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Estimating the price (in)elasticity of off-grid electricity demand

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ABSTRACT

Community-scale power infrastructure may be the only electrification option for tens of millions households that remain out of reach from centralized power grids. The responsiveness of household electricity demand to price is a crucial design input for off-grid systems. While the price elasticity of electricity demand of grid-connected consumers has been abundantly studied, few studies focus on off-grid communities where substantial econometric challenges arise, including the absence of metered consumption data and electricity prices that are simultaneously determined by cost and demand considerations. This study attempts to address these challenges for the case of off-grid micro hydropower consumers. It makes two core contributions: First, we propose the surface area of the contributing hydrologic catchment as a new instrumental variable to estimate elasticity using a cross sectional dataset of existing micro hydropower infrastructure. Second, we provide a first price-elasticity estimate (−0.15) for off-grid electricity demand in Nepal. We surmise that the small (in absolute value) elasticity value found in this study arises from the low levels of consumption observed off-the-grid. We use a Monte Carlo analysis to show that failing to account for this disparity can lead to substantial financial losses caused by suboptimal power infrastructure design.

1. Introduction

The critical role of electricity as a driver of economic development is widely recognized (e.g., Dinkelman, 2011; Rud, 2012) and recent large-scale investments allowed 222 million people worldwide to gain access to electricity between 2010 and 2012 (International Energy Agency (IEA) and The World Bank, 2015). Yet 1.3 billion people, mostly in rural areas (International Energy Agency, 2013) remain unconnected, 620 million of whom will likely remain out of reach of national power grids due to remoteness, low population densities and prohibitive grid extension costs (International Energy Agency (IEA) and The World Bank, 2015). In this context, local power systems that are not connected to the national grids, but generate electricity near the point of consumption are a promising alternative for rural electrification (Narula et al., 2012). Such community-scale off-grid systems may be the only means of accessing electricity in the foreseeable future in many remote regions, notably in mountainous areas, where grid extension costs are compounded by accessibility challenges.

In contrast to large power grids, where electricity is generated at cost-optimal sites and transported to demand centers through high voltage transmission lines, off-grid systems can neither store nor export excess energy. Power generation in off-grid systems therefore has to match household electricity demand at the local level, meaning that the economic viability of the system is constrained by the total electricity demand of the community. In that context, the optimal capacity of a power system is jointly determined by the cost (i.e. the rate at which the unit cost of infrastructure [$ per kW] decreases with capacity) and demand curves. The slope of the demand curve is particularly critical and determined by the *price-elasticity* of energy demand, i.e. how responsive household level electricity consumption will be to changes in the electricity price. Without this information, designers are likely to either over or underestimate the optimal plant capacity, resulting either in capital costs that cannot be recovered by the local sale of electricity, or in forfeited income if a plant fails to supply local demand. Either situation can contribute to a lack of financial sustainability of designed local power supplies. The price elasticity of electricity demand, γ_p, is formally defined as the ratio of relative change in electricity demand kW to the corresponding relative change in price P:

$$\gamma_p = \frac{dkW/kW}{dP/P} \tag{1}$$

γ_p is typically negative (decreasing marginal utility of consumption)

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and, in the case of electricity, has an absolute value smaller than one, meaning that electricity demand is price-inelastic (e.g., Espey and Espey, 2004).

Determining the causal effect of price changes on electricity demand is an arduous task, particularly in the context of rural electrification in developing countries. The direct approach of simply asking community members (e.g., through dedicated techniques like contingent valuation (Thomas and Syme, 1988) is prone to hypothetical biases because the surveyed households have likely never experienced the level of electricity service they are asked to value. To date, there is no general theory of respondent behavior to characterize and control hypothetical bias (Loomis, 2011). An alternative set of methodologies, revealed preferences approaches, use observed behavior (as opposed to stated preferences) to determine elasticity. Recent efforts to privatize electricity markets worldwide increased research interest in assessing how households adapt their electricity consumption in response to price policies (see e.g., (Espey and Espey, 2004; Hondroyiannis, 2004), for a review). Numerous studies use residential power consumption data monitored by utilities to evaluate demand elasticity. However, few (if any) studies have been devoted to off-grid power generation in developing countries. This setting differs from centralized grids in two important ways.

First, because of their local scale, the capacity of off-grid power systems is tailored to local electricity consumption: household demand affects the size of the infrastructure, which, in turn, affects the unit cost of the produced electricity through economies of scale. It follows that price is simultaneously determined by demand and supply considerations in off-grid power systems. In that situation, price is endogenous,[1] and the effect of price on electricity demand is challenging to disentangle from the effect of infrastructure size, itself driven by electricity demand, on electricity costs. In developing countries, these difficulties are often compounded by data constraints: in this study, our inability to observe electricity price, income and electricity consumption at the household level (Section 2.3) may give rise to omitted variables and measurement errors[2] that add onto existing endogeneity concerns. In contrast, grid-connected consumers typically have a limited influence on electricity tariffs, which are exogenously imposed by large power utilities. While electricity prices can become endogenous if block tariffs are implemented [3] (Reiss and White, 2005), this effect appears to be marginal for grid-connected household consumption in developing countries and is largely ignored by previous studies (e.g., (Bose and Shukla, 1999; Tiwari, 2000; Chattopadhyay, 2004; Filippini and Pachauri, 2004).

Second, costs and operational challenges often prevent the installation of household connection meters (Rosa et al., 2012; Casillas and Kammen, 2011). While substantial recent progress has been made in the installation of household metering devices (Lee et al., 2016; Pueyo, 2015), many off-grid power systems remain unmetered. In Nepal, off-grid micro-hydropower schemes are typically operated on capacity-based tariffs (Fulford et al., 2000; Ghale et al., 2000), whereby households pay a fixed fee per unit of electric capacity (e.g. 70 Nepalese Rupees per month for a 100W inlet (Joshi and Amatya, 1996). Without connection meters, household electricity consumption cannot be monitored in many off-grid power supply schemes. This causes a fundamental data problem and requires proxy variables to assess electricity consumption. Another important consequence is that households cannot be billed on their energy consumption, but pay a fixed fee determined by the capacity of their connection (Baral et al., 2012). Electricity consumption choices therefore represent *long-term* decisions, driven by the ownership of electrical appliances and limited by the connection capacity, usually enforced via sealed current limiting devices installed by the utility. This delays the effect of exogenous shocks (e.g., climate, prices and income) on the household's decision to change their level of consumption (Iimi, 2011), and renders short-term dynamic elasticities irrelevant. It also means that existing identification strategies to address price endogeneities in large power grids (i.e. panel adjustment techniques (Alberini and Filippini, 2011) and instrumental variables based on the enforced tariff structure (McFadden et al., 1977; Reiss and White, 2005) cannot be readily transferred to unmetered micro grids because the required detailed information on individual household consumption and pricing structure is generally unavailable.

These estimation challenges limit the use of existing econometric approaches to determine γ_p for off-grid, unmetered households. Local price elasticities are frequently overlooked by practical design manuals, which assume that electricity prices are exogenous and constant (e.g., Junejo et al., 1999; Fraenkel et al., 1991; Junejo, 1997). This assumption is valid for grid-connected plants benefitting from feed-in tariffs (e.g., Basso and Botter, 2012), but may lead to over-designed infrastructure off-grid because it neglects the possibility that excess power generation will saturate local demand, in which case prices will drop substantially. Poor sizing is listed among the likely reasons explaining the low sustainability (i.e. high failure rate) of off-grid infrastructure in developing countries (e.g. Khennas and Barnett, 2000), for micro hydropower).

