The Need for Impact Evaluation in Energy Access Research
—**Supplementary Information**—

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SI1 Top-down Search Filtering

The starting point of our systematic review is a top-down search. We apply several filters to implement this and the table below gives a description of the applied filters and shows how each filter reduces the sample size.

Filter name	Filter description	Sample size
Initial search	Web search of the following search string in Google Scholar, ScienceDirect, and Web of Science for articles written since 2000: ("rural electrification" or "electricity" or "offgrid" or "solar") AND ("impact" or "effect" or "development" or "benefits")	7,247
(1) Title and abstract filter	The first filter was based on title and abstract, and included removing articles that dealt with engineering (e.g. focused on a new technology for rural electrification), dealt with issues with or obstacles to rural electrification (e.g. "how to" increase rural electrification), or those that dealt with the political decisions surrounding rural electrification.	514
(2) Full article relevance filter	The second filter was based on the full articles, but the exclusion reasons were generally the same as for the first filter.	283
(3) Impact filter	The third filter was more selective, asking whether the relevant sources actually dealt with testing the impacts of rural electrification, as opposed to only offering a description of rural electrification in a particular area.	107
(4) Not qualitative filter	The fourth filter removed qualitative studies.	46
(5) Not literature review	The fifth filter removed literature reviews. Note that we used the literature reviews for the bottom-up search that followed the top-down search.	42
(6) Household-level/outcome filter	The final filter removed those studies that did not use household-level as unit-of-analysis or did not assess one of the five outcomes we were interested in.	15

Table SI1: Filtering process in top-down search.

SI2 List of selected studies

ID	Authors	Year	Journal	Technology	Country	Method	Detailed Method
1	Aevarsdottir et al	2017	Working paper	Offgrid	Tanzania	Experiment	Experiment
2	Agoramoorthy and Hsu	2009	*Human Ecology*	Offgrid	India	Observational	Descriptive
3	Aguirre	2017	*The Lahore Journal of Economics*	Grid	Peru	Observational	IV
4	Aklin et al	2017	*Science Advances*	Off-grid	India	Experiment	Experiment
5	Akpan et al	2013	*Energy for Sustainable Development*	Grid	Nigeria	Observational	Descriptive
6	Alkon et al	2016	*Energy for Sustainable Development*	Grid	India	Observational	Descriptive
7	Barkat et al	2002	NRECA report	Grid	Bangladesh	Observational	Descriptive
8	Barron and Torero	2017	*Journal of Environmental Economics and Management*	Grid	El Salvador	Experiment	Experiment
9	Bensch et al	2011	*Journal of Development Effectiveness*	Offgrid	Rwanda	Observational	DID
10	Bensch et al	2013	*Journal of Rural and Community Development*	Offgrid	Senegal	Observational	Descriptive
11	Bridge et al	2016	*Energy Economics*	Grid	Nepal	Observational	IV
12	Chakravorty et al	2014	*Journal of Economic Behavior & Organization*	Grid	India	Observational	IV
13	Chaplin et al	2017	Mathmatica Policy Research	Grid	Tanzania	Observational	Descriptive
14	Cook	2005	Asian Development Bank	Grid	Thailand	Observational	DID
15	Cook	2005	Asian Development Bank	Grid	India	Observational	Descriptive
16	Dinkelman	2011	*American Economic Review*	Grid	South Africa	Observational	IV
17	Furukawa	2014	*Journal of Development Studies*	Offgrid	Uganda	Experiment	Experiment
18	Grimm et al	2015	*Demography*	Grid	Indonesia	Observational	DID
19	Grimm et al	2017	*World Bank Economic Review*	Offgrid	Rwanda	Experiment	Experiment
20	Grogan	2016	*Journal of Human Capital*	Grid	Colombia	Observational	IV
21	Imai et al	2014	*The International Journal of Environmental Sustainability*	Grid	India	Observational	Descriptive
22	Khandker et al	2012	*The Energy Journal*	Grid	Bangladesh	Observational	IV
23	Khandker et al	2013	*Economic Development and Cultural Change*	Grid	Vietnam	Observational	DID
24	Khandker et al	2014	World Bank	Offgrid	Bangladesh	Observational	Descriptive
25	Kudo et al	2017	*World Bank Economic Review*	Offgrid	Bangladesh	Experiment	Experiment
26	Lee et al	2016	Working Paper	Grid	Kenya	Experiment	Experiment
27	Lenz et al	2017	*World Development*	Grid	Rwanda	Observational	DID
28	Madubansi and Shackleton	2006	*Energy Policy*	Grid	South Africa	Observational	Descriptive
29	Rao	2013	*Energy Policy*	Grid	India	Observational	Descriptive
30	Salmon and Tanguy	2016	*World Development*	Grid	Nigeria	Observational	IV
31	van de Walle et al	2017	*World Bank Economic Review*	Grid	India	Observational	IV

