# Greenspace and Rohingya Refugee Mental Health in Bangladesh

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**Abstract**

Refugees are at high risk of developing mental health conditions, and post-displacement environments have been shown to significantly impact refugee mental health outcomes. Despite evidence of a positive relationship between greenspace and mental health in industrialized countries, almost no research has studied the relationship between greenspace and refugee mental health within refugee camps. In this paper, we examine the relationship between greenspace and depression symptoms for Rohingya refugees living in the Kutupalong Expansion Site in Cox's Bazar, Bangladesh, the world's most populous and most densely populated refugee camp complex. We combine data from the 2019 Cox's Bazar Panel Survey with respondent location-specific zonal statistics derived from high-resolution vegetation mappings produced from Sentinel-2 satellite imagery, as well as publicly available data on settlement density and the location of wells and medical centres within the camp. Additionally, we measure the relationship between greenspace and perceived rental value, which we use to approximate willingness to pay for greenspace. In contrast to the majority of previous research, our evidence to date suggests that greenspace proximity is positively related to depression risk. We also find that greenspace proximity is negatively related to perceived rental values, though the coefficient estimate is not significant. We suspect that an omitted variable positively related to vegetation but negatively related to mental welfare explains our current result, and our ongoing efforts seek to determine the mediating factors that explain the surprising result.

***Keywords*** – Refugee Hosting; Vegetation; Greenspace; Mental Health; Hedonic Regression; Rohingya Refugees

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# 1. Introduction

The number of forcibly displaced people in the world continues to rise. As of mid-2023, the United Nations High Commissioner for Refugees (UNHCR) reported 110 million forcibly displaced people globally, of whom 35.3 million are classified as refugees who crossed an international border and received protective status (UNHCR, 2023b, nd). The Rohingya people, a stateless group originally from Myanmar, stand out as particularly vulnerable (UNHCR, 2023a). A large share of the Rohingya refugee population resides in Bangladesh, which has been hosting displaced Rohingya peoples in the Cox's Bazar district for decades. In 2017, the number of Rohingya refugees in Cox's Bazar rose to nearly 1 million when over 700,000 Rohingya asylum-seekers fled a dramatic escalation in targeted violence and discrimination in Myanmar.[1]

Refugees are at high risk of developing mental health conditions such as depression and post-traumatic stress disorder (PTSD) (Byrow et al., 2020). While the traumatic experiences of displacement are a significant driver of this relationship (Steel et al., 2009; Hynie, 2018), post-displacement factors can also be strong determinants of mental health outcomes (Hynie, 2018; Ermansons et al., 2023; Li et al., 2016). Despite the overcrowded, under-resourced, and hazardous living conditions of some refugee camps, there is little research on the relationship between camp characteristics and refugee mental health. Past research argues that proximity and access to vegetation, which we refer to as "greenspace" throughout, are associated with improved mental health (Gascon et al., 2015). However, most of this research has been conducted in industrialized countries, and it is unclear if this relationship holds for developing countries or for refugees in encampment settings.

In this study, we examine the relationship between local greenspace levels and refugee mental health in Cox's Bazar, Bangladesh. We focus on the Kutupalong Expansion Site (henceforth referred to as "Kutupalong"), a cluster of adjacent camps established after August 2017 to accommodate the newly arrived population.[2] Kutupalong is the most populous (613,276 people) and one of the most densely populated (43,000 per km$^2$) refugee camp areas in the world (UNHCR, 2022; Malteser International, 2024).[3] We use data from the Cox's Bazar Panel Survey (CBPS) 2019 wave, which surveyed refugees in Kutupalong on social, economic and health-related factors. Our dependent variable of interest is the respondent's risk of

[1]As of July 2018, UNHCR counted 723,527 refugees who arrived to Cox's Bazar since August 2017 (UNHCR, 2018).

[2]As we define it, the Kutupalong Expansion Site includes the following camps: 1E, 1W, 2E, 2W, 3, 4, 4 Ext, 5, 6, 7, 8E, 8W, 9, 10, 11, 12, 13, 17, 18, 19, 20, and 20 Ext. The Kutupalong Expansion Site is adjacent to the Kutupalong Refugee Camp ("Kutupalong RC"), which was established prior to 2017 to support an earlier wave of Rohingya refugee displacement. Our study does not include the population in Kutupalong RC.

[3]As of 2019, there were 613,276 Rohingya refugees in the camps we consider part of the Kutupalong Expension Site. Based on camp boundaries provided by the Inter-Sector Working Group, we calculate the size of the Kutupalong Expansion Site as roughly 14.3 km$^2$ in area.

depression, assessed using the Patient Health Questionaire (PHQ-9), a widely recognized questionnaire for screening depression symptom severity (Yale MacMillan Center, nd; Gilbody et al., 2007). The CBPS team tracked the geographic coordinates of each survey respondent's home, which we use to generate respondent-specific statistics of local area characteristics. The explanatory variable of interest is the amount of vegetation surrounding each respondent, which measured as the mean Normalized Difference Vegetation Index (NDVI) score for a 250m radius around each respondent's residence.[4] We also generate respondent-level statistics for surrounding settlement density, and we account for local amenity proximity using the respondent's distance to wells and medical centres. Using an ordered logit model, we measure the relationship between surrounding greenspace levels and depression risk severity, controlling for many other potential determinants of depression. To examine the robustness of our results, we also estimate OLS, Poisson, and binary logit models.

Drawing on environmental valuation tools, we additionally examine greenspace proximity and refugee welfare using a hedonic style approach. Following past hedonic regression applications, we measure the marginal effect of greenspace on perceived housing rental value. Under a competitive market, observed prices of composite goods, such as housing (Cheshire and Sheppard, 1995), can be decomposed as a function of the value of each individual attribute (Rosen, 1974). Accordingly, hedonic regression methods can provide estimates of societal willingness-to-pay for improvements in environmental quality. Assuming that households value amenities that improve their welfare, the hedonic regression approach provides an alternative measure of the relationship between vegetation and well-being. As in the mental health analysis, we control for other determinants of perceived rental value using additional CBPS and geospatial data.

Surprisingly, we find that higher surrounding greenspace levels are associated with *higher* risks of depression and appear to be *negatively* related to perceived rental values. The depression result is statistically significant for our main specification and robust to most alternative specifications. Although the perceived rental value result is not statistically significant at the 10% level, we belive that this household-level estimation may be under-powered ($N = 641$). We suspect that these unexpected results are likely due to omitted factors that are positively related to surrounding vegetation levels and positively related to depression and human welfare. There are many possible factors that could explain the result, such as proximity to border fencing, security checkpoints, contaminated water, natural hazard risk, and increased dangerous wildlife encounters. Additionally, more vegetated areas may also have reduced access to public goods not accounted for in our regression framework, such as markets or schools. The study team is currently advancing the study and is using the summer of 2024 to bring more of these variables into the regression framework in order to

[4]The NDVI is a spectral index that uses satellite imagery to measure vegetation levels (Weier and Herring, 2000). It has been extensively used and cross-validated as an effective vegetation measure for neighbourhood greenspace studies (Gascon et al., 2015; Rhew et al., 2011). We discuss the NDVI in more detail in Section 3.

understand what mediating factor drives the negative relationship between greenspace proximity and mental health.

To our knowledge, this study is the first to examine how greenspace proximity influences refugee mental health and welfare in an encampment setting. Our work contributes to several important discourses in the Social Sciences. First, we complement existing knowledge of refugee mental health. Refugees have an elevated risk of mental health conditions (Byrow et al., 2020). Despite heterogeneity in results across studies, the largest meta-analyses of refugee mental health research found that refugees exhibit average rates of depression and post-traumatic stress disorder (PTSD) of 30.8% and 30.6% respectively (Steel et al., 2009; Silove et al., 2017).[5] Despite these elevated levels, many refugees do not receive sufficient support due to insufficient funding for mental health services and a low supply of mental health providers (Silove et al., 2017). Among Rohingya refugees in Cox's Bazar, research also suggests that language barriers, concerns over confidentiality, and cultural stigma also serve as obstacles to mental health care (Tay et al., 2019).

Many studies have found that post-displacement factors significantly impact refugee mental health. Reviews by Hynie (2018), Ermansons et al. (2023), and Li et al. (2016) establish post-displacement income, employment, neighbourhood violence, and social cohesion as strong predictors of refugee mental health. Two past papers examine the impact of post-displacement factors on Rohingya refugee mental welfare. In a study conducted prior to the 2017 influx, Riley et al. (2017) found that daily stressors were important determinants of refugee depression and PTSD symptoms.[6] Additionally, Ritsema and Armstrong-Hough (2023) use the 2019 CBPS wave to find that refugees who observed more crime in their area were much more likely to display symptoms of depression and PTSD, holding other factors constant.

We additionally contribute to the discourse on the mental health benefits of greenspace (Collins et al., 2020). The majority of past research on mental health and greenspace focuses on industrialized country settings (Triguero-Mas et al., 2015). Many previous studies have argued that a positive relationship exists between greenspace and mental health. Proposed mechanisms for this relationship include direct cognitive effects for evolutionary reasons (Collins et al., 2020; Fan et al., 2011; Alcock et al., 2015), and indirect effects. Indirectly, greenspace may enhance mental health through the promotion of exercise and social interactions (Fan et al., 2011), a buffer between stressful situations (Van den Berg et al., 2010), noise reduction (Dzhambov et al., 2018), improvement of air quality, and mitigation of climate hazards such as heatwaves and floods (Lai et al., 2019; Burke et al., 2018; Han et al., 2024). These previous studies have tended to have non-causal estimation approaches, meaning we cannot rule out the possibility that endogenous selection is driving the

[5] These rates significantly exceed non-refugee estimates of 5% for depression and 1.1% for PTSD (Silove et al., 2017; WHO, 2023).

[6] Riley et al. (2017) define daily stressors as stressors that are not directly related to pre-displacement trauma. These include poverty, lack of basic needs, exposure to violence (post-displacement), and overcrowdedness.

findings.[7]

While many observational studies have investigated the relationship between greenspace and mental health, these studies differ by their definition of greenspace,[8] as well as their greenspace measurement approaches.[9] Past studies have also used a variety of different survey modules to measure mental health status.[10] Our study is most closely related to a set of studies that look at the relationship between depression and the quantity of greenspace in the respondent's local area using NDVI data. For example, Beyer et al. (2014) examined the relationship between neighbourhood greenspace and mental health in Wisconsin, USA, using socioeconomic, demographic and mental health data. They found that higher levels of greenspace, measured using NDVI at the census block group level, were significantly associated with lower depression, anxiety, and stress symptoms, even after controlling for a variety of other individual and neighbourhood determinants of mental health. Similarly, Triguero-Mas et al. (2015) find that greenspace is positively related to better mental health in Catalonia, Spain, using NDVI within a 300m buffer of survey respondent residence, general mental health, depression and anxiety questionnaires, and a multitude of other greenspace and control variables. Our work compliments this research by investigating if this relationship holds in the refugee camp context.

Additionally, our work augments a small set of literature on the relationship between refugee mental health and exposure to parks and nature in wealthy countries. Past findings are mixed (Ermansons et al., 2023). In a qualitative study of refugee mental health in three European cities, Rishbeth et al. (2019) found that while many refugees enjoy greenspaces, they often face social and cultural barriers to the full use and enjoyment of these spaces. Our paper adds to the greenspace and refugee mental health discourse by focusing on refugees in a lower-income country. Such countries presently host an estimated 75% of all refugees in the world (UNHCR, 2023b).

In economics, the relationship betweeen welfare and greenspace are most commonly explored through a public good valuation approach. Environmental economists have developed methods to estimate societal

[7]Namely, we cannot rule out the possibility that those with better mental health tend to select into residential areas with more greenspace.

[8]Some studies consider all vegetation when they define greenspace (Payton et al., 2008), while other studies focus only on designated greenspaces like public parks (Day, 2020; Van den Berg et al., 2010). Some research also considers blue spaces like lakes and rivers (Gascon et al., 2015)

[9]Ways of measuring greenspace often varies by proposed mechanism: Studies that focus on recreational benefits use number of visits (White et al., 2021; Day, 2020) or distance to the nearest park (Fan et al., 2011; Anderson and West, 2006), while research focusing on the overall quantity of surrounding greenspace do so at the census tract level (Alcock et al., 2015; White et al., 2013, 2021; Ambrey and Fleming, 2014) or within a buffer surrounding the survey respondent (Van den Berg et al., 2010; Tsurumi and Managi, 2015). Surrounding greenspace variables are quantified either as the percentage of land that falls within the researcher's definition of greenspace by land-cover databases (White et al., 2013; Alcock et al., 2015; Ambrey and Fleming, 2014; Tsurumi and Managi, 2015; Van den Berg et al., 2010) or through remotely sensed vegetation statistics such as the Normalized Difference Vegetation Index (Beyer et al., 2014; Triguero-Mas et al., 2015; Dzhambov et al., 2018; Gariepy et al., 2014; Fan et al., 2011; Payton et al., 2008).

[10]Various mental health surveys are used in observational greenspace-mental health studies. The most used survey is the General Health Questionnaire (GHQ), which is a general mental health indicator (Gascon et al., 2015). Other studies use surveys that focus on diagnosing specific disorders (Gascon et al., 2015).

willingness-to-pay (WTP) for environmental amenities not consumed through markets, such as public parks. WTP reflects the additional benefit obtained due to a marginal increase in the environmental amenity of interest. One branch of the literature is the life satisfaction approach, which looks at tradeoffs between income and public good access, holding self-reported life satisfaction constant and controlling for other determinants of life satisfaction. Empirically, researchers regresses self-reported life satisfaction scores on determinants of life satisfaction, and looks at tradeoffs between income and public good access (such as greenspace) to approximate marginal willingness to pay for public goods (Ambrey and Fleming, 2014; Tsurumi and Managi, 2015). Another common method of determining the WTP for environmental amenities uses a hedonic regression approach with home values as the dependent variable (Anderson and West, 2006; Panduro and Veie, 2013; Payton et al., 2008; Han et al., 2024). While our approaches differ slightly from previous research due to the refugee camp setting and survey design, both of these methods guide our analysis.[11]

Finally, we contribute to a small discourse examining environmental quality in refugee-hosting areas. Past work has largely focused on the effect that hosting refugees has on host population landscapes and natural resources (Salemi, 2021; Maystadt et al., 2020; Aksoy and Tumen, 2021; Black and Sessay, 1998). We augment this growing discourse by focusing our study on how the environment impacts refugees themselves.

The findings of our study augment our understanding of within-camp factors that influence refugee mental health, knowledge that can help humanitarian actors pursue welfare-augmenting camp planning and management. The remainder of this paper is organized as follows. Section 2 provides a brief background of Rohingya history and the current situation in Cox's Bazar following the 2017 wave of displacement. Next, in Section 3 we present the survey and spatial data used in our study and describe our construction of spatial statistics. In Sections 4 and 5, we present the empirical approaches and results. In Section 6 we expand the discussion of the results and consider possible explanations for the unexpected findings. We offer concluding thoughts in Section 7.

[11] Our situation does not allow for a direct application of the life satisfaction approach as we have data on depression and PTSD risk levels, not self-reported life satisfaction. While often negatively correlated with mental health (White et al., 2013; Ettema and Schekkerman, 2016; Lombardo et al., 2018), self-reported life satisfaction is more temporally stable and comparable across individuals than scores from most mental health surveys (Frey et al., 2010). Despite these drawbacks, we use similar empirical approaches used in previous applications of the life satisfaction approach in our analysis of the relationship between greenspace and mental health. Additionally, we cannot apply the hedonic model in its truest form because shelters in Kutupalong are provided institutionally, not through markets, and most encamped refugees in Bangladesh do not pay rent (indicating that housing markets are not competitive in this setting – which means we do not meet an important assumption in the hedonic regression framework). However, we do have data on household perceived rental values, measured using the estimated rental rate that the respondent to the household portion of the survey believes they could receive if renting their unit to someone else. Assuming that this perceived rental rate is on average reflective of societal willingness to pay, we employ this hedonic style approach to approximate willingness to pay for greenspace with the added caveat that we are using a perceived rental value instead of market transactions.

## 2. Background

The Rohingya people are a Muslim Indo-Aryan group from Myanmar, previously known as Burma. They have historical ties to the Arakan region (modern-day Rakhine State), which the Rohingya people see as their homeland, and are also found in parts of eastern Bangladesh (Lee, 2021). Figure 2.1 provides a regional map depicting the proximity of Rakhine State to Cox's Bazar.


Figure 2.1: Regional Context
Figure generated by the authors using FAO GAUL administrative boundary data.

