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Space matters: reducing energy disparity in Nepal through spatially equitable renewable energy subsidies

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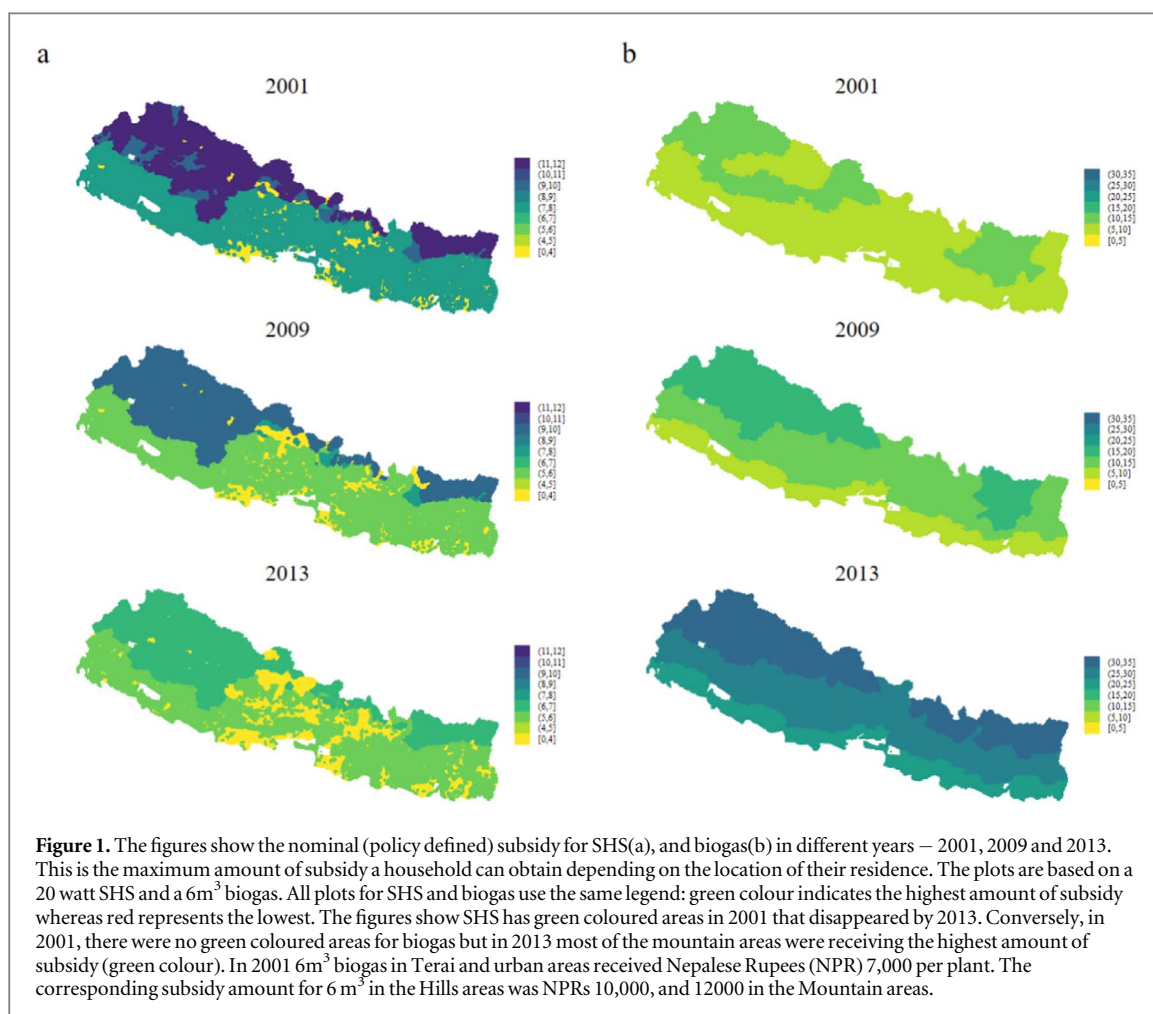
Abstract:

Affordability is a major barrier to the adoption of clean energy technologies in low-income countries, which is partly why many governments provide subsidies to offset some of the upfront (installation) costs. However, simple administrative rules might not fully account for economic geography, resulting in lower subsidies for remote areas. Using regression analysis on a rich dataset of adoption, cost and subsidy for about 4000 Nepalese Village Development Committees over 22 years, we show that administratively determined lumpsum subsidies disproportionately hurt remote communities. Simulations show that adjusting the subsidy spatially to reflect the geographic cost of living, can increase clean technology adoption. Thus, spatial targeting of subsidies is key to accelerating energy access in remote settings such as the Hindu Kush Himalaya.

1. Introduction

Universal access to clean and affordable energy is a global challenge, more severe for the more than two hundred million people residing in the Hindu Kush Himalaya. One such setting is Nepal, where more than two-thirds of Nepalese households still use solid cooking fuels and one in four households live in poverty [1, 2]. Because affordability is a key barrier to the adoption of clean energy technologies (CETs), the Nepalese Government implemented the Renewable Energy Subsidy Policy in 2000 to subsidize selected CETs such as biogas and solar home systems (SHS) [3]. However, within 200 km across its North-South distance, Nepal's geography ranges from 59 meters to 8,848 meters. This abrupt variation in elevation within a very short distance produces huge geophysical and ecological variations that interplay with development and socio-cultural practices to produce an extremely heterogeneous local (geographical) context. In an attempt to capture this enormous geographical variation of the country, the subsidy policies for both biogas and SHS have been differentiated by Nepal's three ecozones—the lowlands (Terai), Hills and the Mountains - and also by the households' remoteness. Before 2017, a household's remoteness was captured by its location within one of Nepal's 3,973 Village Development Committees (VDC) [4, 5]—the smallest administrative unit in Nepal. We limit our analysis up till 2015 because under a new constitution Nepal was restructured into a federal governance system with 753 local governments after 2015.

