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Entrepreneurship, gender and the constraints of time: a randomised experiment on the role of access to light*

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Abstract

This paper provides evidence about whether access to light, which relaxes the time constraint in relation to the number of productive hours available, can stimulate the emergence of currently pent-up productive potential, particularly of women. In doing so, it also brings evidence to the broader question of whether a cheap and renewable source of energy used exclusively for *lighting*, like a solar lamp, allows to reap (some of) the above economic benefits of full scale electrification. To understand and quantify these dynamics, we exploit random variation in solar lamp ownership among 806 parents participating in the companion randomised controlled trail on the effects of access to light on education. Our findings are that access to light contributes to a diversification in household livelihoods from agricultural to non-farm economic activities. This evidence is supported by a consistent set of results across time use, the incidence of different productive activities, and incomes levels. To our knowledge, this constitutes the first robust evidence that small scale lighting source can help stimulate the very first steps in the direction of economic transformation. At the same time, the paper delivers some sobering evidence on the gender dimension of the effect of access to light. While we find evidence that access to light does indeed relax time constraints, and those of women in particular, we find that a large part of the benefits of this additional time ultimately flows to men.

1 Introduction

In the absence of artificial light sources, families must rely on the limited hours of daylight to carry out their activities. This constraint affects the more than 1.3 billion people worldwide who lack access to electricity, 40% of whom live in Sub-Saharan Africa (IEA, 2013), predominantly in rural areas.

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The constraint on productive hours is particularly relevant to women, who overwhelmingly carry the burden of having to fit housework into the time available to them (World Bank, 2012). Necessary but less productive activities typically relegated to women, such as cooking or cleaning the house, may crowd-out more remunerative uses of this limited time remaining. Moreover, an important fraction of daylight hours are often devoted to collecting firewood or sourcing kerosene to ensure some basic level of lighting during the hours of dark, thereby further reducing the time available for other uses.

This paper aims to provide evidence about whether access to light, which relaxes the time constraint in relation to the number of productive hours available, can stimulate the emergence of currently pent-up productive potential, particularly of women. There is evidence that grid electrification increases labour supply and employment, both at the local area level (Dinkelman, 2011; Rud, 2012) and at the household level (van de Walle et al., 2013), as well as household incomes (Khandker et al., 2013, 2012). There is considerably less evidence, however, on the extent to which a cheap and renewable source of energy used exclusively for *lighting*, like a solar lamp, allows to reap (some of) the above benefits of full scale electrification. To the extent this evidence exists, it is ultimately mixed and inconclusive. As electrification is a long and costly process, assessing the effectiveness of readily usable solar lamps is a policy-relevant question and where this paper makes its contribution.

Firstly, we dedicate considerable attention to time use (and indirectly labour supply and employment) effects. We do so despite an emerging set of recent evidence indicating small-scale solar energy products do not appear to influence time allocations. The RCTs in Grimm et al. (2014) and Aklin et al. (2015) find no change in hours worked.[1] Similarly, IDinsight (2015) finds no statistically significant change in the amount of time spent on productive activities (income generating activities, chores, and study). However, we believe there is a compelling case for studying the possible effects of light on time use in greater detail.

Specifically, as the studies above focus on aggregate time dedicated to activities, they cannot identify whether the are changes in the allocation of activities *within* A day. To the extent that the productivity or effectiveness of a task depends on the time of day it is carried out, 'task-shifting' may have economic consequences even in the absence of changes in total time use. Indeed, there is extensive anecdotal evidence suggesting access to light allows tasks to be moved from daytime to night-time and vice-versa. For example, albeit based on a relatively crude matched comparison, Harsdorff & Bamanyaki (2009) find evidence that women owning a solar home system were more likely to carry out domestic work in the evenings after sunset, and did so for more hours. Similarly, some exploratory proxy data on parental time use collected as part of the experiment in Hassan & Lucchino (2014) suggests lamps allowed mothers and fathers of treated students to substitute housework for paid work during the day. To address the limitation of previous studies, therefore, we adopt a diary approach to the collection of

[1] Grimm et al. (2014) find a positive coefficient on hours of house work for spouses, but this not statistically significant

time use. Not only this is generally considered more accurate than the stylised aggregate approach (Kan, 2007; Bonke, 2005), but it also provides valuable information on the timing of activities across the day. We further complement the diary approach with data collected via real-time *experience* sampling implemented using interactive voice response calls, thereby eliminating recall bias. In line with the paper's focus on entrepreneurship, we pay particular attention on quantifying the effect access to light may have on the distribution of time between housework, farm work and entrepreneurial activity.

Building on this, this paper contributes to the very limited evidence on the role of light in promoting entrepreneurship and income diversification. We use the term entrepreneurship in the broadest sense of starting or expanding an economic activity, or generally making changes in how one earns their livelihood. Considerable anecdotal or observational evidence suggests this is a mechanism worth studying. For example, light is often identified as allowing micro-enterprises to extend their working hours (Harsdorff & Bamanyaki, 2009). Furthermore, qualitative evidence from the fieldwork for Hassan & Lucchino (2014) revealed that many mothers in treated households started to produce bags, baskets, and jewellery to be sold in local markets as the availability of light allowed them to engage in such informal entrepreneurial activity in the evenings. This points to possibility that light my facilitate the emergence of new productive activities, thereby enabling diversification at the household and local level. To address this question, we place a considerable emphasis on collecting data on informal and micro non-farm productive activities. Additionally, considering the heavy predominance of agricultural activities in the project region, we also consider whether access to light is associated with changes in the types of farm and livestock activities carried out. To our knowledge, the only econometric evidence in relation to this broad topic are very recent emergent findings in Aklin et al. (2015), suggesting no association between solar micro-grids and the incidence of business ownership. This paper therefore aims to contribute to the currently very scarce evidence on the possible effects of access to light on small-scale entrepreneurship and economic diversification.

Importantly, access to solar-powered light may change household economic activities and circumstances without changing time use. An alternative causal mechanism runs via the effect of lamp ownership on fuel expenditure. Several studies identify a significant negative impact of access to solar-powered light on expenditure on alternative light sources,notably kerosene (see for example, Grimm et al., 2014; Hassan & Lucchino, 2014; IDinsight, 2015). These financial resources could be invested in improving or expanding the household's productive capital, thereby potentially affecting income and wealth. While this area does not constitute the main focus of the paper, we nevertheless include some references to this topic in our data collection to ensure we do not omit this potential mechanism.

To understand and quantify these dynamics, we run a randomised controlled trial (RCT) distributing solar lamps to households in rural Kenya. Our analysis exploits random variation in solar lamp ownership among the parents participating in the companion randomised controlled trail on the effects of access to light on education described in Hassan & Lucchino (2016). The latter randomly distributed solar lamps free of charge to a pool of 2,229 7th grade students across 60 schools in the Gucha South district in Kenya. The results in this paper are drawn from the 806 parents of these students surveyed via mobile phone, and across whom lamp allocation is indirectly randomly assigned.

Our findings are that access to light contributes to a diversification in household livelihoods from agricultural to non-farm economic activities. This evidence is supported by a consistent set of results across time use, the incidence of different productive activities, and incomes levels. To our knowledge, this constitutes the first robust evidence that small scale lighting source can help stimulate the very first steps in the direction of economic transformation. At the same time, the paper delivers some sobering evidence on the gender dimension of the effect of access to light. While we find evidence that access to light does indeed relax time constraints, and those of women in particular, we find that a large part of the benefits of this additional time ultimately flows to men.

The paper is structured as follows. Section 2 presents an overview of the experimental design and the project context. Section 3 details the data collection carried out, how this related to our priors of the relevant causal chain, and presents descriptive statistics of the data. Section 4 presents our identification strategy in detail, including a discussion of the nature of our sample and the outcome of the randomisation. Finally, Section 5 presents the results of the analysis and Section 6 concludes.

2 Project context and research design

This project, alongside its companion RCT in Hassan & Lucchino (2016), is concerned with the impact access to modern forms of lighting compared to traditional fuels (such as kerosene), or indeed no lighting at all. This requires identifying a target area exhibiting both low penetration of the electricity grid and limited presence of off-grid energy providers.

The project was implemented in partnership with Givewatts, a non-profit NGO providing clean energy to school children through schools and other institutions. Drawing on their local knowledge, we identified the Kisii County as a suitable candidate region for the project. Givewatts further agreed to not carry out their own operations in the target area for the duration of the project.

We use existing data to cross-validate this recommendation and further define our target area. The Kisii county is divided into 5 districts, and within 3 of these (Gucha, Gucha South and Masaba) more than 95% of the population is reported as lacking access to electricity in the Kenya Population and Housing Census 2009.[2] We complement this information with satellite night light data (see Lowe (2014) for overview of the data). Night light data offers a more up-to-date snapshot of energy access in the region as well as accurate measurement of light intensity for areas as small as 1 square kilometer. Including Stable Lights 3 from the latest satellite image available (2013), we identify Gucha South as the district with the lowest current levels of electricity assess. We select Gucha South as the target district for the project.

[2]This is the latest official statistical source.

A striking feature of the project area is its geographical and socio-economic homogeneity. Dwellings tend to be constructed with the same similar materials and technique, and are broadly similar in size. These are typically built within the family plot of land, which is also invariably cultivated. The most common local amenity is the primary school. Families also source their basic goods from local 'shopping centres', which amount to little more than a handful of shops/stalls selling basic goods (e.g. vegetables, soap, kerosene) and services (e.g. mobile charging). Figure 1 shows a typical landscape in the project region and illustrate its homogeneity.

This paper bolts onto our companion experiment on the effect of solar lamps on the educational attainment of Grade 7 pupils in the Gucha South district. The latter adopts a randomised saturation design (Baird et al., 2014), whereby 2,229 students across 60 schools are assigned to one of three possible treatment statuses: all students in the class receiving lamp; half the students in the class receiving lamps; and no students receiving lamps. This paper exploits the exogeneity of treatment to establish the causal effect of access to light on the time use and economic activity responses of the mothers and fathers of participating students.

We argue this experimental design mimics individual randomisation across parents despite it resting on a randomised saturation design across classes and students. Indeed, the only departure from a direct individual randomisation consists in the fact that the randomised saturation design will introduce a degree of geographical clustering in the treatment. This introduces two methodological issues, which, however, we believe can be easily addressed.

Firstly, geographical clustering in treatment can bias estimates if influential and omitted factors share a similar spatial distribution. The socio-economic homogeneity of the region already goes some way towards addressing this aspect. More fundamentally though, we collect geolocation data on the homes of the project participants, allowing us to assess the robustness of results to the inclusion of geographical fixed effects (see Section 4.1 for more details).

Secondly, different treatment intensities across locations can be a problem to our identification strategy if we believe the individual intention-to-treat effect varies with the treatment intensity in the individual's neighbourhood. This could be the case if economic responses by a large number of parents triggers local general equilibrium effects. This is unlikely to be the case in our study, as our project participants are ultimately only a fraction of the economically active population in a locality.

Based on these considerations, as well as further evidence presented in Section 4.1, we argue this paper's research design allows for the causal identification of the impact of access to light on the economic livelihoods of the project families.

3 Data collection

The project involved a number of data collection operations. Some of these were designed primarily for the companion randomised controlled trail on the effects of access to light on education described in Hassan & Lucchino (2016) but nevertheless include data pertinent


Figure 1: A typical landscape in the Gucha South district

the the focus of this paper. Other surveys were designed specifically to be used to address this paper's research questions. This section starts by enumerating the type, outcome and timeline of the operations carried out. It then proceeds to detail the topics covered across the survey instruments.

