Barcelona School of Economics

International Trade, Finance, and Development

“Fleeing the Floods: The Local Health Effects of Internally Displaced Malawians”

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ABSTRACT IN ENGLISH (100 words):

NATURAL DISASTERS TAKE LIVES, DESTROY HOMES, TRIGGER EPIDEMICS, AND AFFECT INDIVIDUAL HEALTH. REFUGEES FLEEING TO SAFETY OFTEN ARE CONFINED TO CAMPS AND MAKESHIFT SETTLEMENTS UNTIL THEY CAN RETURN HOME. AS THE CLIMATE CRISIS DEEPENS, CLIMATE REFUGEE FLOWS WILL SWELL IN FREQUENCY AND INTENSITY, ESCALATING PRE-EXISTING ECONOMIC TENSIONS BETWEEN LOCAL COMMUNITIES AND REFUGEES. A BETTER UNDERSTANDING OF THE RELATIONSHIP BETWEEN REFUGEES AND WHERE THEY FLEE IS NEEDED. THIS PAPER FINDS THAT THE PRESENCE OF AN INTERNALLY DISPLACED PERSONS (IDP) SITE CAN NEGATIVELY AFFECT THE PUBLIC HEALTH OF LOCAL COMMUNITIES IN MALAWI. SITES WITH POORER HYGIENE CONDITIONS ARE ASSOCIATED WITH MORE DRASTIC ADVERSE HEALTH EFFECTS. POLICYMAKERS, HUMANITARIAN ORGANIZATIONS, AND RELEVANT STAKEHOLDERS SHOULD PLACE GREATER EMPHASIS ON THE QUALITY OF HEALTH AND HYGIENE WHEN RESPONDING TO IDP FLOWS TRIGGERED BY NATURAL DISASTERS.

ABSTRACT IN SPANISH (100 words)

LOS DESASTRES NATURALES PUEDEN ACABAR CON VIDAS, DESTRUIR VIVIENDAS, PROVOCAR EPIDEMIAS Y AFECTAR SIGNIFICATIVAMENTE A LA SALUD. LOS INDIVIDUOS QUE HUYEN EN BUSCA DE SEGUIRIDAD SUELEN TENER QUE REFUGIARSE EN ASENTAMIENTOS IMPROVISADOS HASTA QUE PUEDAN REGRESAR NUEVAMENTE A SUS HOGARES. MIENTRAS NO SOLUCIONEMOS LA CRISIS CLIMÁTICA, ESTOS DESPLAZAMIENTOS SEGUIRÁN AUMENTANDO TANTO EN NÚMERO COMO EN INTENSIDAD, EMPEORANDO LAS TENSIONES YA EXISTENTES ENTRE LOS REFUGIADOS Y LAS COMUNIDADES RECEPTORAS. ESTE ARTÍCULO ESTUDIA EL EFECTO QUE PUEDEN CAUSAR LOS CAMPAMENTOS TEMPORALES EN LA SALUD DE LAS COMUNIDADES DE

ACOGIDA, ANALIZANDO EL CASO DEL CICLÓN QUE ARRASÓ EL SUR DE MALAWI EN 2019. LOS RESULTADOS OBTENIDOS SUGIEREN EFECTOS SANITARIOS ADVERSOS EN LAS ZONAS DONDE LOS CAMPAMENTOS PRESENTABAN PEORES CONDICIONES HIGÉNICAS. POR ELLO, NO SÓLO LA CANTIDAD DE AYUDAS DESTINADAS A DICHAS CAUSAS DEBE MEJORARSE, SI NO TAMBIÉN SU CALIDAD.

KEYWORDS IN ENGLISH (3)**: NATURAL DISASTERS, INTERNAL MIGRATION, HEALTH**

KEYWORDS IN CATALAN/ SPANISH (3)**: DESASTRES NATURALES, MIGRACION INTERNA, SALUD**

Barcelona School of Economics

Master's Thesis

Fleeing the Floods

The Local Health Effects of Internally Displaced Malawians

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Abstract

Natural disasters take lives, destroy homes, trigger epidemics, and affect individual health. Refugees fleeing to safety often are confined to camps and makeshift settlements until they can return home. As the climate crisis deepens, climate refugee flows will swell in frequency and intensity, escalating pre-existing economic tensions between local communities and refugees. A better understanding of the relationship between refugees and where they flee is needed. This paper finds that the presence of an Internally Displaced Persons (IDP) site can negatively affect the public health of local communities in Malawi. Sites with poorer hygiene conditions are associated with more drastic adverse health effects. Policymakers, humanitarian organizations, and relevant stakeholders should place greater emphasis on the quality of health and hygiene when responding to IDP flows triggered by natural disasters.

Keywords: Health, Natural Disasters, Internal Migration

Contents

1 Introduction

On March 4th, 2019, Cyclone Idai made landfall in Sub-Saharan Africa. In its aftermath, more than 1300 people died, over three million were ultimately affected, and total damages were about $2.2 billion. In Malawi, between 868,900 and 922,900 people were directly affected, half of them children. Around 86,900 people were displaced (UNESCO, 2021). These Internally Displaced Persons (IDP) reacted to the rising flood by making for high ground, where aid organizations and Malawi's government could then provide food and supplies. Often, these individuals made their way to areas that better weathered the storm, where facilities like community centers, schools, and churches were converted into shelters. Most of the displaced stayed close to home, expecting to return in less than three months once the flooding had subsided. In these shelters, lacking sufficient food, mosquito nets, hygiene products, and surrounded by stagnant water, health conditions were often abysmal.

Natural disasters like Cyclone Idai are increasingly a daily reality as hydrocarbons and other greenhouse gasses continue to drastically alter our planet's climate. The consequences are tragic: 38 million people were considered internally displaced last year, 24 million of which were by natural disasters. Sub-Saharan Africa alone had 27.2 million people living in IDP sites at the end of 2021, 3.1 million more people than 2020 (IDMC, 2022). Individuals and communities are differentially exposed to extreme weather events based on geography, but also in terms of wealth, education, and health. Gender, age, class, and other characteristics contribute greatly to the level of governmental and international response. High levels of vulnerability are often the outcome of economic development plans that cause environmental degradation, rapid and unplanned urbanization in hazardous areas, failures of governance, and inadequate livelihood options for the world's most vulnerable.

Understanding the interplay between the social and physical factors that cause natural disaster vulnerability is crucial to helping policymakers mitigate their consequences. Properly preparing for and responding to natural disasters includes considering that involuntary displacement does not simply disrupt the lives of the displaced by separating them from their families, social networks, livelihoods, and assets, but also affects host communities, governments, and the humanitarian sector. Countries that include natural disaster risk and climate change mitigation strategies in their development plans respond more effectively (Cavallo et al, 2021).

As the frequency and intensity of climate disasters increases, preventing the flow of migrant refugees entirely becomes even more unlikely to succeed. Many host governments insist on the establishment of

IDP sites managed by international refugee agencies that are relatively isolated from host communities to avoid overwhelming existing infrastructure around schools, housing, and health facilities. Politicians may prevent the integration of refugees with local communities in an effort to help stem the spread of disease, maintain public safety, control the movement of refugees, and ease tensions between refugees and local communities - but the effectiveness of this strategy is subject to debate. These policies may also be motivated by fears of economic competition with nationals for scarce jobs, water, and land. It may be the case that IDP sites have a negative impact on host communities through resource competition and conflict, but it may also be that greater economic integration between IDP sites and host communities boosts economic outcomes.

This study attempts to fill a void in the existing literature by analyzing the health effects of IDP sites on local communities. Using a difference-in-differences methodology, we find that IDP sites have a statistically significant negative effect on health outcomes of nearby communities, and increase local communities' health-related consumption. Additionally, considering only sites with particularly poor hygiene conditions exacerbates this negative effect. Policymakers, humanitarian organizations, and relevant stakeholders should enact policies that balance supporting vulnerable migrant refugee populations and host communities, in part, by placing greater emphasis on the quality of health and hygiene when supporting IDPs and establishing IDP sites.

Policies that effectively support vulnerable populations, including supplying the necessary health facilities, can have positive spillovers to host communities and function as a development process if implemented correctly. This analysis, studying the impact of proximity to IDP sites on health outcomes, provides valuable insight into what policymakers should focus on in considering natural disaster risk in their development plans. A better understanding of the effects that IDPs have on local communities allows for more effective steps to be taken in preparing for IDP inflows, increasing the probability of a virtuous integration process between local communities and IDP sites.

The remainder of the paper is organized as follows. Section 2 consists of our literature review. Section 3 introduces our data, which is followed by a discussion of our empirical strategy in Section 4. In Section 5, we present the results, analysis, and checks of our differences-in-differences and linear regression models. Section 6 finishes with remarks for economists and policymakers, as well as international and humanitarian aid organizations, regarding the economic and political implications of our findings.

2 Literature review

2.1 The Direct Effects of Natural Disasters

It is clear that natural disasters exact a severe toll in terms of loss of life and livelihood. But the economic costs of such disasters can be severe as well. Over the last thirty years or so, natural disasters have caused tens of billions of economic losses around the world, and are increasing in the severity of their effects (Botzen et al, 2019; Klomp, 2014). Natural disasters can trigger shocks to a country's capital stock by destroying agricultural equipment or factories. Transportation costs can rise precipitously as bridges get washed out and roads become inaccessible or undrivable. Having sufficient insurance to cover losses renders forgone output resulting from natural disasters inconsequential (von Peter et al, 2021). But too often, insurance is largely inaccessible in much of the developing world.

