Land Policy and Human Health: Evidence from Land Grabs in Cambodia

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ABSTRACT: Large Scale Land Acquisitions (LSLAs), often referred to as land grabs, are a common development strategy throughout much of the developing world. Since 1996, the government of Cambodia has leased around 65 percent of its arable land to private companies leading to widespread land use changes. We use geocoded data from the Cambodia Socio-Economic Surveys to estimate localized effects of LSLAs on the health of local populations within a spatial difference-in-differences empirical strategy. We find that the prevalence of fever, a common proxy for malaria, decreases on LSLA land but increases substantially within 10 kilometers of its borders. We present evidence suggesting the main mechanism for these effects is deforestation from the LSLAs. We conclude policy makers should consider health impacts alongside other economic concerns when formulating ecosystem altering land policy.

Keywords: Development and health, Deforestation, Land Use, Natural resources, Policy evaluation

JEL Codes:

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SECTION 1: INTRODUCTION

Large Scale Land Acquisitions (LSLAs), often referred to as land grabs, are long-term leases to land granted by governments to private companies and have become a common strategy for economic growth throughout much of the developing world. Governments around the world have leased at least 200,000 square miles since the 1990s, affecting an estimated 12 million people (Davis et al. 2014). The phenomenon, which peaked in the late 2000s, became known as the global land rush (Nolte et al. 2016; Arezki et al. 2013). While there has been recent focus from researchers on the welfare, labor, and productivity effects of LSLAs, there has been limited empirical research into human health effects of this type of land policy. We examine this relationship within the context of Cambodia.

Cambodia aggressively pursued LSLAs as a development strategy early relative to other countries. From 1996 to 2012, the government of Cambodia leased 65 percent of its arable land to private companies in an effort to use rural land more efficiently (Drbohlav and Hejkrlik 2018). The government claims each LSLA lease agreement is evaluated on its ability to increase agricultural production, protect the environment, improve living standards and minimize adverse social impacts (Kingdom of Cambodia 2005). The government does not specifically mention public health concerns in its assessment of suitable projects.

While the program aimed to increase agricultural output, it directly and permanently altered the rural landscape and helped fuel a sharp increase in deforestation by clearing native forest for plantations and other agricultural endeavors (Davis et al. 2015). From 2000 to 2013, Cambodia lost over 38 percent of its intact forest landscape (Potapov et al. 2017). This radical shift in land use has the potential to influence many aspects of life for local communities including health. In recent years, some evidence has shown there is a causal link between environmental degradation

and negative health outcomes (e.g. Garg, 2019). Using Cambodian LSLAs as a natural experiment and linking geo-located household data, we estimate the impacts of LSLAs on the health outcomes of local communities. We find evidence that LSLAs increase prevalence of fever in neighboring areas while decreasing fever on the LSLA itself. The spatial pattern suggests this is the result of changing patterns of malaria transmission due to deforestation on the LSLAs.

This paper offers contributions to two active areas of research in natural resource economics and development economics. First, it contributes to the emerging development economics literature on the effects of LSLAs and land use policy decisions on local communities in developing countries. Anti (2021) finds that LSLAs in Cambodia result in a labor market shift out of farming for local markets toward agricultural labor and evidence that household welfare declines within a five-kilometer region adjacent to the border of the LSLAs. Jiao et al. (2015) also examine LSLAs in Cambodia using a propensity score matching approach and estimates a negative relationship between LSLAs and household income. Examining LSLAs outside of Cambodia, Deininger and Xia (2016), look at large farm investment in Mozambique and find evidence that large farms result in investment in technology and some evidence of effects on the local labor market. Bunte et al. (2018) examine LSLAs in Liberia and use nightlight data to measure their effects on local economic growth. They look at LSLAs used for agricultural projects and mining projects and find significant effects related to mining LSLAs.

To this point, this literature has focused on the effects of LSLAs on local economic growth, the rural labor market, technology adoption, and household welfare. The question of whether this type large-scale agricultural land policy has effects on human health is understudied. There has been some attention from qualitative public health researchers on the health effects of LSLAs in Cambodia, focusing mainly on displacement and mental health (e.g. Richardson et al. 2014). To

our knowledge, no quantitative study has examined the causal public health spillovers of LSLAs. This paper fills this gap.

Second, this paper extends the body of literature in natural resource economics specifically focused on the effects of landscape changes, mainly deforestation, on malaria incidence. This literature is itself still developing. Within epidemiology and the public health related branches of sociology and economics, there is currently no consensus on the causal connection. The consensus until recently had been that deforestation increases malaria incidence in Africa and the Americas and decreases prevalence in South East Asia (Anon 2005). The argument was that deforestation destroys the local ecological conditions that support malaria disease vectors in South East Asia, forest dwelling mosquitoes, which has a negative effect on disease prevalence.

Recent studies, however, have added nuance to these claims. Several papers point to deforestation increasing communicable disease due to a variety of changes in the interaction between human hosts and the disease vector environments (Garg 2019; Chakrabarti 2018; Berazneva and Byker 2017). Given these conflicting forces, it is unsurprising that the net effect of deforestation on health outcomes is unclear as explored by a recent meta-analysis (Bauhoff and Busch 2020) and many health researchers argue it unlikely that the effect is unidirectional (Guerra et al. 2006). Our paper offers a new context in which to study the impacts of ecosystem change on malaria and health. Specifically, our context is unique in that it focuses on a centralized policy of ecosystem alteration in the context of a developing country, thus linking this the newer ecosystem-health literature with development policy.

We utilize the setting of LSLA implementation in Cambodia, from 1996 to 2012, to estimate the relationship between land policy, deforestation, and health outcomes for individuals living in regions in and around these land investments. We use data on the precise locations and

timing of LSLAs in Cambodia, along with geocoded survey data from the Cambodia Socio-Economic Surveys and remote sensing data within a multi-period spatial difference-in-differences framework to estimate the effects of LSLAs on human health.

We find a distinct spatial pattern in the effects as we assess individuals located immediately on the LSLA out to 10 kilometers from the LSLA's borders. Those residing on the LSLA see decreases in rates of fever, a common proxy for malaria (i.e. Berazneva and Byker 2017). Those residing immediately adjacent within 10 kilometers see large increases in fever of approximately 1.7 percentage points, which is 68 percent over the sample mean, with the effect decreasing with distance from the border of the LSLA. These patterns do not hold for other health-related outcome measures that are not typical symptoms of malaria (cough and diarrhea), suggesting that these results are specifically related to the effect of the LSLAs on the local ecology supporting malaria. The results and their spatial distribution are robust to many different specifications across many sub-populations. We also explore several possible mechanisms and show evidence deforestation likely plays a major role in determining the spatial distribution of malaria cases. Broadly, our results indicate that LSLAs have a significant effect on the local disease environment and the health of local communities, while often overlooked by policy making institutions, the health of local communities should be included when assessing economic policy that alters local ecosystems.

The remainder of this paper proceeds as follows. Section 2 provides background on the LSLA policy, malaria and deforestation trends in Cambodia. Section 3 outlines and describes the data sources we use. Section 4 describes our empirical strategy. Section 5 presents our results, discusses the robustness of our estimates and points to possible mechanisms. Section 6 concludes.

SECTION 2: LSLA POLICY, DEFORESTATION AND MALARIA IN CAMBODIA

2.1 LSLA Policy and Deforestation

Cambodia's current land tenure system has its roots in the Khmer Rouge period of the late 1970s, when the regime abolished all private property rights in the country. Cambodia regained sovereignty in the 1990s from United Nations' administration and established its current government, the Royal Government of Cambodia (RGC). The RGC declined to restore land rights and located all land ownership with the government. From 1996 to 2012, the RGC courted private investors to develop agribusiness projects by awarding long-term leases (50 to 100 years) to large areas of land in the country through the Economic Land Concession (ELC; henceforth the same as LSLA) plan. By 2012, the RGC allocated almost 22 percent of Cambodia's surface area, and 65 percent of its arable land, to private development (Drbohlav and Hejkrlik 2018).

Each LSLA lease agreement was purportedly evaluated on its ability to impact five criteria: (1) increase agricultural production, (2) increase employment, (3) improve living standards, protect the environment, (4) minimize adverse social impacts, and (5) process raw agricultural materials (Kingdom of Cambodia 2005). Evidence from several previous studies shows inconsistent or opposite results for many of these criteria at the local level (Anti 2021; Richardson et al. 2014). For example, LSLAs in Cambodia have led to extreme deforestation. Patopov et al. (2017) estimate that between 2000 and 2013, Cambodia lost over 38 percent of its intact forest landscape. Global Forest Watch (2018) estimates that Cambodia's deforestation between 2001 and 2016 averaged over 121,000 hectares per year with much of this deforestation a result of LSLA development. Davis et al. (2013) estimate that ELCs increased deforestation by over 100 percent in regions where they were leased. Figure 1 depicts the relationship between LSLAs in Cambodia

and deforestation and shows clearly how forest loss has occurred within the boundaries of the LSLAs.

2.2 Malaria in Cambodia

The connection between deforestation and malaria has been widely studied across multiple

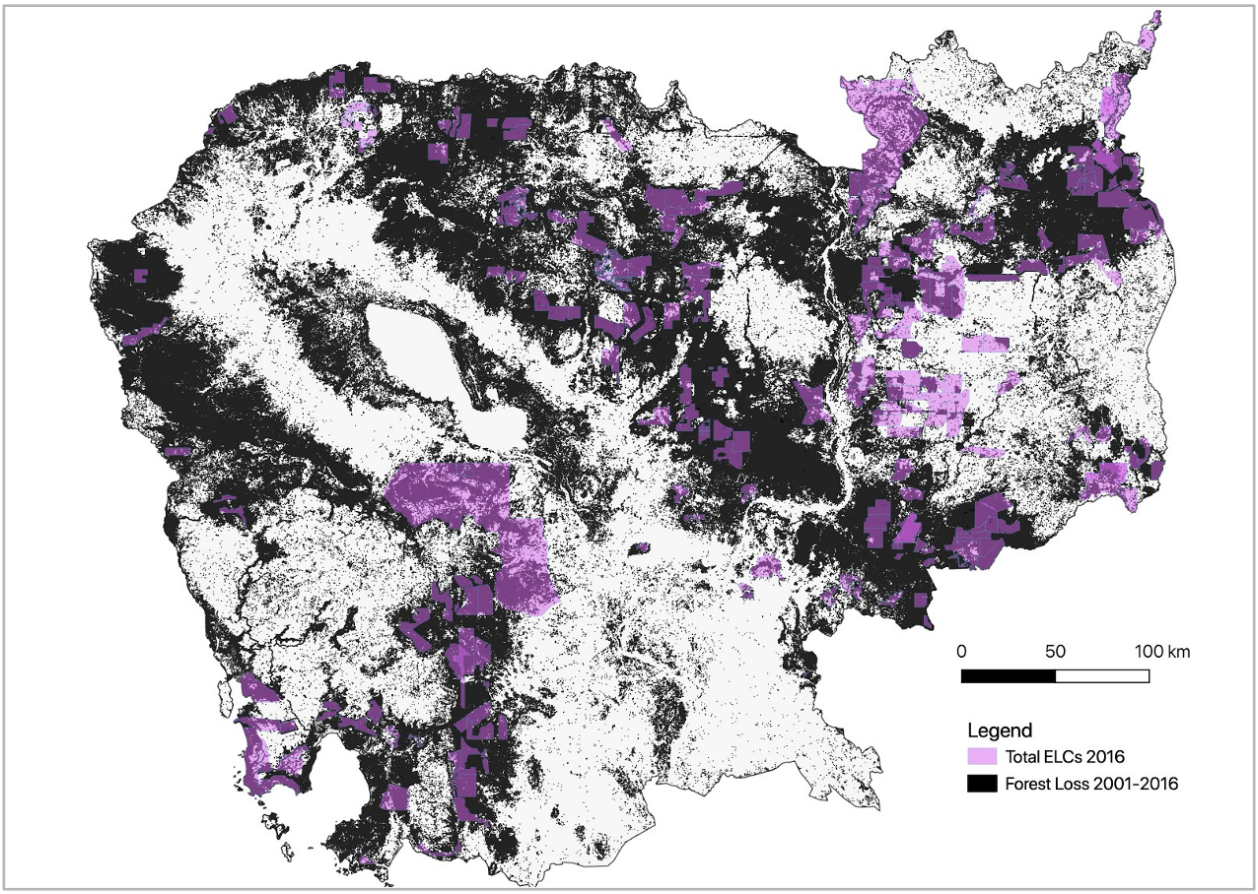

Figure 1: Forest loss and LSLAs in Cambodia

disciplines, but no consensus has emerged (Bauhoff and Busch 2020). One reason for this may be the differences in malarial ecology across the different regions of the tropics. Malaria is a mosquito-borne infectious disease caused by parasites in the *Plasmodium* group and carried by female *anopheles* mosquitoes. In Cambodia, there are 2 *Plasmodium*[3] parasites responsible for malarial infection and 4 *Anopheles*[4] mosquitoes responsible for vector transmission. *Anopheles*

[3] *P. falciparum* (58 percent of cases and by far the most lethal version of malaria) and *P. vivax*: (41 percent)
[4] *An. dirus, An. minimus, An. maculatus, An. sundaicus*

dirus is the primary vector of human *Plasmodium* parasites in the region. *An. dirus* is a forest dwelling mosquito species that thrives in the tropical forests of Cambodia (Sallum et al. 2005). This is important because understanding how land use change affects the disease vector environment provides information on possible mechanisms for the health effects of LSLAs. We rely on ecological research around these species when exploring mechanisms in Section 5 of this paper.

