Appendix EC: Electronic Companion: Additional Numerical Results

To start, we briefly re-introduce the notation for all variables: We use $i \in I$ to index households, $t \in T$ to index the days in the dataset, and $h \in H$ to index the hours of a day. Occasionally, we use $n \in N$ to index all hours of the dataset in chronological order.

A household's capacity investment decisions are denoted with K_i for the storage capacity and W_i for the solar capacity, with unit costs of c_{K_i} and c_{W_i}, respectively.

We denote the energy consumption of a household i in hour h on day t with d_{iht} and the vector of all observations with $\vec{d}_i$. Similarly, O_{iht} and $\vec{O}_i$ correspond to the solar generation of a household. The mismatch between generation and consumption is stored in the battery, whose charge is denoted with l_{iht} and which is in part influenced by the round-trip efficiency of the battery, denoted with e.

The two types of quantities we aim to estimate for each household are the nonmarket valuation, denoted with g_i, and the hourly utility of using energy, denoted with γ_{iht} or $\vec{\gamma}_i$ for the time-series.

We use $\theta_i = (g_i, \vec{\gamma}_i)$ as a shorthand for the behavioral quantities of interest and $x_i = (p_i, s_i, c_{W_i}, c_{K_i}, e)$ as the vector of observables, where p_i is the electricity price paid when buying from the grid and s_i the feed-in tariff, i.e. the amount of money received for selling a unit of energy back to the grid.

EC.1. Model-Free Results

We first want to show model-free evidence of consumption behavior. We regress the hourly electricity consumption per household for each day on an intercept, solar capacity in kWp, and storage capacity in kWh - see Equation (29):

$$d_{iht} = \alpha + \beta_h^1 W_i + \beta_h^2 K_i + \epsilon_{iht}. \tag{29}$$

We run this regression separately for each hour in the day and cluster standard errors by household, which gives us 49 parameter estimates, one for the intercept and 24 parameters each per hour-capacity pair for storage and solar. We find statistically significant consumption effects that demonstrate an interesting time-varying pattern, which we plot in Figure 15 including error bars that show the robust standard errors.

Immediately, one can notice a pattern reminiscent of Jevon's paradox for both technologies as households' electricity consumption is increasing in solar and storage capacity. This may be counter-intuitive as one could have assumed that households choosing to make such investments have sustainability interests which could include electricity conservation, the opposite effect of what we observe in the data. However, the different effects over time can serve as a basis for developing a hypothesis on why households consume more electricity. Based on these patterns, it seems that households increase their demand at times when their capacity investments make it highly likely that they can consume self-generated electricity (that is, solar) —in line with what we describe in Figure 2. For solar capacity, the increase is highest around noon, when the sun is shining, and almost zero at night. For storage capacity, the most pronounced additional consumption effect is in the late afternoon or early evening hours, when the batteries are typically being

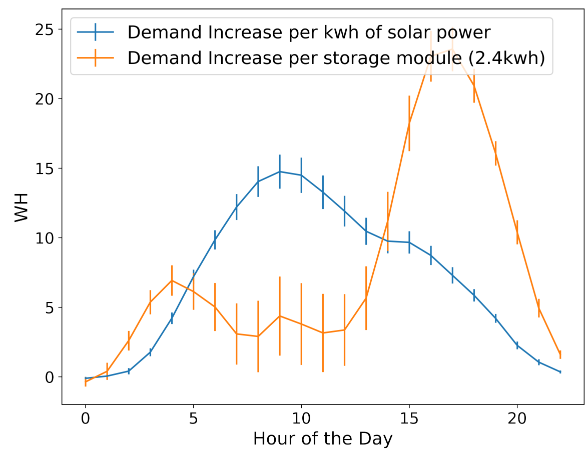


Figure 15 Hour-wise Regression Results of Household Consumption on Storage and Solar Capacity.

discharged. To contextualize the size of the effects, for the average household in the dataset, the combined consumption increase equals a 10.2% increase in overall consumption, a substantial effect.

Of course, there are endogeneity issues with this approach, and we do not observe how households would have behaved without any capacity investments, so we merely take this analysis as an indication that there are dynamics to be uncovered via the structural estimation model to get a more rigorous understanding of the behavior at play. We address this point in section 5.2 and find that energy consumption increases with storage, a phenomenon we call *storage rebound*, analogous to the solar rebound discussed in the literature.

EC.2. Descriptive Statistics for Full Dataset

Below, we present the descriptive statistics of the data set for all households.

Table 8 Dataset Descriptive Statistics - all Households

n = 4,069	Storage (kWh)	PV Power (kw)	#Observations	Daily PV Gen (kWh)	Daily Dem (kWh)
Min	0.00	0.00	10,053	0.00	0.39
Median	4.80	6.00	67,572	16.28	14.50
Average	5.78	6.61	68,054	18.01	18.21
Max	48.00	33.60	105,211	172.95	99.68
Std. Dev.	3.31	3.69	26,610	10.63	12.24

Furthermore, to provide a sense of the geographical spread of customers, which covers all 16 states of Germany, see Figure 16.

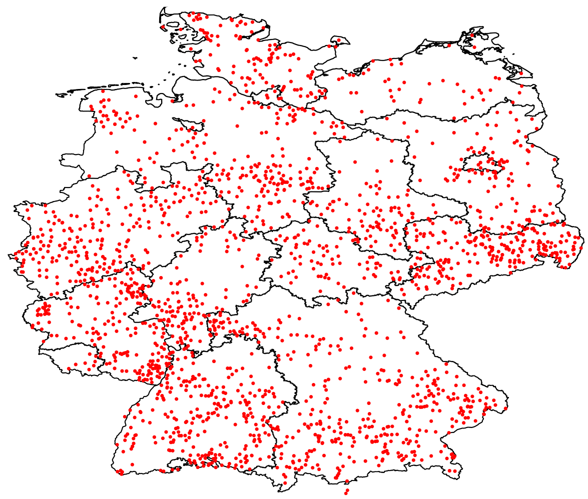


Figure 16 Map of German Households.

EC.3. Impact of (Dis)charging Speed Limits For Storage Modules and Comparison of Main Results With and Without Such A Limit

We simplify the battery operations by not explicitly considering the charging and discharging speed limits (also called the power capacity) of storage. In the case of the batteries of the data provider we collaborate with, the charge and discharge speed is 0.8 kW per 2.4 kWh module. I.e., each module can be charged and discharged in 3 hours and adding modules proportionally increases the charging and discharging speeds. For example, 3 modules have 7.2 kWh capacity and 2.4 kW (dis)charge speed.

We use this simplification to reduce the notational and computational burden and conceptually because these charging limits are seldom binding and have very little impact on the overall storage use in our setting. This happens for two reasons. First, generally speaking, households with more demand or more solar install more storage modules. This means that households that may generate a lot of excess solar power or may draw larger amounts of power (which would require more power capacity from their batteries) also have more modules and thus higher battery speeds. For example, 97% of households with storage in our sample (2886 out of the 2989 households with storage) have 2 or more modules, thus at least 2x0.8 kW = 1.6 kW of power capacity, but the average power draw is less than 1kW. Second, in periods where the charging limit becomes binding, a household is either facing a lot of excess solar (charging limit is binding) or a lot of demand not met through solar (discharging limit). Often, when this is the case, the battery hits its capacity limit (too much excess solar) or is fully emptied (too much demand) at some time in the day. Thus, while considering the power limits would impact the exact timing of when the battery was charged/discharged, it may not change the total amount of energy charged/discharged because the battery will hit 0% or 100% state-of-charge eventually, regardless of exact timing.

In other settings, where battery capacities are substantially larger (relative to demand and generation profiles) or require more than 2-3 hours to fully charge, explicitly controlling for charging rate limitations becomes increasingly important.