Following Burmese independence from British colonization in 1948, the Rohingya people were initially recognized as citizens by political leaders and the 1948 citizenship laws outlined in the Constitution of the Union of Burma (Lee, 2021; Farzana, 2017). However, after a successful military coup in 1962, the legal status of Rohingya residents was increasingly scrutinized. In 1982, the Burma Citizenship Law excluded the Rohingya people as citizens of the country, rendering the population stateless. The argument for stripping the Rohingya people of their citizenship was based on claims that the Rohingya are not indigenous to Rakhine State and had only arrived during the period of British colonial rule (Farzana, 2017). Historians have criticized this claim, pointing to evidence of Muslim Indo-European populations of Arakan during the Medieval Period and even earlier (Charney, 2018; Lee, 2021).

As stateless people, the Rohingya population in Myanmar has faced an erosion of their basic rights. Rohingya populations in Myanmar face numerous human rights abuses, including constraints on travel, marriage, pregnancy, and economic activity, as well as the imposition of forced labour (Lee, 2021).

There have been several periods of large-scale displacement from Myanmar to Bangladesh in recent decades. To our knowledge, the first incident occurred in 1978, when Myanmar's military forces (known as the "Tatmadaw") launched a campaign of violence against Rohingya communities. About 200,000 Rohingya refugees sought refuge in Cox's Bazar in response to the attacks, though many were eventually repatriated back to Myanmar (Mathieson, 2009). A second large-scale refugee exodus occurred in 1991-1992.

In late 2016, the Arakan Rohingya Salvation Army (ARSA), an armed rebel group in Rakhine State, launched an attack on Myanmar border security posts, killing 9 soldiers (Reuters, 2016). The Government of Myanmar responded through collective punishment. According to human rights groups, military forces and aligned militias burned villages to the ground, shot Rohingya villagers indiscriminately, and committed acts of sexual violence against Rohingya women (Amnesty International, 2016). UNHCR reports that approximately 74,000 Rohingya asylum-seekers crossed into Bangladesh in response to the attacks (Tan, 2017).

In August of 2017, the ARSA resumed its attacks on border posts, this time killing 12 soldiers (Reuters, 2017). The Myanmar military again responded with violence targeting the entire Rohingya population, including widespread killings, sexual violence, and burning of Rohingya homes and villages (Lee, 2021). A much larger population of Rohingya people fled the country after this second round of attacks, with over 600,000 fleeing to Cox's Bazar in less than 3 months in 2017 (Filipski et al., 2021). A year after the August 2017 influx, the count of newly arrived Rohingya refugees exceeded 700,000 (UNHCR, 2018), bringing the total number of Rohingya refugees living in Cox's Bazar to close to 1 million people (UNHCR, 2022).

The government of Bangladesh, UNHCR, and other humanitarian partners rapidly mobilized in response to the sudden influx. The Bangladeshi government allocated and cleared land for new camp settlement (Figure 2.2), while partners quickly worked to distribute emergency services and establish necessary amenities such as tube wells, latrines, and medical centers (UNHCR, 2017c,a,b). Despite their early accommodation, the government of Bangladesh seems to consider the situation as temporary. This is evident from its refusal to officially recognize the new sites as refugee camps (Sultana et al., 2023) and its denial of official refugee status to most newcomers – preventing them from legally working or leaving the camps (Filipski et al., 2021). Rohingya refugees in Bangladesh have faced numerous threats of deportation back to Myanmar. Efforts encouraging voluntary return have been unsuccessful, possibly due to insufficient guarantees of safety and legal status upon re-entry (Lee, 2021).

As Rohingya refugees in Bangladesh continue to navigate their uncertain future, they often lack resources and safe living conditions within the camps. Over 600,000 live in the 14.3 km$^2$ Kutupalong Expansion Site, making it the most populated and one of the most densely populated refugee camp in the world (UNHCR, 2022; Malteser International, 2024). Kutupalong is susceptible to extreme weather events like heatwaves and cyclones, as well as natural hazards such as floods, fires, and landslides (Kamal et al., 2022; Mahmud, 2023; Moloney, 2023). Due to a lack of humanitarian resources, there is concern that those living in the camp have limited access to basic needs such as food, amenities, and safe shelters (Hossain et al., 2023; IOM, 2024).[1] A combination of these displacement and post-displacement factors has led to significant physical and mental health concerns for camp residents (Joarder et al., 2020). Despite these crowded conditions, there are still non-negligible amounts of greenspace in some areas of the camp, but access greatly varies by area. Common types of greenspace within Kutupalong include trees, shrublands, and small agricultural plots. In Figure 2.3, we illustrate various land-cover types within Kutupalong using 2019 drone imagery from IOM Needs and Population Monitoring (IOM, 2019).

[1] Most refugees in Kutupalong live in temporary shelters made of tarpulins and bamboo (Kyle, 2021).

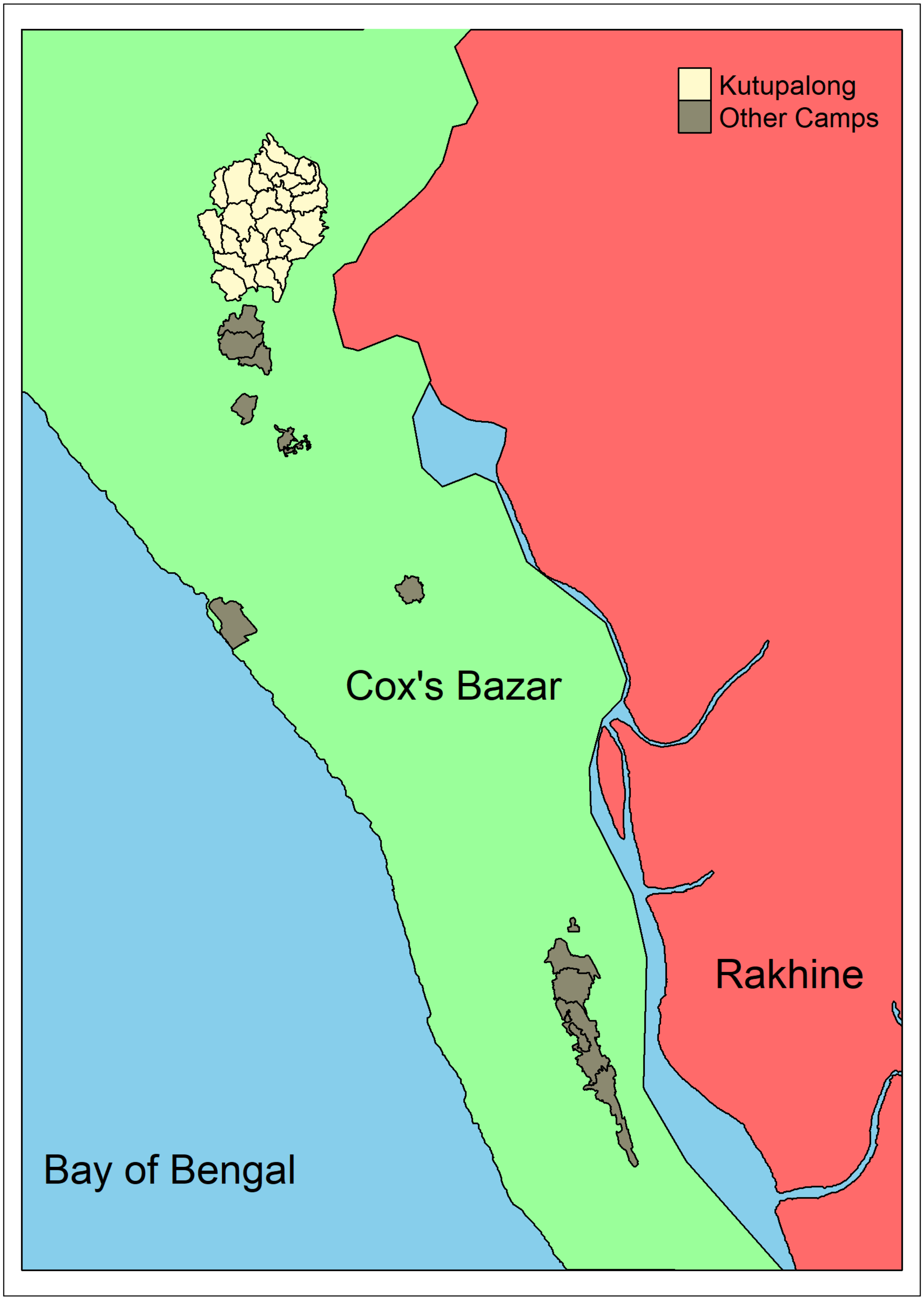


Figure 2.2: Kutupalong and Other Camps in Cox's Bazar

Figure generated by the author using administrative boundary data from GADM and camp outlines from Humanitarian Data Exchange (ISCG, 2022).

**A non-vegetated area**

**A semi-vegetated area**

**A highly vegetated area**

Figure 2.3: Levels of Greenspace in Areas of Kutupalong
Figure generated by authors using drone imagery from IOM Bangladesh - Needs and Population Monitoring.

# 3. Data

We restrict our analysis to the cluster of camps established after the 2017 influx, which we refer to as "Kutupalong". These camps are adjacent to the older Kutupalong Refugee Camp (RC) (Figure 3.1). We omit observations from Kutapalong RC due to potential differences in population characteristics and a lack of survey data due to refusals (Baird et al., 2021).

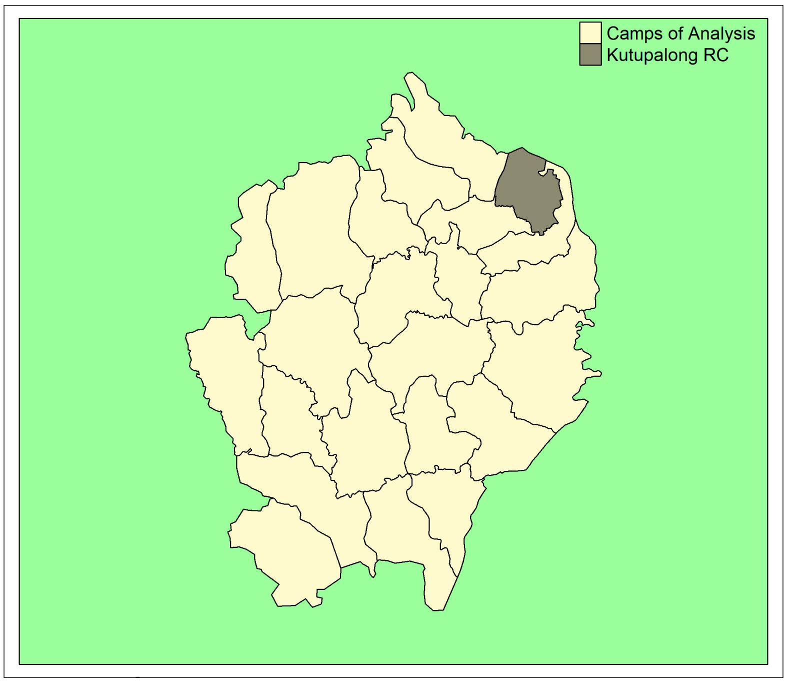


Figure 3.1: Camps Included in Analysis
Figure generated by the authors using camp outline data camp outlines from ISCG (2022).

The data used for our analysis includes both a survey dataset and several sources of geospatial data. Our sample, and many of the variables used for our analysis, comes from the 2019 wave of the Cox's Bazar Panel Survey (CBPS). The CBPS is a comprehensive survey of social, economic, and health characteristics across a representative stratified random sample of Rohingya refugees living in refugee camps across Cox's Bazar as well as Bangladeshi nationals living in the district (Yale MacMillan Center, nd). We augment the CBPS by calculating zonal statistics using spatial data (greenspace, density, and proximity to amenities) corresponding to the geolocations of each CBPS respondent. To protect respondent confidentiality, The CBPS household geolocations are not publicly available. Given these privacy concerns, our current draft uses geo-jittered location data for respondent households. Each sample respondent's geo-location is randomly jittered based on the random selection of a direction (0 to 360 degrees) and a distance (50-115 meters). This random jittering results in random measurement error, which attenuates our results towards zero (Hansen, 2021). For our next draft, our study team will augment the analysis by using non-jittered household geolocations.

## 3.1 The Cox's Bazar Panel Survey

The Cox's Bazar Panel Survey (CBPS) is an ongoing panel data collection project by the Yale Macmillan Centre in conjunction with the World Bank and the Gender and Adolescence: Global Evidence (GAGE) project (Yale MacMillan Center, nd). The 2022 CBPS wave was still forthcoming when this project was being developed, so we only use data from the 2019 wave in this version. The 2019 survey was conducted between March and August of 2019 and sampled 5,020 households, including both refugees and hosts, across the Cox's Bazar district on household characteristics such as housing, income, and food security (Yale MacMillan Center, nd). In addition to the household module, the CBPS also includes individual surveys of two family members per household aged fifteen or older on topics such as labour market participation, observed crime, health, and risk of depression and PTSD (Yale MacMillan Center, nd). We omit the following groups from our analysis: Bangladeshi (host) respondents, refugees not residing in Kutapalong, and refugees in Kutapalong whose local vegetation characteristics are obscured by cloud cover (See Section 3.2.1). Our resulting sample is composed of 1,238 refugees for analyses conducted at the individual level (mental health as the dependent variable) and 641 households for household-level estimations (hedonic-style analysis). It is important to not that while both the PHQ-9 and the HTQ have been used extensively in refugee populations (Rasmussen et al., 2015; Naal et al., 2021; Georgiadou et al., 2017), neither has been validated for the Rohingya refugee population to our knowledge (Ritsema and Armstrong-Hough, 2023).

### 3.1.1 Mental Health Data

The CBPS collects mental health data using two survey modules: the Patient Health Questionnaire (PHQ-9) and the Harvard Trauma Questionaire (HTQ). These surveys are considered among the most effective tools to screen for depression and post-traumatic stress disorder (PTSD) respectively (Gilbody et al., 2007; Rasmussen et al., 2015). PTSD is often caused by specific past traumatic experiences (Qi et al., 2016), while depression can arise from a broad range of stressors and life circumstances. While depression and PTSD are often comorbid (Zlotnick et al., 1997; O'Donnell et al., 2004; Koenen et al., 2008), and some research suggests that environmental characteristics can improve PTSD symptoms (Anwar, 2018), the relationship between greenspace and depression has more existing support in the academic literature (Tran et al., 2022). Consequently, we use the PHQ-9 to construct the dependent variables for the greenspace-mental health analysis and control for past traumatic events the respondent experienced and/or witnessed, which are collected as part of the HTQ.

The PHQ-9 is a nine-question depression questionnaire where each question is scored on a scale of 0 to 3. The module is designed to have an additive interpretation: scores for each of the nine questions are summed up to classify an individual's depression risk level. There are established cutoffs for depression risk severity levels. A score of 0-4 indicates no or minimal depression risk, 5-9 indicates mild depression risk, 10-14 indicates moderate depression risk, 15-19 indicates moderately severe depression risk, and 20-27 indicates severe depression risk (Kroenke et al., 2001). In Appendix A, we outline the exact PHQ-9 questions and scoring procedures. In Figure 3.2, we show the distribution of PHQ-9 scores and depression risk severity cutoffs for refugees within my sample of analysis — the spring Kutupalong sample. In Appendix B (Figure B.2), we also compare the distribution of PHQ-9 scores among Rohingya refugees and Bangladeshis in the CBPS, which suggests that within our data, refugees have worse mental health status than non-refugees.

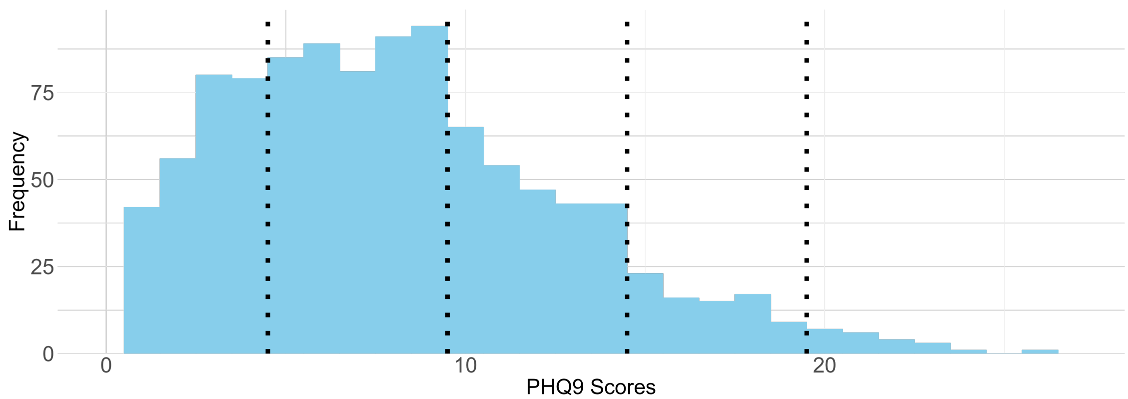


Figure 3.2: PHQ-9 Scores and Severity Thresholds for Rohingya Refugees in Kutupalong — Spring Sample
Vertical lines indicate severity level thresholds: None-Minimal (0-4), Mild (5-9), Moderate (10-14), Moderately Severe (15-19), Severe (19-27).
Figure generated by the authors using CBPS data.