To address this gap, we propose a method to estimate the price-elasticity of off-grid, unmetered electricity demand. The study focuses on Nepal and uses recorded information on the costs and salient features of subsidized micro hydropower schemes to determine average, community-level consumption (in connection capacity, kW) and price (in $\$/kW$ connection fee). Micro hydropower in Nepal is a good example of scantly sustainable off-grid infrastructure despite very favorable conditions. Thanks to the low level of technology of its components, micro hydropower often emerges as the most cost effective rural electrification option for mountainous regions globally (Müller et al., 2016). Nepal has an enormous hydropower potential, a large rural population without access to the power grid, substantial local hydropower expertise, favorable institutions and 50 years of implementation experience. Nonetheless, about 30% of existing micro hydropower plants are not in operation (Khennas and Barnett, 2000). We use an instrumental variable approach to address endogenous pricing and base our identification strategy on the fact that hydropower generation, and therefore electricity price, is strongly affected by water availability, which itself relates to upstream topography. We present evidence in Section 4.1 that the considered instrument – the area of the contributing watershed – is exogenous, i.e. it does not directly affect electricity demand, and is sufficiently correlated to infrastructure costs to provide unbiased (though noisy) estimates of γ_P. Although the relation between infrastructure costs and upstream topography is specific to hydropower, which limits the applicability of this particular method, the general approach of leveraging supply-side environmental constraints as instrumental variables may be extended to characterize demand for other off-grid renewable sources.

We find that the estimated elasticity is significantly lower (in absolute value) than long-run elasticities found elsewhere in the literature. Three important differences come to mind immediately and set this study aside from previous estimations of γ_p. First, isolated micro grids are more prone to outages and voltage fluctuation than larger grids because of their small size and undiversified power source (Vaidya, 2015). Second, the absence of connection meters in the Nepalese dataset sets the marginal cost of consumption (in terms of appliance usage) to zero. Third, off-grid electrification primarily concerns rural communities, which typically have much lower levels of income, appliance ownership and electricity consumption than their urban counterparts. We discuss these particularities and their possible implications on demand elasticity that may explain its lower absolute value (Section 4.2).

[1] An independent variable of a regression model is endogenous if it is correlated to the error term.

[2] For instance, price and consumptions are mismeasured in our study if costs are not completely recovered or if the infrastructure is not used at its full capacity.

[3] Consumers can affect their marginal price by choosing their level of consumption.

The remainder of the paper sets out to estimate the price-elasticity of off-grid electricity demand in rural Nepal. Section 2 describes key modeling assumptions, our estimation approach and the available dataset. Regression results are presented in Section 3, and Section 4 discusses the validity of the empirical strategy (Section 4.1), interprets the estimated elasticity in light of key differences with previous studies (Section 4.2), and explores the practical consequences of approximating off-grid elasticities with more typically estimated on-grid values during design for the specific case of micro hydropower (Section 4.3).

2. Methods

2.1. Model

We represent off-grid power supply as a market, where households pay an agreed-upon fee to a local power utility for a chosen electrical capacity provided by an isolated micro grid. Household connections are unmetered but power consumption is limited by a sealed current-limiting device. Consequently, households do not pay for the average power consumed, but rather decide on the 'size' of their connection and pay for the option of continuously drawing the full amount of energy allowed by their connection. The utility managing the local power infrastructure is in a position of natural monopoly, but price is regulated to ensure equitable access to electricity.[4] This is consistent with anecdotal evidence suggesting that many off-grid electrification schemes in Nepal are subject to some level of participative pricing and do not operate solely on a profit maximizing basis (Khennas and Barnett, 2000, p. 36). In fact, we assume that price is determined so as to allow electricity revenues to exactly compensate infrastructure costs. This setup, where locally owned power utility generate neither profits nor losses is recommended by many local design manuals in Nepal (e.g., Junejo, 1997, p. 61), as a way to ensure full cost recovery while keeping the price low enough to prevent the infrastructure from being underutilized (Apgar and Brown, 1987). We assume that electricity price and connection size are simultaneously determined at the design stage by households and the utility. The utility optimizes the size of the infrastructure to exactly meet the aggregated demand from households and recover costs. This implies that price and connection size are held constant throughout the service life of the infrastructure. It is possible that electricity access increases household productivity and purchasing power, with an impact on electricity demand. We take a reduced form approach and assume that any such feedback effects are already accounted for in the demand specification.

We model household electricity demand as:

$$\ln kW = \gamma_P \ \ln \ P + \sum_i \gamma_i \ \ln X_i + \epsilon_D \tag{2}$$

where kW is the average capacity (in kW) of household connections by community, and P is the connection fee per unit capacity faced by households ($ per kW). Variations of kW between households within communities are included in the error term ϵ_D, γ_P is the price-elasticity of electricity demand and X_i are observable covariates. The log-log functional form is routinely used to model household electricity demand (e.g., Filippini and Pachauri, 2004; Silk and Joutz, 1997; Beenstock et al., 1999) because of its empirical convenience. It is suitable for linear regressions, the estimated coefficients can be readily interpreted as elasticities, i.e. ratios of relative changes in demand against relative changes in a given covariate, and the related standard errors provide measures of the variability of the estimated elasticities.

[4] A price-inelastic demand implies negative marginal revenues for all levels of consumption. Because no level of production would allow marginal revenues to reach (positive) marginal costs, a profit-maximizing monopolist will boundlessly increase price and decrease output. In other words, unregulated electricity prices would cause the utility owner to produce minimal electrical output that they will sell to households paying the highest price.

2.2. Estimation

Electricity price (P) and the capacity of household connections (kW) are simultaneously determined by supply and demand considerations. For instance, favorable site conditions or a highly price-inelastic demand can *simultaneously* lead to large household connection capacities and low electricity prices. The ensuing correlation between P and the error term ϵ_D introduces a bias in the ordinary least squares (OLS) estimation of γ_P (e.g., Dubin et al., 1984).). We address this bias by introducing an instrumental variable (or supply shifter): an observable variable that is significantly correlated to electricity price while not directly affecting electricity demand (i.e. being uncorrelated to ϵ_D). The search for valid supply shifter (also known as instrumental variable) is a significant challenge in applied econometrics, and places this study in line with several recent papers evaluating the impact of electrification and large water infrastructure on economic development (e.g., Dinkelman, 2011; Rud, 2012; Duflo and Pande, 2007). These studies faced a similar identification challenge, namely that access to electricity may be endogenous to household behavior. To overcome this challenge, they all used topographic site conditions as instruments for infrastructure placement. Dinkelman (Dinkelman (2011) used terrain slope and its effect on the placement of transmission lines, Duflo and Pande (2007) exploited non-monotonic relations between slope and dam placement and Rud (Rud, 2012) used variations in groundwater availability and its effect on required pumping energy. While easily obtainable using remote sensing digital elevation models, these variables cannot be used to instrument for off-grid micro hydropower.[5] Instead, we use the area (A) of the hydrologic catchment supplying water to each scheme, which drives the volume of water available for hydropower production. Water availability has been repeatedly shown (see (Elbatran et al., 2015; Cavazzini et al., 2016) to strongly affect the cost of hydro electricity, through its effect on the type, size and efficiency of the turbine. A represents the topographic layout of the hydrologic catchment *upstream* of the community, which we do not expect to affect the community's electricity demand (unlike, say, terrain slope *within* the community, which likely affects local economic activities). The exogeneity and significance of A as a supply-shifting instrument to identify γ_P are discussed in Section 4.1.

