Tracking the Leakage of Development Goods Using iBeacon Technology

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Abstract

The leakage of development goods is a major challenge for governments and a preoccupation of development practitioners and academic researchers. Although commonly reported and lamented, such leakage is challenging to quantify. We address this evidentiary blind spot by piloting the use of iBeacon technology to track how village elders distribute solar lanterns within off-grid communities in western Kenya. We provide evidence on the efficacy of the technology for detecting the lanterns and tracking their movement. We draw on survey data to understand why some households received lanterns and others did not. We find evidence consistent with the faithful execution of program guidelines, as well as evidence for the distribution of lanterns to households with needs along dimensions beyond our designated criterion. Our findings run against common depictions of local African elites as predatory actors and suggest the need to rethink the common equation of "leakage" with malfeasance.[1]

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1 Introduction

The leakage of development goods is a major challenge for governments and the aid industry, and a preoccupation of development practitioners and academic researchers.[2] Every year, millions of dollars of farming inputs, relief food, pharmaceutical supplies, bed nets, and other development goods go missing or are misallocated.[3] This leakage is perceived to undermine the benefits that the goods were designed to bring and may reduce support in donor countries for development aid. It may also feed criminal networks and reinforce the power of politicians and bureaucrats who are complicit in the diversion of these items.

Although commonly reported and lamented, the leakage of development goods is challenging to quantify and characterize precisely. In part this is because deviations from program guidelines, not to mention outright theft, tend to be hidden. But it is also because the sorts of development goods that governments and aid agencies regularly distribute—fertilizer, maize, antimalarial medications, farm tools, and, increasingly, cash—are very difficult to trace once they have been distributed within a community. Common approaches to tracking leakage, such as perception-based surveys (e.g., Transparency International (2023), Olken (2009)) or comparisons between goods allocated and received (e.g., Reinikka and Svensson (2004), Golden and Picci (2005), Olken (2006, 2007), Niehaus and Sukhtankar (2013), Banerjee et al. (2018)), can provide only rough estimates of what may have gone missing. In addition, these approaches tell us little about where the goods may have gone or when in the distribution process the leakage may have occurred. This evidentiary gap hinders our ability to devise strategies to minimize leakage. It also creates challenges for developing a deeper understanding of why local actors entrusted with distributing development goods may diverge from program criteria, as well as how leaked goods flow through markets and patronage networks once they are diverted. Such questions are critical for both policymakers and students of political economy.

We address this evidentiary blind spot by piloting the use of iBeacon technology to track solar lanterns distributed in off-grid communities in western Kenya. iBeacon technology relies on Bluetooth tags that can be tracked remotely as they move through space; commercial versions of the technology include Apple AirTags and Tiles, commonly used for locating lost keys and luggage. When affixed to an item and tracked via a systematic monitoring program, these tags make it possible to follow that item from its initial distribution point to its ultimate beneficiary without the awareness of its distributor or recipient. iBeacon technology thus offers a significant advantage over other approaches to studying leakage, which either make inferences from aggregate measures of missing goods (thus providing no information about the paths that the goods may have taken or who may have ultimately received them) or observe allocation decisions directly via

[2] The first paragraph of J-PAL's governance initiative review paper (J-PAL Governance Initiative, 2019) cites leakages due to corruption as one of the main factors undermining the effectiveness of public spending in poor countries.

[3] A representative set of reports of such leakage and/or misallocation include Bate (2011), Michael (2018), *Daily Nation* (Zambia) (2021), and *Malawi 24* (2016).

audits and other forms of overt monitoring (thus alerting actors to the fact that their behavior is being watched—and likely changing that behavior).

Although iBeacon technology offers significant advantages for studying the distribution of development goods, its use raises challenging ethical questions. A first objective of the study is therefore to demonstrate a set of protocols for deploying this technology ethically. We discuss at length below how our project design sought to balance the potential benefits of using iBeacon technology with the protection of and respect for the communities in which we distributed the tagged lanterns.

Our second objective is to assess the efficacy of the technology for detecting and tracking the movement of development goods distributed in a real world setting. We find that the technology works extremely well for this purpose. As discussed below, we were able to detect 98.8% of the lanterns we distributed in our study area, as well as track their movement across households during the ensuing eight weeks. Our results suggest that iBeacon technology offers a powerful tool for policymakers and practitioners interested in unobtrusively taking inventories of items (for example, to detect whether or when they leave a business, storage facility, or distribution supply chain) or in learning how goods move through markets and communities. This ability makes the technology particularly well suited for collecting outcome data in studies comparing the relative efficacy of different modes of distribution (for example, via local elites, community committees, or direct democracy—as in Olken (2010), Beath, Christia and Enikolopov (2017), or Voors et al. (2018))—and thus offers potentially large payoffs for both policy design and theory building.

Our third objective is to use the information gleaned from the tracking to learn where the tagged items went and, through that knowledge, to better understand when and why deviations from program guidelines occurred. Although inferring which households possessed the lanterns proved more challenging than simply detecting whether they remained in our study area, we were able to generate robust estimates of the characteristics of households that did and did not receive the lanterns. We find that, contrary to expectations (and to the predictions of local development practitioners and researchers, as discussed below), the vast majority of solar lanterns remained in the specific communities in which they were distributed and were distributed according to the specified program priorities. However, we also find that qualification according to the program priorities was not the only significant predictor of receiving a lantern; other dimensions of need also seemed to matter in distribution decisions. Our findings suggest that the village leaders tasked with distributing the lanterns drew on local knowledge about who would benefit most and adjusted their distribution strategies accordingly. We also find evidence of lantern movement across households after their initial distribution. While the number of such cases is insufficient to allow us to draw strong conclusions about what may explain these movements, the patterns we observe raise the possibility that original recipients engaged in welfare-enhancing voluntary transfers to households that may not have met the program criteria but were needy on other dimensions. Taken together, these findings run against common depictions of local African elites as predatory actors seeking to capture development resources for their own ends and suggest the need to rethink the common equation of “leakage” or “misallocation” with malfeasance.

2 iBeacon Technology and its Application

iBeacon technology relies on two components: uniquely identifiable tags (beacons) and a reader (in our case, a smartphone with Bluetooth capability running a customized beacon scanning and logging application). Beacons broadcast signals that advertise their presence, and readers search for nearby beacons, recording the unique name and signal strength of any beacon they detect.[4] Detecting a beacon thus allows a researcher to infer that a tagged item is somewhere within the reader’s detectable range (approximately 20-60 meters for the technology we employ).[5] Inferences about precisely where the tagged item is located can be sharpened by drawing on information about the reader’s location, the beacon’s signal strength (which provides a proxy for the distance between the beacon and the reader), and the locations of nearby dwellings or other structures where the researcher has reason to believe the item might be located.

We tested the efficacy of the iBeacon technology by placing beacons within 244 solar lanterns and distributing them in roughly a dozen contiguous off-grid villages in western Kenya.[6] We then used the technology to identify the households that ultimately received the lanterns, as well as the movement of lanterns across households (and, potentially, out of the study villages) over time.

Solar lanterns are valued goods in the communities in which we worked. About 80% of households in our study villages lack a connection to the electricity grid.[7] Although most households have solar home systems, these systems are inadequate to meet reasonable demands for household lighting.[8] Moreover, in focus groups conducted in nearby villages, we repeatedly probed whether an alternative good might be more valuable. Participants never suggested an alternative good, instead affirming the value and desirability of having a solar lantern.[9]

Prior to distributing the lanterns, we mapped the geolocations of all 2,824 buildings in the study villages. These buildings correspond with roughly 1,600 distinct households, as many households contain

[4]Further details on the iBeacon technology are provided in Appendix A.

[5]Commercial iBeacon products like AirTag and Tile leverage a wider network of smartphone users, enabling a beacon’s owner to track its approximate location even when the owner herself is not within range of the beacon. In contrast, our application collected data only from project iPhones.

[6]For reasons elaborated below, we are deliberately vague about the details of our study site, including the precise number of villages in which we worked.

[7]These figures come from our household survey, described below.

[8]Based on our household survey data, a typical (median) household has three rooms, a three-bulb solar home system, and a latrine outside the home. Thus, the typical household does not have enough light to illuminate each room, the pathway to an outdoor latrine, and inside the latrine for nighttime use.

[9]While we found solar lanterns are available for purchase in local markets, these lanterns were second-hand with unverified quality.

multiple family dwellings or outbuildings (kitchens, animal shelters, etc.). The mapping exercise linked buildings to households, so that a lantern detected in a building could be associated with a specific household for enumeration in the household survey undertaken at the end of the tracking period, as discussed below.

Distribution of lanterns within study communities occurred through village elders, the public official managing the lowest level of administrative units in Kenya. We provided the village elder in each village with between 12 and 34 lanterns (with the number proportional to village size), along with instructions to distribute the lanterns within their own village, prioritizing households containing children under 5 years old.[10] We justified this criterion by citing that young children might need help during the night and that the kerosene lamps that are commonly used in households that lack electric lighting present a danger to the children's health and safety (Lam et al., 2012).

Over the subsequent eight weeks, field officers carrying iPhones running a customized app conducted five rounds of tracking missions in each village during which they were instructed to walk within 20 meters of every building—close enough to detect a tagged lantern if one were present.[11] The app recorded the field officers' walking route as well as the presence and signal strength of any beacons detected during their mission. Figure 1 provides an example of the data collected during a trial tracking mission. The yellow line indicates the field officer's walking path. The orange segments indicate the intervals on that path when a beacon was detected, with the pink dots indicating the points of maximum signal strength for each detected beacon.

Figure 1: A tracking mission.

[10]On average, we provided approximately one lantern for every seven households.

[11]Our tracking data indicate that field officers came within 20 meters of 91% (and within 30 meters of 95%) of all mapped buildings on average during each tracking mission. Further details of the tracking missions are provided in Appendix B.

We matched detected beacons to households by combining data on the geolocations of buildings, the field officer's walking path, and the signal strength of any detected beacons at each point on that path. We began by identifying the point on the walking path that was closest to each building's previously recorded geocoordinates. To account for measurement error in both building locations and beacon signal strength (which can be affected by dense objects located between the beacon and the reader), we identified the segment of the walking path within a one meter radius of this most proximate point. This is the segment where a beacon's signal strength should be strongest if a beacon is located within that building.

In instances where we detected a given beacon in close proximity to a single building or to multiple buildings belonging to a single household, we matched the beacon to that household.[12] Such straightforward cases were somewhat rare, however, representing only approximately one quarter of household match instances. Owing both to the moderate density of buildings in some areas of our study villages and to the relatively broad signal range of our beacons, most beacons were detected in proximity to multiple buildings belonging to distinct households.[13] In such instances, we assigned the beacon to the building (and associated household) for which the signal strength was highest on average in the most proximate segment of the field officer's walking path. Figure 2 provides an illustration. In this example, the same beacon is detected in the segments most proximate to two different buildings: h_2 and h_3, generating two potential matches. However, because the beacon's average signal strength is greater in the segment in closest proximity to h_3, we infer that this is the building in which the lantern is located.[14]

Once we had matched beacons to households, we sought to understand why some households contained beacons (i.e., solar lanterns, distributed as part of our project) and others did not. To do this, after the conclusion of the five rounds of tracking missions, we conducted a household survey during which we attempted to interview every household in which a lantern was ever detected plus a roughly equally sized random sample of other households in each village (total $n = 566$).[15] The survey collected information

[12]For simplicity in this explanation, we refer only to households. However, our mapping exercise and subsequent analyses also included non-household complexes (e.g., schools or churches) to which matches were occasionally made. In practice, the vast majority of matches (91.45%) involved household-associated buildings. Post-tracking interviews with village elders confirmed that lanterns were occasionally kept in non-household buildings—for example, churches serving the sick or elderly.

[13]Further details are provided in Appendix E.

[14]This same procedure is applied to the (not uncommon) situation where two or more beacons are detected in proximity to nearby buildings. In such cases, the beacons are each assigned to the building associated with the beacon's highest signal strength in the most proximate segment of the walking path. See Appendix E for further details.

[15]Sample selection for the household survey was based on our original matching algorithm, which matched beacons to households by identifying the closest household to the point of maximum signal strength for each beacon sighting. However, we later updated our matching algorithm at the analysis stage to reflect the procedures described above. There are therefore occasionally households identified as containing lanterns under the new algorithm but not under the old algorithm. Such households may not appear in our survey data as households containing lanterns; in practice, they account for 44% of matched households for which we lack survey data. However, some such households happened to be randomly selected for the survey ($n = 20$ under the most permissive match criterion); these households were originally selected as "control" units (i.e., households in which lanterns were not detected), but we include them in our analyses as matched households. In cases where we identified the household as containing a lantern under the old algorithm but not under the new algorithm ($n = 17$), we exclude these households from our analyses. These households were not randomly selected, so their inclusion would undermine the representativeness of unmatched (i.e., "control") households.

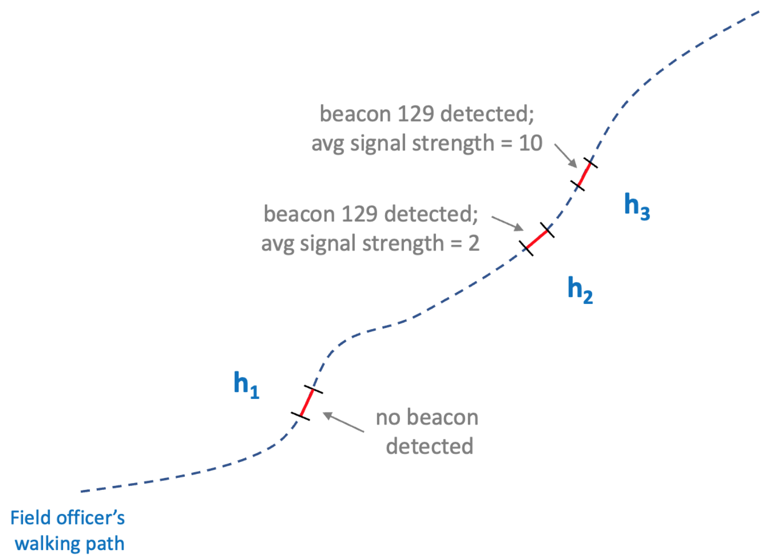


Figure 2: Matching beacon sightings to households.

about household characteristics including, crucially, whether the household contained any children under 5 years of age (the distribution criterion); the sources of lighting the household used after dark; other potential indicators of need; and social connections between household members and the village elder. The objective was to learn what made households that had received the lanterns different from households that had not, thus providing insight into the village elders' distribution decisions.