### 3.1.2 Determinants of Mental Health

The CBPS includes numerous other individual and household-level data on potential determinants of depression, which we include as controls to reduce the influence of omitted variable bias in our estimates. These variables include individual attributes such as age, sex, marital status, self-reported health status, and self-reported change in health status in the last year. Previous work has argued that these individual characteristics are related to mental health outcomes (Ambrey and Fleming, 2014; National Institute of Mental Health, 2023; Ohrnberger et al., 2017).

Income and employment can be important determinants of mental health (Hergenrather et al., 2015; Sareen et al., 2011). The CBPS collects data on household income in the month preceding the interview. This includes income from all sources, including wages, asset earnings, cash assistance, and cash equivalents for crops cultivated and consumed by the household (Baird et al., 2021). We construct a dummy variable for employment status and additionally control for household income in the last month per household member. We omit individuals who report making over 6000 takas (about 71 USD) per month per household member (9 observations), which were major outliers.

The CBPS contains modules related to neighbourhood crime and food insecurity, which are both daily stressors that could impact mental health (Baranyi et al., 2021; Pourmotabbed et al., 2020). The crime module measures experience and perception of different crimes and conflicts in the respondent neighbourhood. We construct two separate crime variables by counting the number of crime and conflict issues within the survey that the respondent perceived occur in their neighbourhood and had directly experienced, respectively. We additionally account for food insecurity-related stressors using the Household Food Insecurity Access Scale module in the CBPS, an established questionnaire for measuring food insecurity (Coates et al., 2007). The questions were presented to respondents in binary format (yes/no), so we count the number of "yes" answers for the respondent as a measure of food insecurity.

#### 3.1.3 Housing Data

The CBPS collects extensive data on housing characteristics, which we use for hedonic regressions. Because most Rohingya refugees in Kutapalong do not pay rent and do not own their homes, we use the respondent's perceived rental value.[1] The CBPS contains many additional housing-related variables that we control for in the hedonic analysis. These include the number of rooms occupied by the household, whether the dwelling has a kitchen, and whether the household has access to a gas/improved cookstove or electricity. We additionally control for the types of bathroom facilities and water sources the household generally uses.

### 3.2 Spatial Data

We generate spatial statistics of potential determinants of mental health and perceived rental value. These include surrounding vegetation, settlement density, and distance to wells and medical centres.[2]

#### 3.2.1 Vegetation

We use the Normalized Difference Vegetation Index (NDVI) to measure vegetation levels in Kutupalong. NDVI is one of the most frequently used vegetation indices in remote sensing due to its simplicity, effec-

[1] The respondent who completed the household questionnaire was asked "Assume you want to rent this dwelling: What will be a monthly rent you will be able to ask for?" (Baird et al., 2021). We use these reported values for our hedonic-style analysis. Household survey respondents who do pay rent were not asked about perceived rental values and instead listed their actual rents. Possible responses for the perceived rental value question have no upper bound, and several large outliers skewed initial results. To address this, we omit all perceived rental values that are higher than the highest actual rent value (2000 takas per month) for this portion of our analysis. While the actual rental values guide our decision around outliers, we consider actual rents to be fundamentally different than perceived rental values. For this reason, we omit actual renters in the hedonic-style analysis.

[2] Throughout, we transform all spatial data into UTM projections to minimize distortions. UTM works by dividing the globe into 60 zones and applying a standard Transverse Mercator projection for each zone to minimize within-zone shape and distance distortion (GISGeography, 2024; Dempsey, 2023). Cox's Bazar is in UTM Zone 46.

tiveness, and cross-study comparability, and it has been validated as an effective metric for neighbourhood greenspace applications (Fang and Liang, 2008; Rhew et al., 2011; Gascon et al., 2015). The NDVI is a spectral index that uses the amount of light from different portions of the electromagnetic spectrum that is reflected by different objects and is particularly good at detecting and measuring vegetation (Streambatch, n.d.; Weier and Herring, 2000). We construct the NDVI as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{3.1}$$

Where $NIR$ and $Red$ are the near-infrared and red electromagnetic spectrum bands (Rhew et al., 2011).

Within the NDVI, estimated values range continuously from −1 to 1, with negative values generally indicating water bodies. Low values (approximately 0-0.1) indicate sparsely vegetated or non-vegetated areas. Moderate values (approximately 0.2-0.5) are suggestive of moderate vegetation. By contrast, higher values (approximately 0.6 and above) indicate dense vegetation (Weier and Herring, 2000; Remote Sensing Phenology, 2018). While NDVI is an effective tool for measuring vegetation, it has some limitations. Firstly, it cannot classify vegetation by type (Streambatch, nd). This restricts our ability to comment on the kind of greenspace (forests, grasslands, woodlands, shrublands, etc.) that influences refugee welfare. Additionally, atmospheric conditions and soil moisture levels can affect the amount of reflectance measured by the sensors and skew measurements (Streambatch, nd).

We create high-resolution (10m) NDVI maps of the study region using Sentinel-2 spectral data.[3] This is the finest resolution of publicly available satellite imagery for the study region and time period. The survey times for Kutupalong are bimodal, with one group interviewed between March and May, and the second group interviewed during June and July. Given differences in response timing, we produce two separate two-month image composites of NDVI data and match them with the approximate survey dates to better represent vegetation cover at the time of the interview. We refer to these two survey groups as the "spring sample" and the "summer sample" (pictured in Figure 3.3). We mask out pixels with water coverage and produce two composite NDVI maps: one using Sentinel-2 observations from April 1, 2019 to May 31, 2019 (to match with the spring sample), and the other using observations from June 15 to July 31 (to match with the summer sample). Our composites take the median NDVI value from the time range in order to enhance image quality and circumnavigate cloud cover.[4]

[3]Sentinel 2 is a system of satellites which are part of the European Union's COPERNICUS program for Earth observation (European Space Agency, nd).

[4]Using the median value for this task is preferable because clouds can create large outliers and skew mean values for individual pixels. Our evaluations of the Sentinel-2 data suggest that NDVI trends within composite windows are not a significant source of bias in our data. Beyond our focus on median values to produce our composite, both our analysis (Figure B.1, Appendix B) and Das and Sarkar (2023) support the notion that mean NDVI trends are quite stable within both composite windows. We chose composite windows to approximately match the survey times, but adjusted composite windows slightly to remain within stable mean NDVI trend windows.

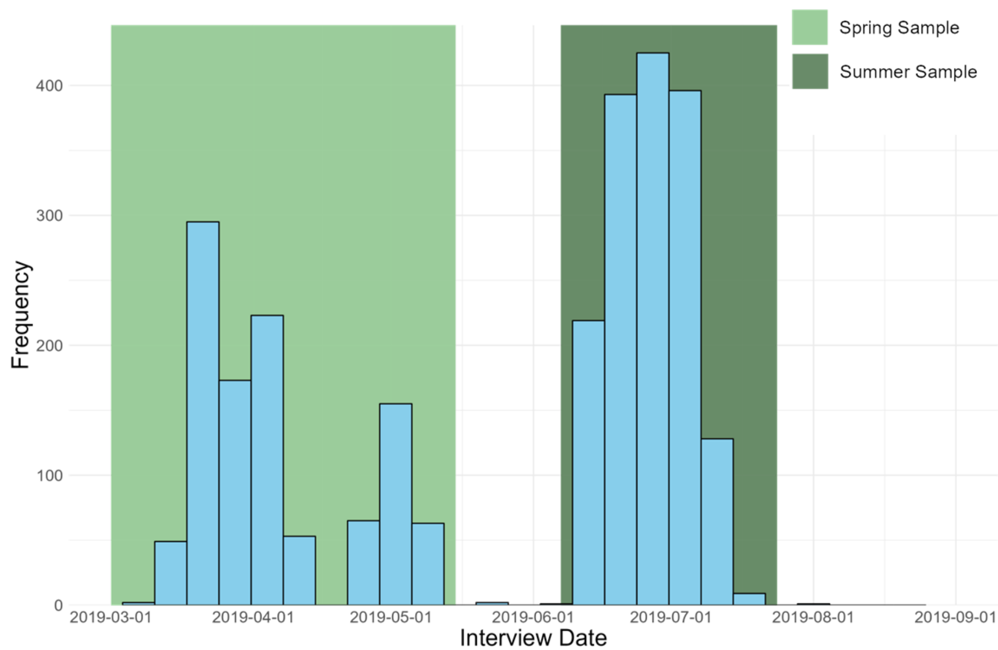


Figure 3.3: Distribution of CBPS Interview Dates for Rohingya Refugees in Kutupalong
Figure generated by the authors using CBPS 2019.

The spring sample coincides with the region's dry season and has clear, cloud-free imagery to generate spatial statistics (Figure 3.4). By contrast, the summer sample coincides with the region's wet season, and we encountered significant NDVI data constraints due to frequent cloud cover. Because vegetation levels vary throughout the year in this region (Das and Sarkar, 2023), and important variables like mental health may vary seasonally for other reasons than can be explained by the data, we restrict our main analysis to refugees interviewed in March, April, and May (2019). Focusing on the spring sample controls for seasonal effects, but also means we cannot study some of Kutupalong's subcamps in the primary specification.[5]

Using our bespoke NDVI maps and jittered respondent geolocations, we generate pixel-level mean NDVI statistics for a set of buffers surrounding each survey respondent's geopoint (Figure 3.5).[6] We use buffers instead of camp or subcamp-level NDVI statistics because measuring greenspace with buffers instead of aggregating spatial characteristics by block group can reduce scale-dependent biases (Banzhaf et al., 2019). While there is no agreed-upon buffer size for NDVI statistics in greenspace studies (Gascon et al., 2015), we select buffer sizes following common choices in previous studies to enhance cross-study comparability. For the primary analysis, we use 250m buffers. We also estimate results for 500m buffers in Appendix C (Tables C.7 and C.8).

[5] We were not given access to the camp names associated with individual survey respondents, so we cannot know which subcamps are included in the spring sample. We estimate fixed effects with anonymized camp names.

[6] A buffer of size x is a circular area of radius x around a focal point. This can be used to calculate zonal statistics. For example, the mean NDVI score for a 100m buffer around an individual's residence is the pixel-level average NDVI score for the pixels that fall within a 100m radius of the residence.

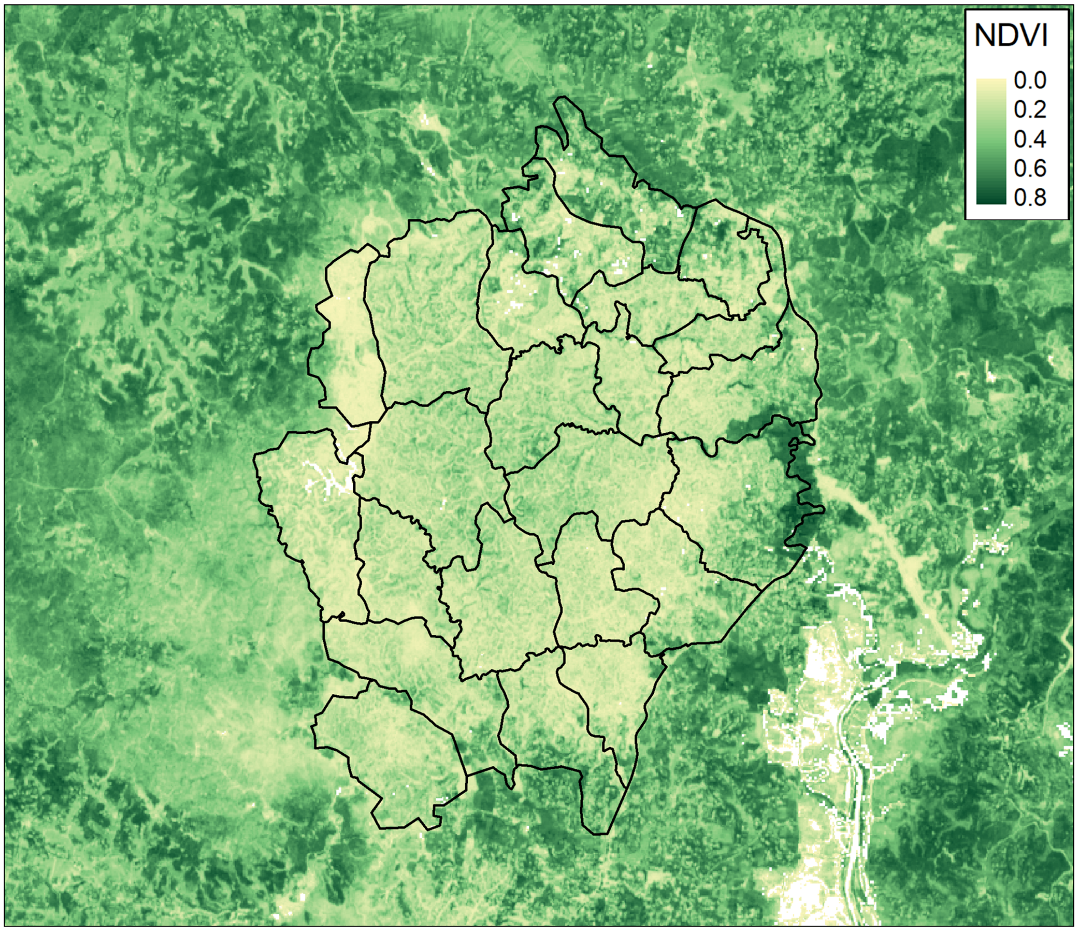


Figure 3.4: April 1, 2019 - May 31, 2019 Composite of NDVI in Kutupalong

Figure generated by the authors using Sentinel-2 satellite imagery and camp outlines from ISCG (2022).

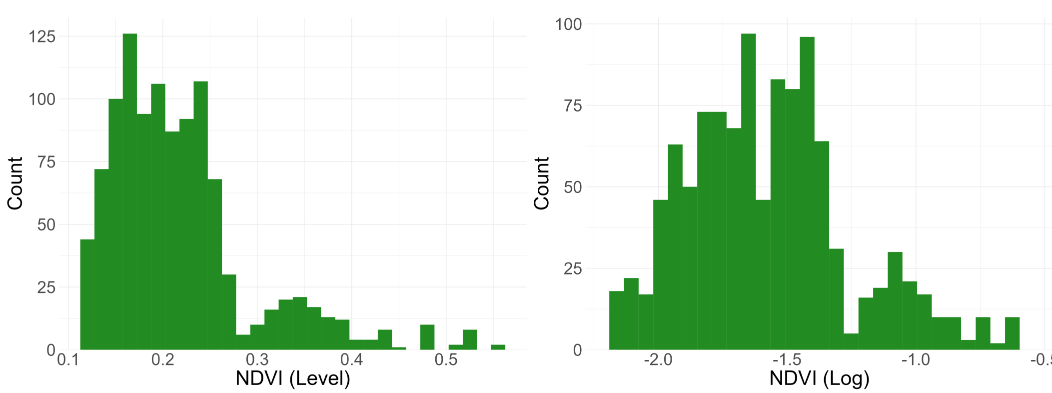


Figure 3.5: Level and log Distributions of NDVI Scores For Rohingya Refugees in Kutupalong — Spring Sample

Figure generated by the authors using CBPS 2019.

### 3.2.2 Settlement Density

Population density could be an important determinant of mental health, and we operationalize this through settlement density mappings. To measure settlement density, we use the 2019 high-resolution (10m) World Settlement Footprint spatial data (DLR, 2019).[7] We use the WSF to measure the proportion of pixels classified as settlements within a buffer around each respondent. To protect respondent privacy, the generated settlement density statistics were discretized by decile. Figure 3.6 illustrates the World Settlement Footprint 2019 data for Kutupalong, demonstrating the considerable population pressure in many areas.