The estimated two-stage-least-squares (2SLS) and first stage specifications are given in Equations (3) and (4) respectively. Control variables include remoteness (R), the number of connected households (HH) and annual precipitation (*precip*) as proxies for local income ,[6] as well as temporal fixed effects through dummy variables for electrification years.

$$\ln kW = \gamma_0 + \gamma_P \ \ln \widehat{P} + \gamma_R \ln R + \gamma_{HH} \ln HH + \gamma_{precip} \ln precip + \gamma_{Yr} \delta_{Yr} + \epsilon_D \tag{3}$$

$$\ln P = \beta_0 + \beta_A \ \ln \ A + \beta_R \ln R + \beta_{HH} \ln HH + \beta_{precip} \ln precip + \beta_{Yr} \delta_{Yr} + u \tag{4}$$

$\widehat{P}$ represents predicted prices from the first stage (Equation (4)) using the supply shifter A; γ_i and β_i are regression coefficients and u and ϵ_D are random error terms.

[5] Micro hydropower does not involve significant water storage (as in Duflo and Pande, 2007) and is rarely used to power groundwater irrigation (as in (Rud, 2012). Further, terrain slope (as in Dinkelman, 2011) cannot be used in rural mountainous areas because local topography affects agricultural productivity and, in turn, power consumption, which makes it endogenous.

[6] Our dataset unfortunately does not provide community-level income, but we control for annual rainfall, remoteness and community size as proxies for agricultural output, access to markets and population density. District-level income and regional fixed effects (administrative zone) are controlled for as robustness check in a second specification.

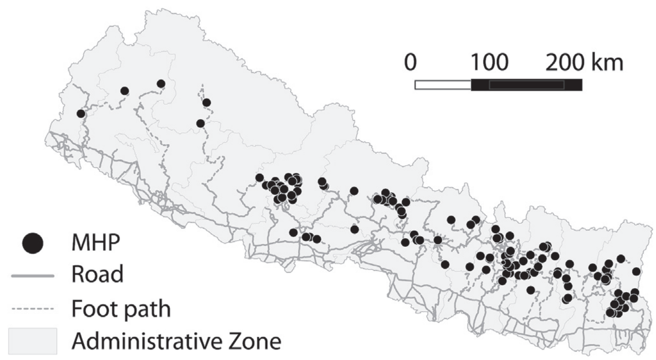

Fig. 1. Approximate location and accessibility of the sampled micro hydropower schemes from the REDB dataset.

2.3. Data

Consumption and price data from off-grid power systems are challenging to obtain in Nepal. Little information is available on unsubsidized micro hydropower plants, which typically remain unmonitored because there are no legal licensing requirements for hydropower plants below 100 kW. Instead, we used a cross sectional dataset of subsidized schemes compiled in a series of Renewable Energy Data Books (REDB) published by the Alternative Energy Promotion Center, a governmental agency in Nepal (Alternative Energy Promotion Centre (AEPC), 2009; Alternative Energy Promotion Centre (AEPC), 2011). The considered plants range between 1 and 100 kW and were built between 2008 and 2011. Among the 242 schemes in the dataset, 101 had information on all considered attributes and were included in the analysis. Fig. 1 provides a map of the approximate location and accessibility of the considered micro hydropower plants.

Data on plant capacity (PC), total construction costs (C), construction subsidies (S) and the number of supplied households (HH) were transcribed from the REDB. Costs and subsidies are given in Nepalese Rupees (1USD ≈ 100NRp) and currency fluctuations are controlled for by including temporal fixed effects for the construction year of the infrastructure in all regressions. After geocoding each scheme at the ward level, we estimated remoteness (R) as the distance along known footpaths to the nearest motorable road recorded in the gROADS dataset (NASA Socioeconomic Data and Applications Center (SEDAC), 2012) (see map in Fig. 1). The REDB dataset was merged with census data (Central Bureau of Statistics, 2001; Central Bureau of Statistics, 2011) to obtain district-level average incomes in 2011, used in the robustness check. Mean annual rainfall over the contributing watersheds were computed using bias-adjusted remote sensing precipitation data from Müller and Thompson (2013).

The REDB dataset does not provide the locations of the infrastructure within the ward, which is necessary to obtain the area A of the contributing watersheds. Instead, our instrument is constructed as follows. The probable location of streams within each ward was first recovered from a digital elevation model (United States National Aeronautics and Space Administration (NASA) and Ministry of Economy, Trade, and Industry (METI) of Japan (2011) using the A^T topographic search algorithm (Ehlschlaeger, 1989). Favorable locations for a micro hydropower intake along the streams were then identified automatically based on their elevation profiles (Fig. 2). In order to minimize costs and friction losses, run-of-river hydropower equipment is preferentially located along steep river slopes between concave and convex sections of the stream's elevation profile. Our algorithm uses local curvature extrema to partition the stream and identify the segment with the highest average slope as a likely location for the micro hydropower plant. The instrument A was then obtained as the upstream-most flow accumulation value along that segment and represents the area of the contributing catchment.

The average capacity kW of household connections for each scheme was computed as the capacity of the plant ($PCap$) normalized by the size of the supplied community (HH):

$$kW = \frac{PCap}{HH}$$

Full cost recovery (Section 2.1) implies that power infrastructure is sized such that unit prices collected by the utility are exactly equivalent to the unit costs of supplying electricity. The unit price of electricity faced by the households were obtained by normalizing total construction costs (TC) by the capacity of the infrastructure and accounting for construction subsidies (S):

$$P = \frac{TC - S}{PCap}$$

Note that P denotes the present value household payments. Fees typically paid by the households on a monthly basis can be retrieved from

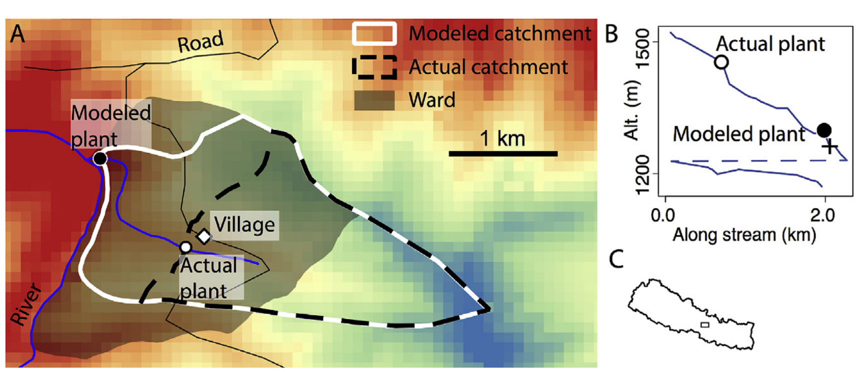

Fig. 2. Illustration of the GIS algorithm to construct the instrument A. Algorithm steps, illustrated for a village Dhading District (map in panel C), are as follows: (i) Streams (blue lines in panel A) draining catchment areas larger than 3.5km^3 are obtained from a high resolution digital elevation model (DEM, displayed as colored background in panel A) using the *r.watershed* function in GRASS (Ehlschlaeger, 1989). (ii) Elevation profiles (blue lines in panel B) are obtained by assessing the altitude of regularly spaced points along the streams. The pixel size of the DEM (30 m), which determines the minimum distance between two adjacent points in the elevation profile, determines the minimum penstock length assumed for the micro hydropower plants. (iv) Points with local maximum and minimum curvatures are identified from the derivatives of elevation along the profiles. (v) The *minimum* curvature point (black dot on panel B) associated with the largest average slope to the nearest downstream *maximum* curvature point (black cross on panel B) was identified as the most appropriate location for the infrastructure. Once the location of interest is identified (black dot on panels A and B), the area A of the contributing catchment (white contour panel A) is obtained. The location of the actual micro-hydropower plant (white dot on panel A) is also affected by non-topographic factors, here the location of the village (white diamond on panel A) and road. The mismatch between the observed and modeled plant locations leads to a measurement error on A represented as the difference between the white and dashed contours on the map on panel A. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Summary statistics of the sampled wards by dataset/electricity source (columns are labeled *REDB* and *NLSS* for micro hydro- and grid-connected users respectively), and the full micro-hydropower (*REDB*) dataset. The table provides median values with the interquartile ranges in parentheses. The electricity price *P* faced by households is given in annual unit costs (per Watt, see Appendix A) for grid connected households. For households supplied by micro hydropower, *P* corresponds to unit costs over the entire service life of the infrastructure: approximate annual costs can be retrieved, for instance, by dividing *P* by 50, if a service life of 30 years and a discount rate of 3% are assumed. Variable *A* is the area (in km^2) the catchment upstream of the most promising micro hydropower site, as identified by the algorithm in Fig. 2.