2.1 Ethical issues

Before turning to our findings, it is important to discuss the ethical concerns raised by using iBeacon technology to track the distribution of development goods, and the steps we took to address these concerns.[16] As previously explained, beacons transmit a signal with their unique identifier. While they collect and transmit no other information (for example, they do not record conversations), recipients of the tagged lanterns might feel that their privacy and autonomy has been violated if they learned that they received lantern containing devices that could make the lanterns' locations known. Village elders might feel similarly harmed if they learned that the lanterns we asked them to distribute were being tracked without their knowledge. In addition to these individual-level harms, the distrust generated by such reactions might "poison the well," undermining future efforts by outsiders to distribute welfare-improving development goods in these communities, thus undermining the communities' welfare more broadly. Along similar lines, backlash could also impair future research efforts. Fully informing the village elders and lantern recipients that the

[16] A fuller discussion of these issues is provided in a companion paper, Hamilton, Nganga and Posner (2020).

lanterns contained tracking devices (and giving them the opportunity to refuse to distribute or accept the lanterns) would solve the problem, but it would likely alter the distribution behavior that we aimed to measure.[17]

Our approach was to inform the village elders that 10% of the lanterns we were distributing in our project contained tracking devices.[18] This statement was true: although all of the lanterns distributed in the study villages contained beacons, we distributed an additional 2,250 solar lanterns, not containing tracking devices, elsewhere in the same county. In addition, every lantern distributed in the study villages contained a label indicating in the local language that it might contain a tracking device and providing a phone number to contact with questions. In designing these features of the project, our goal was to strike a balance between providing full information (recognizing that doing so would almost certainly alter the village elders' distribution behavior) and being completely deceptive about our research objectives.[19]

Prior to the project launch, we conducted a series of focus groups in villages close to our study area in which we fully disclosed our intention to tag and track solar lanterns to learn whether village elders misallocated them.[20] The strong endorsement of our plans by the focus group participants (driven in large part by the expectation that village elders *would* misallocate the lanterns and that it would be useful to document such malfeasant behavior), along with the absence of objections on grounds of privacy, deception, or inadequate disclosure of our research aims, served as a form of inferred/surrogate consent for our use of the tracking technology (Humphreys, 2015). We also consulted widely on our project design, incorporating critical feedback from multiple seminar audiences in both Kenya and elsewhere.[21]

In addition to concerns related to the use of the tracking devices, ethical concerns may also arise from the requirement that our field officers repeatedly come within 20 meters of every building in the study villages. Residents may perceive such periodic visits in close proximity to their homes as violations of privacy and might become suspicions about what the field officers were doing in the villages—perhaps revealing that the lantern distribution was being monitored and thus changing the behavior we sought to study. Our approach was to embed the tracking missions within a parallel research project aimed at assessing malaria risk. This project was in fact real: we recorded the presence of standing water in the vicinity of every

[17]For useful discussions of the challenge of balancing full disclosure with maintaining the validity of research findings, see Baele (2013), Humphreys (2015) and Hoffmann (2020).

[18]The full text of the instructions given the village elders is provided in Appendix C. Village elders also signed a receipt indicating that they had received the solar lanterns and reaffirming their understanding about the potential for tracking. The receipt clarified that participation in the project was entirely voluntary and stated that project organizers might later return to confirm that the solar lanterns remained within the village and that village elders might or might not be notified if this monitoring occurred.

[19]The batteries in our beacons exhausted after approximately six months, thus further limiting the potential for tracking the lanterns.

[20]Some focus groups included village elders, while others explicitly excluded them to empower participants to express honest opinions even if they contradicted the village elder.

[21]Our design was shaped by input from seminar participants at the University of Nairobi, Strathmore University, the Cape Town meeting of the Working Group in African Political Economy, the Evidence in Governance and Politics network, and the East Africa Social Science Translation Summit.

building; collected information on malaria knowledge and exposure, relevant behaviors, and social networks through which health-related information might be usefully disseminated; and are preparing a formal report of our findings that will be shared with village elders and local health officials. Given the high prevalence and negative health impacts of malaria in our study area (Were et al., 2019), the malaria risk assessment project provides a real benefit for our study communities—while also providing a rationale for the mapping of village buildings, the tracking missions, and the household survey.[22]

We also undertook measures to protect our research participants from potential harms stemming from the release of our research findings. For example, we were concerned that village residents might react negatively if our tracking data revealed that their village elder had misallocated the solar lanterns. To prevent this from occurring, all of our data collection was blind. We designed our tracking app not to reveal when beacons were detected over the course of the tracking missions, so field officers had no way of knowing whether a building they visited contained a tagged lantern. The app was also designed to upload the data it collected directly to a remote server, viewable only by the PIs. We also committed in advance not to identify the study villages and only to report aggregate results.

3 Does the Technology Work?

Previous efforts to use remote sensing technology to track development goods have met with limited success. For example, a study employing RFID tags to take inventories of goods held by microenterprises in Sri Lanka was only able to detect about one-quarter of the tagged items on average, with high variability in day-to-day success (de Mel et al., 2016). The study also found that reading tags was time consuming, with 10-15 minutes necessary to take inventories of the approximately 280 items held by each retail firm.

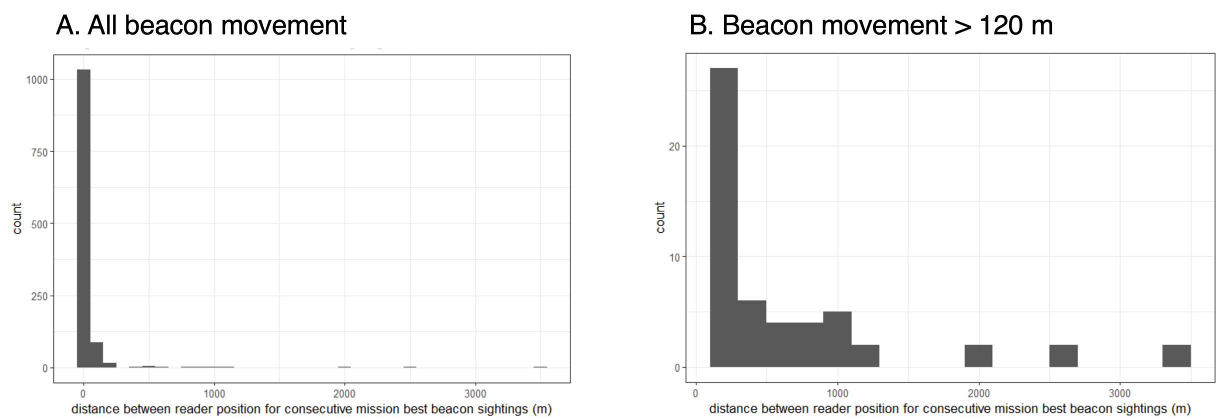
The iBeacon technology was much more successful. In contrast to the Sri Lanka study, where the location of the goods was known and fixed within each microenterprise, we had no idea where in each village the tagged lanterns might be located. Yet we were able to detect 98.8% of them in at least one of the five tracking rounds, 80.3% across all five rounds, and 94% across four of the five. We detected at least 90% of beacons in each tracking round, with no discernible trend toward declining performance over time. Moreover, inventories of all 244 lanterns taken prior to distribution (to confirm that the tags were working) took less than two minutes. We were also able to track the movement of tagged lanterns across households over time—something difficult or impossible to do with the technology used in the Sri Lanka Study.[23]

[22] To keep the lantern project and the malaria project separate, the research staff who conducted the village mapping, tracking missions and household survey were distinct from the staff who distributed the solar lanterns. Staff were fully aware of the projects' connections and expressed no objections. Notwithstanding our explanation for field officers' presence, some community members asked field officers not to approach their homes; field officers honored these requests.

[23] These advantages arise because iBeacon relies on active tags (batteries boost signal transmission) and offer better mobile reader options (e.g., iPhones). A demonstration of the power of similar technology is provided in Jablonski et al. (2023).

A challenge in studying such movement is distinguishing between real movement and measurement error. Although the majority of beacons "moved" across tracking rounds (in the sense the reader's location at the point of highest signal strength for that beacon was not precisely the same), the median distance between beacon sightings was just 5.5m. As shown in Panel A of Figure 3, the distribution of these "movements" is highly skewed. The vast majority are so small that they very likely reflect measurement error rather than the actual movement of lanterns across households.

Figure 3: Distribution of beacon movement across tracking rounds.



Panel A shows the distribution of all beacon movement; Panel B shows the distribution of all beacon movement of > 120 m.

While most beacon movements were small, 35 of the 244 beacons (approximately 15% of the beacons that we detected) moved more than 120 meters across tracking rounds, and in some cases did so more than once (see Panel B of Figure 3). Because we measure such movements based on distances between the readers' positions and because the maximum distance at which a beacon's signal can be detected is 60 meters, 120 meters is the (conservative) threshold above which we can be fairly certain of true movement across households, rather than simply measurement error. Figure 4 shows the movement of these beacons.

4 What Did We Learn About How Development Goods Were Distributed in Our Study Area?

4.1 Leakage

We were able to detect such a high share of the beacons both because the tracking technology worked well and because *almost none of the tagged lanterns leaked out of the study villages.* Only three of the 244 beacons were never detected in any of the five tracking rounds and can be assumed to have either leaked out of our

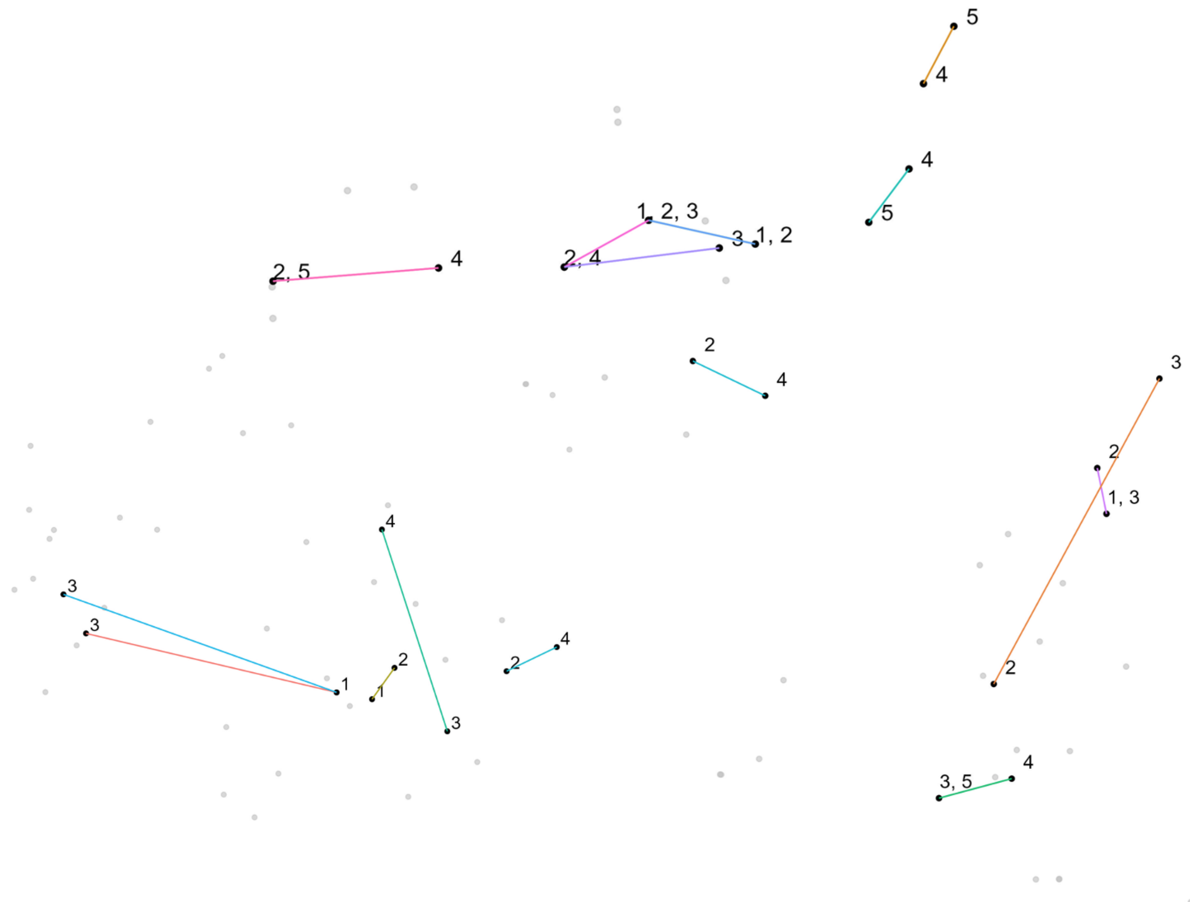


Figure 4: Beacon movement across the five tracking rounds

Grey dots indicate first-round locations of beacons that "moved" less than 120 meters across consecutive tracking rounds. Black dots indicate the locations of beacons that moved more than 120 meters (i.e., likely true movement) across rounds, with lines showing the path of movement. Numbers indicate the round in which the beacon was detected in each location.

study area or failed to work properly. Moreover, the vast majority of detected beacons (over 98% in each round) were detected in their home village. Village elders clearly distributed lanterns across the community; household matches to multiple beacons were rare. These patterns were not what the literature motivating our study led us to expect.[24] It was also not what local experts anticipated we would find. In a prediction survey administered to Kenyan academics and policymakers with significant experience on development issues, the median expectation was that 45% of the lanterns would leak out of the study villages.[25]

One concern is that the low rate of leakage might have been due to the warnings delivered to the

[24]Indeed, in anticipation of the lanterns leaking out of the study villages and potentially being resold at local markets, we arranged for our field officers to visit the main markets closest to our research sites to see if the tracking app detected any project lanterns for sale. Sweeps conducted after the first and fourth tracking rounds detected no tagged lanterns in the markets.