Natural disasters may destroy established, but outdated technology, providing opportunities for modernisation during post-disaster reconstruction, but only if financial flows to developing countries increase. Unfortunately, private flows following natural disasters can amplify the negative effects (David, 2010). And while remittance inflows and international assistance increase significantly in response to natural disaster shocks, aid flows do not (David, 2010) . Natural disasters contribute to financial crises, with dynamic and long-term effects (Chang, 2020).

2.2 Differences in Vulnerability to Natural Disasters

Natural disasters vary in impact among nations, regions, communities, and individuals due to the differences in exposures, sensitivity to risk and access to resources (Clark, 1998; Baez, 2011) . Developed and developing countries experience natural disasters differently. More than 60 percent of economic damages from natural disasters take place in high-income countries, while damages as a share of GDP are significantly greater in less-developed and small countries (Okuyama and Sahin, 2009; Ludwig et al, 2007; Skidmore and Toya, 2013; Sawada, 2006; Felbermayr and Groschl, 2013).

Unsurprisingly, catastrophic natural disasters negatively impact short-run economic growth, and are more pronounced for small and poorer countries (Cavallo et al, 2021). The higher the number of disaster victims, both in terms of number killed and number affected, the higher the levels of child poverty afterwards (Daoud, 2016).

Economic resilience depends on many factors including micro- and macroeconomic stability, social development and institutional capacity (Briguglio et al, 2009). Variation exists across households as well. Poor households are more vulnerable to natural shocks (Morrow and Peacock, 1997; Fothergill and Peek, 2004; Wisner et al, 2018). Households in areas with higher expenditure are more resilient to natural disasters (Arouri et al, 2015).

2.3 Health Effects of Natural Disaster Relocation

Relocation can affect health in many different ways. Relocated and unstably housed single mothers following Hurricane Katrina had significantly higher distress and perceived stress levels than those who had returned to their pre-disaster community (Fussell and Lowe, 2014). Relocation after an earthquake was associated with higher risk of depression, especially with delayed recovery (Najarian et al, 2001). Post-Traumatic Stress Disorder and Major Depressive Disorder incidence spiked after a 1999 flood in southern Mexico (Norris et al, 2004). Displacement following an earthquake in Taiwan was associated with persistently high depression scores amongst the elderly, but increased social support from family and neighbors as well as social participation decreased depressive symptoms (Watanabe et al, 2004). Extreme rainfall reduced citizens' aspirations, even when controlling for household expenditures, wealth, and education, although government policies counter-balanced the negative effects (Kosec and Mo, 2017). In countries with low levels of development, disaster risk plays a more negative role on well-being (Berlemann, 2016).

From a physical health standpoint, displacement due to natural disaster increases the odds of contracting a respiratory disease (Loebach and Korinek, 2019). Epidemics can result from climate-related migration (McMichael et al, 2006). The displaced may flee the effects of the natural disaster only to arrive in another unsafe area with high probabilities of disease transmission or succumbing to mental health issues. Flooding or damage to infrastructure may restrict access to medical care, medication, and other supplies, prolonging injury and illness, exacerbating death rates.

2.4 Economic Effects of IDP Sites on Local Communities

In the long-term, IDP sites can boost the economic activity of the host population by increasing consumption (Alix-Garcia et al, 2018). People who live close to a refugee camp have higher consumption, and are more likely to become engaged in wage employment, representing a shift away from farming

(Loschmann et al, 2019). Welfare is persistently higher in communities with a refugee presence (Maystadt and Duranton, 2019). A natural experiment exploiting forced migration found that greater exposure to refugee shocks resulted in a lower likelihood of working outside the house as employees, and a higher probability of being in professional occupations and having a pension (Ruiz and Vargas-Silver, 2016). However, agricultural workers in host communities can suffer from fiercer competition in labor markets, and face increased prices in the goods market. That being said, new access to a cheap labor force improved self-employed farmers' welfare (Maystadt and Verwimp, 2014).

2.5 Our Contribution: Health Effects of IDP Sites on Local Communities

Little empirical evidence exists measuring the health impacts of refugee camps on local populations. Interviews with 30 Eritrean refugees and 30 host community members found social and health threats to members of the host community Gebrehiwet et al, 2020). Tanzanians who were children when a nearby refugee camp was set up experienced negative health effects that persisted into adulthood, and even had negative spillovers to the next generation (Nsababera, 2020). Javier Baez found that refugees fleeing genocide in Burundi and Rwanda had an adverse effect on the well-being of children and subsequent economic growth in refugee-hosting communities (Baez, 2011). Yet, in Kenya, increased access to cereals resulting from refugee trade networks and employment may have contributed to increased host community energetic status indicators (Gengo et al, 2018).

This paper unites the disaster vulnerability and population health literature with insights from the environmental migration literature to empirically test the health effects on local communities of having an IDP site in close proximity.

3 Data

The World Bank's Integrated Household Survey (IHS) is a routine, comprehensive questionnaire providing cross-sectional data at both the household and individual level in 2010, 2016, and 2020. These data include health-related outcomes and spending behavior of respondent households, as well as a host of other variables such as consumption habits, geovariables, and subjective measures of wellbeing.

To track temporary refugee sites that were established following Cyclone Idai, we used the United Nations' International Organization for Migration's (IOM) Malawi Displacement Data between March and April of 2019 in the four districts hardest affected: Chikwawa, Nsanje, Phalombe and Zomba districts. The data set contains the number of IDPs, households and their needs at the sub-national level. It also provides specific information about numerous variables of interest such as site type, size, accessibility and hygiene level.

3.1 IHS

Data on local communities comes from the World Bank's IHS implemented by the Government of Malawi to monitor and evaluate the changing conditions of Malawian households. There have been five rounds of the IHS, roughly every 5 years, in line with the Malawian National Statistical Office's vision of collecting poverty data more frequently.

We do not use the first and second rounds of the IHS, as these were conducted in 1997 and 2004, respectively. Given the cyclone occurred in 2019, these are not relevant to our analysis. The Third Integrated Household Survey (IHS3) was carried out between March 2010 and March 2011, while IHS4 was implemented between April 2016 and April 2017. IHS5, the most recent survey, was conducted between April 2019 and April 2020, after Cyclone Idai. We carry out our analysis at the household level, but these data do include information at the individual level, providing space for future, more granular studies.

3.2 Site Assessment Data

The United Nations' IOM helps develop effective responses to shifting migration-related dynamics and provides advice to partners. It publishes migration-related data, including assessments of refugee sites. Our Site Assessment Data contain three rounds of questionnaires from March and April of 2019, in the immediate aftermath of Cyclone Idai, and provide information on specific site characteristics such as access to basic necessities like water or bathing facilities, as well as information about IDP groups in sites. The data also include the latitude and longitude of sites.

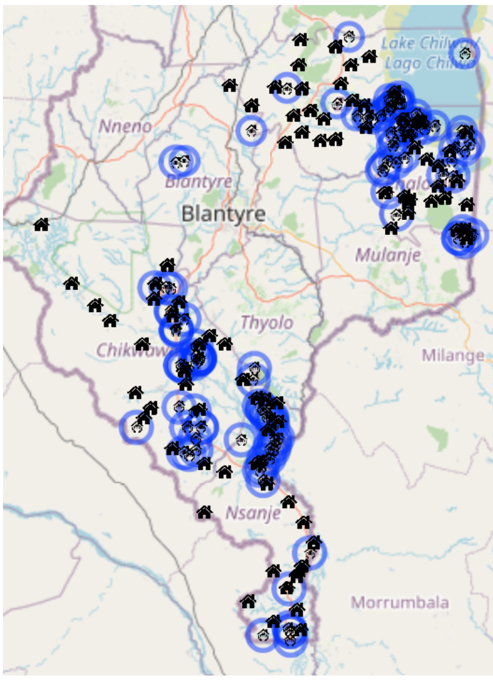
In the first round, conducted at the end of March 2019, 76,471 individuals (17,254 households) were reported across 63 assessed displacement sites. The second round, conducted in the first week of April, includes 110,110 individuals (24,887 households) across 103 displacement sites. An additional 40 sites in the 4 districts were assessed and verified in this data collection round. There is some overlap between rounds, but there are 112 unique sites across the three surveys. The third round of questions, conducted in the third week of April 2019, reflects the gradual decline in sites as individuals begin to return home. This is further reflected in the kinds of questions asked in this survey: instead of site characteristics, questions ask about IDPs' preferences for returning home.

3.3 Treatment

We set as our "treatment" the establishment of an IDP site within a 5km radius of a household. Thus, using the information available for the location of both households and IDP sites, we define our treated group as the households which fall within the aforementioned 5km radius. Our control group is made up of all households which fall outside them. Under this main definition of the treatment, the treatment sample size is 1,288 households. The control group is made up of 1,548 households. The radius aims to represent the area potentially affected due to the establishment of an IDP site after the cyclone.

Accounting for the possibility that the magnitude of the effects caused by the presence of temporary camps in local communities depends not only on the location of the site, but also on other factors such as the site's size and accessibility, we also conduct analyses which redefine the treatment based on these characteristics. For example, only considering households to be treated if they fall within the radius of a site with accessibility restrictions.

Figure 1: Site Radii (Blue) and Households in Southern Malawi



3.4 Variables

To study the effect that the establishment of IDP sites have on local communities' health levels, we analyze five health outcomes: health consumption, outpatient consumption, spending on illnesses, illness incidence, and hospitalization.