3.1 Overview of the operations

Our broadest relevant sampling frame is the population of 2,229 7th grade students across the 60 schools in the Gucha South district in Kenya participating in our companion RCT. Treatment assignment was allocated using this sampling frame. Drawing on this frame, we carried out three data collection efforts relevant to this paper:

- A paper-based collection of mobile phone numbers targeting the parents of all 2,229 students. This operation identified 1,292 unique phone numbers relating to 1,375 students.
- A tablet-assisted face-to-face survey targeting a 55% random sample of 1,181 students selected from the 2,159 we had full baseline data for. The sampling was stratified by school, treatment assignment, gender and high and low baseline math grades. This operation was conducted in January 2016 and reached 876 students (a response rate of 74%).
- A geographical mapping of the homesteads targeting all 2,229 students, which was able to successfully identify the homes of 1775 (80%) of the students. The mapping was conducted in February 2016, recording residential locations at May 2015.

The population of parents who accepted to share their mobile phone number consists of our main sample of interest for the purposes of this paper. Drawing on the sample of parents who offered their contact details, we carried out two main data collection operations:

- A single wave of computer assisted telephone survey targeting all 1,292 unique mobile numbers, which was able to obtain full responses for 806 adults (a 62% response rate). This operation was conducted during November and December 2015
- A repeated experiential sampling time use survey of the the 1,292 unique mobile numbers using Interactive Voice Response calls, conducted at random times of day over the 17 Tuesdays or Thursdays over the period between the 4$^{\text{th}}$ February 2016 and 31$^{\text{st}}$ March 2016 inclusive. The calls successfully got through to the respondent in 55% of cases, and 23% of these respondents completed at least part of the survey. A total of 2,817 person-time observations were collected. The average number of entries per person was 2.18

We also conducted a field visit in November 2015 aimed at gaining a qualitative understanding of the project context and refining our theory of change ahead of the preparation of the survey instruments and operations. This was also an occasion to run some cognitive testing of survey questions. During the fieldwork, we interviewed 13 families, 6 from the control group and 7 from among the treated. We interviewed 4 fathers, 7 mothers, 2 step-parents, and had an impromptu focus group with a group of mothers (some of whom where project participants) while they were selling vegetables on the side of the road. A topic guide was used, but not all topics were discussed in each interview.

3.2 Topics covered

We proceed to present an overview of the topics we collected data on, and descriptive statistics for the sample obtained. We collected a number of background characteristics, but we focus our attention here primarily on metrics concerning the outcomes of interest.

The core of the data analysed in this paper was collected through a mobile phone survey. This mode of data collection imposes some constraints to the scope of the survey, as the engagement and availability of the respondent is typically significantly lower that with conventional face-to-face approaches. The range of data collected should therefore be considered with this limitation in mind.

Gender and other background characteristics

This paper places an important emphasis on how the effects of access to light may differ by gender. As such, we took a number of steps to increase our reach to students' mothers. For example, when collecting mobile contact details, we specifically asked for the mother's own phone number, if she owned her own phone. However, in the majority of cases mobile phones were either shared among the adult members of the household, or primarily of the students' fathers.

To maximise our reach to mothers, we asked if mothers were available in the early stages of the questionnaire. Specifically, after having confirmed we had reached the parents or guardians of the student in question, we asked to speak to their mother if she was available. If so, we asked for the 'initial respondent' to hand the phone over to what we call the 'ultimate respondent'.[3] Women composed 38% of the initial respondents, and this figure rises to 44% of the 'ultimate' respondents. The sample of ultimate respondents consisted of 452 men and 348 women.

Despite the attempts to maximise the participation of women into our survey, they nevertheless accounted for less than half of the participants. To be able to use of data from the full sample, our first step in the analysis is therefore gender neutral. In subsequent steps, we also allow for heterogenous effects across gender. However, this inevitably implies a reduction in the sample used to identify effects for a given gender.

Other background characteristics we collected are the age and highest level of education of the ultimate respondent, and the number of adults and children in the household.

[3] As shown in Section 4.1, the change in respondents was equally likely across treatment and control groups

Time use

In light of the focus of our research, we dedicate a considerable amount of space in our surveys to the documentation of time use. As discussed in Section 1, to improve on existing work on the effects of access to light on time use, we adopt a combination of diary based and experience sampling methods.

The time use module consisted of the largest section of our phone survey of parents. Respondents were asked: *Please tell me what you did yesterday, starting from when you woke up to when you went to sleep for the night, indicating start and end time of each activity and whether this was carried out at home or away from home.* Respondents were also asked to provide a proxy response for the same information for their spouse. All but 2 survey participants responded to the time use model, while 298 (37%) participants were able to provide proxy responses for their spouses. Enumerators were tasked to code the responses as open-ended. However, they were provided with a list of the most commonly occurring activities to be able to address the bulk of the task with ease. The list was drawn from most frequently activities in the 2005 Tanzania Time Use Survey Pilot (Rugaimukamu, 2005).

The specific activities reported were later aggregated into the following main activities: agriculture; livestock; non-farm work; house chores; family care; shopping and sourcing goods; personal care; social engagements; sleep and rest. A further category called 'in transit' covered time spent transferring between places and activities. Figure 8 and Figure 9 display word clouds of the most frequently occurring terms used by the survey respondents to describe the activities grouped under each heading. The clouds reveal a high degree of homogeneity within each high-level activity group. Activities were further grouped to create the broad time aggregates of: productive activities (agriculture; livestock; non-farm work); informal work (house chores; family care; shopping and sourcing goods) and leisure (personal care; social engagements; sleep and rest).

It is worth noting that, contrary to most other groupings, the activities falling within the categories 'non-farm work' and 'social engagements' are relatively heterogenous. For example, social engagements include both having tea with friends as well as economically relevant activities such as attending a meeting at a rotating saving group or helping building a local church. Similarly, 'non-farm work' includes any income-generating activity not directly related to the agricultural or livestock production. These can range from selling produce at the market to running a shop or being a teacher. Respectively, these may arguably be seen as incidences of social and economic diversification, and are therefore particularly relevant to this paper's focus.

Table 1 shows the average number of hours per person over the day spent carrying out each of the main activities and the broad aggregates. The statistics are split by gender and by whether we restrict the sample to main respondents or to proxy information on spouses. Overall, the statistics are plausible and in line with what one would expect. The gender difference in the allocation of activities emerges clearly. Women respondents report 4 hours of informal work per day compared to 1 hour reported by men. These additional hours of work come at the expense of a reduction in productive and leisure activities by 2 and 1 hour respectively. The context portrayed by this data corroborates

Table 1: Time use descriptives statistics

Activity	Men		Women	
	As respondents	As spouses (proxy)	As respondents	As spouses (proxy)
Productive Activities	8.12	6.29	5.75	4.45
Agriculture	2.98	2.79	3.27	2.93
Livestock	1.00	0.41	0.72	0.28
Non-Farm Work	4.13	3.10	1.77	1.24
Informal Work	1.11	2.75	4.30	6.62
Family Care	0.25	0.40	0.30	0.44
House Chores	0.79	2.22	3.63	5.82
Shopping or Sourcing Goods	0.08	0.13	0.37	0.35
Leisure Time	14.21	14.28	13.34	12.15
Personal Care	2.23	2.09	2.14	1.84
Sleeping or Resting	10.54	11.19	10.32	9.58
Social Activities	1.44	1.01	0.87	0.72
Weighted sample size	452	109	346	189

the hypothesis that access to light could have the potential to reduce constraints on productive activities by extending the total hours available, for instance by allowing women to do chores more quickly especially after sunset.

A number of arguments support the view that the previous day diary approach used in our survey delivers more accurate measurements of time allocations than the use of stylised direct questions (see Budlender, 2007, for a review). Indeed, the evidence indicates that answers to stylised questions exhibit systemic error compared to diary approaches (Kan, 2007; Bonke, 2005). Time spent on socially undesirable activities tends to be underreported and vice versa, leading to social desirability bias (United Nations Statistics Division, 2005). Respondent subjectivity may also affect which specific activities are deemed to fall within the broad activity type being asked for. For example, respondents may differ in whether they include unpaid or domestic responsibilities in their estimate of the time they spend 'working'. Our diary approach resolves this by post-coding the specific activities mentioned by the respondent in a way that is consistent across individuals.

Stylised questions can also be more demanding for the respondent. The estimation of total time across a given type of activity is computationally intensive, particularly when activities occur frequently and intermittently. This is in line with impressions gained from our cognitive testing of questions. We invariably found that parents were most comfortable accounting for time by describing atypical day, or even better, the previous day. They were able to recount the sequence of events, including start and end times.[4]

[4]All individuals in our sample consists of mobile phone owners, and therefore have access to clock.

This was particularly the case for agricultural, livestock, selling and domestic activities. Asking for the number of hours per day was found to be quite complex. Moreover, families never responded in terms of hours per week, even if the question was framed that way.[5] By using a diary approach, all computation of time aggregates is carried out at the analysis stage.

The above biases and errors are exacerbated as the recall period lengthens (Paull, 2002). In light of this, our time diary is limited to a one day recall method, whereby respondents narrate the event of the previous day. This reduces recall bias.[6] Surveys where conducted between Tuesdays and Saturdays, to ensure the previous day was always a working day.

We complement the diary approach with experience sampling via Interactive Voice Response (IVR). We do so for two reasons. Firstly, even a previous day diary by still be subject to some recall bias. Additionally, if the day involves many different spells, the diary approach may generate survey fatigue. These concerns are less relevant in the case of experience sampling. More fundamentally however, another main objective of using IVR methods was to experiment with what is still an innovative and largely unexplored approach to survey data collection and assess its viability for research.

Overall, stylised questions suffer from a number of biases, which can particularly affect the measurement of activities occurring in short and unstructured spells. It is arguably these sorts of activities that may be most influenced by the availability of light. By using a combination of previous day recall diaries and experience sampling we can gear our data collection to maximise the ability to detect these activities of this sort.

Furthermore, diaries and experience sampling also allow for the collection of more granular and detailed information on time use that is possible via stylised questions. Critically, these approaches uncover the timing of activities across the time of day and night. This allows the exploration of possible 'task-shifting' effects of access to light, which were beyond the scope of previous work on the issue. Secondly, these approaches allow for the inclusion of contextual variables. Typical examples of these are where and with whom the activity is taking place, and whether the activity is paid. In our survey instruments, we capture whether the activity is carried out at home or away from home. This aims to corroborate the hypothesis that access to light may be particularly relevant for home production.

Economic activity and productive assets

The second main objective of our data collection was to document and measure the household's productive capacity. The intention here is to detect whether a possible change in time use and/or savings on alternative fuel expenditure (see Section 3.2) could trigger an expansion and/or change in the economic activities the household is involved in. Considering the near universal involvement in agriculture, we paid considerable

[5] The only exception to the above was the incidence of casual work, which tended to be reported in number of days this week.

[6] Note, however, that this increases the variation in the data, which reduces the statistical power to detect differences across treatment and control groups.

attention to measuring crop and livestock activity. At the same time, we included a detailed module on non-farm activities in line with the papers' focus.

