.014)	(0.008)
HHI	0.160^{*}	0.434^{***}	0.110	0.499^{***}
	(0.090)	(0.095)	(0.101)	(0.116)
Size kWh	-0.039^{*}	-0.180^{***}	-0.047^{**}	-0.217^{***}
	(0.020)	(0.012)	(0.023)	(0.014)
Duration	-0.119	-0.416^{***}	-0.163^{*}	-0.490^{***}
	(0.077)	(0.031)	(0.093)	(0.036)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate %	10.57	5.96	8.45	3.71
Firm experience rate %	-2.45	-5.30	-2.40	-6.10
Adjusted R^2	0.66	0.68	0.54	0.69
N	2,957	25,331	2,957	25,331

All variables except HHI are on log scale. The variable SPILL captures learning from industry-wide experience, i.e. spillover learning. The variable EXP Firm captures learning from firm-specific experience. For each observation, we compute SPILL as the industry-wide cumulative number of projects excluding the firm that has installed the observed system. For each observation, we compute EXP Firm as the cumulative number of projects by the firm that has installed the observed system. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Table 3 shows the results. In the large segment, industry learning is significant while firm learning is negative (column (1)), with attenuated industry learning effects for BOS (column (3)). The results for small systems show similar patterns. The magnitude of industry learning is lower than for larger systems, with an industry experience rate of 6% for system prices (column 2) and 3.7% for BOS (column 4). However, negative firm learning is more than twice as large when compared to larger systems. In terms of magnitude, a doubling of firm experience is related to an increase in system price by 5.3% and an increase in BOS by 6.1%.

Put differently, firms with more experience ask for higher prices, on average. This effect is more pronounced for small systems, where, as shown earlier, competition is a relevant driver for system prices. These findings indicate that both commercial and especially residential customers are willing (or required) to pay for previous experience, e.g. because it is signaling market share, reputation, and reliability. Furthermore and as expected, industry learning plays a bigger role in explaining system price reductions than intra-firm learning, since the latter reflects less dynamic BOS costs and positive margins for experienced installers. Lastly, even after controlling for firm learning and a range of further variables, experience rates for total system prices and especially for BOS remain much lower than for battery cells and packs.

Discussion

Our results have several findings relevant to scholars, policy makers, and investors in distributed energy storage. First, we provide robust evidence of low learning by doing in system prices for battery storage based on rich project-level data. We estimate experience rates of about 1.3%, much lower than previously reported. When separating experience curves for small (below 10kW) and large (above 10kW) systems, we document experience rates of up to 11% for larger and -2% for smaller systems. These results highlight the benefit of more differentiated projections. Projections that do not account for the relatively stronger learning for large systems may understate future capacity additions, in particular in markets where large systems dominate.

Second, our results show statistically significant and economically relevant effects of market competition on system prices. To increase market penetration, regulators should hence facilitate installer competition, in particular for the smaller residential systems. Furthermore, we find a large effect of system size on system prices, consistent with bottom-up cost modeling (Ramasamy et al., 2021). Further scaling up both large and small systems is associated with lower system prices per kWh. To harness scale economies, regulators should remove barriers for the operation of larger storage systems, e.g. by allowing for additional revenues from providing grid services and trading in peer-to-peer markets.

Third, we report slower learning in BOS costs compared to total system prices, eventually leading to high shares of BOS costs versus battery pack costs. Battery storage hence faces a "BOS cost challenge", as found in the context of soft costs for distributed solar PV (O'Shaughnessy et al., 2019). Future policies should therefore focus on reducing BOS costs. Potential levers for reducing BOS cost include increased price transparency, e.g. by further expanding quote platforms for installers, as well as standardizing permitting and regulatory processes. Given the stickiness of BOS costs, our analysis at the same time underscores the importance of global cost-reductions of battery packs through innovation and production scale-up.