Health consumption:. Continuous variable reporting the household's average annual consumption of health-related goods and/or services, measured in Malawian kwachas.

Outpatient consumption: Continuous variable reporting households' average annual consumption of outpatient medical care, measured in kwachas.

Spending on illnesses: Continuous variable accounting for the amount spent on illnesses by a household in the four weeks prior to being surveyed, also reported in kwachas.

Illnesses: Binary variable reporting whether at least one member of the household suffered one or more transmissible diseases – including cholera, malaria, or tuberculosis – in the last two weeks. Injuries such as fractures or wounds among the local community are excluded from our dataset as they are not considered a plausible effect of the establishment of IDP sites.

Hospitalization: Binary variable taking a value of 1 if at least one member of the household has been hospitalized in the last 12 months and zero otherwise. The 12-month time frame includes hospitalizations before the cyclone, so we can only interpret results related to this outcome as suggestive evidence.

Table 1: Means of Outcome Variables

Treated	0		1		
Variable	Mean	Sd	Mean	Sd	Test
Illness Incidence	0.6	0.483	0.7	0.464	F= 5.055**
Spending on Illnesses	296.9	1334.687	624.1	2834.374	F= 7.794***
Health Consumption	11316.5	25399.279	14978.5	31862.08	F= 5.505**
Outpatient Consumption	4826	19865.563	7688.6	26466.944	F= 5.133**
Hospitalization	0	0.217	0	0.2	F= 0.476

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

4 Empirical Strategy

Our initial model utilizes a simple linear regression on both the treated and control groups in IHS5, using the distance between households and their nearest site to measure the effect on local communities' health outcomes. This approach only takes into account the potential effect of the most proximate site, rather than any compounding effects resulting from lying near multiple sites. In order to address this limitation, we examine another linear regression model which uses the number of 5km radii a household is inside of as the explanatory variable. Doing so, we can capture the marginal effect of lying inside one additional site radius.

The next model employs a difference-in-differences approach which also uses 5km site radii to identify treated households. All households located within a radius are considered the treated group, whereas the control group consists of households which fail to fall within any radius. The radius represents the area potentially affected by an IDP site. In other words, our treatment is whether there is a site within 5km of a household.

The main assumption in difference-in-differences models is that of parallel trends between treated and control groups. In the absence of Cyclone Idai –and therefore, the sites' establishment– the difference in health outcomes between the treated and control groups would have been constant. Without this parallel trend assumption, we would not be able to assume that treated households post-cyclone would have followed a similar trend to the control group, invalidating a difference-in-differences approach. We also need to construct a baseline for the pre-cyclone period. Given that our data is a repeated cross-section, considering the same households before and after the cyclone is infeasible. Instead, we use data from IHS4, setting the pre-cyclone treatment and control groups conditional on whether they fall within a "future" site radius.

Upon initial inspection of the data, urban and rural households display significant wealth disparity. This is likely to have resulted in considerable differences in household responses to Cyclone Idai and the presence of IDP sites. In addition, most of Southern Malawi engages in small-scale agricultural work in rural Malawi. We therefore restricted our sample to only rural respondents.

The post-treated and post-control groups are the households surveyed in IHS5, while the pre-treated and pre-control groups are households surveyed prior to the cyclone in IHS4.

Our main specification is:

$$Y_i = \alpha + \beta_1 Treatment_i + \beta_2 Post_i + \beta_3 (Treatment_i \times Post_i) + \gamma X_i + \epsilon_i \tag{1}$$

where Y_i denotes the health outcome of interest. *Treatment* is a dummy variable equal to one if a household is in a treatment area, and zero if in the control group. *Post* is a time dummy variable equal to one for the household i surveyed in the fifth round of the IHS and equal to zero otherwise. X is a vector of control variables, which can be divided into two categories: Location and Household. Household-level variables include size and annual consumption (the use of further household-level controls did not systematically change the results). The location variables – temperature, precipitation level and floods - allow us to account for differences in location-specific characteristics when interpreting the effect of IDP site proximity. ϵ_i represents the error term.

4.1 Balance in Covariates and Pre-trends

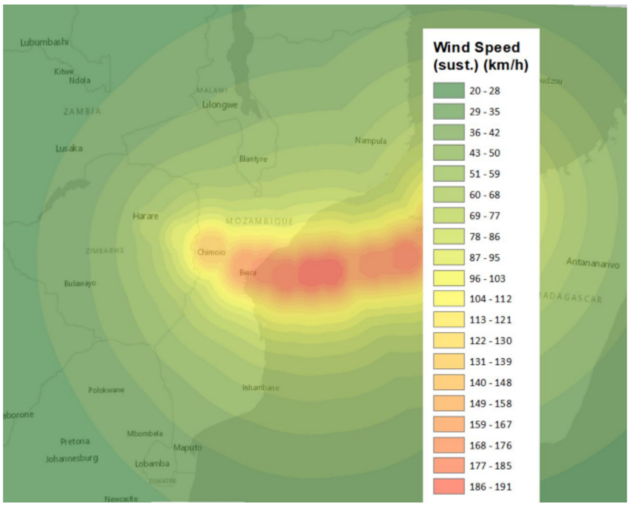
To confirm that households within a site radius prior to the establishment of the site are similar to households outside a site radius, we examine the balance in covariates (see Table 4 in Appendix 8.1). There are no significant differences in total consumption or household size between the treated and control groups in the baseline period. There *are* significant differences in temperature, precipitation, and flood incidence, but it is unlikely that they would systematically affect our outcomes of interest. Temperature, for instance, is only 1º Celsius hotter in treated areas than control ones. The flooding results could be a concern given the prevalence of water-borne diseases in Malawi, but again, the difference is small, less than 3%.

As a further check, a quick visual inspection of trends in the outcome variables of interest for both treatment and control groups is made in Figures 3-7 (Appendix 8.1). Trends do not seem to vary significantly between the two groups for any of the outcome variables.

4.2 Exogenous Site Placement

One potential concern could be that the presence of a site is correlated with greater cyclone intensity, and thus that our treatment is instead picking up the effects of the cyclone rather than that of the sites themselves. Figure 2, from the Center for Disaster Management (CEDIM) Disaster

Figure 2: Cyclone Idai wind speeds



Source: CEDIM Forensic Disaster Analysis "Tropical Storm Idai"

Analysis Group, provides estimated wind speeds for Cyclone Idai (Muhr et al, 2019). The relative consistency in cyclone intensity across Southern Malawi provides some suggestive evidence that the cyclone hit treatment and control households similarly, implying that our model is indeed measuring the effect of IDP sites.

Another potential issue is the nonrandom placement of IDP sites. Representatives from the Malawi Department of Disaster Management (DoDMA) confirm that displaced people tended to flee to elevated positions safe from the flooding, where some provisions were then provided. It seems likely that sites were placed independent of variables besides elevation. Elevated areas should be more likely to contain an IDP Site, but that should have little impact on health outcomes. However, surprisingly, a linear probability model (Table 18, Appendix 8.5) predicting site placement based on household data finds a higher average elevation *reduces* the probability of the establishment of a site. This could be explained by average elevation reducing the impact of flooding, thereby reducing the need for IDP sites. Probit and lasso regressions also included in Appendix 8.5 bolster the linear probability model.

5 Results

The results of the simple linear regression estimation and its extension are described first. Then, the findings of our difference-in-differences analysis are presented. We expand our study to include a heterogeneity analysis, which accounts for differences in effects with regards to both household- and site-specific characteristics.

5.1 Linear regression estimation

The results of our minimum distance linear model for spending on illnesses and outpatient consumption are statistically significant at a 10% level, and are shown in Table 2. Both spending on illnesses and outpatient consumption are negatively correlated with distance to the nearest site. The results obtained indicate that the further a household is from a refugee site, the lower its expenditure on illnesses. Looking at a household's outpatient consumption, being one additional meter away from a site decreases the household's average outpatient consumption by 0.167 local currency units, Malawian kwachas (thus, an additional kilometer decreases outpatient consumption by 167 kwachas).

Table 2: Distance to Site - Linear Regression Results

	Dependent variable:	
	Spending on Illnesses	Outpatient Consumption
	(1)	(2)
Distance	-0.017^{*}	-0.167^{*}
	(0.009)	(0.097)
Annual Mean Temp	-1.412	-18.012
	(5.785)	(61.511)
Annual Mean Precip	-0.126	-3.014
	(0.355)	(3.776)
Floods	21.033	-443.390
	(128.355)	(1,364.745)
Real Annual Consump	0.0004^{***}	0.007^{***}
	(0.0001)	(0.001)
HH Size	73.116^{**}	$1{,}113.529^{***}$
	(31.112)	(330.805)
Constant	362.393	4,754.095
	(1,749.278)	(18,599.310)
Observations	1,346	1,346
R^2	0.025	0.050
Adjusted R^2	0.021	0.045
Residual Std. Error (df = 1339)	2,120.582	22,547.220
F Statistic (df = 6; 1339)	5.693^{***}	11.676^{***}

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

To account for the possibility of a household being located near more than one site, a second linear regression with the number of sites a given household falls into is presented. The previous outcome variables, along with health consumption, remain statistically significant. As shown in Table 5 (Appendix 8.2), average household expenditure on illnesses increases by almost 57 kwachas when a household lies within one additional site radius. Similar results are obtained for the other two health variables, with results significant at the 1% level. Lying in an extra radius increases household health consumption by 1,025 units. Likewise, an additional radius increases outpatient consumption by 867 units.

