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RESEARCH ARTICLE

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The impact of aid on health outcomes in Uganda

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Abstract

The health sector has attracted significant foreign aid; however, evidence on the effectiveness of this support is mixed. This paper combines household panel data with geographically referenced subnational foreign aid data to investigate the contribution of health aid to health outcomes in Uganda. Using a difference-in-differences approach, we find that aid had a strong effect on reducing the productivity burden of disease indicated by days of productivity lost due to illness but was less effective in reducing disease prevalence. Consequently, health aid appeared to primarily quicken recovery times rather than prevent disease. In addition, we find that health aid was most beneficial to individuals who lived closest to aid projects. Apart from the impact of aid, we find that aid tended to not be targeted to localities with the worse socioeconomic conditions. Overall, the results highlight the importance of allocating aid close to subnational areas with greater need to enhance aid effectiveness.

KEYWORDS

AidData, difference-in-differences estimator, health aid, health outcomes, Uganda

1 | INTRODUCTION

Health is a key component of human capital that strongly influences labor productivity and economic growth (Gallup & Sachs, 2001; Wagner, Barofsky, & Sood, 2015). Various health indicators form part of the global 2030 Agenda for Sustainable Development, signifying the credence of addressing health challenges to catalyze economic development. Since the start of the Millennium Development Goals (MDGs) in 2000, over US$200 billion in external financing has been invested to improve health outcomes in low-income countries with US$35.9 billion in 2014 alone (Dieleman et al., 2014). During the MDG era, the global incidence of malaria fell by 37%, malaria mortality rate fell by 58%, and the number of new HIV infections dropped by 40% (United Nations, 2015).

Despite significant increases in aid and improvements in health outcomes, empirical evidence remains inconclusive regarding whether these positive shifts are a result of aid (Quibria, 2010; Rajan, 2005). On the one hand, some cross-country empirical studies that found positive results showcased the effect of health aid ranging from marginal (Gyimah-Brempong & Bonn, 2015; Mishra & Newhouse, 2007; Mishra & Newhouse, 2009) to strong (Bendavid & Bhattacharya, 2014). Notably, this evidence was cited for insecticide-treated bed nets on reduction of malaria incidence (Demombynes & Trommlerová, 2012; Flaxman et al., 2010), deworming medication on intestinal helminthes (Miguel & Kremer, 2004), medical male circumcision on the risk of HIV (Auvert et al., 2005; Bailey et al., 2007; Gray et al., 2007),

Part of this work (manuscript) has been published as a working paper in AidData's working paper series (i.e., working paper #18); however, the analysis has now substantially changed.

and water filters on diarrhea (Brown, Sobsey, & Loomis, 2008). On the other hand some studies found no effect on various health indicators, including infant mortality and life expectancy (Gebhard, Kitterman, Mitchell, Nielson, & Wilson, 2008; Williamson, 2008; Wilson, 2011). Although most of this evidence comes from randomized controlled trials and effectively show whether interventions work and why, they do not reveal whether donor resources allocated to these efforts have been effective (Wilson, 2011).

Although aid can be a good catalyst for development, it may be ineffective for a number of reasons, including but not limited to failure to target the intended population, resource leakages, aid crowding out government expenditure, or projects simply being poorly designed or implemented (Thiele, Nunnenkamp, & Dreher, 2007; Wilson, 2011). For aid to reduce poverty and catalyze growth, it is argued that aid must be preceded by effective planning and favorable policy regimes (Burnside & Dollar, 2000; Fagernas & Roberts, 2004; Gomanee, Girma, & Morrisey, 2005; McGillivray & Ouattara, 2005; Quartey, 2005). However, more empirical evidence is required to ascertain this assertion (Clemens, Radelet, & Bhavnani, 2004; Mosley & Suleiman, 2007; Ram, 2004).

Mixed evidence from the cross-country literature suggests that other approaches are needed to evaluate the impact of aid. In particular, subnational data provide an advantage over cross-country analyses that often fail to control for differences across countries, leading to spurious relations between aid and outcomes (Rajan & Subramanian, 2008). Although significant heterogeneity remains within countries, comprehensive household surveys can allow for mitigating unobserved heterogeneity. Moreover, by identifying areas that did and did not receive aid within countries, subnational data allow for quasi-experimental techniques to gauge aid impacts. Using these data, scholars have found a positive association between aid and development (Dreher & Lohmann, 2015), including reductions in conflict (van Weezel, 2015); disease severity; diarrhea prevalence (De & Becker, 2015); malaria prevalence (Marty, Dolan, Leu, & Runfola, 2017); and neonatal, infant, and child mortality (Kotsadam et al., 2017).

This paper combines nationally representative household panel survey data and geo-referenced subnational aid data to evaluate, for the first time at the subnational level, the impact of aid on health in Uganda. Despite the considerable level of external support to Uganda's health sector, evidence on the impact of aid on health outcomes in Uganda remains anecdotal. Although the country has achieved some progress on health-related MDGs, it remains with substantial challenges in addressing various health outcomes including maternal mortality (Uganda Bureau of Statistics and ICF International Inc., 2002), HIV/AIDS prevalence, and malaria burden (Ministry of Health, 2010; Uganda Bureau of Statistics and ICF International Inc., 2012), among others. Evaluating the impact of aid will allow for better understanding of the appropriate mechanisms for making aid effective as Uganda strives to realize the targets set by the health-related Sustainable Development Goals.