[25]Further information about the prediction survey is provided in Appendix D.

village elders that the lanterns might contain tracking devices. In our effort to balance the need to inform village elders about the possibility of tracking against the danger of altering their behavior, it is possible that we erred too far in the former direction and that village elders, understanding that their behavior was being monitored, went out of their way to follow program guidelines to the letter. To evaluate this possibility, we took advantage of the 2,250 untagged solar lanterns that we distributed outside of our main study sites. We distributed these additional lanterns in two different areas. In one area, we followed the identical protocols as in our main study sites: the lanterns contained labels indicating that they might contain tracking devices and village elders were informed about the possibility that the lanterns might be tracked. In the other area, we provided no such information or labels.

After the untagged lanterns had been distributed, field officers visited 24 of the villages in each of the two areas to see if they could track down where the lanterns had gone. The objective was to mimic the sort of post-hoc audit that often occurs after the distribution of development goods in a typical aid program. The field officers began by asking the village elders for lists of the households that had been given the lanterns. They then visited each household on the list to confirm whether or not it had in fact received a lantern. The visits took place in two waves, with roughly half occurring 3-4 weeks after the lantern distribution and the other half occurring 6-7 weeks after. In all, the field officers visited 1,129 households across the 48 villages.

Although lanterns were slightly more likely to be found in villages where the village elder was told that the lanterns might be tracked, the difference across the two areas was very small and not statistically significant. If knowledge about the possibility of tracking altered the behavior of the village elders, it appears to have done so only minimally. This conclusion is supported by evidence from interviews conducted with the village elders after the project's conclusion. When asked explicitly whether they thought the lanterns they distributed might have contained tracking devices, only a quarter said yes (although nearly half mentioned the tracking devices at some point during the wide-ranging interviews). When asked whether this possibility affected the way they distributed the lanterns, none answered in the affirmative. We therefore think it is reasonable to conclude that informing the village elders that the lanterns might be tagged cannot account for the surprisingly low leakage rates.

4.2 Patterns of (mis-)allocation

Beyond detecting whether tagged items have leaked out of a community, iBeacon technology also offers the promise of identifying the particular households in which the tagged items wind up. This presents an enormous opportunity for learning about how goods are distributed, with important implications for both policy and theory.

Identifying specific recipients of the tagged items is, however, a more challenging task than simply determining whether the items are present somewhere in the study area. Although the protocols described earlier for matching found beacons to households are straightforward in principle, their application in practice was sometimes imperfect. As shown in Appendix E, the difference in signal strength across the best and second best matches was sometimes not very large, thus creating ambiguity regarding which building contained the beacon. Poor cell coverage during the mapping exercise led to inaccurate building geocoordiantes, creating the potential for incorrect matching inferences.[26] This problem, as well as accidental duplication of some household labels during the mapping exercise, occasionally caused ambiguity when integrating the survey and lantern tracking data (for a discussion, see Appendix E). Finally, although beacon detection occurred relatively consistently, matching inferences are likely to be somewhat noisy even under ideal circumstances. For these reasons, we undertake the analyses that follow with multiple datasets, each employing slightly different match standards and data quality controls (see Appendices F and G). In the discussion below, we focus on the subset of results whose strength and robustness across multiple specifications give us confidence in their validity.

To better understand who received the lanterns and why, we draw on household survey data to compare the characteristics of households in which we did and did not detect beacons during the course of our tracking missions. In the top panel of Table 1, we examine household characteristics related to the age distribution of household members, access to alternative lighting sources, and socioeconomic status.

Given the instructions village elders were given about which households to prioritize, a first question is whether lantern households were more likely to contain children under 5 than households where we did not detect a beacon. Table 1 indicates that they were: lantern households were twice as likely to contain children under 5 than other households. Under our least restrictive match criteria and data quality controls, we have survey data for 250 lantern households. Among these households, 153 (61.2%) contained at least one child under 5 years old. Children under age 5 are far more prevalent among lantern households than among the randomly selected households in our survey sample, among which only 31.1% contain at least one child under age 5. Depending on the match criteria and data quality controls employed, the percentage of households in which lanterns were detected that had at least one child under 5 ranged from 61.2% to 69.2% among households for which we have survey data (see Appendix F). These averages mask substantial variation across villages, however, with the share of households with lanterns that contained children under 5 ranging from roughly 40% to as high as 80%.

Having a young child was not the only factor that appears to have shaped the village elders' allocation

[26]Future projects can avoid this problem either by using mapping applications that pre-download maps for manual pin placement or by automatically (rather than manually) dropping pins based on field officer location.

Table 1: Difference in means across households where beacons were and were not detected

	Survey mean	No beacon detected	Beacon detected	Difference	Total n
Child under 5	44.20	30.13	61.20	31.07***	552
Child 5-12 yrs	57.07	49.34	66.40	17.06***	552
Adult 75+ yrs	6.88	7.62	6.00	-1.62	552
Only adults aged 60+	4.35	5.30	3.20	-2.10	552
Already owns lantern	23.01	25.50	20.00	-5.50	552
Connected to electric grid	16.85	21.19	11.60	-9.59**	552
Owns solar home system	69.93	70.20	69.60	-0.60	552
Asset index[a] (above village median)	49.09	49.01	49.20	0.19	552
Housing quality index[b] (above village median)	43.16	48.79	36.29	-12.50**	526
Lived poverty index[c] (above village median)	55.23	47.30	64.66	17.36***	545
VE is immediate family member	23.91	23.65	24.24	0.59	527
VE is extended family member	32.26	31.42	33.33	1.91	527
VE is related	38.14	36.49	40.26	3.77	527
Spoke w VE in past week	47.06	39.86	56.28	16.41***	527
Shared meal w VE in past week	8.54	7.43	9.96	2.52	527
Worships at same church as VE	4.32	3.32	5.58	2.26	486

Note: The analysis presented here employs our most permissive match criterion: a household is coded as having a beacon detected within it if our matching algorithm ever produced this household (main dwelling and/or associated outbuildings) as a match in any round. We constructed the asset, housing quality, and lived poverty indices by extracting the first principal component from principal component analyses including the variables listed below for all households with available data pooled across villages, such that item rotations for the first principal component are consistently in the expected direction. *$p<0.1$; **$p<0.05$; ***$p<0.01$

[a]The asset index construction includes items on the number of cookers/gas stoves, refrigerators, radios, televisions, computers, DVD players, mobile phones, sofas, sewing machines, water tanks, wood/metallic beds, chairs, tables, cars/trucks, motorcycles, bicycles, and animal drawn carts owned in total by members of the household. The first principal component captures 60.80% of variation across these items.

[b]The housing quality index construction include items regarding acres of land accessible for household use, the number of rooms in the house, whether the walls are made of stone, brick or cement, whether the roof is concrete or corrugated iron, whether the floor is cement, tile, or laminate, the location of the water source, the time it takes to retrieve water, the type of toilet, and the location of the toilet. The first principal component captures 61.84% of variation across these items.

[c]The components of the lived poverty index include how often in the past month the household has gone without enough food to eat, without enough fuel to cook, or without medicine or medical treatment because they could not afford it. The first principal component captures 71.54% of variation across these items.

decisions. As shown in Table 1, primary school aged children (5-12) were more common in lantern households than in randomly selected households.[27] Solar lanterns are especially valuable in households with children in this age range because the lanterns make it possible to do schoolwork after dark. Lack of connection to the electric grid, low housing quality (as captured in our housing quality index), and lived poverty (as captured in our lived poverty index) were also significantly more common among lantern households relative to randomly selected households—even though, like having school-aged children, these characteristics were not mentioned as priorities in the distribution instructions. These findings suggest that village elders weighed household need alongside the stated program prioritization in making their allocation decisions.

Given the focus in the distributive politics literature on parochial favoritism (Golden and Min, 2013), we were also interested in whether lanterns were more likely to have been detected in households with family or social ties to the village elder. As shown in the bottom panel of Table 1, we investigated several measures of such ties: whether the village elder was an immediate family member, an extended family member, or related in some more distant way;[28] whether members of the household had spoken to or shared a meal with the village elder during the past week; and whether household members and the village elder worship at the same church. The only connection that we find to be significantly associated with a greater likelihood of having had a lantern detected in one's home is having spoken with the village elder during the past week. Although this finding would seem to validate the expectation of personal favoritism in the distribution of the lanterns, it raises the question of why no other measures of social connection—including measures that capture much closer and more exclusive connections with the village elder—show similar effects. In addition, because we measured contact post-distribution, we cannot rule out the possibility that the association is a post-treatment effect: receiving a lantern, for whatever reason, initiates a relationship with the village elder that results in a greater likelihood of having had a conversation with him during the past week. We thus interpret our results as suggesting little evidence of parochial favoritism by village elders.

The results presented in Table 1 identify households in which beacons were and were not detected based on our most permissive match criteria.[29] They also present associations without accounting for possible correlations among household characteristics. We therefore revisit these findings in a regression framework in Table 2, where we control for the simultaneous impact of all relevant household characteristics and evaluate the robustness of our results across more stringent match criteria. Unlike the difference-in-means analysis, the regression is weighted to reflect the probability of selection into the sample.[30] In column 1, we use the

[27]Older secondary school students often attend boarding schools.

[28]We count a parent, child, brother, or sister as immediate family; an aunt, uncle, niece, nephew, or cousin as extended family; and other relations as more distant.

[29]Replications of these difference-in-means tests under different matching criteria and different quality controls are presented in Appendix F and Appendix G respectively.

[30]For a justification and description of these weighting procedures, see Appendix H.

same match criteria as in Table 1. Here, a household is coded as containing a beacon if a beacon was matched to the household during any of our tracking rounds. In column 2, we limit this set to households that, in addition, confirmed owning a lantern in the household survey. In column 3, we limit the set such that it includes a household as a match if and only if the matching algorithm produced this household as a match in at least three tracking rounds.

Our main results from the difference-in-means analysis are largely unchanged. Across all specifications, we continue to see strong relationships between having children under 5 and having spoken recently with the village elder. Having a school-aged child (between 5- 12 years), being connected to the electric grid (entering negatively), and scoring high on our lived poverty index are all statistically significant in two of the three models. The only household-level measure that loses significance once we control for other characteristics, with which it may be correlated, is housing quality. In addition, three other household characteristics that were not significant in the difference-in-means analysis—being entirely comprised of retirees (adults 60+ years old), scoring below the village median in asset ownership, and having a household member who shared a meal with the village elder during the past week (entering *negatively*)—are significantly associated with having matched a lantern in at least some of the specifications. Taken together, these results (which are reinforced by the additional analyses presented in Appendix G, which employ different approaches to linking the tracking and survey data) give us confidence in the robustness of our central findings: we matched lanterns more often in households that either met the program criteria or had other kinds of demonstrable need.

4.3 Second-order allocation

Our ability to track beacon movement over time allows us to study not just the allocation decisions of the village elders who originally distributed the lanterns but also the reallocation decisions of the households that received them. As noted earlier, we found that roughly 15% of beacons (and hence lanterns) likely truly moved across households during the five rounds of tracking missions. Although this figure is a potentially conservative estimate of actual cross-household lantern movement, it is still less than trade theory might have led us to expect if the original recipients were poorly chosen target recipients.[31] We interpret this as one more piece of evidence that the village elders leveraged local knowledge to make sure that the lanterns were given to households that needed them.

Because we collected household survey data from every household in which a beacon was ever matched in any tracking round, we are in principle in a position to compare the characteristics of households that

[31] As discussed in Section 3, we limit our analysis to beacons that moved more than 120 meters, whose movement we can be confident was across households.

Table 2: Which households received lanterns?

	Dependent variable:		
	Match	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.140***	0.161***	0.122***
	(0.046)	(0.037)	(0.035)
Child between 5 and 12 yrs	0.025	0.082***	0.057***
	(0.019)	(0.019)	(0.019)
Adult 75+ yrs	−0.0001	−0.015	−0.004
	(0.038)	(0.030)	(0.026)
Only adults over 60 yrs	0.016	0.075***	0.073***
	(0.052)	(0.029)	(0.028)
Already owns lantern	−0.044	0.011	−0.015
	(0.032)	(0.031)	(0.023)
Connected to electric grid	−0.068**	−0.036	−0.046*
	(0.028)	(0.029)	(0.026)
Owns solar home system	−0.053	−0.049	−0.027
	(0.041)	(0.041)	(0.029)
Asset index	−0.008	−0.003	−0.015*
	(0.017)	(0.014)	(0.008)
Housing quality index	0.007	−0.010	−0.012
	(0.024)	(0.015)	(0.010)
Lived poverty index	0.061***	0.055***	0.019
	(0.017)	(0.018)	(0.013)
VE is immediate family member	−0.046	−0.043	−0.001
	(0.031)	(0.041)	(0.026)
Spole w VE in past wk	0.100***	0.100***	0.073***
	(0.021)	(0.028)	(0.021)
Shared meal with VE in past wk	−0.057	−0.060*	−0.045*
	(0.040)	(0.034)	(0.025)
Constant	0.141**	0.038	0.028
	(0.060)	(0.050)	(0.037)
Observations	519	467	432
R^2	0.093	0.136	0.080
Adjusted R^2	0.069	0.111	0.052
Residual Std. Error	0.664 (df = 505)	0.600 (df = 453)	0.550 (df = 418)
F Statistic	3.968*** (df = 13; 505)	5.486*** (df = 13; 453)	2.805*** (df = 13; 418)

Note: Regression models are weighted by the probability of selection into the survey sample (see Appendix H). Column 1 employs the same permissive match criteria as in Table 1. Column 2 treats a household as having a beacon detected within it if, in addition to having been matched in any round, the household head verified owning a solar lantern during the endline survey. Column 3 treats a household as having a beacon detected within it if and only if the matching algorithm produced this household as a match in at least three tracking rounds. Households included in the "control" group (i.e., the comparison group of randomly selected households in which beacons were never detected) are constant across match criteria. We dropped some measures of connection with the village elder due to near multicollinearity. *p<0.1; **p<0.05; ***p<0.01

transferred and received lanterns during the course of such second-order allocations. However, because roughly half of the cases of cross-household lantern movement involve "round trip" movements from one household to another and back again across tracking rounds (as illustrated in Figure 4), the already small number of movements in which we can contrast the characteristics of the sending and receiving households becomes smaller still. It is perhaps not surprising, then, that we find no significant differences in the characteristics of sending and receiving households—including whether the receiving household reported having paid for the lantern it possessed.