5.2 Difference-in-differences analysis

We find significant results for IDP site establishment on hospitalization, recent illnesses, and health expenditure. Table 3 shows the results of our main diff-in-diff model with controls included.

Table 3: Differences-in-Differences Results

	Dependent variable:		
	Hospitalization	Illness	Spending on Illnesses
	(1)	(2)	(3)
Post	-0.060^{**}	-0.142^{***}	-292.859^{**}
	(0.030)	(0.027)	(114.741)
Treated	-0.103^{***}	-0.013	170.289
	(0.028)	(0.024)	(105.129)
Diff-in-Diff	0.076^{*}	0.068^{**}	262.231^{*}
	(0.039)	(0.034)	(147.579)
Annual Mean Temp	0.002^{*}	0.0002	-9.061^{**}
	(0.001)	(0.001)	(3.768)
Annual Mean Precip	0.0002^{***}	-0.0001	-0.622^{***}
	(0.0001)	(0.0001)	(0.219)
Floods	-0.026	0.035	101.660
	(0.026)	(0.023)	(97.212)
Real Annual Consump	-0.000	0.00000^{**}	0.001^{***}
	(0.00000)	(0.00000)	(0.0001)
HH Size	0.001	0.037^{***}	26.292
	(0.005)	(0.004)	(19.049)
Constant	-0.537^{*}	0.571^{**}	$2{,}699.310^{**}$
	(0.292)	(0.258)	(1,110.402)
Observations	2,836	2,833	2,835
R^2	0.011	0.046	0.036
Adjusted R^2	0.008	0.043	0.033
Residual Std. Error	0.511 (df = 2827)	0.451 (df = 2824)	1,941.049 (df = 2826)
F Statistic	3.774^{***} (df = 8; 2827)	17.072^{***} (df = 8; 2824)	13.085^{***} (df = 8; 2826)

*p<0.1; **p<0.05; ***p<0.01

The "Diff-in-Diff" coefficient captures the effect the presence of a site has on households.

Both hospitalization and expenditure on illnesses have statistically significant results at the 10%

level. The presence of a household within 5km of a site increases the likelihood that a member of the household was hospitalized in the last year by 7.6% compared to the control group. Spending on illnesses is 262 Malawian kwachas higher among treated households than the control group. Likewise, the likelihood of a household reporting an illness in the last four weeks is higher in the treated group compared to the control group. The increased incidence of illnesses and hospitalization among the treated group, paired with greater spending on health, suggests that households near IDP sites had greater exposure to health-related issues.

5.3 Heterogeneity Analysis

To explore potential heterogeneities in the effects of IDP sites on nearby communities, we first consider heterogeneities with regards to household-specific characteristics. To do so, we implement a triple difference-in-differences approach, incorporating additional interaction terms including household-level variables such as ownership of a non-agricultural business according to the following model:

$$\begin{aligned} DV_i = &\alpha + \beta_1 Post_i + \beta_2 Treated_i + \beta_3 (Post_i \times Treated_i) + \beta_4 (NonAgriBusiness_i) \\ &+ \beta_5 (NonAgriBusiness_i \times Post_i) + \beta_6 (NonAgriBusiness_i \times Treated_i) \\ &+ \beta_7 (NonAgriBusiness_i \times Post_i \times Treated_i) + \gamma X_i + \epsilon_i \end{aligned} \tag{2}$$

Here, β_7 is the triple difference-in-differences coefficient we are interested in. We carried out this analysis for a range of household characteristics, including ownership of a non-agricultural business, household size, religion, and distances to roads and population centers. Ownership of a non-agricultural business (see Table 6, Appendix 8.3) returned the most consistently significant results. The triple difference-in-differences coefficients are all positive, indicating that treated households owning a non-agricultural business had greater spending on illnesses, health consumption, and outpatient consumption compared to treated households without a non-agricultural business. For example, treated business-owning households spent, on average, approximately 2,683 kwachas more on illnesses than non-business-owning households.

All significant triple difference-in-differences coefficient outcomes are spending or consumption-related. One likely explanation is that households owning a non-agricultural business tend to be wealthier than households that do not. If non-agriculture owning households need to increase their spending on health-related activities, they may be unable to do so because of budget constraints. Households that do own such businesses, meanwhile, have enough extra income to justify increased spending in the face of adverse disease environments potentially brought about by proximity to IDP sites.

There are also significant results for religion, household size, and distance from a population center, found in Appendix 10.3. They suggest that treated Christian households tend to have higher illness incidence than Muslim ones, households of greater size tend to spend more on illnesses, and those further away from population centers also spend more on illnesses. Potential explanations include Christian households being poorer than Muslim ones, larger households being more likely to contract disease by simple probability, and more remote households perhaps having to spend more on illness out-of-pocket as opposed to receiving free or subsidized healthcare which may be available at an urban center.

By redefining our treatment variable to depend on IDP site health-related conditions, we shift focus to heterogeneities in site-specific characteristics. The difference-in-differences coefficient after restricting the sample of IDP sites to those with a distance of more than 30 minutes from a health facility yielded a positive effect on illness incidence. This suggests that the new treated households, those in a radius but located far away from health facilities, saw an average increase in the likelihood of contracting an illness of almost 9.1% compared to control households. Control households now include those not in a site radius and those within a site radius, but within 30 minutes of a health facility. This difference-in-differences coefficient is greater than the original model's coefficient (6.8%), suggesting IDP sites located further from a health facility had a stronger illness effect on treated households than did those near a health facility.

Similar results are found when considering sites without access to soap or with less than adequate bathing facilities. These yielded coefficients showing an increase in the probability of contracting an illness of 6.5% and 8.3%, respectively. The latter is larger than the original difference-in-differences coefficient, signaling stronger effects on treated households. These results suggest that sites with particularly bad hygiene conditions tended to have stronger effects on selected health-related outcomes of interest.

5.4 Robustness Checks

Given that covariates such as annual mean temperature and precipitation possess some explanatory power in the models used to predict site location, we use a placebo test approach as a check for whether treated areas are inherently different from control areas in affecting health-related outcomes. This approach "pretends" that the IDP site shock occurred between 2010 and 2016, thus taking 2010 as the pre-treatment year and 2016 as the post-treatment year. We then run the same difference-in-differences used in our main specification, and observe that none of the difference-in-differences coefficients are significant. Placebo test results for illness incidence and spending on illnesses are shown in Table 11 (Appendix 8.4). Results for the remaining relevant outcome variables can be found in Table 12.

Another potential concern is that the selection of a 5km radius is, to some extent, arbitrary. The use of 5km radii for the main analysis was based unscientifically on a visual inspection of maps constructed using the household and IDP site data, which seemed to suggest that using a radius greater than 5km would result in excessive overlap and shrink the size of the control group excessively. Using a smaller radius, meanwhile, posed the risk of shrinking the treatment group too much and having to discard IDP sites due to lack of sample households falling close to them. A radius of 5km seemed appropriate in terms of containing a small number of villages which appeared communicable and relatively easy to move between. Even in the absence of functioning roads, 5km is not an unreasonable distance to walk. With poor road access and self-sustaining agriculture being the main economic activity, villages in such an area may be less likely to interact with each other, making a larger radius problematic. Varying the radius size to see how the results of our analysis change is instructive in better understanding how disease transmission from IDP sites to local communities happens.

We attempted the same analysis with 3km, 4km, 6km, 7km, and 10km radii. We would expect to see stronger effects for smaller radii that include only households closest to the IDP sites, and observe these effects decreasing as the radius expands and households further from IDP sites are added in. However, we actually observe a non-linear pattern in the magnitudes of the difference-in-differences coefficients. For the smallest radii, magnitudes are small. They then increase and peak at 5km and 6km, before dropping off again. One interpretation is that our choice of a 5km radius may be justified. Five kilometers is small enough to capture IDP site effects, but large enough to include several households per radius while maintaining treatment and control groups of relatively equal sizes. An issue with smaller radii is that there may only be a few treated households, and so the smaller magnitudes may simply be a result of probability. If only five treated households are being considered, then, despite the presence of IDP sites, perhaps only one or two households are affected. Once the radius is expanded to consider more treated households, the sample becomes more representative and numbers of affected households may go up. Beyond 6km, distances may become too difficult to traverse for sustained interaction between IDP sites and households, resulting in effects fizzling out.

Indeed, looking at the distance to a major road for each household, on average, households are 10.68 kilometers from a major road. The median household's distance to a major road is 6.3 kilometers. These results, combined with findings from the World Bank's 2017 Malawi Poverty Assessment that 80 percent of rural agricultural households were engaged only in crop or crop and livestock activities, suggest that the degree of geographic isolation in rural Malawi is large. This level of geographic isolation may help explain why the effects of an IDP site seem to drop off so precipitously with a radius larger than 6 kilometers.

5.5 Limitations

The potential limitations this study faces must be acknowledged. The main concern comes from the time frame between the data used for the pre- and post-treatment groups. Given that Cyclone Idai occurred in March 2019, and that the IDP sites were established a few days/weeks after that, we are aware that comparing the average values of household-level variables from the IHS4 (2016/2017) with the ones computed from IHS5 (2019/2020) could slightly bias the results due to the extended time period being studied. The concern is that a separate shock may have occurred during this time which could in part be driving the results. That said, given how we have defined our treatment (5km radii around IDP sites), the likelihood of a shock systematically affecting treated households more or less than control ones is low. The ideal setup when using a difference-in-differences approach in our case would be to take the values for the pre-treatment groups right before Cyclone Idai. Due to availability constraints, the most recent data before the shock was the information collected by the IHS4 between 2016 and 2017, and that is the reason why it is used in our study.

