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ABSTRACT

The Mental Health Effects of Living near Overburdened Hospitals During COVID-19 in Perú*

Perú tops the global ranking in terms of mortality rates from COVID-19. This study explores the effects of geographic proximity to overburdened hospitals on mental health outcomes during the COVID-19 crisis in Perú. By using microdata along with a difference-in-differences approach, the analyses reveal a significant increase in depression symptoms for individuals residing in closer proximity to overwhelmed hospital facilities. Results are consistent regardless of whether we use administrative data or self-reported information from national health surveys. Heterogeneity analyses indicate that women, young adults, and people from relatively more affluent households drive these adverse effects. In line with health and urban economics perspectives, negative externalities, primarily congestion and chaos proxied by in-hospital mortality and hospitalizations, and acoustic pollution from ambulance noise are the channels that explain these adverse effects on mental health.

JEL Classification: I1, I12, I15, I18

Keywords: mental health, depression, COVID-19, hospitals, differences-in-differences, Peru

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1 Introduction

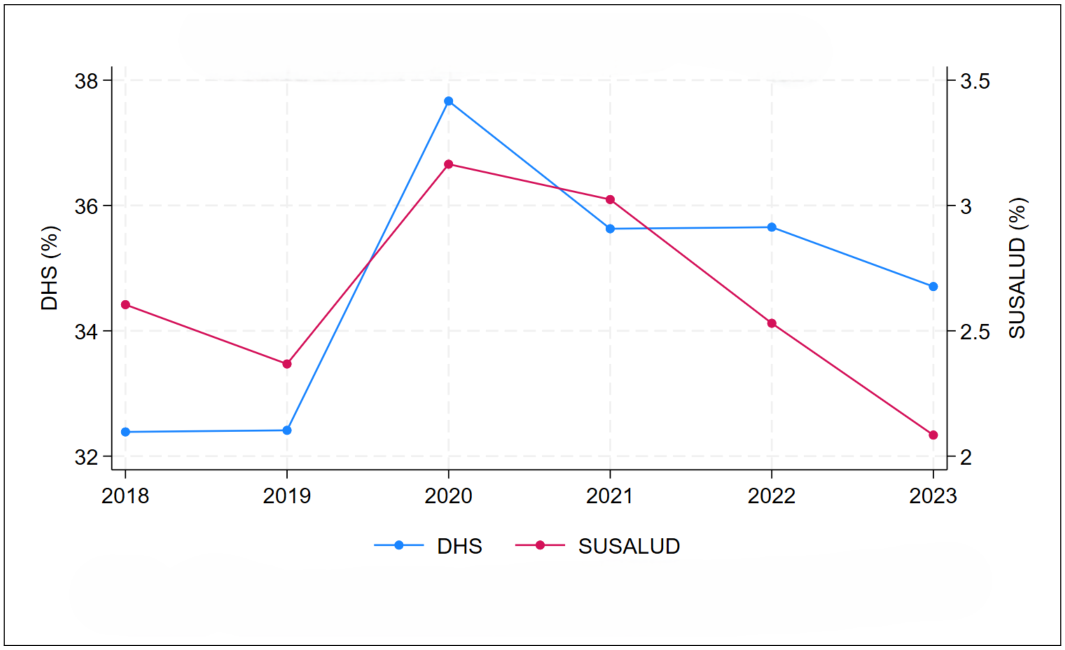
The prevalence of people affected by mental illnesses such as depression, stress, and anxiety associated with the COVID-19 pandemic is a global phenomenon. The fear of getting sick, the trauma of losing household members, and the implosion of the labor markets, particularly in the informal services sector, coupled with an increase in poverty rates, have contributed to a global prevalence and burden of mental health disorders. The urgency of this situation led the World Health Organization (WHO) to create the High Commission on Mental Health and COVID-19 as a global priority due to the substantial individual and societal costs caused by a sharp rise in mental health challenges. Anxiety and depression alone cost the global economy USD 1 trillion per year (WHO, 2023), a burden that hurts disproportionally low- and middle-income countries where around 80% of people with mental disorders do not receive treatment (WHO, 2022).