Fourth, learning at the installer level is negative (reflecting positive margins for experienced installers). Hence, observed price reductions are largely driven by industry-wide experience with again relatively low experience rates of 4-10%. These findings indicate little within-firm appropriability of experience and point to the existence of spillovers across the industry. As such, positive externalities of experience add to the benefits of battery storage for decarbonized energy systems. From a policy perspective, these positive externalities lend support for continued subsidy schemes to facilitate further investment in battery storage. Whether subsidies are suitable for stimulating adoption, learning, and competitive pass-through of learning effects to end-consumers remains an important avenue for future research.

Methods

Experience curve model

To model cost reductions for distributed battery storage systems, we utilize a simple mathematical power law known as the "learning curve" (Wright, 1936). Since we are interested in learning curves for the total system, we predict prices rather than costs. Using prices instead of costs is common in the literature because cost data are often not available. Learning curves based on price data are commonly referred to as experience curves (Schmidt et al., 2017), which we follow in this paper.

Formally, let P_t^{store} be the deflated price per unit of capacity (kWh) for stationary storage systems, P_0^{store} be the price of the first unit of experience EXP, and b be the learning parameter. Then, we can write

$$P_t^{store} = P_0^{store} * EXP_t^b. \tag{1}$$

Assuming a multiplicative error term ϵ, we can log-linearize the relationship to

$$ln(P_t^{store}) = P_0^{store} + \beta_1 ln(EXP_t) + \epsilon, \tag{2}$$

where β is the estimator for b and represents the learning elasticity. We then obtain the learning by doing, i.e. experience, rate as $1 - 2^{\beta}$. Equation 2 estimates a standard one-factor experience curve.

In our extended model, we add competition (HHI), installation-level economies of scale proxied by system size ($SIZE$, in logs), and fixed effects (ϕ) as further variables to the basic one-factor experience curve. Formally, we estimate

$$ln(P_t^{store}) = P_0^{store} + \beta_1 ln(EXP_t) + \beta_2 HHI_{j,t} + \beta_3 ln(SIZE_i) + \beta_4 ln(DURi) + \phi + \epsilon, \tag{3}$$

where HHI captures the Herfindahl-Hirschman index in county j at time t, $SIZE$ and DUR represent system size in kWh and duration in hours of project i, and ϕ are county and installer firm fixed effects. Duration is defined as the ratio of storage capacity (kWh) to power rating (kW).

Finally, we formalize the spillover model as

$$ln(P^{store}) = P_0^{store} + \beta_1 ln(SPILL_t) + \beta_2 ln(EXP_{k,t}) + \delta + \phi + \epsilon, \tag{4}$$

where the first factor $SPILL$ captures industry experience at time t and the second factor, EXP, captures experience of firm k at time t. We likewise extend this model to include the HHI, system size, duration, and fixed effects, as indicated by δ and ϕ. In all our models, we cluster standard errors at the county level to correct for heteroskedasticity.

Experience and competition variables construction

We construct experience, our main explanatory variable, on a per day basis using each system's interconnection date. We use cumulative projects as our main experience proxy to reflect our project-level data where most of the learning, if present, arguably realizes per installed project, regardless of the exact storage capacity. Accordingly, we calculate the cumulative capacity by each firm at any given installation date. In the spillover model, we subtract this firm experience from total experience to obtain our industry experience measure $SPILL$ Nemet et al. (2020). Following previous literature, we accumulate energy storage capacity in kWh (Schmidt et al., 2017; Kittner et al., 2017; Ziegler and Trancik, 2021) as a robustness test.

We use the Herfindahl-Hirschman Index (HHI) to measure competition by county. The HHI shows the sum of squared market shares of all firms in the market and is capped at one for a monopoly. For every county, we define market share as the share of cumulative installations per installer in the previous year (Gillingham et al., 2016).

The California SGIP data and further data sources

The main dataset used in our study is a public export of California's Self-Generation Incentive Program (SGIP) database. This database contains applications for a variety of technologies on plant level between 2000 and today. The first battery storage system is recorded in 2008 (see discussion surrounding Figure 1 and Supplementary Information, Figure 1). Variables include system power and energy capacity, county, eligible costs, incentives, involved firms, and application process and status characteristics. In order to remove outliers in terms of price or system design and address potential data errors, we only include systems within a price range of 200 to 6,000 USD per kWh (400 to 12,000 USD per kW). We also exclude systems with a duration (energy storage capacity divided by power) smaller than one or larger than ten. Overall, these cleaning steps affect less than 1% of observations and, in untabulated analyses, do not materially impact our results. Importantly, we apply a thorough string clean algorithm on firms and counties that adjusts spelling, abbreviations, and typos.