At the same time, the local context across Nepal has been changing rapidly, which we show has impacted the relative effect of the subsidy policy. For example, road networks have expanded considerably in recent decades, as has access to commercial centres [6]. To adjust to this changing context, the Government periodically revised their policies on subsidies for SHS and biogas as well as their categorization of each VDC. This policy revision resulted in VDCs being reshuffled within a category, as well as changing the subsidy amount for each category. Additionally, changes made in 2009, 2013 and 2016 (figure 1) resulted in spatio-temporal variations in the subsidies received by households across Nepal (see Supplementary Note 1).



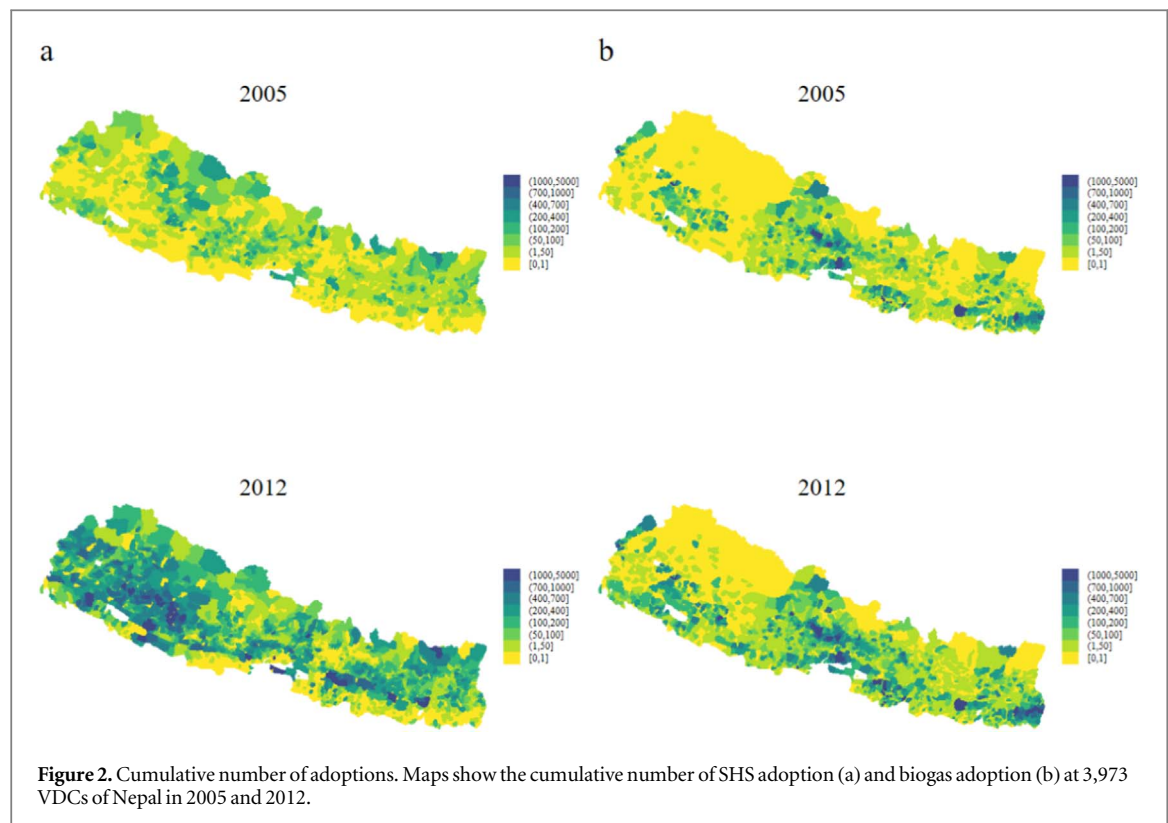
Despite the existence of subsidies, demand for subsidized SHS and biogas remains low across Nepal [7–9]. Critically, adoption is geographically clustered, leading to patchy progress in energy access [10]. Such patchy progress has led to a concern that the subsidies may have disproportionately benefited some places (e.g., VDCs) over others, unwittingly creating inequality in energy access [11–13]. Thus, policymakers are concerned about how to increase the effectiveness of these subsidies and reduce inequalities.

Consequently, we investigate the following questions: (i) does the value of a subsidy vary by geography? and (ii) can we accelerate the adoption of clean energy technologies by implementing targeted subsidy policies that account for economic geography? By focusing on the spatial dimension of subsidies, our paper investigates whether policy-induced variation causes spatial inequities in energy access and therefore whether spatial subsidies may then reduce disparities in energy access [13]. We do this by comparing two separate ways in which subsidy effectiveness can be measured across different locations to see if it helps explain adoption and the persistence of energy poverty.

1.1. Subsidies, costs, and adoption

In Nepal, full electrified VDCs are ineligible for SHS subsidies. All other VDCs are categorized as either (1) accessible, (2) remote or (3) very remote. In 2000, non-electrified accessible VDCs were eligible for a base subsidy of up to 8,000 Nepalese Rupees (NPR) [3], with remote and very remote VDCs being eligible for an additional 25% and 50% of this base, respectively. In 2009, the policy was revised with several VDCs in the North-West being upgraded from the remote to very remote category. At the same time, the subsidy amount was reduced, and then again in 2013 and 2016 to reflect the falling price of SHS in the international market. In 2016, a household in eligible VDC could only receive up to NPR 5,000 for a 10–20watt SHS - less than half of what was provided in 2000 for SHS of the same capacity.

