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From Candles to Light: The Impact of Rural Electrification [*]

Irani Arráiz[†] Carla Calero [‡]

October 2014

Abstract

This paper studies the impact of access to electricity via solar-powered home systems (SHSs) in rural communities in Peru. Applying propensity score matching at the community as well as at the household level, the authors find that households with SHSs spend less on traditional sources of energy—candles and batteries for flashlights—and that the subsequent savings are commensurate to the fee for SHS use. People in households with SHSs spend more time awake, and women in particular change patterns of time use: they spend more time taking care of children, cooking, doing laundry, and weaving for their families, and less time in productive activities outside their homes (farming). Children spend more time doing homework, which has translated into more years of schooling (among elementary school students) and higher rates of enrollment (in secondary school). Although women spend less time farming and men more time on home business activities in households with SHSs than in those without, these changes have had no evident impact on income or poverty.

JEL Classification: *D04, I31, Q42, O12.*
Keywords: Rural electricity, impact evaluation, solar-powered home systems, Peru.

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1 Introduction

Electricity alone is not sufficient to spur economic growth, but it is certainly necessary. Access to electricity is crucial to human development: electricity is indispensable for basic activities that many in the world take for granted—lighting, refrigeration, and the running of household appliances. It is an alarming fact that, even today, hundreds of millions of people lack access to the most basic energy services. According to the International Energy Agency (IEA 2014) an estimated 1.3 billion people lacked access to electricity in 2014; this is nearly one-fifth of the worlds population.

The majority of those without electricity live in rural areas, but there are large variations in electrification rates across and within regions. The relatively high average access rates in certain regions mask problems in some subregions and individual countries. In Latin America, for example, where the electrification rate is 95 percent overall, there is the extreme case of Haiti, which has an overall electrification rate of 28 percent and a mere 9 percent in rural areas. In Peru the electrification rate reaches as high as 90 percent, but in rural areas such as Cajamarca this rate is only 18 percent—the countrys lowest rate. In some districts within Cajamarca up to 96 percent of the population lives without access to electricity.

Providing people in rural areas with access to electrification is a challenge. Most rural communities, as well as many peri-urban areas, are characterized by low population density and a disproportionately high percentage of poor households. Demand for electricity is often limited to residential and agricultural consumers; households that use electricity consume, on average, less than 30 kilowatt-hours (kWh) per month—and this is generally during peak evening hours. As a result, rural electricity systems invariably have much higher investment costs per client and per kilowatt-hour of sales than urban systems. Where the costs of reaching distant communities exceed a certain threshold level, it becomes cheaper to use off-grid sources of supply—mini grids served by mini hydro plants or diesel units, and solar home or community systems. But off-grid electrification faces the same challenge that may discourage grid extension into rural areas: high costs amid low demand.

The high costs of electricity supply in rural areas and the limited capacity of households to pay for service make it difficult to attract investment in rural electrification. A well-planned system of tariffs and subsidies must ensure sustainable cost-recovery while minimizing price distortions. To be financially sustainable, the utility companies serving poor, rural populations must match the costs of efficiently run service providers; any supplement to revenues received from consumers via subsidy funds should go to support efficiently run service providers; any supplement to revenues received from consumers via subsidy funds should go to support efficiently managed utility companies to avoid wasting public funds.

Strong institutions are needed to carefully plan and define the selection criteria for rural electrification projects, while regulatory procedures must be tailored to specific contexts. Challenges abound, including the need for sufficient technical and managerial capabilities, power generation, and the capacity to serve the existing grid-connected demand.

Despite these challenges, the need to increase access is widely recognized. Modern energy services enhance the life of the poor in countless ways. Electricity provides the best and most efficient form of lighting, extending the day and providing extra hours to study or work. Household appliances also require electricity, opening up new possibilities for communication, entertainment, heating, and so on. Electricity enables water to be pumped for crops, and food and medicine to be refrigerated. And modern energy can directly reduce poverty by raising a poor countrys productivity and extending the quality and range of its products—

thereby putting more wages into the pockets of the deprived. For instance, mechanical power can benefit agriculture (plowing and irrigation), food processing (otherwise, a laborious and time-consuming job), textiles, and manufacturing.

There is broad consensus in the research literature that rural electrification programs benefit consumers. But as Ravallion (2008) documents, many early papers suffer from a lack of methodological rigor that does not allow correlation and causation to be distinguished. A good number of recent papers, however—Khandker, Barnes, and Samad (2013); Chakravorty, Pelli, and Marchand (2014); Gonzalez and Rossi (2006); and Dinkelman (2011), among others—have used more robust econometric techniques to establish a clearer causal link between electrification and variables of interest.

Khandker, Barnes, and Samad (2009; 2013) examine the impact of connecting rural communities to the grid in Bangladesh and Vietnam, respectively. Both studies provide credible evidence that rural electrification boosts the income, expenditure, and education outcomes of households. The authors tackle the issue of causality by employing robust econometric techniques, such as propensity score matching (PSM), instrumental variables, and difference-in-differences (DID) to address endogeneity concerns. In Bangladesh the authors (2009) find an increase in annual per capita expenditure of 8.2 percent and an increase in annual total income of 12.2 percent. They also find that electricity leads to a significant improvement in completed years of schooling (0.13 years for girls) and study time for children in rural households—six more minutes for boys and nine more minutes for girls per day. In Vietnam the same authors (2013) find an increase in household income of 28 percent and an increase of household expenditure of 23 percent due to electrification. Household electrification increases school attendance by 6.3 percentage points (pp) for boys and 9.0 pp for girls. Commune electrification increases years of schooling—0.13 years for boys and 0.90 years for girls—for children aged 518.

Aguirre (2014), using an instrumental variable approach, finds that providing households with access to electricity in Peru boosts childrens study time by an extra 93 minutes per day. He uses the topographic distance between the population center and the nearest medium-voltage line as an instrument: this distance is correlated with a households likelihood of being connected to the grid but not with the study time of children at home.

Using a natural experiment in Argentina, Gonzalez and Rossi (2006) find evidence that providing access to a high-quality supply of electricity reduces the frequency of low birth weight (by 20 percent relative to the baseline proportion of 1 child in 100) and child mortality rates in children under five years of age caused by diarrhea and food poisoning (by 33.2 percent relative to the baseline proportion of 25 children in 10,000). The authors argue that electrified households ability to own a refrigerator—and reductions in the frequency and duration of blackouts—reduces the likelihood of food poisoning and increases the variety and quality of the mothers diet by improving her micronutrient consumption.

Dinkelman (2011) investigates the impact of domestic electrification on employment in rural South Africa, where in 1993—a year before the end of apartheid—more than 80 percent of households relied on wood for basic energy needs. By 2001, 2 million households were newly connected to the grid. Newly electrified communities have shifted away from using wood at home, toward electric cooking and lighting. Household electrification has operated as a labor-saving technology, releasing womens time spent in household work to allow them more productivity in the market. By exploiting community-level variation in the timing of electrification, results show that female employment rose by a significant 9 to 9.5 pp in treated areas, while the change in the male employment rate was not statistically significant.

Electrification increased employment for women on the extensive as well as on the intensive margin: women worked about 8.9 more hours per week in treated communities. These positive, significant changes for women are notable, since over the same period, national employment rates fell.