In our setting, across the 3,237 households we use for the main results, the batteries' charging rates are only limiting in 11.9% of hours (measured as the fraction of hours with the same amount of kwh (dis)charged with and without enforcing the speed limit). More importantly, the average (median) storage utilization when the limits are considered are 96.1% (98.8%) of the utilization in the case with unlimited charging speed (based on cumulative kwh discharged). We highlight these facts to show that, in a residential setting with reasonably fast batteries and storage that is designed for daily (dis)charge, not seasonal storage, battery operations are not typically limited by power capacity.

We did also re-estimate the entire model to compare the main nonmarket result under either setting to show that this simplification does not materially impact our findings. We juxtapose the descriptive statistics for the nonmarket valuation for both cases in Table 9.

Table 9 Descriptive Statistics of Nonmarket Valuation With and Without Taking (Dis)charge Speeds / Power Limits of Storage Into Account

n = 3,237	Main Model - No Limit	(Dis)Charge Rate Limit of 3 Hours
Min	0.000	0.000
Median	0.287	0.290
Mean	0.529	0.534
Max	4.000	4.000
Std.Dev.	0.698	0.697

We show three significant digits because the non-market valuations for both sets of results are very similar. Directionally, adding the charging limits should slightly increase non-market valuations because it decreases the utility of the battery modules. However, as shown above, the overall utilization only changes by a few single percentage points, and the non-market valuation is changing even less. With the rate limits in place, the average valuation increases by 0.9% from 0.529 to 0.534 €/kWh, while the median increases by 1.0% from 0.287 to 0.290€/kWh. If rounded to two significant digits, the results are indistinguishable - which highlights empirically why abstracting from power capacity in our context is not impact results substantially.

EC.4. Qualitative Evidence About Residential Storage Marketing

Below, we provide marketing examples of three major players in the German residential storage market. Solarwatt (Figure 17), Sonnen (Figure 18a), and Senec (Figure 18b). All three players emphasize the sustainability benefits of batteries, using language such as ”clean” and highlighting the ability to store one’s own solar generation. The independence or decreased reliance on the grid is also mentioned.

Furthermore, we juxtapose the way Tesla advertises their home energy storage product *Powerwall* in Germany (Figure 19a) and in the USA (Figure 19b). Interestingly, in Germany, the homepage design centers around a sunny day in the backyard, with the sun setting in the background, while the US homepage depicts a dark, stormy day with a single house lit in the center.

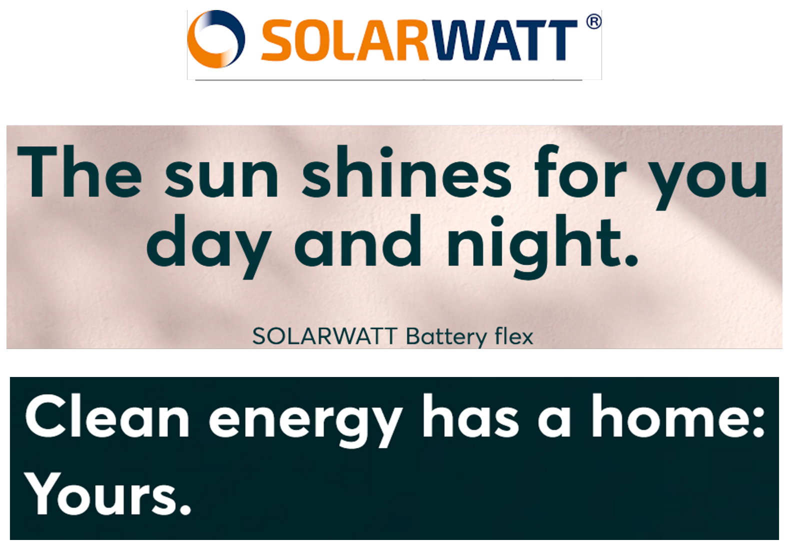
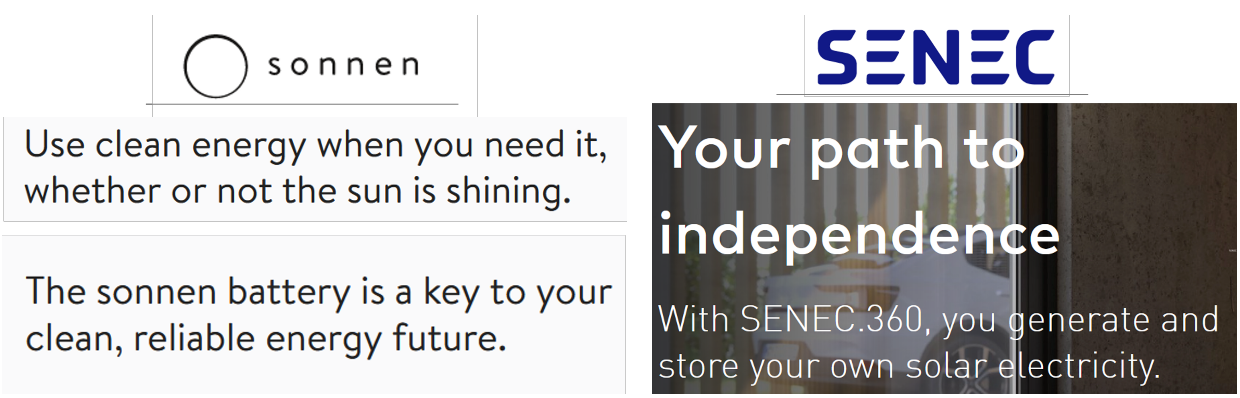
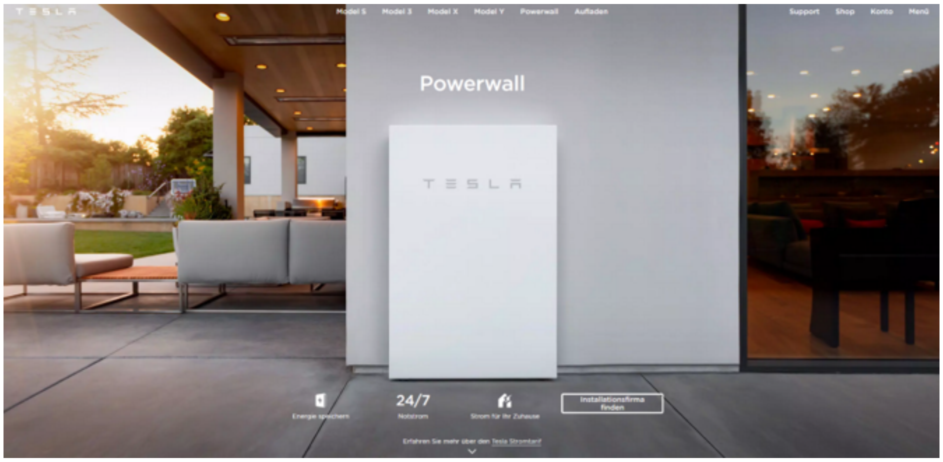


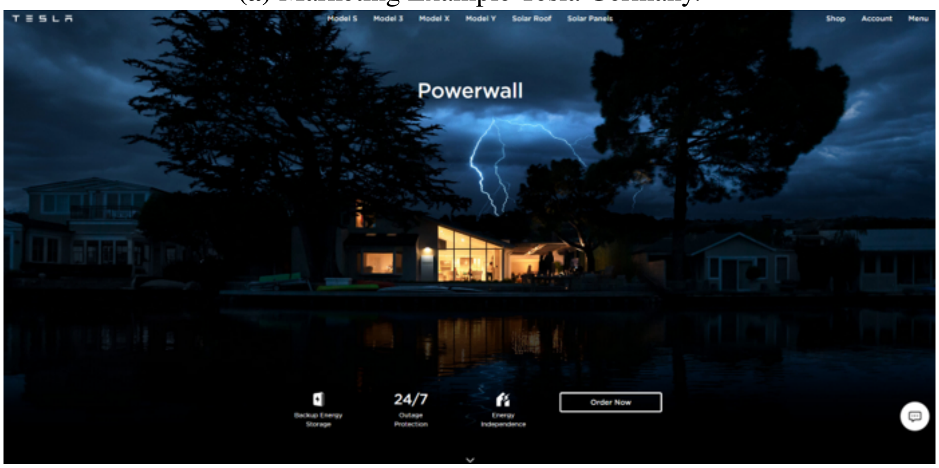
Figure 17 Marketing Example Solarwatt.