During our field visit, we gained an immediate impression of how virtually all families relied on agriculture for a relevant share of their living. Similarly, most, though not all, families owned animals. An accurate measurement of the activities and income flows of rural households is notoriously difficult (see The Wye Group, 2007, for a review). It involves dealing with issues such as distinct and highly seasonal income and expenditure flows, and high degree of measurement error on key parameters such as plot size.[7] We were therefore faced with the challenge of identifying a small number of questions that could act as strong proxies for overall agricultural activities. We addressed this by noting that each crop type is clearly associated with a distinct purpose: maize is planted for subsistence; vegetables can be sold; tea and sugar cane are exclusively for cash. Similarly, poultry is the main income-generating animal, while a typically small number of cows is kept primarily for family consumption. A family's productive capacity can therefore be proxied by simple questions on the type of crops they cultivate and animals they own, and we include these in our survey.[8] We also included questions on the number of each type of animal owned. In light of the high expected measurement error, we opted to not ask about the size of the plot for each crop.[9]

Descriptive statistics on the responses to each of these questions are presented in Table 2. These confirm many of the indications from the Kenya Integrated Household Budget Survey 2006 and the field visit described above. They also evidence the reasonably high level of casual agricultural work. Indeed, around 55% of project families engage in agricultural activities for pay on other people's land.[10]

Around 39% of families relied on incomes other than agriculture and livestock, and these constitute a prime interest for this paper. During the survey, we therefore asked respondents to enumerate all non-farm income-generating activities where an adult member of the household was involved. The activities were coded as open-ended responses. The most frequently occurring terms are displayed in the Figure 7. Similar examples were quoted during the fieldwork, and included being: a teacher, a security guard at a plantation, a motorcycle taxi driver (*boda boda* driver), a soapstone carver, a repairs tailor and running small cafe.

The non-farm activity module replicated the core questions from the corresponding module Kenya Integrated Household Budget Survey 2006.[11] These included questions identifying who was the main adult responsible for the economic activity, the time of day and location this was typically carried out, and whether the household was involved

[7] We tested questions on these topics during the field visit and confirmed the presence of these difficulties.

[8] We coded possible crop types by selecting the most frequently occurring responses among Gucha South respondents to the Kenya Integrated Household Budget Survey 2006 survey

[9] We tested a direct question asking about the size of the land owned by the household during our fieldwork and found a majority were unable to provide an confident answer.

[10] The most common example of these is weeding.

[11] The Kenya Integrated Household Budget Survey 20015/16 survey fieldwork was being carried out during the same period as our project. Responses to that survey may allow opportunities for further analysis.

Table 2: Farm-based productive activities

Variable	Mean	Standard deviation	10^{th} percentile	90^{th} percentile
Agriculture	97.25			
Livestock	82.81			
Casual agricultural work	55.30			
N# of crops types	3.41	1.65	2.00	6.00
Grows Maize	91.06			
Grows Beans	47.55			
Grows FingerMillet	11.38			
Grows Vegetables	53.30			
Grows Bananas	38.92			
Grows SugarCane	54.55			
Grows Tea	11.44			
Grows Coffee	12.29			
Grows Other	20.69			
N# of livestock types	1.45	0.90	0.00	2.00
Owns Cattle	63.01			
Owns Poultry	65.12			
Owns Goats	15.07			
Owns Rabbits	0.63			
Owns Others	1.38			
N# of Cattle	1.19	1.31	0.00	3.00
N# of Poultry	5.61	10.00	0.00	12.00
N# of Goats	0.41	1.20	0.00	2.00
N# of Rabbits	0.03	0.41	0.00	0.00
N# of Other animals	0.27			
Weighted sample size	800			

Table 3: Non-farm productive activities

Variable	All respondents Mean	Respondents with non-farm activities Mean
Non-farm activities	38.63	100.00
Number of non-farm activities	0.44	1.15
Started less than 12 months ago	1.88	4.85
Woman involved in non-farm work	13.75	35.60
Man involved in non-farm work	28.38	73.46
Carried out during hours of darkness	3.50	9.06
Carried out at home	3.50	9.06
Carried out at fixed place away from home	32.07	83.01
Activity is mobile	5.19	13.43
Weighted sample size	800	311

in the activity 12 months ago. Descriptive statistics on the responses to each of these questions are presented in Table 3. We see that if families engage in any non-farm activities, it will typically be only one. Men are twice as likely than women to be the main person involved in the activity, and the activity is typically carried out at a fixed location away from home.

Household income and saving

Our survey also included a small number of questions relating to the financial circumstances of the household. The motivation for this was twofold. On the one hand, we wanted to collect a measure, even if highly approximate, of the families' income flows to attempt to detect any causal links running from time use to productive capacity and ultimately income. Again, the complex financial circumstances of rural families make this a difficult task. Indeed, during our field visit, we confirmed that while families were generally able to estimate revenues for specific activities or events (for example, the sale of vegetables per day or the price of chicken if sold), they had strong difficulties combining all income sources into an estimate for a homogenous time periods. Despite this limitation, the context of a phone survey simply did not afford asking a detailed set of questions on this issue. Therefore, so as to at least collect some measure, we included a question asking respondents to estimate their typical weekly income, separately from farm and non-farm sources.

The second motivation is to document, again in a stylised fashion, what may be happening in terms of the household's savings. Previous research indicates that off-grid solar products deliver significant savings on expenditure on alternative fuels (notably kerosene). We therefore include a question asking the respondent to report their weekly expenditure on lighting fuels. We hypothesise that these savings may trigger an investment dynamic in the household, either by reinvesting these savings directly or by using

Table 4: Income and savings

Variable	Mean	Standard deviation	10[th] percentile	90[th] percentile
Farm income	783.22	969.27	0.00	2000.00
Non-farm income	677.59	1374.02	0.00	2200.00
Total income	1460.81	1744.03	200.00	3200.00
Equivalised total income	122.26	180.04	14.81	280.95
Weeky expenditure on lighting fuel (Kshs)	103.44	101.47	0.00	200.00
Do you feel you are able to set a side part of your income as savings?	38.88			
Savings set in a savings institution?	42.26			
Weighted sample size	800			

this saving stream to support an increased credit capacity. Fully mapping these channels is beyond the scope of this project. However, we seek to gain some proxy signal in relation to these dynamics by asking respondents whether they feel they are setting aside savings on a regular basis and whether they are involved with any financial institutions.[12] Descriptive statistics on the responses to each of these questions are presented in Table 4. The income data includes some very high observations, in the order of several multiples of the sample mean. In the analysis, we trim the top 1% in the total income distribution.

4 Experiment validity and estimation strategy

This paper is concerned with identifying and quantifying the impact, if any, of access to modern light sources on household economic activities in rural developing country contexts. In this section, we discuss and present evidence on the extent to which our project and data can adequately support causal inference. Drawing on the insights from this analysis, we proceed to define our estimation strategy and robustness checks.

4.1 Balancing and internal validity

We proceed to discuss the extent to which the data supports the internal validity of the experimental design. Most notably, to substantiate a claim for causal attribution we would want to show that the randomisation has successfully split the sample in two

[12]The exact wording of the questions was 1) *Do you feel you are able to set a side part of your income as savings on a regular basis?* and 2) *Are you depositing your savings into any form of saving institution?* Enumerators were instructed to *probe for institutions like 'chamas', Savings and Credit Cooperative Organization (SACCOs), microfinance institutions, mobile money etc.*

groups differing only in their allocation to treatment.

Table 5 provides important evidence to that effect. Firstly, it shows that while the likelihood of offering mobile contact details is higher among the treated than the control group, this difference is not statistically significant. Furthermore, participation rates into the phone survey (conditional on having given contact details) are identical across treatment and control groups. This suggest that unobserved factors that determine participation into the survey are not differentially distributed across the two groups, thereby attenuating the concern that these might be driving differences in outcomes we might observe.

Table 5 then proceeds to present a standard set of balancing statistics to evaluate the success of the randomisation. The results in the table show that the distribution of gender, age, education and household structure are very similar across treatment and control groups. On the basis of this evidence, we have reason to believe that the randomisation has been successful in constructing two comparable groups.

Table 5: Balancing statistics

Variable	Control	Treated	P-value of difference
Offered contact details	0.58	0.66	0.13
Weighted sample size	1442	787	
Participated in phone survey	0.63	0.61	0.53
Weighted sample size	791	501	
Initial respondent is female	0.36	0.41	0.16
Ultimate respondent is female	0.43	0.45	0.45
Age of respondent	42.08	41.36	0.31
Completed primary education	0.40	0.44	0.24
Completed secondary education	0.27	0.30	0.33
Number of Adults in the household. Adult is over 18.	2.72	2.84	0.22
Number of Children in the household. Children is under 18	4.05	4.08	0.79
Weighted sample size	495	305	

** p<0.1, ** p<0.01, *** p<0.001.*

As discussed in Section 3, space constraints limited the number of background variables we could collect. This can potentially limit the confidence in the randomisation outcome in two respects. Firstly, a notable omission to the background characteristics considered is a proxy of wealth. Differential wealth status across treatment and control households would be important confounders in the context of this study. The achieved balance in educational status should partly address this concern, to the extent that wealth and education tend to be correlated. Nevertheless, results in this paper should be considered with this caveat in mind.

Secondly, some aspects of the results we discuss in Section 5.3 may raise concerns over the balancing of the incidence of non-farm income streams at baseline. If present, baseline differences in the incidence of non-farm activities would be an important threat to causal inference. Firstly, these are likely to explain a large part of end-line differences otherwise attributable to a treatment effect. More generally, however, causal inference on other outcomes would also be called into question to the extent that the incidence of non-farm activities is a relevant confounding factor. To address this latter concern, we test the robustness of all our results to a specification that controls (among other things) for the reconstructed incidence of non-farm activities at baseline (see Section 4.3 for more details).[13] Reassuringly, the estimated effects on all other margins are confirmed, albeit sometimes attenuated, when estimating such a specification. Overall, therefore, we argue this shows that baseline differences in non-farm work, even *if* present, do not appear to invalidate estimation of treatment effects on other margins.

A final aspect concerning the internal validity of the experiment relates to the geographical distribution of treatment. As discussed in Section 2, identification rests on the exogenous allocation of solar lamps to households induced by a clustered experiment operating at school level. As such, we expect treatment to not be uniformly distributed across space. Figure 2 confirms this. It plots a geographical kernel density estimate of treatment intensity, calculated over areas with radius of 7.5×10^{-3} degrees (800m ca.) around the centroids of hexagonal grid cells of 2.5×10^{-3} degrees in diameter (300m ca.). Actual sample data points are overlaid on the map, colour-coded in green for treated units and red for control units.

The lack of geographical homogeneity in treatment poses a threat to identification to the extent that influential and omitted factors share a similar geographical distribution. The strong economic and cultural homogeneity across the project region observed during the field visit somewhat reduces this concern. Nevertheless, we seek an identification strategy that is robust to this possible bias. Specifically, as presented formally in Section 4.3, we include geographical fixed effects for arbitrarily constructed hexagonal grid cells 1.5×10^{-2} degrees in diameter (1550m ca.), as displayed in Figure 2. In this variant of our estimation strategy, identification hinges on the comparison of treated and control units within the same grid cell, thereby netting out the effect of any local area factors. As such, it rests only on observations falling within cells that include both treated and control units. In our case, this consists of 71% of our sample. Table 6 shows how the balancing of background variables is maintained when including geographical fixed effects and hence restricting the effective sample used.

[13] Assuming an equal hazard of activities ending over the previous 12 months across treated and control groups, the dummy indicator for the reconstructed incidence of non-farm activities at baseline is set as equal to one for all families reporting a non-farm income stream and reporting this was not started in the last 12 months.