In a recent paper Chakravorty, Pelli, and Marchand (2014) examine not only the effect of grid connection, but also the quality of power supply on household incomes in rural India. The authors find that grid connection increased the nonagricultural incomes of rural households by about 9 percent during the study period 19942005. Moreover, higher-quality electricity—in terms of fewer outages and more hours of electricity per day—increased nonagricultural incomes by about 29 percent during the same period. This highlights the importance of providing high-quality power; the potential benefits of electricity are not realized by only connecting households to the grid.

Rud (2012) investigates the effect of electricity provision on industrialization using a panel of Indian states from 1965 to 1984. To do this and to address the endogeneity of investment in electrification, he examines the introduction of a new agricultural technology intensive in irrigation. The logic behind his analysis is that as electric pump sets are used to provide farmers with cheap irrigation water, the uneven availability of groundwater can be used to predict divergence in the expansion of the electricity network and, ultimately, to quantify the effect of electrification on industrial outcomes. Rud also presents a series of tests to rule out alternative explanations that could link groundwater availability to industrialization directly or through means other than electrification. Overall, he finds that the uneven expansion of the electricity network explains between 10 pp and 15 pp of the difference in manufacturing output across states in India.

In this paper we use household- and individual-level data to estimate the impact of electrification using solar-powered home systems (SHSs) in rural areas in the Department of Cajamarca in Peru. We take advantage of the expansion of the electrification program into a second set of communities to control for unobservable factors that may affect participation in the program and its impact. Applying PSM at the community as well as at the household level, we find that households with SHSs spend less on traditional sources of energy—candles and batteries for flashlights—and that the subsequent savings are commensurate to the electricity fee. People in households with SHSs spend more time awake, and women in particular change their daily patterns: they spend more time taking care of children, cooking, doing laundry, and weaving for their families and less time in productive activities outside their homes (farming). Children spend more time doing homework, which has translated in 0.4 more years of schooling (among elementary school children) and higher rates of enrollment (in secondary school).

The main contribution of this paper is to provide further evidence that rural electrification via SHSs is effective. Similar to other studies, we focus on outcomes such as energy expenditure, use of time, and outcomes related to education, health, and fertility. Evidence on solar programs is scarce: most of the literature studies the impact of rural electrification via grid connection. This study makes an important, early contribution to a promising topic: expanding electricity access in rural communities by utilizing solar technology.

The rest of the paper is organized as follows: section 2 describes the business model used by ACCIONA Microenergía Peru (AMP) to serve local communities, section 3 describes the dataset and presents the model used for the estimation, section 4 presents results, and section 5 concludes.

2 The Business Model of ACCIONA Microenergía Peru

ACCIONA Microenergía Peru (AMP) was created in January 2009 with the objective of increasing access to electricity and water in rural communities in the Department of Cajamarca that were not expected to be connected to the grid in the ensuing years. At the moment its activity centers on the provision of electricity.

In August 2009 AMP began the Luz en Casa (Light at Home) program to expand access to basic electricity services powered by solar-powered home systems (SHSs). The program operates in isolated and scattered communities located 3,0004,000 meters above sea level in the northern mountains of Cajamarca, in the Andes. The program involves beneficiaries in the installation and operation of SHSs, and collects a fee for service. SHSs have the capacity to generate between 7 and 10 kWh of direct current per month. This provides the power to light three low-energy bulbs for at least four hours a day, with the possibility of powering low-energy consumption appliances such as a TV, radio, and a mobile-phone charger.[1,2]

The contracts signed between AMP and its clients are for 20 years, equivalent to the duration of photovoltaic (PV) systems, and can be reduced in case the national electric grid reaches the area where the beneficiaries live. The client pays a monthly service fee, which includes the rent of the equipment, its maintenance for the next 20 years, and the amortization of the equipment. Thus, if some component breaks, it can be replaced during the 20 years of service. Under this model, the equipment belongs to AMP and the households do not have to bear the costs of purchasing a SHS, whose investment cost is about $700 in Peru. The monthly fee of about $3.50 (including taxes) is less than the average monthly energy costs that the households incurred before the program was implemented.[3]

When planning where to install SHSs, AMP identifies rural communities that are part of the Peruvian governments Rural Electrification Plan in geographical areas where there is a potential to deploy PV systems for domestic or communal use. Such areas are either inconvenient or impossible to connect to the grid, whether from a technical or economic perspective. AMP coordinates with the national and local government to enable the programs financial viability without compromising its focus on low-income populations.

The AMP business model aims to make electricity affordable for low-income populations—and sustainable over time, since the service fee covers any damage to system components. Because the selection of communities is based on the national governments Rural Electrification Plan and is agreed upon with local authorities, it is unlikely that AMPs fee-for-service model will become financially untenable because the grid is expanded unexpectedly—endangering the customer base before the supplier can recover its investment in the equipment. Other business models where households acquire—and in some cases finance—solar systems have the downside of making the service less attractive to low-income households. Cash purchases involve a high opportunity cost for low-income families and are less sustainable since any

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[1] The average consumption per capita in Peru was 1,248 kWh in 2011 (World Bank, World Development Indicators). The household consumption ranges between 53 kWh/month for an average household classified as socioeconomic level E (the poorest) and 1,050 kWh a month for an average household classified as socioeconomic level A (the wealthiest) (Organismo Supervisor de la Inversión en Energía, OSINERGMIN). When AMP offered a system able to generate more power at a higher cost, households expressed a preference for the more-economical, lower-power option.

[2] Because the system generates direct current (DC) and most appliances use alternate current (AC), households either have to use a power inverter or acquire DC-powered appliances.

[3] Households' average energy cost, according to a socioeconomic study conducted by AMP in 2010 of 600 households in the area of the program, was $5.07.

problem with the system must be paid for by the household.

After potential beneficiary communities have been identified, AMP coordinates awareness meetings with community members to explain its process. If there is enough interest, the community forms a Photovoltaic Electrification Committee (PEC). The committee seeks the active participation of users and also serves as the main communication vehicle between AMP and the community. The PEC members are elected by and among the beneficiaries themselves.

Prior to the installation of SHSs, AMP trains both PEC members and the users. During the training AMP informs all parties of their rights and duties, presents the capabilities and limitations of the PV system, and tells users how to respond to problems. The members of the PEC are given intensive training in the operation of the equipment, preventive maintenance tasks (visual inspection and verification of the proper operation of the SHS), and procedures for participating in the program (collection of fees, payments to AMP, communication of technical failures, inspections, safety, users rights, and commitments to AMP). The training is offered during the awareness meetings and at the time of installation. There is also a specific training for those users selected as local technicians, who are responsible for the installation (under the supervision of AMP staff) and corrective maintenance of the equipment. The relationship between the technicians and AMP is regulated by a professional services contract.

The PECs are responsible for collecting users fees, making payments at the AMP headquarters in Cajamarca, and distributing the corresponding receipts to customers. This management of payments is expensive because it involves, in many cases, the movement of a person from the community to Cajamarca, which carries with it the risk of theft. In some communities, the PEC charges an additional, small contribution of about \$0.35 that helps cover the treasurers cost of transportation; additionally, AMP waives the treasurers own service fee.