(a) Marketing Example Sonnen. **(b)** Marketing Example Senec.



(a) Marketing Example Tesla Germany.



(b) Marketing Example Tesla USA.

EC.5. Nonmarket Valuation Survey

Below, we provide a translation of the survey we asked participants to complete regarding their motivations to consider investing in battery storage. The original survey was provided in German to a German panel on Prolific. We excluded the first page, which contained the consent form, and the last page, where we asked about demographic data. The order of all answer choices was randomized, and Question 2 served as a comprehension check - participants who failed it twice were excluded from the survey.

Q1. [Multiple Selection] Imagine you are considering installing solar panels and battery storage in your home. What reasons would drive your decision on whether or not to invest in a battery? Please select all that apply. If a reason is missing, please add it under "Other".

a Less Reliance on the Grid

b Increased Sustainability of Own Consumption

c Protection against Power-Outages

d Interest in Technology

e Other: [...]

Q2. If you are asked what reasons would drive your decision on whether or not to invest in a battery, what is the investment decision about? This is a comprehension check.

a Batteries

b Electric Vehicles

c Heat Pumps

d Solar Panels

Q3. [Radio Buttons for Ranking] Of the reasons you selected in the last question, please rank them in their importance (in descending order, i.e., reason 1 is the most important to you.

(a) All options that were selected in Q1 are displayed.

EC.6. Main Estimation Detailed Results

Below, we provide detailed results of the latent parameter estimation results of Section 5.1. We start with the average and standard deviation of the utility effects across the population. Let $\hat{\gamma}_{ih} = \frac{1}{t}\sum_t \gamma_{iht}$ denote the mean utility estimate of a household in an hour. We present the descriptive statistics of $\hat{\gamma}_{ih}$ in the population of households in Tables 10-13.

Table 10 Utility-Estimates Descriptive Statistics (0:00-6:00)

n = 3,237 Hours:	0-1	1-2	2-3	3-4	4-5	5-6
Min	0.14	0.14	0.14	0.14	0.14	0.13
Median	0.63	0.63	0.63	0.65	0.67	0.68
Average	0.81	0.81	0.82	0.84	0.87	0.89
Max	12.02	11.97	11.92	13.69	14.82	14.26
Std.Dev.	0.71	0.71	0.75	0.77	0.81	0.83

Table 11 Utility-Estimates Descriptive Statistics (6:00-12:00)

n = 3,237 Hours:	6-7	7-8	8-9	9-10	10-11	11-12
Min	0.13	0.13	0.12	0.12	0.12	0.12
Median	0.65	0.62	0.59	0.58	0.58	0.58
Average	0.88	0.85	0.83	0.83	0.83	0.82
Max	15.54	18.23	19.52	21.16	21.37	21.16
Std.Dev.	0.88	0.93	0.97	1.00	1.03	1.04

Table 12 Utility-Estimates Descriptive Statistics (12:00-18:00)

n = 3,237 Hours:	12-13	13-14	14-15	15-16	16-17	17-18
Min	0.12	0.12	0.12	0.13	0.13	0.13
Median	0.57	0.57	0.60	0.69	0.80	0.85
Average	0.81	0.81	0.84	0.93	1.04	1.10
Max	20.32	19.47	18.16	16.70	17.00	16.77
Std.Dev.	1.01	0.98	0.96	0.97	1.00	0.99

Table 13 Utility-Estimates Descriptive Statistics (18:00-24:00)

n = 3,237 Hours:	18-19	19-20	20-21	21-22	22-23	23-24
Min	0.13	0.13	0.13	0.13	0.13	0.13
Median	0.85	0.81	0.77	0.72	0.67	0.65
Average	1.07	1.03	0.97	0.91	0.86	0.83
Max	17.13	15.70	14.44	14.02	13.20	12.41
Std.Dev.	0.96	0.91	0.86	0.80	0.70	6 0.73

To illustrate what the variability of γ looks like within a household, we plot the distribution of γ_{iht} values over all observed periods for a synthetic household in Figure 20 (based on the average consumption and solar generation of 10 households with similar capacities).

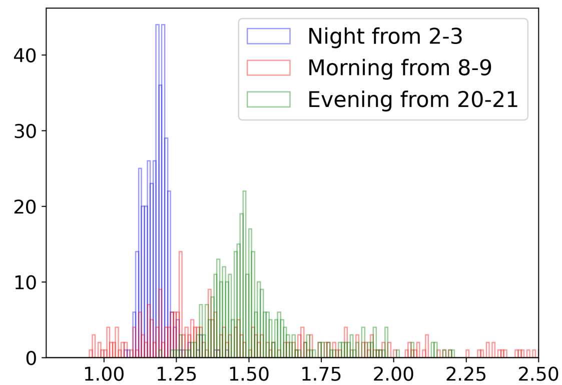


Figure 20 Distribution of Utilities Within One Household Across all Periods.

As one can see, the hourly utilities across the night are lowest overall, least variable, and observe very few outliers, whereas the utility in the morning is most variable overall, but on average higher than at night. Lastly, the evening utilities are highest on average and less variable than the morning utilities. Each household may have different magnitude and variability, but the general pattern of less variability of utilities at night and highest absolute utilities in the evening hours holds true across most households.

EC.7. Consistency of Estimates Across Years

In this appendix, we show the consistency of the nonmarket valuation parameters across years. In particular, we estimate nonmarket valuation separately only using 2018 data (g_i^{18}), only 2019 (g_i^{19}), and the complete dataset g_i (see the appendix EC.8 with regard to 2020 and COVID treatments). We only include households for which we have at least 2,500 hourly observations (about 3.5 months) for each period. We provide the descriptive statistics of the nonmarket valuations for the three sets of data in Table 14. For each of the three data periods, we obtain very consistent estimates of all statistics, with the median being within one cent of each other. The mean for the individual years is only marginally higher, as the 1-year data span results in somewhat higher variability of the estimate compared to the full dataset.

Table 14 Comparing the estimates of nonmarket valuation obtained on the full data (main result) to estimates on only 2018 and 2019 data, in €/kwh, winsorized at 2.5% and 97.5%.

n=1,299	Full-Data	2018	2019
Min	0.00	0.0	0.0
Median	0.27	0.28	0.27
Average	0.48	0.57	0.50
Max	3.13	3.77	2.97
Std. Dev.	0.61	0.78	0.62

Beyond the consistency of the aggregate values we have shown above, in Figure 21 we plot the ratio of nonmarket valuations for individual households - that is, how does the nonmarket valuation change between using 2018 or 2019 data relative to the full dataset for each given household. Again, we see that the vast majority of households is consistently estimated across the years, meaning that our method not only results in reliable estimates across the population but also for individual households. The slightly higher number of outliers for the 2018 data is mainly driven by households that joined in the fall of 2018, so their 2018 nonmarket valuation estimates are only incorporating part of the seasonality and a shorter overall time frame.