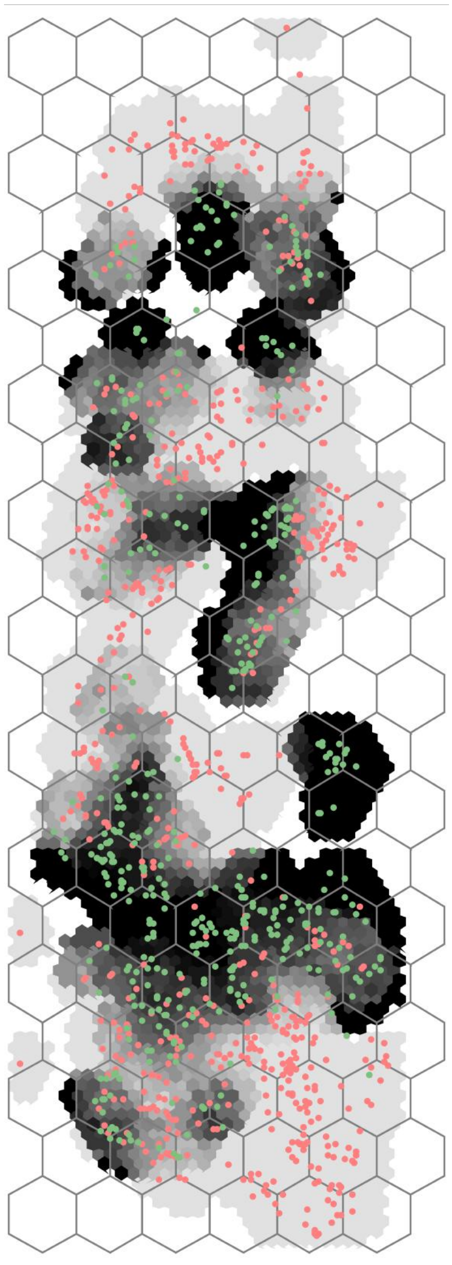


Figure 2: Geographical distribution of treatment

Table 6: Balancing statistics - with geographical fixed effects

Variable	Mean Untreated	Mean Treated	P-value of diff
Initial respondent is female	0.34	0.40	0.19
Ultimate respondent is female	0.38	0.42	0.40
Age of respondent	44.97	43.68	0.20
Completed primary education	0.19	0.25	0.23
Completed secondary education	0.44	0.44	0.94
Number of Adults in the household. Adult is over 18.	2.87	2.97	0.41
Number of Children in the household. Children is under 18	3.82	3.97	0.41
Weighted sample size	324	249	

** p<0.1, ** p<0.01, *** p<0.001.*

Overall, the data available to us does not point to unsurmountable threats to internal validity. While a more extensive set of background characteristics, or indeed a baseline survey, would have provided a more solid basis to evaluate the outcome of the randomisation, the evidence and estimation approach presented in this section should provide a reasonable degree of confidence for causal inference.

It is generally hard to assess the external validity of an RCT. Nevertheless, our sample selection refers to parents of 7th grade pupils that own a mobile phone. These two features are sufficiently general. As for the setting of the experiment, we believe that our results could extend to rural agricultural areas in Kenya, but they might be a bit different in less sedentary rural settings where cattling is the main economic activity.

4.2 Treatment adoption and compliance

Identification rests on the assumption that the treatment is administered as expected and participants comply with it. This may not always be the case. In the context of this study, lamps could be left unused or break, or treated families may sell or lend them to others. Control families may also take initiatives that might invalidate the experiment. In particular, they might choose to purchase a lamp.

Our data provides strong evidence indicating that the treatment was adopted by a majority of the treatment group and that compliance was high. Evidence from the student survey indicates that about 90% of respondents reported that the lamp was working well or with minor problems only; in more than 94% of cases, the solar charge of the lamp was sufficient for the required activities; and in more than 90% of cases the lamp stayed at home during the night. Responses from the parent survey also indicate that being assigned to treatment has a real effect on the light sources available to the household. Table 7 shows how that families assigned to treatment are three times more

Table 7: Compliance with treatment

Variable	Mean Control	Mean Treated	P-value of difference
Solar is main light source	0.20	0.57***	0.00
Kerosene is main light source	0.60	0.28***	0.00
Solar is among light sources	0.24	0.70***	0.00
Has any electrict light source	0.28	0.74***	0.00
Weighted sample size	525	328	

** p<0.1, ** p<0.01, *** p<0.001.*

likely to indicate *solar* as their main light source, or as one among the family's light sources. Equally, they are half as likely to indicate kerosene as their main light source.

Nevertheless, Table 7 also shows that compliance was not complete. As we discuss in Section 4.3, this suggests an instrumental variable estimation strategy would provide important insights on the treatment effect on those that actually comply.

4.3 Estimation strategy

Household level outcomes

In consideration of the evidence presented in the preceding sections, we here set out our estimation strategy. Firstly, in light of the random allocation of the lamp across households, our core specification is a reduced form OLS regression of economic outcomes on treatment. The Intention-To-Treat (ITT) on household-level outcomes is estimated using the following specification:

$$y_{hj} = \beta_0 + \beta_1 \ Treatment_{hj} + \epsilon_{ij} \tag{1}$$

where y_{hj} is the outcome of household h in grid cell j. This specification is referred to as CX in the tables.

In light of randomisation, our core specification can already be interpreted causally. However, to maintain a cautious approach to identification and inference, we also run two robustness specification. These are intended to assess the robustness to imbalances in individual characteristics and geographical location respectively.

The first specification replicates Equation 1 with additional controls for gender, age and educational level of the respondent and the number of adults and children in the household. In light of the discussion in Section 4.1, we also include the reconstructed baseline incidence of non-farm income-generating activities. We estimate:

$$y_{hj} = \beta_0 + \beta_1 \ Treatment_{hj} + X_{hj} + \epsilon_{ij} \tag{2}$$

where X_{hj} is the vector of controls. This specification is referred to as CTL in the tables.

Next, we re-estimate the main specification adding geographical fixed effects over arbitrarily defined grid cells. By estimating the following equation with grid cell fixed effects, we can account for the effect of any local omitted factors λ_j:

$$y_{hj} = \beta_0 + \beta_1\ Treatment_{hj} + \lambda_j + \epsilon_{ij} \tag{3}$$

This specification aims to address the concern that treatment may be correlated with omitted variables across space. If this is the case, estimated coefficients will be different from the main specification. On the contrary, if coefficients do not change significantly, we would conclude that local omitted factors should not be a major concern. We cluster standard errors across the 97 grid cells. The standard error will therefore increase as treatment is known to be geographically uneven.[14] This specification is referred to as *GEO* in the tables.

Additionally, we adopt an instrumental variable approach to estimate the effect of treatment in the context of partial compliance. Specifically, we use the random allocation to treatment to instrument for distribution of access to any source of electric light as observed in the data. Formally, the first and second stages for household level outcomes are:

$$Elec_{hj} = \beta_0 + \beta_1\ Treatment_{hj} + \mu_{ij} \tag{4}$$

$$y_{hj} = \beta_0 + \beta_1\ E\hat{l}ec_{hj} + \epsilon_{ij} \tag{5}$$

The above approach allows for the estimation of the effect of treatment among those who make use of it (Local Average Treatment Effect). This is identified if the treatment does not affect those who do not comply. There is reason to believe this assumption may be inviolated in our context, as, for example, non-compliers will draw a monetary benefit if they sell the lamp. This specification is referred to as *IV* in the tables.

Note that we do not estimate heterogenous treatment effects by gender in these specifications as the outcomes are for the household as a whole.

Using a plurality of specifications allows to test the robustness of the results under differing assumptions on what would allow for causal identification. While results for any single specification will be relevant in their own right, those that remain robust to these differing assumptions will constitute the strongest findings of this paper.

Individual aggregate time use outcomes

The estimation equations require some minor modifications when analysing aggregate time use. This is due to the fact that time use data is collected at the individual, rather than household, level. The respondent reports the activities carried out over the course of the previous day, and then offers a proxy response for their spouse. The latter are likely to be of significantly lower quality due to measurement errors and response

[14]The intra-cluster correlation of treatment across the grid cells in 0.44

biases.[15] As such, we analyse time use data both including and excluding spouse data. Specifically, our core specification becomes:

$$y_{ihj} = \beta_0 + \beta_1\ Treatment_{ihj} + \epsilon_{ij} \tag{6}$$

where y_{ihj} is the outcome of adult i in household h in grid cell j. Estimation is initially restricted to the time use data on main respondents provided by the respondents themselves. The equation is then estimated on data including proxy information on spouses provided by the respondents. When spouses are included, standard errors are clustered at the household level. We adapt the above specifications in the same way to allow them to be estimated on individual level data.

Given the importance of the gender dimension in relation to our research questions, we allow for the possibility of heterogeneous effects by gender in our estimation of time use. We do so by interacting the treatment variable with a gender indicator. Our core specification therefore becomes as follows, and all other specifications are altered in the same way:

$$y_{ihj} = \beta_0 + \beta_1\ Treatment_{ihj} + \beta_2\ Treatment_{ihj} \times Female_{ihj} + \epsilon_{ij} \tag{7}$$

Individual continuous time use outcomes

As discussed in Section 3.2, the experiential time use data varies by respondent and time of day. Similarly, we transform the previous day diaries to identify the activity being undertaken by the respondent and their spouse at 15 minute snapshots across the 24 hours of the day. We use this data to estimate the effect of treatment over the different times of day.

We do so by separately estimating non-parametric specifications of the incidence of each activity type across the course of the day by treatment and control group, and calculating the difference between the two. Specifically, we estimate a kernel-weighted local mean smoothing regression (Nadaraya, 1964; Watson, 1964; Gasser & Mller, 1979) of dummy indicators of the incidence of activity A_{iht} for adult i in household h at time of day t. We estimate the mean and standard errors of the incidence of each activity across the time of day separately for treatment and control group. We then calculate the difference between treatment and control group means. The standard errors of the difference is calculated from the standard errors of the two group means on the assumption of zero covariance between the two. We perform this estimation for the pooled sample, as well as for males and females separately.

[15]During the phone survey, a number of respondents reported they only had imperfect knowledge of the activities carried out by their partner.

5 Results

5.1 Aggregate time Use

We find evidence of treatment effects on the time dedicated to some activities. We report the treatment effects for broad time aggregates (productive activities, informal work, and leisure), as well as the main activities that compose these, in Tables 8, 9 and 10. Table 9 display results for men, Table 10 for women and pooled results are in Table 8. The left panel of each table restricts the sample to time use data on respondents, while the right panel pools information on respondents and proxy information in relation to spouses. Each panel then displays the 4 main specifications discussed in Section 4.3.

The overall picture portrayed by the results across specifications is that the lamp favours a reduction in time spent on agricultural activities in favour of activities of a broadly social nature, particularly for men. We find an intention-to-treat effect indicating a statistically significant reduction in time allocated to agricultural activities by 30 minutes per day.[16] We also find some evidence indicating that men reduce their involvement in informal work (primarily house chores) by around 20-30 minutes per day.

Men appear to reallocate this time primarily to leisure time, in the order of a statistically significant 45-60 minutes per day. This is mainly spent on personal care and social engagements, though the coefficients on the latter are statistically insignificant. Men in treated household also report sleeping in by an additional 10-15 minutes per day. This leads to a, possibly counter-intuitive, *reduction* in total time awake, albeit statistically insignificant. We can speculate that the postponing of wake-up times could be related to men's reduced involvement on the farm.