AMP receives a monthly fee of around \$3.50 per household, which accounts for about 20 percent of the regulated rate; the difference is borne by the Fondo de Compensación Social Eléctrico (FOSE, for its acronym in Spanish). FOSE is a fund (part of the social inclusion policy promoted by the Peruvian government) whereby higher-consumption users (who use more than 100 kWh/month) pay a monthly surcharge on their electricity bills to subsidize the rate of low-consumption users (100 kWh/month or less)—serviced by private operators investing in renewable, off-grid power in rural communities. These private investors must be authorized by the Supervisory Agency for Investment in Energy and Mining in Peru (Organismo Supervisor de la Inversión en Energía, OSINERGMIN) to be eligible for the subsidies.[4] Under this cross-subsidy mechanism, FOSE pays about 80 percent of the set rate to AMP, and the user pays only 20 percent.[5]

This complementary revenue mechanism is key to the fee-for-service business model implemented by AMP. It provides incentives for the private sector to carry out investments in rural electrification programs using renewable energy, and targets low-income populations without jeopardizing the ability of these households to benefit from the service due to high costs. The subsidy targets low-consumption users in rural communities, served by systems under 20 megawatts (MW).

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[4] Organismo Supervisor de la Inversión en Energía (OSINERGMIN) is the supervisory agency for investment in energy and mining in Peru. In 2011 AMP was recognized by OSINERGMIN as a public electricity service, making it the main supplier of electricity relying exclusively on SHSs.

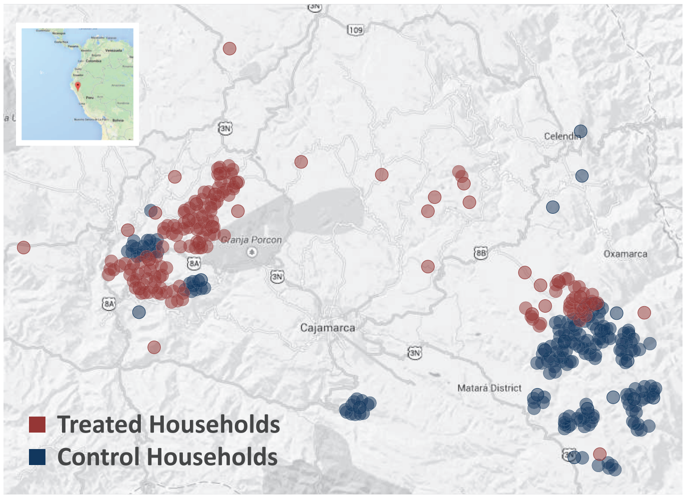
[5] AMP periodically sends all the required documentation to OSINERGMIN to receive the corresponding funds from Fondo de Compensación Social Eléctrico (FOSE). Unlike the fixed rates paid by customers, what AMP receives from FOSE varies according to the rate published monthly by OSINERGMIN. AMP has decided not to pass these changes on to its costumers (the rate that users would have to pay in 2014, according to the rates published by OSINERGMIN, is slightly more than \$3.50).

3 Research Methodology

3.1 Data

Our analysis draws on three sources of information: community-level data, administrative data on AMP's clients, and household-level data. We use the 2007 Peruvian Population and Housing Census to identify communities of 30 or more inhabitants. The census was conducted in October 2007 by the Instituto Nacional de Estadísticas e Informática (INEI, Peru's Office of Statistics). We also gained access to administrative data that identify the 600 households that received SHSs (hereafter referred to as solar panels) in 2010 and the communities where these households were located, as well as the 1,700 households that had signed a contract with AMP to receive a solar panel in 2013 and the communities where these new clients were located (figure 1). In addition, we conducted a household survey of all households that received a solar panel in 2010 and of a sample of the 1,700 households that signed a contract to receive a solar panel in 2013. The survey was conducted between June and August 2013, and the panels were installed right after the survey was completed.

Figure 1: Geographical Location of Treated and Control Households



Source: Authors.

The communities selected to participate in the program were located within a radius of 1.5 to 3 hours from the city of Cajamarca. AMP is headquartered in Cajamarca, so for logistical reasons the agency chose to work in communities that were neither too far from the city nor too close as to have access to electricity via the grid.[6] This criterion together with the financial resources needed to buy the equipment limit the number of communities and households that AMP can incorporate at a time.[7] AMP only invites communities to participate if AMP can guarantee that it will be able to provide these communities the service, if the communities

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[6] The National Plan for Rural Electrification has identified geographic areas where PV systems are good candidates for domestic or communal use, because it is inconvenient or impossible to connect these areas to large-scale power systems. This is the case of areas around the city of Cajamarca where households have low purchasing power, are geographically dispersed, and the road infrastructure is poor.

[7] The 600 solar panels incorporated in 2010 were financed via a grant from Fundación ACCIONA Microenergía while the 1,700 solar panels incorporated in 2013 were financed via a loan from the Inter-American Development Bank.

choose to participate, in the short term. There are no other criteria—such as the community poverty levels—used to select eligible communities.

The sample size was calculated using data from the annual household surveys conducted by INEI, limiting the data to nonelectrified communities located in the districts served by AMP. We set the sample size at 1,320 households (for a statistical power of 0.8 and a significance level of 0.05), which allowed us to measure impacts between 0.16 and 0.21 standard deviations for continuous variables and between 8 and 10.5 pp for discrete variables depending on the assumptions used for intercluster correlation.

3.2 Identification Strategy

We sought to estimate the impact of access to electricity—via solar panels—on household members' well-being, as measured by (i) spending on traditional sources of energy, (ii) use of time, (iii) education, and (iv) income (that is, the average impact of treatment on the treated, ATT). The causal effect of the program is the difference between the mean value of the outcome variable in two different scenarios: one in which the household participates in the program and one in which it does not. The main difficulty in estimating this causal effect is that households cannot simultaneously participate and not participate in the program, and therefore it is necessary to construct a counterfactual.

When the treatment is assigned randomly, the counterfactual is easily estimated by averaging the value of the outcome variable for the nontreated. But when the treatment is not randomly assigned, as in our case, participants and nonparticipants may differ in their characteristics—both observable and unobservable. Therefore, the simple comparison of averages between participants and nonparticipants does not provide an unbiased estimate for the causal effect. Moreover, it may be precisely the difference in those characteristics that explains why some households decide to participate in the program and others do not. Therefore, to identify the causal effect of the program, it is necessary to consider the effect of observable and unobservable characteristics on both the decision to participate and the outcome variables.

To account for observable characteristics, we use propensity score matching (PSM) to find, in a group of nonparticipants, those households who are similar to the participants in all relevant pretreatment characteristics. There are several alternative ways to match participants and nonparticipants and, in general, results depend on the matching algorithm and the variables included to estimate the propensity score.

We carried out two matching exercises. The first matching exercise uses data from the 2007 census at the community level to select, from the list of communities to receive service in 2013, the control community where we interviewed households that had signed a contract with AMP to get a solar panel in 2013. The second matching exercise uses data from the household survey to match households using a panel since 2010 with households that were going to get a panel installed immediately after the survey was administered between June and August 2013. We use temporary invariant variables in the second matching exercise to guarantee that household and individual characteristics were identical before the treatment. We match observations using the kernel algorithm with a small, uniform bandwidth in the common support. This approach lowers the variance, and the quality of the matching is controlled using a small bandwidth (Caliendo and Kopening 2008; Heinrich, Maffioli, and Vázquez 2010).

But matching methods are not robust against hidden bias that arises from the existence of unobserved variables that simultaneously affect assignment to the treatment and the outcome variable. We address these issues by considering only households that either signed a contract to get the service from AMP in 2010 (treated) or households that signed a contract to get the service in 2013 (controls) in communities being offered the service for the first time.[8] This suggests that these households share some unobservable characteristics. We also conducted sensitivity analysis to determine how strong an unmeasurable variable must be to influence the selection process so as to undermine the implications of the analysis.