We analyzed the impact of aid along two dimensions. First is an assessment of disease prevalence. Second is the productivity burden of disease, proxied by days of productivity lost due to sickness. Given the possibility to identify areas that did and did not receive aid, a difference-in-differences approach with panel data fixed-effects regressions is used to minimize treatment effect estimation bias that may arise from the possibility of unobserved individual heterogeneity and time-invariant individual characteristics, as well as endogeneity in the treatment variable. The study aims to provide further insight on subnational level aid impacts, drawing a distinction with preceding analyses that rely on macrolevel and cross-country level data.

This paper demonstrates varying results. Aid contributed to improving health outcomes, particularly in reducing disease prevalence as demonstrated by a fall in the proportion of people who reported being sick. The impact is stronger with regard to reduction of the productivity burden of disease, reflected by a drop in number of days of productive work lost due to illness. Overall, aid is seen to primarily quicken recovery times rather than prevent disease. On the flipside, these resources tended not to have been targeted to localities with the worst socioeconomic conditions. In addition, our findings demonstrate the novelty and importance of allocating aid close to communities that require targeted support. Doing so facilitates access to resources and enhances aid effectiveness.

The rest of the paper is organized as follows: The next section details the data and methods of analysis; Sections 3 and 4 provide descriptive and empirical results, respectively; and Section 5 concludes.

2 | DATA AND METHODS

2.1 | The data

We make use of the National Panel Survey for Uganda that was constructed using the 2005/06 National Panel Survey as the first wave. The National Panel Survey households were revisited in subsequent years including the split-off households. This paper uses the socioeconomic modules of the 2005/06, 2009/10 and 2010/11, and 2013/14 waves. The modules capture data on major development indicators (including public health) at a microlevel, such as household economic dynamics, sociodemographics, health status, and education. The surveys contain spatial locations in each enumeration area, which allows for matching the data with other geographically referenced data.

With this unique feature, we combine survey data with geographically referenced foreign aid data produced by AidData. The foreign aid dataset includes aid projects recorded in Uganda's Aid Management Platform. Although we establish that the AidData dataset risks underestimating[1] the total health aid dollars (value) allocated to Uganda compared to other platforms (Appendix S1), its power lies in providing the only source of subnational aid flow data.

AidData codes each aid project with a geographic precision code that references the spatial extent of the project, including the country, region, district, county, or subcounty. We consider projects allocated to a specific area (lowest possible location) to facilitate measuring the distance of household location to an aid location. This amounts to $262,147,467, or 92% of all aid disbursements allocated for the years of aid projects considered (2011–2013) in our analysis. Projects included in the analysis are summarized in Table 1, and project locations are shown in Figure 1. Although 24 projects were dropped due to imprecise spatial information, the corresponding resources only accounted to 8% of aid dollars.

We code individuals as living within 5- to 50-km radii from an aid project at 5-km intervals. This approach follows from Kotsadam et al. (2017) who examine the impact of aid on infant mortality in Nigeria using 25- and 50-km buffers. Table 2 shows the distances people traveled for medical consultations. Eighty percent (80%) of individuals traveled 5 km or less for medical consultations; 95% of individuals traveled 15 km or less for medical consultations; and about 98% of individuals traveled 30 km or less for medical consultations. Ideally, distances closer to 5-km radius could be examined; however, the minimum distances between survey individuals and some aid projects were greater than 10 or 20 km, hence requiring larger distances to be used.

2.2 | Empirical approach

We employ a two-stage approach to examine the impact[2] of aid. First, we examine the impact of aid on disease prevalence—measured by whether an individual fell sick during the 30 days prior to the survey interview. This variable is used to examine the impact of aid on reducing the likelihood of falling sick (disease prevalence or prevention). Second, we isolate the subset of individuals who fell sick in both the baseline (2010–2011) and end line (2013–2014) to examine the impact of aid on the productivity burden of disease. This is measured by days of productivity lost owing to illness (i.e., the days an individual could not undertake usual activities as a result of sickness). We are interested in investigating whether aid quickens recovery time from illness or not. The shortcoming of the two outcome variables is that they are susceptible to social desirability bias due to self-reporting. However, productivity burden of disease is less subjective because the number of days one did not work because of illness are more precise, compared, for example, to disease severity indicated by the number of days of suffering from illness. Additionally, the strength of self-reported health measures is that they provide an important indicator of health status (Reichmann, Katz, Kessler, Jordan, & Losina, 2009), and self-reported health outcomes have been established to be good predictors of outcome indicators such as functional ability and mortality, even after controlling for other objective health measurement (Kuhn, Rahman, & Menken, 2006). The predictive power of self-reported indicators is related to its multifaceted nature, because they incorporate multiple health dimensions such as functional or activity limitation, chronic and acute morbidity, self-assessment of severity, and awareness of past health trajectory, among others.

We define individuals as treated by indicating whether individuals fell (or reside) within a certain distance to any aid project, where we use 5- to 50-km radii at 5-km intervals (i.e., using 5-km, 10-km, and up to 50-km distances). To avoid spillover effects, we exclude individuals who live more than the threshold distances and less than 100 km of any aid project from the analysis (e.g., when defining treated individuals as living within 25 km of an aid project, we remove individuals living within 25 to 100 km from the analysis). In addition, any individual that did not live within the specified distance to an aid project but lived in a district that was coded as receiving aid was dropped. This ensures that the control

[1]We note that unfortunately the AidData dataset provides an underestimate of the total health aid dollars allocated to Uganda when compared to other sources. For the time period of aid projects considered for this paper, AidData indicates that US$300.6 million was disbursed; Organization for Economic Co-operation and Development - Creditor Reporting Standard (OECD-CRS) indicates US$608.63 million, whereas Institute for Health Metrics and Evaluation (IHME) reports US$2,344.21 million. This notwithstanding, AidData remains the only source that provides subnational aid flow data.