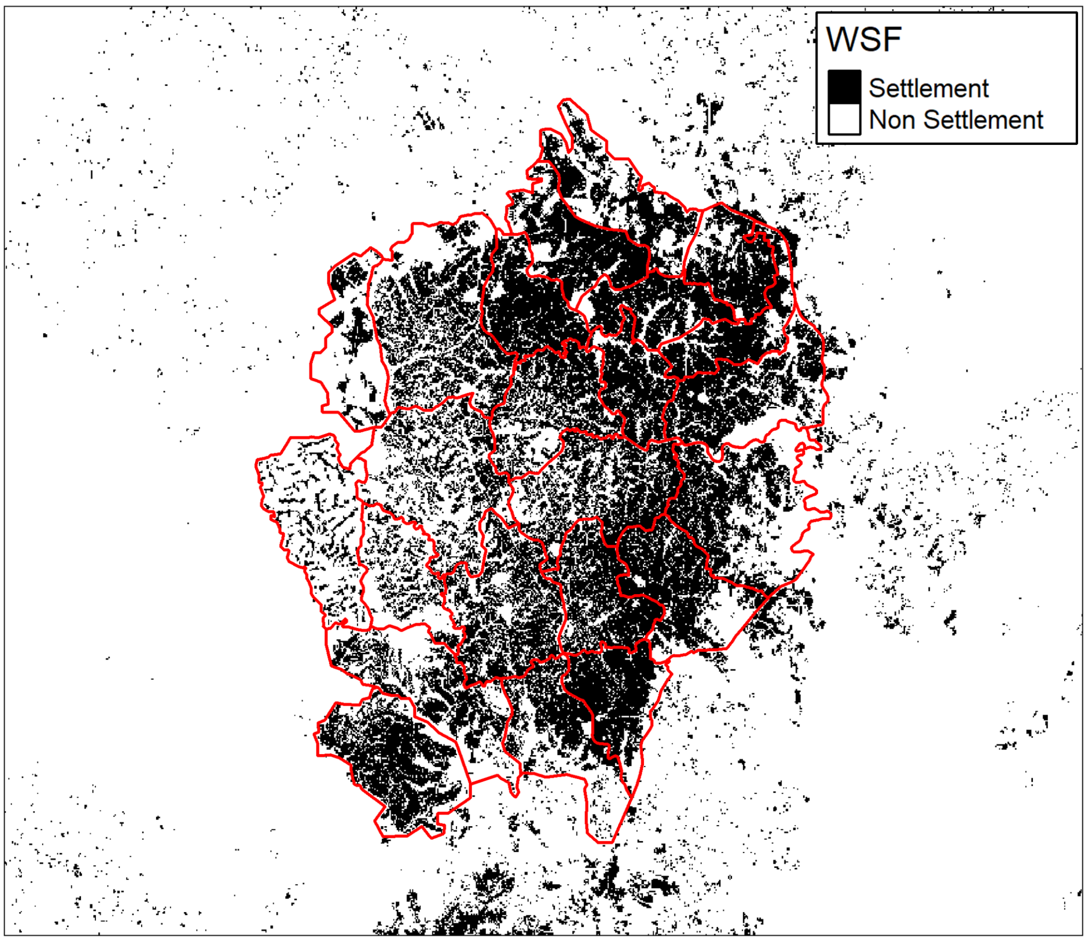


Figure 3.6: 2019 Settlement Footprint in Kutupalong
Figure generated by the authors using World Settlement Footprint data (DLR, 2019) and camp outlines from ISCG (2022).

### 3.2.3 Distance to Wells and Medical Centres

Access to amenities could affect mental health and perceived rental value, and refugees may also face trade-offs between amenity access, settlement density, and vegetation levels. We control for distance to several

[7] The WSF data is generated using a binary Random Forest classification approach to determine settlement presence. (Marconcini et al., 2021).

amenities using publicly available, spatially explicit information on amenity locations. At present, we have such information for tube wells and medical centres in 2019.

We use data on the location and quality of tube wells within refugee camps across Cox's Bazar, which was compiled by UNICEF and the Cox's Bazar WASH sector (REACH, 2019). These data were collected between April and July 2019. A contamination risk score was provided for most wells, which is based on proximity to latrines and well conditions. We omit wells with a contamination risk score of "high" and "very high," which make up about 10% of the observations.

To account for distance to medical centres, we use data on the location of medical centers from the Common Facility Mapping dataset provided by the Inter Sector Coordination Group (ISCG, 2020), which geo-located health facilities in Cox's Bazar refugee camps in 2019. We include health centers that provide regular treatment for most common conditions (Health Posts, Community Health Clinics, Primary Health Centers, and Secondary Health Facilities).

We calculate the distance from each survey respondent's location to the nearest well and medical centre using Euclidian distance in meters. This approach may understate distance due to landscape characteristics, and a least-cost path approach may have been preferable. However, since we do not have direct access to the true points, we decided to use Euclidian distance for simplicity and transparency. This approach is justified because Euclidian distances and least-cost path distances are very positively correlated in most situations (Etherington and Penelope Holland, 2013).

### 3.3 Descriptive Statistics

Table 3.1, summarizes the determinants of depression by PHQ-9 risk level in accordance with PHQ-9 scoring procedures. Because the "Severe" category has very few observations, we combine the "Moderately Severe" and "Severe" depression risk categories for our descriptive statistics and in our analysis. In Table 3.2, we summarize the determinants of perceived rental value by distributional cutoffs. Respondents strongly anchor to specific values such as 500 and 1000 takas/month, so we chose cutoffs to distribute data relatively evenly.

The descriptive statistics by PHQ-9 risk level (Table 3.1) suggest that there is very little variation in mean NDVI, settlement density, and distance to amenities across depression risk categories. The summary statistics demonstrate the expected results for many of the controls. For instance, individuals with better self-reported health status are in the lower depression risk categories in larger proportions than those with worse self-reported health status, and the same is true for self-reported changes in health status over the last year. Similarly, food insecurity and age appear to be positively correlated with depression risk, as does being female. Income per household member and employment seem to be negatively related to depression risk levels; however, the relationship for income is not monotonic, which could be attributed to sample size.

Finally, both experiencing and witnessing traumatic events appear to be postively correlated with depression risk levels, as is experiencing and perceiving neighbourhood crime and conflict.

Similarly, in Table 3.2, which outlines the means and percentages of determinants of housing value by perceived monthly rental value cutoffs, we see very little variation in NDVI, settlement density, and distance to amenities across categories. Like Table 3.1, the statistics on regression covariates related to shelter and amenity characteristics align with previous hedonics literature to some extent. Respondents with higher perceived rental values tend to occupy more rooms as a household and have a separate kitchen, a gas or improved cookstove, and electricity. There is also notable variance in the different types of toilet facilities and water sources used by households across perceived rental values. The household average perceived and experienced crime rates surprisingly seem to be positively related to perceived rental values, but this relationship is weak and non-monotonic.

In Figures B.3 and B.4 (Appendix B), we visually compare log mean NDVI (250m) and the dependent variables of interest. These figures show histograms of both variables, as well as a corresponding scatterplot and line of best fit. Figure B.3 shows a mild negative correlation between log mean NDVI and PHQ-9 scores within the sample. Figure B.4 shows a very weak negative correlation between log mean NDVI and perceived rental values and shows the tendency for respondents to anchor to perceived rental values of 500 and 1000 takas per month (approximately 6-12 USD).

Table 3.1: Means and Percentages of Determinants of Depression by PHQ-9 Risk Level. Kutupalong Refugees, Spring Sample.

| | None-Minimal | Mild | Moderate | Moderately Severe/Severe | Total |
|---|---|---|---|---|---|
| N | 320 | 539 | 285 | 118 | 1,262 |
| Mean NDVI (250m) | 0.22 | 0.22 | 0.21 | 0.21 | 0.22 |
| WSF Prop. (250m) | 5.77 | 5.62 | 5.68 | 5.63 | 5.67 |
| Dist. Nearest Well (m) | 19.37 | 18.23 | 18.36 | 20.69 | 18.78 |
| Dist. Nearest Health Ctr. (m) | 158.30 | 170.72 | 179.77 | 164.23 | 169.00 |
| # Perceived Crime Issues | 2.12 | 2.94 | 3.51 | 4.03 | 2.96 |
| # Experienced Crime Issues | 0.40 | 0.56 | 0.85 | 0.92 | 0.62 |
| # Experienced Traumas | 2.82 | 2.71 | 3.47 | 4.05 | 3.04 |
| # Witnessed Traumas | 2.76 | 3.24 | 3.89 | 3.36 | 3.28 |
| Food Insecurity Score | 4.80 | 5.18 | 5.62 | 5.67 | 5.23 |
| Age | 26.15 | 30.96 | 34.39 | 34.60 | 30.85 |
| Household Income ÷ Size | 645.82 | 707.28 | 549.17 | 621.99 | 648.26 |
| Employment Status | | | | | |
| Unemployed (%) | 75.94 | 75.14 | 78.60 | 85.59 | 77.10 |
| Employed (%) | 24.06 | 24.86 | 21.40 | 14.41 | 22.90 |
| Sex | | | | | |
| Male (%) | 50.31 | 42.86 | 37.19 | 33.90 | 42.63 |
| Female (%) | 49.69 | 57.14 | 62.81 | 66.10 | 57.37 |
| Marital Status | | | | | |
| Married (%) | 65.94 | 74.54 | 67.72 | 81.36 | 71.45 |
| Never Married (%) | 30.00 | 15.06 | 15.79 | 7.63 | 18.32 |
| Widowed (%) | 3.44 | 8.36 | 15.09 | 10.17 | 8.80 |
| Divorced/Seperated (%) | 0.62 | 2.04 | 1.40 | 0.85 | 1.43 |
| Health Status | | | | | |
| Very good (%) | 4.69 | 2.41 | 0.70 | 0.85 | 2.46 |
| Good (%) | 67.19 | 51.95 | 44.21 | 22.88 | 51.35 |
| Regular (%) | 14.69 | 18.18 | 18.25 | 16.10 | 17.12 |
| Bad (%) | 12.81 | 25.97 | 33.33 | 51.69 | 26.70 |
| Very bad (%) | 0.62 | 1.48 | 3.51 | 8.47 | 2.38 |
| Health Change | | | | | |
| Much better (%) | 4.06 | 2.97 | 1.40 | 0.00 | 2.61 |
| Better (%) | 40.94 | 30.80 | 27.72 | 13.56 | 31.06 |
| The same (%) | 30.00 | 25.05 | 20.35 | 19.49 | 24.72 |
| Worse (%) | 23.44 | 39.70 | 47.02 | 56.78 | 38.83 |
| Much worse (%) | 1.56 | 1.48 | 3.51 | 10.17 | 2.77 |

**Data:** All data is from the Cox's Bazar Panel Survey except for author-generated geospatial data (Mean NDVI (100m), WSF Prop. (100m), Dist. Nearest Well, and Dist. Nearest Health Ctr.).
**Abbreviations:** N is the sample size. "#" is short for number. PHQ-9 risk levels are depression risk levels according to Patient Health Questionaire 9 scores (combining Moderately Severe/Severe due to small sample sizes). NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance.
**Units:** Units for household income adjusted for household size is hundreds of takas/month.
**Statistics:** This table summarizes the relationships between depression risk levels and various demographic and environmental factors. The sample for this table is all refugees in the Kutupalong spring sample. For continuous variables, we report conditional means. For factor variables, we report relative percentages (%). For sample size (N), we report counts by PHQ-9 risk level.
**Difference In Sample Size:** Sample size in regressions is slightly lower than in descriptive statistics because the regressions omit respondents with missing data for one or more variables. The descriptive statistics omit these variables only for the missing responses.

Table 3.2: Means and Percentages of Determinants of Housing Value by Perceived Monthly Rental Value Cutoffs. Kutupalong Refugee Households, Spring Sample.

| | 0-499 Takas | 500-999 Takas | 1000+ Takas | Total |
|---|---|---|---|---|
| N | 161 | 285 | 265 | 711 |
| Mean NDVI (250m) | 0.22 | 0.22 | 0.22 | 0.22 |
| WSF Prop. (250m) | 5.66 | 5.60 | 5.88 | 5.71 |
| Dist. Nearest Well (m) | 18.13 | 18.40 | 19.15 | 18.62 |
| Dist. Nearest Health Ctr. (m) | 167.62 | 170.56 | 165.55 | 168.03 |
| Avg # Experienced Crime Issues | 0.51 | 0.72 | 0.62 | 0.64 |
| Avg # Perceived Crime Issues | 2.85 | 3.17 | 2.90 | 3.00 |
| Rooms | 1.64 | 1.86 | 1.97 | 1.85 |
| Seperate Kitchen | | | | |
| No (%) | 72.67 | 73.68 | 64.53 | 70.04 |
| Yes (%) | 27.33 | 26.32 | 35.47 | 29.96 |
| Gas/Improved Cookstove | | | | |
| No (%) | 24.84 | 27.02 | 14.72 | 21.94 |
| Yes (%) | 75.16 | 72.98 | 85.28 | 78.06 |
| Electricity | | | | |
| No (%) | 76.40 | 66.32 | 72.83 | 71.03 |
| Yes (%) | 23.60 | 33.68 | 27.17 | 28.97 |
| Toilet Facility | | | | |
| Sanitary (%) | 13.04 | 9.86 | 6.04 | 9.15 |
| Pacca latrine (water seal) (%) | 9.32 | 13.73 | 16.98 | 13.94 |
| Pacca latrine (pit) (%) | 44.10 | 45.42 | 50.19 | 46.90 |
| Kacha latrine (perm) (%) | 19.25 | 16.55 | 19.25 | 18.17 |
| Kacha latrine (temp) (%) | 14.29 | 14.44 | 7.55 | 11.83 |
| Water Source | | | | |
| Supply (%) | 4.97 | 4.91 | 4.53 | 4.78 |
| Water supply tanks (%) | 0.62 | 1.05 | 5.66 | 2.67 |
| Tubewell/Well (%) | 94.41 | 94.04 | 89.81 | 92.55 |

**Data:** All data is from the Cox's Bazar Panel Survey except for author-generated geospatial data (Mean NDVI (100m), WSF Prop. (100m), Dist. Nearest Well, and Dist. Nearest Health Ctr.).
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance. The Avg # of perceived and experienced crime issues is the household-level average score for those categories (since those questions were asked at the household level).
**Statistics:** This table summarizes the relationships between depression risk levels and various demographic and environmental factors. The sample for this table is households in the Kutupalong spring sample. For continuous variables, we report conditional means. For factor variables, we report relative percentages (%). For sample size (N), we report counts by PHQ-9 risk level.
**Cutoffs:** Respondents strongly anchor to perceived rental values of 500 and 1000. Cutoffs of 499 and 999 were chosen to distribute categories as evenly as possible.
**Units:** Units for household income adjusted for household size is hundreds of takas/month.
**Difference In Sample Size:** Sample size in regressions is slightly lower than in descriptive statistics because the regressions omit respondents with missing data for one or more variables. The descriptive statistics omit these variables only for the missing responses.

# 4. Methods

For our estimation of the relationship between greenspace and mental health, our primary specification uses an ordered logit model at the individual level. As a robustness check, we also estimate our model using ordinary least squares (OLS), Poisson, and binary logit approaches. Our complementary analysis on perceived rental value applies a standard OLS hedonic regression methodology. These empirical approaches are outlined below.

## 4.1 Greenspace and Mental Health

### 4.1.1 Ordered Logit

We use an ordered logit model to measure the average marginal effect of greenspace proximity - as measured by the mean NDVI within a buffer area around the respondent's geo-location - on the probability of being in each depression risk severity category as measured by the PHQ-9. In our preferred specification, we use 250m buffers to produce our NDVI and settlement density estimates. To reduce omitted variable bias, we control for determinants of mental health that could be related to both depression and surrounding vegetation. We model underlying depression levels as a latent (unobservable) depression level $PHQ^*$ as follows:

$$PHQ_i^* = X_i'\beta + W_i'\gamma + \phi_c + \delta \ln\left(NDVI_i\right) + \epsilon_i \tag{4.1}$$

The outcome variable $PHQ_i^*$ is the latent depression level of individual $i$. We control for $X_i$, a matrix of individual determinants of depression (past traumatic experiences, food insecurity, self-reported health status and health change, income/employment status, age, sex, and marital status). We additionally account for the neighbourhood-level and geospatial determinants of depression using $W_i$. This includes the number of times the respondent witnessed or experienced crime in the respondent's neighbourhood, the percentage of the respondent's nearby land area with settlement cover (based on 250m buffer estimates), as well as Euclidean distance to tube wells and medical centres. We include camp fixed effect $\phi_c$ to account for factors constant within each smaller camp area, such as governance quality. Our variable of interest is $NDVI_i$, the logged mean Normalized Difference Vegetation Index score for a 250m buffer around individual $i$.[1]

The depression risk levels are categorized based on the values of $PHQ^*$ when they cross unknown latent depression thresholds $\tau_1 - \tau_3$ (Wooldridge, 2010). The PHQ-9 survey scores depend on the latent depression scores $PHQ^*$ and are categorized according to the scoring procedures outlined in Appendix A. The PHQ-9

[1] As mentioned in Section 3, we masked non-positive NDVI pixels. This removes water as a confounding variable and also makes the natural logarithm operation valid.

traditionally has 5 depression risk severity categories (see Appendix A). Very few Rohingya refugees in the sample are in the highest risk category, so we combine the two highest risk categories. Consequently, we classify $PHQ$ risk categories as follows.

$$PHQ = \begin{cases} 0 & \text{if } \tau_1 \geq PHQ^* \\ 1 & \text{if } \tau_1 \leq PHQ^* \leq \tau_2 \\ 2 & \text{if } \tau_2 \leq PHQ^* \leq \tau_3 \\ 3 & \text{if } \tau_3 \leq PHQ^* \end{cases} \tag{4.2}$$

We report the average marginal effect of an increase in greenspace on the probability of being in each depression risk category. Since the logistic function is nonlinear, marginal effects vary for different levels of greenspace. Following Hansen (2021), we estimate the average marginal effect for regressor $k$ (i.e. $NDVI$) on the probability of being in depression risk category $j$ (in percentage points) by computing marginal effects for each individual in the sample and taking the expected value as follows:

$$AME_{k_i}^{(j)} = \mathbb{E}\left(\frac{\partial P(PHQ_i = j)}{\partial k_i}\right) = \beta_k \mathbb{E}\left[g(\tau_{j-1} - X_i'\beta - W_i'\gamma - \delta \ln NDVI_i) - g(\tau_j - X_i'\beta - W_i'\gamma - \delta \ln NDVI_i)\right]$$

Where $g$ is the probability density function of the logistic distribution, $P$ is the probability, and $\beta_k$ is the coefficient on regressor $k$.