After identifying the households in the control group (that is, nonbeneficiaries with the same probability of participation as beneficiaries), it was necessary to check that the observable characteristics of the control group were equal to the characteristics of the treatment group (those households that participated in the program in the first round of solar panel installation) (Rosenbaum and Rubin 1983). We tested this by: (i) a difference in mean test before and after the matching; and (ii) a joint test to ensure that all the characteristics in the control group were equal in mean to those in the treatment group.

We estimated the impact of the program by estimating the parameters τ_T in the following equation:

$$\tau_T = \frac{1}{N_T} \sum_{i \in T} (\widehat{Y}_i^1 - \widehat{Y}_i^0) \tag{1}$$

Where:

$$\widehat{Y}_i^1 = \begin{cases} Y_i & \text{if } Z_i = 1 \\ \dfrac{1}{\#\jmath_M(i)} \displaystyle\sum_{j \in \jmath_M(i)} Y_j & \text{if } Z_i = 0 \end{cases}$$

$$\widehat{Y}_i^0 = \begin{cases} Y_i & \text{if } Z_i = 0 \\ \dfrac{1}{\#\jmath_M(i)} \displaystyle\sum_{j \in \jmath_M(i)} Y_j & \text{if } Z_i = 1 \end{cases}$$

and Z_i is the treatment indicator for each unit $i = 1, ...N$; Y_i is the potential outcome for unit i; and $\jmath_M(i)$ is the set of indices for the $\#\jmath_{M(i)}$ matches for unit i found around the bandwidth defined in the algorithm.

We calculate bootstrapped standard errors for the estimates to account for the two step matching procedure. Because the kernel-based matching estimator is asymptotically linear, the bootstrap provides a valid inference for the standard errors (Abadie and Imbens, 2008).

4 Results

4.1 Participation Model

As mentioned above, we estimate the effect of the program using matching methods. The balance in the observable characteristics of the first matching exercise, intended to select the communities to be used as controls from the list of communities to be served in 2013, is presented in table 1. In general, the census variables do not display statistically significant differences in mean values. Only in a few cases are differences obvious: wall materials, or the presence of a radio, TV, or cell phone. This evidence reflects that the preintervention characteristics of the control and treated communities that resulted from the matching exercise are similar.

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[8] Some households that signed the contract in 2013 were located in communities where AMP was extending the service initially provided in 2010.

Table 1: Matching at the Community Level, Census 2007

Variables	Mean		t-stat†	
	Treated	Control	t	p>| t |
No. of houses in the community	48.182	58.393	0.787	0.435
Dwelling characteristics				
Detached house	0.965	0.923	-1.013	0.316
No. of rooms	2.027	1.862	-1.383	0.173
Walls other than bricks or concrete block	0.903	0.961	2.444	0.018**
Dirt floor	0.986	0.985	-0.110	0.913
Water via public distribution network	0.333	0.458	1.271	0.210
Sewerage system	0.003	0.014	1.028	0.309
Septic tank	0.667	0.673	0.074	0.941
Dwelling without sewage disposal	0.322	0.310	-0.171	0.865
Household characteristics				
Number of household members	4.336	4.227	-0.685	0.497
Home with electricity	0.001	0.029	1.356	0.182
Home with radio	0.868	0.822	-1.764	0.084*
Home with TV	0.004	0.033	2.499	0.016**
Home with refrigerator	0.000	0.001	0.884	0.381
Home with cell phone	0.101	0.030	-2.432	0.019**
Home uses firewood to cook	0.970	0.929	-1.112	0.272
Home with chimney	0.046	0.084	0.900	0.373
Household head characteristics				
Indigenous household head	0.003	0.001	-1.357	0.181
Literate	0.782	0.792	0.493	0.624
Years of schooling	3.938	4.022	0.407	0.686
Employee	0.022	0.022	-0.015	0.988
Laborer	0.143	0.127	-0.343	0.733
Independent worker	0.716	0.720	0.059	0.954
Unpaid worker	0.119	0.111	-0.128	0.899
Household worker	0.000	0.010	1.203	0.235
Household head works	0.710	0.612	-1.384	0.173

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%.

We then estimate a model of participation in the program, using a logit regression with data from the household survey, and construct a control group of nonbeneficiary households with similar characteristics as beneficiary households. The explanatory variables we include in this model are dwelling characteristics, household characteristics, household head characteristics, and household member characteristics. These variables are expected to explain the likelihood of entering into the program, since poorer households are less likely to have access to electricity and more likely to be interested in becoming AMP's clients. Including these variables guarantees that members of both treatment and control households have similar productive activities and that dwellings have similar living conditions.

Table 2 shows the balance in the observable characteristics after the matching. After the matching, the equality of means in the treated and nontreated groups cannot be rejected for any of the variables. We also observe a reduction in the mean and median bias of the observable variables included in the participation model after matching between treatment and control groups: from 14.9 to 2.4 (mean bias) and from 13.3 to 1.8 (median bias). Moreover, the pseudo R2 from a probit of treatment status on all the variables decreases from 0.140 to

0.008, and the corresponding p-value of the likelihood-ratio test of the joint insignificance of all the regressors increases from 0 to 0.999, indicating that after the match our regressors are not able to determine which households received solar panels in 2010 and which households were to get them in 2013. Therefore, treated and untreated households in the matched sample are indistinguishable from each other across the variables included in the participation model.

Table 2: Matching at the Household Level

Variables	Mean			t-stat†	
	Treated	Control	%bias	t	p>| t |
Number of household members	3.992	3.960	1.8	0.23	0.816
Detached house	1	1	.	.	.
No. of rooms	2.552	2.522	2.4	0.33	0.741
Walls (other than bricks or concrete block)	0.997	0.996	1.6	0.22	0.822
Dirt floor	0.995	0.999	-4.9	-1.16	0.248
Kitchen	0.745	0.714	7.2	0.97	0.331
Water via public distribution network	0.496	0.517	-4.2	-0.57	0.572
Sewerage system	0.008	0.004	3.8	0.64	0.525
Septic tank	0.879	0.892	-3.5	-0.53	0.596
Dwelling without sewage disposal	0.113	0.104	2.5	0.38	0.702
JUNTOS	0.086	0.076	3.4	0.47	0.639
Home with electricity	0.003	0.001	2.4	0.66	0.512
Home with radio	0.954	0.956	-0.9	-0.11	0.911
Home with TV	0.043	0.046	-1.7	-0.22	0.826
Home with refrigerator	0	0	.	.	.
Home with cell phone	0.517	0.511	1.4	0.19	0.852
Home with fixed phone	0	0	.	.	.
Home uses firewood to cook	0.997	0.997	0.1	0.01	0.989
Home with chimney	0.528	0.515	2.7	0.36	0.718
Household head gender (female)	0.166	0.165	0.3	0.04	0.970
Household head age	48.319	48.609	-1.8	-0.25	0.802
Indigenous household head	0.005	0.005	0.6	0.14	0.892
Literate	0.828	0.802	6.9	0.92	0.357
Years of schooling	3.509	3.473	1.6	0.22	0.822
Household head works	1	1	.	.	.
Farmer	0.895	0.908	-4.3	-0.57	0.569
Unskilled worker	0.059	0.062	-1.3	-0.17	0.868
Employee	0.008	0.007	1.3	0.22	0.830
Laborer	0.054	0.057	-1.8	-0.23	0.822
Independent worker	0.912	0.909	0.8	0.10	0.920
Unpaid worker	0.027	0.026	0.2	0.03	0.978
Household worker	0	0	.	.	.

Source: Authors' own calculations.