From 2000 to 2015, roughly 680,000 units of subsidized SHS were installed, with a cumulative capacity of 13.7 MW in 2,137 eligible VDCs (see figure 2). On average, a VDC adopted 10.6 SHS per year with an average installed capacity of 244.5 watts. The average installation cost for SHS was NPR 17,813 out of which, households, on average, received a subsidy of NPR 6,571.



For a biogas plant, the subsidy policy is somewhat different. A typical biogas plant costs roughly NPR 47,500 to install, of which the average subsidy would cover NPR 13,722. Biogas subsidies began as early as July 1992. This was to help scale up a much-needed technology for agricultural households because it supplies clean energy using locally sourced manure [10]. In 2000, biogas subsidy was based on three features of VDCs - urbanization, road access and ecological belt. Thus, for a 6 cubic meter biogas plant, the three categories of subsidy would equal NPR7,000, NPR10,000 and NPR12,000, respectively. In 2009, the subsidy policy replaced the VDC categories by making a geographical distinction, namely: Terai, Hills, and Mountains and additional small subsidies were provided (a) in areas with low adoption rates and (b) to households from socially marginalized communities. More than 345,000 biogas plants were installed in 2,934 different VDCs from 1993 to 2015 (figure 2(b)). On average, every year 3.7 biogas plants are installed in a single VDC per one thousand households with an average capacity of 6.1 cubic meters.

1.2. Spatial-temporal variation of subsidy and installation cost

In figures 3(a) and (b), we plot the spatio-temporal variation of the subsidies and installation costs of both biogas and SHS. These figures show that while both subsidies and costs increase with elevation, the gap between subsidies and costs widens with elevation. This increasing gap indicates that households in higher elevation areas pay a higher effective costs for adopting SHS or biogas. Even though the subsidy amounts are higher for remote and mountainous areas, the subsidy offsets less of the cost of installation because of differences in the cost of living [7]. In figures 3(c) and (d), we show the same costs and subsidies over time. The figures show that the cost of SHS is decreasing, mainly influenced by the falling price of SHS technologies in the international market [14–16]. In our dataset, on average, SHS costs have reduced by almost half from NPR 18,247 in 2001 to NPR 9,320 in 2015.

In contrast to the case of SHS, the cost of biogas has continued to increase over time. On average a biogas plant cost NPR 31,830 in 1993, less than half the cost of NPR 78,543 in 2015. This is mainly because biogas is a local solution that needs local resources such as sand and labour to build a digester. The cost of these inputs has been increasing in more remote areas. For example, the labour wage in Nepal quadrupled from 1996 to 2010 [17, 18]. Recognising this, the government has been revising the subsidy amounts for biogas plants to adjust for the increasing installation cost. For example, in 2016, a household would receive an average of NPR 29,482 for a 6 cubic meter plant — more than three times what the subsidy was in 2000. Conversely, reflecting the lower cost of SHS globally, subsidies for SHS have been reduced across all geographic regions. These adjustments are reflected in figure 3 and show that the subsidies do follow the cost of the technologies over the years. However, the adjustments are far from perfect: while the gap between subsidy and cost has decreased for SHS, the gap has