### 4.1.2 Robustness Checks

One advantage of the ordered logit specification is its straightforward interpretability. However, the ordered logit approach reduces the amount of PHQ-9 variation exploited in the estimation procedure, as all observations within the same category are classified the same. To ensure that our results are not influenced by this within-category reduction in variation, we estimate OLS and Poisson models. For these estimators, we use the same independent variables as the ordered logit specification and use raw PHQ-9 scores to construct the dependent variables. Additionally, since past studies of depression have used a binary logit model with a depression cutoff of PHQ-9 $\geq 10$ (Ritsema and Armstrong-Hough, 2023), we estimate average marginal effects for a binary logit model with the same cutoff to enhance cross-study comparability. However, it is important to note that the logit average marginal effects are not directly comparable to the OLS and Poisson results.

The OLS Model is:

$$PHQ\_Raw_i = \alpha + X'\beta + W'\gamma + \delta \ln(NDVI_i) + \epsilon_i \tag{4.3}$$

Where $PHQ\_Raw_i$ is the raw PHQ-9 score (0-27) for individual $i$, $\alpha$ is a constant, and all independent variables are identical to the ordered logit specification.

While OLS provides a useful benchmark case, raw PHQ-9 scores are skewed towards lower values, making linear model fit difficult. A Poisson regression is useful in cases with skewed data to improve model fit and avoid unrealistic predictions sometimes encountered with linear models, such as negative depression scores (Green, 2021). Again, following Hansen (2021), we model the Poisson regression as follows:

$$\mathbb{E}\left[PHQ\_Raw_i \mid X, W, \ln NDVI\right] = e^{\alpha + X'\beta + W'\gamma + \delta \ln(NDVI_i)} \tag{4.4}$$

Taking the natural logarithm of both sides, we can directly interpret the coefficients as marginal effects on this transformed dependent variable.

$$\ln \mathbb{E}\left[PHQ\_Raw_i \mid X, W, \ln NDVI_i\right] = \alpha + X'\beta + W'\gamma + \delta \ln(NDVI_i) \tag{4.5}$$

## 4.2 Perceived Rental Values

We use a hedonic-style approach to measure the relationship between perceived rental values and surrounding vegetation at the household level. We control for other determinants of perceived rental value, including housing and neighbourhood characteristics. The hedonic-style model is:

$$P_h = \alpha + H_h'\beta + W_h'\gamma + \phi_c + \delta \ln(NDVI_h) + \epsilon_h \tag{4.6}$$

The dependent variable $P_h$ is the perceived rental value for household $h$. $H_h$ is a matrix of housing factors that influence home value, including number of rooms, kitchen and cookstove access, electricity, bathroom facility, and water source type. $W_h$ is a matrix of (dis)amenity factors, including settlement density, witnessed and experienced neighbourhood crime, and distance to amenities, and contains the same variables as $W_i$ in the previous specifications. $\phi_c$ represents camp fixed effects. Our explanatory variable of interest is $NDVI_h$ — the pixel-level mean Normalized Difference Vegetation Index score for a 250m buffer around household $h$ (in logs).

We use ordinary least squares to measure the marginal effect of each regressor on perceived rental value.

# 5. Results

## 5.1 Mental health

### 5.1.1 Ordered Logit

In Table 5.1, we report abridged results for the average marginal effects of each geospatial variable on the probaility of being in each depression risk category for our primary sample of interest. We present the full results of our estimation in Table C.3 (Appendix C).

Table 5.1: Ordered Logit: Average Marginal Effects on the Probability of Being in Each Depression Risk Category. Spring Kutupalong Sample.

| | None/Minimal | Mild | Moderate | Moderately Severe/Severe |
|---|---|---|---|---|
| Log Mean NDVI (250m) | -0.10300** | -0.00934 | 0.06437** | 0.04796** |
| | (0.05024) | (0.00588) | (0.03145) | (0.02367) |
| WSF Prop. (250m) | -0.01390* | -0.00126 | 0.00868* | 0.00647* |
| | (0.00733) | (0.00085) | (0.00460) | (0.00345) |
| Dist. Nearest Well (m) | 0.00040 | 0.00004 | -0.00025 | -0.00019 |
| | (0.00072) | (0.00007) | (0.00045) | (0.00034) |
| Dist. Nearest Health Ctr. (m) | -0.00014 | -0.00001 | 0.00009 | 0.00007 |
| | (0.00012) | (0.00001) | (0.00007) | (0.00005) |
| Controls | Yes | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes | Yes |

Standard errors in parentheses. N = 1238

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data:** Data for all variables presented here were generated by author using geospatial data and respondent locations. Coefficients for all controls besides camp fixed effects (past traumatic experiences, food insecurity, health status, health change, income, employment, age, sex, marital status, crime, camp fixed effects) are from the Cox's Bazar Panel Survey and are reported in Table C.3 (Appendix C).
**Abbreviations:** NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

The estimated average marginal effects run counter to most previous research. Using 250m buffers, we find that a one percent increase in mean NDVI is associated with a 0.0103 percentage point decrease in the probability of being in the "None/Minimal" depression risk category and a 0.000934 percentage point decrease in the probability of being in the "Mild" depression risk category. The sign of this relationship flips for the higher depression risk categories, where a one percent increase in mean NDVI is associated with a 0.006436 percentage point increase in the probability of being in the "Moderate" depression risk category and a 0.004796 percentage point increase in the probability of being in the "Moderately Severe/Severe" category. We show these average marginal effects in Figure 5.1 with their corresponding 95% confidence intervals.

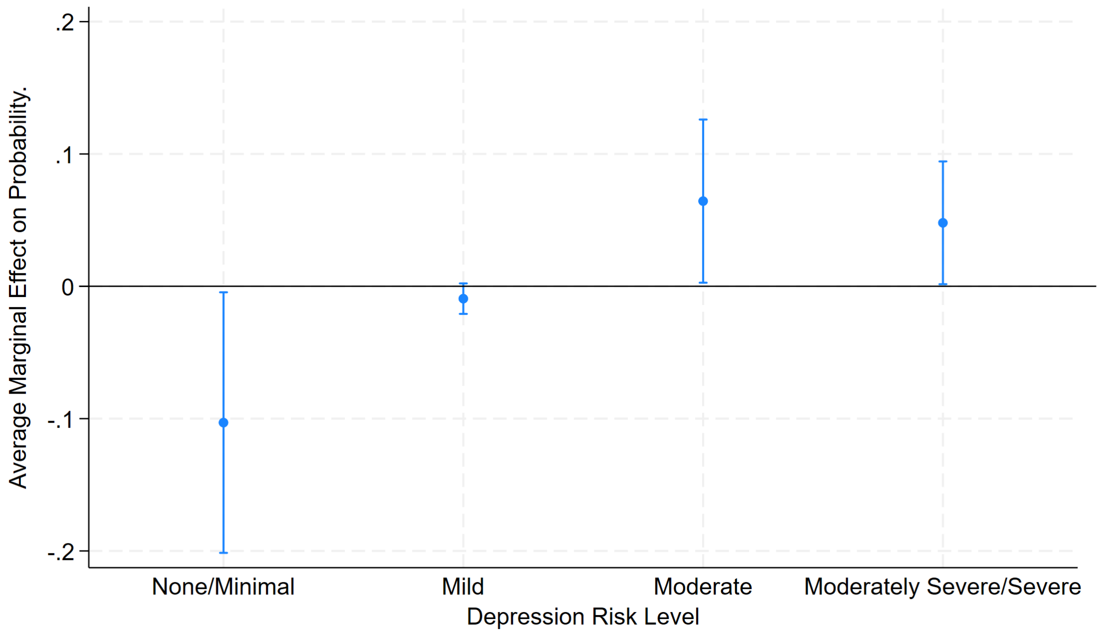


Figure 5.1: Marginal effects of NDVI on the Probability of Being in Each PHQ-9 Depression Risk Category
This figure shows the marginal effect of a one percent increase on the probability of being in each PHQ-9 depression risk category in percentage points. Bars are 95% confidence intervals. NDVI is the pixel-level logged mean value for a 250m buffer.

Although there is a negative correlation between settlement density and NDVI, marginal increases in settlement density are also associated with decreases in the probability of being in lower depression risk categories and increases in the probability of being in the higher depression risk categories.[1] The results for both NDVI and settlement density are statistically significant at the 10% level for all depression risk categories except "Mild" — which notably has the largest sample size. Excluding the "Mild" category, the NDVI results are also marginally statistically significant at the 5% level.

While not statistically significant at the 10% level, increases in distance to wells are associated with an increase in the probability of being in the lower depression risk categories and a decrease in the probability of being in the higher depression risk categories, an unintuitive result. The relationship between risk of depression and proximity to medical centres aligns with our priors, with increases in distance being associated

[1] In the spring Kutupalong sample, log NDVI and WSF have a correlation of -0.4715. If looking at NDVI in levels, we get a correlation of -0.4727. The direction (but not always the significance) of the relationship between NDVI, depression risk, and perceived rental value is robust to removing settlement density for all main specifications. However, removing settlement density changes the sign of the NDVI coefficient for some supplemental specifications. Notably, in nearly all alternative models of greenspace and mental health that include summer observations with spring imagery-based vegetation statistics (both versions with and without summer dummies), removing settlement density results in vegetation being negatively (but insignificantly) related to depression risk. The sign of the relationship between vegetation and depression risk also flips when using 500m buffers for the binary logit model when estimating over the spring sample.

with a decrease in the probability of being in the lower depression risk categories and increases in the probability of being in the higher depression risk categories. Like distance to wells, distance to medical centres is not statistically significant at the 10% level.

### 5.1.2 Robustness Checks

Comparing these alternative models to the ordered logit specification, we find consistent results (Table 5.2). The coefficient estimates from the OLS, Poisson, and binary logit specifications have the same sign as the ordered logit specification for both NDVI and settlement density. However, these results are not statistically significant at the 10% level. Looking at distances to wells and medical centres, the sign of all results align with ordered logit except for the binary logit results for distance to the nearest well. Since none of the distance measures are statistically significant for any specification, those results should be interpreted with caution. Overall, these results suggest that increases in NDVI and settlement density within a 250m buffer are associated with higher depression risk levels and that this relationship is robust to various specifications. Table C.6 (Appendix C) shows the main specification results for all controls besides camp fixed effects.

Table 5.2: Comparing Models for the Relationship Between Greenspace and Depression Symptoms. Kutupalong Refugees, Spring Sample.

| | OLS | Poisson | Logit |
|---|---|---|---|
| Log Mean NDVI (250m) | 0.49315 | 0.08197 | 0.10273 |
| | (0.67562) | (0.08383) | (0.07028) |
| WSF Prop. (250m) | 0.06270 | 0.01195 | 0.01111 |
| | (0.09467) | (0.01222) | (0.01032) |
| Dist. Nearest Well (m) | -0.00013 | -0.00011 | 0.00020 |
| | (0.01166) | (0.00141) | (0.00098) |
| Dist. Nearest Health Ctr. (m) | 0.00077 | 0.00011 | 0.00016 |
| | (0.00156) | (0.00019) | (0.00016) |
| Controls | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes |

Standard errors in parentheses. N = 1238. OLS $R^2$ is 0.289. The constant is 1.24468 for OLS and 1.25417 for Poisson.

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

**Dependent Variables:** Dependent variables are raw PHQ-9 scores (1-27) for OLS. The log expected value of raw PHQ-9 scores for Poisson, and a binary indicator of if PHQ $\geq$ 10 for Logit.
**Data:** Data for all variables presented here were generated by author using geospatial data and respondent locations. All controls (coefficients reported in Table C.6 - Appendix C) are from the Cox's Bazar Panel Survey. Camp fixed effects included but not reported.
**Standard Errors:** Heteroskedasticity-robust standard errors used for OLS and Poisson models.
**Comparing Models:** OLS and Poisson coefficients (marginal effects) can be directly compared. However, here we report average marginal effects for Logit, which cannot be directly compared with OLS and Poisson.
**Cutoffs:** For the Logit Models, we used a cutoff of 10 (inclusive) to indicate if an individual has risk of depression.
**Abbreviations:** NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

In Tables C.1, C.2, C.4, C.5, C.7, and C.8, we report results for some additional specifications. In Tables C.1 and C.4, we report results for the various models when we include the full sample, but summer observations enter with a dummy variable (assuming NDVI scores associated with spring imagery). In Tables C.2 and C.5, we report results for the full sample without a dummy variable for summer observations. In Tables C.7 and C.8, we show results for the spring sample using 500m buffers to measure vegetation and settlement density. The sign of the relationships in both summer sample specifications for NDVI and settlement density are robust to the main results in all econometric models besides OLS — where we see the sign flip for NDVI. Additionally, the sign of the relationship flips for NDVI and settlement density for 500m buffers for OLS, Poisson, and binary logit. The vast majority of results for the supplemental specifications are not statistically significant at the 10% level.

### 5.1.3 Perceived Rental Values

In Table 5.3, we report the marginal relationship between greenspace proximity and perceived rental value. Consistent with the greenspace-mental health analysis, both greenspace levels and settlement density are inversely related to perceived rental value, but these results are not statistically significant at the 10% level. The null results could be due to reduced statistical power due to estimating the regression at the household level ($N = 641$). If we assume that the perceived rental values of the respondents are representative of each adult respondent within the household, regression results have similar magnitudes to the main specification for both greenspace and settlement density, but they are both significant at the 10% level (Table C.9, Appendix C).[2]

Perceived rental value is positively related to distance to wells and medical centres, which is unexpected, but those coefficients are not statistically significant under any specification. Most other controls exhibit expected relationships. Perceived rental values are positively related to occupying more rooms, having electricity, having access to a separate kitchen, and having a gas or improved cookstove. Toilet facilities and water source types also influence perceived rental value. Surprisingly, perceived and experienced crime rates are insignificant.

[2] In the specification where we assume that household survey responses for rents are representative of the entire household, we estimate the regression at the adult respondent level — which roughly doubles the sample size.

Table 5.3: Hedonic-Style Regression: Dependent Variable is Perceived Rental Value at the Household Level (Capped at the Highest Actual Rent Value of 2000 Takas/Month).

| | Coefficient | Standard Error |
|---|---|---|
| Log Mean NDVI (250m) | -102.70 | (95.49) |
| WSF Prop. (250m) | -14.06 | (14.41) |
| Dist. Nearest Well (m) | 1.26 | (1.46) |
| Dist. Nearest Health Ctr. (m) | 0.17 | (0.24) |
| Avg # Experienced Crime Issues | 18.68 | (21.48) |
| Avg # Perceived Crime Issues | 7.80 | (8.20) |
| Rooms | 109.95*** | (29.65) |
| Separate Kitchen | 51.96 | (45.52) |
| Gas/Improved Cookstove | 119.11* | (66.05) |
| Electricity | 40.25 | (42.01) |
| Toilet Facility: | | |
| Pacca latrine (water seal) | 273.74*** | (80.95) |
| Pacca latrine (pit) | 169.32** | (66.77) |
| Kacha latrine (perm) | 243.27*** | (79.80) |
| Kacha latrine (temp) | 132.10 | (82.92) |
| Water Source: | | |
| Water supply tanks | 431.77** | (173.82) |
| Tubewell/Well | 180.05 | (111.15) |
| Camp Fixed Effects | Yes | Yes |

Standard errors in parentheses. N=641. $R^2 = 0.145$. Constant = -6.75

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data**: All data comes from the Cox's Bazar Panel Survey, except spatial statistics which were generated by author using geospatial data and respondent points [Log Mean NDVI (100m), WSF Prop. (100m), Dist. Nearest Well, Dist. Nearest Health Ctr.].
**Base Categories:** Base of Toilet Facility is "Sanitary", base of Water Source is "Supply".
**Fixed Effects:** Camp fixed effects included in regressions but not reported here.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre. "#" is short for number.
**Units:** Units for household income adjusted for household size is hundreds of takas/month. The Avg # of perceived and experienced crime issues is the per-household average score for those categories (since those questions were asked at the household level).
**Standard Errors:** Breusch–Pagan and White tests indicate heteroskedasticity. We use Hubert-White robust standard errors.