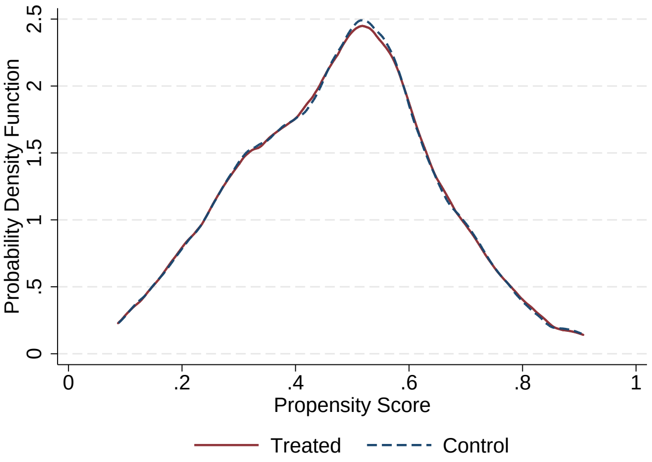
Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%.

Figure 2 presents the distribution of the propensity score for beneficiaries and nonbeneficiaries in the matched sample.

4.2 Impact of the Program on Household Well-Being

We estimate the effect of the program using equation (1). The treatment variable is an indicator variable equal to one for households that obtained a solar panel in 2010, and equal to zero for households that obtained a solar panel in 2013. The results capture the impact of

Figure 2: Distribution of the Propensity Score, Matched Sample



Source: Authors' own calculations.

the use of solar panels during an average of two years and nine months.

4.2.1 Spending on Energy

Data from the survey indicate that households with panels use them mainly for lighting: 100 percent of households used the panels for lighting purposes, while relatively few used the systems to charge their cell phones (19 percent), to watch TV (5 percent), and to listen to the radio (4 percent). The fact that solar panel users need to either use a power inverter or acquire DC-powered appliances may limit their use of the panels to power these devices.

Table 3 shows the estimates of equation (1) for a set of variables related to spending on energy. We used data from 1,329 households (548 treated and 781 controls); the matched sample included a total of 1,008 households (399 treated and 609 controls).

Our estimations confirm the positive impact of treatment on traditional spending on energy: a smaller proportion of households with solar panels bought candles (76 pp less) and batteries for lighting (7.3 pp less) than those without solar panels. They also spent less money on candles (7.1 soles) and batteries for lighting (3.0 soles). While these savings seem small, they are enough to cover the fee that households pay to use solar panels—10 soles.

There is no difference in the percentage of households that bought fuel for lighting purposes or in their expenditure on fuel for lighting, but the proportion of households that used fuel for lighting was less than 1 percent. The results also show that, consistent with the households' use of solar panels (only 4 percent of households use the panels to power a radio), there was no difference between groups in the expenditure on batteries for radios.[9]

Also, fewer households with solar panels bought firewood—34.5 pp—and those that did spent less than their peers without solar panels (by 13 soles overall). These results are driven by changes in how household members used their time, which is discussed below.

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[9] As noted earlier, because the system generates direct current (DC) and most appliances use alternate current (AC), households either have to use a power inverter or acquire DC-powered appliances, either of which may prove to be a large investment.

Table 3: Spending on Energy (Previous Month)

Dependent variable	Mean		Diff.	Bootstrap	t-stat†	Critical $\Gamma^{\ddagger}$
	Treated	Controls		S.E.		(hidden bias)
% of households who bought candles	0.177	0.937	-0.760	0.029	-26.53***	(-) > 2
Exp. on candles for lighting in soles	1.230	8.292	-7.062	0.579	-12.20***	(-) > 2
Exp. on candles for religion in soles	0.038	0.459	-0.421	0.247	-1.71*	(-) > 2
Quantity of candles bought	2.981	35.134	-32.153	1.407	-22.86***	(-) > 2
% of households who bought batteries	0.874	0.947	-0.073	0.022	-3.32***	(-) > 2
Exp, on batteries for lighting in soles	0.194	3.166	-2.972	0.178	-16.68***	(-) > 2
Exp. on batteries for radio in soles	3.519	3.515	0.004	0.212	0.02	(-) > 2
Quantity of batteries bought	2.230	3.748	-1.518	0.212	-7.16***	(-) > 2
% of households who bought coal	0.011	0.003	0.008	0.006	1.24	(-) > 2
Exp. on coal in soles	0.269	0.003	0.266	0.270	0.99	(-) > 2
% of households who bought fuel	0.003	0.006	-0.004	0.008	-0.48	(-) > 2
Exp. on fuel in soles	0.011	0.107	-0.096	0.114	-0.84	(-) > 2
% of households who bought firewood	0.651	0.996	-0.345	0.025	-13.98***	(-) > 2
Exp. on firewood in soles	6.135	19.099	-12.964	3.625	-3.58***	(-) > 2

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

The potential presence of selection bias is a source of concern. We ran sensitivity analysis for the matching estimator using Rosenbaum bounds to determine the critical level of Γ at which we would have to question the results.[10] That critical value quantifies the "worst case" effect that an unobservable variable would need to have to cause the odds ratio of treatment assignment to differ between treatment and control cases (in otherwise similar cases, in terms of the observable variables included in the participation model). The value not only quantifies the effect of an unobserved variable on the odds ratio of treatment assignment, but assumes that this variable's effect on results would be so strong as to almost perfectly determine whether the result would be bigger for the treatment (overestimation of treatment effect) or control (underestimation of treatment effect) case in each pair of matched cases in the data.

The critical level of Γ at which we would have to question the results of a positive effect on a reduction on spending on energy is above 2 in all cases; Aakvik (2001) argues that $\Gamma = 2$ "must be considered to be a very large number" because it implies that two subjects with the same observable characteristics differ in their odds of participating in a program by a factor of two, or 100 percent, and that this is unlikely given that the participation model adjusts for many important background characteristics. The sensitivity analysis presented in table 3 was done under the assumption that any unobservable variable that made households more likely to participate in the program in 2010 also made them more likely to spend less on energy. In the case of reduced spending on candles for lighting, for example, the magnitude of hidden bias required to upset the result is extremely high: Γ equal to 24 for the result not being significant at 10 percent, and to 21 for it not being significant at 5 percent. This magnitude ($\Gamma = 21$) is

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[10] The sensitivity analysis is done using matched pairs—one near neighbor matching algorithm. See Becker and Caliendo (2007) and DiPrete and Gangl (2004).

equivalent to the combined effect of increasing the average education of the household head by 14.5 years, increasing the share of employed household heads by 99.2 pp (so all of them are employees rather than independent workers, laborers, or nonpaid workers), reducing the average age of the household head by 18.3 years, reducing the proportion of dwellings with dirt floors by 99.5 pp (so all dwellings have concrete or tile floors), reducing the proportion of households that cook with firewood by 99.7 pp (so none use firewood), and reducing the household size by three persons. The assumption is that an unobservable variable—equivalent to the combined effects described above—causes the odds ratio of treatment assignment to differ between treatment and control cases, and that the households more likely to participate in 2010 were also more likely to spend less on candles. After the sensitivity analysis we can say that these results seem robust to the possible presence of selection bias.