Table SI2: Summary of studies. Columns (2)-(4) provide basic bibliographic information, where outlets in normal (and not italics) font are not peer reviewed. Columns (5) and (6) give technology (grid versus offgrid) and country information. The final two columns indicate what method was used to assess energy access; column (7) distinguishes between 'observational' or 'experimental' studies, and column (8) differentiates observational studies further in ones using 'descriptive' methods (e.g., regression analysis), 'IV' (= instrumental variables) estimation, or 'DID' (= difference-in-differences) estimation.

SI3 Coding of impacts

#	StudyID	Study	Method	Technology	Outcome	Impact	Point estimate	Sig?	Measure
1	1	Aevarsdottir et al 2017	Exp	Offgrid	Energy expenditure	+	−0.295	Yes	Expenditure index
2	1	Aevarsdottir et al 2017	Exp	Offgrid	HH income	+	+0.125	Yes	Income index
3	1	Aevarsdottir et al 2017	Exp	Offgrid	HH savings	+	+40534.9	Yes	Savings
4	1	Aevarsdottir et al 2017	Exp	Offgrid	Business creation	+	+0.045	Yes	Mobile money index
5	1	Aevarsdottir et al 2017	Exp	Offgrid	Education	0	+1.029	No	Time spent on education
6	2	Agoramoorthy and Hsu 2009	Desc	Offgrid	Energy expenditure	+	+130.38	Yes	Savings in energy cost
7	2	Agoramoorthy and Hsu 2009	Desc	Offgrid	Education	+	+1.26	n/a	Study hours
8	3	Aguirre 2017	IV	Grid	Education	+	+2.289	Yes	Children's study time (average hours/day)
9	4	Aklin et al 2017	Exp	Offgrid	Energy expenditure	+	−49.36	Yes	Kerosene spending private market
10	4	Aklin et al 2017	Exp	Offgrid	HH income	0	+656.69	No	Monthly HH expenditure
11	4	Aklin et al 2017	Exp	Offgrid	HH savings	0	+224.17	No	HH savings
12	4	Aklin et al 2017	Exp	Offgrid	Business creation	0	−0.03	No	Business ownership
13	4	Aklin et al 2017	Exp	Offgrid	Education	0	−0.02	No	Lighting use for study
14	5	Akpan et al 2013	Desc	Grid	Business creation	0	+0.794	No	Business profits (log)
15	6	Alkon et al 2016	Desc	Grid	Energy expenditure	+	+0.42	Yes	Energy expenditure (log)
16	7	Barkat et al 2002	Desc	Grid	Energy expenditure	+	−159.8	n/a	HH fuel consumption
17	7	Barkat et al 2002	Desc	Grid	HH income	+	+36439.4	Yes	HH net income
18	7	Barkat et al 2002	Desc	Grid	HH savings	+	+14886	Yes	HH savings
19	7	Barkat et al 2002	Desc	Grid	Education	+	+0.144	Yes	Overall adult literacy
20	8	Barron and Torero 2017	Exp	Grid	Energy expenditure	+	−0.259	Yes	Kerosene expenditure
21	9	Bensch et al 2011	DID	Offgrid	Energy expenditure	0	626.4	No	Energy expenditure equivalent (FRw)
22	9	Bensch et al 2011	DID	Offgrid	HH income	+	+204.2	Yes	HH income per work-age adult (1,000 FRw)
23	9	Bensch et al 2011	DID	Offgrid	Education	+	+0.31	Yes	Children's study hours at home
24	10	Bensch et al 2013	Desc	Offgrid	Education	+	+21	Yes	Study time (min/day/child)
25	11	Bridge et al 2016	IV	Grid	HH income	+	+0.146	Yes	Consumption per capita (log)
26	12	Chakravorty et al 2014	IV	Grid	HH income	+	+0.554	Yes	Adult income equivalent (log)
27	13	Chaplin et al 2017	DID	Grid	Energy expenditure	+	+70.44	Yes	HH electricity use (in kWh/month)
28	13	Chaplin et al 2017	DID	Grid	HH income	+	+1124708	Yes	HH non-electricity consumption (in TZS/year)
29	13	Chaplin et al 2017	DID	Grid	Education	+	+0.2	Yes	Study time at night (hours/child, aged 5-14)
30	14	Cook 2005	DID	Grid	HH income	0	not reported b/c not sig		HH income (log)
31	14	Cook 2005	DID	Grid	Education	+	+0.012	Yes	Schooling per HH member (average years, log)
32	15	Cook 2005	Desc	Grid	HH income	+	+36.1	Yes	Consumption expenditures per capita