Although improving, malaria is a serious and persistent public health problem in Cambodia with an incidence of 23.7 per 1,000 people (World Bank 2021). This corresponds with an estimated 208,300 cases and 345 deaths as of 2017 (WHO 2018). This is 5.6 and 6.1 times more than the two countries with the next highest incidences of malaria in the region, Indonesia and Laos respectively, reflecting that malaria transmission is still a major health challenge for the country. Almost all cases of malaria occur in the rural areas of the country with the urban centers considered free of the disease (WHO 2018). Because of this and the location of LSLAs, we focus our study on the rural population.

SECTION 3: DATA

3.1 Land Use Data

Land use data on LSLAs come from Open Development Cambodia (ODC). It is a vector dataset derived from news reports, government press releases, and other public documents of all LSLAs in Cambodia from 1996 to 2012. Anti (2021) uses this data to analyze rural labor market effects of LSLAs and household spillovers, and Davis et al. (2013) uses the data to examine the relationships between LSLAs and deforestation. Most entries contain the actual polygon of the LSLA, and for others it contains the centroid. For most of the entries in the dataset, we have access

to either the date of the contract between the government and the leasing company or the government's sub-decree announcing the partnership. We follow Anti (2021) and use this information to date the establishment of the LSLA. Since very few of the observations contain both dates, we simply use whichever is available. For the few that contain both, we use the contract signing date. There are 17 LSLA points that have no data with which to date their establishment. We leave these in the data and accept the measurement error that they introduce into the estimations since it should only attenuate any findings. Figure 2 displays the ODC data and the spatial distribution of these LSLAs over time.

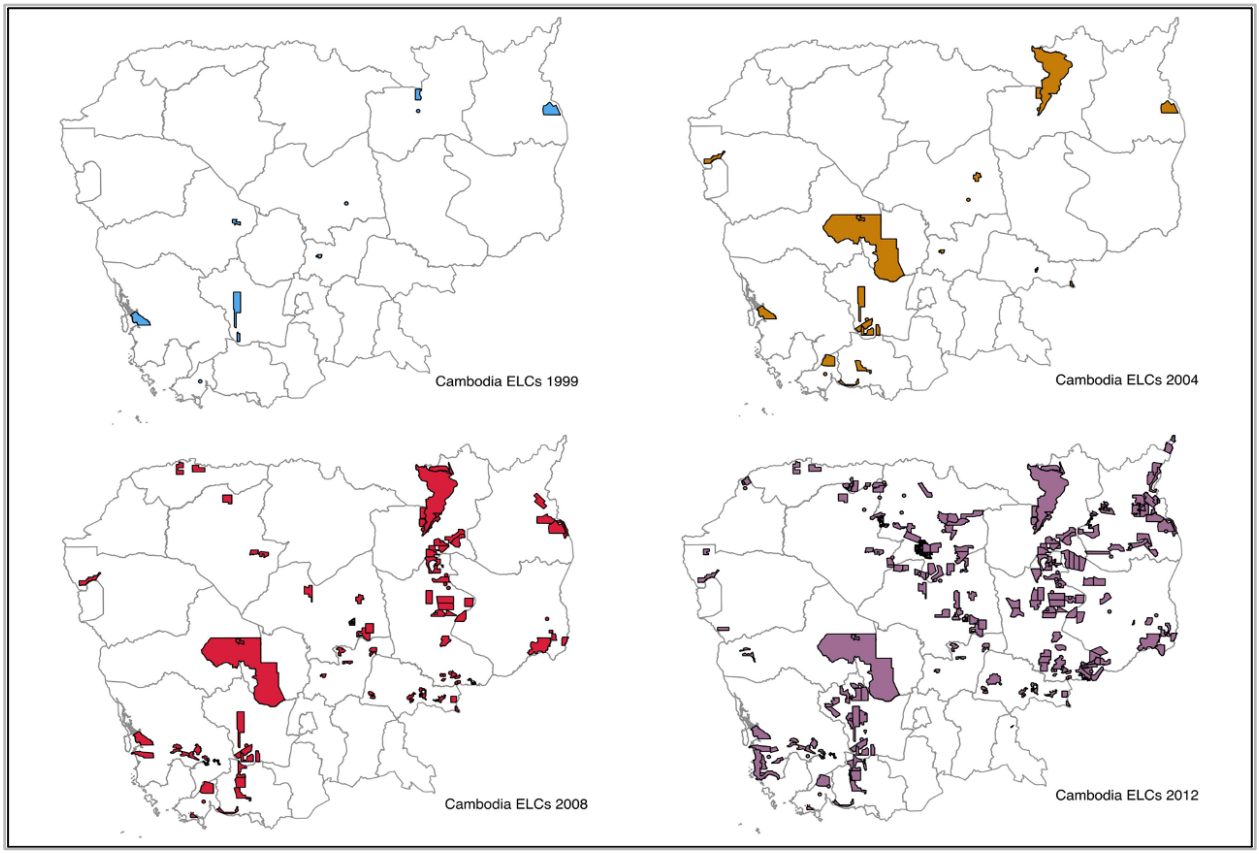

Figure 2: LSLA expansion over time in Cambodia

3.2 Cambodia Socio-Economic Surveys (CSES)

The Cambodia Socio-Economic Surveys (CSES) were collected in 1999, 2004, and annually between 2007 and 2016, and are nationally representative cross-sectional surveys. We append this data into a pooled dataset of repeated cross sections covering these years.[5] The CSES is a general survey covering many dimensions of Cambodian life, including labor, welfare, agricultural production, and importantly for our purposes, health. The size of the survey has been 3,600 households (340 villages) annually except for 2007, 2009, and 2014, when the National Institute of Statistics expanded the sample to include 12,000 households (870 villages).

The CSES does not come with its villages geocoded. For this, we rely on the geocoding performed by Anti (2021), which exploits the rich geocoding contained in a dataset on the distances to upper secondary schools (DUSS) available from the Cambodian Ministry of Youth, Education, and Sports. Through this method, we know the precise geographic coordinates of 95.8 percent of the CSES villages. With this, we follow Kotsadam and Tolonen (2016), Benshaul-Tolonen (2019) and Anti (2021) and measure the linear distance between a respondent's village and its closest LSLA, to measure the proximity of a respondent and LSLAs. Figure 3 displays a portion of the pooled villages and their locations on a map of Cambodia relative to the LSLAs contained in the ODC data to illustrate a portion of the spatial variation available for the study. This figure focuses on the northwest region of Cambodia for visual clarity.

The CSES also collects information from village leaders on general trends in their villages each year of the survey. We make use of several aspects from this section of data including village leaders' perceptions on health issues, population and stated access to shops and health infrastructure. While not part of the core analysis, these data add important information to explore

[5] The CSES does resample villages and could therefore be used in a pseudo panel framework, however, the resampling is not by design and the sample size per village per year is smaller than the literature indicates is necessary to adequately calculate precise means (Verbeek and Nijman 1993; Devereux 2007).

mechanisms and add nuance to the results. Table A.1 contains summary statistics for the CSES data.

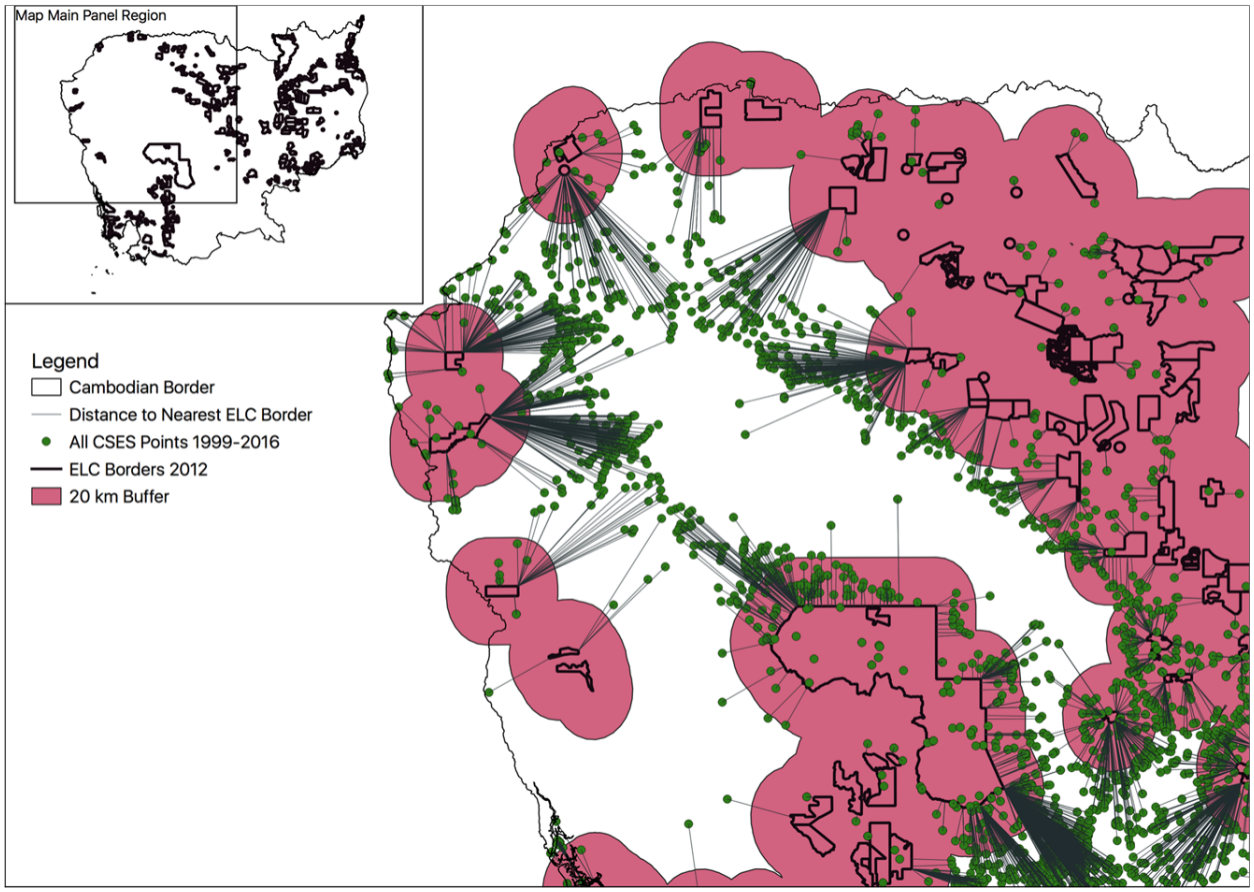

Figure 3: Pooled CSES villages and their measured distance from LSLAs

3.3 Deforestation Data

Deforestation data come from Hansen et al. (2013) over the period 2000 to 2016. This is a raster dataset derived from the US Government's Landsat data, and processed to indicate the year and loss extent of forest. The spatial resolution is one arc second per pixel, so each pixel corresponds roughly to the size of a baseball diamond. It is commonly used in studies on resource use and forest loss in both economics (Berazneva and Byker 2017) and the natural sciences (Davis et al. 2015) and is available over the entire world. We use it to measure the precise amount of forest loss that

has occurred on each of the polygons contained in the ODC data and the amount of deforestation in close proximity to the polygon. Figure 4 uses this data to illustrate cumulative deforestation in four-year intervals starting in 2001. Since 2000 Cambodia has lost over 40 percent of its intact forest.