4.2.2 Use of Time

Table 4 shows the estimates of equation (1) for a set of variables related to use of time and disaggregated by gender.[11] We used data from 1,421 economically active men, 595 treated and 826 controls; the matched sample had a total of 1,090 men, 435 treated and 663 controls. For women we used data from 1,246 economically active women, 508 treated and 738 controls; and the matched sample had a total of 972 women, 373 treated and 599 controls

Members of households with solar panels spent more time awake than members of households without solar panels—on average, 25 more minutes in the case of men and 42 more minutes in the case of women. And although the percentage of men and women engaged in productive activities outside their homes did not vary between groups, the time spent in these productive activities declined in the case of women: women in households with panels spent 1 hour and 38 minutes less in productive activities outside their homes than women in households without panels—a difference that is due to a reduction in the time spent on agricultural activities. Results also show that a larger proportion of women spent time working on their home businesses, and a large proportion of both men and women spent time engaged in various activities—including home businesses—without receiving any payment. A larger percentage of men spent time working in their home, and spend more time in these activities, in households with panels than in those without. These changes, however, have not affected overall household income (table 5). We cannot find any impact of the program on income per capita or poverty. There is also no obvious impact on the income generated either by men or women—even though women in households with solar panels were spending less time on farming activities and men more time on their home businesses.

Table 6 lists results related to the use of time on other (nonpaid) activities. For this analysis we used data from 1,674 men aged 12 and older, 732 treated and 942 controls; the matched sample had a total of 1,280 men, 535 treated and 745 controls. We used data for 1,821 women aged 12 and older, 853 treated and 968 controls; the matched sample had a total of 1,430 women, 659 treated and 771 controls. Women in households with solar panels spent more time weaving (11 minutes per day) than women in households without panels. They also spent more time on domestic chores such as cooking (27 minutes), doing laundry (12 minutes), and collecting firewood (6 minutes). They spent more time taking care of children (26 minutes) and taking care of themselves (9 more minutes on grooming). Men spent more time reading (4 minutes), collecting firewood (8 minutes), and taking care of themselves (12

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[11] The survey collected data on how every household member aged 7 and older spent the previous 24 hours, which composed a regular day of work or school.

Table 4: Use of Time: Productive Activities

Dependent variable	Mean		Diff.	Bootstrap	t-stat†	Critical Γ‡
	Treated	Controls		S.E.		hidden bias
Men that spent time...						
Eating, sleeping, and resting (%)	1.000	0.999	0.001	0.001	0.86	(-) > 2
Eating, sleeping, and resting (minutes)	643.924	669.147	-25.223	8.362	-3.02***	(-) 1.2-1.3
In productive activities (%)	0.971	0.977	-0.006	0.012	-0.49	(-) > 2
In productive activities (minutes)	450.549	465.454	-14.905	14.528	-1.03	(-) > 2
In agricultural activities (%)	0.798	0.840	-0.042	0.032	-1.27	(-) 1.7-1.8
In agricultural activities (minutes)	291.327	318.592	-27.265	17.834	-1.53	(-) 1.3-1.4
In animal husbandry (%)	0.664	0.688	-0.024	0.037	-0.64	(-) 1.2-1.3
In animal husbandry (minutes)	102.579	107.990	-5.411	8.739	-0.62	(-) > 2
In their home business (%)	0.034	0.018	0.016	0.011	1.41	(-) 1.0-1.1
In their home business (minutes)	13.577	5.469	8.108	4.187	1.94*	(-) > 2
Working w/o pay (%)	0.131	0.061	0.070	0.023	3.11***	(-) > 2
Working w/o pay (minutes)	28.540	15.380	13.160	6.299	2.09**	(-) > 2
Women that spent time...						
Eating, sleeping, and resting (%)	0.998	0.999	-0.001	0.002	-0.57	(-) > 2
Eating, sleeping, and resting (minutes)	642.071	684.440	-42.368	9.995	-4.24***	(-) 1.3-1.4
In productive activities (%)	0.947	0.964	-0.017	0.018	-0.99	(-) 1.5-1.6
In productive activities (minutes)	252.081	349.706	-97.625	16.089	-6.07***	(-) 1.5-1.6
In agricultural activities (%)	0.445	0.557	-0.112	0.045	-2.47**	(-) 1.5-1.6
In agricultural activities (minutes)	88.576	150.424	-61.848	13.444	-4.60***	(-) 1.7-1.8
In animal husbandry (%)	0.881	0.877	0.004	0.029	0.13	(-) 1.1-1.2
In animal husbandry (minutes)	135.252	147.857	-12.604	9.582	-1.32	(-) > 2
In their home business (%)	0.056	0.027	0.029	0.017	1.71*	(-) > 2
In their home business (minutes)	12.463	12.627	-0.164	5.680	-0.03	(-) > 2
Working w/o pay (%)	0.068	0.028	0.040	0.020	2.05**	(-) > 2
Working w/o pay (minutes)	11.217	6.964	4.253	4.611	0.92	(-) > 2

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

minutes). The increased time spent on collecting firewood indicates that households with solar panels collected more firewood for free and consequently needed to buy less, saving some money as shown previously.

Most of these results are robust to the possible presence of selection bias. But some are sensitive to possible deviations from the identifying unconfoundedness assumption—for example, results related to the proportion of men that spent time on their home businesses or reading. In the first case, the magnitude of hidden bias that would undo the hypothesis test that supports the result—Γ equal to 1.3 for the result becoming significant at 5 percent (and equal to 1.1 for becoming significant at 10 percent)—is equivalent to the effect of an additional 7.6 years of schooling. The assumption is that the treatment effect on the proportion of men that spent time on their home businesses is underestimated, and that households more likely to participate in 2010 were also more likely to have men spending less time on their home businesses. In the second case, the magnitude of hidden bias that would undo the hypothesis test that supports the result—Γ equal to 1.1 for the result to become not significant at 5

Table 5: Income and Poverty

Dependent variable	Mean		Diff.	Bootstrap S.E.	t-stat†	Critical $\Gamma^{\ddagger}$ (hidden bias)
	Treated	Controls				
Monthly income per capita	194.664	188.128	6.536	17.159	0.38	(+) > 2
% of poor households	0.815	0.802	0.012	0.031	0.39	(-) 1.7-1.8
% of vulnerable households	0.978	0.987	-0.008	0.010	-0.91	(-) > 2
Monthly personal income	303.715	312.977	-9.261	22.490	-0.41	(+) > 2
Monthly personal income (men)	456.791	428.641	28.151	39.983	0.70	(+) > 2
Monthly personal income (women)	140.913	172.343	-31.430	23.058	-1.36	(-) 1.2-1.3

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

percent (and equal to 1.2 for the result becoming not significant at 10 percent)—is equivalent to the effect of an additional 2.8 years of schooling. The assumption is that the treatment effect on the time men spent reading is overestimated, and that households more likely to participate in 2010 were also more likely to include men who read more.

4.2.3 Children and Education

The patterns of how children used their time also changed, and this could have the largest impact in the long run.[12] Table 7 reports the impact of solar panels on study time and educational outcomes for school-age children. We present the results for the entire sample (children aged 7-18) and for two subsamples: children aged 6-14 (elementary school), and aged 11-18 (middle and secondary school).[13]

Thanks to electricity, children now spend more time doing homework (9 minutes more per day, table 7).[14] Although the same proportion of children are enrolled in school, attend school, and do homework—and spend the same time in class—children in households with panels have gained an edge in terms of years of schooling: a difference of 0.4 years of schooling for children enrolled in elementary schools and who have been exposed to electricity for an average of two years and nine months.[15] This difference cannot be attributed to the children's age or school location—travel time to school is statistically the same for both groups. Moreover, although the percentage of children that completed elementary school is the same in both groups, rates

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[12] For this analysis we used data from 1,345 children aged 6 to 18 years, 647 treated and 698 controls; the matched sample had a total of 1,037 children, 497 treated and 540 controls.