Table SI3: Summary of impact coding for all studies. Columns (2) and (3) provide study identifier information. Columns (4) and (5) list the method used ('Exp'= experimental; 'Desc'= descriptive; 'IV'= instrumental variables; 'DID'= difference-in-differences) and whether grid or offgrid technology was assessed. Columns (6)-(10) show the outcome which was evaluated, whether we coded the impact 'positive' (+), 'neutral' (0), or negative (−), together with point estimates, whether estimates are statistically significant, and how the outcome was measured. *Note:* We note significance levels in column (9) as 'n/a' if a study reports results to be statistically significant but does not list a standard error, t-statistic, or p-value.

#	StudyID	Study	Method	Technology	Outcome	Impact	Point estimate	Sig?	Measure
33	16	Dinkelman 2011	IV	Grid	HH income	+	+1.107	Yes	Monthly earnings for men (log)
34	17	Furukawa 2014	Exp	Offgrid	Education	0	mixed +/− results		Study time and test scores
35	18	Grimm et al 2015	DID	Grid	HH income	−	−0.0698	Yes	Female labor market participation
36	18	Grimm et al 2015	DID	Grid	Education	+	−0.0637	Yes	Child labor market participation
37	19	Grimm et al 2017	Exp	Offgrid	Energy expenditure	+	−557	Yes	Energy expenditure
38	19	Grimm et al 2017	Exp	Offgrid	HH income	0	+7249	No	Total expenditures
39	19	Grimm et al 2017	Exp	Offgrid	Education	+	+14	Yes	Share of HH studying at night
40	20	Grogan 2016	IV	Grid	HH income	0	+0.0789	No	Employment in agriculture
41	20	Grogan 2016	IV	Grid	Education	+	+2.0538	Yes	+1 year of schooling at age 8
42	21	Imai et al 2014	Desc	Grid	HH income	+	+2700	Yes	Monthly income
43	22	Khandker et al 2012	IV	Grid	HH income	+	+0.113	Yes	Expenditure per capita (log)
44	22	Khandker et al 2012	IV	Grid	Education	+	+0.233	Yes	Completed school years (boys)
45	23	Khandker et al 2013	DID	Grid	Energy expenditure	+	−2.6	Yes	Kerosene use
46	23	Khandker et al 2013	DID	Grid	HH income	+	+0.28	Yes	Total income (log)
47	23	Khandker et al 2013	DID	Grid	Education	+	+0.063	Yes	Enrollment rate (boys)
48	24	Khandker et al 2014	Desc	Offgrid	Energy expenditure	+	−2.31	Yes	Kerosene consumption
49	24	Khandker et al 2014	Desc	Offgrid	HH income	+	+0.086	Yes	Income per capita (log)
50	24	Khandker et al 2014	Desc	Offgrid	HH savings	0	+0.067	No	Total assets (log)
51	24	Khandker et al 2014	Desc	Offgrid	Education	+	+14.1	Yes	Evening study time (boys)
52	25	Kudo et al 2017	Exp	Offgrid	Energy expenditure	+	−0.234	Yes	Household lighting expenditures
53	25	Kudo et al 2017	Exp	Offgrid	Education	+	+12.95	Yes	Study hours; school attendance; performance
54	26	Lee et al 2018	Exp	Grid	Energy expenditure	+	+2.2	Yes	Electricity spending (US$/month)
55	26	Lee et al 2018	Exp	Grid	HH income	0	+4.5	No	HH Employment
56	26	Lee et al 2018	Exp	Grid	HH savings	0	+110	No	Total assets (US$)
57	26	Lee et al 2018	Exp	Grid	Education	0	−0.1	No	Average test scores
58	27	Lenz et al 2017	DID	Grid	Energy expenditure	+	−1858	Yes	Energy expenditures (FRw/month)
59	27	Lenz et al	DID	Grid	HH income	0	+00h38	No	Time spent on productive activity (hours)
60	27	Lenz et al	DID	Grid	Education	+	+00h19	Yes	Study time at night (hours)
61	28	Madubansi and Shackleton 2006	Desc	Grid	Energy expenditure	+	−8.80	Yes	Paraffin consumption/month
62	29	Rao 2013	Desc	Grid	HH income	+	+0.34	Yes	Non-farm income (log)
63	30	Salmon and Tanguy 2016	IV	Grid	HH income	+	+0.413	Yes	Husband's hours of work
64	31	van de Walle et al 2017	IV	Grid	Energy expenditure	+	+0.229	Yes	Fuel expenditure per capita (log)
65	31	van de Walle et al 2017	IV	Grid	HH income	+	+0.084	Yes	Consumption per capita (log)