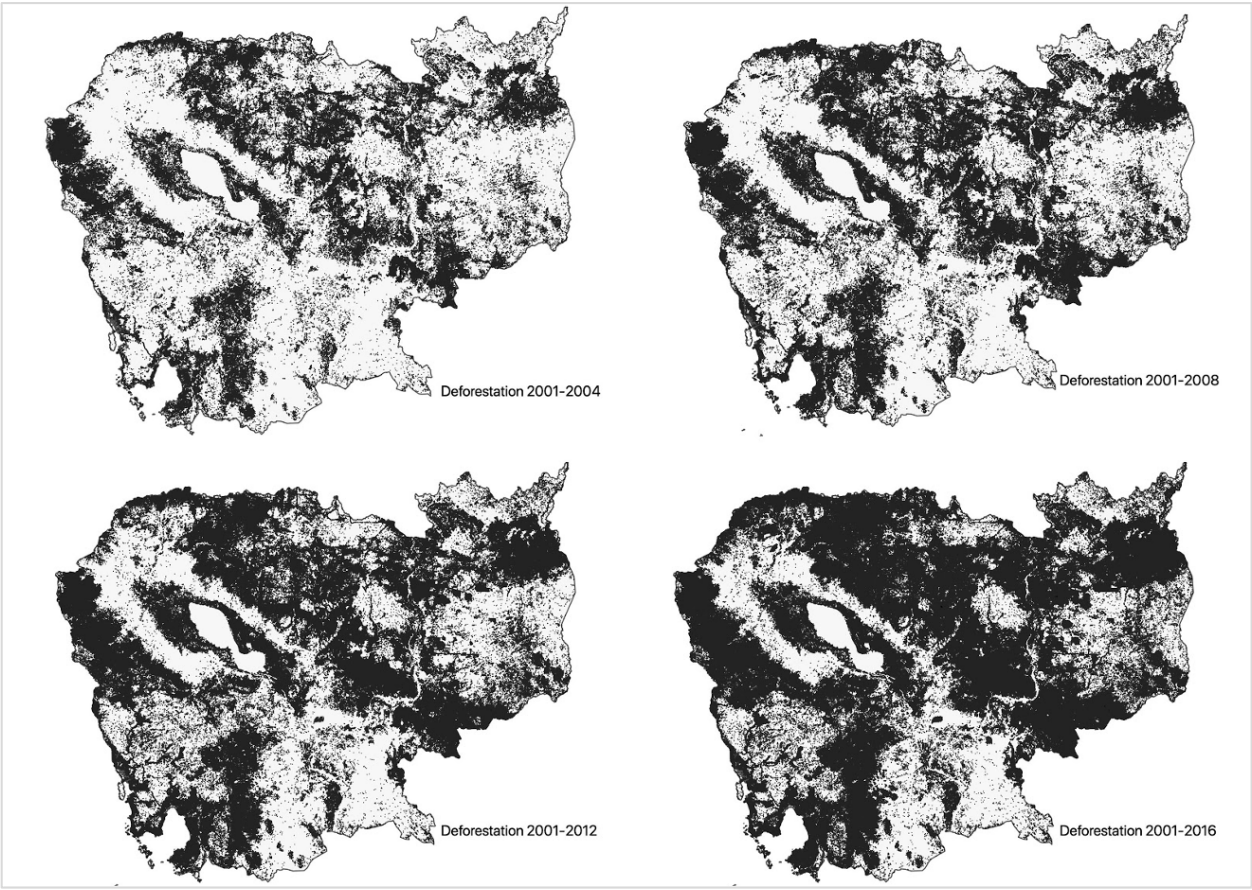

Figure 4: Cumulative tree canopy lost in Cambodia, shown over 4 time periods

SECTION 4: EMPIRICAL STRATEGY

4.1 LSLAs and Health Outcomes

We exploit the spatial and temporal variation in the data to estimate the health effects of LSLAs over space within a multiperiod spatial difference-in-differences (DID) empirical framework. We use the same core spatial DID approach using repeated cross-sectional survey data developed and

employed by Kotsadam and Tolonen (2016), Kotsadam et al. (2018), Benshaul-Tolonen (2019), Golz and Barnwal (2019), and Anti (2021).

We begin by estimating the following specification with ordinary least squares (OLS),

$$Y_{icdtj} = \beta_0 + \sum_s \gamma_s LSLA_{c,s} \times After_{ct} + \sum_s \kappa_s LSLA_{c,s} + X_i + \mu_t + \lambda_{p*t} + \delta_d + \alpha_{dj} + \varepsilon_{icdtj} \quad (1)$$

where the set s is composed of distance bands. We undertake the analysis using two sets, one with the bands 0, 1-5, 5-10, 10-15, and 15-20 kilometers from an LSLA, and one with 20-25 and 25-30 added. Since the threshold for where the effect goes to zero is not known, any choice on our part is arbitrary and risks a violation of the stable unit treatment value assumption (SUTVA). The first set establishes the untreated group as those beyond 20 kilometers from an LSLA, and the second set establishes the untreated group as those beyond 30 kilometers. This allows us to estimate effects over discrete distance bands and has the advantage of allowing for non-linear effects over space. This is important since we have no *a priori* understanding of how the environmental disturbance will affect disease incidence spatially.

The outcome variable Y_i is a binary variable for whether a respondent i reports having a fever in the two weeks prior to their interview for the CSES survey in village c, district d, year t, and month j. This outcome variable is a standard proxy for the incidence of malaria in the development and health literature (Asif et al. 2018; Berazneva and Byker 2017). To rule out other health effects from LSLAs besides malaria, we also examine whether the respondent had a cough or diarrhea, which are not proxies for malaria, in the past two weeks prior to their CSES interview (WHO 2018).

The variable $LSLA_{c,s}$ is a binary variable equivalent to one if the respondent is within the range of s from an LSLA at any point between 2004 and 2016 and zero otherwise. Its inclusion in the specification controls for time-invariant variables associated with ever being in proximity to an LSLA. The variable $After_{c,t}$ is a binary variable equal to one if the respondent was surveyed after the LSLA had been leased and is zero otherwise. The interaction $LSLA_{c,s} \times After_{c,t}$ is the DID measurement and is equal to one if the respondent lives in a CSES village within a certain distance to an LSLA after the LSLA is leased.

We also include X_i as a vector of individual and household characteristics, such as age, sex, age of household head, and size of one's household. The vector μ_t is year fixed effects controlling for year-specific health shocks, and δ_d is district fixed effects controlling for any time-invariant health determinants at the district level like public health infrastructure or governmental institutions. The vector α_{dj} denotes district-month fixed effects to control for regional seasonal variation in disease incidence. The vector λ_{p*t} is a linear time trend at the province level controlling for variables consistently changing over time within provinces. We cluster our standard errors at the village level. We do not employ survey weights following Solon et al. (2015).

For the estimates of the coefficients $\sum_s \gamma_s$ to measure the causal effect of being within a certain proximity to an LSLA, trends in human disease must be the same between the regions within 20 kilometers to LSLAs and those farther away after controlling for everything on the right hand side of equation (1).

We also amend the specification to examine how the effect changes over time. To do this, we estimate the following event study specification looking at the effects over time within distance band n,

$$Y_{icdtj} = \beta_0 + \sum_e \chi_e LSLA_{c,n} \times Time_e + \sum_s \gamma_s LSLA_{c,s} \times After_{ct}$$

$$+ \sum_j \kappa_j LSLA_{c,j} + X_i + \mu_t + \lambda_{p*t} + \delta_d + \alpha_{dj}$$

$$+ \varepsilon_{icdtj} \tag{2}$$

where all the variables are defined as before. The set of e is the set of time aggregated time periods before and after treatment and j is the set of distance bands 0, 0-5, 5-10, and 15-20 kilometers. The set s is the same set as j but with n removed. The set of e in any particular estimation will vary depending on data availability over time.

This specification also has the benefit of providing insight into whether the parallel trends assumption necessary for a causal interpretation of DID holds. If the pretreatment periods exhibit small, statistically insignificant coefficients and the post-treatment periods exhibit statistically significant coefficients this indicates that the parallel trends assumption holds, and it is unlikely the outcome variable changed prior to treatment.

4.2 DID Robustness

While the DID approach is an extremely common strategy for plausibly estimating causal effects with observational data, there have been recent highly influential papers in the econometrics literature highlighting the potential for bias in contexts, such as ours, when treatment occurs in multiple time periods for different groups (e.g. Goodman-Bacon 2021; Callaway and Sant'Anna 2020).

To check whether this bias is in fact a problem in our context, we follow the approach outlined by Callaway and Sant'Anna (2020) to estimate their proposed adjusted DID parameter. This approach requires the separate estimation of all the various two-by-two DID comparisons contained in the dataset and then aggregating these decomposed estimates into one composite DID

estimate. Callaway and Sant'Anna's R package for performing this estimation does not allow for our particular spatial DID strategy. To address this, we have written our own extension to the original code offered by Callaway and Sant'Anna (see Supplemental Materials). We do this for the two separate groups for which we find significant results, zero to five kilometers, and five to 10 kilometers.

SECTION 5: RESULTS

5.1 Main Results

Table 1 contains the results of estimating equation (1). The estimates show a statistically significant negative effect on fever for those living on the LSLAs themselves, and then a statistically significant positive effect for those in both the regions within zero to five kilometers and five to 10 kilometers from the LSLAs.

Both the negative effect of being on the LSLA and the positive results of being adjacent to the LSLA are economically significant. Being on the LSLA itself results in a decline in the likelihood of having a fever with the prior two weeks of 2.2 percentage points, a decrease of 88 percent of the sample mean. Being within ten kilometers of an LSLA results in an increase of 1.7 percentage points in the probability of having a fever in the past two week, a 68 percent increase in the incidence of fever over the sample mean. The results are almost identical between the two different specifications using 20 kilometers and 30 kilometers as the threshold for the DID comparison and gives us confidence that our estimates do not suffer from a SUTVA violation.