[13] We established these age groups to account for children who fell behind or for children who were ahead of their grade level: 71.4 percent of children in elementary school are at their grade level while only 58.6 percent of children in secondary school are at their grade level; 97.8 percent of children enrolled in primary school are between ages 6 and 14, while 99.5 percent of children enrolled in secondary school are between ages 11 and 18.

[14] Teachers who live and teach in communities served by the project mentioned that they have noticed an improvement in the school performance of children in households with solar panels, which allows the teachers to demand more from them in terms of academic performance. Teachers also mentioned they now can spend more time preparing for class, thanks to the panels they have installed in their own houses.

[15] We believe the difference is due to the extra time they devote to doing homework, but more importantly to the quality of the light they use while doing their homework. If the teachers perception of an improvement in the school performance of children in households with solar panels is true, a more demanding academic environment would also contribute to this difference.

Table 6: Use of time: Other Activities

Dependent variable	Mean		Diff.	Bootstrap	t-stat†	Critical Γ‡
	Treated	Controls		S.E.		hidden bias
Men that spent time...						
Weaving (%)	0.007	0.009	-0.002	0.007	-0.27	(+) 1.4-1.5
Weaving (minutes)	0.511	1.320	-0.809	1.279	-0.63	(+) > 2
Reading (%)	0.220	0.171	0.049	0.029	1.72*	(+) 1.2-1.3
Reading (minutes)	12.944	9.422	3.522	1.781	1.98**	(+) 1.1-1.2
Taking care of children (%)	0.180	0.153	0.027	0.028	0.95	(+) 1.5-1.6
Taking care of children (minutes)	9.721	7.381	2.339	1.740	1.34	(+) > 2
Collecting firewood (%)	0.387	0.353	0.034	0.035	0.98	(+) 1.5-1.6
Collecting firewood (minutes)	32.794	24.624	8.171	3.604	2.27**	(+) 1.1-1.2
Cooking (%)	0.062	0.071	-0.010	0.019	-0.51	(+) 1.5-1.6
Cooking (minutes)	7.934	7.127	0.807	2.446	0.33	(+) > 2
Doing laundry (%)	0.062	0.062	0.000	0.017	-0.03	(+) 1.2-1.3
Doing laundry (minutes)	4.391	3.481	0.910	1.235	0.74	(+) 1.1-1.2
On personal care (%)	0.978	0.956	0.022	0.012	1.75*	(+) 1.2-1.3
On personal care (minutes)	42.896	31.197	11.699	2.020	5.79***	(+) 1.9-2.0
Women that spent time...						
Weaving (%)	0.540	0.440	0.100	0.046	2.18**	(+) 1.1-1.2
Weaving (minutes)	67.181	56.146	11.035	5.693	1.94*	(+) 1.2-1.3
Reading (%)	0.125	0.122	0.003	0.025	0.12	(+) 1.7-1.8
Reading (minutes)	6.859	6.310	0.549	1.559	0.35	(+) > 2
Taking care of children (%)	0.756	0.663	0.094	0.033	2.83***	(+) 1.1-1.2
Taking care of children (minutes)	69.278	42.878	26.400	5.117	5.16***	(+) 1.4-1.5
Collecting firewood (%)	0.341	0.304	0.037	0.030	1.21	(+) 1.7-1.8
Collecting firewood (minutes)	24.440	18.410	6.030	2.571	2.34**	(+) 1.3-1.4
Cooking (%)	0.786	0.693	0.093	0.031	2.98***	(+) 1.4-1.5
Cooking (minutes)	137.862	108.172	29.690	6.346	4.68***	(+) 1.3-1.4
Doing laundry (%)	0.435	0.339	0.096	0.036	2.69***	(+) 1.4-1.5
Doing laundry (minutes)	43.750	31.739	12.011	3.980	3.02***	(+) 1.2-1.3
On personal care (%)	0.961	0.959	0.002	0.014	0.18	(+) 1.6-1.7
On personal care (minutes)	43.289	34.634	8.655	1.965	4.41***	(+) 1.4-1.5

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

of enrollment in secondary school are larger for children with electricity.[16] Because returns on education range between 7 to 11 percent, these differences, if they persist, can translate into higher incomes in the future for children in households with electricity.[17]

It is important to point out that because only a small percentage of households use solar panels to watch TV (5 percent of households)—and that because time spent watching TV may reduce time spent studying, consequently affecting student performance—the external validity of these findings is limited. These results might not be extrapolated to electrification

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[16] The percentage of children who repeated a grade is statistically the same in both groups so the higher enrollment rate cannot be attributed to differences in grade retention.

[17] See Psacharopoulos and Patrinos (2002), and Duflo (2001).

Table 7: Use of Time: Children and Education

Dependent variable	Mean		Diff.	Bootstrap	t-stat†	Critical $\Gamma^{\ddagger}$
	Treated	Controls		S.E.		(hidden bias)
Children 7-18 enrolled in school						
% of children enrolled	0.875	0.839	0.036	0.027	1.36	(+) 1.9-2.0
% of children that attended school	0.916	0.933	-0.017	0.023	-0.74	(+) 1.2-1.3
Travel time to school	69.871	60.285	9.587	8.492	1.13	(-) 1.0-1.1
Minutes spent in school	301.339	303.847	-2.509	9.424	-0.27	(+) > 2
% of children that do homework	0.948	0.923	0.024	0.023	1.05	(+) 1.3-1.4
Minutes spent doing homework	92.507	83.668	8.839	4.151	2.13**	(+) > 2
Children 6-14 enrolled in elementary school						
% of children enrolled	0.953	0.922	0.031	0.028	1.11	(+) > 2
% of children that attended school	0.986	1.000	-0.014	0.008	-1.63	(+) 1.1-1.2
Age	9.274	9.039	0.235	0.253	0.93	(+) > 2
Years of schooling	2.607	2.229	0.378	0.187	2.02**	(+) 1.2-1.3
Children 11-18 enrolled in high/middle school						
% of children enrolled	0.720	0.604	0.116	0.058	1.99**	(+) 1.0-1.1
Age	14.882	14.705	0.178	0.319	0.56	(+) > 2
Years of schooling	8.000	7.707	0.293	0.262	1.12	(+) > 2
% children 11-17 that completed elem. school	0.696	0.681	0.015	0.055	0.27	(+) 1.5-1.6

Source: Authors' own calculations.

Note: (†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

in general, especially in cases where access to electricity is provided via an expansion of the grid, and electricity consumption is not limited either by technology or household purchasing power. Although evidence points to the importance of rural electrification for children's education, the existing literature offers mixed views on the relationship between the role of TV and student performance (van de Walle and others 2013).

Recent empirical work sheds light on the effects of rural electrification on children's education. Using a randomized encouragement design, Barron and Torero (2014) find a positive impact of rural electrification on the amount of time school-age children spend studying at home in El Salvador (an additional 10 minutes per day). In a similar vein, based on panel data from Peru, Dasso, Fernández, and Ñopo (2014) report positive effects of electrification on school enrollment among girls (3.5 pp among girls of all ages, 15.84 pp for girls aged 3-5, and 3.5 pp for girls aged 6-12). Khandker and others (2012) find a positive effect of rural electrification on enrollment rates (6 pp for boys and 7.4 pp for girls), study time (1.4 hours per week for boys and 1.6 hours per week for girls—or about 12-14 minutes per day), and years of schooling (0.3 years for boys and 0.5 years for girls) in India.