We merge in publicly available battery price data from Bloomberg to compute BOS costs from total system prices. To get average prices for batteries used in stationary storage systems, we adjust the Bloomberg data in all years. Following the relationship between average prices and average prices for stationary storage systems in 2021, we add 15.15% to the price index in order to reflect higher average prices for batteries used in stationary storage applications (as compared to the raw battery packs prices). Finally, we extract Consumer Price Index data from FRED to deflate all monetary variables to 2021 values.

Robustness checks

To test the sensitivity of our results to our modeling assumptions, we run a battery of robustness checks. Specifically, we (i) alter the definition of experience to cumulative installed capacity in kWh, (ii) change the sample period to start in 2014, (iii) consider only systems which the program administrator marked as paid, (iv) drop systems installed by SolarCity/Tesla as the corresponding price data might represent appraised values (Barbose and Darghouth, 2019), (v) exclude installations by firms with less than 20 observations, (vi) set a different size threshold of 50 kWh that defines the segments (small/large), and (vii) use unadjusted Bloomberg battery prices to calculate BOS costs. Supplementary Information, Tables 5 to 17 contain the results. Our experience rates and further results remain robust and largely similar in terms of magnitude.

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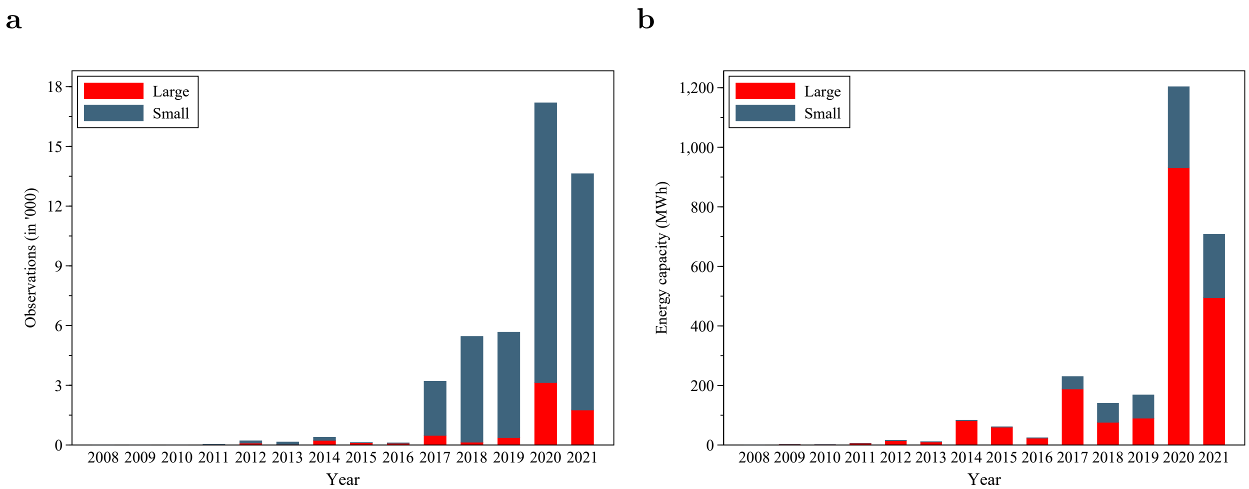
Supplementary Information



Supplementary Figure 1: Battery systems and installed capacity by application year in California. a, number of subsidized storage systems. **b,** installed storage capacities. We do not include systems marked as “cancelled” or “waitlist”.