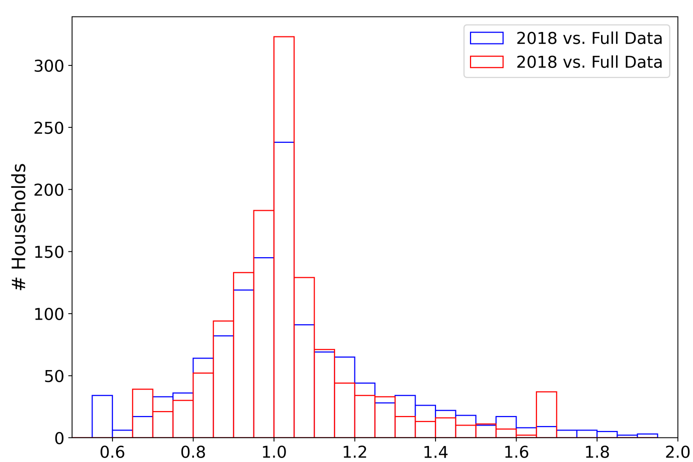


Figure 21 Ratio of Nonmarket Valuation Estimated on Non-COVID / All Data (g_i^{18}/g_i and g_i^{19}/g_i).

Beyond focusing on the nonmarket valuation that we can consistently estimate, we can also infer consumption preferences γ in a consistent manner. Because of the number of parameters to estimate, we only report the means of the hourly distributions for each of the 3 data periods for each hour of the day (see Tables 15-18).

Table 15 Average Utility-Estimates Average Across Three Data-Periods (0:00-6:00)

n = 1,299 Hours:	0-1	1-2	2-3	3-4	4-5	5-6
2018	0.80	0.80	0.81	0.83	0.87	0.88
2019	0.78	0.78	0.79	0.81	0.84	0.86
Full	0.76	0.76	0.77	0.79	0.82	0.83

Table 16 Average Utility-Estimates Average Across Three Data-Periods (6:00-12:00)

n = 1,299 Hours:	6-7	7-8	8-9	9-10	10-11	11-12
2018	0.86	0.82	0.80	0.80	0.81	0.79
2019	0.84	0.80	0.78	0.78	0.78	0.77
Full	0.82	0.78	0.76	0.76	0.77	0.76

Table 17 Average Utility-Estimates Average Across Three Data-Periods (12:00-18:00)

n = 1,299 Hours:	12-13	13-14	14-15	15-16	16-17	17-18
2018	0.78	0.78	0.82	0.91	1.02	1.07
2019	0.76	0.76	0.78	0.86	0.98	1.03
Full	0.74	0.74	0.77	0.85	0.96	1.01

Table 18 Average Utility-Estimates Average Across Three Data-Periods (18:00-24:00)

n = 1,299 Hours:	18-19	19-20	20-21	21-22	22-23	23-24
2018	1.04	1.00	0.95	0.89	0.84	0.82
2019	1.02	0.98	0.93	0.87	0.82	0.79
Full	0.99	0.96	0.91	0.85	0.80	0.78

EC.8. Impact of COVID on Estimates

Because part of the data set is from 2020 and COVID may have affected energy consumption and, therefore, our estimates, we show the robustness of our results to different treatments of COVID-affected periods. Our main results from Section 5 include all available data, including all days from 2020. We subsequently show in Table 19 how the non-market valuation differs between estimating the same model a) on all data, b) only the COVID period for which we use March-June 2020 data, and c) all data excluding the COVID months. Excluding the COVID period would slightly increase our estimates of nonmarket valuation.

We chose to estimate our main model on all data for three reasons: First, COVID changed, among many other aspects, the energy consumption of households, but the period from March to June is also sunnier than average, allowing storage to be charged more often and decreasing the average nonmarket valuation. Overall, it is not possible to fully disentangle the effects of COVID from other contemporaneous effects because the ”treatment” was not assigned randomly.

Second, it is hard to exactly pinpoint on which days households were affected by COVID as we do not have information on household composition. Furthermore, regulation and lockdowns were neither uniform across states nor uniform across households, for example, employee types. Thus, exactly making a COVID / non-COVID distinction per individual household is difficult. Because we did not want to make arbitrary cutoff decisions for the main analysis, we opted to combine all available data.

Third, depending on what time period we exclude for COVID, we decrease the number of observations remaining for the main analysis, making the estimation more variable.

To nevertheless provide a comparison regarding the inclusion and exclusion of COVID, we treat the period from March to June 2020 as the COVID period and re-estimated the model without these periods (see Figure 24 for consumption differences in April and July). We then compare the original nonmarket valuation g_i with the one obtained by excluding COVID $\tilde{g}_i$. In Figure 22, we show the ratio of $\tilde{g}_i/g_i$ across all households and see that excluding COVID, on average, slightly increases the nonmarket valuation, but the direction of bias depends on the individual household's behavior change due to COVID. Most individual households' nonmarket valuations do not differ by more than 20% between the different ways of estimating the value.

In Table 19, we present the descriptive statistics of the nonmarket valuation estimated on a) the complete data, b) the non-COVID data and c) the COVID data. We only include households for which we have at least 2,500 hourly observations (about 3.5 months) for each of the Non-COVID and COVID periods. The median nonmarket valuation excluding COVID is 14% higher than when we include all data. In contrast, the median nonmarket valuation for the COVID period is 45% lower than the estimates based on complete data. This is partially a COVID effect but partially simply due to seasonality, where nonmarket valuation tends to be lower in the summer as storage is used more frequently, but our nonmarket valuation is an

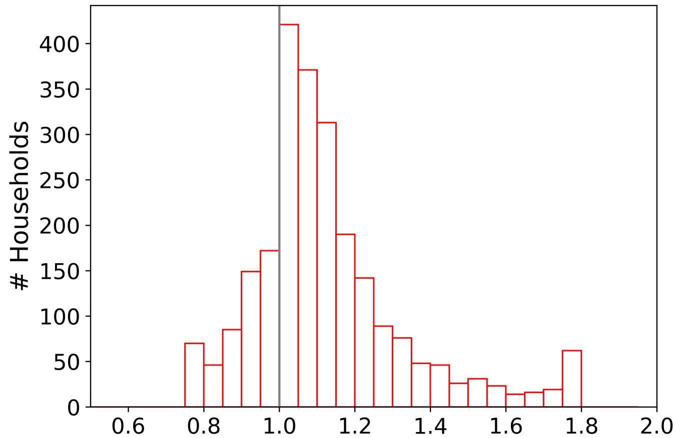


Figure 22 Ratio of Nonmarket Valuation Estimated on Non-COVID / All Data ($\tilde{g}_i/g_i$).

average across all seasons. What COVID changed is that some households increased consumption at home, rendering electricity more valuable and thus reducing the minimum nonmarket valuation required to make storage viable. It is also important to point out that the split into COVID/Non-COVID periods reduces the available data for the estimation and increases the standard deviation of the nonmarket valuations, which is reflected in the COVID estimation having a standard deviation of 0.92 and an overall more right-skewed distribution.

Table 19 Comparing the estimates of nonmarket valuation obtained on the full data (main result) to estimates on only COVID, (Mar-Jun 2020) and Non-COVID observations (outside Mar-Jun 2020), in €/kwh, winsorized at 2.5% and 97.5%.

n=2,409	Full-Data	Non-COVID	COVID
Min	0.00	0.00	0.00
Median	0.29	0.33	0.16
Average	0.49	0.54	0.55
Max	2.50	2.82	4.00
Std. Dev.	0.53	0.69	0.92

Lastly, to highlight the extent of the impact of COVID demand, in Figure 23, we juxtapose the combined electricity demand of German households for a week in mid-April between 2019 and 2020 (adjusted for the number of households in the sample). The effect of COVID can be seen in 10-15% higher electricity consumption throughout the day (and identical consumption throughout the night). In June, the aggregate consumption profile is in magnitude very similar between both years, i.e. the effect of COVID has subsided. Although analyzable in the aggregate, it is impossible on an individual level to disaggregate COVID-related effects from COVID-unrelated consumption variability.