An alternative approach to learning about the how lanterns moved after their initial distribution by the village elder is to compare the characteristics of households in which beacons were detected in our first and fifth tracking rounds. In the first, we can attribute the allocation directly to the village elder.[32] In the fifth, it also captures the process of household to household reallocation that took place over the ensuing eight weeks. Table 3 presents these comparisons.[33]

Having a child under 5 or between 5 and 12; having above-median levels of lived poverty; and having spoken recently with the village elder remain strong predictors of detecting a beacon in a household in both round 1 and round 5. However the coefficient on having a child under 5, the variable that captures the household characteristic that village elders were asked to prioritize, reduces somewhat in size across the two rounds, whereas the coefficients on the other measures of need (having a school-aged child and lived poverty) increase. In addition, having an elderly household member, being a household comprised only of retirees, and not being connected to the electric grid—all measures of need that are not statistically significantly associated with having a lantern in round 1—become significantly associated with having one in round 5. Although none of these cross-round differences in coefficient size are statistically significant, they are all consistent with the redistribution of lanterns from the households that originally received them from the village elder to households with greater needs.

5 Rethinking "leakage"

We motivated this paper by presenting the leakage of development goods as a problem. In keeping with the common perspective in the academic and policy literatures, we equated deviations from program guidelines as evidence of malfeasance or corruption. While theft and diversion of development goods surely is an issue in some contexts, our findings suggest that a pair of more innocuous—and potentially even *welfare-enhancing*—explanations may be at work when goods do not wind up where their donors intended.

[32] The first tracking round in each village occurred within approximately one week after village elders received lanterns.

[33] The validity of these comparisons would be undermined by significant decay in beacon detection rates across tracking rounds—for example due to leakage of lanterns outside of the study villages over time or because the beacons became inoperative. However, as shown in Table A2 of Appendix B, beacon detection rates are quite constant across tracking rounds.

Table 3: Which households received lanterns? (Rounds 1 and 5 only)

	Dependent variable:	
	Round 1 Match	Round 5 Match
	(1)	(2)
Child under 5 yrs	0.130^{***}	0.098^{***}
	(0.037)	(0.037)
Child between 5 and 12 yrs	0.041^{**}	0.047^{***}
	(0.017)	(0.013)
Adult 75+ yrs	−0.016	-0.047^{*}
	(0.026)	(0.026)
Only adults over 60 yrs	0.037	0.088^{**}
	(0.037)	(0.036)
Already owns lantern	−0.033	−0.026
	(0.020)	(0.016)
Connected to electric grid	−0.031	-0.045^{**}
	(0.020)	(0.023)
Owns solar home system	−0.017	−0.024
	(0.025)	(0.023)
Asset index	−0.013	−0.006
	(0.010)	(0.015)
Housing quality index	−0.005	−0.022
	(0.012)	(0.014)
Lived poverty index	0.027^{***}	0.048^{***}
	(0.010)	(0.018)
VE is immediate family member	0.014	−0.043
	(0.014)	(0.035)
Spole w VE in past wk	0.064^{***}	0.081^{***}
	(0.021)	(0.027)
Shared meal with VE in past wk	−0.007	-0.058^{**}
	(0.025)	(0.024)
Constant	0.029	0.062^{*}
	(0.040)	(0.033)
Observations	430	426
R^2	0.080	0.090
Adjusted R^2	0.052	0.062
Residual Std. Error	0.556 (df = 416)	0.586 (df = 412)
F Statistic	2.792^{***} (df = 13; 416)	3.144^{***} (df = 13; 412)

Note: Columns 1 and 2 employ the same matching criteria as column 1 for Table 2 but for the first and fifth tracking rounds only. Households included in the "control" group (i.e., the comparison group of randomly selected households in which beacons were never detected) are constant across match criteria. *p<0.1; **p<0.05; ***p<0.01

Although divergence from the requested prioritization of households with children under 5 was somewhat rare (and more rare than the conventional wisdom had led us to expect), the deviations that did occur tended to be toward households with significant needs. Our program guidelines had a strong and defensible rationale: the kerosene lanterns that are commonly used in Kenya for lighting after dark in off-grid communities are especially dangerous for young children (Lam et al., 2012). But, like the guidelines imposed in most donor projects, they captured only one dimension of hardship. Our findings are consistent with village elders drawing on their own local knowledge about who would benefit most from the solar lanterns and deviating from program guidelines where they felt it was necessary to help those who would otherwise have been excluded.[34] For example, in our post-survey, several village elders recounted instances in which they gave lanterns to households that did not have young children but that contained elderly residents. In a strict definitional sense, such deviations are misallocations. But they have the intention, and effect, of improving the welfare of people in the community.

The village elders' behavior in this regard is in keeping with the behavior of local elites charged with distributing development goods in other studies. Basurto, Dupas and Robinson (2020) find that chiefs in Malawi use their informational advantages to direct subsidies to people who need it most, even when they fail to qualify via proxy means testing. In an audit of a subsidized bed net distribution program using confederates posing as would be recipients, Dizon-Ross, Dupas and Robinson (2017) find that health workers were willing to bend the rules to give bed nets to particularly needy applicants with small children, even if they failed to meet the program guidelines—a phenomenon they term "benevolent leakage." These findings, and ours, suggest that the application of local knowledge to channel development goods to needy recipients who would otherwise have not received them is an underappreciated source of what is commonly interpreted as "leakage."

Instances of "leakage" may also occur when development goods are discovered in the hands of people who do not meet program criteria but who obtained the goods from qualifying recipients. Our analysis of lantern movement identified several instances of such second-order allocation. Assuming that the exchanges behind such movements are voluntary, we can infer that they are welfare improving for both the original recipient and the new owner. Both parties are made better off, even while the location of the good in a household that may not meet program criteria appears in the data as a case of "misallocation."

[34] Anticipating the desire of village elders to deviate in some instances from the instruction that lanterns be distributed to households containing children under 5, and not wanting them to feel they were violating our trust if they did, we were careful to present our distribution guidelines as a *prioritization* rather than a requirement. In our post-survey, several village elders expressed appreciation for this leeway, explicitly contrasting our instructions with the instructions provided in other development projects in which they were given lists of pre-selected beneficiaries, some of whom they felt should not have been included.

6 Conclusion

Current approaches to measuring the leakage of development goods fall short. Both perception-based surveys and comparisons of goods allocated versus received provide estimates of what may have gone missing, but tell us little about when in the distribution process the goods may have disappeared or where they went. This leaves researchers and policymakers with a weak empirical grasp of how leakage operates and whom it benefits. It also makes it challenging to distinguish between actual malfeasance and deviations from program guidelines that have the intention and effect of targeting needy but otherwise excluded recipients.

In this paper, we introduce and pilot the use of iBeacon technology to address these weaknesses. Our evidence demonstrates that the technology can be a powerful tool for detecting the presence of development goods distributed in a real world setting and for tracking their movement over time. This latter capacity makes the technology well-suited not just for studying leakage but also for developing deeper understandings—crucial for both theory and policy—of how goods flow through markets and patronage networks.

Our application of iBeacon technology to the tracking of solar lanterns distributed in off-grid communities in western Kenya illustrates the technology's power to generate insights into how development goods are distributed. Contrary to both theoretical expectations and the predictions of local experts, we find lanterns very rarely, if ever, leaked outside of our study area. We find that the village elders who were tasked with distributing the lanterns by and large adhered to the program criteria in choosing beneficiaries. Moreover, we find evidence that village elders prioritized other indicators and dimensions of need beyond the official distribution criterion. Finally, we find evidence of second-order allocation across households that suggests welfare-improving transfers to households that did not originally receive lanterns but would benefit from having them. All of these deviations from program guidelines are technically "leakage." But they have the effect of improving, not undermining, community welfare—an implication strongly at odds with the project's motivation, in which leakage was equated with malfeasance and corruption.

One explanation for the divergence between our findings and expectations could be that some important feature makes the context we studied relatively unusual. Notably, aid and research projects occur with great frequency in the study region, and local leaders may know that bad reputations deter beneficial future projects. In such a context, even the small possibility that aid providers could become aware of malfeasant behavior may have been enough to dissuade village elders from diverting the lanterns for private ends. Post-interviews indeed found that village elders had previous experiencing collaborating in aid distribution, and other local administrators clearly had experience dealing with aid and research organizations. If the study site was atypical, then deployments of iBeacon technology to other settings will allow researchers and practitioners to update, and potentially qualify, the implications of the results reported here.

Another possible explanation is that, thanks to the technology we employ, our study is measuring leakage at a different level from most other studies. It may be that most of the (malfeasant) leakage in development programs occurs during the procurement process and in the initial stages of distribution (for example, as the goods are traveling between the port or production facility and the local warehouse or supply depot), with relatively less leakage occurring at the final stage when goods are distributed to their intended recipients by local officials who are more deeply embedded within their communities (Tsai, 2007). Employing technologies like iBeacon makes it possible to study this last stage of the distribution process, and, accordingly, to deepen our understanding of how and when leakage occurs.

The promise of the technology for these purposes does not, however, mean that it will work in all settings or for all applications. First, not all development goods are amenable to tagging. While iBeacon tags can feasibly be placed within lanterns, cook stoves, computers, bicycles and other durable goods that donors and governments regularly distribute, they cannot be used for cash, whose distribution has become a favored means of aiding poor communities (Leisering, 2018). Other commonly distributed goods like relief food, fertilizer, or pharmaceuticals also present a problem, but for a different reason: the taggable item is the bag or the carton that the good comes in rather than the good itself. When these containers become separated from the quantity of interest, as they often do in the course of their distribution, it becomes challenging to identify the end recipient or to track the container's movement over time. For example, when a family receives a bag of maize, it is often transferred to a storage receptacle and the bag is discarded or repurposed, potentially winding up in another household. Beacons are also incapable of detecting the siphoning off of some of the bag's contents en route to its destination—a common form of theft (*Herald* (Zimbabwe), 2020). When medical supplies are distributed from central warehouses, they can be feasibly tracked as they make their way to regional health facilities, as in the pioneering study by Jablonski et al. (2023). But the tracking breaks down at the last stage of the distribution process when the cartons containing the tracking devices are unpacked for sale at local clinics and pharmacies—and this is where much of the misallocation and diversion occurs (*Daily Monitor* (Uganda), 2017). iBeacon technology works best for tracking durable and non-divisible goods.

Second, the applicability of the technology is limited by the setting in which the goods are distributed. For beacons to be detectable, members of the research team need to be able to come within 20 meters of every location in which a tagged item might be located. The locations also cannot be so spread out that tracking missions become infeasible or, conversely, too densely situated, lest it be challenging or impossible to identify the buildings from which the signals are emanating.

Finally, while iBeacon tags are cheaper than alternatives like GPS tags, the cost of tagging every item during large-scale distributions would be prohibitive at present. The technology will therefore likely be most useful for quickly verifying the presence of high-value goods (e.g., laptops in schools or medical equipment in clinics) or for learning about which method(s) of distribution are most efficient and welfare-enhancing. While these conditions limit the applicability of the technology, they still leave a wide range of applications for which iBeacon technology can be a useful tool for studying leakage and the distribution (and movement) of development goods.

In addition to generating insights into how development goods are distributed in a real setting, our study also provided an opportunity to think hard about how to deploy iBeacon technology ethically. Researchers and practitioners who are excited about the potential learning that can come from employing iBeacon and similar remote sensing technologies will need design their studies in a way that balances the payoffs from being able to track where tagged items go alongside the privacy and autonomy of the people and communities they are studying.

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8 Appendices

A Further details on iBeacon technology

iBeacon technology is a Bluetooth-based tracking technology that relies on two components: uniquely identifiable tags (beacons) and a reader (in our case, an iPhone). Beacons transmit a signal that readers can detect. Readers collect data on any detectable beacons that are in range. In plain terms, a beacon continuously "shouts its name" so that any nearby reader might "hear" it. A reader records the "name" of any beacon(s) it "hears," along with other data. Figure A1 shows one of the beacons employed in this project.

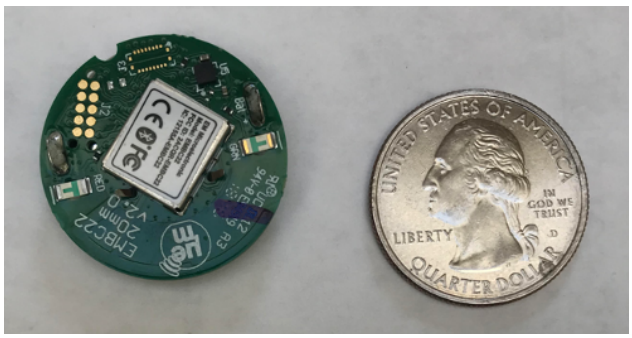

Figure A1: An iBeacon

A.1 Comparison to other tracking technologies

iBeacon tags are similar to active RFID tags insofar as they contain a power source (a battery) and actively transmit signals; these features allow for greater signal range. Unlike traditional RFID technologies, iBeacon operates with the standard Bluetooth Low Energy iBeacon protocol and does not require a specialized reader. Any iOS or Android device can serve as a reader using its Bluetooth capabilities and an appropriate reading application. Unlike GPS technology, iBeacon technology does not involve triangulation and therefore cannot give the precise location of tags. Instead, readers merely record whether any beacon signals are detectable. Commercially available iBeacon technology like Apple AirTags and Tile trackers, which consumers often use to track objects like keys or luggage, confidentially leverage many smartphone users as reading devices, allowing tracking even when the beacon owner's phone is not in proximity to the beacon. This process can increase the effective range of iBeacon tags. While more limited in terms of precisely locating tags, iBeacon tags is considerably cheaper than GPS tags. A GPS tracker may cost \$100 and last for 1 week. An iBeacon tag could cost less than \$10 and last for 2 years.