[2]The health outcome metrics captured in our analysis (disease prevalence and productivity burden of disease or disease burden) are related to major disease symptoms reported by individuals in the household panel survey data such as fever, severe headache, skin rash, sore throat, diarrhea, cough, weight loss, chills, malaria, and child birth-related illnesses. These symptoms can be categorized under three major health program areas of HIV/AIDS, malaria, and maternal and child health based on the World Health Organization's (WHO's) classification of symptoms.

TABLE 1 Aid project summary

Project title	Minimum distance to household (km)	Disbursements	Donor
The project for installation of electric facilities at the Omoro Health Centre	21.32	$25,958	Japan
The project for construction of ROTOM Health Centre in the Kabala District	9.16	$233,601,049	Japan
The project for improvement of Bukonte Health Centre in the Namutumba District	4.85	$105,242	Japan
The project for improvement of facilities at Kyotera Medical Centre	9.40	$88,061	Japan
Regional outreach addressing HIV/AIDS through development strategies[a]	0.55	—	United States
The project for construction of a maternity ward at Amai Community Hospital	2.82	$28,315,466	Japan

Source: Author's compilation based on AidData database. Values are in U.S. dollars.
[a]No aid disbursement or commitment data were reported for this project.

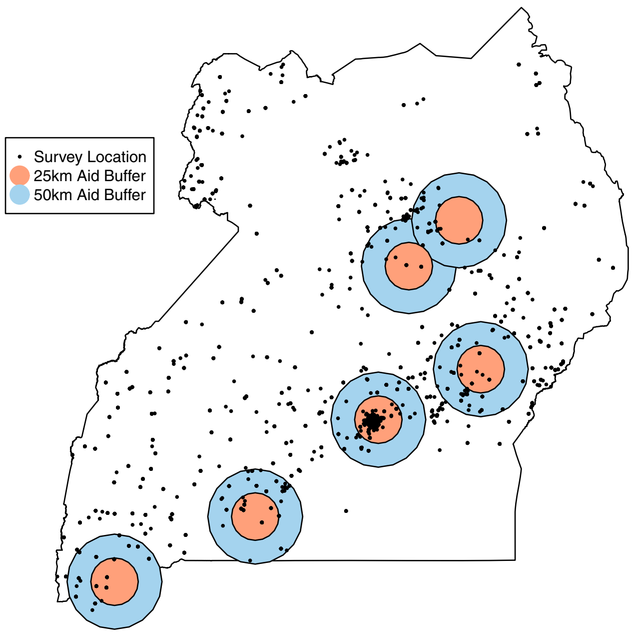

FIGURE 1 Locations of aid projects and survey points
Source: Author's computation using ArcGIS [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Distance traveled to medical consultation

Distance of medical consultation (km)	% of those who fell sick	Cumulative %
0–5	79.98	79.98
5–10	12.16	92.14
10–15	3.43	95.57
15–20	1.30	96.87
20–25	0.75	97.62
25–30	0.30	97.92
30–35	0.36	98.28
35–40	0.22	98.50
40–45	0.22	98.72
45–50	0.17	98.89
>50	1.11	100

Source: Author's computation from survey data. Values are from the 2010 survey; values based on the subsample of individuals who reported consulting someone after falling sick.

group does not include individuals who may have benefited from other health aid projects that were included in the AidData dataset.

We estimate models on the full sample and on a restricted sample balanced on key variables. The propensity score approach was used to balance variables at baseline conditions. Specifically, we balance on the outcome variables (disease prevalence or productivity burden) at baseline (2010), the trend in the outcome variable from 2009 to 2010, and the trend from 2005 to 2009. Balancing on trends ensures that the treated and control groups in the restricted sample have parallel trends, hence satisfying the common trend assumption of difference-in-difference estimation strategy. We implement the matching routine for each aid buffer distance, creating separate restricted samples for each aid project distance. Appendix S2 shows differences in variables across treatment and control groups in a matched an unmatched sample. All health-related variables—even those not balanced on—become more similar across treated and control groups using the matched sample. However, the degree of balance across treated and control groups for other variables generally does not improve using the matched sample.

Note that the regression models contain only about 2,300 observations out of 52,071 due to missing values, attrition, and dropping individuals that lived outside the aid buffer (thresholds) discussed above. Given this shortfall, results should be interpreted restrictively to imply impacts of aid projects near beneficiary communities, rather than generalizing across Uganda.

After creating a balanced sample, we use a difference-in-differences approach to examine the impact of aid. Here, we use the 2010–2011 survey as the baseline and the 2013–2014 survey as the end line. The difference-in-differences (diff-in-diff) model with fixed effects is estimated as follows:

$$h_{i,t} = \beta_0 + \beta_1 \text{Year}_t + \beta_2 \text{Year}_t \times \text{Aid}_i + \gamma X_{i,t} + \delta_i + \epsilon_{i,t},$$

where $h_{i,\ t}$ is the measure of health outcome (disease prevalence or productivity burden of disease), Year_t is a binary variable that is 1 in the end line year (2013–2014) and 0 in the baseline year (2010–2011). Aid_i is a binary treatment variable that equals 1 if an individual lives within a specified distance from an aid project, $X_{i,\ t}$ is a vector of individual and household level controls that could also be correlated with the health outcome, γ is a vector of coefficients on these controls, δ_i are individual fixed effects, and $\epsilon_{i,\ t}$ is the error term. The use of individual fixed effects in our diff-in-diff estimation strategy helps to minimize potential within-country individual heterogeneity. The coefficient of interest is β_2, which measures the impact of aid on the outcome of interest. Standard errors are clustered on households. The controls include household consumption on health-related goods and services; amount of household consumption on food; whether individuals in a household use a mosquito net at night; access to water (distance from the household to a water source); individual's age; and welfare proxies such as whether every individual in the household owns two pairs of clothes, whether every individual in the household owns a pair of shoes, and the number of rooms in the household.