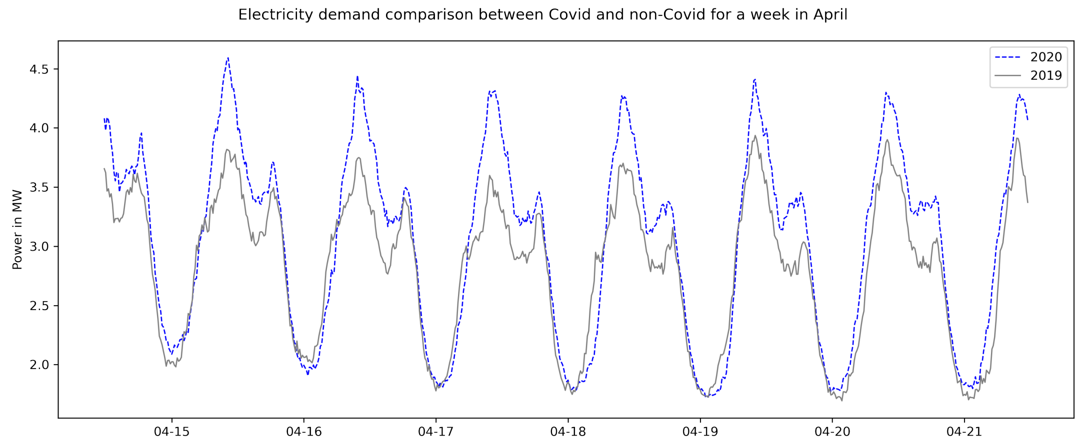


Figure 23 Electricity Demand Comparison Between a COVID and Non-COVID Year for a Week in April.

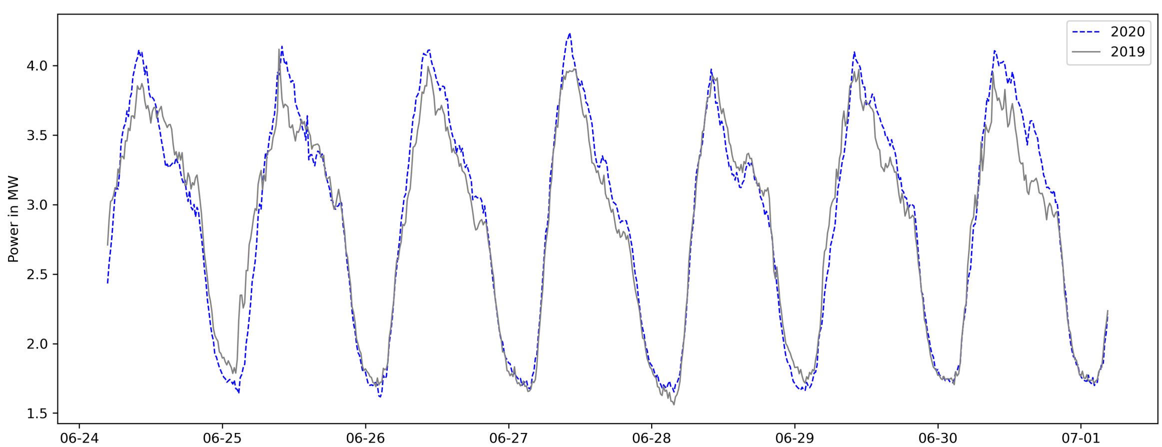


Figure 24 Electricity Demand Comparison Between a COVID and Non-COVID Year for a Week in June/July.

EC.9. Descriptive Statistics Regarding the Effect of Solar and Storage Capacities on Carbon Emissions

Below, we present the descriptive statistics of the impact of solar energy and storage capacity emission introduced in Section 5.2. The data in Table 20 contains the previously observed estimates and corresponds to Figure 5. The data in Table 21 contains the future estimates and corresponds to Figure 6.

Table 20 Descriptive Statistics of Emission Savings Per Technology for Past Observations (in kg CO2 per year per kWp (Solar) or kWh (Storage))

	Solar Avg.	Solar Marginal	Storage Avg.	Storage Marginal
n	3,237	3,237	2,989	2,989
Min	-170.3	-194.7	-276.8	-465.4
Median	200.0	463.6	-36.5	-74.5
Average	203.1	472.4	-26.3	-56.8
Max	662.3	1427.3	143.0	257.0
Std. Dev.	85.5	177.4	41.6	71.3

Table 21 Descriptive Statistics of Emission Savings Per Technology for Future Grid (in kg CO2 per year per kWp (Solar) or kWh (Storage))

	Solar Future	Storage Future
n	3,237	2,989
Min	-292.0	-167.9
Median	0.0	1.8
Average	8.3	18.0
Max	601.8	151.5
Std. Dev.	57.9	38.7

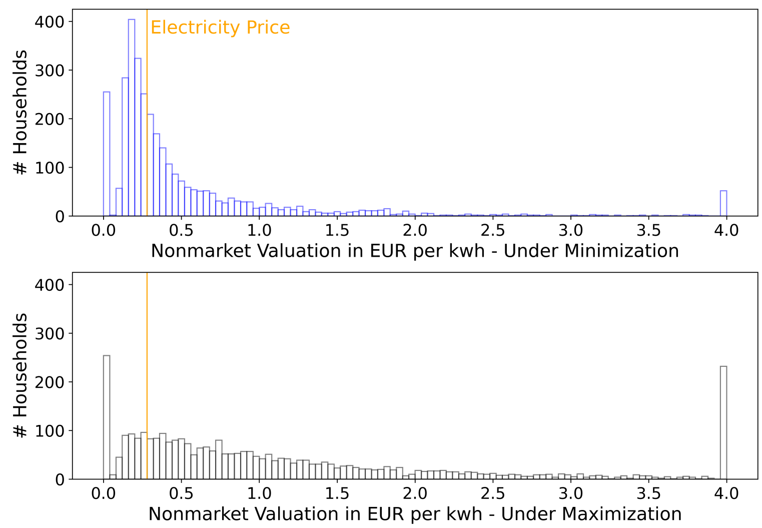


Figure 25 Distribution of Nonmarket valuation under Minimization and Maximization of its Value.

EC.10. Range of Possible Nonmarket Valuation Estimates

As stated in Section 4.5, where we introduce the estimation of the nonmarket value in (13), the main result we present shows the minimum level of nonmarket valuation, consistent with the observed investment in capacities. As a robustness test, we present the results if one re-estimated the model to be the maximum value, i.e., the value of nonmarket effects beyond which a household would have been better off investing in more storage. We juxtapose the descriptive statistics in Table 22 and plot the corresponding distributions in Figure 25.

Table 22 Descriptive Statistics of Nonmarket Valuation under Minimization and Maximization

n = 3,237	Minimization	Maximization
Min	0.00	0.00
Median	0.29	0.81
Mean	0.53	1.18
Max	4.00	4.00
Std.Dev.	0.69	1.14

As expected, under maximization, the nonmarket values increase for each household, which increases all descriptive statistics. By studying Figure 25, we can see that, in particular, the dispersion and incidence of nonmarket valuations that we truncated at 4€ rises. This occurs because the marginal value of a unit of storage is rapidly decreasing. To illustrate that point, imagine a household that owns 3 storage modules. In that case, the capacity of the first one will be used almost daily, the capacity of the next module less often, and the third module's capacity might only be used on seldom occasions. Under maximization of the nonmarket value, we find the value of that valuation at which a fourth module becomes marginally profitable. For some households, this extra module may only be used a few times a year and thus would necessitate very high nonmarket valuations. This dynamic explains the more frequent occurrence of high nonmarket values. In turn, seeing the more concentrated distribution of nonmarket value under minimization gives credence to the fact that households do trade-off the cost and value of investing in a marginal value of storage.