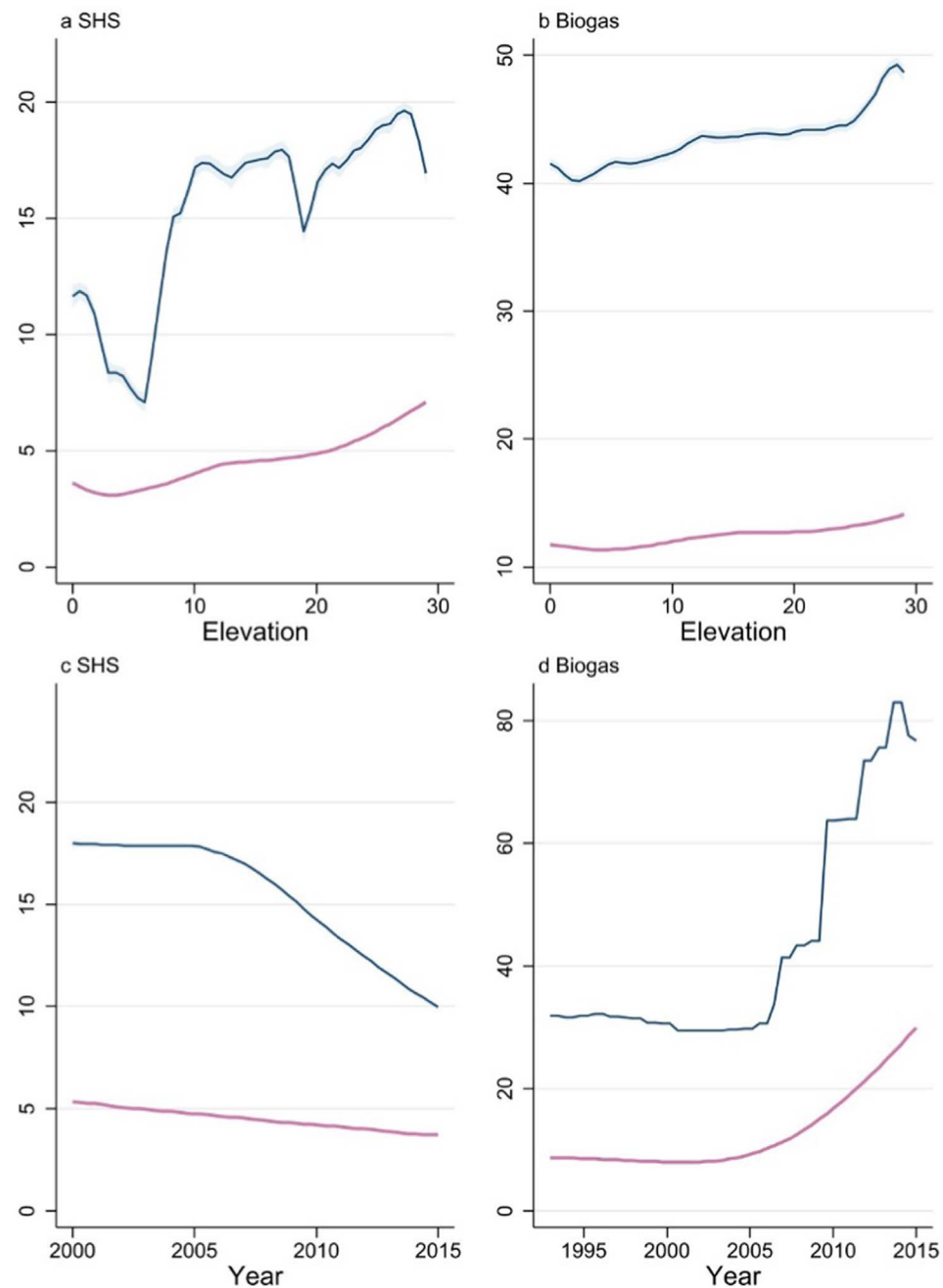


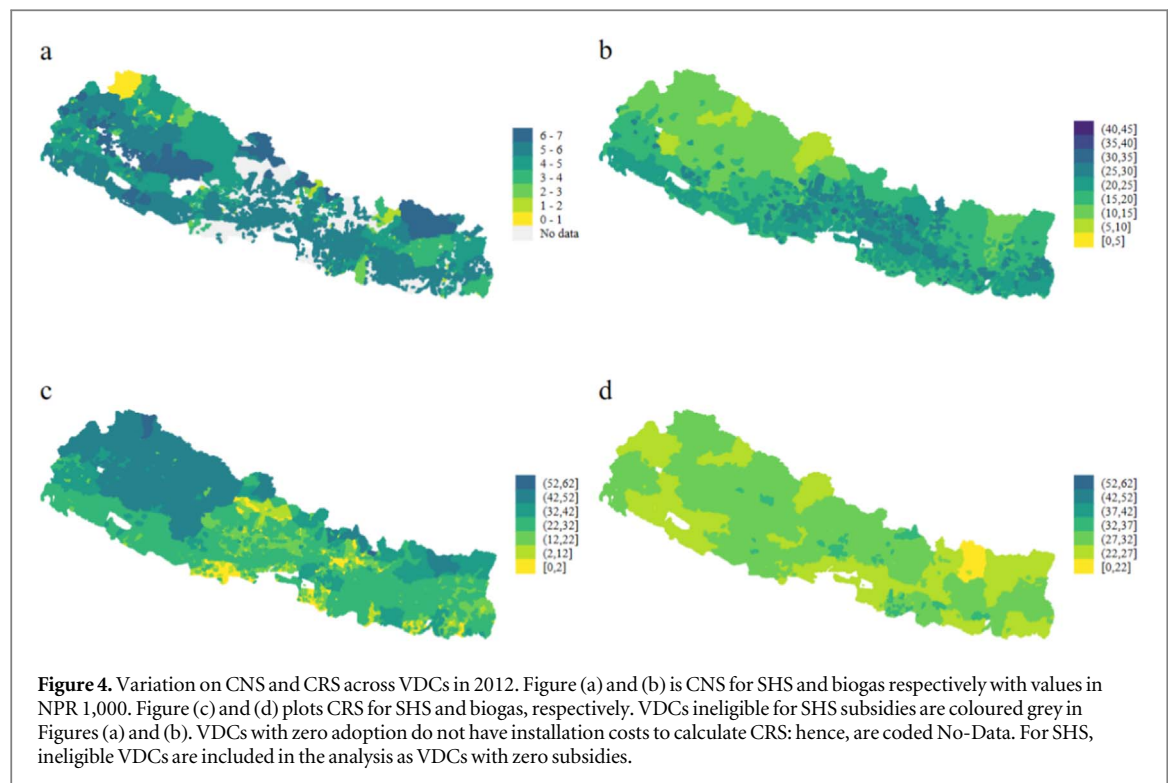
Figure 3. Spatio-temporal variation of subsidies (maroon) and installation costs (blue): Change in installation costs and subsidies over elevation (a), (b) in 2006, and (c) and (d) across years, for SHS and biogas. The costs and subsidies are in thousands of NPR.

increased for biogas. Such that, in 2000, the subsidy covered 24% and 26% of the installation costs for SHS and biogas, respectively. However, in 2011, the percentages were 41% for SHS and 23% for biogas. These examples demonstrate how small changes in subsidies in response to broader spatio-temporal variations in cost, have contributed to the spatial variation in any subsidy's ability to offset installation costs.

1.3. The household's expectation of a subsidy

Several studies in the past have investigated the effect of subsidies on household choices [19–22], focusing on the value of subsidies over time against the opportunity cost. Other studies have looked beyond the subsidy to factors such as the influence of peers, community groups and locational characteristics [23–28]. These studies suggest many factors influence adoption and the evaluation of subsidy policies is not new. However, the existing literature has rarely examined if it matters where the subsidy is received.