Another possible limitation, which further study may want to expand on, is the fact that certain health-related variables we analyze are aggregated for simplicity. When measuring illness incidence, we selected the illnesses and injuries reported by the households which we considered might feasibly be affected by proximity to IDP sites. In particular, we focused on those of a transmissible nature. However, we do not distinguish between specific illnesses/injuries as we incorporate them into our regressions through a dummy variable. Future research may seek to use more fine-grained data in order to account for the incidence of different diseases, such as cholera and tuberculosis. This could be of great benefit to Malawi's public health authorities in preventing outbreaks of said diseases, given that these are among the deadliest in the region.

Lastly, as Cyclone Idai is such a recent event, we are not able to measure the possible medium- and long-term effects of IDP sites on local communities, so we limit our study to its short-term impact. Further research may look to examine these longer-term effects as data becomes available, providing policymakers with valuable insights.

6 Conclusion

At a glance, our results suggest that IDP sites have a negative effect on different health related outcomes in nearby communities. Hospitalization and health expenditures go up in the presence of a site. Illnesses increase in the treated group. This negative effect on households' health outcomes decreases as the distance to sites increases.

On their own, these results could pressure policymakers in local communities to pursue policies that keep refugees isolated from local communities. However, our results incorporating measures of site hygiene quality indicate that better health characteristics, such as decreased proximity to health centers or access to improved bathing facilities, reduce the negative effects that refugee settlements have on surrounding communities. These reduced negative effects could potentially be offset by the benefits of greater economic integration between refugee camps and the local economy. As discussed in our literature review, research has found that can have positive economic effects on host communities through boosting local consumption, fostering transitions away from agriculture, increasing welfare, and improving farmer's welfare through access to cheap labor.

Additionally, our results show that the incidence of illnesses in local communities within the radius of a settlement increased the further the IDP site was from a health facility. Increased incorporation of refugees raises the possibility of positive spillovers for local communities. For example, health services in isolated refugee settlements only serve refugees, whereas health services that are equally accessible to refugees and the local population serve both. These health services can persist for local communities once refugees return home if the initial investment in infrastructure or training of locals is sufficient. The possibility that refugees remain in the local community, instead of returning home, can trigger a virtuous growth cycle by expanding demand for local goods and services, and contributing to output. But this virtuous cycle only exists if there is integration with the local community.

We are already feeling the effects of our changing climate. As these changes continue to throw our planet's delicate balance off, increasingly worse natural disasters will result in growing numbers of refugees searching for safety. Preventing their flow won't be possible, as politicians in the United States, Europe, and around the world have consistently seen on grander scales. Rather than resort to knee-jerk policy which isolates refugees, policymakers should focus on implementing an inclusive response plan which contributes resources to health and hygiene measures for refugees. This approach may help mitigate the negative health effects of emergency refugee flows, and can potentially pave the way for greater levels of economic integration with local communities.

7 References

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8 Appendices

8.1 Pre-trends

Table 4: Balance in Covariates

Treated	0		1		
Variable	Mean	Sd	Mean	Sd	Test
Temperature	23.469	1.851	24.154	1.842	F= 63.485***
Precipitation	1167.436	310.989	1137.611	318.234	F= 4.15**
Floods	0.073	0.26	0.11	0.313	F= 7.787***
Total Consumption	330050.537	352680.116	330221.375	377737.668	F= 0
HH Size	4.439	2.107	4.451	2.219	F= 0.016

Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01

Figure 2: Parallel Trends - Hospitalization Incidence

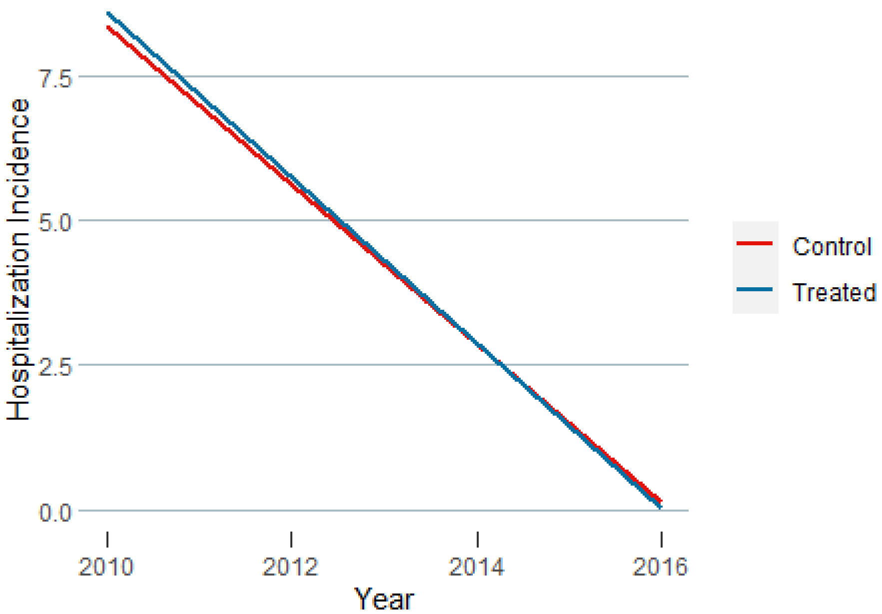


Figure 3: Parallel Trends - Illness Incidence

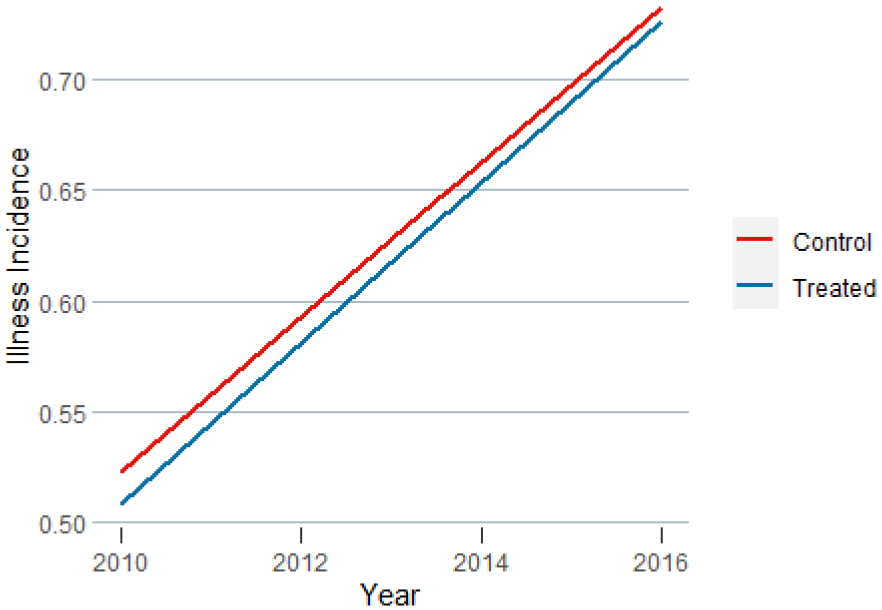


Figure 4: Parallel Trends - Spending on Illnesses

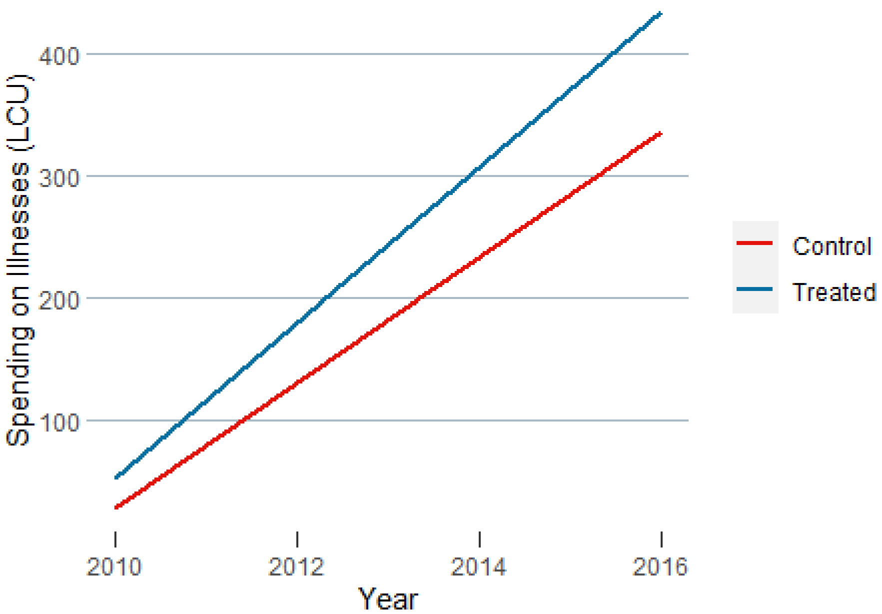


Figure 5: Parallel Trends - Health Consumption

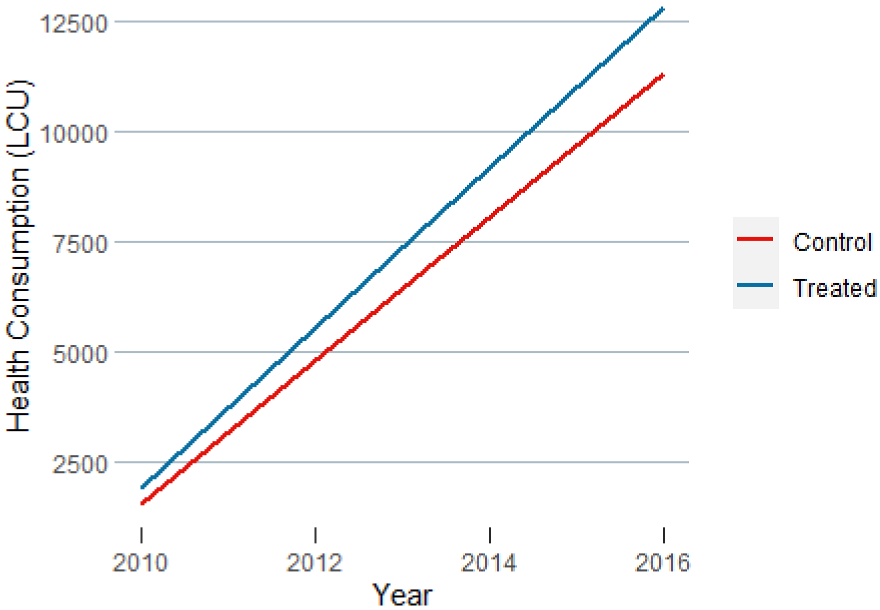
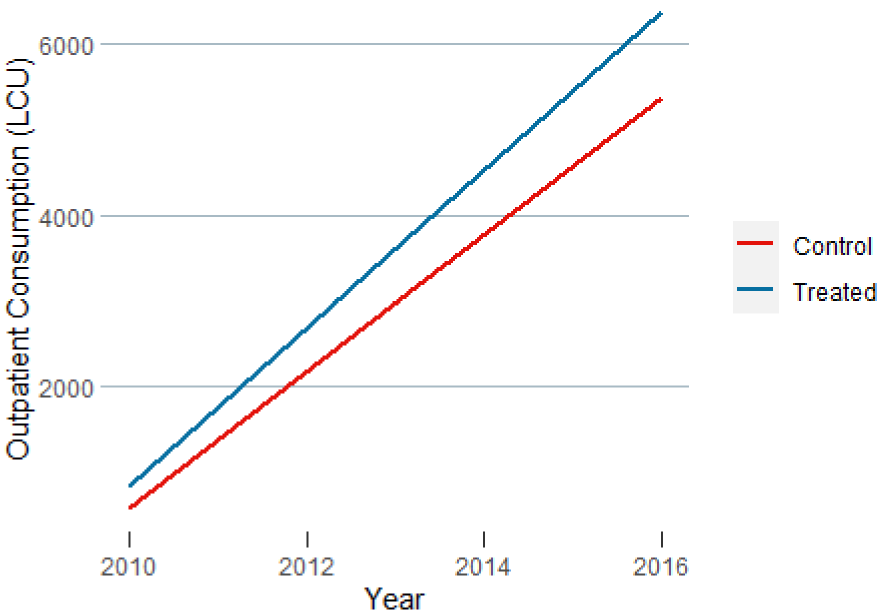


Figure 6: Parallel Trends - Outpatient Consumption



8.2 Linear Regression Results

Table 5: Continuous Treatment (Number of Site Radiuses) - Linear Regression Results

	Dependent variable:		
	Spending on Illnesses	Health consumption	Outpatient Consumption
	(1)	(2)	(3)
Continuous Treatment	56.835*	1,025.679***	867.404***
	(30.384)	(391.152)	(322.548)
Annual Mean Temp	−0.996	16.431	−28.921
	(5.721)	(73.651)	(60.734)
Annual Mean Precip	−0.050	−2.633	−3.201
	(0.342)	(4.401)	(3.629)
Floods	−6.036	328.073	−907.744
	(129.726)	(1,670.042)	(1,377.135)
Real Annual Consump	0.0005***	0.011***	0.007***
	(0.0001)	(0.002)	(0.001)
HH Size	70.799**	2,000.353***	1,092.553***
	(31.080)	(400.115)	(329.939)
Constant	−11.448	−7,331.624	5,467.899
	(1,686.396)	(21,710.060)	(17,902.350)
Observations	1,346	1,346	1,346
R^2	0.025	0.087	0.053
Adjusted R^2	0.021	0.083	0.049
Residual Std. Error (df = 1339)	2,120.549	27,299.180	22,511.210
F Statistic (df = 6; 1339)	5.700***	21.311***	12.428***

*p<0.1; **p<0.05; ***p<0.01

8.3 Heterogeneity Results

Table 6: Heterogeneity Analysis - Re-defining Treatment by Site Conditions

	Dependent variable:		
	Illness		
	(1)	(2)	(3)
Post	−0.162***	−0.156***	−0.155***
	(0.027)	(0.027)	(0.026)
Distance Treated	−0.018		
	(0.029)		
Distance Diff-in-Diff	0.091**		
	(0.039)		
Soap Treated		−0.008	
		(0.028)	
Soap Diff-in-Diff		0.065*	
		(0.038)	
Bathing Treated			−0.031
			(0.028)
Bathing Diff-in-Diff			0.083**
			(0.041)
Annual Mean Temp	0.0002	0.0002	0.0005
	(0.001)	(0.001)	(0.001)
Annual Mean Precip	−0.00004	−0.00004	−0.00003
	(0.0001)	(0.0001)	(0.0001)
Floods	0.038	0.039	0.041*
	(0.025)	(0.025)	(0.024)
Real Annual Consump	0.00000***	0.00000***	0.00000***
	(0.00000)	(0.00000)	(0.00000)
Constant	0.680**	0.677**	0.599**
	(0.264)	(0.275)	(0.264)
Observations	2,543	2,543	2,543
R^2	0.023	0.022	0.022
Adjusted R^2	0.021	0.020	0.020
Residual Std. Error (df = 2535)	0.457	0.458	0.458
F Statistic (df = 7; 2535)	8.667***	8.233***	8.242***

*p<0.1; **p<0.05; ***p<0.01

Table 7: Heterogeneity Analysis - Religion

	Dependent variable:
	Illness
Post	-0.173^{**}
	(0.078)
Treated	-0.225^{**}
	(0.103)
Diff-in-Diff	0.384^{***}
	(0.144)
Annual Mean Temp	0.0003
	(0.001)
Annual Mean Precip	-0.00005
	(0.0001)
Floods	0.042^{*}
	(0.023)
Real Annual Consump	0.00000^{**}
	(0.00000)
HH Size	0.036^{***}
	(0.005)
Religion	-0.041
	(0.065)
Religion*Post	0.027
	(0.081)
Religion*Treated	0.213^{**}
	(0.105)
Triple Diff	0.574^{**}
	(0.270)
Observations	2,686
R^2	0.047
Adjusted R^2	0.043
Residual Std. Error	0.451 (df = 2673)
F Statistic	11.083^{***} (df = 12; 2673)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8: Heterogeneity Analysis - Household Size

	Dependent variable:
	Spending on Illnesses
Post	−180.146
	(243.280)
Treated	285.972
	(234.021)
Diff-in-Diff	−451.902
	(349.245)
Annual Mean Temp	−8.892**
	(3.766)
Annual Mean Precip	−0.622***
	(0.219)
Floods	98.946
	(97.198)
Real Annual Consump	0.001***
	(0.0001)
HH Size	17.216
	(33.835)
HH Size*Post	−24.952
	(49.591)
HH Size*Treated	−26.919
	(47.989)
Triple Diff	2,702.499**
	(1,115.638)
Observations	2,835
R^2	0.039
Adjusted R^2	0.035
Residual Std. Error	1,939.139 (df = 2823)
F Statistic	10.314*** (df = 11; 2823)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9: Heterogeneity Analysis - Distance to Population Center

	Dependent variable:	
	Spending on Illnesses	Perception Healthcare
	(1)	(2)
Post	−198.341	−0.087
	(251.467)	(0.068)
Treated	−174.902	−0.074
	(255.837)	(0.069)
Diff-in-Diff	−47.315	−0.078
	(369.753)	(0.100)
Annual Mean Temp	-9.694^{**}	−0.002
	(4.401)	(0.001)
Annual Mean Precip	-0.702^{***}	-0.0003^{***}
	(0.249)	(0.0001)
Floods	104.273	0.039
	(97.925)	(0.026)
Real Annual Consump	0.001^{***}	-0.00000^{***}
	(0.0001)	(0.00000)
HH Size	27.198	0.016^{***}
	(19.070)	(0.005)
DistPopCenter	−0.336	-0.005^{***}
	(3.746)	(0.001)
DistPopCenter*Post	−6.293	0.001
	(11.442)	(0.003)
DistPopCenter*Treated	8.175	0.002
	(5.508)	(0.001)
Triple Diff	$2{,}957.511^{**}$	3.569^{***}
	(1,229.966)	(0.332)
Observations	2,835	2,836
R^2	0.040	0.066
Adjusted R^2	0.036	0.062
Residual Std. Error	1,938.174 (df = 2822)	0.523 (df = 2823)
F Statistic	9.782^{***} (df = 12; 2822)	16.621^{***} (df = 12; 2823)
Note:		*p<0.1; **p<0.05; ***p<0.01

8.4 Robustness Checks

Table 10: Placebo Test Results - Hospitalization, Illness, and Spending on Illnesses