		REDB (Micro hydro) Sample	NLSS (Grid) Counterfactual	REDB (Micro hydro) Full dataset
		$N = 101$	$N = 79$	$N = 252$
Power consumption [W/HH]	*kW*	103 (92, 114)	329 (277, 413)	100 (88,112)
Electricity price [NRp/W]	*P*	102 (80, 137)	3.8 (3.3, 4.6)	141 (83,195)
Connected households	*HH*	130 (49, 231)	113 (72, 210)	180 (83, 289)
Remoteness [km to nearest road]	*R*	45 (18, 71)	3 (1, 7)	
Annual Income [1000USD]	*Y*	1.0 (0.9, 1.3)	4.3 (2.0, 6.8)	
Area of contributing catchment [km^2]	*A*	30 (19, 119)	28 (22, 102)	
Capacity of micro hydro plant [kW]	*PCap*	13 (5, 27)		17 (6, 30)
Total cost of micro hydro plant [1000NRp]	*TC*	2558 (815, 4585)		5367 (1252, 9300)
Construction subsidies [1000NRp]	*S*	1007 (327, 2037)		1840 (487, 4941)

P by accounting for the interest rate and the service life of the infrastructure. This distinction does not affect our estimation of the price elasticity of demand because the proportionality factor relating the present value to monthly annuities is absorbed in the intercept when regressing on log-transformed values.

Lastly, we rely on the 2010 Nepal Living Standards Measurement (NLSS (Central Bureau of Statistics, 2012) to assess the validity of the estimation approach. We consider a subset of 79 grid-connected rural communities that were matched to the REDB dataset based on population size (*HH*), upstream topography (*A*), remoteness (*R*) and administrative district through genetic matching (Sekhon, 2011). This dataset is representative of a counterfactual situation, where the price of electricity, which is exogenously determined by the national power utility, is not affected by the local suitability for micro-hydropower infrastructure. This property will be used to assess the exogeneity of the supply shifting instrument *A*. The NLSS is a household expenditure survey that does not provide specific information on household electricity demand. Instead, unit price indices and electricity consumptions were derived from annual power expenditures and appliance ownership as described in Appendix A.

Table 1 provides comparative summary statistics suggesting that (i) the 101 micro hydropower plants sampled for the analysis are representative (if slightly smaller) of the full dataset and (ii) the sample of 79 grid-connected communities used to establish the exogeneity of *A* (Section 4.1) is comparable to our corresponding sample of 101 off-grid communities. Table 1 also shows that the considered micro hydropower communities are substantially more remote than their grid-connected counterpart, despite *R* being used as a matching criterion. This discrepancy arises from a strong association between physical accessibility and grid access, as power grids co-evolve with transportation networks (Lipscomb et al., 2013).

3. Results

The estimated 2SLS regression coefficients are shown in Table 2. Columns (1) and (3) are the preferred 2SLS and first stage specifications. Regional fixed effects and district-level income obtained from census data are added to the regressions in columns (2) and (4) to further control for (unobserved) local income. Adding these control parameters decreases (in absolute value) our elasticity estimate. However, it also affects the strength of the first stage (the partial F statistic decreased from 8.2 to 5.3), which may suggest that this discrepancy arises from a weak instrument bias in the second specification (columns (2) and (4)).

In both specifications, price-elasticity of demand has the expected negative sign but is not statistically significant, likely because of measurement errors on *A*, as discussed in Section 4.1. In the context of this study, however, the relevant test to consider is arguably not whether γ_P is different from zero (though obtaining a negative estimate is an important reality check), but rather whether the obtained off-grid elasticity is significantly different from values measured on the grid. Anecdotally, the estimated value of −0.15 is lower (in absolute value) than previously estimated elasticities in neighboring India based on macro- (−0.63) (Bose and Shukla, 1999) and micro-data (−0.29 during the dry season) (Filippini and Pachauri, 2004), although the difference with the micro-data estimate (−0.29) is not statistically significant due to large standard errors on our estimate.

At a global level, estimates from both specifications (−0.15 and −0.10) are significantly smaller (at the 95% confidence level) than the mean value (−0.58) of a set of 101 elasticities found in the literature for grid-connected residential users[7] (Table 3). Our estimates also reject the median of previous elasticity estimates (−0.39) at the 90% level, and confidence level increases to 95% comparing our estimate to the subset of 43 studies that specifically considered long-run elasticities (mean: −0.96, median: −0.74), which are conceptually closer to the unmetered context as discussed in Section 1.

4. Discussion

4.1. Is the estimated elasticity reliable?

We propose a new instrumental variable, the area *A* of the contributing hydrologic catchment, to estimate the price elasticity of demand using on a cross-sectional dataset of existing micro hydropower infrastructure. The approach can reliably predict elasticity if three key criteria are satisfied: (i) Household power consumption and electricity prices are accurately determined using observed infrastructure characteristics; (ii) the instrumental variable has a strong first stage (i.e. *A* is strongly related to *P*) and (iii) the exclusion restriction holds (i.e. *A* does not directly affect *kW*). This section presents arguments supporting the validity of each criterion.

4.1.1. Measurement of P and kW

Direct observations of electricity prices and household connections are difficult to obtain off-grid, unless a dedicated field survey is con-

[7] Elasticity values from the literature cover 7 countries (US, Israel, Australia, Paraguay, Canada, Switzerland and India) and were obtained in Bohi and Zimmerman (1984), Fan and Hyndman (2011), Filippini (1999, 2011).

Table 2
First Stage and Two-Stage Least Squares Estimations. Instrument A has a partial F stat of 8.2 for the first stage in the preferred specification (1 and 3). The price-elasticity of demand as defined by the slope of the linear fit to log-log data is −0.148, but with a large standard error of 0.138. This estimate is somewhat decreased (in absolute value) when adding district-level income and administrative zone fixed effects to control for income (2). However, these controls are imprecise proxies of (unobserved) household income. This leads to a weak first stage (4) and likely biases the elasticity estimate in (2). To evaluate the exclusion restriction, electricity consumption is regressed against the instrument A for a counterfactual sample of grid-connected communities (5 and 6). In these specifications, there is no significant relation between the instrumental variable A and electricity consumption (kW) for communities that are not supplied by micro -hydropower electricity, which suggests that the exclusion restriction holds, i.e. A is exogenous. The area of the contributing catchment A was constructed using the identical topographic optimization algorithm applied for the main analysis. Intercepts are included in all specifications (coefficient not displayed).