Table 1: CSES Adults - Estimates of Equation (1)

VARIABLES	(1) Fever	(2) Fever	(3) Cough	(4) Cough	(5) Diarrhea	(6) Diarrhea
$LSLA_{c,[0]} \times After_{ct}$	-0.022***	-0.025***	-0.002	-0.012	-0.009*	-0.009
	(0.008)	(0.009)	(0.014)	(0.014)	(0.005)	(0.006)

$LSLA_{c,(0,5]} \times After_{ct}$	0.017***	0.017***	-0.009	-0.010	-0.004*	-0.004
	(0.006)	(0.006)	(0.012)	(0.012)	(0.002)	(0.002)
$LSLA_{c,(5,10]} \times After_{ct}$	0.016**	0.016**	-0.007	-0.007	0.002	0.002
	(0.007)	(0.007)	(0.017)	(0.017)	(0.002)	(0.002)
$LSLA_{c,(10,15]} \times After_{ct}$	0.010	0.010	-0.011	-0.012	-0.000	-0.001
	(0.007)	(0.007)	(0.017)	(0.017)	(0.003)	(0.003)
$LSLA_{c,(15,20]} \times After_{ct}$	0.012	0.011	-0.022*	-0.022*	-0.005	-0.005
	(0.008)	(0.008)	(0.013)	(0.013)	(0.003)	(0.003)
$LSLA_{c,(20,25]} \times After_{ct}$		0.030*		-0.050***		-0.019***
		(0.017)		(0.005)		(0.001)
$LSLA_{c,(25,30]} \times After_{ct}$		-0.006		0.017		0.007***
		(0.007)		(0.017)		(0.003)
Dep. Var. Mean	0.025	0.025	0.051	0.051	0.005	0.005
Observations	145,067	145,067	145,067	145,067	145,067	145,067
R-squared	0.030	0.030	0.043	0.043	0.014	0.014

Robust standard errors clustered at the CSES village level in parentheses
All controls from equation (1) included, but coefficients are not shown
*** p<0.01, ** p<0.05, * p<0.1

Table 2 contains the estimates of the effects of the LSLA on the prevalence of fever for respondents on the LSLA, and within zero to five, and five to 10 kilometers away. The signs and general magnitudes are consistent with our main results, although our estimates attenuate. Despite this attenuation, we take this as evidence the health effects observed in close proximity to LSLAs are significant and not the result of potential bias as described in Goodman-Bacon (2021). It does lead us to interpret the economic significance in our main results with caution. However, even the attenuated effects suggested by the Callaway and Sant'Anna estimates can be considered large in an economic sense. For example, the estimated effect of a 0.7 percentage point increase in the likelihood a respondent had a fever in the past week is a 28 percent increase over the sample mean.

Table 2: Callaway and Sant'Anna Robust DID Estimates

VARIABLES	(1) Fever
$LSLA_{c,[0]} \times After_{ct}$	-0.007
$LSLA_{c,(0,5]} \times After_{ct}$	0.007***
	(0.0007)
$LSLA_{c,(5,10]} \times After_{ct}$	0.011***

	(0.0008)

Bootstrapped standard errors are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These results are most consistent with LSLAs causing a decrease and then an increase in the prevalence of malaria over space. We base this on several pieces of evidence. First, the results for the other health measures, respondents reporting diarrhea and cough in the two weeks before being surveyed are small, below one percentage point, and are generally not statistically significant. As stated above, malaria was a common and pervasive public health issue during the time frame of our study. Malaria usually presents with a fever and rarely is associated with cough or diarrhea (WHO 2018) and fever can be used as a proxy for malaria (Berazneva and Byker 2017).

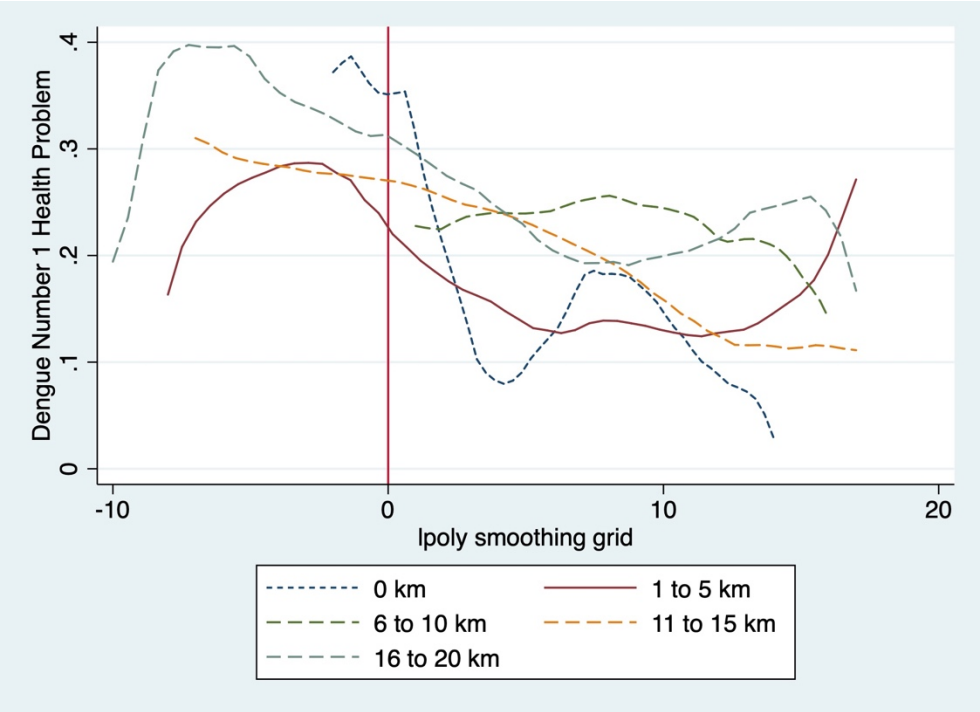

Figure 5: Dengue reported as number 1 public health concern in village

Second, other common diseases have fever as the primary symptom, which one may suspect, are driving our results. Among these, dengue is the primary concern. We find this unlikely. Dengue in Cambodia is a largely urban illness (WHO 2018). Additionally, we have evidence from

interviews with village leaders that match our finding's spatial dimensions. These data come from a module in the CSES asking village leaders about local trends in their villages. In this questionnaire, village leaders were asked what the number one public health issue was in their communities. Village leaders living on LSLAs stated that dengue became a less prominent public health concern after the LSLA arrived but, in villages in areas close but not on LSLAs, heads reported malaria as the number one public health issue much more after the LSLA.

Figures 5 and 6 show these trends over time and space by estimating local polynomial smoothing regressions over time relative to the establishment of the closest LSLA. Figure 5 clearly shows Dengue declining as a concern among all village leaders in regions close to LSLAs over time in relatively similar ways, suggesting that Dengue is likely not the driver of the regression results.

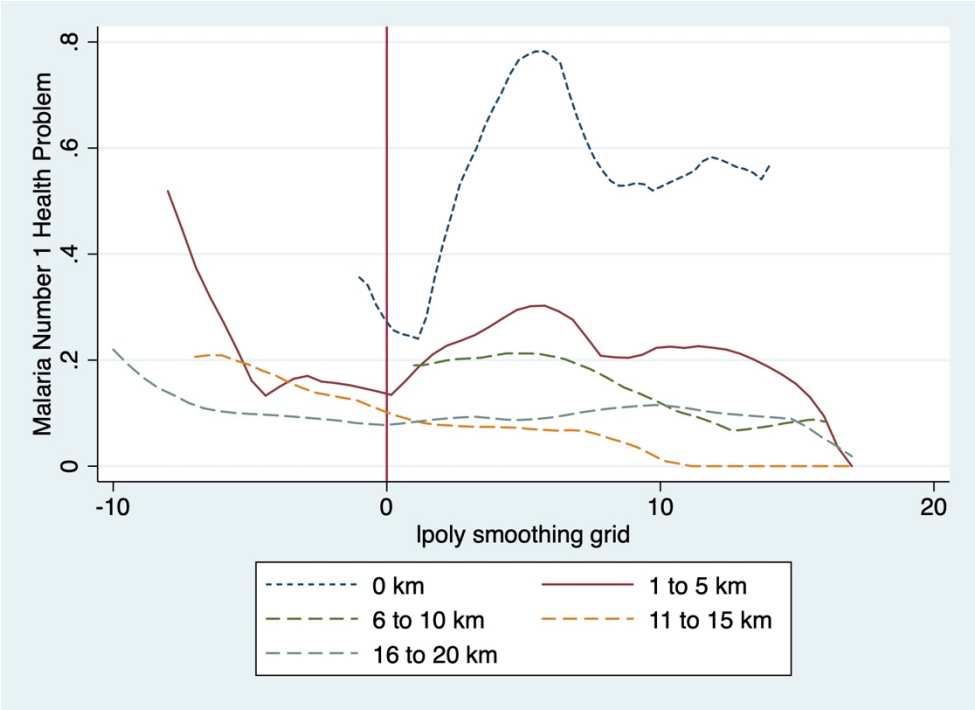

Figure 6: Malaria reported as number one public health concern in village

Figure 6 shows increases in malaria reported as a problem for the regions on and immediately adjacent to the LSLA. However, malaria does appear to rise as a number one health concern on the LSLA. This is confounding given the DID results. We suggest the most convincing explanation for this discrepancy is a reaction to the increases in malaria happening in communities surrounding the LSLAs. It could also represent a perception particular to workers that have migrated from urban areas or abroad to work on the LSLA's farm.

To investigate the effect of the LSLAs over time, we estimate the event study outlined in equation (2). Figure 7 and 8 illustrate the effects of being within zero to five kilometers and then five to 10 kilometers of the LSLA over time. Here we see a pattern consistent with a causal effect of the LSLA on malaria prevalence near but not on the LSLA. The point estimates for the coefficients prior to the LSLA are relatively close to zero before the arrival of the LSLA and statistically insignificant. They then become statistically significant after the leasing of the LSLA

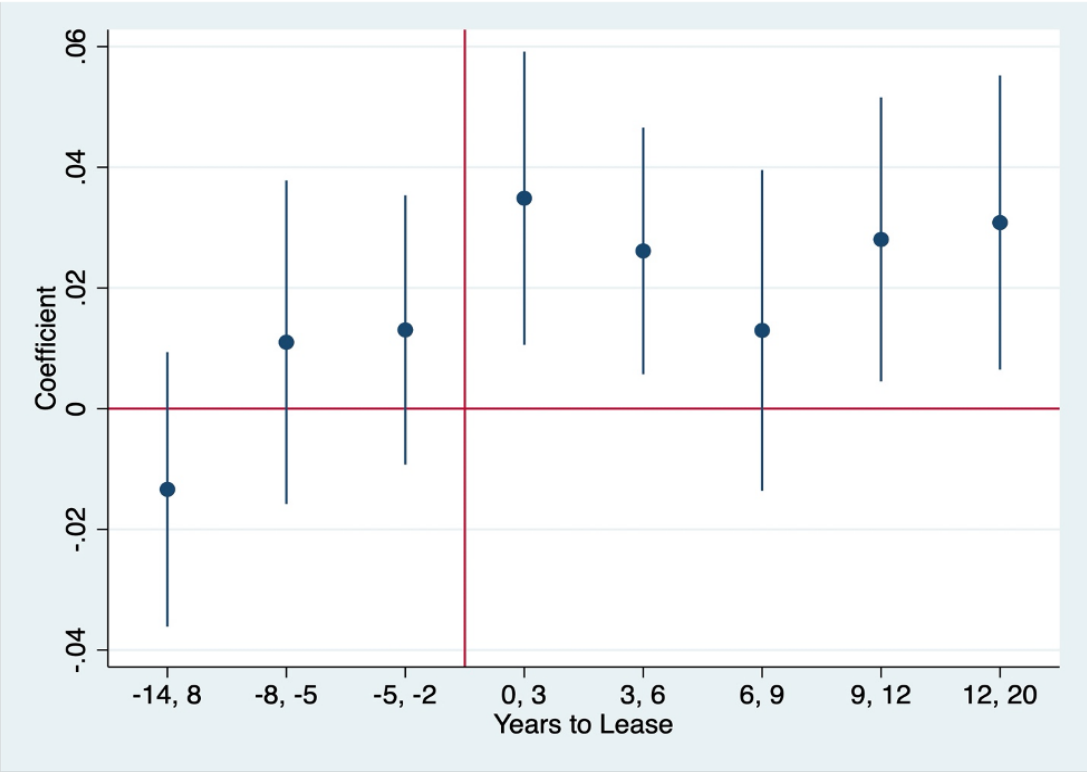

Figure 7: Event Study, 0-5 km from LSLA, Outcome: Fever

within five kilometers and between five and 10 kilometers of their village. A particularly interesting feature of this effect in the zero to five kilometer region is how durable it appears over time.