Consider how location affects the perceived value of the subsidy. Households choose among available biogas or SHS prototypes from listed sales agents, who deduct the lump sum amount of the subsidy from the sale price. Normally, the subsidy amount is collected by the agent or distributor directly from the government by showing



proof of sale and use (e.g., photos, signed certificates by households). Thus, when a household adopts, they should be attentive to the real value of the subsidy (not the nominal amount). This would be true if households are aware of the cost-of-living differences across space, which varies substantially across VDCs (see Supplementary figure 3 (available online at stacks.iop.org/ERC/4/101005/mmedia)).

For biogas, the subsidy level offered by the centralized distributor (typically located in the commercial centre) may not capture the true spatial cost because the cost of materials such as cost of labour or local building materials varies from point to point [17, 29, 30]. In this case, if households understand the local cost context (e.g., the cost index developed by the Local Bodies Fiscal Commission of Nepal), then they should (at least approximately) normalize the subsidy by this index. We compute a Cost Normalized Subsidy (CNS) by simply dividing the subsidy by the cost index (figures 4(a) and (b)). Then we test if CNS, which is spatially more appropriate, better explains adoption, especially in the case of biogas.

Second, the case of SHS is different because installing SHS does not require local resources or labour. Instead, SHS is supplied in ready-to-use boxes. In the case of SHS then, the actual sale price is likely most salient, and normalization by cost index less so. If so, a household may simply consider what proportion of installation cost is offset by the subsidy [22]. Therefore, we calculate the cost ratio subsidy (CRS) to see if there is a difference (figures 4(b) and (d)).

2. Method

2.1. Data

We used a dataset provided by the Alternative Energy Promotion Centre (AEPC) on Nepalese household adoption of SHS and biogas from 1993 to 2015. This dataset is created by technology promoters and sales agents (who deduct the subsidies when selling SHS and biogas to households to then claim subsidies from the AEPC). The claim is verified by AEPC for reimbursement and to maintain the records for auditing by the Auditor General of Nepal. This process means subsidy records are verified more than once.

As stated, the Biogas subsidy started in 1992 (July) and the SHS subsidy started in 2000 [3, 10]. Therefore, our data constitutes an unbalanced panel of adoption in the 3,973 VDCs, ranging from 1993 to 2015 for biogas and from 2000 to 2015 for SHS. For each variable, we sum, average or collapse at the VDC level—since it serves as our primary unit of analysis.

Our dataset has the year (of adoption), VDC (where the adoption occurred), subsidy amount, installation cost and capacity. To enhance our analysis, we merged several other datasets. The socio-economic information was obtained from the Nepal Housing and Population Census of 2001 and 2011. We used a road network map from the Department of Local Infrastructure and Agricultural Road and the Department of the Road to identify

areas with road access for 2001, 2006 and 2011 [31, 32]. For urbanization, we obtained historical records of municipalities from the Ministry of Federal Affairs and the General Administration of Nepal. We also combined the community forest user group (CFUG) data from the Department of Forest of Nepal. The fatalities during the decade long civil war were obtained from Uppsala Conflict Data Program [33].

2.2. Statistical estimation strategy

To exploit the variation in subsidies, installation costs, and adoption of SHS and biogas in the 3,973 VDCs between the period of 1993 to 2015, we used linear high-dimensional fixed effects models [34–36]. Since all data are aggregated at the VDC level, we modelled the aggregate adoption of each technology (j) as a function of the subsidy and other key variables. Note, we include fixed effects for VDCs (v), for the time trend (t), and for the VDC-trend (vt), to sweep out anything peculiar to the VDC, any secular trend across time, and any VDC specific time trend. Note, this annual trend (t) is different from any differences that are year (y) specific. Thus, our estimating equation is shown below.

$$APH_{jvy} = \alpha + \Gamma_v + \Gamma_t + \Gamma_{v*t} + \beta*subsidy_{jvy} + CI_{jvy} + X_{jvy} + \varepsilon \quad (1)$$

Where,

- APH_{jvy} is the adoption of technology j in v VDC in y year
- $subsidy_{jvy}$ is the subsidy for technology j in v VDC in y year,
- CI_{jvy} is the installation cost for technology j in v VDC in y year,
- X_{jvy} are other covariates
- Γ_v is VDC fixed effect,
- Γ_t is the secular time trend
- Γ_{v*t} is the VDC specific time trend
- ε is the regression error term.

We also provide additional details on the estimation strategy in SI Note 3(B).

To deal with the potential correlation between the subsidy and other unobserved unit-specific confounders (other variables that might also affect adoption), we use multiple fixed effects. As shown in figure 3, subsidy and adoption costs are changing in the same direction, hence, not controlling for cost would bias the estimates. Although subsidy is provided as a lump sum amount, the cost and subsidy may be behaviourally correlated as policymakers may be aware of the increasing cost over time. Therefore, we estimated the effect by excluding the CI_{jvy} but controlling the cost trend using district by year fixed effect. The estimated effects are positive and significant, with our preferred models having the almost same size as the effect. Adoption is a terminal action. Some VDCs may see a high rate of adoption that dries up potential adopters while other VDCs may see an increase in potential adopters due to population growth. Therefore, we use $PHH_{tv\chi_{(n-1)}}$, potential adopters to control for the influence of change in potential adopters at VDC. Potential adopter is calculated by subtracting the total adoption of j technology at that v VDC in a year before from the number of households in the VDC. We provide descriptive statistics of variables in Supplementary Note 4.