The COVID-19 pandemic has brought unprecedented strain on global health systems, with wide-ranging repercussions beyond immediate health outcomes. This research shed light on an unexplored consequence: the mental health costs of living near overburdened health facilities during a health crisis, using the case of Perú. With 657 deaths per 100,000 inhabitants, Perú tops the global ranking of COVID-19 mortality rates. In 2021 alone, there were 1,368,950 people treated for mental health problems in Perú (MINSA, 2024), which is equivalent to 5.5% of the total population over 14 years of age. Figure 1 shows the population with symptoms of depression in the period 2018-2023 according to the Demographic and Family Health Survey (DHS). One observes that during the peak of the pandemic, in 2020 and 2021, there was a substantial increase in the proportion of people who suffered from symptoms of depression. Consistently, and for the same period, we also observe an increase in the proportion of patients treated for depression and anxiety, according to administrative data from the National Superintendence of Health (SUSALUD). However, the public funding allocated to the national program for the protection and promotion of mental health was only 0.09% of public spending in 2021, the same proportion allocated during the pre-pandemic period.

The main objective of this study is to investigate the increase in the prevalence of mental illnesses during the COVID-19 pandemic for individuals living near chaotic and congested health facilities. Specifically, the question we answer is whether, compared to the pre-pandemic situation, individuals who live in the proximity of health facilities that absorbed the demand for hospitalizations and the excess deaths during the coronavirus health emergency show a higher prevalence of symptoms of depression relative to those individuals who live further away. If so, what are the specific channels that explain the increase in mental health problems? And what is the extent of the heterogeneity of mental health effects across socio-demographic groups?

From a theoretical point of view, the direction of this relationship is not clear. On the one hand, proximity to hospitals can provide psychological comfort and timely access to care due to re-

Figure 1: Share of people with depression symptoms



Note: Authors' elaboration. Source: DHS's self-reported depression index and the SUSALUD administrative dataset on users treated in outpatient consultation.

ductions in transaction costs such as transportation and information costs, making it easier for individuals to invest in their health. On the other hand, living close to health facilities in times of public health crises can adversely affect mental health due to negative spillover effects such as exposure to overcrowded spaces and traffic congestion, the heightened fear of infection, the acoustic noise of ambulances, and the visual exposure to a high number of funeral processions and the continuous operation of hospital crematoriums. The availability of longitudinal microdata before and after the COVID-19 pandemic allows us to evaluate which of these opposing forces dominate the changes in the incidence of mental illness in Perú.

Microdata from the National Demographic and Family Health Survey (DHS) in the period 2018 to 2023 and two complementary sources of administrative data from the Ministry of Health and SASALUD allow the identification of geo-located health facilities, the distance from these health facilities to the dwelling units of each individual considered in the household survey, and the magnitude of hospital congestion and collapse as measured by the monthly rate of occupancy of intensive care unit (ICU) beds. We focus on all Category III health facilities, which have inpatient care infrastructure and, thus, absorbed the demand for COVID-19 hospitalizations[1].

Implementing a difference-in-differences approach allows us to estimate that, relative to the pre-pandemic situation, individuals who live less than 3 kilometers from strained health facil-

[1] See Appendix Table A.1 for the description of different types of health facilities in Perú.

ities present a statistically significant change of 15% in symptoms of depression compared to individuals who live at a greater distance. The internal validity of the econometric identification assumptions is examined in considerable detail, which gives us confidence in the causal interpretation of the results. Administrative data from medical consultations corroborate these detrimental changes in mental health. Acoustic pollution, proxied by ambulance use, and congested health facilities, which are proxied by the extent of excess hospitalizations and deaths, are the channels that drive our results. Heterogeneity analyses show that contrary to what one could expect, these adverse changes in mental health disproportionately affected the population groups with the lower epidemiological risks: women, the relatively young, and the more affluent individuals. These features highlight the role of differential perceived health risks and unequal exposure to the burden of the disease due to entrenched social norms, insulation from chronic stressors, and adaptive resilience.