Table SI4: Summary of impact coding for all studies. Columns (2) and (3) provide study identifier information. Columns (4) and (5) list the method used ('Exp'= experimental; 'Desc'= descriptive; 'IV'= instrumental variables; 'DID'= difference-in-differences) and whether grid or offgrid technology was assessed. Columns (6)-(10) show the outcome which was evaluated, whether we coded the impact 'positive' (+), 'neutral' (0), or negative (−), together with point estimates, whether estimates are statistically significant, and how the outcome was measured. *Note:* We note significance levels in column (9) as 'n/a' if a study reports results to be statistically significant but does not list a standard error, t-statistic, or p-value.

SI4 Sample description

This section describes the sample of the 30 identified studies that assess impacts from rural electrification that met the inclusion criteria of our systematic review.

- Section SI4.1 shows basic descriptives by country.
- Section SI4.2 shows studies over time.
- Section SI4.3 looks at how the used method breaks down by technology.
- Section SI4.4 presents data on variable coverage.

SI4.1 Studies by country

This section describes our sample of 31 identified studies by geography. Table SI5 below shows a breakdown of studies by country. Some interesting patterns arise:

By far, the most studies are conducted in India ($n = 8, 26\%$), with a generally strong focus on South-East Asia, where about half of all our studies are situated ($n = 16, 51\%$). Over a third of studies ($n = 12, 38\%$) come from Africa with Rwanda (3), Nigeria (2), South Africa (2), and Tanzania (2) contributing each at least two studies. The remaining three studies, accounting for roughly 10% of the sample, come from Latin and South America.

#	Country	Total	Method				Technology	
			Descriptive	IV	DID	Experimental	Grid	Off-grid
1	India	8	5	2	0	1	6	2
2	Bangladesh	4	2	1	0	1	2	2
3	Rwanda	3	0	0	2	1	1	2
4	South Africa	2	1	1	0	0	2	0
5	Nigeria	2	1	1	0	0	2	0
6	Tanzania	2	0	0	1	1	1	1
7	Colombia	1	0	1	0	0	1	0
8	El Salvador	1	0	0	0	1	1	0
9	Indonesia	1	0	0	1	0	1	0
10	Kenya	1	0	0	0	1	1	0
11	Nepal	1	0	1	0	0	1	0
12	Peru	1	0	1	0	0	1	0
13	Senegal	1	1	0	0	0	0	1
14	Thailand	1	0	0	1	0	1	0
15	Uganda	1	0	0	0	1	0	1
16	Vietnam	1	0	0	1	0	1	0
	Total	31	10	8	6	7	22	9

Table SI5: Breakdown of assessed studies ($N = 31$) by country, separately for method and technology. Column (3) shows the total number of studies for a given country, with columns (4)-(7) separating them into descriptive, IV, DID, and experimental methods. Columns (8) and (9) split the sample by grid and offgrid technology. All data are counts.

SI4.2 Studies over time

From the pattern of studies in our sample over time, we find that most impact evaluations of energy access (26 out of 30, 83%) were published only after 2010. In fact, the majority of studies

were published in the last four years. The other remarkable pattern is that experimental impact evaluations are a very recent phenomenon, with 7 out of 8 such studies being published only in 2017 and 2018.