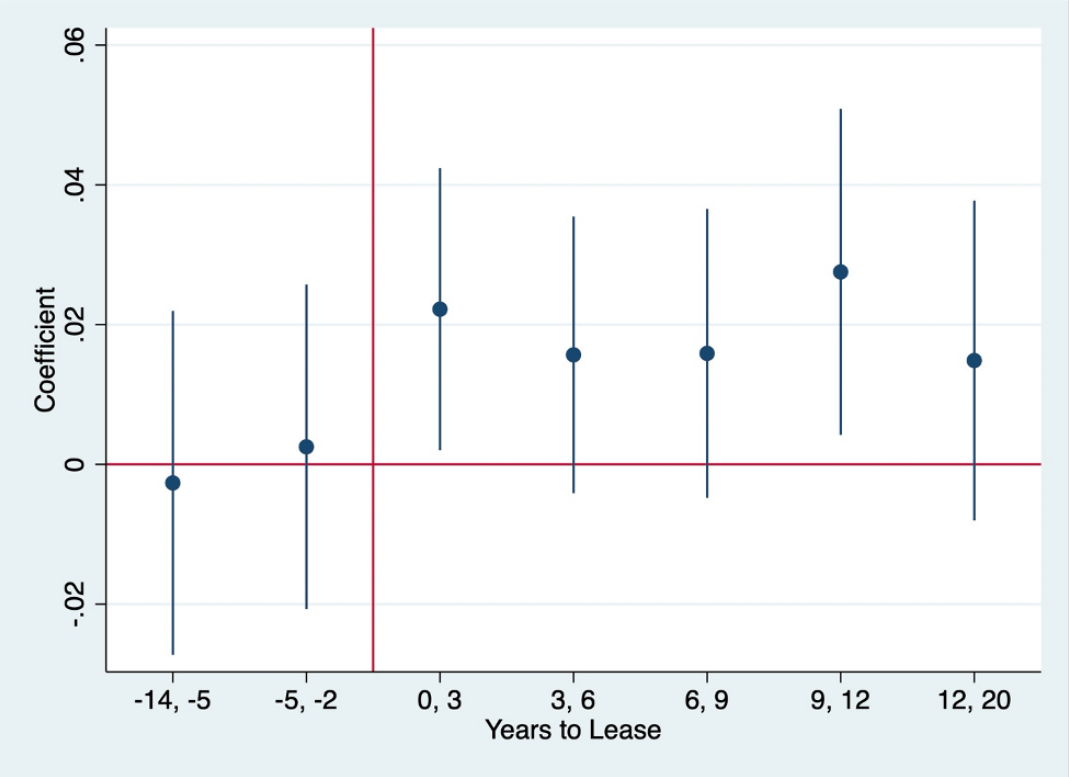

Figure 8: Event Study, villages 5-10 km from LSLA, Outcome: Fever

Estimates of equation (2) provides a heterogeneous treatment effect over time for those living on the LSLA (those at zero kilometers). We can see in Figure 9 that the negative effect of the LSLA on fever is only statistically significant in the first three years after the LSLA is leased, when land clearing is most recent.

In the Appendix we present estimates of equation (2) for our other health variables of cough and diarrhea. While nothing in the event study set up indicates our results for equation (1) are misleading there seems to be an insignificant but persistent decrease in diarrhea on and near the LSLA after implementation (Figure A.2.4 and Figure A.2.5). While not significant, this may

point to increased access to clean water due to the LSLA. No other configuration of equation (2) with these other health variables yields results that were unexpected given Table 1.

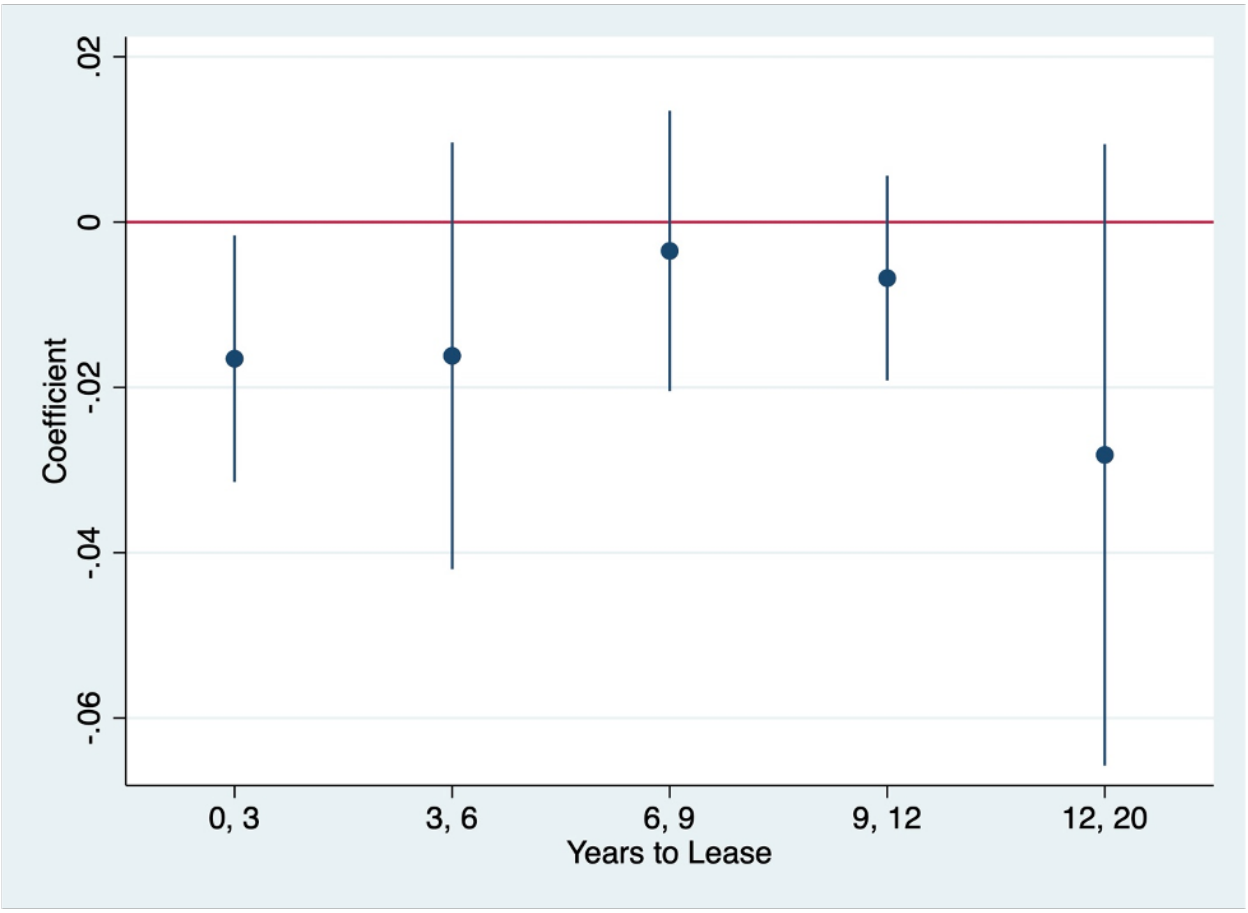

Figure 9: Heterogenous effects over time, villages on an LSLA, Outcome: Fever

5.2 Mechanisms

Our results show that there are significant effects of LSLAs on fever but not cough or diarrhea, which is consistent with an interpretation of LSLAs affecting local health through increases/decreases in the prevalence of malaria. Negative effects on fever are seen on the LSLA whereas increases in fever are seen from zero to 10 kilometers from the LSLA. This spatial pattern could have multiple mechanisms. In this section, we explore each.

5.2.1 Deforestation

To assess the role of LSLA deforestation as a mechanism for malaria incidence we first construct a hypothesis for how deforestation leads to differing spatial malaria incidence. We draw from ecological research to establish the connection between deforestation and disease vector populations and then use findings from public health literature to explain the current hypotheses linking these spatial changes to malaria incidence.

In Cambodia, clear cutting forest has been observed to decrease *anopheles* mosquitos on the affected land (Bauhoff and Busch 2020; Anon 2005). Tropical ecologists, examining the relationships between habitat disturbance and mosquito population, have also established this relationship (Alroy 2017). Research shows mosquito populations increase in slightly disturbed habitat, but decrease significantly as tropical habitat is eliminated. This relationship between deforestation and disease vector populations matches the spatial variation of our results. Mosquito populations decreasing heavily on the cleared LSLAs leads to less malaria, but increasing populations in the slightly disturbed surrounding landscape contribute to the rise in malaria cases. Public health literature supports these findings as well. Brock et al. (2019), found similar spatial patterns of malaria incidence in a different country in south east Asia (Malaysia). They present evidence that forest fragmentation leads to increases in malaria with incidence rates the highest about five kilometers away from deforestation. The prevailing explanation they provide is that malaria incidence increases on the boundaries of cleared land and increased fragmentation leads to more boundaries at which this can occur.

To empirically test the hypothesis of whether deforestation is a mechanism through which the LSLAs are affecting health, we make use of the Hansen et al. (2013) to measure the extent of deforestation on a respondent's closest LSLA. Table 3 presents equation (1) estimated for three different groups: the full sample results and then two subgroups, one where deforestation on the

LSLA was in the top quartile (high deforestation) and one for clusters that were near LSLAs with deforestation in the bottom 3 quartiles. This analysis reinforces the view that deforestation is a plausible mechanism. Individuals from treated villages that experienced high deforestation on their LSLA are driving the statistically significant negative effect on fever rate on the LSLAs. This is consistent with LSLAs that are clear-cut, driving down prevalence of malaria vectors. In clusters with low LSLA deforestation, we see the significant effect is in the spatial bands from zero to 10 kilometers. This is consistent with the fragmentation theory where less deforested LSLAs lead to more patchy landscapes that increase the boundary effects where malaria is likely higher.

Table 3: CSES Adults - Estimates of Equation (1) using subgroups of the treated population based on deforestation

VARIABLES	(1) Full Sample	(2) Low Deforestation On LSLA	(3) High Deforestation On LSLA
$LSLA_{c,[0]} \times After_{ct}$	-0.022***	-0.014	-0.041**
	(0.008)	(0.009)	(0.016)
$LSLA_{c,(0,5]} \times After_{ct}$	0.017***	0.017**	0.011
	(0.006)	(0.002)	(0.016)
$LSLA_{c,(5,10]} \times After_{ct}$	0.016**	0.014*	0.013
	(0.007)	(0.007)	(0.014)
$LSLA_{c,(10,15]} \times After_{ct}$	0.010	0.009	0.016
	(0.007)	(0.007)	(0.020)
$LSLA_{c,(15,20]} \times After_{ct}$	0.012	0.011	-0.035
	(0.008)	(0.008)	(0.031)
Observations	145,067	133,026	110,107
R-squared	0.030	0.031	0.030

Robust standard errors clustered at the CSES village level in parentheses
All controls from equation (1) included, but coefficients are not shown
*** p<0.01, ** p<0.05, * p<0.1

Another way to think about deforestation in this context is as a treatment intensity measure. We use the Hansen at al. data to estimate the amount of deforestation on LSLAs near a respondent's village at the time of response. For each village, we measure the total amount of

annual tree canopy loss (in square kilometers) and the amount lost on LSLAs within the treatment buffer. This allows us to control for deforestation both as a direct result of LSLA clear cutting and secondary deforestation effects in surrounding communities.

By interacting deforestation on the LSLA in years after treatment, we estimate how deforestation that occurred after LSLA implementation affects our health measures. If deforestation is in fact the driver of this effect, then we should see those in areas closer to areas with heavier deforestation experience larger effects. This leads to the following specification,

$$Y_{icdtj} = \beta_0 + \sum_s \gamma_s LSLA_{c,s} \times After_{ct} \times Def_{ct} + \sum_s \rho_s LSLA_{c,s} \times After_{ct} + \sum_s \kappa_s LSLA_{c,s} + X_i + Def_{ct} + \mu_t + \lambda_{p*t} + \delta_d + \alpha_{dj} + \varepsilon_{icdtj} \quad (3)$$

where Def_{ct} is the amount of deforestation on a cluster's closest LSLA. Results for equation (3) are in Table 3. We replicate our original findings in this model in column 1. The second column shows the interaction variables. Our results show only one statistically significant effect in the interaction variables, more LSLA deforestation leads to less fever from zero to five kilometers. We interpret this as reflecting the same story as our high deforestation subgroup above where more deforestation spills out and influences the ecosystem of disease vectors closest to the LSLA.