This study contributes directly to the literature on mental health and economic geography in developing settings. Empirical results for developed countries show that proximity to health facilities benefits people's mental health due to access to timely care, access to preventive care, and psychological comfort (Tomita et al., 2017; Pfeiffer et al., 2011). It is also reported a higher prevalence of mental illnesses associated with exposure to air pollution (Cheng et al., 2024), increased ambient temperature (Bakian et al., 2015), neighborhood quality (Kling et al., 2007), and urbanization and traffic congestion (Panaite et al., 2019). However, the study of mental health prevalence, drivers, and effects on economic outcomes in developing countries remains poorly understood (Lund et al., 2018; Angelucci and Bennett., 2024; Haushofer et al., 2020). Our study provides insights into how the proximity to health facilities in contexts of chaos and strain on the healthcare system leads to a deterioration of mental health among nearby residents who witness or experience these challenges firsthand. Our results challenge traditional assumptions about the benefits of living near health facilities, particularly in low- and middle-income countries.

This study is related to the growing literature that reports a dramatic increase in mental distress in developing countries amid COVID-19 (Banko-Ferran et al., 2023; Vlassopoulos et al., 2023; Bau et al., 2022). In particular, this literature assesses different pathways that connect mental health and COVID-19 such as the role of social distancing (Araujo-Leal et al., 2023), the distress about contracting the virus (Hollingue et al., 2020), job and income losses (Kampfen et al., 2020), school and daycare closures (Etheridge and Spantig, 2020; Zamarro and Prados, 2021), proximity to patients with COVID-19 (Hernandez et al., 2022), vaccine distribution (Perez-Arce et al., 2021), and remote work (Bertoni et al., 2021). Our study expands this literature by offering a new mental health pathway: the proximity to noisy, chaotic, and congested health facilities amid COVID-19. The availability of administrative microdata allows us to explore specific mechanisms linked to acoustic pollution and congested facilities highlighted in the environmental and urban economics literature. This study is the first to explore these specific pathways with longitudinal information nationally.

Perú offers a relevant policy setting as the country experienced one of the most severe isolation policies accompanied by the highest number of deaths per capita from COVID-19 worldwide[2]. A few studies have addressed how this unique situation has affected some economic variables of interest, including domestic violence (Aguero, 2021) and employment (Higa et al., 2023; Vaccaro and Paredes, 2022). However, nationwide quantitative studies on mental health using pre-pandemic information are still missing in this setting. We assess the heterogeneity of the mental health effects of COVID-19 across relevant socio-demographic groups that display varying epidemiological risks and complex interplay of historical exposure to adverse shocks and social roles. Older and poorer individuals, shaped by past traumatic events such as Perú's civil war, hyperinflation, and cholera epidemic, may have developed coping mechanisms or psychological resilience. Our research also echoes global research showing important gender disparities in mental health outcomes during disasters. In this way, we expand the increasingly growing literature highlighting the unequal distribution of mental health due to COVID-19 (Miguel and Mobarak, 2021; Aknin et al., 2022; Quintana-Domeque and Zeng, 2023).

The study has the following structure: Section 2 shows the theoretical framework relating distance to health facilities and mental health. Section 3 details the methodology and sources of information used, while section 4 presents and discusses the results and the assessment of the econometric identification assumptions. Finally, section 5 presents some final remarks.

2 Theoretical Framework

Mental health is part of the durable stock of individuals' human capital, which relates to personal and collective productivity and well-being[3]. From a theoretical point of view, one can assess the relationship between mental health and the proximity of dwelling units to health facilities from the perspectives of health economics, environmental economics, and the geography of urban health.

Grossman's seminal model of health (Grossman, 1972) predicts a positive relationship between people's health and the proximity of dwelling units to health facilities. Lower monetary and time transaction costs explain this positive association, allowing higher access to medical care, which is an important market input in the production of health. Lower transaction costs make it easier for people to invest more in their health and influence timely preventive, routine, and emergency health demand decisions, allowing changes in how individuals reallocate their re-

[2] To illustrate this point, in-person school classes were suspended for two years, and restrictions such as curfews and strict isolation policies were frequent and heightened.