## 6. Discussion

Our analysis of the relationship between greenspace and depression risk and the relationship between greenspace and perceived rental values both yield unexpected results. While most previous research finds that greenspace exposure is associated with lower depression risk, we find a positive relationship. Moreover, while many past studies find a positive relationship between housing prices and greenspace, we estimate a negative (though non-significant) relationship between perceived rental values and greenspace. These results are surprising, but there are several plausible factors that could explain this relationship.

Firstly, we could be seeing this relationship because of how we measure vegetation. NDVI does not differentiate vegetation types, and there may be type-specific relationships that we are not capturing. For example, surrounding tree cover may influence mental health differently than surrounding grasslands. Additionally, there could still be highly localized relationships that we cannot measure using a 250m buffer. We use this buffer to ensure that the respondent's true location characteristics are included after geo-jittering the geolocations by 50m-115m in a random direction. Moreover, this result may be due to endogenous selection: individuals with higher depression may tend to locate in greener areas for non-random and unknown reasons.

Additionally, it might be the case that in this setting, greenspace constitutes a public "bad" (as opposed to a public good) and/or is associated with other public bads, such as wildlife attacks (McPherson, 2018). Similarly, this relationship could exist if greenspace is inversely related to unmeasured factors that positively influence mental health and perceived rental values, like amenities that necessitate clearing of land for their construction. In other words, refugees in Kutupalong may face significant opportunity costs to greenspace.

The observed relationships between settlement density, risk of depression, and perceived rental value are more intuitive. People who live in denser areas experience increased competition over resources and may impose negative externalities on each other. The result that settlement density is positively related to risk of depression and negatively related to perceived rental values aligns with these concepts. When considering the greenspace and settlement density results together, the implications are intriguing. In Kutupalong, it appears optimal to live in relatively non-vegetated, sparsely populated areas. This result aligns with the idea that there are unmeasured common goods that are inversely related to greenspace and that these benefits are realized more for people living in less densely populated areas.

We find inconclusive results in our analysis of how distance to wells and medical centres relates to risk of depression and perceived rental values. This result could be due to our use of Euclidian distance instead of least cost path estimates, or my assumption that respondents always travel to the closest facility. The distance variables may also have been affected by the random displacement of respondent locations.

## 7. Conclusion

In this paper, we used a combination of survey data and spatial statistics to measure the relationship between surrounding greenspace levels and depression symptoms for Rohingya refugees living in Kutupalong, Cox's Bazar. Additionally, we measured the relationship between greenspace and perceived rental value, which we argued reflects willingness to pay for greenspace.

In contrast to previously measured relationships in industrialized countries, we found that greenspace is positively related to depression symptoms, even when controlling for many potentially confounding variables, and that this result is statistically significant and robust to most empirical approaches we used. We also find that greenspace is negatively related to perceived rental values, but that this result is not statistically significant at the 10% level. These results suggest that relationships previously established in industrialized countries may not hold in refugee camps.

We also considered how population density relates to mental health and perceived rental values. In doing so, we found that although settlement density is negatively related to greenspace, it is also positively related to depression symptoms and negatively related to perceived rental values. We could be observing this relationship due to increased competition over resources in more densely populated areas or because of negative externalities.

Together, these results suggest that the optimal residence location in Kutupalong has relatively low vegetation levels and settlement density. While greenspace may truly be causing increases in depression levels and decreases in perceived rental values, there are other potential explanations for this relationship. It is possible that there is a tradeoff between greenspace and unmeasured camp amenities, which could be driving this result. Furthermore, greenspace could be positively related to undesirable camp characteristics, such as an increased likelihood of wildlife attacks.

There are several limitations to this project. Firstly, the survey data are cross-sectional, which prohibits us from identifying a causal relationship between our variables of interest. Secondly, using the Normalized Difference Vegetation Index means we cannot differentiate between different types of vegetation, which could obscure true relationships for specific types of vegetation. Thirdly, respondent locations were displaced by roughly 50m-115m in random directions to protect respondent privacy, which introduces attenuation bias and makes it impossible to study highly localized relationships. Fourth, there are many potential determinants of depression and perceived rental values that we were unable to control for, which could introduce endogeneity and may explain why our results differ from previous studies. Finally, cultural perceptions around mental health differ for Rohingya refugees when compared to the subjects of previous studies, and to our knowledge, neither of the mental health surveys used have been validated for the Rohingya people.

We are eager to unlock our puzzling findings, and our next draft will seek to do so by incorporating the following changes. First, we will use the true respondent geo-locations to measure their local zonal statistics (greenspace, settlement density, amenity proximity). Furthermore, we will bring in as much complementary geospatial data as we can locate. For example, we hope to bring in more data on amenity proximity (such as schools and markets), proximity to camp borders, and proximity to camp border fencing. Furthermore, we will speak with UNHCR experts in the field to gather qualitative knowledge on why greenspace may be inversely related to mental health. To address our identification challenges, we will additionally use both the 2019 and 2022 waves to exploit plausibly exogenous changes to refugee household locations (due to fires, landslides, or camp closures).

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# A. Data Description

The following appendices are outlined as follows: Appendix A is a data description, where we start by presenting the Patient Health Questionaire 9 (British Columbia, nd) in full and then provide a data dictionary for all variables used in our analysis. Appendix B contains additional figures. Appendix C has complete tables for all regressions presented in the main body of the paper and small tables for the geospatial variables of interest for supplemental specifications mentioned in the paper.

## Patient Health Questionnaire (PHQ-9)

Name: ______________________________ Date: ______________________

| Over the last 2 weeks, how often have you been bothered by any of the following problems? | Not at all | Several days | More than half the days | Nearly every day |
|---|---|---|---|---|
| 1. Little interest or pleasure in doing things | 0 | 1 | 2 | 3 |
| 2. Feeling down, depressed, or hopeless | 0 | 1 | 2 | 3 |
| 3. Trouble falling or staying asleep, or sleeping too much | 0 | 1 | 2 | 3 |
| 4. Feeling tired or having little energy | 0 | 1 | 2 | 3 |
| 5. Poor appetite or overeating | 0 | 1 | 2 | 3 |
| 6. Feeling bad about yourself – or that you are a failure or have let yourself or your family down | 0 | 1 | 2 | 3 |
| 7. Trouble concentrating on things, such as reading the newspaper or watching television | 0 | 1 | 2 | 3 |
| 8. Moving or speaking so slowly that other people could have noticed? Or the opposite – being so fidgety or restless that you have been moving around a lot more than usual | 0 | 1 | 2 | 3 |
| 9. Thoughts that you would be better off dead or of hurting yourself in some way | 0 | 1 | 2 | 3 |

For office coding: Total Score ______ = ______ + ______ + ______

Total Score ______

If you checked off any problems, how difficult have these problems made it for you to do your work, take care of things at home, or get along with other people?

☐ Not difficult at all ☐ Somewhat difficult ☐ Very difficult ☐ Extremely difficult

# How to Score the PHQ-9

**Major depressive disorder (MDD) is suggested if:**

- Of the 9 items, 5 or more are checked as at least 'more than half the days'
- Either item 1 or 2 is checked as at least 'more than half the days'

**Other depressive syndrome is suggested if:**

- Of the 9 items, between 2 to 4 are checked as at least 'more than half the days'
- Either item 1 or 2 is checked as at least 'more than half the days'

PHQ-9 scores can be used to plan and monitor treatment. To score the instrument, tally the numbers of all the checked responses under each heading (not at all=0, several days=1, more than half the days=2, and nearly every day=3). Add the numbers together to total the score on the bottom of the questionnaire. Interpret the score by using the guide listed below.

| **Guide for Interpreting PHQ-9 Scores** | | |
|---|---|---|
| Score | Depression Severity | Action |
| 0 - 4 | None-minimal | Patient may not need depression treatment. |
| 5 - 9 | Mild | Use clinical judgment about treatment, based on patient's duration of symptoms and functional impairment. |
| 10 - 14 | Moderate | Use clinical judgment about treatment, based on patient's duration of symptoms and functional impairment. |
| 15 - 19 | Moderately severe | Treat using antidepressants, psychotherapy or a combination of treatment. |
| 20 - 27 | Severe | Treat using antidepressants with or without psychotherapy. |

**Functional Health Assessment**
The instrument also includes a functional health assessment. This asks the patient how emotional difficulties or problems impact work, life at home, or relationships with other people. Patient response of 'very difficult' or 'extremely difficult' suggest that the patient's functionality is impaired. After treatment begins, functional status and number score can be measured to assess patient improvement.

**Note:** Depression should not be diagnosed or excluded solely on the basis of a PHQ-9 score. A PHQ-9 score $\geq 10$ has a sensitivity of 88% and a specificity of 88% for major depression.[1] Since the questionnaire relies on patient self-report, the practitioner should verify all responses. A definitive diagnosis is made taking into account how well the patient understood the questionnaire, as well as other relevant information from the patient.



**Reference:** Kroenke K, Spitzer RL, Williams JB. The PHQ-9: Validity of a brief depression severity measure. J Gen Intern Med. 2001;16(9):606-613.

| Variable Name | Description | Variable Type | Units/Categories | Question Answered (Q) /How Variable Was Generated (G) | Notes |
|---|---|---|---|---|---|
| PHQ-9 Score | Raw depression risk score derived from responses to the Patient Health Questionaire-9. | Ordinal | Score for Patient Health Questionnaire (1-27) | G: Generated according to PHQ-9 scoring procedure. | - |
| PHQ-9 Risk Level | Depression risk levels corresponding with Patient Health Questionaire-9 depression risk cutoffs. | Ordinal | Depression risk levels (0-4): (1) None-Minimal, (2) Mild, (3) Moderate, (4) Moderately Severe/Severe | G: PHQ-9 scores translated to depression risk levels according to PHQ-9 scoring procedure. (Categories 4 and 5 combined into one) | The PHQ-9 has 5 depression risk categories, but we combine the "Moderately Severe" and "Severe" categories because "Severe" had very few observations. |
| Perceived Rental Value | The monthly rent the respondent perceives they could receive for the rental of their home. | Numerical (continuous and bounded) | Takas/Month | Q: Assume that you want to rent this dwelling. What would be a monthly rent you will be able ask for? | - |
| Mean NDVI | The pixel-level mean Normalized Difference Vegetation Index score within a radius (buffer) from each respondent's survey location (their household). | Numerical (continuous and bounded) | Pixel level mean NDVI scores for a buffer from each respondent. (0-1) | G: Generated using survey respondent locations and Normalized Difference Vegetation Index scores form a composite of Sentinel-2 satellite imagery from March-May of 2019. | In general NDVI is bounded between (-1,1). However, we filter out negative NDVI scores (water) before generating the statistic. We calculate mean NDVI scores for 250m and 500m buffers. |
| WSF Prop. | The pixel-level proportion of settlement area as classified by World Settlement Footprint 2019 within a radius (buffer) from each respondent's survey location (their household). | Numerical (discrete and bounded) | Pixel level proportion of settlement area for a buffer from each respondent according to WSF2019. Discretized by decile (1-10). | G: Generated using survey respondent locations and World Settlement Footprint 2019 data. | We calculate WSF Prop. For 250m and 500m buffers. |
| Dist. Nearest Well | The (Euclidian ) distance to the nearest tubewell from each respondent's survey location (their household) | Numerical (continuous and unbounded) | Metres | G: Generated using survey respondent locations and tubewell location data from the UNICEF WASH Sector. | Euclidian Distance |
| Dist. Nearest Health Ctr. | The (Euclidian ) distance to the nearest health centre that provide general treatment for common health issues from each respondent's survey location (their household). Selected health facility types are: Health Posts, Community Health Clinics, Primary Health Centers, and Secondary Health Facilities. | Numerical (continuous and unbounded) | Metres | G: Generated using survey respondent locations and medical centre locations obtained by ISCG. | Euclidian Distance |
| # Perceived Crime/Conflict | The count of crime/conflict types the respondent perceives are an issue in their neighbourhood. | Numerical (discrete and bounded) | Count of crime/conflict issues (0-9) | G: Generated as count of crime/conflict issues where the respondent answered yest to the question "Is (...) currently an issue in your neighborhood?". | Crimes and conflicts included are: (1) Bribery/corruption, (2) Harassment, (3) Theft, (4) Forced Eviction, (5) Physical violence/assault, (6) Gender based violence (harassment, assault, rape, domestic violence), (7) Business disputes (lending, employment, etc.), (8) Family disputes (divorce, inheritance, etc.), (9) Indebtedness |
| # Experienced Crime/Conflict | The count of crime/conflict types the respondent has experienced in their area. | Numerical (discrete and bounded) | Count of crime/conflict issues (0-9) | G: Generated as count of crime/conflict issues where the respondent answered yest to the question "Have you experienced (...) at any time during the past 12 months in this area?". | Crimes and conflicts included are: (1) Bribery/corruption, (2) Harassment, (3) Theft, (4) Forced Eviction, (5) Physical violence/assault, (6) Gender based violence (harassment, assault, rape, domestic violence), (7) Business disputes (lending, employment, etc.), (8) Family disputes (divorce, inheritance, etc.), (9) Indebtedness |

| Variable Name | Description | Variable Type | Units/Categories | Question Answered (Q) /How Variable Was Generated (G) | Notes |
|---|---|---|---|---|---|
| # Experienced Trauma Events | Count of trauma events the respondent said they have experienced | Numerical (discrete and bounded) | Count of trauma events (0-12) | G: Count. | This is part 1 of the Harvard Trauma Questionnaire, which is used to diagnose PTSD. Part 2 deals with symptoms, which I omit due to significant overlap with PHQ-9 symptoms. Trauma events included are: (1) Imprisonment, (2) Serious injury, (3) Combat situation, (4) Rape or sexual abuse, (5) Forced isolation form others, (6) Being close to death, (7) Forced separation from family members (8) Murder of family or friend, (9) Unnatural death of family or friend, (10) Murder of stranger or strangers, (11) Lost or kidnapped, (12) Torture. |
| # Witnessed Trauma Events | Count of trauma events the respondent said they have witnessed | Numerical (discrete and bounded) | Count of trauma events (0-12) | G: Count. | This is part 1 of the Harvard Trauma Questionnaire, which is used to diagnose PTSD. Part 2 deals with symptoms, which I omit due to significant overlap with PHQ-9 symptoms. Trauma events included are: (1) Imprisonment, (2) Serious injury, (3) Combat situation, (4) Rape or sexual abuse, (5) Forced isolation form others, (6) Being close to death, (7) Forced separation from family members (8) Murder of family or friend, (9) Unnatural death of family or friend, (10) Murder of stranger or strangers, (11) Lost or kidnapped, (12) Torture. |
| Food Insecurity Score | Count of Household Food Insecurity Access Scale questions the respondent said yes to. | Numerical (discrete and bounded) | Count of food security issues (0-9) | G: Count. | These questions come from HFAIS scale. Typically this is scored by intensity, but since I don't have intensity scores for each variable I score as sum of "yes" answers. |
| Household Income ÷ Size | Household income in the last month per household member. | Numerical (continuous and unbounded) | (100s of takas/month)/ Count of household members | G: Variable generated by dividing values from the question "What was your total household monthly income in the last month?" by household headcount from the household roster module. | - |
| Rooms | Number of rooms the household occupies. | Numerical (discrete and unbounded) | Count of rooms | Q: How many rooms does your household occupy? | Sometimes dwellings in Kutupalong are occupied by multiple households. This question focuses on how many rooms are occupied by the household. |
| Age | Age of the survey respondent. | Numerical (discrete and unbounded) | Years | Q: How old is (…)? | - |
| Employment Status | Employment Status of the survey respondent. | Categorical | Binary indicator (Yes/No) | G: Generated as binary indicator of whether the respondent gave a nonzero answer to the question "In the last four weeks, on average how many hours per week did you spend on your main job?" | - |
| Sex | Self-reported sex of the survey respondent. | Categorical | Binary indicator (Male/Female) (+ "Other" option not included due to low sample size) | Q: (…) ‘s Sex | - |
| Marital Status | Marital status of the survey respondent. | Categorical | Married, Never Married, Widowed, Divorced/Separated | Q: What is (…)’s marital status? | We combined Divorced and Separated into one category because they had very small sample sizes. |
| Health Status | Self-reported health status of the survey respondent. | Categorical | (1-5) Scale. (Very good, Good, Regular, Bad , Very bad) | Q: In general, would you say that your health is [...]? | - |

| Variable Name | Description | Variable Type | Units/Categories | Question Answered (Q) /How Variable Was Generated (G) | Notes |
|---|---|---|---|---|---|
| Health Change | Self-reported change in health status over the past year of the survey respondent. | Categorical | (1-5) Scale. (Much better, Better, The same, Worse, Much worse) | Q: Comparing your current health status to your health status one year ago would you say your health is now [...]? | - |
| Separate Kitchen | Indicator of whether the dwelling the household occupies has a separate kitchen. | Categorical | Binary indicator | Q: Does this dwelling have a separate kitchen? | - |
| Gas/Improved Cookstove | Indicator of whether the dwelling the household occupies has a gas or improved cookstove. | Categorical | Binary indicator | Q: Does this dwelling have a gas / improved cookstove? | - |
| Electricity | Indicator of whether the dwelling the household occupies has electricity. | Categorical | Binary indicator | Q: Do you have electricity at your household? | - |
| Toilet Facility | Indicator of what type of toilet facility the household generally uses. | Categorical | 1-6 Scale. Various toilet facility types. | Q: What kind of toilet facility do members of your household usually use? | - |
| Water Source | Indicator of what source of drinking water the household generally uses. | Categorical | 1-5 Scale. Various types of water sources. | Q: What is the main source of drinking water? | We combined Well and Tubewell due to low Well Sample Size |