Table 3: Deforestation on LSLA as Treatment Intensity

	(1)		(1 cont.)
VARIABLES	Fever	INTERACTION VARIABLES	Fever
$LSLA_{c,[0]} \times After_{ct}$	-0.020**	$LSLA_{c,[0]} \times After_{ct} \times Def_{ct}$	-0.01
	(.009)		(0.01)
$LSLA_{c,(0,5]} \times After_{ct}$	0.023***	$LSLA_{c,(0,5]} \times After_{ct} \times Def_{ct}$	-0.03***

	(0.007)		(0.01)
$LSLA_{c,(5,10]} \times After_{ct}$	0.016**	$LSLA_{c,(5,10]} \times After_{ct} \times Def_{ct}$	-0.007
	(0.007)		(0.01)
$LSLA_{c,(10,15]} \times After_{ct}$	0.008	$LSLA_{c,(10,15]} \times After_{ct} \times Def_{ct}$	0.01
	(0.008)		(.05)
$LSLA_{c,(15,20]} \times After_{ct}$	0.012	$LSLA_{c,(15,20]} \times After_{ct} \times Def_{ct}$	-0.04
	(0.008)		(0.1)
Observations	145,067		
R-squared	0.030		

Robust standard errors clustered at the CSES village level in parentheses
All controls from equation (3) included, but coefficients are not shown
*** p<0.01, ** p<0.05, * p<0.1

5.2.2 Migration

Since we use repeated cross-sectional data, migration is both a possible mechanism and a threat to our identification. There are two mechanisms by which migration might influence results, selection on healthy people and population density. It is likely that there was net migration inwards to regions close to LSLAs for work opportunities (Anti 2021, Appendix Table A.3).

If migration is occurring based on unobservable variables correlated with health outcomes, it could bias our results. We address this by following Kotsadam and Tolonen (2016), Benshaul-Tolonen (2018), and Anti (2021) and use variables on migration available in the CSES to identify when individuals arrived in their village. Using this we can identify those that did not move to their village of residence since before an LSLA was within 20 kilometers of their village. We then remove them from the sample and check whether our main results hold for those in the sample

who only moved to their village before the LSLA phenomenon arrived in their general proximity, or never moved. Appendix Table A.2 contains the results of equation (1) using this sub-sample for the CSES respondents. One can see that the results largely hold. The coefficients for those residing in the zero to five kilometer region around LSLAs actually get larger in magnitude. We lose significance on the coefficient for those living on LSLAs, this is likely due to lost power from dropping observations.

Another potential migration mechanism may be that healthier individuals move from non-treated areas onto the LSLA. We do not find this convincing since we do not see effects in other health metrics. Inward migration also may lead to higher population densities and population density is often linked to higher transmission of diseases including malaria (WHO 2021). Therefore, if LSLAs bring in more people to the region that may be a possible mechanism for increased incidence of malaria. Appendix Table A.2 shows that LSLAs likely increase population for villages on the LSLA, however, the effect on LSLAs for malaria is negative. From this, it would appear that changes in population density are not driving our results.

Additionally, deforestation may be viewed as a proxy for density but again, our results run counter to expectations of increased density, providing further support for a more complex deforestation mechanism.

5.2.3 Other Potential Drivers

It is conceivable that if there is an influx of internal migrants, then perhaps health outcomes are deteriorating near the LSLAs due to there simply being less access to health systems servicing a larger population. We find this argument unconvincing because we find statistically significant

effects only on the fever proxy for malaria, and a deterioration in access to the health system would result in other measures of health besides prevalence of fever.

Another plausible argument is that LSLAs lead to economic agglomeration effects and improvements in infrastructure such as roads, health clinics, and government services and that this is operating behind our results. In fact, many policy makers and private sector advocates of LSLAs argue LSLAs will lead to these types of agglomeration effects. However, we find this to be unconvincing since any agglomeration effect should benefit those on the LSLAs as well as those just adjacent to the LSLAs essentially equally. We would not expect to observe the stark shift from a negative effect to a positive effect on the prevalence of fever over such a limited region near to the LSLA.

To find some empirical basis for this, we again make use of the village module of the CSES to investigate whether village leaders report any improvement in the time it takes to access various health service providers like private clinics, drug stores and health centers. Appendix Table A.2 columns (2) through (4) contains these results. They indicate proximity to LSLAs has no statistically significant effect on access to this type of infrastructure.

Finally, results from Anti (2021) show increases in agricultural employment and decreases in welfare and expenditure for those living near LSLAs. Since they are themselves affected by the LSLA we cannot control for them in our analysis. However, these results may correspond to several mechanisms for malaria incidence. While expenditure changes and decreases in welfare likely exacerbate adverse health impacts, the fact we only see effects on fever make it unlikely that this is solely responsible for our results in this paper. Increased agricultural labor may change how people interact with their environment putting them in places where disease vectors are more

common. It is difficult in this analysis to completely attribute or disregard these mechanisms and it is possible several are occurring simultaneously.

SECTION 6: CONCLUSION

Although LSLAs are common across the developing world and there has been growing interest among researchers in understanding their effects on local people, there has been little quantitative analysis measuring their effects on public health. This study uses geocoded survey data from the CSES to estimate the effects of proximity to LSLAs using a spatial multiperiod DID approach.

We find a distinct pattern of effects related to respondents reporting whether they have had a fever in the prior two weeks, a proxy for malaria in the region, while it finds no distinct effect of proximity to LSLAs on other health measures of diarrhea and cough. This pattern of effects on reported fever shows a large negative effect for those living on the LSLA and positive effects for those living within zero to 10 kilometers of the border of the LSLA. We exploit the availability of village-level perception data in the CSES and remote sensing data to explore the many possible mechanisms that drive this pattern of effects over space.

The explanation most consistent with our results is that certain types of deforestation on the LSLAs are driving these heterogeneous effects over space. More intense deforestation is driving the large negative effect on fever on the LSLA, and less intense deforestation is resulting in increases in the mosquito population in adjacent regions and increases in fever in that region. This suggests that land policy, especially when it involves heavily forested land containing disease vectors, can have significant effects on other dimensions of life in neighboring communities beyond economic production, income, and labor market decisions. It also reinforces recent findings that disruption of local ecosystems can have large negative effects on localized patterns

of disease transmission and that effects can be heterogeneous over space. As a result, policy makers should consider the effects on health in local communities of their decisions over land and forest resources and be aware that these effects are most pronounced within 10 kilometers.

This study leads to several lines of follow-up work. First, one could exploit in more depth measures of forest fragmentation available from the remote sensing literature to examine what specific type of deforestation pattern leads to increases in fever in adjacent regions. Second, a focus on specific types of agricultural activity on these parcels could provide more information on mechanisms by which health outcomes are affected. Finally, this research should lead to broader questions about land tenure and health, and how land ownership, land use and local health are related.

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SUPPLEMENTAL APPENDIX

Land Policy and Human Health: Evidence from Land Grabs in Cambodia

Sebastian Anti and Ian Luby

SECTION A.1: CALLAWAY AND SANT'ANNA EXTENSION

The script for the extension of Callaway and Sant'Anna (2021) can be found in the file "Callaway_and_Sant_Anna_Extension.R"