	2SLS		First Stage		Reduced FormCounterfactual	
	log(kW) (1)	log(kW) (2)	log(P) (3)	log(P) (4)	log(kW) (5)	log(kW) (6)
log(P)	−0.148	−0.101				
	(0.138)	(0.179)				
log(A)			0.053**	0.042*	−0.005	−0.010
			(0.018)	(0.019)	(0.007)	(0.008)
log(R)	−0.045***	−0.042*	−0.023	0.014	−0.074***	−0.064***
	(0.019)	(0.024)	(0.049)	(0.058)	(0.015)	(0.016)
log(HH)	0.035	0.044	−0.085	−0.051	0.112***	0.094**
	(0.027)	(0.030)	(0.060)	(0.066)	(0.038)	(0.040)
log(Precip)	0.020	−0.042	0.113	0.097	0.022	−0.112*
	(0.054)	(0.075)	(0.133)	(0.188)	(0.056)	(0.062)
log($Y_{District}$)		0.249		0.025(0.131)		0.058***
		(0.157)				(0.020)
Year Fixed Effects	Y	Y	Y	Y	NA	NA
Zone Fixed Effects	N	Y	N	Y	N	Y
Observations	101	101	101	101	79	79
Partial F on log(A)			8.2	5.3		

Note: *p<0.1; **p < 0.05; ***p < 0.01. Standard Errors are in parentheses.

Table 3
Estimates and Student-t confidence interval bounds of the price elasticity of off-grid electricity demand estimated in this study (columns (1) and (2), compared to samples of elasticities previously estimated in the literature for grid connected residential consumers (columns (3) and (4). Our estimates for off-grid elasticity (90%CI: $[-0.37, 0.08]$) are significantly smaller (in absolute value) than the mean (−0.39) and median (−0.58) of previous estimates. The confidence level increases to 95% (95%CI: $[-0.42, 0.13]$) when compared to the subset of existing estimates for long range elasticity (mean: −0.96, median: −0.74), which is conceptually closer to off-grid unmetered elasticity.

Quantile	Off-Grid		Grid-connected	
	This Study		(Bohi and Zimmerman, 1984; Fan and Hyndman, 2011; Filippini, 1999; Filippini, 2011)	
	Preferred Specification (1)	Additional Income Controls (2)	All EstimationsN = 101 (3)	Long Range OnlyN = 43
2.5%	−0.42	−0.46	−2.20	−2.26
5%	−0.37	−0.39	−1.65	−2.20
Mean (Median)	−0.15	−0.10	−0.58 (−0.39)	−0.96 (−0.74)
95%	0.08	0.20	−0.07	−0.18
97.5%	0.13	0.25	−0.03	−0.06

ducted. Here we leverage existing data on the cost and size of power infrastructure to estimate these parameters. It is important to note that these estimates are not directly based on community demand characteristics other than the number of connected households in the community. Rather, they are constructed from observed infrastructure characteristics, assuming that their capacity and cost was optimized to allow for electricity revenues to exactly compensate costs (Section 2.1). While anecdotal evidence suggests that a large number of micro-hydropower plants are not financially sustainable, often precisely due to the challenge of estimating local demand (e.g., (Dhungel, 2009), all schemes recorded in the REDB dataset benefitted from subsidies and private loans, which entails some level of due diligence. In Nepal, local utilities are required to show evidence supporting a positive net present value of the infrastructure over 15 years (assuming a 4% discount rate) to be eligible for subsidies (Chitrakar, 2004). Under these conditions, it is reasonable to assume that REDB infrastructure is designed to cover peak household consumption while recovery costs. We note, however, that departure from these assumptions will not affect the resulting elasticity estimate, as long as the introduced relative profit and/or capacity margin remain constant over their support (e.g., the utility retains a profit of, say, 20% on the unit price of electricity and/or the infrastructure has a reserve extra capacity of 20%). These margins would be absorbed in the intercept term of Equation (2).

4.1.2. First stage specification

Although a partial F-statistic of 8.2 signals a fairly weak first stage, we expect the 2SLS estimator to be median unbiased, even at these relatively low levels of significance, because the system is just-identified (i.e. there are as many instruments as endogenous variables) ((Angrist and Pischke, 2008), p. 209). We tested the robustness of our estimates to decreasing sample sizes by applying 2SLS to 1000 random subsamples of the original dataset. We found that mean elasticity estimates remain unaffected by decreasing sample sizes when up to 50% of the original observations are discarded[8] (Table 4). This indicates that the estimated elasticity is unlikely subject to small-sample biases emerging from a weak instrument. However, weak instruments can also have a strong effect on the precision of 2SLS estimates (Angrist and Pischke, 2008). Although our results allowed to reject an elasticity of −0.39 (the

[8] A potential weakness of the resampling analysis can arise if observations are very similar to each other, in which case an estimation based on random subsamples will likely produce similar results to that with the whole dataset. To evaluate this issue, coefficients of variation across subsamples are displayed in Table 4, and suggest that electricity price varies noticeably across subsamples.

Table 4
Sensitivity of elasticity estimates to small sample sizes. Mean and standard deviation elasticity estimates (N = 1000, no replacement) are given by sampling ratio. Expected 2SLS elasticity estimates remain almost identical to the full sample estimate (i.e $\hat{\gamma}_P = -0.15$) if 50% or more of the original observations are included. Columns 4 and 5 show coefficient of variations (across samples) of the (within sample) mean value of electricity demand and price. Results show that, while electricity demand (outcome) is fairly homogeneous ($CV_{\mu_{kW}} \leq 2\%$), price (cause) varies noticeably ($CV_{\mu_P} \approx 10 - 15\%$) across samples for sampling ratios of 50–70%. This suggests that the stability of mean elasticity estimates for decreasing sample sizes is unlikely an artifact of the homogeneity of the original dataset.

Sampling Ratio	μ_{γ_P}	σ_{γ_P}	$CV_{\mu_{kW}}$	CV_{μ_P}
90%	−0.15	0.05	0.01	0.06
70%	−0.15	0.11	0.02	0.11
50%	−0.16	1.29	0.02	0.14
40%	−0.21	1.68	0.02	0.17
20%	−0.04	7.04	0.04	0.24

median of 101 elasticity values from the literature) at the 90% confidence level, our estimate of γ_P was too imprecise to be significantly different from zero and fails the Wu-Hausman endogeneity test (Green William, 2000), meaning that the 2SLS estimate is too noisy to be statistically different from an OLS estimate. Such errors in elasticity estimates can have dire practical consequences, as discussed in Section 4.3. Nonetheless, we argue that first stage uncertainties in this study do not arise from a lack of correlation between streamflow (proxied by A) and infrastructure costs: a power-law relation between these variables is well-established and reported by numerous empirical engineering studies in a variety of settings (see (Elbatran et al., 2015; Cavazzini et al., 2016). Rather, uncertainties arise from measurement errors on A, in which case they can be avoided in other settings with more precise information on the location of the infrastructure. Indeed, a fundamental weakness of our estimation is that we do not observe the exact position of micro hydropower schemes, which is necessary to measure A, the area of the contributing watershed. Instead we have to rely on a basic topographic optimization algorithm to estimate the likely location of the plant. We showed in Müller et al. (2016). that similar topographic algorithms are able to identify the region of the ward that is most likely to contain micro hydropower plants. This provides a good approximation of A, as seen in the case described in Fig. 2, because distances between predicted and actual plant locations are typically much smaller than the length scale of the contributing catchment. In other words, neighboring schemes likely collect water from the same stream and so are associated with very similar contributing catchments, no matter their exact layout. However, this approach fails to account for important factors, other than topography, affecting site selection at the local level (e.g., land ownership, relative placement with other infrastructure, accessibility). As a result, it is improbable that the infrastructure layout predicted by the algorithm exactly corresponds to the actual placement of existing infrastructure (Fig. 2), producing measurement uncertainties on the instrument A. This suggests that accuracy of the method can be substantially improved in situations, where accurate information on the location of micro hydropower infrastructure can be obtained.