	Dependent variable:		
	Hospitalization	Illness	Spending on Illness
	(1)	(2)	(3)
Post	−7.697***	0.155***	−80.485
	(0.120)	(0.026)	(73.050)
Treated	0.132	−0.009	46.737
	(0.112)	(0.025)	(68.078)
Diff-in-Diff	−0.203	0.008	94.993
	(0.156)	(0.034)	(94.966)
Annual Mean Temp	−0.005	−0.001*	−5.067**
	(0.004)	(0.001)	(2.412)
Annual Mean Precip	−0.0002	−0.0002***	−0.373***
	(0.0002)	(0.0001)	(0.139)
Floods	−0.074	0.039	173.157*
	(0.150)	(0.033)	(91.492)
Real Annual Consump	−0.00000***	0.00000***	0.001***
	(0.00000)	(0.00000)	(0.0001)
HH Size	1.041***	0.030***	−15.102
	(0.019)	(0.004)	(11.841)
Constant	5.679***	0.893***	1,572.038**
	(1.167)	(0.257)	(711.021)
Observations	2,961	2,972	2,960
R^2	0.832	0.084	0.063
Adjusted R^2	0.832	0.082	0.061
Residual Std. Error	2.103 (df = 2952)	0.464 (df = 2963)	1,280.945 (df = 2951)
F Statistic	1,829.290*** (df = 8; 2952)	34.171*** (df = 8; 2963)	24.969*** (df = 8; 2951)

*p<0.1; **p<0.05; ***p<0.01

Table 11: Placebo Test Results - Health and Outpatient Consumption and Perception of Healthcare Standards

	Dependent variable:		
	Health Consump	Outpatient Consump	Perception Healthcare
	(1)	(2)	(3)
Post	448.223	−1,160.821	0.074**
	(1,345.949)	(1,112.264)	(0.030)
Treated	607.201	445.644	−0.014
	(1,253.276)	(1,035.681)	(0.028)
Diff-in-Diff	1,303.499	883.069	−0.012
	(1,750.235)	(1,446.357)	(0.039)
Annual Mean Temp	−54.372	−36.088	−0.002**
	(44.405)	(36.695)	(0.001)
Annual Mean Precip	−6.666***	−4.023*	−0.001***
	(2.569)	(2.123)	(0.0001)
Floods	3,175.586*	2,306.598*	0.024
	(1,689.668)	(1,396.306)	(0.038)
Real Annual Consump	0.023***	0.015***	−0.00000***
	(0.002)	(0.001)	(0.00000)
HH Size	104.452	−197.370	0.015***
	(217.844)	(180.022)	(0.005)
Constant	18,106.870	12,295.790	3.692***
	(13,091.390)	(10,818.450)	(0.292)
Observations	2,973	2,973	2,973
R^2	0.119	0.062	0.091
Adjusted R^2	0.117	0.060	0.088
Residual Std. Error (df = 2964)	23,659.670	19,551.850	0.528
F Statistic (df = 8; 2964)	50.023***	24.680***	37.054***

*p<0.1; **p<0.05; ***p<0.01

Table 12: Differences-in-Differences - 3km Radius

	Dependent variable:			
	Hospitalization	Illness	Spending on Illnesses	Perception Healthcare
	(1)	(2)	(3)	(4)
Post	-0.045	-0.123^{***}	-194.455^{*}	0.034
	(0.028)	(0.025)	(105.826)	(0.029)
Treated	-0.077^{***}	-0.001	253.062^{**}	0.015
	(0.029)	(0.026)	(111.547)	(0.030)
Diff-in-Diff	0.067	0.038	69.155	0.080^{*}
	(0.043)	(0.038)	(164.380)	(0.044)
Annual Mean Temp	0.001	0.0003	-7.209^{**}	-0.005^{***}
	(0.001)	(0.001)	(3.648)	(0.001)
Annual Mean Precip	0.0001^{***}	-0.0001	-0.519^{**}	-0.0005^{***}
	(0.0001)	(0.00005)	(0.215)	(0.0001)
Floods	-0.027	0.038^{*}	117.172	0.056^{**}
	(0.026)	(0.023)	(97.077)	(0.026)
Real Annual Consump	-0.000	0.00000^{**}	0.001^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.0001)	(0.00000)
HH Size	0.001	0.037^{***}	27.449	0.016^{***}
	(0.005)	(0.004)	(19.078)	(0.005)
Constant	-0.343	0.532^{**}	$2,140.060^{**}$	4.265^{***}
	(0.285)	(0.252)	(1,084.089)	(0.293)
Observations	2,836	2,833	2,835	2,836
R^2	0.008	0.045	0.034	0.054
Adjusted R^2	0.005	0.042	0.031	0.051
Residual Std. Error	0.511 (df = 2827)	0.451 (df = 2824)	1,942.805 (df = 2826)	0.526 (df = 2827)
F Statistic	2.865^{***} (df = 8; 2827)	16.630^{***} (df = 8; 2824)	12.423^{***} (df = 8; 2826)	20.225^{***} (df = 8; 2827)

*p<0.1; **p<0.05; ***p<0.01

Table 13: Differences-in-Differences - 4km Radius

	Dependent variable:			
	Hospitalization	Illness	Spending on Illnesses	Perception Healthcare
	(1)	(2)	(3)	(4)
Post	-0.056^{*} (0.029)	-0.124^{***} (0.026)	-246.074^{**} (109.991)	0.045 (0.030)
Treated	-0.085^{***} (0.028)	-0.006 (0.024)	130.566 (105.330)	0.027 (0.029)
Diff-in-Diff	0.074^{*} (0.040)	0.034 (0.035)	225.461 (152.702)	0.036 (0.041)
Annual Mean Temp	0.002 (0.001)	0.0004 (0.001)	-7.407^{**} (3.704)	-0.005^{***} (0.001)
Annual Mean Precip	0.0002^{***} (0.0001)	-0.00005 (0.0001)	-0.540^{**} (0.216)	-0.0005^{***} (0.0001)
Floods	-0.028 (0.026)	0.038^{*} (0.023)	108.203 (97.399)	0.056^{**} (0.026)
Real Annual Consump	-0.000 (0.00000)	0.00000^{**} (0.00000)	0.001^{***} (0.0001)	-0.00000^{***} (0.00000)
HH Size	0.001 (0.005)	0.037^{***} (0.004)	26.530 (19.072)	0.016^{***} (0.005)
Constant	-0.426 (0.288)	0.506^{**} (0.254)	$2{,}236.449^{**}$ (1,094.578)	4.231^{***} (0.296)
Observations	2,836	2,833	2,835	2,836
R^2	0.009	0.045	0.034	0.053
Adjusted R^2	0.006	0.042	0.031	0.050
Residual Std. Error	0.511 (df = 2827)	0.451 (df = 2824)	1,943.164 (df = 2826)	0.526 (df = 2827)
F Statistic	3.197^{***} (df = 8; 2827)	16.576^{***} (df = 8; 2824)	12.288^{***} (df = 8; 2826)	19.759^{***} (df = 8; 2827)

*p<0.1; **p<0.05; ***p<0.01

Table 14: Differences-in-Differences - 6km Radius

	Dependent variable:			
	Hospitalization	Illness	Spending on Illnesses	Perception Healthcare
	(1)	(2)	(3)	(4)
Post	-0.077^{**}	-0.145^{***}	-325.226^{***}	0.001
	(0.032)	(0.028)	(122.045)	(0.033)
Treated	-0.122^{***}	-0.024	126.964	-0.002
	(0.028)	(0.024)	(104.773)	(0.028)
Diff-in-Diff	0.104^{***}	0.061^{*}	246.189^{*}	0.100^{**}
	(0.039)	(0.034)	(147.154)	(0.040)
Annual Mean Temp	0.002^{**}	0.0004	-8.296^{**}	-0.005^{***}
	(0.001)	(0.001)	(3.784)	(0.001)
Annual Mean Precip	0.0002^{***}	-0.00005	-0.610^{***}	-0.0005^{***}
	(0.0001)	(0.0001)	(0.223)	(0.0001)
Floods	-0.027	0.038^{*}	114.427	0.055^{**}
	(0.026)	(0.023)	(97.106)	(0.026)
Real Annual Consump	-0.000	0.00000^{**}	0.001^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.0001)	(0.00000)
HH Size	0.001	0.037^{***}	27.760	0.016^{***}
	(0.005)	(0.004)	(19.077)	(0.005)
Constant	-0.563^{*}	0.505^{*}	$2{,}511.404^{**}$	4.307^{***}
	(0.294)	(0.259)	(1,117.342)	(0.302)
Observations	2,836	2,833	2,835	2,836
R^2	0.013	0.046	0.034	0.055
Adjusted R^2	0.010	0.043	0.031	0.052
Residual Std. Error	0.510 (df = 2827)	0.451 (df = 2824)	1,942.684 (df = 2826)	0.526 (df = 2827)
F Statistic	4.488^{***} (df = 8; 2827)	16.841^{***} (df = 8; 2824)	12.468^{***} (df = 8; 2826)	20.501^{***} (df = 8; 2827)