EC.11. Nonmarket Valuation Estimation if Demand Is Fixed

As discussed in Section 4.1, we observe a correlation between capacity investments and energy consumption in our data, which motivated our choice of structural model. An alternative approach would have been to assume demand was exogenous and thus independent of capacities. In this section, we show that this would underestimate the non-market valuations and subsequently juxtapose our main structural model results with the results if demand were exogenous (henceforth also called fixed).

As indicated in Equation (13), g_i for a household represents the minimum nonmarket valuation such that $U_i(K_i, W_i, \theta_i, x_i) - U_i(K_i - 2.4, W_i, \theta_i, x_i) = c_{K_i}2.4$. In this section, we are particularly interested in demand and capacities and, therefore, will suppress the subscripts and other variables for brevity of exposition. We will use $\vec{d}(K)$ to denote the observed demand under storage capacity K_i and $\vec{d}(K-2.4)$ to denote the counterfactual sequence of demands to which the household should adjust its demands if it only had reduced storage capacity $K - 2.4$. We omit the i subscript for notational convenience throughout the appendix but note that each analysis is conducted for each household and with each household's individual parameters:

$$\begin{aligned}
&\min g \\
&\quad \text{s.t. } U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K-2.4)) = c_K 2.4, \\
&\quad\quad U(K-2.4,W,\vec{d}(K)) \leq U(K-2.4,W,\vec{d}(K-2.4)), \\
&\quad\quad U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K-2.4)) \leq U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K)).
\end{aligned} \tag{30}$$

The first line in Equation (30) restates the optimization condition from before. The second line indicates that in a hypothetical scenario where the household's storage is reduced to $(K-2.4)$, its utility when it adjusts its demand to $U(K-2.4, W,\ \vec{d}(K-2.4))$ is at least as high as its utility when maintaining the original demand $U(K-2.4, W,\ \vec{d}(K))$ - (refer to Equation (7)). Consequently, the difference between the realized utility $U(K, W, \vec{d}(K))$ and the counterfactual utility is lower if the demands are fixed - compared to our model where they are adjusted.

To see how this affects the estimation of the nonmarket value, see Equation (31), wherein the first line, we estimate g' as the valuation of the nonmarket with fixed demands.

$$\begin{aligned}
&\min g' \\
&\quad \text{s.t. } U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K)) = c_K 2.4, \\
&\quad\quad \frac{\partial U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K))}{\partial g} > 0, \\
&\quad\quad g' \leq g.
\end{aligned} \tag{31}$$

As shown in Appendix A.1, the utility difference between reality and counterfactual is increasing in g. Because we need to increase this difference until it is equal to the marginal cost of the module $c_K 2.4$, the higher utility difference for the fixed demand means that the nonmarket valuation under the fixed demand is lower than the nonmarket valuation obtained through the structural model $g' \leq g$.

EC.11.1. Nonmarket Valuation Estimation if Demand Is Fixed - Empirical Comparison If we have fixed demands, we can estimate the nonmarket valuation without considering the consumption utility, as constant demand means constant consumption utility (see Equation (5)). As we show in Equation (32), this reduces to studying the expected amount of energy that is bought and sold to the grid with the current storage capacity, compared to a smaller battery. As previously, we write $l_n(K)$ to denote the charge in a storage capacity environment K.

$$\begin{aligned}
&\min g' \text{ s.t.} \\
&\quad U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K)) = c_K 2.4, \\
&\quad U(K,W,\vec{d}(K)) - U(K-2.4,W,\vec{d}(K)) = \\
&\quad (p+g)\mathbb{E}_{\vec{O},\vec{d}}\Big[\Big(d_n - O_n - l_n(K)e\Big)^+ - \Big(d_n - O_n - l_n(K-2.4)e\Big)^+\Big] + \\
&\quad s\,\mathbb{E}_{\vec{O},\vec{d}}\Big[\Big(O_n - d_n - (K - l_n(K))\Big)^+ - \Big(O_n - d_n - (K - l_n(K-2.4))\Big)^+\Big].
\end{aligned} \tag{32}$$

This way of estimating the nonmarket valuation allows one to remove most modeling assumptions, and the difference in utility between both solutions arises because the storage capacity is smaller, which impacts utility through the available charge $l_n(K) \geq l_n(K-2.4)$. We juxtapose the empirical results of the estimation of nonmarket valuation as in Equation (32) with our main model specification from Equation (13) in Table 23.

Table 23 Comparing the Nonmarket Valuations Between the Structural Model and an Estimation in Which Demands Do Not Change With Capacities

n = 3,237	Structural Model	Fix Demands
Min	0.00	0.00
Median	0.29	0.17
Mean	0.53	0.34
Max	4.00	4.00
Std. Dev.	0.69	0.54

As predicted through the theoretical results above, estimating the nonmarket valuation with fixed demands lowers each estimate, thus lowering the descriptive statistics. The average is 17 cents instead of 29 cents, and the median valuation decreases to 34 cents instead of 53. Although the magnitude of the effect decreases, the estimate of the nonmarket valuation with fixed demand retains the distribution, as shown in Figure 26, where we juxtapose the distributions resulting from both estimations.

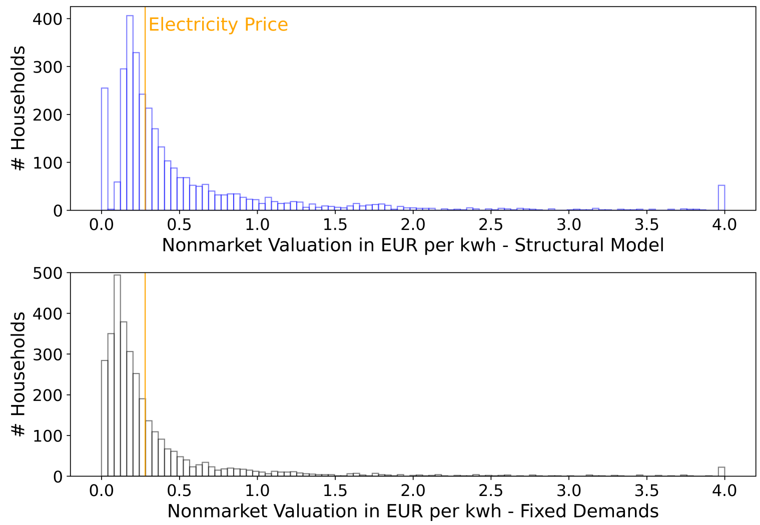


Figure 26 Distribution of Nonmarket Valuation under Endogenous and Exogenous (Fixed) Demands.

EC.12. Future Investment Results Under Different Cost Parameters

In this appendix, we show how the households' capacity investments differ if one assumes different cost reductions for the hypothetical future scenario we describe in Section 5.3. We repeat Table 4 in Table 24 to illustrate the different assumptions. The electricity price is 38 cents for all scenarios, as this is the expected medium/long-term electricity price in Germany (Martin 2023) - except for Alternative 4, so we can look at the sensitivity of investments to the electricity price.