4.1.3. Exclusion restriction

In addition to being strongly associated with the endogenous variable, a valid instrument must be truly exogenous, meaning that it should not be directly correlated to the dependent (left hand side) variable in the original equation. This so-called *exclusion restriction* cannot be directly tested because a good instrument is by definition strongly correlated to its endogenous variable, which is itself correlated to the dependent variable. An important concern in using local topography-based instruments (e.g., Dinkelman, 2011; Duflo and Pande, 2007) is that terrain steepness in and around the community is likely correlated to economic activity in a rural setting. This, in turn, affects electricity consumption and violates the exclusion restriction. Unlike previous instruments, A is an aggregate measure of catchment topography *upstream* of the community.[9] The spatial disconnect between economic activities in the vicinity of the community and the location of upstream crests and mountain ranges that determine the boundary of the watershed ensures that local electricity prices are not affected by A.

To support this claim, we constructed a counterfactual dataset of grid-connected communities by sampling 79 communities from the Nepal Living Standard Measurement Survey to match the considered dataset of micro-hydropower - connected communities (Section 2.3). For each counterfactual community, A was determined using the identical topographic search algorithm applied in the main analysis (Fig. 2) to determine the most likely location of a fictitious micro hydropower plant that would have supplied electricity if these communities were not connected to the grid. The counterfactual dataset was analyzed to determine whether electricity consumption is affected by A in communities, where electricity is not supplied by local micro-hydropower. Results (Table 2, Columns (5) and (6) show no significant correlation between A and kW. If the matched NLSS sample is representative of the micro-hydropower-connected communities included in analysis (see Table 1), this shows that local site conditions *only* affect electricity demand through their effect on infrastructure costs.

4.2. Why is the estimated elasticity different from previous studies?

Our results suggest that household demand for unmetered electricity in rural Nepal is little sensitive to price. These findings are in line with Lee et al. (2016), who found that the demand of unconnected households for electricity access is little affected by the level of subsidies offered on the connection costs. We here discuss three key characteristics of off-grid electricity systems that distinguish them from large power grids and may give rise to the observed price-inelastic demand.

First, power supply in developing countries is often intermittent, and likely more so in decentralized systems because of their small size and undiversified power source (Vaidya, 2015). Power outages may attenuate long-run price-elasticities through their effect on appliance purchase decisions. If households have to rely extensively on an alternate source of energy because electricity is intermittent, appliance purchase decisions (and therefore peak electricity consumption) will be driven by the price of the alternate energy, rather then electricity. It follows that changes in electricity prices will not dramatically affect appliance ownership, because households would have to compare the full cost of a new appliance to the utility it can produce during the short fraction of time, when electricity is available. In other words, price-elasticity will likely decrease for increasingly intermittent power supply. Yet in the context of Nepal, it is unclear that power supply is more reliable for grid-connected users. Load shedding and blackouts are common on the national grid, and the NLSS dataset suggests that there is no statistically significant difference in power intermittency between micro-hydropower- and grid-connected households[10].

Second, consumers are generally billed according to the size of the connection (*Watts*), rather than based on actual consumption (*kWh*). In such an unmetered setup, households are effectively billed according to their *peak* consumption, rather than their monthly average. This will affect demand elasticities in so far that there is some source of unforeseen variation in the underlying primitives (e.g., electricity price

[9] While a geomorphologic relation exists between the average slope and catchment area (e.g., Willgoose, 1994), this relation is unlikely to emerge at scales where runoff accumulation is small enough for micro-hydropower to be feasible.

[10] Two-sample t-tests comparing the power availability (in average hours per day) of grid-connected and micro-hydro households fail to reject the null at the 90% level.

or consumption utility).[11] Metered households will hedge price uncertainty by purchasing excess appliances that will allow them to consume more, whenever the instantaneous price of electricity is low. As a result, they do not use their full stock of appliances continuously and can adjust their consumption with electricity price. In contrast, unmetered households have weaker incentives to conserve electricity than their metered counterparts. Under these conditions, unmetered households will use their electrical appliances more intensively, have a smaller spare capacity at their disposal to adjust their consumption and, consequently, a more inelastic (i.e. less sensitive to price) electricity demand than metered users. However, we surmise that this effect is unlikely to dominate in Nepal, where electricity prices are typically predictable because heavily regulated by publicly managed power utilities (Baral et al., 2012).

Lastly, off-grid systems are generally found in rural settings where income, appliance ownership and power consumption are low. Credit constraints can have a substantial effect on household electricity demand (Lee et al., 2016). Our data suggest that off-grid communities in Nepal are poorer and less accessible (in terms of remoteness and community size) than their grid-connected counterparts, they are also less likely to own advanced electric appliances (Table 5) and their peak electricity consumption is lower (Table 1). Thus, a possible effect on elasticity is that households may respond differently to price at different levels of consumption due to varying costs of substitution. Intuitively, if households can only consume a limited amount of electricity (e.g., because of budget constraints), they will first use it for services that are expensive to substitute. For instance, budget-constrained households will first invest in phones, radios and TVs, which are challenging to substitute, before investing in fans and electric heat, which can be substituted by labor and combustion (Table 5). It follows that at low levels of consumption, electricity is more expensive to substitute and therefore more price-inelastic, akin to a vital good. In the extreme, price and income will have little effect on households' demand for the marginal amount of energy required to provide basic, non substitutable services (e.g., kerosene for lighting (Adkins et al., 2010).

This argument is formally investigated in Appendix B, where we show that electricity demand becomes more inelastic at low levels of consumption because the relative price of its substitute increases. The available data do not allow this hypothesis to be empirically tested, but

[11] Otherwise, both metered and unmetered households will adjust their stock of appliances so as to constantly use them at their full capacity. In that case, peak consumption becomes equivalent to average consumption and connection meters will not affect long term consumption decisions.

Table 5
Average number of appliances owned per household for the subset of communities of the NLSS data set that are supplied by off-grid micro hydropower schemes (NLSS Micro Hydro), and the subset of grid-connected communities that were matched to the REDB sample used in the main analysis.

$N_{Households}$	NLSS(Grid)800	NLSS (Micro Hydro)237
Phone	1.014	0.565
Radio	0.620	0.620
TV	0.560	0.211
Fan	0.600	0.084
Fridge	0.030	0.013
Computer	0.028	0.000
Elect. Heat	0.027	0.000
Washing Machine	0.001	0.000