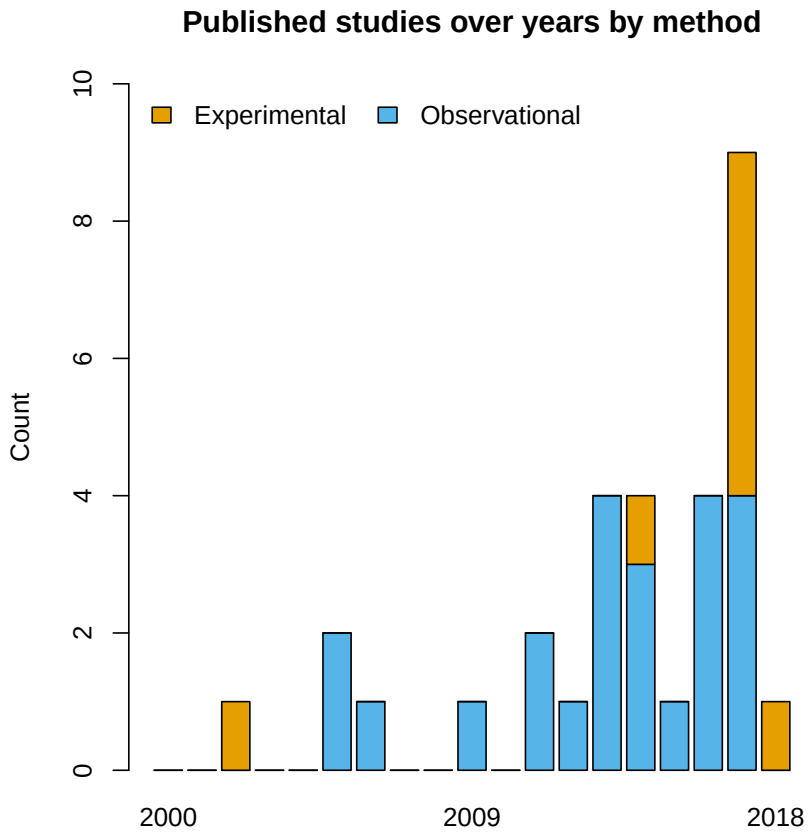

Figure SI1: Publication of studies ($N = 31$) over time and by method. The plot shows when the studies identified in our systematic review were published and what method, i.e., observational or experimental, they use. All data are counts.

SI4.3 Studies by technology

For the 31 studies that assess impacts from electricity access, we first show descriptively how the identified studies' methods correlate with the type of electricity access technology. As shown in Table SI6, observational studies are by far the predominant form of analysis in electricity access research: 24 studies, or more than three out of four, are observational. Of these, many are using a

descriptive method (10 out of 24, 42%), whereas the majority seeks causal identification of estimates through either IV (8 out of 24, 33%) and DID (6 out of 24, 25%) approaches. However, as shown before, this pattern seems to be changing towards more experimental work more recently. In 2017, we record 9 studies overall, 5 of which were experimental.

Method		Total	Technology		Peer review	
Simple	Detailed	N	Grid	Offgrid	Yes	No
Observational	Descriptive	10	7	3	7	3
	IV	8	8	0	8	0
	DID	6	5	1	4	2
Experimental	Experiment	7	2	5	5	2
Total		31	22	9	24	7

Table SI6: Descriptive information of assessed studies ($N = 31$), separately by method. Column (3) shows the number of assessed studies broken down by the used method (descriptive, instrumental variables (IV), difference-in-differences (DID), or experiment). Columns (4)-(5) show a breakdown by used technology (grid, offgrid), while columns (6)-(7) show whether a study was published in a peer-reviewed journal or not. All data are counts.

Most of our understanding of impacts from energy access relies on studies focusing on grid access (22 out of 31 studies; 71%) as means of electrification. Combining this information with the used method, we find that observational methods are predisposed towards studying grid access, while experimental methods tend to focus on offgrid technology. This difference is highly statistically significant ($t = 3.146, p = 0.003$) in a simple t-test. The results are equally strong in χ^2 tests of identical distribution of grid and offgrid technology relative to observational and experimental methods ($\chi^2(1) = 7.887, p = 0.005$) or the four categories of descriptive, IV, and experimental methods ($\chi^2(3) = 9.829, p = 0.020$).

Finally, our data consist of mostly peer-reviewed studies (77%), and limiting the sample to peer-reviewed publications produces equally strong results. The results for the t-test become $t = 3.285, p = 0.003$ and $\chi^2(1) = 7.899, p = 0.005$ and $\chi^2(3) = 9.582, p = 0.022$ for the corresponding two χ^2 tests.