We first apply diff-in-diff with fixed-effect model for the case of productivity burden of disease, and because this might as well be a count variable, we also estimated an ordered probit model within the diff-in-diff estimation framework. Because disease prevalence is a binary variable, we estimate binary outcome models (e.g., linear probability model [LPM])[3]—also within the diff-in-diff estimation framework.

As an alternative approach, we also use aid intensity as a treatment variable, measured by the amount of aid disbursed within specified distance(s).

The health outcomes in the survey data capture a broad range of symptoms, including fever, severe headache, skin rash, sore throat, diarrhea, cough, weight loss, chills, malaria, and child birth-related illnesses. The aid projects match well to include a range of diseases and symptoms as outcome variables. Projects such as the construction of the ROTOM Health Centre or the improvement of Bukonte Health Centre should generally help to alleviate a broad range of illnesses. Even targeted projects such as the HIV/AIDs interventions can be expected to alleviate a range of symptoms. For example, the WHO classification of HIV/AIDs symptoms includes influenza-like illnesses, fever, headache, skin rash, sore throat, weight loss, diarrhea, cough, and severe illnesses (at a later stage if untreated) that are related to tuberculosis, cryptococcal meningitis, and cancers (WHO, 2016). Consequently, both broad and specific aid projects included in this analysis should help alleviate or prevent the broad range of symptoms included in the outcome variables.

[3]Binary outcome models include the LPM and probit. We do not include fixed effects for probit models as individual fixed effects in nonlinear models can result in biased estimators (Greene, 2004).

3 | DESCRIPTIVE EVIDENCE

Table 3 shows that between 2005 and 2013, health and other socioeconomic conditions generally improved. Disease prevalence declined by 17.1 percentage points—from 0.409 to 0.238 between 2005 and 2013. The productivity burden of disease declined by 4.6 to 4.1 days from 2005 to 2010, although it increased to 5.2 days from 2010 to 2013. The proportion of people using mosquito nets substantially increased, from 18.2% in 2005 to 60.3% in 2013. Consumptions along health and food increased—health spending increased by UGX78,431 from 2005 to 2013 and food spending increased by UGX1,087,032 over the same period. Households where every member had at least one pair of shoes increased from 44.7% to 60%, and the households where every member owns at least two pairs of clothes increased from 85.8% to 92.9%. The number of rooms households owned decreased by two over the 8-year time period, likely representing a shift to living in urban areas where overcrowding is prevalent.

Table 4 summarizes variables near aid projects (within 25-km radius) and far from aid projects (over 25 km). There is no significant difference between individuals near and far from aid projects according to disease prevalence and productivity burden; however, the other variables suggest that aid was allocated to areas with better socioeconomic conditions. Individuals who live near aid projects are about 9 percentage points more likely to use a mosquito net, spend 278,200 more on health care annually, spend 1,734,746 more on food annually, live 0.46 km closer to a water source, are about 9 percentage points more likely to live in a household where everyone owns at least two pairs of clothes, and are about 32 percentage points more likely to live in a household where everyone owns at least one pair of shoes.

TABLE 3 Trends in variables over time

	2005	2009	2010	2013
Disease prevalence	0.409	0.383	0.293	0.238
Productivity burden	4.671	4.298	4.141	5.220
Mosquito net	0.182	0.380	0.471	0.603
Health spending	195,170	282,737	216,629	273,601
Food spending	768,537	1,328,966	1,350,644	1,855,569
Distance to water source	1.096	0.875	0.674	0.696
Own clothes	0.858	0.827	0.842	0.929
Own shoes	0.447	0.495	0.472	0.600
Number rooms	4.726	3.436	3.261	2.765
Age	20.419	24.037	24.835	25.970
Observations	10,623	18,036	16,402	7,010

Source: Author's computation from the Uganda National panel Survey (2005/06) and Uganda National Panel Survey (2009–2013). Values for health and food spending are in Ugandan shillings.

TABLE 4 Variables across aid (baseline year, 2010)

	Within 25 km of aid	Over 25 km of aid	*p*-value
Disease prevalence	0.286	0.294	.58
Productivity burden	3.993	4.164	.62
Mosquito net	0.548	0.459	.00
Health spending	455,519	177,319	.00
Food spending	2,840,266	1,105,520	.00
Distance to water source	0.281	0.737	.00
Own clothes	0.920	0.829	.00
Own shoes	0.746	0.428	.00
Number rooms	3.363	3.245	.13
Age	24.806	24.840	.95

Source: Author's computation from the Uganda National Panel Survey (2009/10) and AidData aid data. Mean values reported. Observations weighted using sample weights.

4 | EMPIRICAL RESULTS

4.1 | Impact on disease prevalence

Tables 5.1 and 5.2 show the impact of aid (using the binary aid variable) on disease prevalence, using the full and matched samples, respectively (Appendix S3 reports results of first-stage regressions in matching algorithm; Appendix S4 reports model results with all covariates). In the full sample, the level and trends of disease prevalence are balanced across treatment and control groups, but they achieve near perfect balance in the matched sample. The coefficients for aid impacts are negative but only significant for the 15-km buffer in both the diff-in-diff LPM and probit models. The matched sample does not produce significant effects across all buffers, implying a statistically insignificant impact of aid on disease prevalence.