[3] Mental health is a state of cognitive, behavioral, and emotional well-being that allows people to cope with unfavorable social, economic, geopolitical, and environmental circumstances.

sources in health production (Buchmueller et al., 2006; Bertoli and Grembi, 2017). On the other hand, Grossman's theoretical model can incorporate external adverse shocks that help explain how proximity to collapsed health facilities can negatively affect mental health. The mechanism is negative externalities that impose an uncompensated cost on people living near collapsed health facilities by causing chronic stress, anxiety, sleep disorders, and other health problems (Murphy and King, 2022; Alexander and Currie., 2017). These negative spillover effects, such as poor environmental conditions, high acoustic pollution, and traffic congestion, can increase the depreciation rate of human capital, leading to a more rapid deterioration of mental health that requires higher investment and effort to maintain the same health stock. For instance, hospitals experienced increased acoustic and environmental stressors due to heightened activity and infrastructure strain during COVID-19, potentially impacting nearby residents.

A complementary theoretical framework that also allows addressing the relationship between mental health and proximity to health services is offered by the field of economic geography, which analyzes the role of the spatial distribution of health facilities by integrating concepts of health economics, geography, and urban economics. A central tenet is that the spatial distribution of health facilities affects the accessibility and availability of health services, which has consequences in preventing, diagnosing, and treating mental illnesses. A key theoretical element of this conceptual framework is agglomeration economies (Glaeser et al., 1992) that may lead to positive feedback on mental health (Baicker and Chandra, 2010; Skinner et al., 2023). Like the predictions that emerge from the neoclassical model of health demand, the conceptual framework of economics geography offers competing mechanisms to predict changes in the mental health of individuals living near health facilities during the COVID-19 pandemic. On the one hand, urban agglomeration favors access to health services due to proximity, network development, transportation costs, concentration of health personnel, and knowledge externalities, all of which positively affect mental health (Chandra and Staiger, 2007; Vlahov et al., 2007). On the other hand, urban agglomeration economies can transform into diseconomies and adversely affect mental health, particularly during crises such as COVID-19 due to the recurrence of urban stressors such as congestion, noise pollution, and overcrowding of health facilities (Lambert et al., 2015; Patil, 2014). For instance, the physiological effects of noise pollution are disrupted sleep and heightened stress, which, along with exposure to overcrowded and degraded facilities, may contribute to poorer mental outcomes (Alvaro et al., 2013; WHO, 2011).

Therefore, the conceptual frameworks of health economics and economics geography highlight elements of opposition in the direction of change in mental health for people living close to overrun health facilities during the COVID-19 pandemic. The final effect will depend on which of these opposing factors carry a greater weight on people's mental health. It is an empirical open question.

3 Methodology

3.1 Sources of information

This research uses three complementary sources of information to generate geo-referenced microdata that link administrative data from health facilities to household survey data.

3.1.1 Demographic and Family Health Survey (DHS)

The DHS is a nationwide household survey collected by the National Institute of Statistics and Informatics of Peru since 1986. This survey collects annual information from approximately 30,000 households through two-stage, balanced, stratified, and independent sampling at the departmental level in urban and rural areas. The main modules cover socio-demographic variables and the health status of mothers and children aged five and under. A mental health module focusing on depression symptoms has been added since 2013 and collects information for men and women aged 15 and over.

DHS allows us to use self-reported information from individuals who respond to a battery of depression symptoms questions. Although there are different ways to measure depression, one of the most widely used is the Patient Health Questionnaire (PHQ9) (Spitzer et al., 1999; Cjuno et al., 2022), from which a standard index of depression symptoms is constructed. The PHQ9 consists of the sum of nine indicators[4]. Each indicator is scored on a scale of 0 to 3 and reaches a maximum of 27 points, where a higher score indicates a higher probability of severe depression. The reference timeline for each indicator is the last two weeks before the survey takes place. Thus, for example, the indicator 'how often you have thoughts of death or wanting to hurt yourself takes four potential values: 0 (no day), 1 (from 1 to 6 days), 2 (from 7 to 11 days), and 3 (from 12 days or more). It is recognized that PHQ9 is not free of measurement error; however, it is a standard screening tool supported by the DSM5, which is a validated and recognized manual for diagnosing mental disorders worldwide.