There are no other statistically significant results for women, most likely due to the lower sample size. The pattern across coefficients, however, provides some indication that women transfer time saved on agriculture to informal work (primarily house chores by 15 minutes) and social engagements by 10 minutes per day. There also is some indication that women in treated households do postpone going to sleep by some 10-15 minutes on average, and report a corresponding increase in time awake. To reiterate, non of these results are statistically significant.

Some results indicate the lamp may trigger an increased engagement beyond the farm context. Beyond statistically insignificant but positive coefficients on social engagements for both men and women, we also generally find positive (though insignificant) coefficients on non-farm work, and positive and significant effects on time spent in transit. Again, these effects are larger work men than for women.

Overall, access to light appears to trigger a move away from the farm and toward increased leisure and social participation. It may also be associated with an increased involvement in non-farm work, though the evidence is weak. These effects are stronger for men than for women, with some indication that this is because the extension of productive hours leads women to take on house chores previously carried out by men. We are not aware of any other studying identifying a causal effect of access to light on

[16]Note this is robust to the inclusion of imputed baseline non-farm activities in Specification CTL

aggregate time use.

5.2 Time use over the course of the day

As discussed in Section 1, our time use data allows us to explore any treatment effects on the timing of different activities. These treatment effects are visualised in Figure 3, and Figures 4 and 5 for men and women respectively. Each panel displays the estimated treatment effect (blue line) and 90% confidence interval (light blue shaded area) across all hours of the day. The panels in the top row of each Figure display the treatment effects across the broad time aggregates, with the panels below each representing their component parts. The red horizontal line runs at zero, and the vertical lines represent approximate sunrise and sunset times.[17]

[17] As Kenya lies on the Equator, sunrise and sunset times are broadly constant across the year.

Table 8: Aggregate time use - Pooled men and women

Outcome	Main respondents only				Respondents and spouses			
Specification	CX	CTL	GEO	IV	CX	CTL	GEO	IV
Productive Activities	-0.46	-0.53*	-0.64	-1.00	-0.21	-0.28	-0.45	-0.43
	(0.28)	(0.26)	(0.45)	(0.62)	(0.25)	(0.24)	(0.38)	(0.52)
Agriculture	-0.58*	-0.44*	-0.60*	-1.27*	-0.36*	-0.26	-0.38	-0.75*
	(0.23)	(0.22)	(0.33)	(0.51)	(0.21)	(0.20)	(0.28)	(0.44)
Livestock	-0.11	-0.06	-0.32*	-0.25	-0.07	-0.04	-0.25*	-0.14
	(0.11)	(0.11)	(0.17)	(0.24)	(0.09)	(0.09)	(0.12)	(0.18)
Non-Farm Work	0.23	-0.02	0.28	0.51	0.22	0.01	0.19	0.46
	(0.32)	(0.28)	(0.53)	(0.70)	(0.27)	(0.24)	(0.41)	(0.57)
Informal Work	0.05	-0.01	-0.20	0.11	-0.10	-0.16	-0.08	-0.21
	(0.23)	(0.19)	(0.30)	(0.50)	(0.21)	(0.20)	(0.24)	(0.43)
Family Care	0.04	0.02	-0.05	0.08	-0.02	-0.03	-0.05	-0.05
	(0.05)	(0.05)	(0.08)	(0.11)	(0.06)	(0.05)	(0.07)	(0.12)
House Chores	0.03	-0.03	-0.11	0.06	-0.07	-0.14	-0.02	-0.14
	(0.21)	(0.18)	(0.27)	(0.45)	(0.19)	(0.19)	(0.24)	(0.41)
Shopping or Sourcing Goods	-0.02	-0.00	-0.04	-0.04	-0.01	-0.00	-0.01	-0.02
	(0.06)	(0.05)	(0.10)	(0.12)	(0.05)	(0.05)	(0.07)	(0.10)
Leisure Time	0.30	0.43	0.63	0.66	0.20	0.31	0.25	0.42
	(0.27)	(0.27)	(0.45)	(0.58)	(0.25)	(0.25)	(0.43)	(0.52)
Personal Care	0.19*	0.20*	0.21	0.42*	0.11	0.10	0.09	0.24
	(0.11)	(0.11)	(0.14)	(0.23)	(0.10)	(0.11)	(0.14)	(0.22)
Sleeping or Resting	-0.12	-0.02	0.11	-0.27	-0.11	0.02	0.04	-0.22
	(0.21)	(0.21)	(0.31)	(0.45)	(0.19)	(0.19)	(0.28)	(0.40)
Social Engagements	0.23	0.25	0.31	0.51	0.19	0.19	0.12	0.40
	(0.18)	(0.18)	(0.22)	(0.40)	(0.16)	(0.16)	(0.20)	(0.33)
In Transit	0.17*	0.16*	0.04	0.36*	0.13*	0.13*	0.05	0.27*
	(0.09)	(0.10)	(0.08)	(0.21)	(0.08)	(0.08)	(0.07)	(0.16)
Total time awake	-0.15	-0.17	-0.06	-0.34	-0.14	-0.17	-0.13	-0.29
	(0.18)	(0.19)	(0.26)	(0.40)	(0.16)	(0.16)	(0.25)	(0.33)
Time wake up	0.21*	0.23*	0.23*	0.45*	0.18*	0.20*	0.23*	0.37*
	(0.10)	(0.11)	(0.13)	(0.23)	(0.09)	(0.09)	(0.12)	(0.20)
Time go to sleep	0.05	0.06	0.17	0.12	0.03	0.03	0.09	0.07
	(0.13)	(0.14)	(0.18)	(0.29)	(0.11)	(0.11)	(0.17)	(0.23)
At Home	0.33	0.43	0.14	0.72	-0.06	-0.00	-0.09	-0.13
	(0.33)	(0.32)	(0.50)	(0.73)	(0.30)	(0.29)	(0.42)	(0.62)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Table 9: Aggregate time use - Men

Outcome	Main respondents only				Respondents and spouses			
Specification	CX	CTL	GEO	IV	CX	CTL	GEO	IV
Productive Activities	-0.41	-0.47	-0.56	-0.87	-0.25	-0.38	-0.45	-0.51
	(0.37)	(0.35)	(0.50)	(0.80)	(0.35)	(0.34)	(0.47)	(0.72)
Agriculture	-0.61*	-0.49	-0.72*	-1.31*	-0.58*	-0.44	-0.69*	-1.20*
	(0.32)	(0.30)	(0.40)	(0.72)	(0.30)	(0.28)	(0.36)	(0.62)
Livestock	-0.16	-0.14	-0.39*	-0.35	-0.07	-0.04	-0.25	-0.14
	(0.17)	(0.16)	(0.23)	(0.36)	(0.14)	(0.14)	(0.18)	(0.29)
Non-Farm Work	0.37	0.15	0.54	0.80	0.40	0.09	0.48	0.83
	(0.48)	(0.40)	(0.61)	(1.03)	(0.43)	(0.38)	(0.53)	(0.89)
Informal Work	-0.29	-0.33*	-0.55*	-0.62	-0.36	-0.35	-0.33	-0.74
	(0.19)	(0.19)	(0.29)	(0.42)	(0.23)	(0.24)	(0.31)	(0.49)
Family Care	0.04	0.03	-0.02	0.09	0.01	0.02	-0.01	0.02
	(0.07)	(0.07)	(0.08)	(0.14)	(0.08)	(0.08)	(0.10)	(0.16)
House Chores	-0.25	-0.29*	-0.42	-0.55	-0.31	-0.32	-0.24	-0.64
	(0.18)	(0.17)	(0.26)	(0.38)	(0.21)	(0.22)	(0.27)	(0.44)
Shopping or Sourcing Goods	-0.08	-0.07	-0.12	-0.16	-0.06	-0.05	-0.07	-0.12
	(0.05)	(0.05)	(0.10)	(0.11)	(0.05)	(0.05)	(0.07)	(0.10)
Leisure Time	0.73*	0.83*	1.07*	1.57*	0.61*	0.72*	0.61	1.26*
	(0.37)	(0.36)	(0.50)	(0.82)	(0.35)	(0.34)	(0.51)	(0.73)
Personal Care	0.39**	0.40**	0.38*	0.85**	0.22	0.21	0.18	0.45
	(0.15)	(0.15)	(0.19)	(0.33)	(0.14)	(0.14)	(0.17)	(0.29)
Sleeping or Resting	0.04	0.13	0.26	0.09	0.04	0.15	0.13	0.08
	(0.29)	(0.29)	(0.37)	(0.63)	(0.27)	(0.26)	(0.35)	(0.55)
Social Engagements	0.29	0.30	0.44	0.62	0.35	0.35	0.30	0.73
	(0.27)	(0.26)	(0.31)	(0.58)	(0.24)	(0.23)	(0.27)	(0.49)
In Transit	0.24	0.23	0.10	0.51	0.16	0.16	0.07	0.34
	(0.15)	(0.16)	(0.13)	(0.34)	(0.13)	(0.13)	(0.09)	(0.27)
Total time awake	-0.42	-0.43	-0.31	-0.91	-0.45*	-0.47*	-0.42	-0.93*
	(0.28)	(0.28)	(0.35)	(0.61)	(0.26)	(0.26)	(0.37)	(0.55)
Time wake up	0.37*	0.38*	0.40*	0.80*	0.36*	0.38*	0.41*	0.75*
	(0.17)	(0.17)	(0.19)	(0.38)	(0.15)	(0.15)	(0.18)	(0.33)
Time go to sleep	-0.05	-0.05	0.09	-0.11	-0.09	-0.09	-0.01	-0.19
	(0.19)	(0.19)	(0.26)	(0.40)	(0.17)	(0.17)	(0.25)	(0.35)
At Home	0.53	0.66	0.21	1.14	0.15	0.31	0.08	0.30
	(0.45)	(0.44)	(0.50)	(0.98)	(0.42)	(0.41)	(0.51)	(0.86)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Table 10: Aggregate time use - Women