A.2 Beacon range

The effective range of an iBeacon varies depending on several factors:

- **Beacon characteristics:** Different iBeacon hardware has different advertising capabilities. In addition, manufacturers may program beacons to have more or less signal transmission power depending on the size of the battery and desired lifetime of the beacon. For instance, manufacturers determine how frequently and how "loudly" beacons advertise their presence. Our beacons are programmed to maximize signal transmission power and to transmit once per second, limiting the lifetime of the beacon's battery to about six months.
- **Reader characteristics:** Like beacons, readers can have different abilities to detect bacons either because of hardware or manufacturer programming. For instance, iPhones check for beacon signals approximately once per second. Additionally, newer mobile phones are equipped with more sensitive antennas to receive Bluetooth signals; an older phone may not be able to "hear" the signal from a distant beacon while a newer phone could. We employ an iPhone 7 and an iPhone 8 as readers in this project.
- **Environmental factors:** Some materials interfere with signals more than others; for instance, chain link fences and liquids in particular can diminish the range of the beacons.

Considering these factors, there is no guaranteed range at which a reader can detect a beacon. Nonetheless, users may be able to define an upper limit to the range for a particular beacon-reader combination. In our case, this maximum line-of-sight range is about 100 meters. However, in real-world applications with obstacles and non-optional antenna alignment, 20-60 meters is a more realistic expectation.

B Details of the tracking missions

B.1 Data collection during the tracking missions

We worked with Geocene to develop a customized beacon scanning app for the tracking missions. The app completely automates data collection, minimizing opportunities for human error. In addition, the app blinds enumerators to the data collected, thus minimizing risks to both participating communities and enumerators. The user interface is minimal, consisting of three options: (1) "Start" data collection, (2) "Stop" data collection, and (3) "Sync" data to our cloud-based server. Figure A2 shows screen shots of the application.

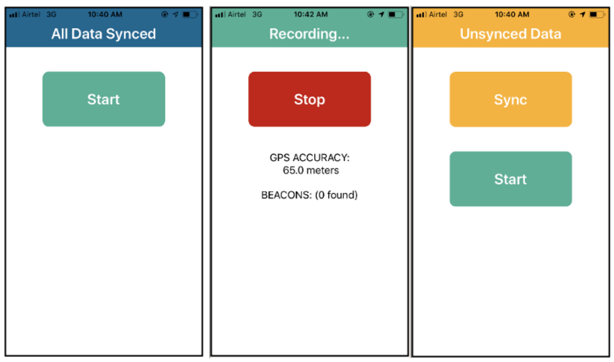

Figure A2: Reading application interface

When a user initiates data collection, the application automatically records data at one-second intervals until the user stops data collection. Data is collected regardless of whether the reader detects any beacons. Data collection does not rely on the availability of a cell coverage. The data collected include the following:

- **Mission ID**: A mission is a single instance of data collection. It begins when a user presses "Start" and ends when the user presses "Stop." Mission IDs are universally unique identifiers (UUIDs).

- **Timestamp, latitude, and longitude of the reader**: These data allow us to track the routes the field officers took during their tracking missions. During the course of data collection, we used these data to confirm that the field officers came within 20 meters of every building during their missions. In the analysis phase of the project, we used these data to match found beacons to households, as described in the paper.

- **Beacon identifying information**: In raw form, a beacon's identity consists of three elements: a UUID, a major code, and a minor code. The UUID is the same for all beacons employed in our project. This UUID is how the reading application "listens" only to beacons associated with our project (and not, for example, beacons from other manufacturers for other applications). The major and minor codes are five digits each. The major and minor code together create an identifier unique to each individual beacon within the project.

- **Received signal strength indicator (RSSI)**: The RSSI is basically an indicator of how well the iPhone can "hear" the beacon. The RSSI takes values ranging from about -30dB to -90dB. These values are exponents, so numbers closer to zero indicate stronger signals.

The collected data is stored locally on the iPhone until the field officer secures internet access. At this point, the field officer can manually sync data to our cloud-based server. It is never possible to access the collected data through the iPhone application—only through Periscope, an online, password-protected platform that is only accessible to the PIs. From Periscope, the PI's can download several types of data files, including files that track the path of the iPhone during the tracking mission (where the unit of observation is the mission-second) and beacon sightings files (where the unit of observation is an in-range beacon second). These latter files allow us to track the approximate location and RSSI of sighted beacons, which allow us to match sighted beacons households, as described in the paper. Periscope also has an integrated mapping function, as illustrated in Figure 1.

B.2 Some statistics from the tracking missions

We instructed field officers to come within 20 meters of every building in each village during their tracking rounds. The mean mission building coverage rate at 20 meters was 90.75% (median = 94.4%). The distribution of this coverage rate is shown in Figure A3.

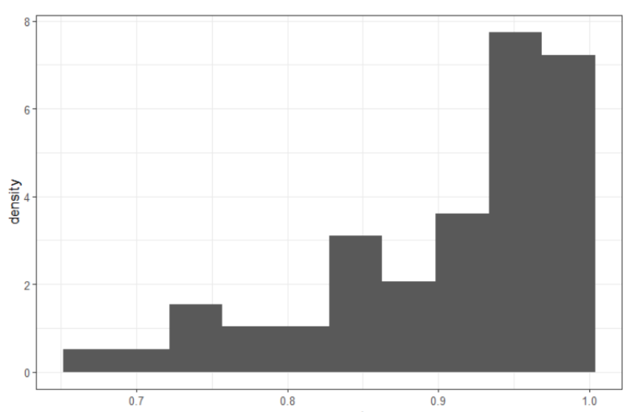

Figure A3: Coverage rate at 20 meters by villge-round (all buildings)

Although 20 meters is the conservative distance at which a beacon signal should be detectable, beacons should also be detectable at a distance of 30 meters under most circumstances. The mean mission building coverage rate at 3om was 96.9% (median = 93.5%). The distribution is shown in Figure A4

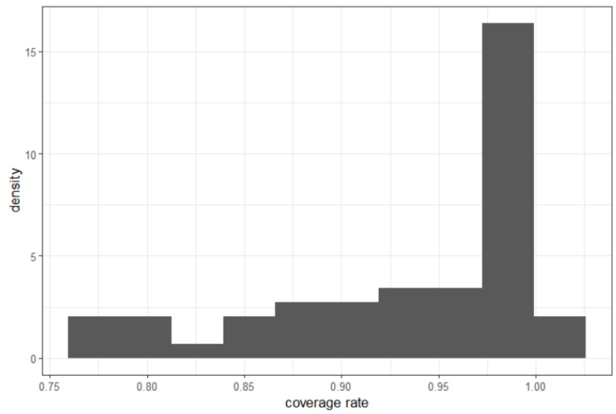

Figure A4: Coverage rate at 30m by village-round (all buildings)

There was some variation in the coverage rates across rounds, but no clear trend:

Table A1: Coverage rate across tracking rounds

	mean coverage rate at 20m	mean coverage rate at 30m
round 1	96.1	97.7
round 2	84.9	89.8
round 3	89.7	92.2
round 4	91.4	93.8
round 5	92.1	94.3

Households may have been missed because occupants asked them not to approach, because they were fenced and inaccessible, because adverse whether cut tracking missions short, or because of human error.

As reported in the paper, we were able to detect 98.8% of the beacons in at least one tracking round. The distribution of detection rates across tracking rounds was as follows:

Table A2: Detection rate across tracking rounds

	percentage of beacons detected
round 1	95.9
round 2	93.4
round 3	92.6
round 4	94.2
round 5	91.0

C Information provided to village elders

C.1 Instructions to village elders for distributing the lanterns

We are here as part of the Lighting Kenya Project. In this project, we are distributing solar lanterns to several sub-locations in [redacted] County. We chose this sub-location specifically because we know there is a particularly great need here for lighting after dark.

We want to make sure that the lanterns we distribute remain in the villages in which we distribute them. We have placed tracking devices in some of the lanterns we are distributing and plan to use them to confirm that the lanterns remain where they are supposed to be. The tracking devices only reveal the approximate locations of the lanterns but do not collect any other information. For example, they do not record conversations.

For budget reasons, we are not able to put the tracking devices in all of the lanterns we are distributing. Only 10% of the lanterns we are distributing in [redacted] County have tracking devices. This means that for every lantern that contains a tracking device, there are nine that do not. The lanterns we give you may or may not contain tracking devices.

This is what the solar lanterns look like. [Hold up a lantern and demonstrate its function.] As you will notice, the lantern contains a label explaining that it may contain a tracking device. Again, for budget reasons we were not able to put the tracking devices in all the lanterns that we are distributing in [redacted] County. Only one out of every ten lanterns has such a device.

We have prepared boxes of lanterns for each village elder. The box you will receive contains a number of lanterns determined by the size of your village. Larger villages will receive more lanterns, and smaller villages will receive fewer. We ask that you only distribute the solar lanterns you receive within your own village.

We are eager for people in this area to benefit from the lanterns we are distributing, so we request that you distribute them in your villages within one week.

While we recognize that many people in your villages would benefit from receiving a solar lantern, we request that the first priority be households with children under 5 years old. These young children may require help during the night, and tin lamps present a danger for their health and safety. The smoke from tin or kerosene lamps are especially harmful to the health of children. In addition, young children may not understand the danger of tin or kerosene lamps, so they are more likely to knock them over. This can result in fire or burns. Solar lanterns can help prevent these accidents.

Thank you in advance for your participation in the Lighting Kenya Project.

C.2 Receipt/Consent Form

Acknowledgement of Receipt of Solar Lanterns

I acknowledge having received X solar lanterns from the Lighting Kenya Project, which I agree to distribute within my village within one week.

I understand that the project organizers may return later to confirm that the solar lanterns remained within the village, and that I may or may not be notified if they do.

I also understand that tracking devices have been placed in 10% of the solar lanterns that are being distributed in [the project area] and that the purpose of the tracking devices is to confirm that the solar lanterns remain where they are supposed to be.

I also understand that I have been requested to prioritize distributing the solar lanterns to households with children under 5 years old, as young children may require help during the night and tin lamps present a danger for their health and safety.

I understand that my participation in this project is entirely voluntary.

I acknowledge receipt of a card with information about who to contact if I have any questions, comments or concerns about the Lighting Kenya Project.

Signature:

Date:

D Prediction survey

To better understand whether our findings regarding leakage and misallocation were surprising, we collected information about the predictions of local experts in Kenya. During seminar presentations to the economics and development departments at the University of Nairobi, Kenyatta University, and Strathmore University, and at a lunch presentation at the Busara Center for Behavioral Economics, we paused our talk after we had explained the details of the project but before we revealed what we had found. Before continuing with our presentation, we administered a brief survey asking seminar participants to indicate their expectations about leakage (what share of the 244 lanterns we are distributing do you think are likely remain in the study villages?) and deviations from program guidelines (what share of lanterns do you think were found in households containing at least one child under 5 years old?).

We collected surveys from 70 seminar participants, who, on average, had 4.5 years of experience studying/working on development issues. The median prediction for the share of lanterns that would remain in the study villages was 55% (mean = 62%). The median prediction for the share of lanterns that would be found in households meeting the primary program criterion (i.e., containing children under 5) was 65% (mean = 57%). The distribution of predictions are displayed in Figure A5 below. We do not highlight the results about expected deviations from program guidelines in the paper because of ambiguity about whether the respondents were responding in terms of the total number of lanterns that were distributed or from among the lanterns they predicted would remain in the study villages.

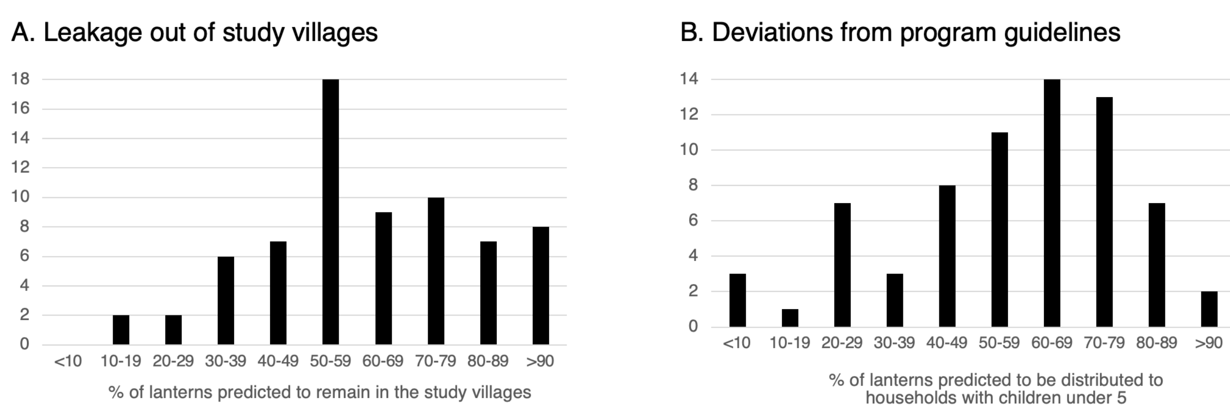

Figure A5: Predictions about leakage and misallocation.

Panel A shows the distribution of predictions about the share of lanterns that would remain in the study villages; Panel B shows the distribution of predictions of the share of lanterns that would be found in households containing at least one child under 5 years old.

E From tracking data to distribution inferences: Processes and complications

E.1 Matching found beacons to households

In matching found beacons to buildings, one of the complications highlighted in the paper is that beacons were sometimes detected in the vicinity of multiple buildings.[35] In 73.4% of match cases, the beacon was detected near more than one building belonging to distinct complexes. As shown in Figure A6, the modal case (26.6% of cases) is a beacon detected near two buildings from different complexes during the same mission. This case slightly edges out unambiguous cases where the beacon was sighted near only one building (27.2% of cases).