SECTION A.2: APPENDIX CHARTS AND FIGURES

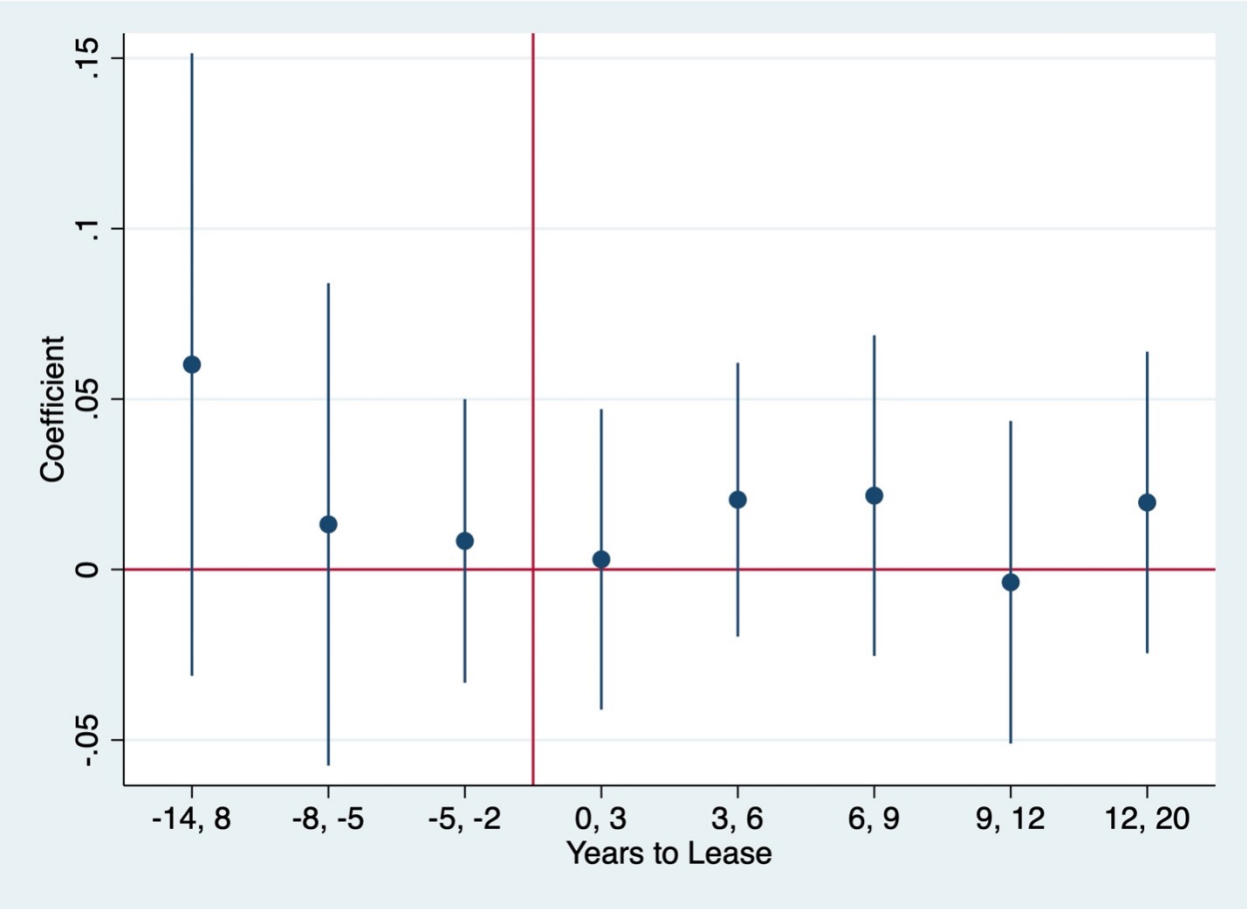

Figure A.2.1: Event Study, villages 0-5 km from LSLA, Outcome: Cough

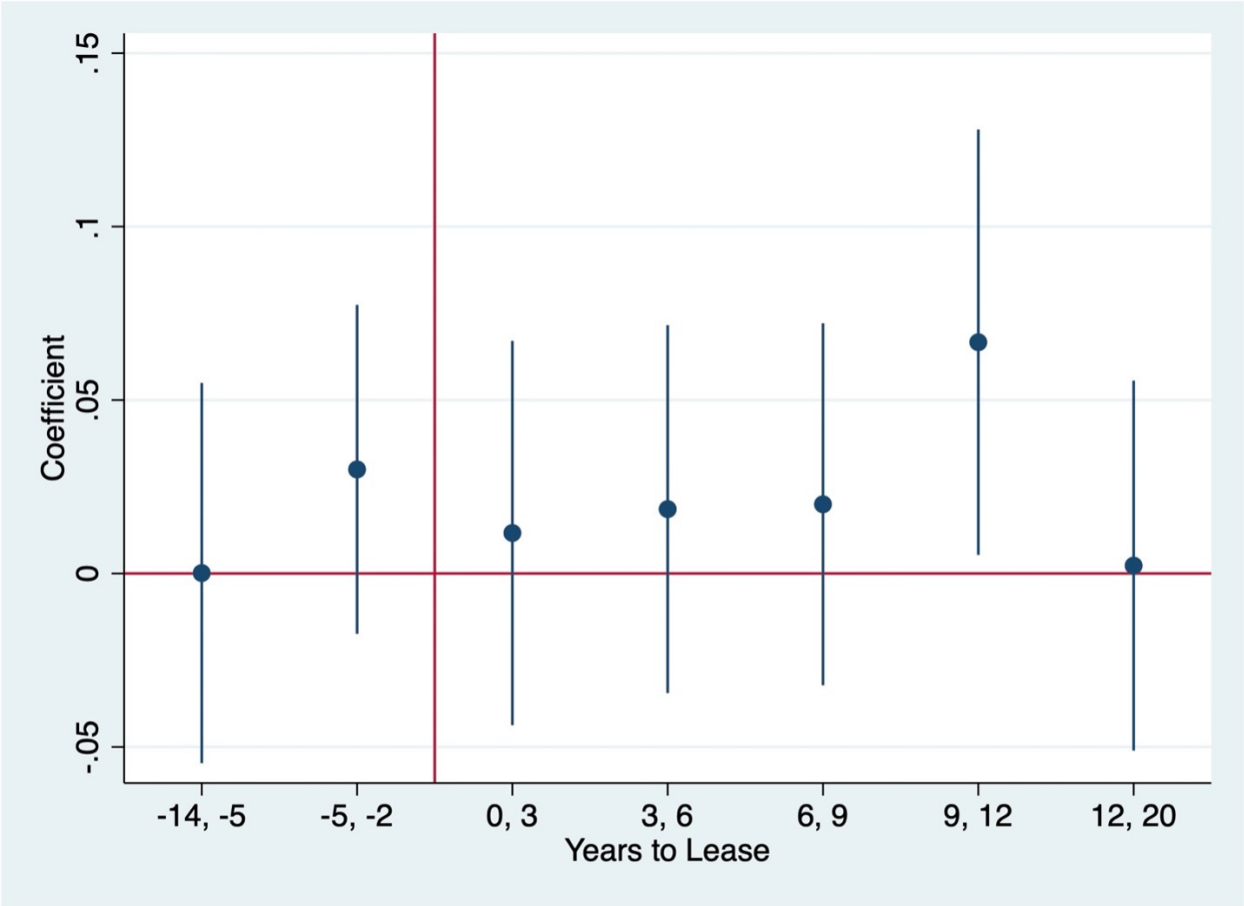

Figure A.2.2: Event Study, villages 5-10 km from LSLA, Outcome: Cough

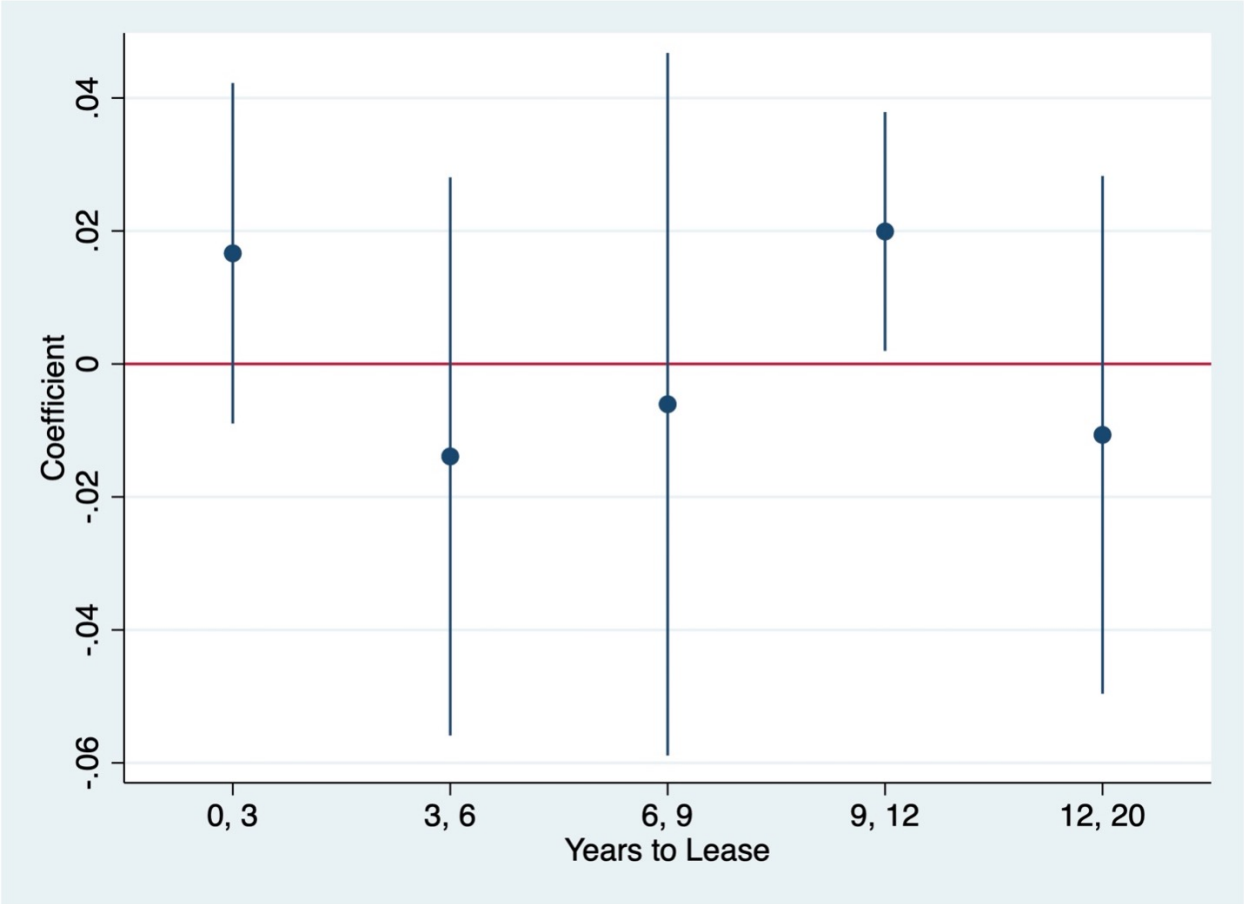

Figure A.2.3: Heterogenous effects over time, villages on LSLA, Outcome: Cough

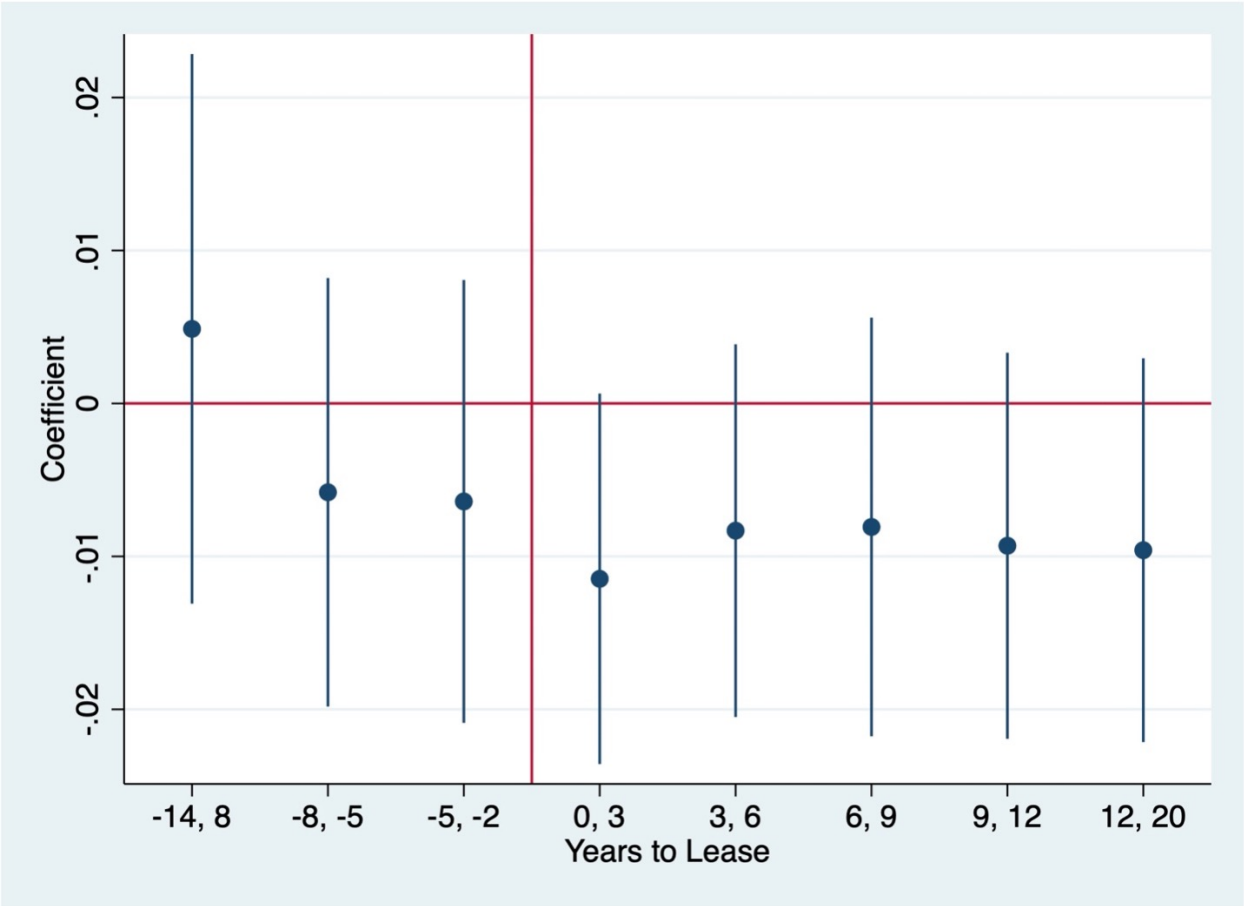

Figure A.2.4: Event Study, villages 0-5 km from LSLA, Outcome: Diarrhea

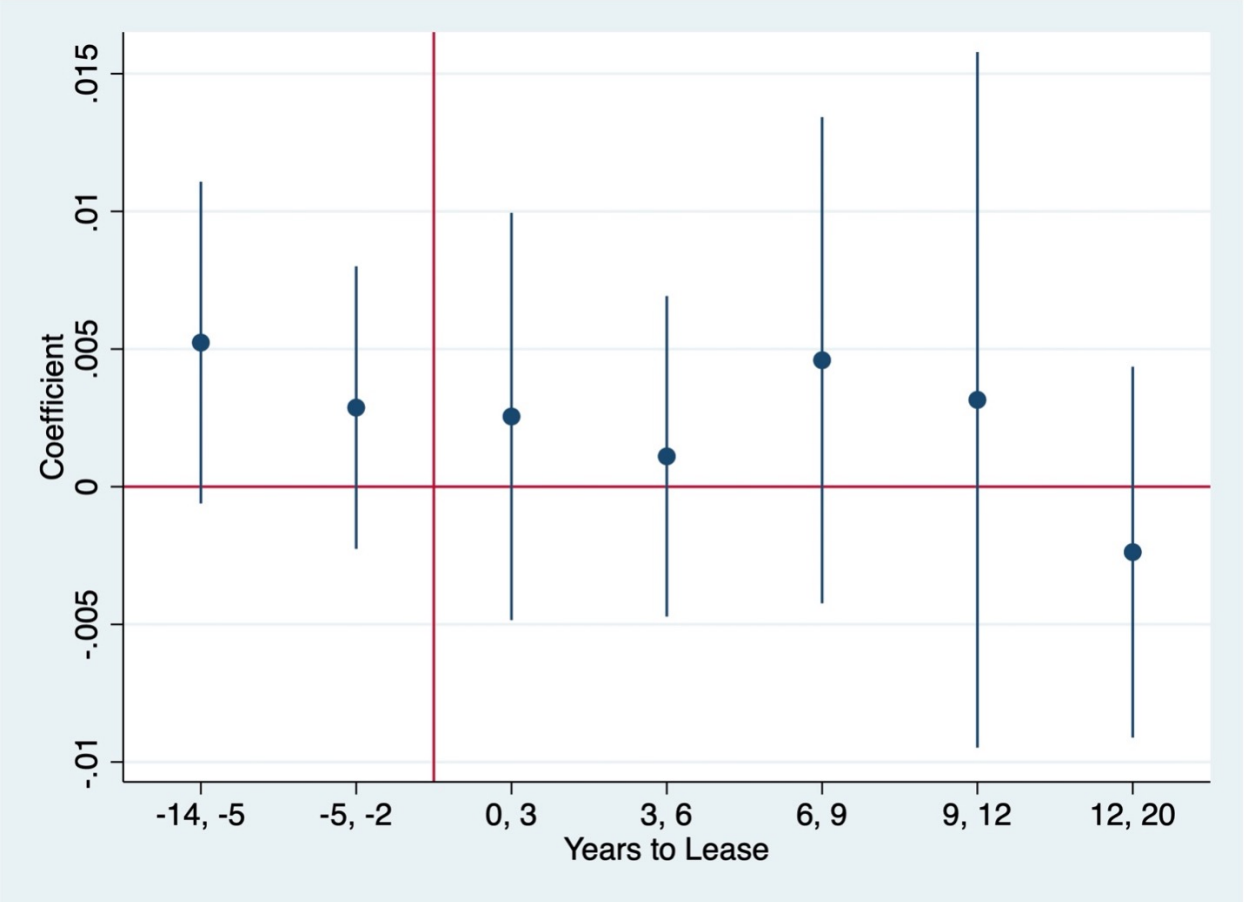

Figure A.2.5: Event Study, villages 5-10 km from LSLA, Outcome: Diarrhea

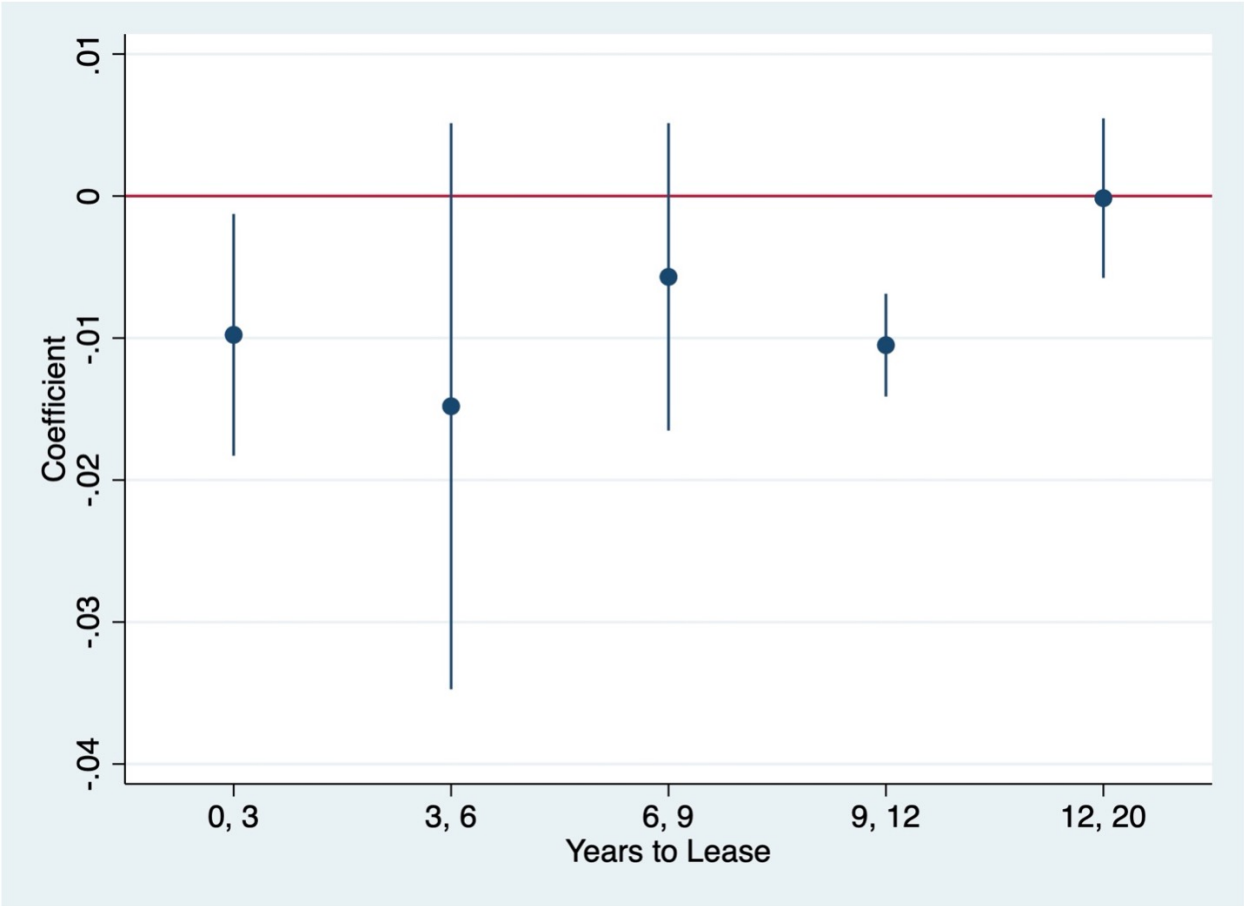

Figure A.2.6: Heterogenous Effects over Time, villages on LSLA, Outcome: Diarrhea

SECTION A.3: APPENDIX TABLES

Table A.1: CSES Summary Statistics

Variables	Obs.	Mean
Fever (Last 2 weeks)	145,067	0.037
Cough (Last 2 weeks)	145,067	0.055
Diarrhea (Last 2 weeks)	145,067	0.008
Lives within 20 km of LSLA	145,067	0.298
Age	145,067	26.52
Female	145,067	0.519
Education Level	145,067	4.006

Table A.2: Estimates of Equation (1) - Non Movers

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Fever	Fever	Cough	Cough	Diarrhea	Diarrhea
$LSLA_{c,[0]} \times After_{ct}$	-0.024	-0.027*	-0.017	-0.013	-0.026**	-0.025*
	(0.015)	(0.015)	(0.032)	(0.032)	(0.013)	(0.013)
$LSLA_{c,(0,5]} \times After_{ct}$	0.029***	0.028***	0.002	-0.004	-0.005	-0.005
	(0.011)	(0.010)	(0.019)	(0.019)	(0.004)	(0.004)
$LSLA_{c,(5,10]} \times After_{ct}$	0.017*	0.016*	-0.001	-0.008	-0.005	-0.005

	(0.009)	(0.009)	(0.024)	(0.023)	(0.003)	(0.003)
$LSLA_{c,(10,15]} \times After_{ct}$	-0.004	-0.003	-0.014	-0.026	-0.003	-0.004
	(0.010)	(0.010)	(0.026)	(0.024)	(0.004)	(0.004)
$LSLA_{c,(15,20]} \times After_{ct}$	-0.003	-0.004	-0.039*	-0.051**	-0.007*	-0.007*
	(0.013)	(0.013)	(0.022)	(0.020)	(0.004)	(0.004)
$LSLA_{c,(20,25]} \times After_{ct}$		0.020		-0.236***		-0.010
		(0.013)		(0.076)		(0.006)
$LSLA_{c,(25,30]} \times After_{ct}$		-0.013*		0.006		0.001
		(0.008)		(0.019)		(0.005)
Observations	75,680	75,680	75,680	75,680	75,680	75,680
R-squared	0.036	0.036	0.051	0.052	0.017	0.017

Robust standard errors clustered at the CSES village level in parentheses
All controls from equation (X) included, but coefficients are not shown