3.1.2 National Superintendence of Health (SUSALUD)

SUSALUD constitutes an administrative database of the National Registry of Health Service Provider Institutions. This database contains detailed information on each health facility's geo-referenced location, equipment, human resources, services, hospitalizations, and deaths. By 2023, we can identify 58 Category III health facilities, corresponding to health establishments that have outpatient, emergency, hospitalization, and intensive care. Of these, 41 correspond to hospitals and general and specialized clinics, which form the target group for this study as they

[4] These indicators are (i) anhedonia, (ii) apathy, (iii) sleep disorder, (iv) fatigue, (v) appetite disturbance, (vi) impaired concentration, (vii) psychomotor agitation or retardation, (viii) suicidal ideation, and (ix) generalized dissatisfaction.

were the health facilities that provided care for COVID-19 patients. These 41 health facilities are distributed in the capitals of eight departments. Appendix Figure A.1 shows their geographic distribution. The remaining 17 correspond to specialized health institutes mainly responsible for research and academic functions, providing highly specialized health services, such as the Heart Institute.

3.1.3 Registry of the availability of ICU beds of the Ministry of Health (RUCI)

RUCI is an administrative database containing the official registry of beds for health establishments in Peru from April 7, 2020, onwards. This dataset provides information on the occupancy rate of standard beds, ICU beds, and mechanical ventilators for adults, neonates, and pediatrics. Therefore, the database's importance lies in its ability to identify the specific period when Category III health facilities were overrun by observing the occupancy rates for ICU beds.

These datasets are linked using the geographical coordinates of the specific clusters where respondents and health facilities are located. The closest geodesic distance between health facilities and dwelling units' geographical coordinates defines the link. As a result, we have a geo-referenced dataset that has as its unit of analysis individuals over 15 years of age who live at an identified specific distance from the health facilities. Indeed, 46% of our sample live within a 3-kilometer distance from the closest health facility.

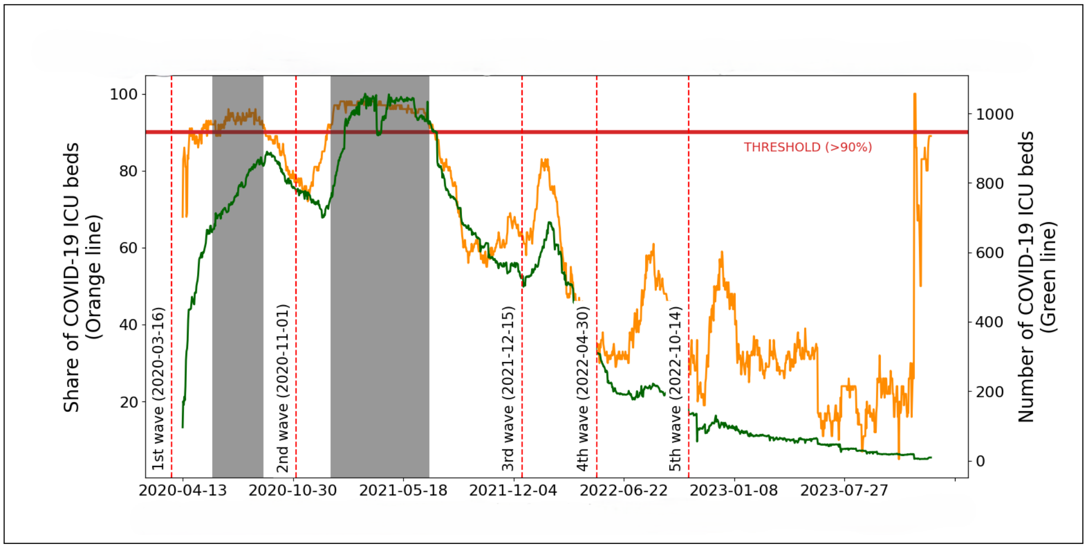
3.2 Definitions

From a methodological point of view, identifying the timing when the health facilities collapse becomes critical. We define hospital 'h' as overburned when the use rate of ICU beds exceeds a threshold of 90% in a given month. Figure 2 shows the percentage and number of ICU beds used for people infected with COVID-19 from 2020 to 2023. The months of May-August 2020, and the months of January-June 2021 exceeded this critical level. For all months of 2022 and 2023, the ICU occupancy rates were below the threshold level, which coincides with the introduction of vaccines against the coronavirus in Perú. It is pertinent to recall that this information comes from Category III health facilities, the hospitals that absorbed the demand for hospitalization of COVID-19 patients. Sensitivity analyses consider alternative thresholds for the ICU use rate ranging from 65% to 94%.