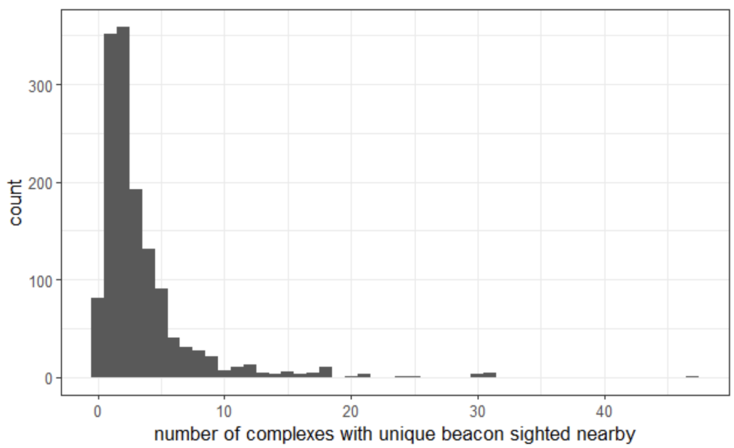

Figure A6: Distribution of potential number of matches per sighting.

Detecting a beacon in proximity to multiple buildings is not necessarily a problem for matching if there is a significant differential in the beacon's signal strength detected in proximity to each building. Among cases where beacons were detected near multiple complexes, the mean difference in linear signal strength between the best building match and the second-best building match of a distinct complex is 12.2 (median = 9.8). Figure A7 shows the full distribution of these differences.

[35] In the vicinity of or near means that on the tracking path points closest to the building, the reader detected a beacon. Complexes refer to grouped sets of buildings belonging to the same household or institution. For example, we might detect a beacon near a main dwelling as well as near a kitchen *of the same household complex*. These figures reflect matches to different buildings belonging to distinct complexes, e.g., kitchens for two different households.

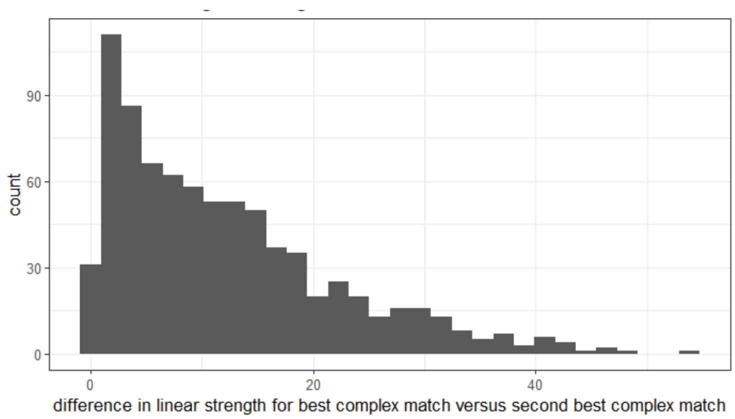

Figure A7: Distribution of signal strength differentials.

E.2 Merging tracking data with the household survey data

Several complications also arose when merging tracking data with survey data. First and foremost, buildings lacked unique identifiers. During the initial mapping exercise, field officers had to manually create building labels and accidentally, unintentionally used some building labels twice. In addition, field officers also encountered difficulties accurately recording building locations during the mapping exercise because of poor cell coverage, which later caused problems during the household survey. During the survey, we provided survey enumerators with the coordinates of the target household. However, enumerators sometimes arrived at this location only to find themselves between multiple houses. When ambiguous cases like this occurred, enumerators interviewed both households and recorded both sets of answers under the same household label. Thus, duplicate labels occurred in both tracking data (arising from labeling errors during the mapping exercise) and during the survey (arising from inaccurate household coordinates). Labels thus cannot serve as unique identifiers for merging these data sets. Geo-coordinates are an alternative potential unique identifier, and we employed them as such when processing tracking information and inferring matches. Yet while survey tablets recorded the interview location, these coordinates usually did not precisely match the originally recorded household location. Thus, geo-coordinates cannot serve as unique identifiers to merge tracking and survey data.

These difficulties generated four case types when merging tracking and survey data, displayed in Table A3. For ambiguous cases (case types 2 through 4), we resolved cases using the tracking-to-survey data assignment that minimized discrepancy in distances between the mapping/tracking coordinates and the interview coordinates. For case type 3, we discarded the extra survey data for the discrepant household since it inclusion would undermine the integrity of sample construction: unmatched households are representative only if they are randomly selected, and these households were not randomly selected.

We also investigated whether these resolutions were consequential to the confusion matrix of inferred versus reported lantern ownership. For example, imagine a survey enumerator arrived at (inaccurately recorded) household geocoordinates only to find herself between two households. She interviews both households and records them under under the same label. During the interview, one household reported owning a lantern and one did not. Tracking data indicate the household under this label possessed a lantern. In this example, picking one household versus the other would be consequential to the confusion matrix: our inferences about lantern ownership from tracking data could be confirmed or contradicted by reported ownership, but the evaluation depends on how we resolve the case. Conversely, if neither or both households reported owning a lantern, it would not be consequential; our tracking-based inference would either always be confirmed or always be contradicted by reported ownership. While some consequential resolutions occurred, they were dropped due to other restrictions. We are confident that resolution decisions from ambiguous cases (case types 2 to 4) does not undermine findings because we also conduct robustness tests using only case type 1 data (see Appendix G).

Table A3: Summary of merge resolution cases

Case type	Duplicated in intended sample	Duplicated in survey	Number of cases	Number of retained cases	Of retained cases...		
					Number of matched cases	Number of unmatched cases	Number of consequential resolutions
1	no	no	545	531	293	238	NA
2	no	yes	9	8	5	3	0
3	yes	no	15	13	7	6	0
4	yes	yes	4 (2 pairs)	2	2	0	0

Finally, we dropped household interviews from our data set if they met one of the following conditions:

- *The recorded household label was not in the intended sample.* In this case, the enumerators likely interviewed an intended household by made a mistake when entering the household label. We considered attempting to reassign these cases to an "un-interviewed" household from the intended sample, but there were often multiple candidates that were off by a single digit. Reassignment thus seemed as likely to produce error as accurate resolution. This rule eliminates 6 households.

- *The household was non-randomly selected for the sample but is not a matched household under the improved algorithm.* Our analyses are based on an improved algorithm, while our sample selection occurred under the original algorithm. Some households that generated a match under the original algorithm did not generate a match under the improved algorithm. Although we do not think these households have a lantern, we cannot use them as part of our non-lantern control group. They were not randomly selected and will therefore undermine the representativeness of that group. This rule eliminates 17 households.

- *The interviewee was under 18 years old.* These individuals should not have been interviewed under our research plan and ethical approvals, so we do not use the resulting data. This rule eliminates 3 households.

We are then left with a total of 566 interviews, 251 of which are matched under our improved tracking algorithm and 305 of which are both (pseudo-)randomly selected and not matched under our improved algorithm.[36]

[36]It is not perfect random selection because those 17 houses that were antiquated matches from the original algorithm should have been eligible for random selection but were not. We cannot correct this problem post-hoc.

F Difference-in-means tests under alternative match criteria

Table A4: Difference in Means (Confident Matches)

	Survey mean	No beacon detected	Beacon detected	Difference	Total n households
Child under 5	42.20	30.13	66.01	35.88***	455
Child between 5 and 12 yrs	56.48	49.34	70.59	21.25***	455
Adult aged 75+	7.03	7.62	5.88	-1.73	455
Only adults aged 60+	5.05	5.30	4.58	-0.72	455
Already owns lantern	23.74	25.50	20.26	-5.24	455
Conneted to electric grid	16.92	21.19	8.50	-12.70***	455
Owns solar home system	69.89	70.20	69.28	-0.92	455
Asset index (above village median)	48.79	49.01	48.37	-0.64	455
Housing quality index (above village median)	42.82	48.79	31.33	-17.46***	439
Lived poverty index (above village median)	52.01	47.30	61.18	13.89**	448
VE is immediate family member	25.29	23.65	28.78	5.13	435
VE is extended family member	32.64	31.42	35.25	3.83	435
VE is related	38.62	36.49	43.17	6.68	435
Spoke w VE in past week	45.75	39.86	58.27	18.41***	435
Shared meal w VE in past week	7.82	7.43	8.63	1.20	435
Worships at same church as VE	3.72	3.32	4.55	1.22	403

Table A5: Difference in Means (Verified Matches)

	Survey mean	No beacon detected	Beacon detected	Difference	Total n households
Child under 5	45.14	30.13	68.75	38.62***	494
Child between 5 and 12 yrs	59.31	49.34	75.00	25.66***	494
Adult aged 75+	6.68	7.62	5.21	-2.41	494
Only adults aged 60+	4.25	5.30	2.60	-2.69	494
Already owns lantern	25.71	25.50	26.04	0.54	494
Conneted to electric grid	17.21	21.19	10.94	-10.25**	494
Owns solar home system	69.03	70.20	67.19	-3.01	494
Asset index (above village median)	48.99	49.01	48.96	-0.05	494
Housing quality index (above village median)	43.25	48.79	34.59	-14.19**	474
Lived poverty index (above village median)	54.41	47.30	65.45	18.15***	487
VE is immediate family member	23.78	23.65	24.00	0.35	471
VE is extended family member	32.48	31.42	34.29	2.87	471
VE is related	38.43	36.49	41.71	5.23	471
Spoke w VE in past week	46.71	39.86	58.29	18.42***	471
Shared meal w VE in past week	8.07	7.43	9.14	1.71	471
Worships at same church as VE	4.15	3.32	5.52	2.20	434

G Robustness to alternative data quality controls and specifications

The main results presented in Table 1 and Table 2 assume that survey enumerators interviewed the household they reported and that the interviewed household represents the target household. We include households in these analyses that had duplicated labels during the census and/or survey exercises, resolving such ambiguities by assigning data to households in a matter that minimizing geographic discrepancies between interview locations and the originally recorded household locations from the census (see appendix E).

In the tables that follow, we apply different data controls to confirm that main trends hold.

- In section G.1, we only include households in the analyses if the most proximate household to the recorded interview location is the target household ($n = 356$). In other words, we exclude a household if the interview purportedly for this household occurred closer to a different household than the target household based on initial mapping exercise coordinates. Although failure to mean this standard does not necessarily indicate that the enumerator went to the wrong household, that is one potential explanation for the discrepancy.
- In section G.2, we only include households in the analyses if the recorded interview location fell within one kilometer of the target household ($n = 548$). Although failure to meet this standard does not necessarily indicate that the enumerator went to the wrong household, this is one potential explanation for the discrepancy.
- In section G.3, we only include households in the analyses if the numeric ID assigned to the household was unique in both the census and the survey data (i.e., case type 1, $n = 528$). We exclude any cases where we used discretion to resolve potentially ambiguous data assignment (see appendix E).
- In section G.4, we only include households eligible for inclusion under all the above included criteria ($n = 340$). In other words, we exclude any household that raises identifiable concerns about whether matching and survey data are correctly assigned to households.

Note that all variable construction applied prior to the application of these various data quality controls. In this respect, the covariates are not robust to data quality controls.

For the results originally presented in Table 2, we also examine robustness to several alternative model specifications in Appendix G.5. While each of the above regressions are weighted to reflect probability of inclusion in the sample, Table A14 shows the main analysis reported in Table 2 re-run without weights. In Table A15 shows the main analysis reported in Table 2 re-run using logit rather than ordinary least squares.

G.1 Most proximate household to survey site is interviewed household

Table A6: Difference-in-Means Results

	Survey mean	No beacon detected	Beacon detected	Difference	Total n
Match					
Child under 5	45.51	25.75	62.96	37.21***	356
Child between 5 and 12 yrs	60.96	52.10	68.78	16.69**	356
Adult aged 75+	7.02	8.38	5.82	-2.56	356
Only adults aged 60+	4.21	4.79	3.70	-1.09	356
Already owns lantern	22.47	26.95	18.52	-8.43	356
Conneted to electric grid	13.76	17.37	10.58	-6.78	356
Owns solar home system	71.35	72.46	70.37	-2.08	356
Asset index (above village median)	47.19	47.90	46.56	-1.34	356
Housing quality index (above village median)	39.37	47.24	32.43	-14.81**	348
Lived poverty index (above village median)	59.26	52.47	65.08	12.61*	351
VE is immediate family member	24.78	24.85	24.71	-0.14	339
VE is extended family member	33.33	33.94	32.76	-1.18	339
VE is related	38.94	38.18	39.66	1.47	339
Spoke w VE in past week	50.44	42.42	58.05	15.62**	339
Shared meal w VE in past week	8.26	7.27	9.20	1.92	339
Worships at same church as VE	3.77	3.27	4.24	0.97	318
Verified Match					
Child under 5	45.48	25.75	66.88	41.13***	321
Child between 5 and 12 yrs	62.93	52.10	74.68	22.58***	321
Adult aged 75+	6.85	8.38	5.19	-3.19	321
Only adults aged 60+	4.05	4.79	3.25	-1.54	321
Already owns lantern	24.92	26.95	22.73	-4.22	321
Conneted to electric grid	13.40	17.37	9.09	-8.27*	321
Owns solar home system	69.78	72.46	66.88	-5.57	321
Asset index (above village median)	47.35	47.90	46.75	-1.15	321
Housing quality index (above village median)	40.00	47.24	32.24	-15.00**	315
Lived poverty index (above village median)	58.23	52.47	64.29	11.82*	316
VE is immediate family member	24.26	24.85	23.57	-1.28	305
VE is extended family member	33.44	33.94	32.86	-1.08	305
VE is related	39.02	38.18	40.00	1.82	305
Spoke w VE in past week	49.84	42.42	58.57	16.15**	305
Shared meal w VE in past week	7.54	7.27	7.86	0.58	305
Worships at same church as VE	3.85	3.27	4.51	1.24	286
Confident Match					
Child under 5	44.26	25.75	68.22	42.47***	296
Child between 5 and 12 yrs	60.14	52.10	70.54	18.45**	296
Adult aged 75+	7.09	8.38	5.43	-2.96	296
Only adults aged 60+	4.73	4.79	4.65	-0.14	296
Already owns lantern	23.31	26.95	18.60	-8.34	296
Conneted to electric grid	13.51	17.37	8.53	-8.84*	296
Owns solar home system	71.28	72.46	69.77	-2.69	296
Asset index (above village median)	47.30	47.90	46.51	-1.39	296
Housing quality index (above village median)	38.97	47.24	28.35	-18.89**	290
Lived poverty index (above village median)	55.67	52.47	59.69	7.22	291
VE is immediate family member	26.15	24.85	27.97	3.12	283
VE is extended family member	33.92	33.94	33.90	-0.04	283
VE is related	39.22	38.18	40.68	2.50	283
Spoke w VE in past week	49.82	42.42	60.17	17.75**	283
Shared meal w VE in past week	7.77	7.27	8.47	1.20	283
Worships at same church as VE	3.36	3.27	3.48	0.21	268