*p<0.1; **p<0.05; ***p<0.01

Table 15: Differences-in-Differences - 7km Radius

	Dependent variable:			
	Hospitalization	Illness	Spending on Illnesses	Perception Healthcare
	(1)	(2)	(3)	(4)
Post	−0.092***	−0.130***	−287.936**	0.010
	(0.034)	(0.030)	(130.482)	(0.035)
Treated	−0.137***	−0.015	158.437	−0.013
	(0.028)	(0.025)	(108.353)	(0.029)
Diff-in-Diff	0.113***	0.028	162.851	0.071*
	(0.040)	(0.035)	(150.894)	(0.041)
Annual Mean Temp	0.002**	0.001	−7.925**	−0.004***
	(0.001)	(0.001)	(3.790)	(0.001)
Annual Mean Precip	0.0002***	−0.00004	−0.580***	−0.0005***
	(0.0001)	(0.0001)	(0.222)	(0.0001)
Floods	−0.029	0.039*	121.825	0.058**
	(0.025)	(0.023)	(97.091)	(0.026)
Real Annual Consump	−0.000	0.00000**	0.001***	−0.00000***
	(0.00000)	(0.00000)	(0.0001)	(0.00000)
HH Size	0.0003	0.037***	28.329	0.016***
	(0.005)	(0.004)	(19.098)	(0.005)
Constant	−0.613**	0.453*	2,353.213**	4.159***
	(0.292)	(0.258)	(1,112.693)	(0.301)
Observations	2,836	2,833	2,835	2,836
R^2	0.014	0.045	0.033	0.053
Adjusted R^2	0.011	0.042	0.031	0.050
Residual Std. Error	0.510 (df = 2827)	0.451 (df = 2824)	1,943.493 (df = 2826)	0.526 (df = 2827)
F Statistic	4.943*** (df = 8; 2827)	16.508*** (df = 8; 2824)	12.164*** (df = 8; 2826)	19.667*** (df = 8; 2827)

*p<0.1; **p<0.05; ***p<0.01

Table 16: Differences-in-Differences - 10km Radius

	Dependent variable:			
	Hospitalization	Illness	Spending on Illnesses	Perception Healthcare
	(1)	(2)	(3)	(4)
Post	0.028	−0.187***	−333.026**	−0.038
	(0.042)	(0.037)	(159.735)	(0.043)
Treated	0.048	−0.037	13.179	−0.056*
	(0.033)	(0.029)	(125.045)	(0.034)
Diff-in-Diff	−0.067	0.101**	187.394	0.121***
	(0.046)	(0.040)	(173.117)	(0.047)
Annual Mean Temp	0.001	0.0005	−4.749	−0.004***
	(0.001)	(0.001)	(3.627)	(0.001)
Annual Mean Precip	0.0001**	−0.00005	−0.431*	−0.0004***
	(0.0001)	(0.0001)	(0.220)	(0.0001)
Floods	−0.029	0.037	134.680	0.059**
	(0.026)	(0.022)	(97.074)	(0.026)
Real Annual Consump	−0.000	0.00000**	0.001***	−0.00000***
	(0.00000)	(0.00000)	(0.0001)	(0.00000)
HH Size	0.001	0.037***	26.468	0.015***
	(0.005)	(0.004)	(19.126)	(0.005)
Constant	−0.230	0.513**	1,521.341	4.084***
	(0.282)	(0.248)	(1,071.873)	(0.290)
Observations	2,836	2,833	2,835	2,836
R^2	0.007	0.047	0.031	0.054
Adjusted R^2	0.004	0.044	0.028	0.051
Residual Std. Error	0.512 (df = 2827)	0.451 (df = 2824)	1,945.889 (df = 2826)	0.526 (df = 2827)
F Statistic	2.326** (df = 8; 2827)	17.296*** (df = 8; 2824)	11.265*** (df = 8; 2826)	20.040*** (df = 8; 2827)

*p<0.1; **p<0.05; ***p<0.01

8.5 Diff-in-Diff

Variables	Coefficients
Intercept	9.889691e-01
Mean_Precip	1.685555e-03
Mean_Temp	-2.438683e-03
Mean_Electric	0.000000e+00
Mean_Incline	0.000000e+00
Mean_Elevation	-7.127166e-04
Mean_Pop_Dens	2.260559e-06
Mean_Rural_Intense	-3.533716e-04
Mean_Dist_Road	3.290345e-03
Mean_Dist_Ag_Mkt	-2.779856e-03
Mean_Potable	-2.523443e-02
Mean_Toilet	-1.299264e-03

Lasso Results

Table 18: Linear Probability Results

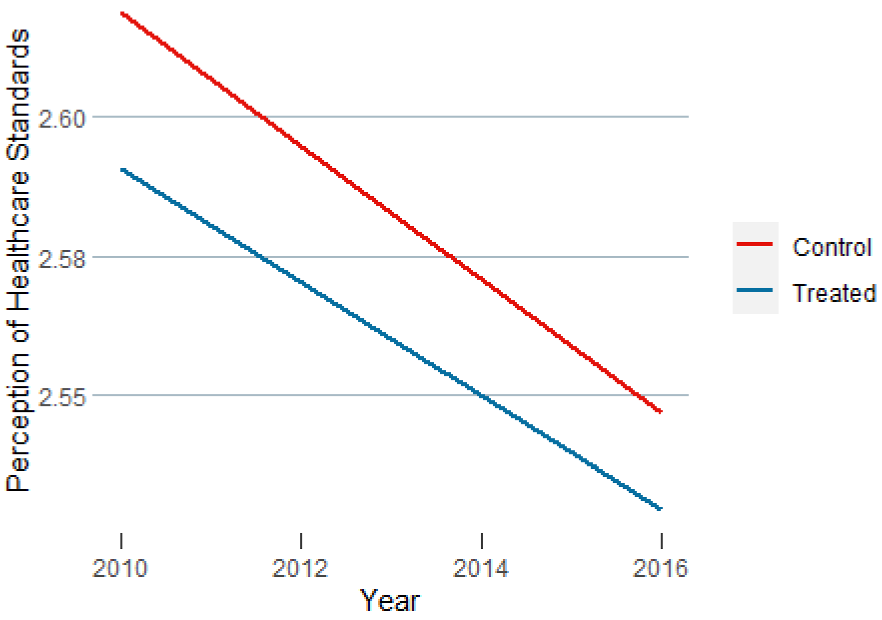
	Dependent variable:
	Site_Indicator
Mean_Precip	0.003***
	(0.001)
Mean_Temp	−0.003**
	(0.001)
Mean_Electric	0.010
	(0.081)
Mean_Incline	0.004
	(0.005)
Mean_Elevation	−0.001***
	(0.0002)
Mean_Pop_Dens	0.00001
	(0.00004)
Mean_Rural_Intense	0.001
	(0.003)
Mean_Dist_Road	0.003
	(0.002)
Mean_Dist_Ag_Mkt	−0.003
	(0.002)
Mean_Potable	−0.017
	(0.023)
Mean_Toilet	−0.016
	(0.040)
Constant	0.999***
	(0.061)
Observations	247
R^2	0.506
Adjusted R^2	0.482
Residual Std. Error	0.292 (df = 235)
F Statistic	21.845*** (df = 11; 235)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 19: Probit Probability Results

	Dependent variable:
	Site_Indicator
Mean_Precip	0.003***
	(0.001)
Mean_Temp	−0.003**
	(0.001)
Mean_Electric	0.010
	(0.081)
Mean_Incline	0.004
	(0.005)
Mean_Elevation	−0.001***
	(0.0002)
Mean_Pop_Dens	0.00001
	(0.00004)
Mean_Rural_Intense	0.001
	(0.003)
Mean_Dist_Road	0.003
	(0.002)
Mean_Dist_Ag_Mkt	−0.003
	(0.002)
Mean_Potable	−0.017
	(0.023)
Mean_Toilet	−0.016
	(0.040)
Constant	0.999***
	(0.061)
Observations	247
Log Likelihood	−41.098
Akaike Inf. Crit.	106.196
Note:	*p<0.1; **p<0.05; ***p<0.01

8.6 Perceptions of Healthcare

Figure 7: Parallel Trends - Perception of Healthcare Standards



As further analysis, we also run our linear and diff-in-diff models to measure the effect of an IDP site on local community perception of the quality of the healthcare they receive. Perception is a subjective variable coded at three different levels: 1 when the household reported that medical attention received was ”less than adequate”, 2 when ”just adequate” and 3 when perceived to be ”more than adequate”.

Our linear models find that perceptions of healthcare quality do not change significantly as the distance to an IDP site changes or the number of sites within 5km of a household increases. However, in our diff-in-diff, the results are significant at the 5% level, and indicate a higher level of satisfaction with the quality of medical care received by treated households versus the control group. Results are robust to the inclusion of different controls.

Changing the radius size causes the magnitudes of our results to vary without a clear trend. Proximity to sites with less than adequate bathing facilities also improves perception of healthcare quality, with the coefficient of 0.27 proving greater than the original value of 0.088. There are also significant results for religion, household size, and distance from a population center, as Christians, for example, tend to have an improved perception of healthcare quality compared to Muslims.

These findings could be due to a higher level of illnesses in treated areas due to the presence of an IDP site, but could also reflect a higher need for healthcare, thereby increasing the probability of feeling more satisfied with the same quality of medical care. The presence of an IDP site may increase the total supply of health services available to the local community, another potential reason why households in treated areas perceive healthcare to be better than the control group.

Additionally, the linear model's finding that the quality of healthcare received are not related to the distance or number of sites a household is contained in show that sites are not a main driver of healthcare perceptions. The Diff-in-Diff analysis is better able to take the true drivers of perceptions of healthcare into account by holding other factors constant across time, supporting our decision to use a Diff-in-Diff.