Given the excess demand for hospitalization related to COVID-19, the rationing of ICU beds was felt in all health facilities simultaneously during the public health emergency. The standard allocation of public health care services according to place of residence was no longer in effect. Thus, there is minimal inter-facility variation in the use rate of ICU beds during the critical months.

The other important definition refers to proximity to health facilities. We define the cutoff

Figure 2: Timeline of health facility overburden during the COVID-19 pandemic



Note: Authors' elaboration. Source: Administrative data from the Ministry of Health of Perú (SUSALUD). The shaded areas represent the timing when the occupancy rate of ICU beds exceeds 90%.

value of 3 kilometers to describe individuals who are closer and further away from a health facility. Thus, the target group comprises those residing less than 3 kilometers from the nearest health facility. Those living between 3 and 15 kilometers from the nearest health facility are the comparison group. Sensitivity analyses consider different distance thresholds within this range.

The administrative dataset consists of 41 hospitals distributed across the capital cities of 9 departments. We restrict the sample to the urban areas for comparability as few observations reside in rural areas within up to 15 kilometers of the closest health facility. For this purpose, we use the 2017 Population and Housing Census cartography prepared by the Peruvian National Institute of Statistics. Appendix A.1 shows the geographic distribution of health facilities within each capital city. Furthermore, we restrict the sample to only individuals who reside permanently in the dwelling units.

Table 1 shows descriptive statistics for the sample from the 2018 to 2023 DHS surveys. This sample comprises 10935 individuals in the target group (46% of our sample) and 12652 in the comparison group (54%). We are dealing with a relatively young sample of 35-year-olds on average, of which 58% are women and 22% lack access to health insurance. The share of households under the poverty line is 23%, with a higher proportion among households located further away from hospitals. Likewise, we observe higher levels of education among those living closer to health facilities.

Regarding the depression symptom index, we observe an average score of 2.54 for the sample in the analysis period, which takes 2.47 and 2.61 when considering each group separately. By looking at the components of the depression symptoms, we observe substantial variation in their incidence. While the most prevalent symptoms are anhedonia, apathy, and sleep disorders, suicidal ideation and generalized dissatisfaction show the lowest values.

3.3 Econometric Specification

The main econometric specification follows a difference-in-differences approach that allows one to identify and estimate the change in the depression index before and after the health system crisis for individuals living near health facilities relative to those living further away. For each individual 'i' whose nearest health facility is 'h' in time 't', we follow the specification,

$$\begin{aligned} index_{iht} = \alpha_1 Collapse_{ht} + \alpha_2 Group3km_{ih} + \\ \beta Collapse_{ht} * Group3km_{ih} + \theta' X_{iht} + \delta_h + \delta_t + \varepsilon_{iht} \end{aligned} \tag{1}$$

Where $index_{iht}$ is the self-reported depression index that ranges from 0 to 27. The main independent variable of interest is the interaction of the proximity to health facilities ($Group3km_{ih}$) and the timing of facility collapse ($Collapse_{ht}$). $Group3km_{ih}$ takes 1 for people living less than 3 km from a health facility and 0 for people between 3 km and 15 km, while $Collapse_{ht}$ is a variable that takes the value of 1 when the use rate of ICU beds exceeds a threshold of 90%, 0 otherwise. The parameter of interest is β, which is associated with the interaction term. The baseline specification includes hospital-fixed effects (δ_h), time (quarter) fixed effects (δ_t), and a set of control covariates (X) that considers relevant individual and household characteristics. Alternative specifications consider DIRESA-fixed effects, city-fixed effects, and department-fixed effects. We report the standard errors in three ways: robust, clustered at the geographic-cluster survey coordinates, and Conley's standard errors (Conley, 1999), the last correct potential spatial or temporal correlations of the errors.