Table A7: Regression Results

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.328***	0.370***	0.383***
	(0.040)	(0.043)	(0.045)
Child between 5 and 12 yrs	0.051	0.106**	0.096*
	(0.037)	(0.043)	(0.055)
Adult 75+ years	−0.042	−0.029	−0.072
	(0.106)	(0.092)	(0.073)
Only adults over 60 yrs	0.165	0.209	0.300***
	(0.138)	(0.128)	(0.106)
Already owns lantern	−0.093	−0.033	−0.085*
	(0.060)	(0.054)	(0.049)
Connected to electric grid	−0.147***	−0.161***	−0.122**
	(0.048)	(0.056)	(0.055)
Owns solar home system	−0.085	−0.101	−0.085
	(0.069)	(0.081)	(0.065)
Asset index	0.001	0.012	−0.006
	(0.038)	(0.039)	(0.041)
Housing quality index	−0.006	−0.016	−0.035
	(0.025)	(0.024)	(0.034)
Lived poverty index	0.089***	0.089***	0.063***
	(0.017)	(0.021)	(0.024)
VE is immediate family member	−0.026	−0.043	0.006
	(0.044)	(0.047)	(0.046)
Spole w VE in past wk	0.105**	0.112*	0.126**
	(0.046)	(0.064)	(0.056)
Shared meal with VE in past wk	−0.040	−0.083	−0.094**
	(0.046)	(0.058)	(0.043)
Constant	0.388***	0.285***	0.232***
	(0.071)	(0.079)	(0.081)
Observations	343	310	285
R^2	0.207	0.256	0.248
Adjusted R^2	0.176	0.224	0.212
Residual Std. Error	0.453 (df = 329)	0.441 (df = 296)	0.442 (df = 271)
F Statistic	6.624*** (df = 13; 329)	7.854*** (df = 13; 296)	6.880*** (df = 13; 271)

Note: See notes to Table 2 *p<0.1; **p<0.05; ***p<0.01

G.2 Survey occurred within 1km of household location

Table A8: Difference-in-Means Results

	Survey mean	No beacon detected	Beacon detected	Difference	Total n
Match					
Child under 5	44.34	30.10	61.45	31.35***	548
Child between 5 and 12 yrs	57.12	49.16	66.67	17.50***	548
Adult aged 75+	6.93	7.69	6.02	-1.67	548
Only adults aged 60+	4.38	5.35	3.21	-2.14	548
Already owns lantern	22.45	24.75	19.68	-5.07	548
Conneted to electric grid	16.79	21.40	11.24	-10.16**	548
Owns solar home system	70.26	70.57	69.88	-0.69	548
Asset index (above village median)	48.91	48.83	49.00	0.17	548
Housing quality index (above village median)	42.91	48.60	36.02	-12.58**	522
Lived poverty index (above village median)	55.45	47.44	64.92	17.48***	541
VE is immediate family member	23.85	23.55	24.24	0.69	524
VE is extended family member	32.25	31.40	33.33	1.93	524
VE is related	37.98	36.18	40.26	4.08	524
Spoke w VE in past week	47.14	39.93	56.28	16.35***	524
Shared meal w VE in past week	8.59	7.51	9.96	2.45	524
Worships at same church as VE	4.33	3.33	5.58	2.25	485
Verified Match					
Child under 5	45.31	30.10	69.11	39.01***	490
Child between 5 and 12 yrs	59.39	49.16	75.39	26.23***	490
Adult aged 75+	6.73	7.69	5.24	-2.46	490
Only adults aged 60+	4.29	5.35	2.62	-2.73	490
Already owns lantern	25.10	24.75	25.65	0.91	490
Conneted to electric grid	17.14	21.40	10.47	-10.93**	490
Owns solar home system	69.39	70.57	67.54	-3.03	490
Asset index (above village median)	48.78	48.83	48.69	-0.14	490
Housing quality index (above village median)	42.98	48.60	34.24	-14.36**	470
Lived poverty index (above village median)	54.66	47.44	65.79	18.35***	483
VE is immediate family member	23.72	23.55	24.00	0.45	468
VE is extended family member	32.48	31.40	34.29	2.89	468
VE is related	38.25	36.18	41.71	5.54	468
Spoke w VE in past week	46.79	39.93	58.29	18.35***	468
Shared meal w VE in past week	8.12	7.51	9.14	1.63	468
Worships at same church as VE	4.16	3.33	5.52	2.19	433
Confident Match					
Child under 5	42.35	30.10	66.45	36.35***	451
Child between 5 and 12 yrs	56.54	49.16	71.05	21.89***	451
Adult aged 75+	7.10	7.69	5.92	-1.77	451
Only adults aged 60+	5.10	5.35	4.61	-0.75	451
Already owns lantern	23.06	24.75	19.74	-5.01	451
Conneted to electric grid	16.85	21.40	7.89	-13.51***	451
Owns solar home system	70.29	70.57	69.74	-0.83	451
Asset index (above village median)	48.56	48.83	48.03	-0.80	451
Housing quality index (above village median)	42.53	48.60	30.87	-17.73***	435
Lived poverty index (above village median)	52.25	47.44	61.59	14.15**	444
VE is immediate family member	25.23	23.55	28.78	5.23	432
VE is extended family member	32.64	31.40	35.25	3.85	432
VE is related	38.43	36.18	43.17	6.99	432
Spoke w VE in past week	45.83	39.93	58.27	18.34***	432
Shared meal w VE in past week	7.87	7.51	8.63	1.12	432
Worships at same church as VE	3.73	3.33	4.55	1.21	402

Table A9: Regression Results

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.274***	0.319***	0.287***
	(0.060)	(0.059)	(0.065)
Child between 5 and 12 yrs	0.079**	0.151***	0.131***
	(0.036)	(0.040)	(0.050)
Adult 75+ years	0.033	0.042	−0.004
	(0.080)	(0.083)	(0.078)
Only adults over 60 yrs	0.067	0.119	0.206**
	(0.095)	(0.080)	(0.081)
Already owns lantern	−0.062	0.019	−0.045
	(0.057)	(0.052)	(0.049)
Connected to electric grid	−0.129***	−0.104**	−0.136**
	(0.044)	(0.048)	(0.061)
Owns solar home system	−0.046	−0.065	−0.060
	(0.066)	(0.071)	(0.059)
Asset index	−0.025	−0.007	−0.024
	(0.017)	(0.019)	(0.018)
Housing quality index	0.003	−0.020	−0.024
	(0.027)	(0.023)	(0.027)
Lived poverty index	0.068***	0.071***	0.039
	(0.021)	(0.024)	(0.024)
VE is immediate family member	−0.024	−0.030	0.014
	(0.047)	(0.059)	(0.056)
Spole w VE in past wk	0.134***	0.142***	0.142***
	(0.028)	(0.045)	(0.040)
Shared meal with VE in past wk	−0.032	−0.075	−0.112***
	(0.050)	(0.046)	(0.040)
Constant	0.285***	0.142*	0.147*
	(0.090)	(0.083)	(0.083)
Observations	515	463	428
R^2	0.160	0.227	0.191
Adjusted R^2	0.138	0.204	0.166
Residual Std. Error	0.463 (df = 501)	0.437 (df = 449)	0.435 (df = 414)
F Statistic	7.345*** (df = 13; 501)	10.121*** (df = 13; 449)	7.539*** (df = 13; 414)
Note: See notes to Table 2			*p<0.1; **p<0.05; ***p<0.01

G.3 Non-duplicates only

Table A10: Difference-in-Means Results

	Survey mean	No beacon detected	Beacon detected	Difference	Total n
Match					
Child under 5	44.89	30.93	62.03	31.10***	528
Child between 5 and 12 yrs	57.58	50.17	66.67	16.49***	528
Adult aged 75+	6.44	7.22	5.49	-1.73	528
Only adults aged 60+	3.98	4.47	3.38	-1.09	528
Already owns lantern	22.92	25.43	19.83	-5.60	528
Conneted to electric grid	16.29	19.93	11.81	-8.12*	528
Owns solar home system	69.89	69.76	70.04	0.28	528
Asset index (above village median)	48.86	48.45	49.37	0.91	528
Housing quality index (above village median)	43.45	49.28	36.28	-13.00**	504
Lived poverty index (above village median)	54.89	46.67	64.83	18.16***	521
VE is immediate family member	23.41	23.51	23.29	-0.22	504
VE is extended family member	31.94	31.23	32.88	1.65	504
VE is related	38.10	36.49	40.18	3.69	504
Spoke w VE in past week	46.63	39.30	56.16	16.87***	504
Shared meal w VE in past week	8.33	7.37	9.59	2.22	504
Worships at same church as VE	4.30	3.44	5.42	1.98	465
Verified Match					
Child under 5	45.80	30.93	69.19	38.26***	476
Child between 5 and 12 yrs	59.87	50.17	75.14	24.96***	476
Adult aged 75+	6.30	7.22	4.86	-2.35	476
Only adults aged 60+	3.78	4.47	2.70	-1.76	476
Already owns lantern	25.42	25.43	25.41	-0.02	476
Conneted to electric grid	16.60	19.93	11.35	-8.58*	476
Owns solar home system	69.12	69.76	68.11	-1.65	476
Asset index (above village median)	48.74	48.45	49.19	0.74	476
Housing quality index (above village median)	43.76	49.28	35.20	-14.09**	457
Lived poverty index (above village median)	53.94	46.67	65.22	18.55***	469
VE is immediate family member	23.57	23.51	23.67	0.16	454
VE is extended family member	32.38	31.23	34.32	3.09	454
VE is related	38.55	36.49	42.01	5.52	454
Spoke w VE in past week	46.26	39.30	57.99	18.69***	454
Shared meal w VE in past week	7.93	7.37	8.88	1.51	454
Worships at same church as VE	4.06	3.44	5.10	1.66	419
Confident Match					
Child under 5	42.69	30.93	65.99	35.06***	438
Child between 5 and 12 yrs	57.08	50.17	70.75	20.58***	438
Adult aged 75+	6.85	7.22	6.12	-1.09	438
Only adults aged 60+	4.57	4.47	4.76	0.29	438
Already owns lantern	23.74	25.43	20.41	-5.02	438
Conneted to electric grid	15.98	19.93	8.16	-11.77**	438
Owns solar home system	69.86	69.76	70.07	0.31	438
Asset index (above village median)	48.63	48.45	48.98	0.53	438
Housing quality index (above village median)	43.26	49.28	31.72	-17.56***	423
Lived poverty index (above village median)	51.74	46.67	61.64	14.98**	431
VE is immediate family member	25.12	23.51	28.57	5.06	418
VE is extended family member	32.54	31.23	35.34	4.11	418
VE is related	38.76	36.49	43.61	7.12	418
Spoke w VE in past week	45.45	39.30	58.65	19.35***	418
Shared meal w VE in past week	7.89	7.37	9.02	1.65	418
Worships at same church as VE	3.87	3.44	4.76	1.33	388

Table A11: Regression result

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.273***	0.316***	0.277***
	(0.062)	(0.059)	(0.063)
Child between 5 and 12 yrs	0.079**	0.156***	0.124***
	(0.035)	(0.042)	(0.048)
Adult 75+ years	0.012	0.027	0.003
	(0.075)	(0.081)	(0.078)
Only adults over 60 yrs	0.137	0.163	0.252**
	(0.134)	(0.111)	(0.108)
Already owns lantern	−0.052	0.024	−0.031
	(0.064)	(0.058)	(0.053)
Connected to electric grid	−0.095*	−0.067	−0.109
	(0.054)	(0.056)	(0.068)
Owns solar home system	−0.030	−0.050	−0.045
	(0.072)	(0.072)	(0.064)
Asset index	−0.026	−0.011	−0.021
	(0.018)	(0.020)	(0.020)
Housing quality index	−0.001	−0.016	−0.040
	(0.030)	(0.024)	(0.026)
Lived poverty index	0.065***	0.065***	0.044*
	(0.021)	(0.025)	(0.024)
VE is immediate family member	−0.046	−0.044	0.002
	(0.041)	(0.058)	(0.053)
Spole w VE in past wk	0.141***	0.148***	0.138***
	(0.033)	(0.046)	(0.041)
Shared meal with VE in past wk	−0.052	−0.094**	−0.103**
	(0.049)	(0.048)	(0.042)
Constant	0.263***	0.124	0.136*
	(0.091)	(0.082)	(0.080)
Observations	497	450	416
R^2	0.154	0.214	0.183
Adjusted R^2	0.131	0.190	0.156
Residual Std. Error	0.464 (df = 483)	0.440 (df = 436)	0.437 (df = 402)
F Statistic	6.770*** (df = 13; 483)	9.123*** (df = 13; 436)	6.919*** (df = 13; 402)