TABLE 5.1 Disease prevalence, full sample—Binary aid treatment

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff LPM										
Year * Aid	0.0402	0.00873	−0.137**	−0.0810	−0.0606	−0.0405	−0.0199	−0.00342	0.00360	0.00736
	(0.111)	(0.0867)	(0.0557)	(0.0544)	(0.0494)	(0.0465)	(0.0445)	(0.0434)	(0.0414)	(0.0400)
Probit (diff-in-diff framework)										
Year * Aid	−0.270	−0.296	−0.344**	−0.0771	−0.0621	0.0260	0.0577	0.0770	0.0872	0.0867
	(0.337)	(0.250)	(0.154)	(0.138)	(0.128)	(0.117)	(0.107)	(0.104)	(0.0986)	(0.0944)
Observations	920	966	1,162	1,284	1,382	1,512	1,716	1,820	2,040	2,338
D.P. 2010 p-value	.41	.24	.135	.085	.23	.255	.255	.43	.72	.74
D.P. 2010 − 2009 p-value	.55	.385	.18	.38	.69	.97	.615	.53	.14	.125
D.P. 2009 − 2005 p-value	.4	.465	.43	.355	.375	.33	.84	.835	.77	.655

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Linear probability model (LPM) includes individual fixed effects. "D.P. 2010 p-value" denotes the p-value from a t test examining the difference in disease prevalence (D.P.) between treatment and control groups in the baseline year, 2010. "D.P. 2010 − 2009 p-value" denotes the p-value from a t test examining the difference in trends of disease prevalence from 2009 to 2010 between treatment and control groups. "D.P. 2009 − 2005 p-value" denotes the p-value from a t test examining the difference in trends of disease prevalence from 2005 to 2009 between treatment and control groups.

***$p < .01$.

**$p < .05$.

*$p < .1$.

TABLE 5.2 Disease prevalence, matched sample—Binary aid treatment

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff LPM										
Year * Aid	−0.215	−0.116	−0.0700	−0.0296	−0.0296	−0.0138	0.00849	0.0159	0.0108	0.000947
	(0.142)	(0.123)	(0.0695)	(0.0636)	(0.0568)	(0.0510)	(0.0466)	(0.0447)	(0.0431)	(0.0433)
Probit (diff-in-diff framework)										
Year * Aid	−0.370	−0.288	−0.276	−0.101	−0.0750	0.00185	0.0338	0.0627	0.0678	0.0302
	(0.423)	(0.352)	(0.184)	(0.155)	(0.142)	(0.129)	(0.112)	(0.108)	(0.104)	(0.106)
Observations	120	212	604	848	1,036	1,240	1,532	1,628	1,720	1,720
D.P. p-value	1	1	1	1	1	1	1	1	1	1
D.P. 2010 − 2009 p-value	1	1	1	1	1	1	1	1	1	1
D.P. 2009 − 2005 p-value	1	1	1	1	1	1	1	1	1	1

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Linear probability model (LPM) includes individual fixed effects. "D.P. 2010 p-value" denotes the p-value from a t test examining the difference in disease prevalence (D.P.) between treatment and control groups in the baseline year, 2010. "D.P. 2010 − 2009 p-value" denotes the p-value from a t test examining the difference in trends of disease prevalence from 2009 to 2010 between treatment and control groups. "D.P. 2009 − 2005 p-value" denotes the p-value from a t test examining the difference in trends of disease prevalence from 2005 to 2009 between treatment and control groups.

***$p < .01$.

**$p < .05$.

*$p < .1$.

Tables 5.3 and 5.4 show the impact of aid intensity (disbursements) on disease prevalence using the full and matched samples, respectively (see Appendix S5 for model results with all covariates). We arrive at similar conclusions as with the binary variables. The LPM using the full sample shows that a 1% increase in aid disbursements is associated with about a 1 percentage point decrease in disease prevalence at the 15- and 20-km buffers, but results are statistically insignificant in the matched sample.

TABLE 5.3 Disease prevalence, full sample—Aid intensity

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff LPM										
Year * ln(Aid Disb.)	−0.00360	−0.00594	−0.0148***	−0.00973**	−0.00572	−0.00428	−0.00480	−0.00479	−0.00231	−0.00260
	(0.00777)	(0.00772)	(0.00437)	(0.00423)	(0.00351)	(0.00337)	(0.00334)	(0.00329)	(0.00304)	(0.00280)
Probit (diff-in-diff framework)										
Year * ln(Aid Disb.)	−0.00102	0.000839	−0.0210	−0.00209	−0.00166	0.00402	0.000803	0.000352	0.000564	−0.00234
	(0.0234)	(0.0219)	(0.0144)	(0.0110)	(0.00937)	(0.00869)	(0.00779)	(0.00776)	(0.00681)	(0.00619)
Observations	890	894	1,018	1,138	1,208	1,284	1,408	1,438	1,594	1,892
D.P. *p*-value	.435	.15	.01	.01	.075	.05	.02	.025	.1	.19
D.P. 2010 − 2009 *p*-value	.1	.1	.015	.15	.38	.555	.845	.925	.36	.265
D.P. 2009 − 2005 *p*-value	.225	.235	.23	.22	.235	.32	.8	.86	.715	.58

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Linear probability model (LPM) includes individual fixed effects. "D.P. 2010 *p*-value" denotes the *p*-value from a *t* test examining the difference in disease prevalence (D.P.) between treatment and control groups in the baseline year, 2010. "D.P. 2010 − 2009 *p*-value" denotes the *p*-value from a *t* test examining the difference in trends of disease prevalence from 2009 to 2010 between treatment and control groups. "D.P. 2009 − 2005 *p*-value" denotes the *p*-value from a *t* test examining the difference in trends of disease prevalence from 2005 to 2009 between treatment and control groups. For the log of aid disbursements, we use ln(1 + Aid Disbursements) to retain values of zero.