Outcome	Main respondents only				Respondents and spouses			
Specification	CX	CTL	GEO	IV	CX	CTL	GEO	IV
Productive Activities	-0.40	-0.60	-0.59	-0.89	-0.05	-0.17	-0.33	-0.10
	(0.39)	(0.40)	(0.55)	(0.86)	(0.33)	(0.33)	(0.46)	(0.69)
Agriculture	-0.55*	-0.38	-0.46	-1.23*	-0.14	-0.07	-0.08	-0.30
	(0.32)	(0.32)	(0.45)	(0.71)	(0.27)	(0.26)	(0.35)	(0.56)
Livestock	-0.03	0.03	-0.22	-0.07	-0.04	-0.03	-0.23*	-0.09
	(0.13)	(0.14)	(0.19)	(0.29)	(0.10)	(0.10)	(0.14)	(0.21)
Non-Farm Work	0.18	-0.25	0.10	0.41	0.14	-0.07	-0.01	0.29
	(0.36)	(0.37)	(0.49)	(0.80)	(0.28)	(0.28)	(0.38)	(0.58)
Informal Work	0.31	0.40	0.04	0.70	-0.00	0.03	-0.00	-0.01
	(0.36)	(0.36)	(0.44)	(0.81)	(0.34)	(0.35)	(0.41)	(0.72)
Family Care	0.03	0.01	-0.09	0.07	-0.06	-0.07	-0.09	-0.13
	(0.08)	(0.08)	(0.12)	(0.19)	(0.08)	(0.08)	(0.10)	(0.17)
House Chores	0.24	0.31	0.10	0.53	0.03	0.05	0.05	0.06
	(0.34)	(0.34)	(0.40)	(0.75)	(0.32)	(0.33)	(0.40)	(0.68)
Shopping or Sourcing Goods	0.04	0.08	0.03	0.10	0.03	0.05	0.04	0.07
	(0.10)	(0.10)	(0.14)	(0.23)	(0.08)	(0.08)	(0.10)	(0.18)
Leisure Time	-0.19	-0.08	0.11	-0.42	-0.16	-0.11	-0.06	-0.34
	(0.37)	(0.38)	(0.61)	(0.83)	(0.31)	(0.32)	(0.48)	(0.66)
Personal Care	-0.06	-0.06	-0.00	-0.13	0.01	-0.01	0.01	0.03
	(0.15)	(0.16)	(0.17)	(0.34)	(0.13)	(0.14)	(0.15)	(0.28)
Sleeping or Resting	-0.33	-0.20	-0.06	-0.72	-0.23	-0.11	-0.03	-0.47
	(0.29)	(0.30)	(0.36)	(0.66)	(0.24)	(0.24)	(0.31)	(0.51)
Social Engagements	0.19	0.18	0.18	0.43	0.05	0.02	-0.04	0.11
	(0.23)	(0.23)	(0.29)	(0.50)	(0.18)	(0.18)	(0.21)	(0.37)
In Transit	0.09	0.08	-0.02	0.20	0.11	0.10	0.05	0.22
	(0.08)	(0.08)	(0.08)	(0.18)	(0.07)	(0.07)	(0.09)	(0.15)
Total time awake	0.20	0.17	0.26	0.45	0.18	0.15	0.16	0.39
	(0.22)	(0.22)	(0.28)	(0.48)	(0.16)	(0.16)	(0.20)	(0.33)
Time wake up	0.00	0.03	0.02	0.00	-0.01	0.02	0.04	-0.03
	(0.10)	(0.11)	(0.12)	(0.23)	(0.08)	(0.09)	(0.10)	(0.18)
Time go to sleep	0.20	0.19	0.28	0.44	0.17	0.16	0.20	0.35
	(0.18)	(0.19)	(0.21)	(0.41)	(0.12)	(0.13)	(0.15)	(0.26)
At Home	-0.05	0.12	-0.11	-0.12	-0.39	-0.32	-0.38	-0.82
	(0.46)	(0.47)	(0.63)	(1.02)	(0.38)	(0.39)	(0.53)	(0.80)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

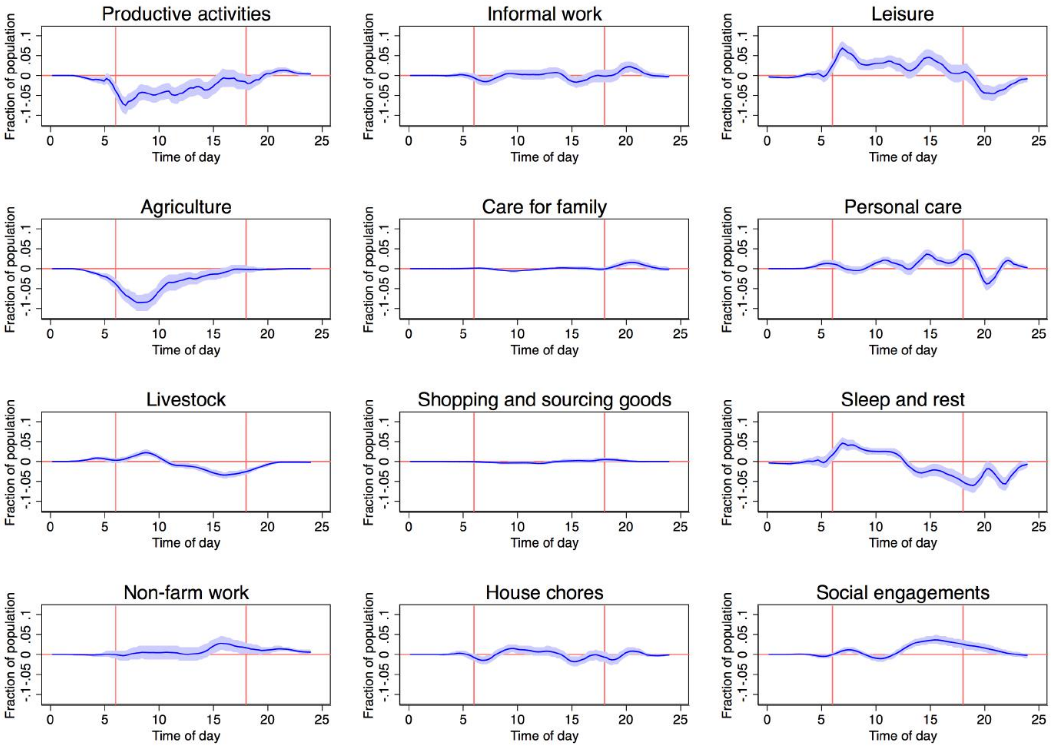


Figure 3: Change in time use - Men and women

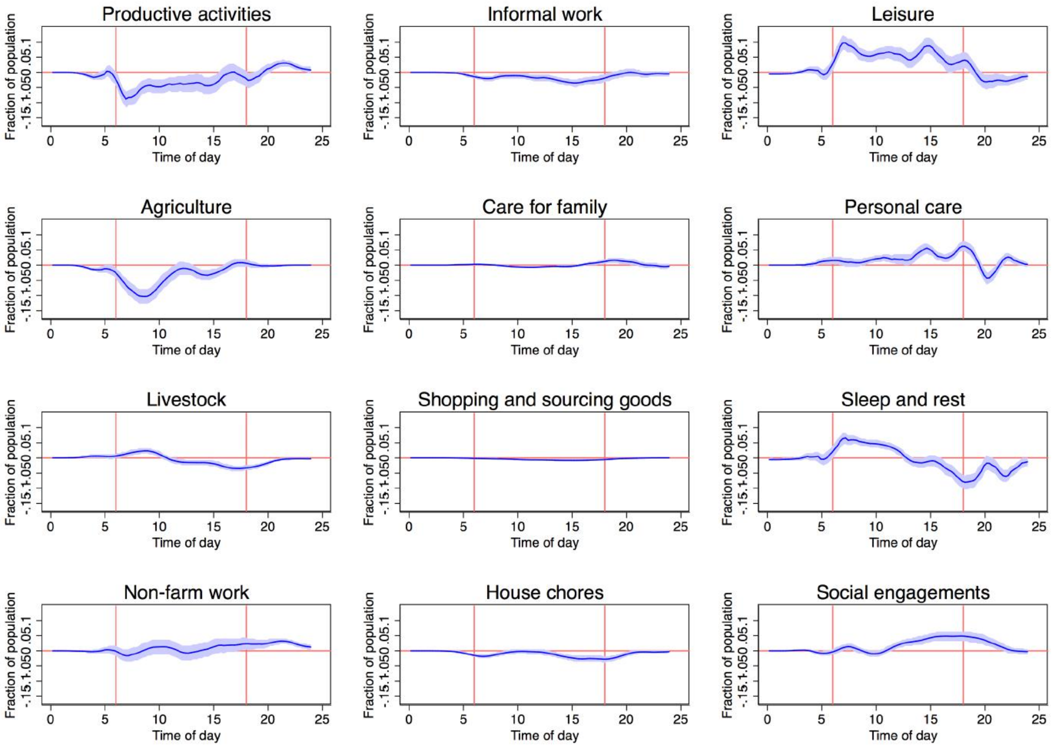


Figure 4: Change in time use - Men. Respondents only.

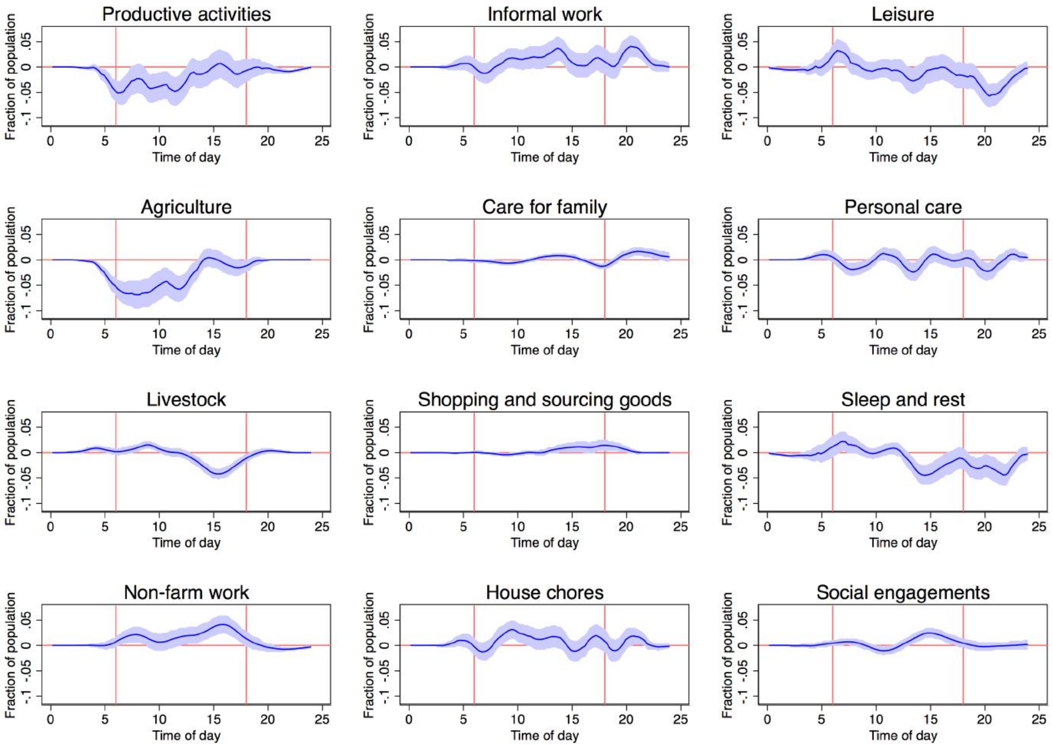


Figure 5: Change in time use - Women. Respondents only.

The results displayed in these Figures provide interesting insights that go beyond what can be inferred from aggregate data. In particular, many of the panels exhibit a 'waveform' shape, whereby peaks are compensated by throughs at different times of day and evidencing 'task shifting'. For example, this is particularly clear in the trade-off between productive activities, informal work and leisure. While we have already shown in Section 5.1 a treatment effect leading to a net shift from productive to leisure activities for men, Figure 3 and 4 paint a more detailed picture on how and when this materialises. Specifically, we see that productive work gives way to leisure (primarily rest) in the morning, but the reverse occurs during the evenings as men in treated households increase their involvement in non-farm work and in social engagements, as they sleep later. Similarly, women also partly increase leisure time (and informal work) in the morning at the expense of productive activities, but reduce leisure time in the evenings to make time for an increase in informal work (split equally between family care and house chores). Women in treated households also see a notable increase in non-farm work and social engagements in the late afternoon, mainly at the expense of livestock activities and resting.

The Figures also provide further evidence that lamps influence wake-up and sleep times. As with responses to the direct questions on wake-up times, the pattern of reported activities indicates treated individuals, and men in particular, delay their wake-up time. In contrast to the answers to direct questions, we find stronger evidence indicating that treated household delay going to sleep, both for men and women.