Note: See notes to Table 2 *p<0.1; **p<0.05; ***p<0.01

G.4 Most restrictive

Table A12: Difference-in-Means Results

	Survey mean	No beacon detected	Beacon detected	Difference	Total n
Match					
Child under 5	45.88	25.93	64.04	38.12***	340
Child between 5 and 12 yrs	61.18	52.47	69.10	16.63**	340
Adult aged 75+	7.06	8.64	5.62	-3.02	340
Only adults aged 60+	4.12	4.32	3.93	-0.39	340
Already owns lantern	22.35	26.54	18.54	-8.00	340
Conneted to electric grid	13.53	16.67	10.67	-5.99	340
Owns solar home system	71.76	72.22	71.35	-0.87	340
Asset index (above village median)	46.76	46.91	46.63	-0.28	340
Housing quality index (above village median)	39.64	47.47	32.57	-14.90**	333
Lived poverty index (above village median)	59.10	52.23	65.17	12.94*	335
VE is immediate family member	24.38	25.00	23.78	-1.22	324
VE is extended family member	33.33	34.37	32.32	-2.06	324
VE is related	39.20	38.75	39.63	0.88	324
Spoke w VE in past week	50.00	41.25	58.54	17.29**	324
Shared meal w VE in past week	8.33	7.50	9.15	1.65	324
Worships at same church as VE	3.95	3.36	4.52	1.16	304
Verified Match					
Child under 5	45.66	25.93	67.11	41.19***	311
Child between 5 and 12 yrs	63.02	52.47	74.50	22.03***	311
Adult aged 75+	7.07	8.64	5.37	-3.27	311
Only adults aged 60+	3.86	4.32	3.36	-0.97	311
Already owns lantern	24.44	26.54	22.15	-4.40	311
Conneted to electric grid	13.18	16.67	9.40	-7.27	311
Owns solar home system	70.42	72.22	68.46	-3.77	311
Asset index (above village median)	46.95	46.91	46.98	0.07	311
Housing quality index (above village median)	40.66	47.47	33.33	-14.14*	305
Lived poverty index (above village median)	57.84	52.23	63.76	11.53*	306
VE is immediate family member	24.32	25.00	23.53	-1.47	296
VE is extended family member	33.78	34.38	33.09	-1.29	296
VE is related	39.53	38.75	40.44	1.69	296
Spoke w VE in past week	49.32	41.25	58.82	17.57**	296
Shared meal w VE in past week	7.77	7.50	8.09	0.59	296
Worships at same church as VE	3.96	3.36	4.65	1.30	278
Confident Match					
Child under 5	44.21	25.93	68.29	42.37***	285
Child between 5 and 12 yrs	60.35	52.47	70.73	18.26**	285
Adult aged 75+	7.37	8.64	5.69	-2.95	285
Only adults aged 60+	4.56	4.32	4.88	0.56	285
Already owns lantern	23.16	26.54	18.70	-7.84	285
Conneted to electric grid	12.98	16.67	8.13	-8.54*	285
Owns solar home system	71.58	72.22	70.73	-1.49	285
Asset index (above village median)	47.02	46.91	47.15	0.24	285
Housing quality index (above village median)	39.29	47.47	28.69	-18.78**	280
Lived poverty index (above village median)	55.71	52.23	60.16	7.93	280
VE is immediate family member	26.10	25.00	27.68	2.68	272
VE is extended family member	34.19	34.37	33.93	-0.45	272
VE is related	39.71	38.75	41.07	2.32	272
Spoke w VE in past week	49.26	41.25	60.71	19.46**	272
Shared meal w VE in past week	8.09	7.50	8.93	1.43	272
Worships at same church as VE	3.49	3.36	3.67	0.31	258

Table A13: Regression Results

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.337***	0.372***	0.380***
	(0.042)	(0.043)	(0.040)
Child between 5 and 12 yrs	0.055	0.109**	0.089*
	(0.037)	(0.046)	(0.053)
Adult 75+ years	−0.069	−0.035	−0.078
	(0.094)	(0.088)	(0.064)
Only adults over 60 yrs	0.241	0.243*	0.357***
	(0.162)	(0.147)	(0.127)
Already owns lantern	−0.073	−0.023	−0.061
	(0.060)	(0.055)	(0.052)
Connected to electric grid	−0.133***	−0.141***	−0.111**
	(0.045)	(0.051)	(0.051)
Owns solar home system	−0.062	−0.080	−0.058
	(0.083)	(0.085)	(0.082)
Asset index	0.002	0.009	0.003
	(0.040)	(0.040)	(0.043)
Housing quality index	−0.016	−0.013	−0.071**
	(0.033)	(0.025)	(0.028)
Lived poverty index	0.087***	0.082***	0.070***
	(0.018)	(0.022)	(0.022)
VE is immediate family member	−0.049	−0.050	−0.011
	(0.039)	(0.046)	(0.041)
Spole w VE in past wk	0.120***	0.129**	0.132**
	(0.043)	(0.063)	(0.053)
Shared meal with VE in past wk	−0.066*	−0.094	−0.092**
	(0.037)	(0.058)	(0.044)
Constant	0.351***	0.257***	0.201**
	(0.075)	(0.081)	(0.085)
Observations	328	300	275
R^2	0.215	0.250	0.262
Adjusted R^2	0.183	0.216	0.225
Residual Std. Error	0.452 (df = 314)	0.443 (df = 286)	0.438 (df = 261)
F Statistic	6.620*** (df = 13; 314)	7.344*** (df = 13; 286)	7.129*** (df = 13; 261)

Note: See notes to Table 2 — *p<0.1; **p<0.05; ***p<0.01

G.5 Alternative model specifications

Table A14: Main specifications, Unweighted

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	0.271***	0.316***	0.284***
	(0.060)	(0.060)	(0.066)
Child between 5 and 12 yrs	0.078**	0.150***	0.130***
	(0.036)	(0.039)	(0.049)
Adult 75+ years	0.034	0.042	−0.004
	(0.080)	(0.082)	(0.077)
Only adults over 60 yrs	0.063	0.114	0.201**
	(0.095)	(0.082)	(0.083)
Already owns lantern	−0.065	0.016	−0.046
	(0.060)	(0.055)	(0.050)
Connected to electric grid	−0.116**	−0.090*	−0.120*
	(0.050)	(0.055)	(0.067)
Owns solar home system	−0.048	−0.067	−0.062
	(0.065)	(0.069)	(0.058)
Asset index	−0.024	−0.007	−0.024
	(0.017)	(0.019)	(0.019)
Housing quality index	0.005	−0.017	−0.021
	(0.026)	(0.022)	(0.026)
Lived poverty index	0.067***	0.070***	0.038
	(0.021)	(0.024)	(0.024)
VE is immediate family member	−0.027	−0.033	0.012
	(0.046)	(0.058)	(0.054)
Spole w VE in past wk	0.130***	0.138***	0.136***
	(0.028)	(0.044)	(0.039)
Shared meal with VE in past wk	−0.029	−0.070	−0.106***
	(0.051)	(0.048)	(0.041)
Constant	0.288***	0.146*	0.152*
	(0.088)	(0.079)	(0.081)
Observations	519	467	432
R^2	0.155	0.218	0.182
Adjusted R^2	0.133	0.196	0.156
Residual Std. Error	0.464 (df = 505)	0.439 (df = 453)	0.437 (df = 418)
F Statistic	7.111*** (df = 13; 505)	9.730*** (df = 13; 453)	7.143*** (df = 13; 418)

Note: See notes to Table 2 *p<0.1; **p<0.05; ***p<0.01

Table A15: Main specifications, Logistic regression

	Dependent variable:		
	Matched	Verified Match	Confident Match
	(1)	(2)	(3)
Child under 5 yrs	1.209***	1.525***	1.394***
	(0.288)	(0.319)	(0.349)
Child between 5 and 12 yrs	0.358**	0.779***	0.694***
	(0.164)	(0.192)	(0.269)
Adult 75+ years	0.143	0.218	−0.068
	(0.372)	(0.479)	(0.482)
Only adults over 60 yrs	0.298	0.632	1.142***
	(0.469)	(0.508)	(0.441)
Already owns lantern	−0.308	0.102	−0.245
	(0.282)	(0.285)	(0.269)
Connected to electric grid	−0.589**	−0.546	−0.788*
	(0.261)	(0.354)	(0.462)
Owns solar home system	−0.224	−0.347	−0.326
	(0.307)	(0.365)	(0.302)
Asset index	−0.124	−0.046	−0.151
	(0.087)	(0.110)	(0.115)
Housing quality index	0.028	−0.095	−0.119
	(0.126)	(0.136)	(0.177)
Lived poverty index	0.320***	0.366***	0.201
	(0.105)	(0.133)	(0.129)
VE is immediate family member	−0.132	−0.171	0.069
	(0.219)	(0.310)	(0.295)
Spole w VE in past wk	0.611***	0.719***	0.699***
	(0.142)	(0.233)	(0.216)
Shared meal with VE in past wk	−0.144	−0.370	−0.547**
	(0.242)	(0.262)	(0.227)
Constant	−0.948**	−1.776***	−1.747***
	(0.429)	(0.443)	(0.469)
Observations	519	467	432
Log Likelihood	−314.831	−257.584	−235.901
Akaike Inf. Crit.	657.662	543.167	499.803

Note: See notes to Table 2 *p<0.1; **p<0.05; ***p<0.01

H Explanation for weighting decisions to correct for selection bias

H.1 Difference in means estimand

Where Y_i is receipt of a lantern and X_i is the status of a given covariate, the difference in means estimand can be defined as:

$$DIM = P(X_i = x|Y_i = 1) - P(X_i = x|Y_i = 0)$$

However, we do not observe data for all households. Let R_i represent whether the observation was recorded (i.e., whether the household was selected for inclusion in the survey). We can thus rewrite

$$P(X_i = x|Y_i = y) = P(X_i = x|Y_i = y, R_i = 1) \cdot P(R_i = 1|Y_i = y) + P(X_i = x|Y_i = y, R_i = 0) \cdot P(R_i = 0|Y_i = y)$$

Turning to the first term of the difference in means estimand, our selection process ensures by design that $P(R_i = 1|Y_i = 1) = 1$ and $P(R_i = 0|Y_i = 1) = 0$. Thus,

$$\begin{aligned}
P(X_i = x|Y_i = 1) &= P(X_i = x|Y_i = 1, R_i = 1) \cdot P(R_i = 1|Y_i = 1) + P(X_i = x|Y_i = 1, R_i = 0) \cdot P(R_i = 0|Y_i = 1) \\
&= P(X_i = x|Y_i = 1, R_i = 1) \cdot 1 + P(X_i = x|Y_i = 1, R_i = 0) \cdot 0 \\
&= P(X_i = x|Y_i = 1, R_i = 1)
\end{aligned}$$

Thus no correction for selection bias is required on the first term. Turning to the second term, our selection process ensures by design that $P(X_i = x|Y_i = 0, R_i = 1) = P(X_i = x|Y_i = 0, R_i = 0)$. Because of random selection, R_i is orthogonal to X_i. Thus,

$$\begin{aligned}
P(X_i = x|Y_i = 0) &= P(X_i = x|Y_i = 0, R_i = 1) \cdot P(R_i = 1|Y_i = 0) + P(X_i = x|Y_i = 0, R_i = 0) \cdot P(R_i = 0|Y_i = 0) \\
&= P(X_i = x|Y_i = 0, R_i = 1) \cdot P(R_i = 1|Y_i = 0) + P(X_i = x|Y_i = 0, R_i = 1) \cdot P(R_i = 0|Y_i = 0) \\
&= P(X_i = x|Y_i = 0, R_i = 1) \cdot [P(R_i = 1|Y_i = 0) + P(R_i = 0|Y_i = 0)] \\
&= P(X_i = x|Y_i = 0, R_i = 1) \cdot 1 \\
&= P(X_i = x|Y_i = 0, R_i = 1)
\end{aligned}$$

Thus no correction for selection bias is required on the second term. The difference-in-means calculations do not require weighting.

H.2 Regression estimands

H.2.1 Explanation for necessity of correction

In simplified form, the regression models try to predict lantern possession $Y_i = y$ based on binary covariate $X_i = x$. We can define the coefficient estimand as

$$\beta_x = P(Y_i = 1|X_i = 1) - P(Y_i = 1|X_i = 0)$$

However, we once again do not observe data for all households. Let R_i represent whether the observation was recorded (i.e., whether the household was selected for inclusion in the survey). We can thus rewrite

$$P(Y_i = 1|X_i = x) = P(Y_i = 1|X_i = x, R_i = 1) \cdot P(R_i = 1|X_i = x) + P(Y_i = 1|X_i = x, R_i = 0) \cdot P(R_i = 0|X_i = x)$$

By design, our selection process ensures that $P(Y_i = 1|X_i = x, R_i = 0) = 0$. Thus, we can simplify the expression

$$\begin{aligned} P(Y_i = 1|X_i = x) &= P(Y_i = 1|X_i = x, R_i = 1) \cdot P(R_i = 1|X_i = x) + 0 \cdot p(R_i = 0|X_i = x) \\ &= P(Y_i = 1|X_i = x, R_i = 1) \cdot P(R_i = 1|X_i = x) + 0 \\ &= P(Y_i = 1|X_i = x, R_i = 1) \cdot P(R_i = 1|X_i = x) \end{aligned}$$

where by design $0 < P(R_i = 1|X_i = x) < 1$. Thus, $P(Y_i = 1|X_i = x) \neq P(Y_i = 1|X_i = x, R_i = 1)$, implying that our selection process will bias estimands for β_x. We must correct for the probability of selection into the sample. We do so by introducing weights into the regression models reflecting $P(R_i = 1)$, which we defined solely based on Y_i, i.e., R_i is orthogonal to X_i given Y_i.

H.2.2 Generation of weights for correcting selection bias

We generated weights for the regression models based on the sampling strategy, defining weights as the inverse of probability of selection into the intended sample. Our sampling strategy selected matched households with probability one; all matched households therefore have weight one. To select unmatched households, we first subtracted the number of matched households from the total sample size. We then allocated the remaining sample across villages proportional to village size, defined as the number of households identified in the census exercise. In practice, the probability of selection for unmatched households was approximately 20%; unmatched households thus have weights of approximately 5 in the regression models. However, the probability and weights vary somewhat across villages owing to the necessity of rounding when allocating randomly selected households across villages.

Several caveats bear mentioning here. First, these probabilities and weights are based on the intended sample selection method. We deviated from this selection method in practice because some households were not available to be interviewed, resulting in data losses among matched households and in the selection of replacement households among unmatched households. Weights do not correct for deviation from the intended sampling strategy, which may introduce additional estimation bias. Second, the sampling method was based on our original matching algorithm, which simply selected the closest household to the maximum signal strength as the matched household for a given beacon sighting. After data collection concluded in its entirety, we replaced this algorithm with a more sophisticated one. We used the older matching algorithm to generate weights within the regression because we used the older algorithm to generate the household survey sample. In cases where a household was matched under the new algorithm but not the old algorithm, and where we happened to have collected data from the household via random selection, the probability of selection was still less than one despite its matched status. Finally, survey enumeration generated updates to the household census, as field staff identified some census buildings as labelled incorrectly for usage (e.g., a building labeled as a main household dwelling was actually an outbuilding for another household). Our original census thus slightly overestimated the number of households. However, sample selection used the original household census for sample allocation across villages. Thus, we use the uncorrected census information to generate selection probabilities and regression weights.