Supplementary Table 1: Descriptive statistics

	mean	*sd*	*min*	*p25*	*p50*	*p75*	*max*
Price kWh	1121.47	482.35	253.33	893.60	1032.13	1176.90	5959.64
Price kW	2625.11	1080.18	497.51	1924.67	2594.14	2894.91	11919.29
BOS cost kWh	918.42	448.75	6.39	690.90	854.49	1003.05	5662.51
Incentive kWh	419.42	313.78	34.72	230.12	279.15	433.38	2755.69
Size kWh	36.97	172.40	2.41	8.52	13.20	26.40	8400.00
Size kW	16.17	78.45	0.54	4.94	5.00	10.00	3000.00
Duration	2.38	0.47	1.00	1.91	2.64	2.64	7.92
EXP #	14871.33	8572.74	1.00	7439.00	14881.00	22348.00	29625.00
EXP Firm #	809.46	1049.75	1.00	69.00	345.00	1078.00	4178.00
EXP MWh	615.24	284.62	0.03	383.42	641.02	864.19	1095.03
HHI	0.18	0.12	0.05	0.11	0.15	0.21	1.00
Observations	28956						

This table reports summary statistics for all major regression variables and some additional variables for all SGIP-administered systems connected by the of December 2021. The Herfindahl-Hirschmann-index (HHI) is normalized between zero (perfect competition) and one (monopoly) by construction.

Supplementary Table 2: Descriptive statistics - large segment

	mean	*sd*	*min*	*p25*	*p50*	*p75*	*max*
Price kWh	1288.94	602.84	382.16	952.73	1066.67	1404.99	5350.18
Price kW	3024.53	1164.04	723.93	2413.96	2755.69	3320.41	11396.12
BOS cost kWh	1023.17	484.79	169.13	779.50	886.80	1147.86	4897.64
Incentive kWh	636.85	385.22	102.15	269.11	443.89	1039.25	2755.69
Size kWh	214.97	495.33	15.00	39.60	39.60	120.00	8400.00
Size kW	97.50	225.38	10.02	15.00	15.00	60.00	3000.00
Duration	2.44	0.49	1.00	2.00	2.64	2.64	7.67
EXP #	16333.38	10012.74	8.00	6338.00	19760.00	25022.00	29625.00
EXP Firm #	537.46	891.73	1.00	22.00	112.00	687.00	4176.00
EXP MWh	650.70	345.40	2.15	324.51	790.57	932.40	1095.03
HHI	0.19	0.14	0.05	0.11	0.14	0.24	1.00
Observations	3061						

This table reports summary statistics for all major regression variables and some additional variables for the subsample of larger systems, i.e. above 10 kW.

Supplementary Table 3: Descriptive statistics - small segment

	mean	*sd*	*min*	*p*25	*p*50	*p*75	*max*
Price kWh	1101.70	462.09	253.33	893.42	1024.96	1157.35	5959.64
Price kW	2577.95	1059.99	497.51	1854.94	2561.11	2858.84	11919.29
BOS cost kWh	906.06	442.67	6.39	687.99	848.25	991.22	5662.51
Incentive kWh	393.72	293.78	34.72	210.68	268.30	389.96	2755.69
Size kWh	15.93	7.39	2.41	8.39	13.20	26.40	79.20
Size kW	6.56	2.36	0.54	4.94	5.00	10.00	20.00
Duration	2.37	0.46	1.00	1.70	2.64	2.64	7.92
EXP #	14698.51	8369.56	1.00	7540.00	14500.00	21876.00	29625.00
EXP Firm #	841.61	1062.31	1.00	83.00	381.00	1148.00	4178.00
EXP MWh	611.05	276.27	0.03	384.97	628.18	851.55	1095.03
HHI	0.18	0.12	0.05	0.11	0.15	0.21	1.00
Observations	25895						

This table reports summary statistics for all major regression variables and some additional variables for the subsample of residential, i.e. small, systems with a power rating of 10 kW or less.