The results in Figures 3, 4 and 5 support some important points. Firstly, the evidence of 'task shifting', especially when moving from one side of sunset to the other strongly substantiates the belief that the differences we identify between treated and control households are driven by access to light, and ultimately the treatment.

Secondly, 'task shifting' is economically important even in the absence of changes to aggregate time allocations if the productivity of a task depends on the timing when this is carried out. Social engagements are a case in point. As discussed in Section 3.2, these include socially and economically relevant activities such as listening to the radio or paying a visit to members of the community. Being able to reap the social benefits of participating in these also depends on the ability to attend at the most propitious moment. The same applies, for example, for the timing of when to sell at the market.

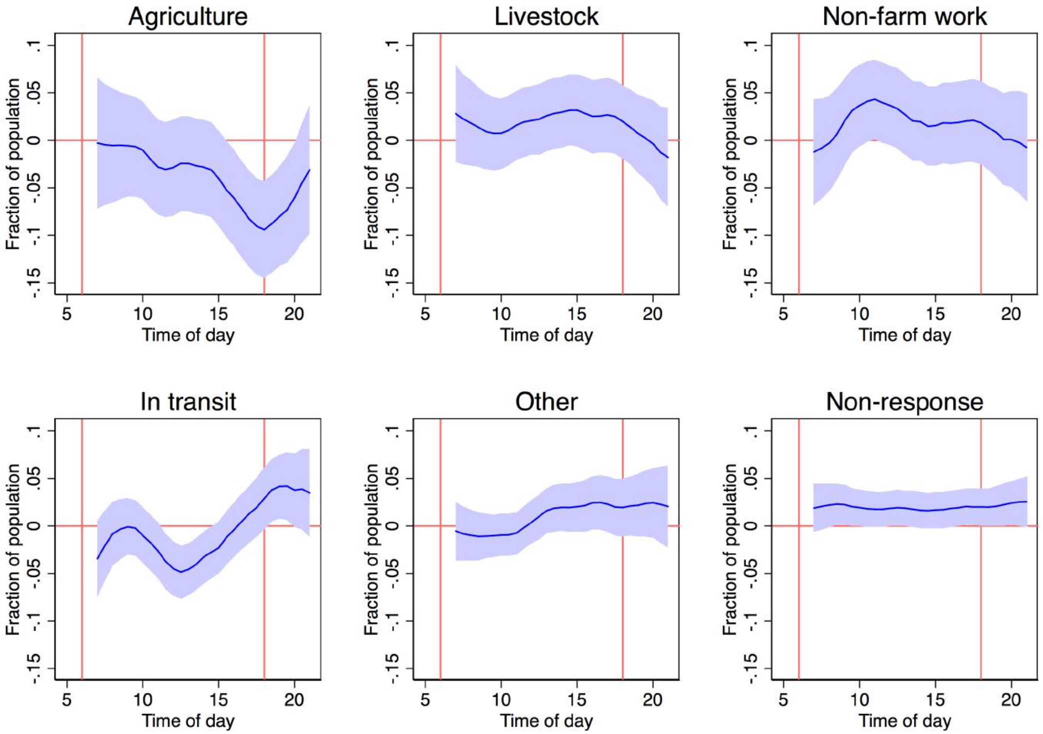


Figure 6: Change in time use via experience sampling

Table 11: IncomeSources

Outcome	CX	CTL	GEO	IV
Agriculture	0.20	0.50	0.98	0.44
	(1.18)	(1.14)	(1.11)	(2.57)
Livestock	3.39	2.31	1.50	7.40
	(2.65)	(2.65)	(3.95)	(5.79)
Casual agricultural work	-3.31	-1.37	-7.69	-7.22
	(3.56)	(3.53)	(6.11)	(7.79)
Non-farm activities	7.28*	0.95	8.88	15.86*
	(3.51)	(1.03)	(5.77)	(7.67)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Figure 6 shows the equivalent results using data collected via experience sampling. Overall, the results are much less clear-cut, not least because the more limited sample implies estimates are subject to a higher degree of uncertainty. We can nevertheless identify some of the same patterns we have identified so far: statistically significant reductions in agricultural activities and increases in non-farm work, albeit statistically insignificant. To the extent that social engagements are proxied by 'In transit' and 'Other', we again see an increase in social participation in the afternoon and evening among the treated.

5.3 Productive activities and income

In this section, we report estimates of treatment effects on household economic activities and productive capacity. In particular, the hypothesis is that changes in time use and 'task shifting' made possible by the lamp may lead to a change in the household's involvement in productive activities both at the extensive and intensive margins. Ultimately, we also test whether these changes lead to a change in incomes.

Table 11 gives an initial overview of the possible effects of access to light. As one might expect given the highly agricultural project region, we find that access to light does not alter the household's propensity to engage in agriculture or livestock activities. However, we find some evidence indicating that access to light may lead to an economically significant increase in the incidence of non-farm income-generating activities, in the order of 7 percentage points. However, as discussed in Section 4.1, we may have reason to believe this difference was present at baseline. We discuss the effects on farm and non-farm activities in more detail in the next two subsections, before presenting results on incomes.

Farm activities

Despite the lack of aggregate effects on the extensive margin in relation to agricultural and livestock income streams, the lamp may nevertheless bring about a change in the extent or composition these activities. This section therefore reports results in relation

Table 12: Crops

Outcome	CX	CTL	GEO	IV
N# of crops types	-0.07	-0.09	-0.14	-0.16
	(0.12)	(0.12)	(0.18)	(0.26)
Grows Maize	0.40	0.72	2.82	0.87
	(2.05)	(2.08)	(3.03)	(4.47)
Grows Beans	-4.30	-5.14	-2.07	-9.38
	(3.57)	(3.63)	(5.00)	(7.76)
Grows FingerMillet	-1.95	-1.99	0.78	-4.25
	(2.25)	(2.27)	(3.27)	(4.90)
Grows Vegetables	2.31	1.58	-0.44	5.02
	(3.57)	(3.62)	(5.50)	(7.78)
Grows Bananas	-0.97	-1.04	-6.54	-2.10
	(3.49)	(3.50)	(4.28)	(7.59)
Grows SugarCane	1.08	1.68	-1.54	2.35
	(3.57)	(3.62)	(5.14)	(7.76)
Grows Tea	-1.52	-2.20	-6.25*	-3.32
	(2.24)	(2.23)	(2.99)	(4.88)
Grows Coffee	-4.85*	-4.76*	-8.43*	-10.56*
	(2.24)	(2.25)	(3.75)	(4.91)
Grows Other	2.61	2.09	7.36*	5.69
	(2.93)	(2.99)	(4.13)	(6.39)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

to crop composition (Table 12), and the ownership of livestock (Tables 13 and 14). Overall, we do not find strong evidence of treatment effects on the specific nature of the agricultural and livestock activities activities carried out by the household. There are a couple notable exceptions, however, that fit well with the results described in other sections and anecdotal evidence from the fieldwork.[18]

Firstly, assignment to treatment is associated with a 5 percentage point reduction in the incidence of coffee cultivation. Coffee is exclusively a cash crop, and this result brings further support to evidence suggesting that access to light favours a move away from farm-based livelihoods. At the same time, we find some evidence of an intention-to-treat effect on the number of poultry owned. At around 1 chicken, compared to an average of 5.6 in the sample, the economic magnitude of the result not insubstantial. This result chimes very well with qualitative evidence collected in the field (see Box 1).

[18]Naturally, we would expect a fraction of all coefficients estimated to be statistically significant by pure chance.

Table 13: Livestock - Extensive

Outcome	CX	CTL	GEO	IV
N# of livestock types	0.07	0.05	0.02	0.15
	(0.06)	(0.06)	(0.09)	(0.14)
Owns Cattle	4.20	3.17	-0.83	9.14
	(3.44)	(3.45)	(5.00)	(7.53)
Owns Poultry	2.56	1.64	6.13	5.58
	(3.39)	(3.41)	(4.67)	(7.40)
Owns Goats	1.10	1.60	-1.28	2.40
	(2.57)	(2.53)	(4.32)	(5.59)
Owns Rabbits	-0.48	-0.57	-0.37	-1.05
	(0.50)	(0.50)	(0.30)	(1.09)
Owns Others	-0.63	-0.57	-1.37	-1.38
	(0.80)	(0.80)	(1.20)	(1.74)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Table 14: Livestock - Intensive

Outcome	CX	CTL	GEO	IV
N# of Cattle	0.09	0.05	0.01	0.19
	(0.09)	(0.10)	(0.11)	(0.20)
N# of Poultry	1.23*	1.01	2.15**	2.68*
	(0.68)	(0.70)	(0.76)	(1.49)
N# of Goats	-0.02	-0.02	-0.08	-0.05
	(0.08)	(0.08)	(0.13)	(0.18)
N# of Rabbits	-0.03	-0.04	-0.02	-0.07
	(0.02)	(0.02)	(0.01)	(0.05)
N# of Other animals	0.11	0.15	-0.48	0.25
	(0.39)	(0.43)	(0.98)	(0.84)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Box 1 A very entrepreneurial family

While undoubtedly an outlier compared to the other families in the target community, the stories collected from this family strongly illustrate the potential economic benefits of the lamp.

The family was in the treatment group, although it turns out they were one of the few families that had already bought a lamp before the project. Interestingly, this purchase was part of a clear strategy. The father had estimated that with the savings on kerosene generated by having a solar lamp, he could quickly save enough to buy a 'hen in a box' kit. The kit costs around 1,500 KSh (USD $15) and consists of a hen and a metal cage (to protect it from predatory birds). It is designed to provide the basic inputs to start a small poultry farm. When we interviewed the family, less than a year from the purchase of the first lamp, we saw three such cages and about a dozen adult chickens.

The mother is a teacher, but runs a retail activity on the side. She buys wholesale in the town where she teaches and sells retail every afternoon in her community. While this activity predated the purchase of a solar lamp, the lamp permits her to stay at the market a little longer into the twilight hours, thereby extending her working hours.

Non-farm activities

Table 15 summarises results in relation to non-farm activities. We find a potentially sizeable treatment effect on the incidence of non-farm income generating-activities. Our core cross-sectional specification identifies a 7 percentage point intention-to-treat effect. The inclusion of geographical fixed effects does not meaningfully alter the estimated size of the effect (indicating this is not due to the omission of local factors), though clustering at the geographical grid level makes the estimate statistically insignificant. We also identify a statistically significant treatment effect on the number of non-farm income-generating activities, in the order of 0.13 units compared to a mean of 0.44 in the sample. At the same time, however, Table 15 also shows that the incidence of activities started less than 12 months ago is only an insignificant 1 percentage point higher among treated households.

One's overall interpretation of these coefficients ultimately depends on one's belief on the accuracy and consistency of respondents' answers. If we believe the responses are always fully consistent, we would suspect that a difference in the mean incidence between treated and control groups was already present at baseline, in the order of 6 percentage points. As one would expect, the intention-to-treat effect disappears when we control for this imputed baseline incidence of non-farm activities, as shown in Specification CTL.[19] Given randomisation, the ex-ante likelihood of the realisation of such imbalance is very low. The p-value for a standard t-test on the reconstructed baseline variable is 0.05. Nevertheless, this is little consolation if one takes the responses to the two above questions as suggesting that that is indeed the state of the world this project has been

[19] In Table 15 we still identify a statistically significant impact on the number of non-farm activities when controlling for the imputed baseline incidence of non-farm activities as per Equation 2. However, the result disappears if we control for the imputed baseline number of non-farm activities.