SI4.4 Variable coverage

For our systematic review, we identified five main outcome variables for which we assess electrification impacts. Here, we show how the coverage of these variables breaks down by method.

From the relative frequencies of how often a given outcome is assessed, as shown in Figure SI2, we can see that effects of electricity access on household income (assessed 22 times, 34%), educational outcomes (assessed 19 times, 29%), and energy expenditures (assessed 16 times, 25%) are by far the most common, accounting for almost 9 out of 10 assessed outcomes. Effects on household savings (assessed 5 times, 8%) and local business creation (assessed 3 times, 4%) are much less common.

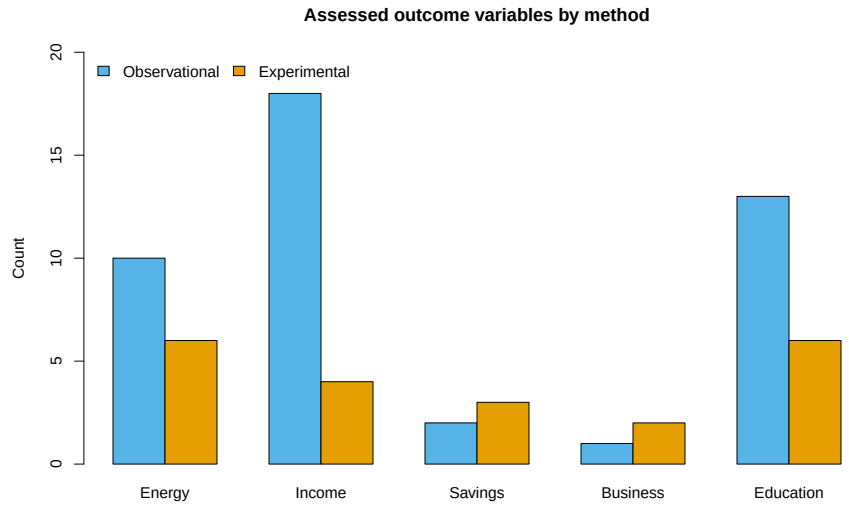

Figure SI2: Variable coverage by type of method. The barplot shows the number of assessed studies ($N = 31$) that include the five main outcome variables for observational methods (blue color) and experimental methods (orange color): Energy expenditure, household income, household savings, business creation, and education, all of which are measured at the household level.

Although the figure shows the break-down by the type of method, it is key to remember that our sample only includes 7 experimental studies and 24 observational ones. On a per-study basis, experimental electricity access research hence assesses many more outcomes. Table SI7 clarifies this point. Our 7 experimental studies assess as many as 25 outcomes, that is, 3.1 outcomes per study, compared to 39 outcomes assessed in almost three times more 22 observational studies, for 1.8 outcomes per study on average.

Interestingly, there is quite a bit of variation within observational studies in that research using instrumental variables assesses the fewest outcomes, which also cluster in the household income and education categories. Difference-in-differences methods are more similar to experimental approaches in terms of how many outcomes they assess and how outcome categories are spread across studies.

Method		Outcome variables						Total	
Simple	Detailed	Energy	Income	Savings	Business	Education	Sum	Study #	Per study
Observational	Descriptive	5	5	2	1	4	17	10	1.7
	IV	1	7	0	0	3	11	8	1.4
	DID	4	6	0	0	6	16	6	2.7
Experimental	Experiment	6	4	3	2	6	21	7	3.0
Total		16	22	5	3	19	65	31	2.1

Table SI7: Coverage of variables in assessed studies ($N = 31$), separately by type of method. Columns (3)-(7) show counts of how many studies assess one of the five main outcome variables: Energy expenditure, household income, household savings, business creation, and education, all of which are measured at the household level. Columns (8) and (10) show the total and average number of variables covered by method type. All data are counts.

When testing for statistical independence the distribution shown in Table SI7 fails to be statistically significant at conventional levels ($\chi^2(12) = 12.387, p = 0.415$), yet the descriptive pattern is nonetheless insightful. Contrasting observational (i.e., collapsing descriptive, IV, and DID methods into a single category) and experimental studies comes to the same qualitative conclusion with $\chi^2(4) = 5.581, p = 0.233$.