4 Results

4.1 Main results

Table 2 shows the main results on the self-reported depression index following Eq. 1. The estimated coefficients show a statistically significant increase in depression symptoms for individuals living near collapsed health facilities relative to the change experienced by individuals living relatively far away. Residing within 3 km of health facilities is associated with an increase of about 0.38 points in the depression index compared to people between 3 km and 15 km. This corresponds to a 15% increase in the average index of the comparison group, people who live between 3 km and 15 km from hospitals. These informative effects hold regardless of whether robust, clustered, or Conley-adjusted standard errors are estimated.

Table 1: Descriptive statistics

Variables	Total		Less than 3km		Between 3km and 15km	
	Mean	St.dev	Mean	St.dev	Mean	St.dev
Depression Index (PHQ9)	2.54	4.0	2.46	4.0	2.61	4.0
Anhedonia	0.44	0.8	0.42	0.8	0.45	0.8
Apathy	0.43	0.7	0.41	0.7	0.44	0.7
Sleep disorders	0.39	0.8	0.39	0.8	0.39	0.8
Fatigue	0.32	0.7	0.31	0.7	0.33	0.7
Appetite disturbance	0.31	0.7	0.30	0.7	0.32	0.7
Impaired concentration	0.23	0.6	0.22	0.6	0.23	0.6
Psychomotor issues	0.20	0.6	0.20	0.6	0.20	0.6
Suicidal ideation	0.07	0.3	0.07	0.3	0.07	0.4
Generalized dissatisfaction	0.16	0.5	0.15	0.5	0.17	0.5
Age	35.75	12.4	36.46	12.8	35.13	12.1
Woman	58%	0.5	59%	0.5	58%	0.5
Weight (kg)	70	14	71	15	70	14
Height (cm)	159	9	159	9	158	9
Lack health insurance	22%	0.4	22%	0.4	23%	0.4
Have diabetes	3%	0.2	3%	0.2	3%	0.2
Ingested alcohol last year	80%	0.4	81%	0.4	80%	0.4
Domestic violence	10%	0.3	9%	0.3	11%	0.3
Household size	5	2	5	2	5	21
Poor household	23%	0.4	18%	0.4	27%	0.4
Has secondary education	47%	0.5	42%	0.5	52%	0.5
Has post-secondary education	44%	0.5	50%	0.5	38%	0.5
Household member died in last 5 yers	5%	0.2	6%	0.2	5%	0.2
Head of household	44%	0.5	43%	0.5	44%	0.5
Spouse of head of household	33%	0.5	32%	0.5	34%	0.5
Son/daughter	14%	0.3	14%	0.4	14%	0.3
Sample	23,587		10,935		12,652	

Note: Simple averages. Source: 2018-2023 DHS.

Three additional specifications that vary according to the inclusion of alternative fixed effects at the DIRESA (administrative-based health region), city, or state levels show similar results, as we can observe in columns 2-4.