Table 24 A Households Average Capacity Investment in Storage and Solar Given Different Cost Reductions

n = 3,237	Main Scenario	Altern. 1	Altern. 2	Altern. 3	Altern. 4
Storage Cost Reduction	25.0%	12.5%	25.0%	0.0%	25.0%
Solar Cost Reduction	22.0%	22.0%	11.0%	0.0%	22.0%
Avg.Storage Capacity (kWh)	3.5	2.1	3.5	1.0	3.0
Avg. Solar Capacity (kWp)	6.3	6.3	6.3	6.3	6.3
% of Households With Storage	54%	32%	54%	15%	40%
Electricity Price (in cents)	38	38	38	38	33

In Alternative 1, we see the substantial effect that storage cost reductions can have. If storage costs decrease only by 12.5% from their 2020 values (as opposed to the 25% assumed in the main scenario), households invest in 40% less storage capacity (from 3.5 to 2.1 kWh), and the share of households investing in storage decreases from 54% to 32%.

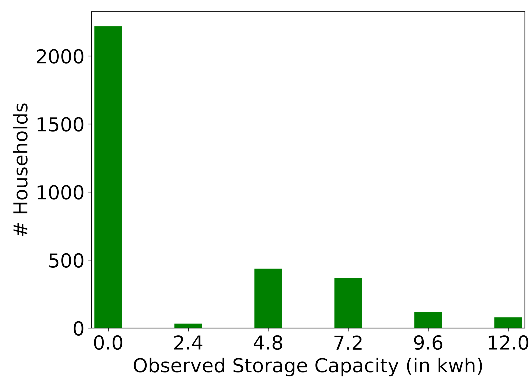


Figure 27 Household Storage Installations for Future Scenario - Alternative 1.

In Alternative 2 we see that solar costs do not drive the effects; even without any feed-in subsidy, solar is already profitable in 2020, so whether costs decrease by 22% as assumed in our main analysis or by 11% as in this alternative scenario does not change the household's investment decision. Rather, as mentioned in the main part of the manuscript, the roof space is the main constraint for households to invest in more storage, so we do not allow a household to invest in more capacity than observed. As such, further solar cost is not a driving factor behind further residential solar installations in Germany - though it may well be driving adoption in other countries with lower electricity prices or in nonresidential settings.

In Alternative 3, we test how the technology investment would change if the technology costs remained at 2020 levels, but electricity prices increased from 28 cents in 2020 to 38 cents and subsidies were removed.

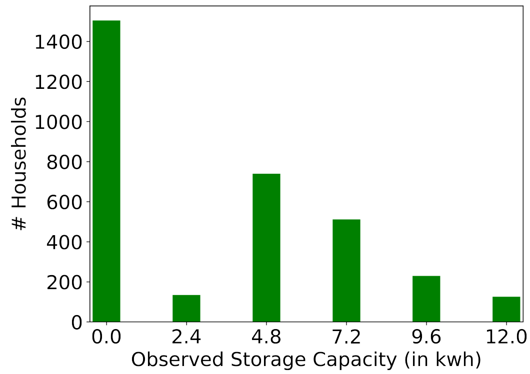


Figure 28 Household Storage Installations for Future Scenario - Alternative 2.

With this increase, even without nonmarket valuation, 15% of the households would invest in storage. Of those who invest, the average installation, as shown in Figure 29, is 6.9kWh.

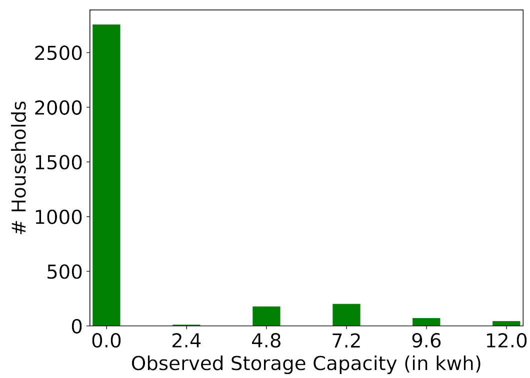


Figure 29 Household Storage Installations for Future Scenario - Alternative 3.

In Alternative 4, we study the effect of the electricity price on storage investments - in comparison to the main scenario, the technology costs are reduced by the same percentages, but the electricity price is at 33 cents instead of 38. This reduction in the price of electricity 13% (33 cents / 38 cents) lowers the average storage capacity by 17% from 3.5 kWh to 2.9 kWh and the share of households that invest in storage from 54% to 40%. However, storage investment is higher than in alternative 1, suggesting a marginal decrease in the cost of 12. 5% technology drives storage adoption more than a 15% (38cents/33cents) increase in electricity prices.

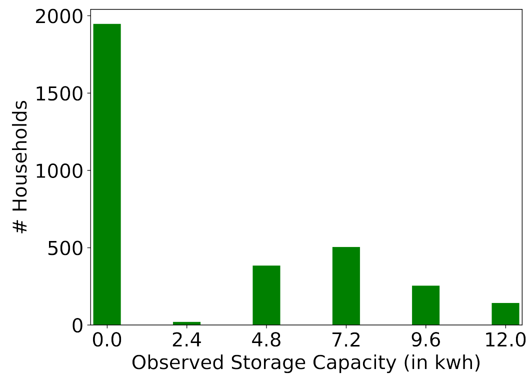


Figure 30 Household Storage Installations for Future Scenario - Alternative 4.

EC.13. Estimating Consumption Preferences for Standard Load Profiles

Because the company from which we obtained the data is a solar and storage manufacturer, we do not observe households without either solar or storage in our dataset. Because we are interested in quantifying the nonmarket valuation that drives the early adoption of the technology, as well as the interplay of residential storage and emissions as well as the utility, the outside option is not a central concern in this paper. Yet, using external household data is useful to ensure that our utility model is able to back out realistic preference parameters, as this is the basis for our counterfactual models.

To test our model on outside data, we did obtain four *standard load profiles*. These load profiles are the default household electricity load profiles that utilities as planing basis for households that have no solar. Two profiles are from Berlin's utility for 2018 and 2020[17], one from a German utility called Stadtwerke Boehmetal (SWBT)[18], and one from the German power plant association (Vereinigung Deutscher Elektrizitaetswerke (VDEW))[19].

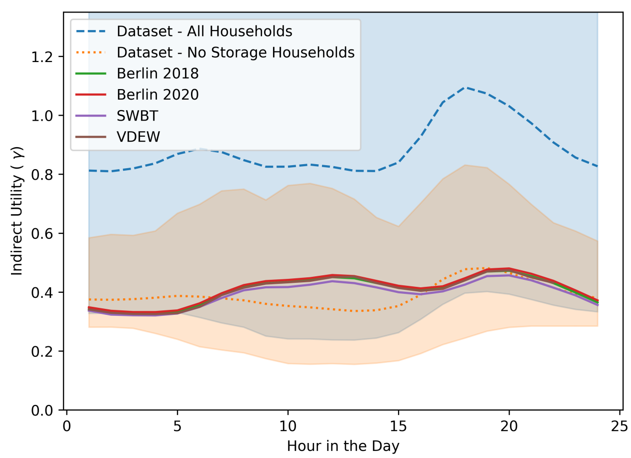


Figure 31 Estimated Average Consumption Preferences for All Households from Dataset, Households without Storage, and Four Publicly Available Consumption Ddatasets.

In Figure 31, we compare our estimates of household consumption preferences in our data set with publicly available data on household energy consumption from different utilities in Germany. For our dataset, we present the results for all households (dashed line), and for those households without storage (dotted line). The shaded areas contain 95% of households' values.

Even though the households in our dataset consume more electricity during daytime hours than regular households, we are able to identify the same general consumption preferences as in the public data sets. Note that the average consumption preferences across all our households are shifted up, due to the impact of nommarket valuation. In comparison, for the households without storage in our dataset (i.e. no nonmarket valuation), our average estimates and the public data correspond very well, both in level and patterns. We view this evidence as support for the choice of our utility specification, as, through the inclusion of the shadow price, we are able to back out preferences consistent with public data despite the consumption data we observe being different.