SI5 Regression results

In order to be able to control for the confounding of technology in the relationship between method type and how positively an impact is assessed, we estimate several OLS regression models. Our dependent variable is whether an impact is positive (= 1) or neutral (= 0). In a first set of models, we regress this outcome variable on a binary indicator of whether a study uses an experimental (= 1) or an observational (= 0) method and another technology indicator that scores 1 for offgrid access and zero for grid electrification. In a second set of models, we create dummy variables for IV, DID, and Experiments and use studies with descriptive design as the baseline. We cluster standard errors by study throughout.

Table SI8 shows the results for different samples. Model (1) uses the full sample, models (2) and (3) estimate regressions separately for grid and offgrid samples, models (4) and (5) exclude IV and DID studies, while models (6) and (7) present results for the strict variable coding and for peer-reviewed studies only. We report standard errors clustered by study in parentheses and show in the last line of the table whether statistically significant coefficients remain statistically significant at the 10% level when applying wild cluster bootstrap correction.

	(1) Full sample	(2) Grid sample	(3) Offgrid sample	(4) w/o IV	(5) w/o DID	(6) Strict	(7) Peer review
Experimental method	-0.34**	-0.48**	-0.24	-0.33**	-0.39**	-0.47**	-0.28
	(0.15)	(0.18)	(0.18)	(0.15)	(0.15)	(0.17)	(0.19)
Offgrid technology	0.00			0.02	0.04	-0.00	-0.12
	(0.12)			(0.12)	(0.14)	(0.12)	(0.13)
Observations	64	38	26	53	49	46	41
Studies	31	22	9	23	25	24	24
R^2	0.133	0.174	0.059	0.121	0.173	0.284	0.158
Wild cluster bootstrap	sig	not sig	not sig	not sig	sig	sig	not sig

Dependent Variable: 1=Positive impact; 0=Neutral impact.
Standard errors in parentheses and clustered by study.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table SI8: OLS regression results. The table shows estimation results from OLS models with study clustered standard errors. Columns show different samples. Column (1) shows results for the full sample, column (2) for grid studies, column (3) for offgrid studies, column (4) for when excluding studies that use instrumental variables (IV), column (5) for when excluding studies that use difference-in-differences (DID), column (6) for strict variable coding, and column (7) for peer-reviewed studies.

We find support that experimental studies produce significantly fewer positive impacts than observational studies. The estimate coefficient is negative in all models and mostly statistically significant at the 5% level, even though levels of statistical significance attenuate when correcting standard errors for few clusters.

Estimating the same models for all four method types provides a similar result, as shown in Table SI9. Again, the estimated coefficient for studies using experimental methods is negative throughout and statistically significant in most models at the 5% level. As before, results become weaker with the wild cluster bootstrap correction.

	(1) Full sample	(2) Grid sample	(3) Offgrid sample	(4) w/o IV	(5) w/o DID	(6) Strict	(7) Peer review
IV	0.03	0.01	—		0.05	0.00	-0.01
	(0.13)	(0.14)			(0.14)	(0.04)	(0.18)
DID	-0.08	-0.07	-0.19*	-0.08		-0.18*	-0.08
	(0.12)	(0.15)	(0.08)	(0.12)		(0.10)	(0.16)
Experiment	-0.36**	-0.50**	-0.29	-0.36**	-0.38**	-0.53***	-0.32
	(0.15)	(0.21)	(0.19)	(0.15)	(0.15)	(0.15)	(0.21)
Offgrid technology	0.00			0.00	0.06	0.00	-0.11
	(0.13)			(0.13)	(0.15)	(0.11)	(0.14)
Observations	64	38	26	53	49	46	41
Studies	31	22	9	23	25	24	24
R^2	0.141	0.181	0.072	0.126	0.174	0.314	0.163
Wild cluster bootstrap	sig	not sig	not sig	sig	sig	sig	not sig

Dependent Variable: 1=Positive impact; 0=Neutral impact.
Standard errors in parentheses and clustered by study.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table SI9: OLS regression results. The table shows estimation results from OLS models with study clustered standard errors. Columns show different samples. Column (1) shows results for the full sample, column (2) for grid studies, column (3) for offgrid studies, column (4) for when excluding studies that use instrumental variables (IV), column (5) for when excluding studies that use difference-in-differences (DID), column (6) for strict variable coding, and column (7) for peer-reviewed studies. *Note:* In model (3), we cannot estimate an IV coefficient as no study using IV methods assesses an offgrid intervention.

Notwithstanding obvious data limitations due to separation in the fairly small data, we take these empirical results as a good indication that the used method type does matter for how positively impacts from electricity access are evaluated.