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Village-Level Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		Infrastructure Present			Worst Health Challenge for the Village							
VARIABLES	Ln(Pop)	Health Center	Drug Store	Private Clinic	Malaria		Dengue		Resp. Disease		Adult Malnutrition	
$LSLA_{c,[0]} \times After_{ct}$	0.683**	0.071	-0.020	-0.042	0.489**	0.245	-1.006***	-0.884***	-0.031	-0.067	-0.010	0.010
	(0.274)	(0.094)	(0.095)	(0.084)	(0.239)	(0.253)	(0.185)	(0.161)	(0.078)	(0.070)	(0.014)	(0.013)
$LSLA_{c,(0,5]} \times After_{ct}$	-0.066	0.021	0.000	0.039	0.195*	0.172**	-0.228**	-0.128	-0.086	-0.062	-0.010	-0.022
	(0.134)	(0.074)	(0.067)	(0.076)	(0.099)	(0.083)	(0.089)	(0.082)	(0.070)	(0.064)	(0.043)	(0.038)
$LSLA_{c,(5,10]} \times After_{ct}$	-0.087	0.020	0.023	-0.034	-0.037	-0.088	-0.039	0.003	0.035	0.032	0.022	0.009
	(0.134)	(0.061)	(0.054)	(0.069)	(0.099)	(0.086)	(0.104)	(0.079)	(0.064)	(0.055)	(0.024)	(0.021)
$LSLA_{c,(10,15]} \times After_{ct}$	0.048	0.080	0.064	0.083	0.005	-0.011	-0.056	0.001	0.110*	0.077	0.006	-0.018*
	(0.112)	(0.059)	(0.054)	(0.074)	(0.079)	(0.064)	(0.123)	(0.096)	(0.056)	(0.050)	(0.009)	(0.010)
$LSLA_{c,(15,20]} \times After_{ct}$	0.113	-0.041	0.044	0.167**	0.061	0.082	-0.173	-0.076	0.103*	0.102	0.034*	0.024*
	(0.118)	(0.092)	(0.063)	(0.066)	(0.091)	(0.065)	(0.121)	(0.105)	(0.060)	(0.074)	(0.019)	(0.013)
$LSLA_{c,(20,25]} \times After_{ct}$	0.195	0.230***	0.140	-0.034	-0.016	-0.142	0.049	0.139	0.020	0.092	-0.001	-0.010
	(0.308)	(0.050)	(0.100)	(0.145)	(0.356)	(0.376)	(0.326)	(0.335)	(0.033)	(0.083)	(0.008)	(0.014)
$LSLA_{c,(25,30]} \times After_{ct}$	-0.990*	-0.160	-0.147	-0.171	-0.032	0.034	-0.242	-0.221	0.018	-0.048	0.026	0.023
	(0.539)	(0.158)	(0.115)	(0.121)	(0.048)	(0.049)	(0.198)	(0.150)	(0.047)	(0.070)	(0.025)	(0.015)
Province-Month FE	No	No	No	No	No	Yes	No	Yes	No	Yes	No	Yes
District-Month FE	No	No	No	No	Yes	No	Yes	No	Yes	No	Yes	No
Observations	4,989	3,324	3,320	3,339	3,048	3,225	3,143	3,322	3,143	3,322	3,143	3,322
R-squared	0.583	0.225	0.397	0.336	0.658	0.551	0.462	0.311	0.376	0.236	0.245	0.165

Notes: Robust standard errors clustered at the district level in parentheses.
All regressions control for year-province fixed effects, district fixed effects, district linear time trends, and an indicator for rural location.
*** p<0.01, ** p<0.05, * p<0.1