EC.14. Estimating the Model Under A Different Functional Form

Of the several parts of our objective function, most are calculating costs and prices that are expressed in euros. The consumption utility term, however, relies on our assumption of its functional form of $\ln(d_{iht}+1)$. To test the effect that changing this part of the model to a different function form can have, we here re-estimate our results with an objective function for which we assume a different U^B_{iht} and re-estimated the model with updated utility function $\tilde{U}$. We require the alternative utility function to meet the following criteria: i) it needs to be a concave function to capture the observation that household's energy consumption is finite in reality, ii) it needs to have an analytically tractable derivative w.r.t. consumption, as we need that derivative to find γ and compute it billions of times, iii) the sign of the function or the derivative cannot switch for it to be numerically optimizable, iv) it ideally should be a one-parameter function as we use variation in demand to identify γ and can only uniquely identify one parameter per time-period.

Examples of functions that are used in other applications, but do not work in our circumstance are d^γ as its derivative $\frac{\partial d^\gamma}{\partial d} = \gamma d^{\gamma-1}$ is not analytically tractable or $\frac{d^{1-\gamma}}{1-\gamma}$ as the sign of the utility flips and approaches infinity when $\gamma = 1$ making it numerically unstable.

We ended up changing our utility function for consumption from $U^B_{iht} = \gamma_{iht}\ln(d_{iht}+1)$ to $\tilde{U}^B_{iht} = \gamma_{iht}\sqrt{d_{iht}}$, which changes both the functional form of the concavity and omits the shift of demand (d+1) implemented for the log function. Please see an outline of the derivation of the original utility function followed by the alternative specification below.

The original utility function and approach:

$$
\begin{aligned}
U^B_{iht} =& \gamma_{iht}\ln(d_{iht}+1),\\
U_{iht} =& \quad U^B_{iht} + U^C_{iht} + U^X_{iht} = \quad \gamma_{iht}\ln(d_{iht}+1) - \\
& (p_i+g_i)\,\mathbb{E}_{\vec{O}_i,\vec{d}_i}[(d_{iht}-O_{iht}-l_{iht}e)^+] + s_i\,\mathbb{E}_{\vec{O}_i,\vec{d}_i}[(O_{iht}-d_{iht}-(K_i-l_{iht}))^+],\\
\frac{\partial U_{iht}}{\partial d_{iht}} =& \frac{\gamma_{iht}}{d_{iht}+1} - \bar{\lambda}_{ih}(K_i,\theta_i,\vec{O}_i,\vec{d}_i,x_i) = 0,\\
\gamma_{iht} =& (d_{iht}+1)\bar{\lambda}_{ih}(K_i,\theta_i,\vec{O}_i,\vec{d}_i,x_i).
\end{aligned} \tag{33}
$$

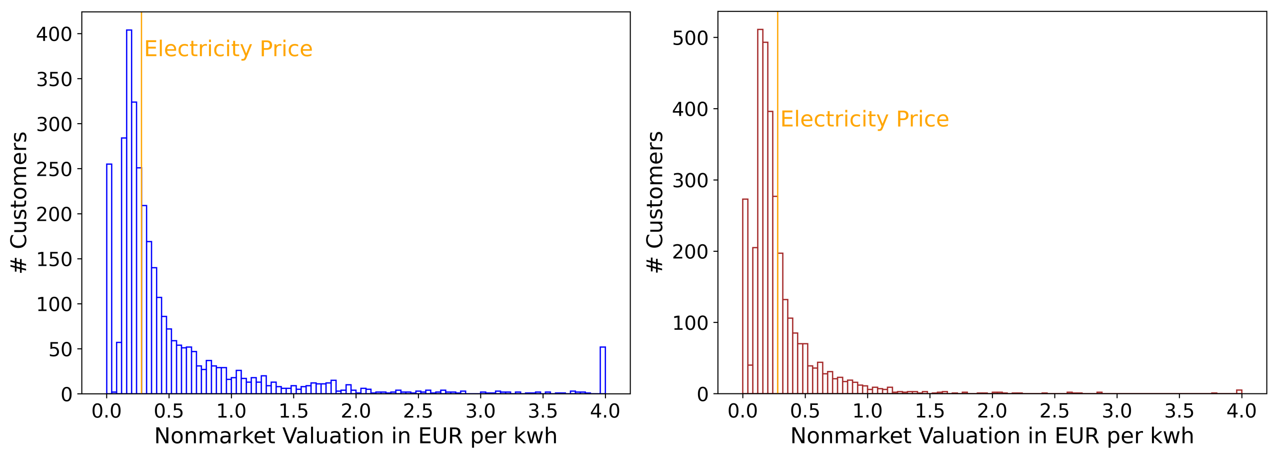
The alternative utility function and approach:

$$
\begin{aligned}
\tilde{U}^B_{iht} =& \gamma_{iht}\sqrt{d_{iht}},\\
\tilde{U}_{iht} =& \quad U^B_{iht} + U^C_{iht} + U^X_{iht} = \quad \gamma_{iht}\sqrt{d_{iht}} - \\
& (p_i+g_i)\,\mathbb{E}_{\vec{O}_i,\vec{d}_i}[(d_{iht}-O_{iht}-l_{iht}e)^+] + s_i\,\mathbb{E}_{\vec{O}_i,\vec{d}_i}[(O_{iht}-d_{iht}-(K_i-l_{iht}))^+],\\
\frac{\partial \tilde{U}_{iht}}{\partial d_{iht}} =& \frac{\gamma_{iht}}{2\sqrt{d_{iht}}} - \bar{\lambda}_{ih}(K_i,\theta_i,\vec{O}_i,\vec{d}_i,x_i) = 0,\\
\gamma_{iht} =& 2\sqrt{d_{iht}}\,\bar{\lambda}_{ih}(K_i,\theta_i,\vec{O}_i,\vec{d}_i,x_i).
\end{aligned} \tag{34}
$$

We then re-estimated the entire model for each household and provide a comparison of the nonmarket valuations from the main specification against the results from this alternative model in Table 25 and Figure 32.

n = 3,237	Main Model	Alternative Specification
Min	0.00	0.00
25%	0.18	0.14
Median	0.29	0.21
Mean	0.53	0.29
75%	0.56	0.33
Max	4.00	4.00
Std. Dev.	0.69	0.32

Table 25 Nonmarket Valuation Comparison Between Main Model and Alternative Specification.



(a) Original Model **(b)** Alternative Utility Function

Figure 32 Nonmarket Valuation Distributional Comparison Between Main Model and Alternative Specification.

As is evident, the distribution and the order of magnitude of the effect remain the same, but the alternative model specification results in somewhat lower valuations across the board. The median value decreases by 28% from 29 cents to 21 cents. The reduction of the nonmarket valuation is smaller (relatively and absolutely) for households with lower values of nonmarket valuation, e.g., the 25th percentile decreases by 22% in value. In comparison, the outlier values of the nonmarket valuation are substantially reduced, which occurs because the derivative of the alternative model w.r.t. consumption is steeper for all levels of consumption, resulting in higher utility from consuming electricity (for the same parameters) and lower required nonmarket valuation to make storage an optimal investment. $\frac{\partial \gamma \ln(d+1)}{\partial d} = \frac{\gamma}{d+1}$, while $\frac{\partial \gamma \sqrt{d}}{\partial d} = \frac{\gamma}{2\sqrt{d}}$. Clearly, $\frac{\gamma}{d+1} \leq \frac{\gamma}{2\sqrt{d}}$, if $d \geq 0$ with a strict inequality if $d \neq 1$.

Overall, despite changing from the main approach with a logarithmic mapping where demand is augmented by 1, to the square-root approach without the adjustment, the high-level finding of substantial nonmarket valuation, and the approximate shape of the distribution remain the same across both model types, which lends further credibility to the robustness of our findings.