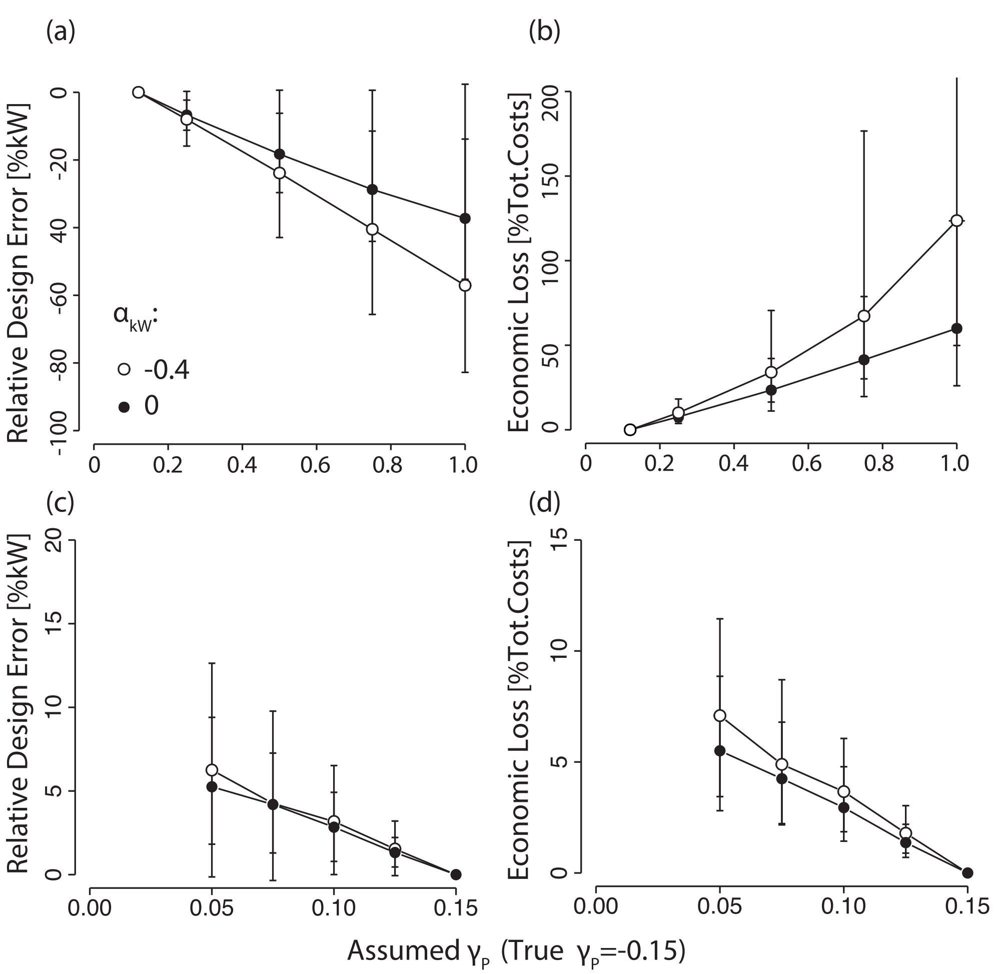

Fig. 3. Relative design error (a and c) on micro hydro infrastructure and related economic losses (b and d) caused by an over-estimation (a and b) or under-estimation (c and d) of price elasticity of demand $|\gamma_P|$. Median values over 1000 Monte Carlo runs are shown, with inter-quartile distances as error-bars. In all panels, α_{kW} is the exponent of the power-law function describing micro hydropower total costs ($TC = \alpha_0 \cdot kW^{\alpha_{kW}}$), and a negative value indicates economies of scale (Müller et al., 2016).

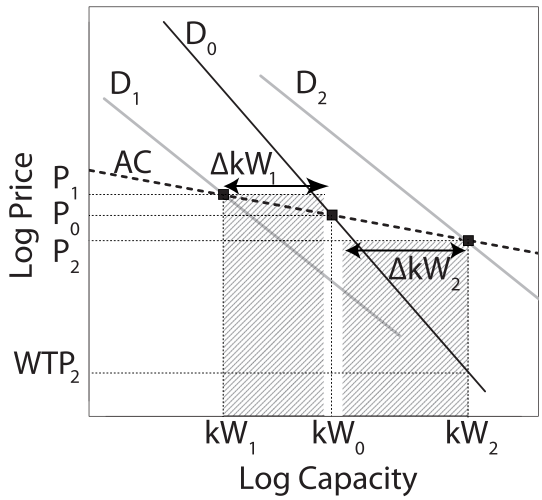

Fig. 4. Effect of the price-elasticity of demand on micro hydropower design. Electricity price and micro hydropower capacity are determined by equating average costs (*AC*) and average demand (D_0), in order for electricity revenue to recover infrastructure costs. Over-estimating the elasticity of demand (e.g., by taking values from grid-connected system found in previous studies) under-estimates the slope of the demand curve (D_1 and D_2). If the resulting infrastructure is *under*-designed (kW_1), household demand remains unfulfilled (i.e. households would purchase an additional capacity of ΔkW_1 at price P_1). If the infrastructure is *over*-designed (kW_2), it produces excess electricity (i.e. households only purchase a capacity of $kW_2 - \Delta kW_2$ at price P_2). An over-designed infrastructure is financially unsustainable because the willingness to pay of households for the amount of electricity produced (WTP_2) is insufficient to recover its costs (P_2). We quantify the economic loss related to design error by using cost-recovery prices (P_1 and P_2) to compute the value of the unfulfilled demand or excess production (i.e. the areas of the grey rectangles on the Figure). WTP_2 represents households' willingness to pay for.

similar dependencies between price-elasticity and power consumption were also observed empirically in previous studies (Reiss and White, 2005) and may explain the low absolute value found for off-grid elasticity in Nepal.

4.3. *What are the practical consequences of using a wrong elasticity value when designing an off-grid power supply?*

We used a Monte Carlo analysis to evaluate the effect of a misestimated demand elasticity on the design of off-grid micro hydropower plants. Flow, costs and demand conditions were randomly sampled from observational data. The power capacity allowing micro hydropower infrastructure to achieve full cost recovery was then determined by using 'true' (i.e. $|\gamma_P| = 0.15$) and 'wrong' (i.e. $|\gamma_P| \neq 0.15$) elasticity values successively .[12] The procedure was repeated 1000 times and the relative design error on the determined capacity was recorded at each run. In order to assign a monetary value to the design error, we assumed that the infrastructure was designed (and the price of electricity determined) by the power utility based on the 'wrong' elasticity value. If the infrastructure is under-designed, household demand is unfulfilled. Households could consume more electricity than provided by the infrastructure, until reaching the consumption level dictated by their actual demand curve at that price. Conversely, if the infrastructure is over-designed, excess electricity is generated. Households will only consume the produced electricity up to the point, where they reach their demand curve for the encountered electricity price (Fig. 4). We quantify the consequences of design errors at each run by using (cost-recovery) electricity price to assign a monetary value to these deficits or excesses of production. While this allows to assign a monetary value to accurate elasticity information, it does not properly convey the serious implications of over-design on infrastructure sustainability. Households' willingness to pay for the electricity produced in excess will fall below average generation costs (Fig. 4). It follows that an (even slightly) over-designed power supply infrastructure will not recover its costs. This has potentially disastrous consequences for off-grid micro-hydropower plants that are over-designed and lack the cross-financing capabilities of large public utilities.

Our analysis suggests that over- (under) estimating the price-elasticity of demand generally leads to significantly under- (over-) designed infrastructure (Fig. 3(a) and (c). This points towards suppressed (or unfulfilled) household electricity demand, as observed by Bose and Shukla (1999) for grid-connected Indian households. Caution must be used in interpreting the *direction* of design errors because the micro hydropower schemes considered in the REDB dataset are subsidized. It follows that the observed consumption and price data (i.e. where the 'true' and 'wrong' demand curves intersect) are generally located at lower prices and higher consumption levels than would typically occur if costs were fully recovered. Under these conditions, overestimating price-elasticity results in under-designed infrastructure because a more elastic (i.e. flatter) demand curve requires a lower plant capacity to recover its costs. Nonetheless, the *magnitude* of the design errors (Fig. 3(a) and (c) and of the related economic losses (Fig. 3(b) and (d), particularly when $|\gamma_P|$ is over-estimated, indicates the importance of using an appropriate elasticity value. This can be seen as a cautionary tale against the danger of using estimates from grid-connected users. Assuming a price-elasticity of −0.3 (e.g., Filippini and Pachauri, 2004, in India) leads to a relative design error of 10% and economic losses of about 15% of infrastructure costs.[13] Economic losses increase to 20%, when considering the median (−0.4) of previously estimated values from the literature (Bohi and Zimmerman, 1984; Fan and Hyndman, 2011; Filippini, 1999, 2011), and reach 50% when specifically considering the subset of long-run elasticities (median: −0.75). These effects are amplified if the design infrastructure allows economies of scale (i.e. $\alpha_{kW} < 0$, see Fig. 3).