***$p < .01$.

**$p < .05$.

*$p < .1$.

TABLE 5.4 Disease prevalence, matched sample—Aid intensity

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff LPM										
Year * ln(Aid Disb.)	−0.00105	−0.00789	−0.00689	−0.00402	−0.00193	−0.000651	−0.000511	−0.00114	0.000623	−0.000185
	(0.0106)	(0.0132)	(0.00581)	(0.00506)	(0.00398)	(0.00363)	(0.00358)	(0.00350)	(0.00314)	(0.00290)
Probit (diff-in-diff framework)										
Year * ln(Aid Disb.)	−0.0543*	−0.0474	−0.0185	−0.00107	−0.000758	0.00362	−0.001000	−0.00178	−0.00147	−0.00200
	(0.0326)	(0.0314)	(0.0167)	(0.0117)	(0.0100)	(0.00906)	(0.00825)	(0.00808)	(0.00727)	(0.00681)
Observations	60	68	316	556	696	836	1,048	1,100	1,316	1,640
D.P. *p*-value	1	1	1	1	1	1	1	1	1	1
D.P. 2010 − 2009 *p*-value	1	1	1	1	1	1	1	1	1	1
D.P. 2009 − 2005 *p*-value	1	1	1	1	1	1	1	1	1	1

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Linear probability model (LPM) includes individual fixed effects. "D.P. 2010 *p*-value" denotes the *p*-value from a *t* test examining the difference in disease prevalence (D.P.) between treatment and control groups in the baseline year, 2010. "D.P. 2010 − 2009 *p*-value" denotes the *p*-value from a *t* test examining the difference in trends of disease prevalence from 2009 to 2010 between treatment and control groups. "D.P. 2009 − 2005 *p*-value" denotes the *p*-value from a *t* test examining the difference in trends of disease prevalence from 2005 to 2009 between treatment and control groups. For the log of aid disbursements, we use ln(1 + Aid Disbursements) to retain values of zero.

***$p < .01$.

**$p < .05$.

*$p < .1$.

4.2 | Impact on productivity burden of disease

Tables 6.1 and 6.2 show the impact of aid (with the binary aid variable) on the productivity burden of disease using the full and matched samples, respectively (Appendix S6 reports results for all covariates). Models using the 5- to 50-km aid buffers were estimated using the full sample; however, there were too few observations to estimate models using the 5- and 10-km aid buffers with the matched sample. In the full sample, the level and trends of

TABLE 6.1 Productivity burden of disease, full sample—Binary aid treatment

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff fixed effect model										
Year * Aid	5.219	−8.763	−2.941	−2.217	−0.769	−0.643	−0.183	−0.352	−1.068	−1.154
	(6.213)	(8.209)	(2.244)	(2.295)	(1.938)	(1.859)	(1.705)	(1.672)	(1.614)	(1.597)
Ordered probit model (diff-in-diff)										
Year * Aid	−0.102	−0.266	−0.352	−0.127	−0.0770	−0.000417	0.0711	0.0423	0.00642	0.0400
	(0.212)	(0.212)	(0.211)	(0.199)	(0.190)	(0.179)	(0.174)	(0.170)	(0.162)	(0.154)
Observations	255	264	328	377	399	441	506	535	591	678
P.B. p-value	.325	.75	.82	.56	.69	.82	.615	.515	.52	.505
P.B. 2010 − 2009 p-value	.84	.225	.32	.6	.66	.91	.975	.845	.775	.94
P.B. 2009 − 2005 p-value	.235	.325	.53	.86	.585	.94	.985	.62	.855	.91

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Ordinary least squares model includes individual fixed effects. "D.B. 2010 p-value" denotes the p-value from a t test examining the difference in productivity burden (P.B.) between treatment and control groups in the baseline year, 2010. "P.B. 2010 − 2009 p-value" denotes the p-value from a t test examining the difference in trends of productivity burden from 2009 to 2010 between treatment and control groups. "P.B. 2009 − 2005 p-value" denotes the p-value from a t test examining the difference in trends of productivity burden from 2005 to 2009 between treatment and control groups.

***$p < .01$.

**$p < .05$.

*$p < .1$.

TABLE 6.2 Productivity burden of disease, matched sample—Binary aid treatment

	(1) 15 km	(2) 20 km	(3) 25 km	(4) 30 km	(5) 35 km	(6) 40 km	(7) 45 km	(8) 50 km
Diff-in-diff fixed effect model								
Year * Aid	−11.58***	−10.70***	−10.02***	−9.208***	−7.219**	−4.988**	−4.728*	−3.707*
	(3.487)	(3.496)	(3.225)	(2.869)	(2.823)	(2.279)	(2.485)	(2.049)
Ordered probit model (diff-in-diff)								
Year * Aid	−0.749	−0.930*	−1.113**	−0.764*	−0.704	−0.529	−0.509	−0.196
	(0.637)	(0.449)	(0.403)	(0.389)	(0.364)	(0.347)	(0.383)	(0.346)
Observations	66	90	102	115	141	163	175	189
P.B. p-value	.795	.99	.99	.84	.72	.56	.53	.495
P.B. 2010 − 2009 p-value	.805	.91	.705	.65	.625	.79	.365	.2
P.B. 2009 − 2005 p-value	.995	.92	.855	.93	.995	.405	.79	.79

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Ordinary least squares model includes individual fixed effects. "D.B. 2010 p-value" denotes the p-value from a t test examining the difference in productivity burden (P.B.) between treatment and control groups in the baseline year, 2010. "P.B. 2010 − 2009 p-value" denotes the p-value from a t test examining the difference in trends of productivity burden from 2009 to 2010 between treatment and control groups. "P.B. 2009 − 2005 p-value" denotes the p-value from a t test examining the difference in trends of productivity burden from 2005 to 2009 between treatment and control groups.