3. Results and discussion

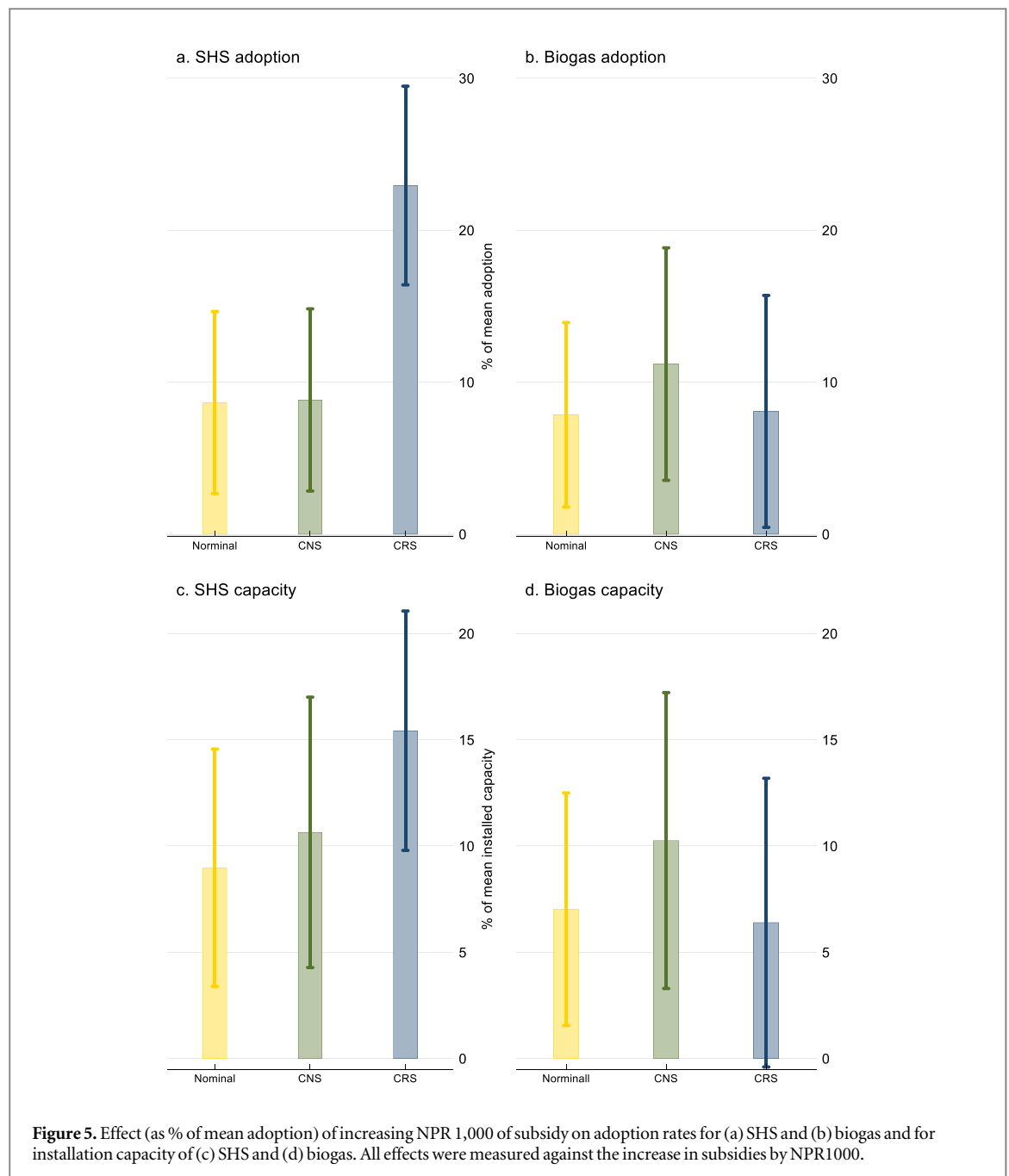
3.1. Comparison of the nominal and spatial adjusted subsidies

We model how subsidy impacts aggregate (VDC level) adoption of clean energy technologies. In figure 5 and Table 1, we present the three estimated effects: the percent increase in annual adoption because of an NPR 1,000 increase in (1) nominal subsidy, (2) CNS, and (3) CRS. Note that NPR 1,000 is roughly 22 percent and 8 percent of the mean SHS and biogas subsidy.

For SHS, we see that a subsidy of NPR 1,000 would change mean annual adoption by 9% nominally, by the same 9% in cost-normalized terms and 23% in cost-ratio terms. Other factors also matter such as installation cost, road access, and installed capacity of micro-hydro (all negatively associated with the adoption of SHS). Similarly, membership in community forest groups and family size are positively associated with SHS adoption. For biogas, a subsidy of NPR 1,000 would change the mean annual adoption by 8% nominally, by 11% in CNS terms and by 8% in CRS terms.

If our models correctly captured the household response to spatial values of subsidy, then we should also expect a similar effect on installed capacity. We report these findings in figures 5(c) and (d). For SHS, we found that the effect of nominal, CNS and CRS are 9%, 11% and 15% of the mean annual installed capacity. For biogas, the effects are 7%; 10% and 6% of the mean installed capacity. The detailed results are reported in Supplementary Note 5.

The results illustrate that the type of technology—SHS (ready-to-use) versus biogas (use local resources) matters. Figure 4 shows that the actual sale price of SHS—proxied in our analysis as CRS—had the biggest effect.



The figure also shows that for biogas, normalizing to reflect local costs had the highest effect. These results imply that the effect of spatially varying subsidy measures depends on the type of technology.