Supplementary Table 4: BOS costs experience curves

BOS costs in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.115^{***}	-0.087^{***}	0.104^{***}	0.084^{***}
	(0.010)	(0.018)	(0.018)	(0.010)
HHI		0.084		0.660^{***}
		(0.103)		(0.133)
Size kWh		-0.049^{**}		-0.216^{***}
		(0.023)		(0.016)
Duration		-0.176^{*}		-0.518^{***}
		(0.092)		(0.038)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Learning rate (%)	7.66	5.88	−7.48	−5.97
Adjusted R^2	0.16	0.52	0.06	0.68
N	2,956	2,956	25,331	25,331

This table shows regression results for balance-of-system (BOS) cost. We calculate BOS as total system price from the SGIP minus adjusted battery pack price as obtained from Bloomberg. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 5: Experience curve – sample and period robustness

Price in 2021 USD/kWh	After 2013		Paid	
	(1)	(2)	(3)	(4)
EXP #	-0.011		-0.014	
	(0.010)		(0.012)	
EXP kWh		-0.039^{***}		-0.047^{***}
		(0.014)		(0.016)
Experience rate %	0.74	2.64	0.99	3.20
Adjusted R^2	0.00	0.01	0.00	0.01
N	28,258	28,258	25,701	25,701

This table shows robustness tests for one factor experience curves using all connected systems. In columns (1) and (2), we exclude systems connected in 2013 or before. In columns (3) and (4), we only include systems which the SGIP administrator marks as "paid". All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Supplementary Table 6: Experience curve – robustness to excluding installers

Price in 2021 USD/kWh	No SCTE		≥20 instals	
	(1)	(2)	(3)	(4)
EXP #	-0.034^{**}		-0.013	
	(0.014)		(0.011)	
EXP kWh		-0.055^{***}		-0.042^{***}
		(0.019)		(0.015)
Experience rate %	2.35	3.75	0.89	2.87
Adjusted R^2	0.01	0.01	0.00	0.01
N	25,564	25,564	27,102	27,102

This table shows robustness tests for one factor experience curves using all connected systems. In columns (1) and (2), we exclude systems installed by SolarCity/Tesla (SCTE) as the corresponding system prices might be appraised values. In columns (3) and (4), we only include systems by installers with at least 20 installations over the sample period. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance.

Supplementary Table 7: Segment experience curve – cumulative capacity

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP kWh	-0.224^{***}	-0.162^{***}	0.010	-0.006
	(0.010)	(0.026)	(0.021)	(0.012)
HHI		0.074		0.504^{***}
		(0.102)		(0.123)
Size kWh		-0.036^{*}		-0.165^{***}
		(0.019)		(0.013)
Duration		-0.149^{**}		-0.410^{***}
		(0.071)		(0.032)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	14.36	10.64	-0.72	0.44
Adjusted R^2	0.39	0.65	0.00	0.67
N	2,957	2,957	25,331	25,331

This table shows regression results by segment when changing the definition of the experience variable from projects to cumulative capacity in kWh. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 8: Segment experience curves – starting with 2014 installations

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.173^{***}	-0.126^{***}	0.039^{***}	0.022^{***}
	(0.008)	(0.018)	(0.011)	(0.007)
HHI		0.161^{*}		0.580^{***}
		(0.091)		(0.107)
Size kWh		-0.039^{**}		-0.173^{***}
		(0.019)		(0.013)
Duration		-0.121^{*}		-0.426^{***}
		(0.072)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.28	8.36	-2.75	-1.52
Adjusted R^2	0.39	0.65	0.01	0.66
N	2,949	2,949	25,298	25,298

This table shows regression results by segment when excluding systems installed before 2014. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 9: Segment experience curves – systems classified as paid

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.185^{***}	-0.083^{***}	0.026^{*}	0.026^{***}
	(0.007)	(0.026)	(0.015)	(0.007)
HHI		0.326^{**}		0.623^{***}
		(0.125)		(0.123)
Size kWh		-0.038^{*}		-0.169^{***}
		(0.021)		(0.012)
Duration		-1.184^{***}		-0.441^{***}
		(0.204)		(0.037)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	12.06	5.62	−1.80	−1.84
Adjusted R^2	0.54	0.81	0.01	0.67
N	2,057	2,057	23,634	23,634