***$p < .01$.

**$p < .05$.

*$p < .1$.

TABLE 6.3 Productivity burden of disease, full sample—Aid intensity

	(1) 5 km	(2) 10 km	(3) 15 km	(4) 20 km	(5) 25 km	(6) 30 km	(7) 35 km	(8) 40 km	(9) 45 km	(10) 50 km
Diff-in-diff fixed effect model										
Year * ln(Aid Disb.)	0.304	−0.407	−0.238	−0.155	−0.0312	−0.0584	−0.0334	−0.0160	−0.0446	−0.0740
	(0.362)	(0.637)	(0.174)	(0.190)	(0.137)	(0.148)	(0.145)	(0.146)	(0.127)	(0.128)
Ordered probit model (diff-in-diff)										
Year * ln(Aid Disb.)	−0.00334	−0.0116	−0.0340	−0.0132	−0.00525	0.000394	0.00408	0.00683	0.00195	0.00502
	(0.0135)	(0.0160)	(0.0186)	(0.0168)	(0.0147)	(0.0138)	(0.0135)	(0.0134)	(0.0122)	(0.0110)
Observations	250	253	295	344	357	389	433	440	483	570
P.B. p-value	.41	.335	.565	.375	.36	.425	.4	.38	.455	.445
P.B. 2010 − 2009 p-value	.645	.035	.445	.86	.815	.665	.85	.70	.705	.91
P.B. 2009 − 2005 p-value	.235	.255	.53	.97	.625	.820	.975	.82	.745	.755

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Ordinary least squares model includes individual fixed effects. “D.B. 2010 p-value” denotes the p-value from a t test examining the difference in productivity burden (P.B.) between treatment and control groups in the baseline year, 2010. “P.B. 2010 − 2009 p-value” denotes the p-value from a t test examining the difference in trends of productivity burden from 2009 to 2010 between treatment and control groups. “P.B. 2009 − 2005 p-value” denotes the p-value from a t test examining the difference in trends of productivity burden from 2005 to 2009 between treatment and control groups. For the log of aid disbursements, we use ln(1 + Aid Disbursements) to retain values of zero.

***$p < .01$.

**$p < .05$.

*$p < .1$.

TABLE 6.4 Productivity burden of disease, matched sample—Aid intensity

	(1) 15 km	(2) 20 km	(3) 25 km	(4) 30 km	(5) 35 km	(6) 40 km	(7) 45 km	(8) 50 km
Diff-in-diff fixed effect model								
Year * ln(Aid Disb.)	−0.895	−0.594*	−0.641***	−0.704***	−0.553**	−0.527***	−0.588***	−0.306
	(0.590)	(0.341)	(0.220)	(0.222)	(0.231)	(0.187)	(0.172)	(0.253)
Ordered probit model (diff-in-diff)								
Year * ln(Aid Disb.)	−0.102	−0.0894*	−0.0709*	−0.0685*	−0.0531	−0.0303	−0.0570	−0.00838
	(0.0590)	(0.0435)	(0.0340)	(0.0327)	(0.0327)	(0.0328)	(0.0308)	(0.0253)
Observations	47	69	76	84	126	113	127	176
P.B. p-value	.87	.82	.885	.98	.645	.6	.635	.485
P.B. 2010 − 2009 p-value	.91	.74	.67	.485	.835	.815	.76	.28
P.B. 2009 − 2005 p-value	.84	.575	.75	.485	.605	.570	.965	.43

Source: Author's computation using the Uganda National Panel Survey data and AidData database. Coefficients reported with standard errors in parentheses. Standard errors clustered on households. Ordinary least squares model includes individual fixed effects. “D.B. 2010 p-value” denotes the p-value from a t test examining the difference in productivity burden (P.B.) between treatment and control groups in the baseline year, 2010. “P.B. 2010 − 2009 p-value” denotes the p-value from a t test examining the difference in trends of productivity burden from 2009 to 2010 between treatment and control groups. “P.B. 2009 − 2005 p-value” denotes the p-value from a t test examining the difference in trends of productivity burden from 2005 to 2009 between treatment and control groups. For the log of aid disbursements, we use ln(1 + Aid Disbursements) to retain values of zero.

***$p < .01$.

**$p < .05$.

*$p < .1$.

disease prevalence are balanced across treatment and control groups, but the balance improves with the matched sample.[4]

The diff-in-diff fixed effect and ordered probit (diff-in-diff) models for the full sample do not generate any significant results for productivity burden of disease. Using the matched sample, the diff-in-diff fixed effect model shows aid

[4]For example, using the 15-km aid buffer, the p-value between the levels of disease prevalence is .82 in the full sample and .80 in the matched sample—a slight reduction; however, the p-value on the difference between the trends increase from .32 and .53 for the 2009–2010 and 2005–2009 trends, respectively, to .81 and .99.

significantly reducing the productivity burden of disease across all models, where the coefficient grows smaller as the aid buffer (distance) increases. The diff-in-diff fixed effect model results indicate aid reducing the burden by 11.5 days among individuals who live within 15 km of aid, where the impact lessens to reducing burden by 4.9 days using the 40-km buffer. The effect of aid on disease burden is only significant at the 10% level of significance using the diff-in-diff fixed effect model.