We conducted five robustness analyses to confirm our result (Supplementary Notes 6, 7 and 8). First, a correlation between the installation costs and subsidy could bias the estimates. So, we estimated the effect of subsidy without installation cost. Second, we estimated the effect of the subsidy on the total number of adoptions without normalizing it by population size to see if the subsidy increased VDC level adoption, irrespective of its market potential. Third, we deflated the value of subsidy (using inflation data from the World Bank) and re-estimated the model to check the consistency of estimates after inflation adjustments [37].

Fourth, we were concerned that the non-random assignment of subsidies created an endogeneity problem—i.e., higher subsidies are given to low adoption locations, inducing a form of circularity, or some unobserved factor was correlated with the subsidy. As shown in Supplementary Note 7, we accounted for many potential endogeneity challenges by using VDC, year and VDC-by-year fixed effects. Our results remained unchanged. Fifth and finally, we considered alternate specifications and subsample analyses (see Supplementary Note 8). Results from all these checks showed that our main estimates are broadly consistent and robust.

Table 1. Estimated effect of policy option on adoption.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Nominal	SHS CNS	CRS	Nominal	Biogas CNS	CRS
Subsidy	1.157*** (0.388)	1.181*** (0.388)	0.468*** (0.064)	0.274** (0.104)	0.390*** (0.131)	0.122** (0.057)
Installation cost	−0.389*** (0.073)	−0.345*** (0.063)	−0.261*** (0.051)	0.025 (0.019)	0.012 (0.020)	0.101*** (0.032)
Potential Adopter	0.004 (0.157)	0.007 (0.163)	−0.060 (0.138)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Dalit Hill (Proportion of population)	134.531 (91.719)	112.042 (96.455)	81.270 (121.344)	4.338 (19.194)	5.346 (19.415)	3.173 (19.403)
# of household members in community forest (cumulative)	3.544** (1.448)	3.519** (1.446)	3.615** (1.490)	0.445 (0.456)	0.456 (0.459)	0.410 (0.454)
Nepali as the main language (Proportion)	1.386 (25.265)	1.285 (25.893)	−0.243 (25.470)	6.445 (5.835)	5.904 (5.651)	6.324 (5.938)
MHP cumulative capacity (kW)	−0.248*** (0.059)	−0.256*** (0.061)	−0.230*** (0.057)	0.001 (0.008)	0.001 (0.008)	0.001 (0.008)
Average Household Size	0.003*** (0.000)	0.003*** (0.000)	0.001*** (0.000)	0.028 (0.057)	0.026 (0.057)	0.028 (0.057)
Proportion of households with a female as house- hold head	−470.331 (745.483)	−531.859 (758.313)	−1,408.916 (1,275.627)	37.951 (32.707)	37.462 (32.763)	37.507 (32.724)
Conflict caused death in District	0.039 (0.042)	0.039 (0.042)	0.098 (0.087)	0.012 (0.014)	0.012 (0.014)	0.012 (0.014)
1 if Access to Road	−3.154*** (1.173)	−3.291*** (1.166)	−3.173** (1.213)	0.126 (0.647)	0.109 (0.645)	0.168 (0.645)
Observations	63,388	63,388	59,028	89,028	89,028	89,028
R-squared	0.491	0.491	0.504	0.580	0.580	0.579
Controls	—	—	—	—	—	—
Household	Yes	Yes	Yes	Yes	Yes	Yes
VDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Secular time trend	Yes	Yes	Yes	Yes	Yes	Yes
VDC specific time trends	Yes	Yes	Yes	Yes	Yes	Yes