This table shows regression results by segment when including only those systems that the SGIP administrator marks as paid. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 10: Segment experience curve – excluding SolarCity/Tesla

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.186^{***}	-0.110^{***}	0.028	0.033^{***}
	(0.005)	(0.028)	(0.022)	(0.003)
HHI		0.070		0.166^{***}
		(0.108)		(0.050)
Size kWh		-0.101^{***}		-0.168^{***}
		(0.015)		(0.017)
Duration		-0.444^{***}		-0.322^{***}
		(0.073)		(0.027)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	12.10	7.34	−1.99	−2.34
Adjusted R^2	0.45	0.70	0.01	0.66
N	2,684	2,684	22,869	22,869

This table shows regression results for the large and small segment when excluding systems installed by SolarCity/Tesla. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 11: Segment experience curves – firms with at least 20 observations

Price in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.169^{***}	-0.132^{***}	0.032^{**}	0.023^{***}
	(0.008)	(0.017)	(0.014)	(0.008)
HHI		0.162^{*}		0.586^{***}
		(0.083)		(0.107)
Size kWh		-0.029		-0.171^{***}
		(0.022)		(0.013)
Duration		-0.119		-0.448^{***}
		(0.075)		(0.034)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	11.08	8.76	-2.24	-1.58
Adjusted R^2	0.42	0.64	0.01	0.64
N	2,683	2,683	24,408	24,408

This table shows regression results for the large and small segment when excluding very small installer firms, i.e. those with less than 20 installations over the sample period. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 12: Segment learning curves – new segment definition

Price in 2021 USD/kWh	Large (> 50 kWh)		Small (≤ 50 kWh)	
	(1)	(2)	(3)	(4)
EXP #	-0.163^{***}	-0.156^{***}	0.006	0.020^{***}
	(0.008)	(0.019)	(0.012)	(0.007)
HHI		-0.025		0.557^{***}
		(0.106)		(0.103)
Size kWh		-0.061^{***}		-0.146^{***}
		(0.022)		(0.012)
Duration		0.050		-0.472^{***}
		(0.063)		(0.031)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Experience rate %	10.71	10.27	-0.43	-1.42
Adjusted R^2	0.34	0.63	0.00	0.67
N	1,344	1,344	26,944	26,944

This table shows regression results by segment when deviating from the 10 kW size threshold applied by the California Public Utilities Commission for budget purposes. In this robustness check, smaller systems have a storage capacity of 50 kWh or less. Large systems have a capacity of more than 50 kWh. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 13: BOS experience curves – cumulative capacity

BOS costs in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP kWh	-0.151^{***}	-0.098^{***}	0.109^{***}	0.075^{***}
	(0.012)	(0.030)	(0.026)	(0.017)
HHI		0.072		0.609^{***}
		(0.117)		(0.158)
Size kWh		-0.047^{*}		-0.207^{***}
		(0.024)		(0.016)
Duration		-0.204^{**}		-0.505^{***}
		(0.090)		(0.040)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Learning rate (%)	9.96	6.58	−7.88	−5.37
Adjusted R^2	0.16	0.52	0.03	0.67
N	2,956	2,956	25,331	25,331

This table shows regression results for balance-of-system (BOS) cost when using cumulative capacity as a proxy for experience. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 14: BOS experience curves – excluding SolarCity/Tesla

BOS costs in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.133^{***}	-0.058^{*}	0.089^{***}	0.093^{***}
	(0.006)	(0.029)	(0.026)	(0.006)
HHI		−0.007		0.130^{**}
		(0.104)		(0.059)
Size kWh		-0.133^{***}		-0.206^{***}
		(0.016)		(0.021)
Duration		-0.522^{***}		-0.388^{***}
		(0.085)		(0.033)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Learning rate (%)	8.83	3.93	−6.35	−6.67
Adjusted R^2	0.22	0.59	0.04	0.67
N	2,683	2,683	22,869	22,869

This table shows regression results BOS costs when excluding SolarCity/Tesla systems. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 15: BOS experience curves – unadjusted battery pack price