# B. Additional Figures

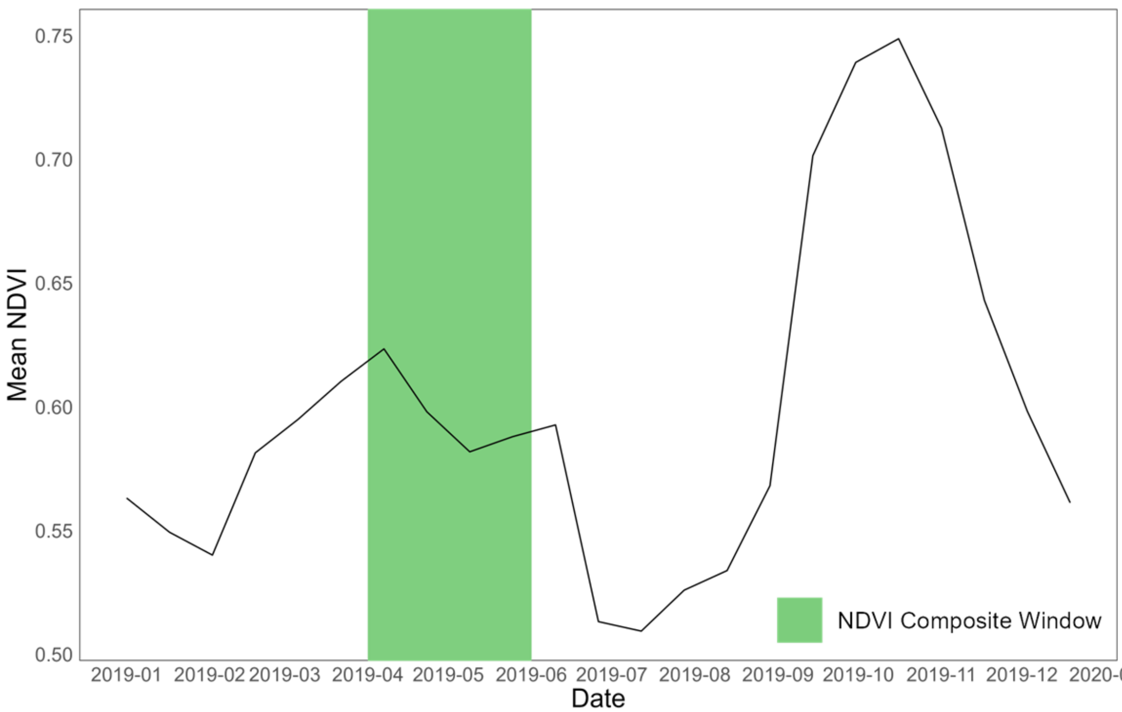


Figure B.1: NDVI Time Series and Spring Sample Composite Window

Note: Figure generated by authors using mean NDVI data from Modis MOD13Q1 V6.1 for a region encompassing most of Bangladesh, Northern Rakhine, and West Bengal. Multiple time series were generated for a set of different regions with minimal difference in NDVI time series. NDVI time series of just Cox's Bazar was very noisy due to cloud cover.

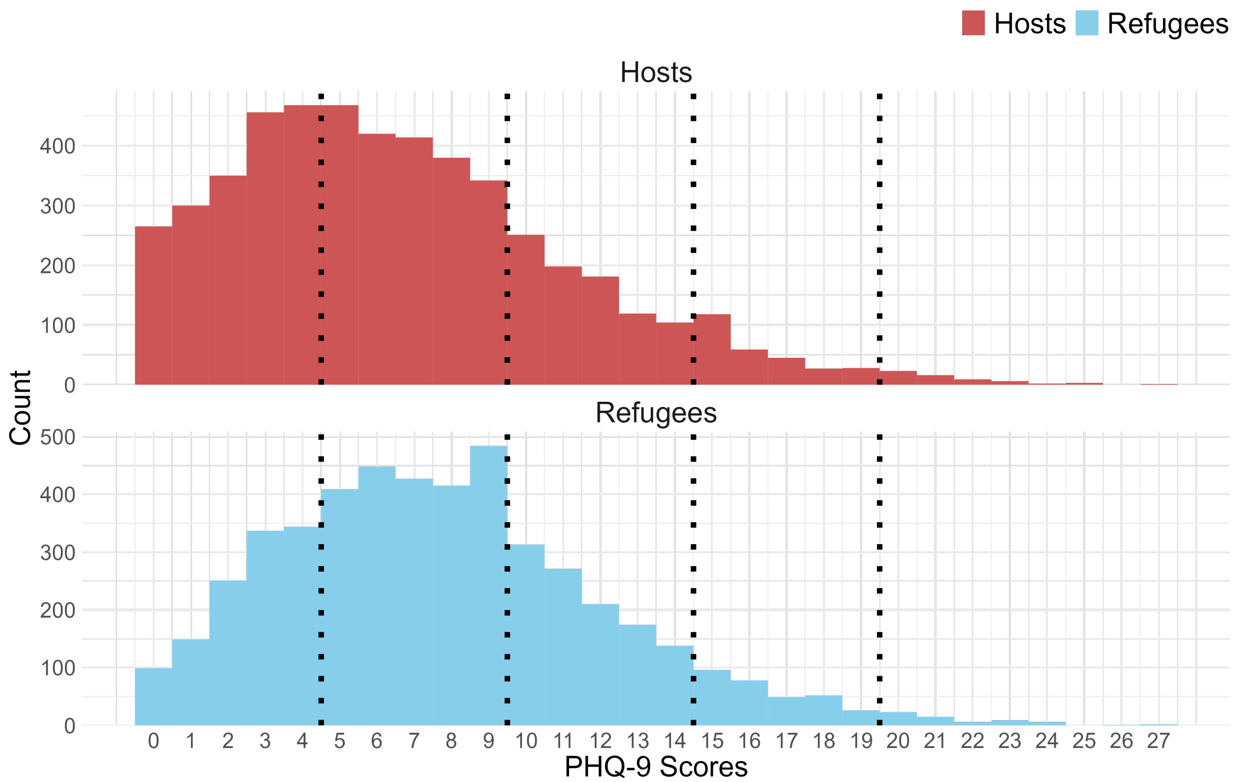


Figure B.2: Distribution of PHQ-9 Scores and Severity Thresholds for Hosts and Refugees

Vertical lines indicate severity level thresholds: None-Minimal (0-4), Mild (5-9), Moderate (10-14), Moderately Severe (15-19), Severe (19-27).

This figure shows the distribution of PHQ-9 scores for refugees and hosts within the CBPS sample. The host sample is omitted from my analysis, but this reinforces previous research suggesting that refugees have higher risk of mental health disorders than non-refugees.

Figure generated by author using CBPS data.

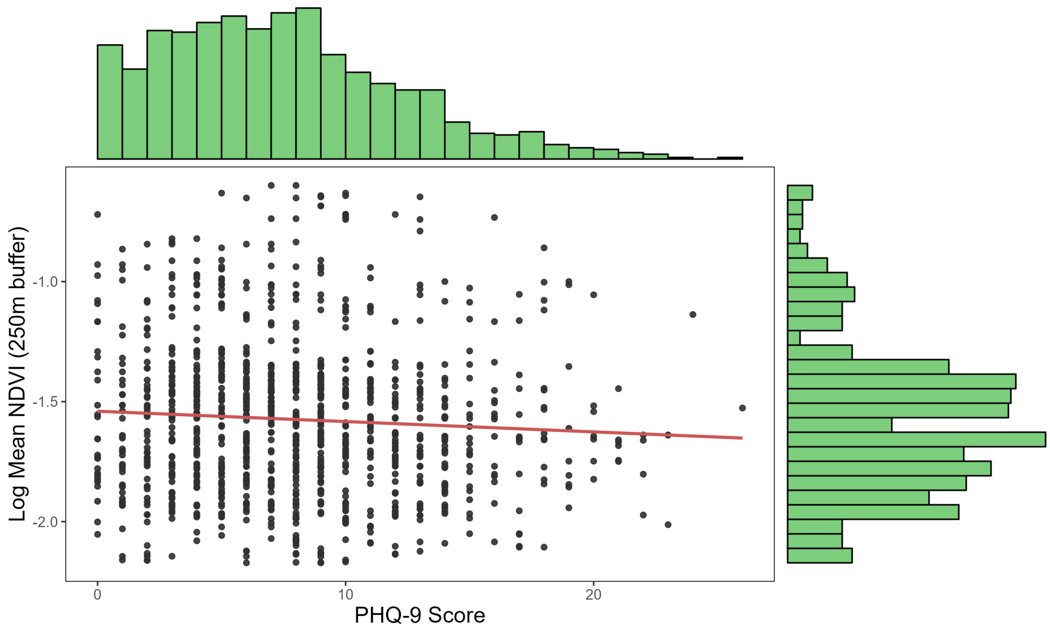


Figure B.3: PHQ-9 Scores and Log Mean NDVI — Kutupalong Spring Sample

This figure shows the marginal distributions of PHQ-9 and log-mean NDVI scores for Rohingya refugees in the Kutupalong spring sample. The histogram opposite the axis label shows how each variable is distributed on their own, and the scatterplot shows how the variables relate to each other. The line within the scatterplot is a line of best fit. Figure generated by the authors using CBPS data and NDVI statistics using Sentinel-2 and respondent locations.

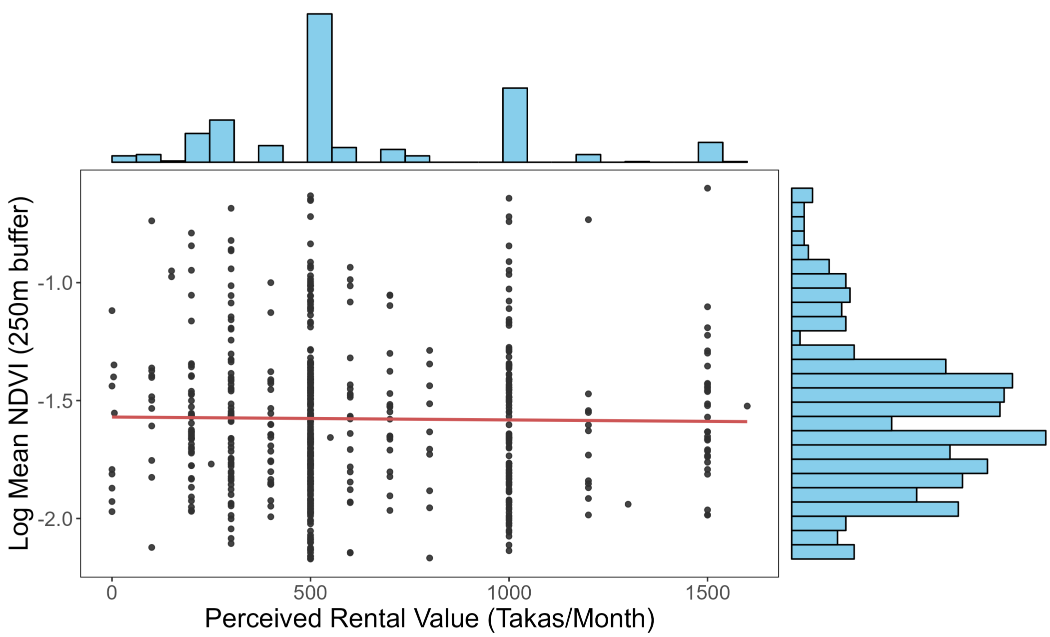


Figure B.4: Perceived Rental Values and Log Mean NDVI — Kutupalong Spring Sample

This figure shows the marginal distributions of perceived rental values and log-mean NDVI scores for Rohingya refugees in the Kutupalong spring sample. The histogram opposite the axis label shows how each variable is distributed on their own, and the scatterplot shows how the variables relate to each other. The line within the scatterplot is a line of best fit. Figure generated by the authors using CBPS data and NDVI statistics using Sentinel-2 and respondent locations.

# C. Additional Tables

Table C.1: Ordered Logit: Average Marginal Effects on the Probability of Being in each Depression Risk Category. Full Kutupalong Sample With Summer Dummy.

| | None/Minimal | Mild | Moderate | Moderately Severe/Severe |
|---|---|---|---|---|
| Log Mean NDVI (250m) | -0.05253 | -0.00186 | 0.03400 | 0.02039 |
| | (0.04159) | (0.00196) | (0.02693) | (0.01619) |
| WSF Prop. (250m) | -0.01002** | -0.00036 | 0.00648** | 0.00389** |
| | (0.00507) | (0.00031) | (0.00329) | (0.00198) |
| Dist. Nearest Well (m) | 0.00109** | 0.00004 | -0.00070** | -0.00042** |
| | (0.00049) | (0.00003) | (0.00032) | (0.00019) |
| Dist. Nearest Health Ctr. (m) | -0.00013* | -0.000004 | 0.00008* | 0.00005* |
| | (0.00008) | (0.000004) | (0.00005) | (0.00003) |
| Not Spring Sample | 0.11647*** | 0.00413 | -0.07539*** | -0.04521*** |
| | (0.03718) | (0.00318) | (0.02419) | (0.01467) |
| Controls | Yes | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes | Yes |

Standard errors in parentheses. N= 2939

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data:** Data for all variables presented here were generated by the authors using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification with the addition of a summer observation dummy variable.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.2: Ordered Logit: Average Marginal Effects on the Probability of Being in each Depression Risk Category. Full Kutupalong Refugee Sample Without Summer Dummy.

| | None/Minimal | Mild | Moderate | Moderately Severe/Severe |
|---|---|---|---|---|
| Log Mean NDVI (250m) | -0.05470 | -0.00180 | 0.03535 | 0.02116 |
| | (0.04172) | (0.00192) | (0.02696) | (0.01619) |
| WSF Prop. (250m) | -0.01000** | -0.00033 | 0.00646** | 0.00387* |
| | (0.00508) | (0.00030) | (0.00329) | (0.00198) |
| Dist. Nearest Well (m) | 0.00111** | 0.00004 | -0.00072** | -0.00043** |
| | (0.00049) | (0.00003) | (0.00032) | (0.00019) |
| Dist. Nearest Health Ctr. (m) | -0.00011 | -0.000004 | 0.00007 | 0.00004 |
| | (0.00008) | (0.000004) | (0.00005) | (0.00003) |
| Controls | Yes | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes | Yes |

Standard errors in parentheses. N= 2939

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data:** Data for all variables presented here were generated by the authors using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.3: Ordered Logit: Average Marginal Effects on the Probability of Being in each Depression Risk Category. Spring Kutupalong Sample. All Covariates Reported Except Camp Fixed Effects.