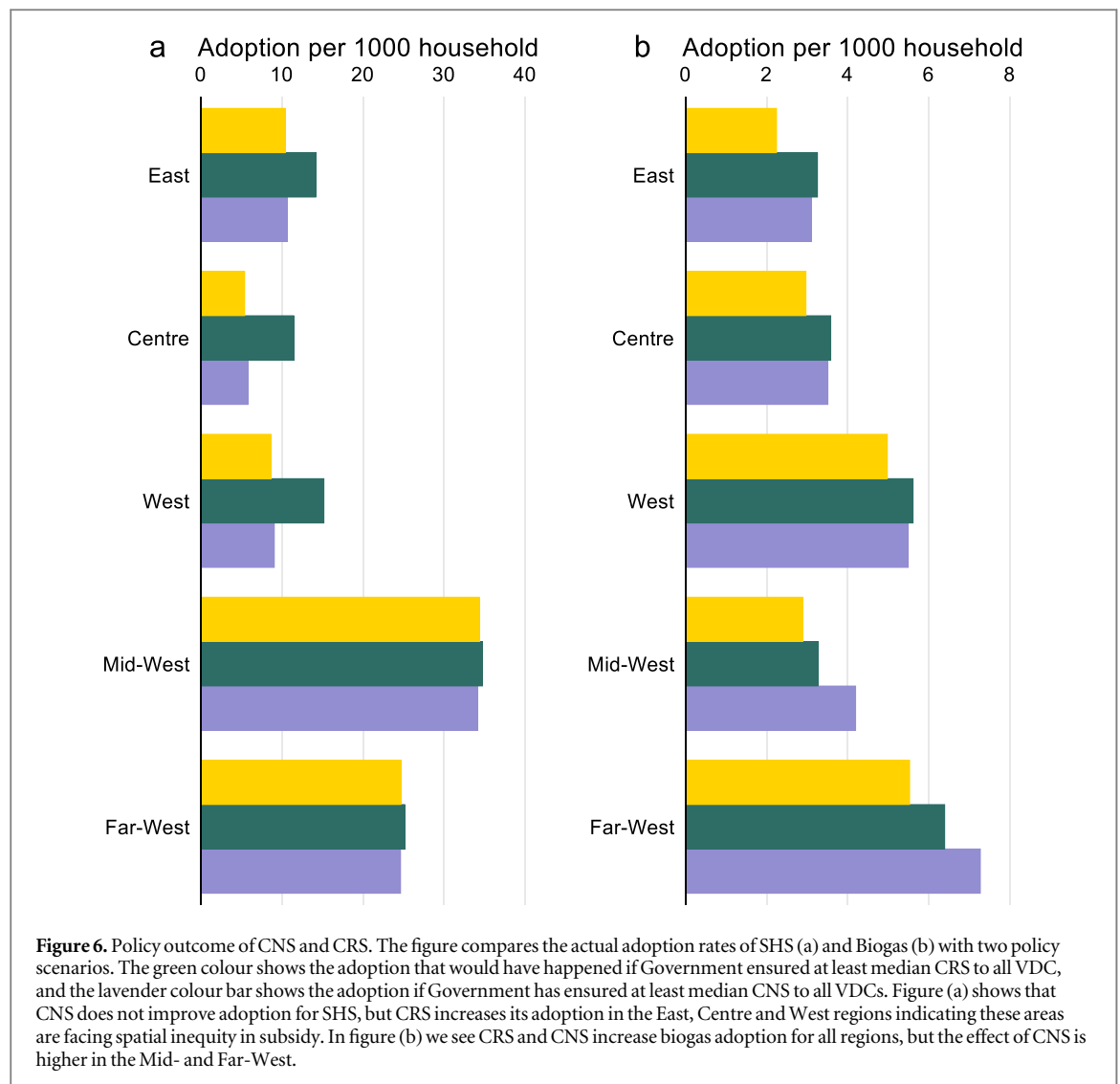
Note: The table presents the estimated effect of Nominal, CNS and CRS on adoption using a high dimensional fixed effect regression model. The 1–3 column is for SHS and 4–6 for biogas. The dependent variable is # of adoptions per 1,000 households per VDC per year. The first two columns present the estimates for the Nominal subsidy which is a mean subsidy at a VDC. Columns 3 & 4 present the estimates for CNS which is the mean subsidy divided by the cost index. The unit of CNS is a thousand NPR. Columns 5 & 6 present the estimates for the cost ratio. CRS is the subsidy as a percentage of the installation cost with the SHS being from 2000–2015 and biogas from 1993–2016. Robust standard errors in parentheses. Error clustered at the district level. ***p < 0.01, **p < 0.05, *p < 0.10.

3.2. Heterogenous effect of the spatial subsidy on adoption:

In theory, calibrating subsidies for spatial differences could lead to higher adoption in areas such as the Mountain belt and other remote areas, at least compared to nominal subsidies. To examine this question, we re-estimated the effects of three subsidy measures in various subsamples of VDCs. First, we considered VDCs with roads and without roads. Second, we considered VDCs in three ecological belts. Third, we considered VDCs in five development regions. As shown in Supplementary Note 9, compared to nominal and the CNS subsidy measure, the CRS subsidy had the greatest impact on SHS adoption in VDCs in the Mountains, without roads, and in the relatively impoverished Mid- and Far-West regions. Likewise, compared to nominal and the CRS subsidy measures, the CNS subsidy had the greatest impact on biogas adoption in VDCs without roads, in the Mountain belt and in the Far-West regions.

We conducted one additional thought experiment: what would happen if subsidies were increased to be at least equal to the median of CNS and CRS in VDCs receiving less than the median value of the subsidies? Figure 6 compares the actual adoption with the simulated adoption if the policy ensured at least a median CNS and CRS in all areas. The results show that while both would increase adoption, the outcomes vary by region and by technology.

We know that decentralized energy systems such as SHS and biogas are crucial for energy access in remote areas of the Himalayas [38] and that clean energy technology has the potential to improve human development



in low-income settings [26, 39]. In line with previous studies [40, 41], we found a positive association between subsidies and CET adoption in Nepal, finding that is contingent on where in space a household is located.

We also argue that spatially explicit subsidies should be technology specific. For example, SHS being a ready-to-use CET, the selling price by the dealer captures most of the associated costs. Hence, having a subsidy based on installation cost improves targeting household expectations. In contrast to SHS, however, biogas relies heavily on local resources, which are directly affected by VDC specific costs [42]. In this case, a local cost index is more appropriate for setting subsidy levels. Therefore, adjustments for both spatially varying costs and technology types can help to reduce energy access disparities.

While the paper utilizes large data sets, we could improve the analysis by using yearly data on variables such as cost index, historical road networks and grid expansion. It is also possible that several households may have adopted CETs without subsidy, but we only focus on those with subsidies.

4. Conclusion

By testing and comparing the spatial targeting of adoption and energy access, we show that applying spatial subsidies can help to address energy justice and energy access. Our results demonstrate that inequity in spatial subsidy and the resulting inequity in energy access is likely in countries where policies ignore economic geography [43]. Further, we test and show that these unequal spatial subsidies may be a reason for the low uptake of clean energy technologies [22].

However, we do recognise that in low-income countries with weak institutions, micro-level data is often unavailable, which is probably why policymakers design simple targeting rules. It is also likely that delivering spatially targeted subsidies faces implementation challenges on the ground. Nonetheless, we believe that ignoring spatially varying costs will continue to lead to inequality and poor energy access [44, 45]. Thus,

policymakers and funders must decide if the costs of collecting such micro-data and of implementing targeted subsidies are justified by the ability to reduce energy poverty, especially in remote hilly jurisdictions. Given the low uptake of subsidized technologies, future research could further investigate if other drivers of technology demand in remote areas also have spatial dimensions. Additionally, future research should consider if the same patterns hold for other technologies and geographies beyond Nepal.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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