BOS costs in 2021 USD/kWh	Large		Small	
	(1)	(2)	(3)	(4)
EXP #	-0.125^{***}	-0.094^{***}	0.090^{***}	0.072^{***}
	(0.009)	(0.018)	(0.017)	(0.010)
HHI		0.097		0.651^{***}
		(0.100)		(0.127)
Size kWh		-0.047^{**}		-0.208^{***}
		(0.023)		(0.015)
Duration		-0.166^{*}		-0.501^{***}
		(0.089)		(0.037)
County FE	No	Yes	No	Yes
Firm FE	No	Yes	No	Yes
Learning rate (%)	8.27	6.33	−6.47	−5.11
Adjusted R^2	0.20	0.54	0.05	0.68
N	2,956	2,956	25,331	25,331

This table shows regression results for BOS cost, using average battery pack prices reported by Bloomberg to calculate BOS. In other words, we do not adjust battery pack prices according to their application in stationary storage. All variables except HHI are on log scale. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 16: Spillover – cumulative capacity

Price in 2021 USD/kWh	Price		BOS	
	(1)	(2)	(3)	(4)
SPILL kWh	-0.259^{***}	-0.152^{***}	-0.207^{***}	-0.109^{***}
	(0.029)	(0.021)	(0.033)	(0.029)
EXP Firm kWh	0.066^{***}	0.073^{***}	0.067^{***}	0.083^{***}
	(0.012)	(0.007)	(0.016)	(0.009)
HHI	0.009	0.342^{***}	0.009	0.409^{***}
	(0.099)	(0.097)	(0.108)	(0.124)
Size kWh	-0.045^{**}	-0.181^{***}	-0.054^{**}	-0.217^{***}
	(0.019)	(0.013)	(0.024)	(0.015)
Duration	−0.110	-0.404^{***}	-0.155^{*}	-0.480^{***}
	(0.077)	(0.032)	(0.092)	(0.038)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate (%)	16.45	10.03	13.39	7.26
Firm experience rate (%)	−4.69	−5.16	−4.75	−5.96
Adjusted R^2	0.66	0.69	0.54	0.69
N	2,957	25,331	2,957	25,331

This table shows robustness tests for the spillover analysis. All variables except HHI are on log scale. The variable SPILL captures learning from industry-wide experience, i.e. spillover learning. The variable EXP Firm captures learning from firm-specific experience. For each observation, we compute SPILL as the industry-wide cumulative capacity excluding the cumulative capacity of the firm that installs the system. For each observation, we compute EXP Firm as the cumulative capacity of the firm that installs the system. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.

Supplementary Table 17: Spillover – excluding SolarCity/Tesla

Price in 2021 USD/kWh	Price		BOS	
	(1)	(2)	(3)	(4)
SPILL kWh	-0.166^{***}	-0.018^{**}	-0.131^{***}	0.029^{**}
	(0.033)	(0.007)	(0.031)	(0.012)
EXP Firm #	0.061^{***}	0.033^{***}	0.070^{***}	0.035^{***}
	(0.012)	(0.005)	(0.013)	(0.007)
HHI	0.096	0.148^{***}	0.036	0.131^{**}
	(0.111)	(0.044)	(0.108)	(0.050)
Size kWh	-0.100^{***}	-0.174^{***}	-0.127^{***}	-0.206^{***}
	(0.016)	(0.016)	(0.016)	(0.019)
Duration	-0.460^{***}	-0.318^{***}	-0.528^{***}	-0.372^{***}
	(0.073)	(0.027)	(0.084)	(0.032)
County FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry experience rate (%)	10.89	1.21	8.68	−2.06
Firm experience rate (%)	−4.34	−2.32	−4.95	−2.44
Adjusted R^2	0.71	0.67	0.61	0.67
N	2,684	22,869	2,683	22,869

This table shows robustness tests for the spillover analysis. Specifically, we exclude observations from SolarCity/Tesla as they might represent appraised values. All variables except HHI are on log scale, SPILL and EXP Firm # are defined as in Table 3 of the paper. Clustered standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ indicate significance, FE fixed effects.