Results from the ordered probit (diff-in-diff) model show aid's impact on reducing the productivity burden of disease among individuals who live within 20, 25, and 30 km of aid, and the effect on the burden is significant at the 5% level using the 25-km aid radius and at the 10% level using the 20- and 30-km radii. The findings imply that the impact of health aid on productivity burden of disease is stronger for shorter distances (with easy access to health aid services) than longer distances. The results highlight that a prime determinant of aid effectiveness is proximity to health aid services, as results using larger aid radii are consistently smaller and statistically less significant. These strongly emphasize the importance of targeting aid at the lowest level possible—that is, for aid to yield the desired health outcome, it must be targeted fairly close to intended beneficiaries. Channeling aid closer to communities in need potentially maximizes effectiveness, given the associated minimal resource leakages and delivery points.

Tables 6.3 and 6.4 show the impact of aid intensity on the productivity burden of disease using the full and matched samples, respectively (see Appendix S7 for results with all covariates). Like with the binary aid variable, the impact of aid intensity (disbursements) is only significant using the matched sample. The diff-in-diff fixed effect model using the matched sample indicates that a 1% increase in aid disbursements is associated with about 52% to 70% decrease in the number of days an individual had to stop their normal activities due to falling sick.

5 | CONCLUSIONS

This paper uses a difference-in-differences with fixed-effect approach with data from Uganda's National Panel Survey and geo-coded data from AidData to investigate the impact of health aid on health outcomes. Results from descriptive statistics suggest that aid was not targeted to areas with individuals with the worst socioeconomic conditions, although health conditions were similar across areas that were near and far from aid projects. However, these results suggest that the poorest segments of society may be left out of the benefits of health aid.

Results examining the impact of aid shows some evidence that aid reduced disease prevalence (the proportion of people falling sick), but the evidence is stronger that aid reduced productivity burden of disease as measured by days of productivity lost given that people could not perform normal activities due to illness. The results suggest that health aid facilities (services) primarily benefited sick individuals to treat illnesses rather than having a preventative effect.

The impact of health aid on reducing the productivity burden of disease is more powerful when we restrict those in areas who potentially benefited from aid to be closer to aid projects. This result suggests that aid more effectively reduces productivity burden if channeled to locations closer to intended beneficiaries and highlights the importance of ease in accessibility of the health services provided through aid projects. Accordingly, our findings suggest that health aid can reduce the productivity burden of disease more effectively if channeled in such a way that it is made to reach those who are in need. Put differently, proximity to health aid projects is paramount for increased effectiveness. Moreover, channeling aid to the lowest level possible offers an additional advantage of driving the Universal Health Coverage strategy of promoting primary health care through the “close to client” health system.

Although the paper provides insight into the nature of health aid in Uganda, there are some limitations to the analysis. First, the aid information captured by AidData underestimates the amount of health aid allocated to Uganda when compared to other sources. Not including all allocated projects could bias results; however, the bias should generally be against finding an impact. For example, if projects not included in the AidData dataset were allocated to areas that our analyses deemed as not receiving aid, then these “control” areas could have experienced notable improvements in health outcomes if the projects were effective. Larger improvements in health outcomes in control areas would only make the observed impact in our analyses smaller. However, additional work would therefore be useful in ensuring that subnational aid datasets capture the full range of aid projects.

Second, the paper provides descriptive evidence on aid allocation, which indicates that areas that received aid tended to have better socioeconomic conditions compared to areas that did not receive. However, caution should be taken when making statements about whether aid was appropriately allocated based on these results. The results suggest that donors may need to better consider the spatial distribution of socioeconomic indicators; however, we examine only aid projects from a small band of years. Different conclusions about aid allocation may be found when considering broader subsets of aid projects; for example, aid in other years (outside our years of analysis) could have been targeted to areas with particularly poor health and socioeconomic conditions.

Third, the paper finds that individuals who have greater ease of access to aid projects (in terms of aid proximity) benefit more from these projects. We assume that being closer to an aid project generally corresponds to ease of access. Although this generally should hold true, it is important to note that distance may not always be a perfect proxy for ease of access. For example, individuals living closer to an efficient public transportation may have an easier time accessing a health facility compared to an individual who lives closer to the facility but without an efficient mean of transportation.

Fourth, the variable capturing the productivity burden of disease is a self-reported measure; consequently, it may be subject to bias similar to other forms of self-reported health assessments (Cook, 2010). Specifically, the survey question used asks how many days a person could not perform their usual activities due to being sick. Some individuals may interpret the question to mean the number of days they could not perform only some of their usual activities, whereas others may interpret it as the number of days they were bedridden and could not perform any major activity. However, this variable appears less subjective than other variables that could have been used. For example, another variable asks how many days a person suffered from an illness (disease severity), where a disproportionate number of people report 7 days, suggesting that many people approximate the number of days they suffer. The distribution of the productivity burden variable, though, does not experience this problem. In addition, matching on the level and trend of the variable as well as including individual fixed effects helps to mitigate bias from any factors that would cause people in treatment and control groups to systematically interpret this question differently.

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Additional Supporting Information may be found online in the supporting information tab for this article.

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