Table 15: Non-farm Activities

Outcome	CX	CTL	GEO	IV
Non-farm activities	7.28*	0.95	8.88	15.86*
	(3.51)	(1.03)	(5.77)	(7.67)
Number of non-farm activities	0.13**	0.06*	0.16*	0.28**
	(0.04)	(0.02)	(0.07)	(0.10)
Started less than 12 months ago	0.68	0.95	3.35	1.48
	(1.00)	(1.03)	(2.04)	(2.19)
Weighted sample size	800			

Woman involved in non-farm work	8.19	4.21	0.93	20.71
	(5.47)	(4.79)	(7.87)	(13.97)
Man involved in non-farm work	-0.14	4.08	11.48	-0.35
	(5.02)	(4.15)	(7.68)	(12.66)
Carried out during hours of darkness	6.73*	5.75*	7.18	17.02*
	(3.39)	(3.43)	(4.87)	(8.93)
Carried out at home	-2.54	-3.75	-4.36	-6.41
	(3.24)	(3.20)	(5.06)	(8.21)
Carried out at fixed place away from home	1.78	2.51	-1.98	4.49
	(4.22)	(4.25)	(5.88)	(10.61)
Activity is mobile	0.45	-0.08	9.01	1.13
	(3.83)	(3.83)	(5.55)	(9.65)
Weighted sample size	309			

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

implemented in.

On the other hand, if one believes that the responses to the above two survey questions need not be fully consistent, then it is no longer implied that baseline differences were present. In particular, there is reason to be skeptical of the data quality in relation to whether activities were started less than 12 months before. Activities were reported as being recent in only 15 households (8 in the control group and 7 in the treatment group). Even just a handful of cases of incorrect reporting would therefore have a large effect on the estimated treatment coefficient. On the contracry, the variable identifying whether households are involved in non-farm income-generating activities is derived from whether the individual responded to the non-farm module of the survey. This involved 5 questions for each non-farm activity, making it less likely that entire activities would be reported incorrectly.

In summary, a cautious interpretation of the estimates would indicate that the treatment effect on the incidence of non-farm income streams is bracketed between a statistically insignificant 1 percentage point and a statistically significant 7 percentage points.

Qualitative interviews reveal some anecdotes on the types of activities that may have emerged thanks to having access to light. Indeed, on a few occasions, albeit often after direct prompting, the families identified ways in which the lamp had allowed them to increase their productive activity. Examples of this include carrying out clothing repairs or soapstone carving at night, or being able to stay a little longer to sell vegetables at the market. Similarly, control families quoted clothing repairs or small household retail as income-generating activities that they believe could be enabled by having access to solar lamps.

Aside from effects on the extensive margin, the lamp can also affect how existing activities are operated. In the bottom panel of Table 15 we present results on the whether the lamp influences the timing, location and manager of the activity, estimated on the subsample of households that engage in at least one non-farm activity.

We find evidence that the lamp increases the likelihood that the activity is carried out primarily during the hours of darkness by around 7 percentage points (compared to a mean of 9 percentage points in the sample). This result confirms the previous indications of 'task-shifting' of productive activities into the evening, particularly for men, seen in Section 5.2.

On the other hand, access to light does not appear to influence the location of the activity. Indeed, contrary to commonly held expectations around the increase in home-based production, the coefficient on whether the activity is carried out at home is negative (thought not significantly different from zero).

Treatment is also not associated with any change in the gender of the person involved in the productive activity. The coefficients on the involvement of the woman and/or the man are jumpy across specifications and all statistically insignificant. This indicates that the treatment is gender-neutral, meaning it does not alter the existing gender balance in the involvement in non-farm work. As we saw in Table 3, men are twice as likely to be managing the non-farm activity than women.

Table 16: Incomes

Outcome	CX	CTL	GEO	IV
Farm income	-137.44*	-137.26*	-153.70	-297.85*
	(72.51)	(73.63)	(97.34)	(160.10)
Non-farm income	293.08*	191.11*	405.28*	635.14*
	(115.60)	(95.02)	(207.74)	(253.47)
Total income	155.64	53.85	251.58	337.29
	(141.08)	(124.24)	(222.84)	(304.89)
Equivalised total income	6.98	-0.22	27.11	15.12
	(14.11)	(12.75)	(19.63)	(30.50)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

Incomes

As a final link in the possible causal chain triggered by access to light, we present some summary results on treatment effects on income levels, as seen in Table 16.

We find strong evidence of an economically large shift in incomes from farm to non-farm activities. We identify a statistically significant intention-to-treat effect on the level of income from non-farm sources of around 290 Kenyan Shillings (USD $2.90) per week, or equivalent to 20% of the mean household income in our sample. Similarly, we find a statistically significant intention-to-treat effect whereby incomes from farm activities fall by 140 Kenyan Shillings per week (USD $1.40; 9% of mean household income) Importantly, introducing controls, notably the imputed incidence of non-farm income-generating activities at baseline, has no effect on the estimate on farm income while the estimate for non-farm incomes is attenuated but still sizeable.[20] This indicates the effects are driven by changes in the intensive margin. While the effect on farm income becomes marginally insignificant, the inclusion of geographical fixed effects does not dramatically alter the story.

At the same time, we do not detect any change in total income. The treatment effect on total household income and total equivalised household income are generally positive, but not statistically significant.[21] This raises the question as to why families might be induced toward this shift if it leaves them no better off. One explanation could relate to the diversification of risks across income streams. Alternatively, it could be that the process of transformation in economic activities is still ongoing and is not fully developed at only 7 months from treatment.

[20] Both results are also robust to the inclusion of the imputed number of non-farm activities at baseline.

[21] All the results presented in this section omit the top 1% of incomes. As these were several dozens of times the average in the sample, they raised the concern that they could distort the results. Indeed, including these, we find much larger treatment effects on non-farm incomes and statistically insignificant reduction in farm incomes, thereby leading to large statistically significant impacts on overall income. The omission of outliers therefore reflects a cautious approach.

Table 17: Savings

Outcome	CX	CTL	GEO	IV
Weeky expenditure on lighting fuel (Kshs)	-21.87**	-24.35***	-6.10	-47.48**
	(7.07)	(6.94)	(8.16)	(15.08)
Do you feel you are able to set a side part of your income as savings?	-2.14	-4.56	-2.02	-4.65
	(3.48)	(3.39)	(6.01)	(7.59)
Savings set in a savings institution?	-1.49	-3.11	-3.23	-3.26
	(3.53)	(3.45)	(6.42)	(7.69)

*Standard errors in parentheses. * p<0.1, ** p<0.01, *** p<0.001.*

5.4 Savings

There is plenty of evidence showing that solar lighting products generate net savings on alternative fuel expenditures. If re-invested, these savings could constitute an additional, or even the primary, mechanism through which access to light can lead to changes in household economic circumstances. In this section, we present a small set of results attempting to gauge the strength of this mechanism in the context of our project. Results are displayed in Table 17.

In line with previous work, we identify a statistically significant intention-to-treat effect causing a fall in expenditure on alternative lighting fuel. However, at 20 Kenyan Shillings per week (USD $0.20), or a mere 1.4% of average weekly incomes in our sample, it is considerably smaller than identified in other studies (Grimm et al., 2014; Hassan & Lucchino, 2014; IDinsight, 2015).[22] In line with this, we find no evidence of treatment effects on self-reported savings behaviour. We conclude that any effect of access to light on savings appears to be small, if present at all.

6 Conclusion

Economic development and structural change are long processes involving the evolution and transformation of all aspects of the economy and society. Existing work shows that large scale electrification has an important part to play in this transformation. However, considering a quarter of humanity lives in areas where off-grid solutions such as solar lamps or home systems are the only options allowing some form of energy access, there is very little research into whether, albeit commensurate to their much smaller size, these can trigger similar mechanisms of socio-economic transformation.

To our knowledge, this paper is one of very few recent works tackling this issue, and the only one that finds evidence that small scale lighting solutions can help stimulate the

[22]The treatment effect is also not robust to the inclusion of geographical fixed effects.

very first steps in the direction of economic transformation. By exploiting experimental variation in the ownership of solar lamps, we identify treatment effects leading to a shift in household livelihoods from agricultural to non-farm economic activities. We find robust evidence indicating that household income streams change in an economically substantial way in line with this shift. These results are complemented by treatment effects causing a reduction in cash crop cultivation. At the same time, we find tentative evidence indicating a substantial treatment effect on the incidence and number of non-farm income-generating activities the household is involved in.

The emerging picture is backed up by detailed evidence on household time use. We find robust evidence that treated households reduce the time they dedicate to agricultural work, and some indication of an increase in time spent in non-farm contexts (specifically on social engagements and non-farm work). Beyond aggregate time use, detailed time diaries reveal strong evidence of 'task-shifting', particularly between morning and the late afternoon and evenings. This confirms statistically relevant increases in non-farm work and social engagements for men in the evenings, and for women in the late afternoons. Women increase time spent on informal work in the evenings.

Our results suggest that the shift in the household economic activities emerges primarily because of a changed use of time, rather than through saving and investment. Indeed, we find, at best, economically minor effects on savings on alternative lighting fuels expenditure, and no change in savings behaviour. Noting the observed changes in income streams, and that the timing of activities change more than in the total time dedicated to each, we speculate that access to light allows an productivity-increasing reallocation of activities across the times of day.

It is often argued that the flexibility to reallocate activities over an extended range of hours of the day is particularly relevant to the increased economic participation and empowerment of women. This paper speaks to directly to this topic and delivers some sobering results. In line with expectations, we do evidence that access to light allows women extend their day into the evenings, but this additional time is primarily dedicated to house chores. Importantly, we find a corresponding reduction in the incidence of house chores amongst men, who are therefore the ultimate beneficiaries of this additional time. Like men, women in treated households increase their engagement in non-farm work and social activities in the late afternoon. However, we find no evidence that access to light influences the gender distribution among those responsible for non-farm income-generating activities.

This paper therefore contributes novel evidence indicating that a cheap and renewable source of energy used exclusively for *lighting* can indeed help reap at least a modest fraction the benefits of full scale electrification. In particular, it can favour household diversification away from farm livelihoods toward non-farm micro-entrepreourial endeavours by allowing an improved re-allocation of activities over the course of the day. Contrary to the common narrative about the time constraints of women, however, the effect of access to light does not appear to flow in any larger part to women. If anything, we find that effects of the intervention we study are gender-neutral, in the sense that they do not alter, but rather emerge within, the prevailing balance of power between genders. As perhaps would be the case in most of the world, this means that women, albeit benefitting, may not be reaping their full fair share of these benefits.

7 Annex

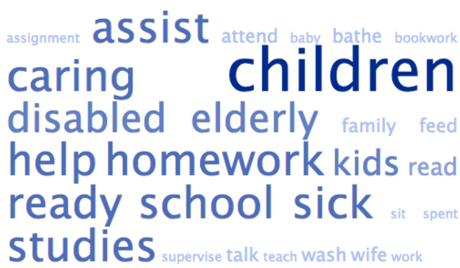
Figure 7: Non-farm activites word cloud

Figure 8: Activity word clouds - 1

(a) Social engagements

(b) Agriculture

(c) Personal care



(d) Family care

(e) Sleep and rest

(f) Shopping and sourcing goods

Figure 9: Activity word clouds - 2

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