Enrollment rates in secondary school, however, are sensitive to possible deviations from the identifying unconfoundedness assumption. The result is sensitive to moderately strong confounding variables so long as such confounding variables have a very strong impact on enrollment rates. For instance, the magnitude of hidden bias that would undo the hypothesis test that supports this result—Γ equal to 1.1 for the result not being significant at 10 percent—is equivalent to the effect of an additional 7.9 years of schooling of the household head (an increase of 110 percent) or an increase by 34.6 pp in the share of households that benefit from the conditional cash-transfer program Juntos; the assumption is that the treatment effect on enrollment rates is overestimated and that households most likely to participate in 2010 were also most likely to send their children to secondary school.[18] It is important to point out that the number of years of schooling of the household head (3.77)—and, specifically female household heads (2.76)—are statistically the same in the treatment and control groups, and that there is no obvious reason to think that households most likely to participate in 2010 were more likely to send their children to secondary school.

4.2.4 Health and Fertility

We also looked at variables relating to health and fertility (table 8).[19] Reductions in the use of candles and fuel for lighting could potentially reduce air pollutants and affect the incidence of respiratory diseases. Barron and Torero (2014) find that electrification leads to a reduction in indoor air pollution, which contributes to reducing pollutant exposure among household members and the incidence of respiratory infections among children. We, however, cannot detect a difference in the incidence of respiratory diseases between the groups or in the incidence or number of burn accidents; the proportion of people reporting being affected by respiratory diseases or burn accidents was less than 1 percent in both groups.

Table 8: Fertility and Health

Dependent variable	Mean		Diff.	Bootstrap S.E.	t-stat†	Critical Γ‡ (hidden bias)
	Treated	Controls				
Number of children 3 year old and older	1.605	1.684	-0.079	0.124	-0.64	(-) > 2
Number of children under 2 years of age	0.164	0.164	0.000	0.035	0.01	(-) > 2
Number of pregnancies	3.699	3.686	0.013	0.314	0.04	(-) 1.1-1.2
Number of current pregnancies	0.011	0.031	-0.019	0.020	-1.00	(-) > 2
Incidence of respiratory diseases	0.003	0.001	0.002	0.002	1.01	(-) > 2
Incidence of burn accidents	0.003	0.007	-0.004	0.007	-0.54	(-) > 2
Number of burn accidents	0.003	0.018	-0.015	0.019	-0.79	(-) > 2

Source: Authors' own calculations.
(†) t test for difference in means: *** denotes significance at 1%, ** significance at 5%, and * significance at 10%. (‡) Odds ratio of treatment assignment: (+) denotes sensitivity analysis assuming overestimation of treatment effect and (-) underestimation of treatment effect.

We also did not find a difference in the fertility rate of the groups—measured as the number of children under 2 years of age in the household, the number of pregnancies during a women's lifetime, and the number of current pregnancies. A study conducted by the World Bank Independent Evaluation Group (IEG 2008)—focusing on cross-sectional data from Ghana, Peru, the Lao People's Democratic Republic, and the Philippines—points to a relationship between rural electrification and fertility. It finds a negative correlation in several country studies and points to improved access to information technologies as a key reason for this

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[18] Juntos is a conditional cash-transfer program implemented by the Peruvian State. About 8.6 percent of households in the treatment group are beneficiaries of Juntos. One of the conditions that household beneficiaries of Juntos must comply with is enrolling and sending their children to school.

[19] For the fertility analysis we used data from 1,819 women aged 12 and older, 852 treated and 967 controls; the matched sample had a total of 1,003 women, 396 treated and 607 controls. For the health analysis we used data from 4,836 household members, 2,188 treated and 2,648 controls; the matched sample had a total of 3,307 household members, 1,464 treated and 1,843 controls.

outcome. La Ferrara, Chong and Duryea (2008) provide evidence from Brazil supporting the idea that television soap operas and the role models they offer have a negative effect on fertility. Jensen and Oster (2009) also highlight the impact of television on womens status and fertility. Using data from India, they investigate the rollout of cable TV and find that women's fertility and acceptance of domestic violence (as reported by women themselves in interviews) decreases with the introduction of cable TV at the village level. On a somewhat similar note, Peters and Vance (2011) find that electrification has opposite effects on fertility in urban and rural areas, positive in the former and negative in the latter.

These results are robust to the possible presence of selection bias. The only result sensitive to possible deviations from the identifying unconfoundedness assumption is the number of pregnancies: the magnitude of hidden bias that would undo the hypothesis test that support this result—Γ equal to 1.2 for the result becoming significant at 5 percent—is equivalent to the effect of an additional 1.34 persons in the household. The assumption is that the treatment effect on the number of pregnancies is underestimated, and that households more likely to participate in 2010 were also more likely to include women who had undergone fewer pregnancies.

5 Conclusion and Policy Recommendations

This paper evaluates the impact of rural electrification on household well-being. Using a fee-for-service model, AMP offers access to affordable electricity to low-income households—80.8 percent of its clients are poor—without jeopardizing the organizations financial viability. AMP's fee-for-service model does not require large outlays of money. Any equipment that needs to be replaced, as well as system maintenance, is covered by the monthly fee that the client pays to AMP. Savings of what households would normally spend on traditional sources of energy—candles and batteries for flashlights—allow these households to cover the subsidized monthly fee for electricity.

AMP clients mainly use the electricity provided for lightning. Although they have the ability to connect low-power consumption appliances, only a small percentage of beneficiaries use the available energy to connect a radio or TV or to charge a mobile phone. Electric light has allowed households to lengthen the day: people spend more time awake, and women in particular have changed how they use their time. Women in households with solar panels spend less time in productive activities outside the household but more time in household-related activities such as taking care of children and cooking; a larger percentage also spend more time on their home businesses.

The most important result is related to children's study time. Children in households with panels spend more time doing homework, and this has translated in an advantage in school: a gain of 0.4 years of schooling for children enrolled in elementary school who have been exposed to electricity for an average of two years and nine months. This difference cannot be attributed to children's age—statistically the same—or the location and availability of schools: travel time to school and enrollment is statistically the same for children in households with and without panels. Moreover, although the percentage of children who completed elementary school is the same in both groups, enrollment rates in secondary school are higher for children with electricity. If these differences persist over time, it is expected that children in households with electricity will be able to generate higher incomes in the future.

These households' economic benefits and welfare promise to improve further if the energy provided by the panels is harnessed beyond its use for lighting (savings on batteries for radio, greater access to information through radio and TV, and so on). Understanding and addressing the reasons why households are limiting the use of the panel to lighting might increase the benefits that electricity brings to these homes.

AMP seems to have achieved a balance between financial viability and a focus on low-income customers. Working in coordination with the Peruvian government, and having obtained the first rural electric concession based exclusively on solar PV systems, AMP has reduced the likelihood of an unexpected power grid expansion that would eat into its customer base before it recoups its investment in equipment. This coordination reduces risk to the fee-for-service model used by AMP and gives it financial viability. Because evidence suggests that the increase in coverage comes mainly from extensive growth of the network (into new communities) rather than intensive growth (connecting unconnected homes in communities that are already electrified), the fee-for-service model requires taking into account the national expansion of the network to stay viable in the long term. In Peru the Ministry of Energy and Mines has developed a National Plan for Rural Electrification that identifies geographic areas where PV systems are good candidates for domestic or communal use, whether because it is inconvenient or impossible to connect them to large-scale power systems (as in the case of dispersed households with low purchasing power and poor road infrastructure). Such government initiatives support the financial viability of AMP's fee-for-service model without compromising a focus on low-income populations.

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