5. Conclusion

The price-elasticity of electricity demand is a crucial input for the design of financially sustainable rural electrification infrastructure and must be estimated at the local level. Our empirical findings suggest that household electricity demand in rural Nepal (−0.15) is more inelastic than the residential demand observed for grid-connected users in previous studies. We posit that this difference arises from the much lower level of power consumption observed off the grid in rural Nepalese communities. Regardless of its cause, this discrepancy suggests that specific methods are needed to estimate the price-elasticity of *off-grid* electricity demand. Compared to grid-connected systems, estimating elasticities in an off-grid context involves substantial econometric complications, including the absence of metered consumption data and simultaneously determined electricity prices. We use an instrumental variable approach to address these challenges in Nepal. The approach, which uses commonly available salient features of existing infrastructure and a topography-based instrument derived from remote sensing is particularly applicable to developing countries, where household level observation data are scarce. We surmise that the method provides an unbiased, though noisy, estimate of the price elasticity of off-grid electricity

[12] Empirical flow duration curves were constructed using streamflow observation from 25 gauges in Nepal, as described in Müller and Thompson (2016). Costs and demand conditions were (independently) sampled from the REDB dataset described in Section 2.3. Scale coefficients of the cost and demand functions were computed as $a = \frac{y}{x^b}$, where x and y are randomly selected observations of electricity prices and capacities and b the (given) elasticities. Micro hydropower capacity was determined so as to allow full-cost recovery, as described in Müller et al. (2016). We assumed a nominal head of 100 meters and a single turbine with a constant efficiency of 0.55 and a cutoff flow ratio of 0.2 (Basso and Botter, 2012; Müller et al., 2016).

[13] Average costs of Micro hydropower infrastructure in Nepal are approximately 2100 USD/kW, according to the REDB dataset.

demand in Nepal.

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Appendix A. Obtaining price and demand from NLSS data

The NLSS dataset does not include direct data on electricity consumption and unit price, but provides household level estimates of monthly electricity expenditure, the number of appliances owned by category (e.g., telephone, fan, TV, fridge and computer) and the number of rooms in the dwelling, which is related to the energy required for electric lighting. The relation between annual electricity expenditure (Exp) and appliance ownership can be modeled as

$$\mathsf{Exp}_{iv} = \pi_v \sum_a \phi_a n_{ai} + \epsilon_{iv},$$

where π_v is the unit price per unit of power capacity enforced in village v, ϕ_a the average wattage of appliance type a and n_{ai} the number of these appliances owned by household i; $\epsilon_{iv} \sim \mathcal{N}(0, \sigma_i^2)$ is a normally distributed error at the household level. We assume that ϕ_a is constant across households and villages, and that π_v is independent and identically distributed across villages (but constant within the villages). We wish to estimate ϕ_a. These assumptions allow the expression to be rewritten as:

$$\mathsf{Exp}_{iv} = (u_v + \overline{\pi}) \sum_a \phi_a n_{ai} + \epsilon_{iv} = \sum_a \psi_a n_{ai} + u_v' + \epsilon_{iv}$$

with $\overline{\pi} = \mathsf{E}\left[\pi_v\right]$ and $\psi_a = \overline{\pi}\phi_a$, and where $u_v' = u_v \sum_a \phi_a n_{ai} \sim \mathcal{N}(0, \sigma_v^2)$ is a village level error that we assume to be orthogonal to ϵ_{iv}. We can estimate ψ_i using village-level random effects (e.g., through Reduced Maximum Likelihood estimation) and obtain the total wattage of the electrical appliances owned by the households (i.e. peak electricity demand):

$$\widehat{D}_i = \frac{\sum_a n_{ai} \widehat{\psi}_a}{\overline{\pi}},$$

Similarly, price can be estimated using the estimated random effects $\widetilde{u}$, which represent local (community level) relative variations in electricity prices.

$$\widehat{P}_v = \overline{\pi}\left(1 + \widetilde{u}\right)$$

The (unknown) average unit price of electricity $\overline{\pi}$ can be approximated by assuming specific values for the wattage of particular appliances. In Table 1, we assumed $\phi_{TV} = 60$ W for a cathode ray tube television (CRT TV) (Lawrence Berkeley National Laboratory) and used $\overline{\pi} \approx \psi_{TV}/\phi_{TV} = 4.1$ $[NRp/W]$ per year. Nonetheless, because $\overline{\pi}$ is a constant proportionality factor for both $\widehat{D}_i$ and $\widehat{P}_v$, it is absorbed in the intercept when regressing, and the specific value assumed for $\overline{\pi}$ does not affect the estimated coefficients.

Appendix B. Effect of substitute goods on demand elasticity

We use a simple model to investigate the effect of substitute goods on the price-elasticity of electricity demand. We consider two utility-relevant inputs: Electrically powered appliances E and substitute goods S. Electrical appliances are purchased and operated on a per-unit electricity cost p_E, and substitute goods are obtained at a marginal cost p_S. Both prices are constant and known to the households. In this reduced form approach, the term 'substitute goods' stands for anything that can replace an electrical appliance, ranging from alternate sources of lighting or heating (such as kerosene or gas) over different ways of food procuration (such as dining out) down to various forms of information and entertainment (in replacement for a TV). To avoid trivial substitution effects based on the *level* of consumption, we employ a CES (constant elasticity of substitution) utility function:

$$u(E, S) = \frac{1}{\alpha} \ln\left(E^\alpha + S^\alpha\right).$$

As its name suggests, this class of functions has the property that the relative ratio of inputs is independent of wealth or the absolute magnitude of consumption[14]. The parameter $\alpha \in (-\infty, 1]\backslash\{0\}$ measures the substitutability of the goods, with $\alpha = 1$ and $\alpha \to -\infty$ representing the case of perfect substitutes and complements respectively.

In these conditions, households decide on their electricity consumption by solving the utility maximization problem:

$$\max_{\{E,S\}} \left\{u(E, S) - p_E E - p_S S\right\}$$

We use first order conditions ($u'(S) = p_S$ and $u'(E) = p_E$) to obtain the demand curve for electricity:

$$E^* = \frac{1}{p_E} \frac{1}{1 + \left(\frac{p_S}{p_E}\right)^{-\frac{\alpha}{1-\alpha}}},$$

which we use to derive its own-price elasticity:

$$\gamma_P = \frac{\partial E}{E} \Big/ \frac{\partial p_E}{p_E}$$
$$= \frac{1}{\alpha - 1}\left[1 - \frac{\alpha}{1 + r^{\frac{\alpha}{\alpha-1}}}\right].$$

Here $r = \frac{p_S}{p_E} \geq 0$ is the relative price of the substitute with respect to electricity price. We expect r to increase at low level of electricity consumption because budget-constrained households will allocate the consumed electricity in priority to appliances that are hard (expensive) to substitute. Lastly, taking the derivative of γ_P with respect to r, we have

$$\frac{\partial \gamma_P}{\partial r} = \frac{\alpha^2}{(\alpha - 1)^2} \frac{r^{\frac{1}{\alpha-1}}}{\left(1 + r^{\frac{\alpha}{\alpha-1}}\right)^2} \geq 0,$$

Thus, electricity becomes more inelastic (i.e. γ_P increases and becomes closer to zero) as the relative price of its substitute increases, which itself occurs for decreasing levels of consumption.

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[14] Formally, when marginal prices for each input are equal to p_E and p_S respectively, the optimal consumption ratio $\frac{E^*}{S^*} = \left(\frac{p_E}{p_S}\right)^{-\frac{1}{1-\alpha}}$ is independent of the absolute value of prices or the level of consumption.

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