| | None/Minimal | | Mild | | Moderate | | Moderately Severe/Severe | |
|---|---|---|---|---|---|---|---|---|
| Log Mean NDVI (250m) | -0.10300** | (0.05024) | -0.00934 | (0.00588) | 0.06437** | (0.03145) | 0.04796** | (0.02367) |
| WSF Prop. (250m) | -0.01390* | (0.00733) | -0.00126 | (0.00085) | 0.00868* | (0.00460) | 0.00647* | (0.00345) |
| Dist. Nearest Well (m) | 0.00040 | (0.00072) | 0.00004 | (0.00007) | -0.00025 | (0.00045) | -0.00019 | (0.00034) |
| Dist. Nearest Health Ctr.(m) | -0.00014 | (0.00012) | -0.00001 | (0.00001) | 0.00009 | (0.00007) | 0.00007 | (0.00005) |
| # Experienced Crimes | -0.02961*** | (0.00941) | -0.00268** | (0.00131) | 0.01851*** | (0.00589) | 0.01379*** | (0.00444) |
| # Perceived Crimes | -0.01905*** | (0.00410) | -0.00173** | (0.00078) | 0.01191*** | (0.00258) | 0.00887*** | (0.00201) |
| # Experienced Traumas | -0.01677*** | (0.00374) | -0.00152** | (0.00069) | 0.01048*** | (0.00237) | 0.00781*** | (0.00182) |
| # Witnessed Traumas | -0.01954*** | (0.00378) | -0.00177** | (0.00079) | 0.01221*** | (0.00240) | 0.00910*** | (0.00188) |
| Food Insecurity Score | -0.03019*** | (0.00511) | -0.00274** | (0.00117) | 0.01887*** | (0.00324) | 0.01406*** | (0.00257) |
| Age | -0.00396*** | (0.00076) | -0.00036** | (0.00015) | 0.00247*** | (0.00048) | 0.00184*** | (0.00037) |
| HH Income (100s) ÷ Size | -0.00036 | (0.00107) | -0.00003 | (0.00010) | 0.00022 | (0.00067) | 0.00017 | (0.00050) |
| Employed | 0.00887 | (0.02407) | 0.00072 | (0.00176) | -0.00552 | (0.01494) | -0.00407 | (0.01087) |
| Female | -0.08314*** | (0.02182) | -0.00526* | (0.00309) | 0.05143*** | (0.01346) | 0.03697*** | (0.00963) |
| Marital Status: | | | | | | | | |
| Never Married | 0.02284 | (0.02676) | 0.00162 | (0.00143) | -0.01413 | (0.01644) | -0.01033 | (0.01150) |
| Widowed | 0.03133 | (0.03606) | 0.00170 | (0.00129) | -0.01921 | (0.02138) | -0.01381 | (0.01478) |
| Divorced/Seperated | 0.04691 | (0.07347) | 0.00119 | (0.00454) | -0.02832 | (0.04234) | -0.01977 | (0.02706) |
| Health Status: | | | | | | | | |
| Very good | 0.14457* | (0.07641) | -0.01351 | (0.02338) | -0.08570** | (0.03906) | -0.04537** | (0.01805) |
| Good | 0.06631*** | (0.02573) | 0.00283 | (0.00435) | -0.04342** | (0.01767) | -0.02573** | (0.01118) |
| Bad | -0.05753** | (0.02692) | -0.02148** | (0.01060) | 0.04393** | (0.02073) | 0.03508** | (0.01611) |
| Very bad | -0.08794* | (0.04880) | -0.04343 | (0.03916) | 0.06915* | (0.04086) | 0.06222 | (0.04634) |
| Health Change: | | | | | | | | |
| Much better | -0.02779 | (0.05617) | -0.00419 | (0.01169) | 0.01845 | (0.03811) | 0.01352 | (0.02961) |
| Better | 0.03697 | (0.02541) | 0.00054 | (0.00192) | -0.02291 | (0.01580) | -0.01460 | (0.01020) |
| Worse | -0.02889 | (0.02524) | -0.00443 | (0.00405) | 0.01921 | (0.01696) | 0.01412 | (0.01213) |
| Much worse | -0.09472* | (0.04888) | -0.03233 | (0.02982) | 0.06676* | (0.03685) | 0.06029 | (0.04139) |
| Camp Fixed Effects | Yes | | Yes | | Yes | | Yes | |

Standard errors in parentheses. N=1238

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data:** All data is from the Cox's Bazar Panel Survey except for author-generated geospatial data (Mean NDVI (100m), WSF Prop. (100m), Dist. Nearest Well, and Dist. Nearest Health Ctr.).
**Fixed Effects:** Camp fixed effects included in regressions but not reported here.
**Base Categories:** Base of marital status is "Married"; base of health status is "Regular"; base of health change is "The Same".
**Abbreviations:** N is the sample size. "#" is short for number. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.
**Units:** Units for household income adjusted for household size is hundreds of takas/month.

Table C.4: Comparing Models for the Relationship Between Greenspace and Depression Symptoms. Full Kutupalong Refugee Sample With Summer Dummy.

| | OLS | Poisson | Logit |
|---|---|---|---|
| Log Mean NDVI (250m) | -0.03687 | 0.00726 | 0.02338 |
| | (0.53826) | (0.06898) | (0.05529) |
| WSF Prop. (250m) | 0.06068 | 0.01016 | 0.00537 |
| | (0.06256) | (0.00823) | (0.00678) |
| Dist. Nearest Well (m) | -0.00859 | -0.00133 | -0.00109* |
| | (0.00702) | (0.00092) | (0.00066) |
| Dist. Nearest Health Ctr. (m) | 0.00106 | 0.00014 | 0.00006 |
| | (0.00090) | (0.00012) | (0.00010) |
| Non-Spring Sample | -1.52779*** | -0.22128*** | -0.17502*** |
| | (0.37907) | (0.05069) | (0.05100) |
| Controls | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes |

Standard errors in parentheses. N=2939. OLS $R^2$ is 0.279. OLS and Poisson constants are 2.33131 and 1.30696 respectively

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Dependent Variables:** Dependent variables are raw PHQ-9 scores (1-27) for OLS. The log expected value of raw PHQ-9 scores for Poisson, and a binary indicator of if PHQ $\geq$ 10 for Logit.
**Data:** Data for all variables presented here were generated by the authors using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification. Camp fixed effects included but not reported.
**Standard Errors:** Heteroskedasticity-robust standard errors used for OLS and Poisson models.
**Comparing Models:** For OLS and Poisson we report marginal effects. For Logit we report average marginal effects.
**Cutoffs:** For the Logit Models, we used a cutoff of 10 (inclusive) to indicate if an individual has risk of depression.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.5: Comparing Models for the Relationship Between Greenspace and Depression Symptoms. Full Kutupalong Refugee Sample Without Summer Dummy.

| | OLS | Poisson | Logit |
|---|---|---|---|
| Log Mean NDVI (250m) | -0.01284 | 0.01139 | 0.02709 |
| | (0.53884) | (0.06918) | (0.05545) |
| WSF Prop. (250m) | 0.06016 | 0.01023 | 0.00544 |
| | (0.06274) | (0.00825) | (0.00680) |
| Dist. Nearest Well (m) | -0.00881 | -0.00136 | -0.00111* |
| | (0.00701) | (0.00092) | (0.00066) |
| Dist. Nearest Health Ctr. (m) | 0.00089 | 0.00012 | 0.00004 |
| | (0.00090) | (0.00012) | (0.00010) |
| Controls | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes |

Standard errors in parentheses. N=2939. OLS $R^2$ is 0.277. OLS and Poisson constants are 0.83472 and 1.18560 respectively

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Dependent Variables:** Dependent variables are raw PHQ-9 scores (1-27) for OLS. The log expected value of raw PHQ-9 scores for Poisson, and a binary indicator of if PHQ $\geq$ 10 for Logit.
**Data:** Data for all variables presented here were generated by the authors using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification. Camp fixed effects included but not reported.
**Standard Errors:** Heteroskedasticity-robust standard errors used for OLS and Poisson models.
**Comparing Models:** For OLS and Poisson we report marginal effects. For Logit we report average marginal effects.
**Cutoffs:** For the Logit Models, we used a cutoff of 10 (inclusive) to indicate if an individual has risk of depression.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.6: Comparing Models for the Relationship Between Greenspace and Depression Symptoms. Spring Kutupalong Sample. All Covariates Reported Except Camp Fixed Effects.

| | OLS | | Poisson | | Logit | |
|---|---|---|---|---|---|---|
| Log Mean NDVI (250m) | 0.4931 | (0.6756) | 0.0820 | (0.0838) | 0.1027 | (0.0703) |
| WSF Prop. (250m) | 0.0627 | (0.0947) | 0.0120 | (0.0122) | 0.0111 | (0.0103) |
| Dist. Nearest Well (m) | -0.0001 | (0.0117) | -0.0001 | (0.0014) | 0.0002 | (0.0010) |
| Dist. Nearest Health Ctr. (m) | 0.0008 | (0.0016) | 0.0001 | (0.0002) | 0.0002 | (0.0002) |
| # Experienced Crimes | 0.4320*** | (0.1345) | 0.0466*** | (0.0142) | 0.0485*** | (0.0123) |
| # Perceived Crimes | 0.2191*** | (0.0580) | 0.0273*** | (0.0068) | 0.0106* | (0.0055) |
| # Experienced Traumas | 0.2799*** | (0.0530) | 0.0349*** | (0.0066) | 0.0315*** | (0.0050) |
| # Witnessed Traumas | 0.2586*** | (0.0486) | 0.0348*** | (0.0061) | 0.0298*** | (0.0052) |
| Food Insecurity Score | 0.4303*** | (0.0702) | 0.0553*** | (0.0091) | 0.0330*** | (0.0072) |
| Age | 0.0445*** | (0.0111) | 0.0055*** | (0.0012) | 0.0042*** | (0.0010) |
| HH Income (100s) ÷ Size | 0.0086 | (0.0134) | 0.0012 | (0.0018) | -0.0007 | (0.0017) |
| Employed | -0.2638 | (0.3115) | -0.0350 | (0.0404) | -0.0210 | (0.0331) |
| Female | 0.9189*** | (0.2952) | 0.1187*** | (0.0380) | 0.0952*** | (0.0281) |
| Marital Status: | | | | | | |
| Never Married | -0.3509 | (0.3339) | -0.0749 | (0.0478) | 0.0494 | (0.0378) |
| Widowed | -0.1578 | (0.5076) | -0.0361 | (0.0542) | -0.0029 | (0.0438) |
| Divorced/Seperated | -0.8368 | (0.8311) | -0.0901 | (0.0960) | -0.0803 | (0.0833) |
| Health Status: | | | | | | |
| Very good | -1.6481** | (0.6857) | -0.2641** | (0.1209) | -0.1570* | (0.0833) |
| Good | -1.0189*** | (0.3164) | -0.1474*** | (0.0404) | -0.0550 | (0.0357) |
| Bad | 1.0567*** | (0.4008) | 0.1051** | (0.0458) | 0.0641 | (0.0436) |
| Very bad | 1.5348 | (1.1660) | 0.1111 | (0.1077) | 0.1346 | (0.1024) |
| Health Change: | | | | | | |
| Much better | 0.5691 | (0.6886) | 0.0665 | (0.1088) | 0.0109 | (0.1029) |
| Better | -0.2569 | (0.3033) | -0.0355 | (0.0436) | -0.0275 | (0.0341) |
| Worse | 0.6631** | (0.3343) | 0.0875** | (0.0429) | 0.0285 | (0.0362) |
| Much worse | 2.3965** | (1.0762) | 0.2330** | (0.1024) | 0.1698* | (0.0960) |
| Constant | 1.2447 | (1.2500) | 1.2542*** | (0.1456) | | |
| Camp Fixed Effects | Yes | | Yes | | Yes | |
| Observations | 1238 | | 1238 | | 1238 | |
| $R^2$ | 0.289 | | | | | |

Standard errors in parentheses. N = 1238

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Dependent Variables:** Dependent variables are raw PHQ-9 scores (1-27) for OLS. The log expected value of raw PHQ-9 scores for Poisson, and a binary indicator of if PHQ $\geq$ 10 for Logit.
**Data:** All data is from the Cox's Bazar Panel Survey except for author-generated geospatial data (Mean NDVI (250m), WSF Prop. (250m), Dist. Nearest Well, and Dist. Nearest Health Ctr.).
**Comparing Models:** OLS and Poisson coefficients (marginal effects) can be directly compared. However, here we report average marginal effects for Logit, which cannot be directly compared with OLS and Poisson.
**Cutoffs:** For the Logit Models, we used a cutoff of 10 (inclusive) to indicate if an individual has risk of depression.
**Base Categories:** Base of marital status is "Married"; base of health status is "Regular"; base of health change is "The Same".
**Abbreviations:** N is the sample size. "#" is short for number. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance.
**Units:** Units for household income adjusted for household size is hundreds of takas/month.

Table C.7: Ordered Logit: Average Marginal Effects on the Probability of Being in each Depression Risk Category. Spring Kutupalong Sample. 500m NDVI and WSF Buffers.

| | None/Minimal | Mild | Moderate | Moderately Severe/Severe |
|---|---|---|---|---|
| Log Mean NDVI (500m) | -0.04811 | -0.00429 | 0.03004 | 0.02236 |
| | (0.07410) | (0.00681) | (0.04625) | (0.03449) |
| WSF Prop. (500m) | -0.00397 | -0.00035 | 0.00248 | 0.00184 |
| | (0.00943) | (0.00085) | (0.00589) | (0.00439) |
| Dist. Nearest Well (m) | 0.00059 | 0.00005 | -0.00037 | -0.00028 |
| | (0.00071) | (0.00007) | (0.00044) | (0.00033) |
| Dist. Nearest Health Ctr. (m) | -0.00009 | -0.00001 | 0.00006 | 0.00004 |
| | (0.00012) | (0.00001) | (0.00007) | (0.00005) |
| Controls | Yes | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes | Yes |

Standard errors in parentheses. N = 1238

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Data:** Data for all variables presented here were generated by the author using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.8: Comparing Models for the Relationship Between Greenspace and Depression Symptoms. Spring Kutupalong Sample. 500m NDVI and WSF Buffers.

| | OLS | Poisson | Logit |
|---|---|---|---|
| Log Mean NDVI (500m) | -1.02465 | -0.12446 | -0.00856 |
| | (0.99094) | (0.12272) | (0.10307) |
| WSF Prop. (500m) | -0.13431 | -0.01536 | -0.00696 |
| | (0.12225) | (0.01535) | (0.01311) |
| Dist. Nearest Well (m) | -0.00214 | -0.00043 | -0.00003 |
| | (0.01142) | (0.00137) | (0.00096) |
| Dist. Nearest Health Ctr. (m) | 0.00012 | 0.00002 | 0.00009 |
| | (0.00156) | (0.00019) | (0.00016) |
| Controls | Yes | Yes | Yes |
| Camp Fixed Effects | Yes | Yes | Yes |

Standard errors in parentheses. N = 1238. OLS $R^2$ is 0.290. OLS and Poisson constants are 0.47969 and 1.12102 respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Dependent Variables:** Dependent variables are raw PHQ-9 scores (1-27) for OLS and Poisson, and a binary indicator of if PHQ $\geq 10$ for Logit.
**Data:** Data for all variables presented here were generated by the author using geospatial data and respondent locations. All controls are from the Cox's Bazar Panel Survey and are identical to the ones used in the main specification. Camp fixed effects included but not reported.
**Standard Errors:** Heteroskedasticity-robust standard errors used for OLS and Poisson models.
**Comparing Models:** For OLS and Poisson I report marginal effects. For Logit I report average marginal effects.
**Cutoffs:** For the Logit Models, I used a cutoff of 10 (inclusive) to indicate if an individual has risk of depression.
**Abbreviations:** N is the sample size. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.

Table C.9: Hedonic-Style Regression: Dependent Variable is Perceived Rental Value (Capped at the Highest Actual Rent Value of 2000 Takas/Month).

| | Coefficient | Standard Error |
|---|---|---|
| Log Mean NDVI (250m) | -132.71$^{*}$ | (71.55) |
| WSF Prop. (250m) | -18.12$^{*}$ | (10.76) |
| Dist. Nearest Well (m) | 1.18 | (1.09) |
| Dist. Nearest Health Ctr. (m) | 0.24 | (0.18) |
| # Experienced Crimes | 11.59 | (14.86) |
| # Perceived Crimes | 9.73 | (6.09) |
| Rooms | 91.96$^{***}$ | (22.22) |
| Separate Kitchen | 57.13$^{*}$ | (33.95) |
| Gas/Improved Cookstove | 134.97$^{***}$ | (49.27) |
| Electricity | 40.52 | (31.11) |
| Toilet Facility: | | |
| Pacca latrine (water seal) | 265.36$^{***}$ | (58.74) |
| Pacca latrine (pit) | 171.23$^{***}$ | (49.08) |
| Kacha latrine (perm) | 242.49$^{***}$ | (58.45) |
| Kacha latrine (temp) | 122.73$^{**}$ | (60.86) |
| Water Source: | | |
| Water supply tanks | 434.69$^{***}$ | (123.70) |
| Tubewell/Well | 175.52$^{**}$ | (82.47) |
| Camp Fixed Effects | Yes | Yes |

Standard errors in parentheses. N=1139. $R^2 = 0.136$. Constant = -13.25

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

**Data**: All data comes from the Cox's Bazar Panel Survey, except spatial statistics which were generated by author using geospatial data and respondent points [Log Mean NDVI (100m), WSF Prop. (100m), Dist. Nearest Well, Dist. Nearest Health Ctr.].
**Base Categories:** Base of Toilet Facility is "Sanitary", base of Water Source is "Supply".
**Fixed Effects:** Camp fixed effects included in regressions but not reported here.
**Abbreviations:** N is the sample size. "#" is short for number. NDVI is the Normalized Difference Vegetation Index. WSF is the World Settlement Footprint for 2019. "Dist." is short for distance; "Ctr" is short for Centre.
**Units:** Units for household income adjusted for household size is hundreds of takas/month.
**Standard Errors:** Breusch–Pagan and White tests indicate heteroskedasticity. We use Hubert-White robust standard errors.