Table 2: Average Impacts on the Depression Index

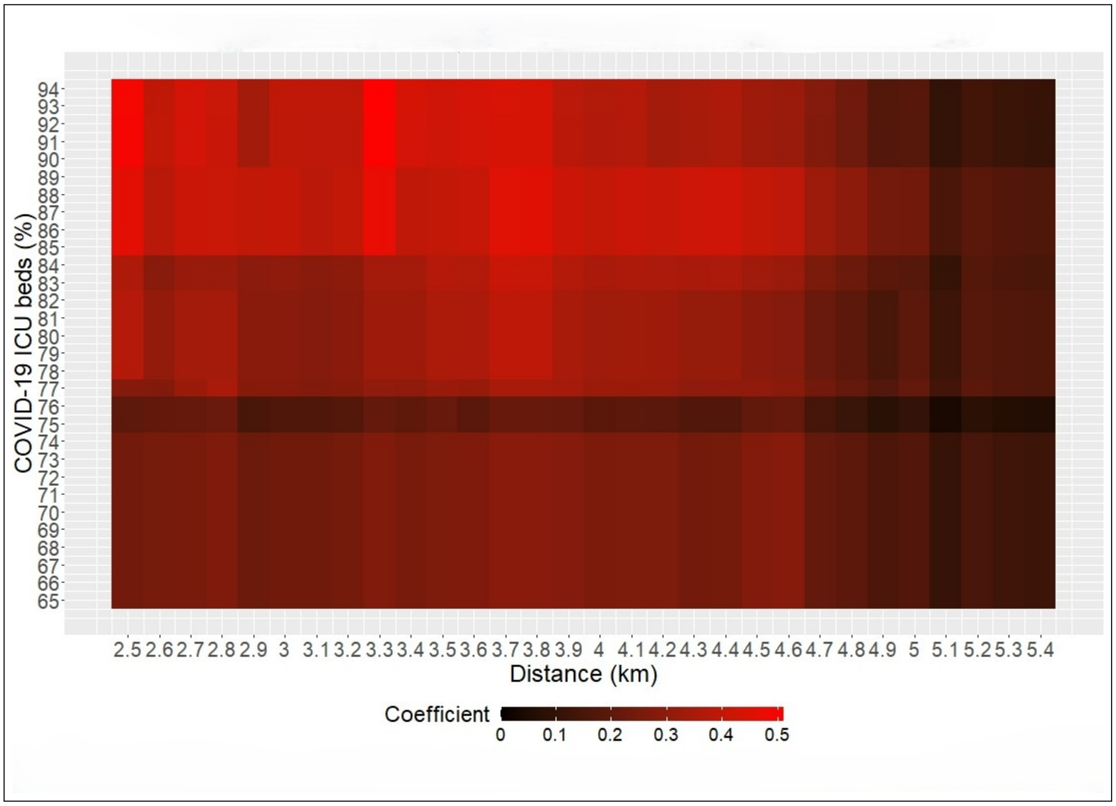
	(1)	(2)	(3)	(4)
	Dependent variable: depression index			
Collapse*Group3km	0.377	0.385	0.377	0.377
	(0.202)**	(0.201)**	(0.201)*	(0.164)*
	[0.192]*	[0.192]*	[0.192]*	[0.192]*
	{0.063}***	{0.043}***	{0.191}**	{0.167}**
N	23587	23587	23587	23587
Mean depression index	2.54	2.54	2.54	2.54
Control covariates	X	X	X	X
Quarter fixed effects	X	X	X	X
Hospital fixed effects	X			
Diresa fixed effects		X		
City fixed effects			X	
Department fixed effects				X

Note: Robust (parentheses), clustered (brackets), and spatial correlation adjusted (braces) standard errors. Control covariates include age, age2, gender, education categories, weight, height, health insurance, has diabetes, alcohol consumption, domestic violence, household size, poverty status, head of household indicator, spouse indicator, son/daughter indicator, household member died in the past 5 years, longitude, and latitud. *** 1%, **5%, * 10%.

Multiple sensitivity tests allow us to evaluate the robustness of the main results. First, the positive and statistically significant effects hold when we implement alternative definitions of the dependent variable. These variations include index standardization and a simple average of its components, as reported in Appendix Table A.2. Second, we estimate a parametric difference-in-difference Poisson estimator, given that the distribution of the original dependent variable takes zero and positive continuous values. This estimator yields the same results as observed in Appendix Table A.2. Third, we consider variations in the definition of the main independent variables, $Group3km_{ih}$ and $Collapse_{ht}$, to evaluate the plausibility of the story assessed in this study. Following the 3 km cutoff point to define the groups in and out of the vicinity of the hospitals, we vary the cutoff distance from 2.5 km to 5.4 km. We do not consider lower thresholds because of sample size issues. Likewise, we vary the percentage of occupied ICU beds in an extensive range, covering 65% to 94% when defining hospital collapse. If the story offered in this study is plausible, one would expect that greater distances to hospitals and lower ICU bed occupancy rates would imply a gradual decrease in the reported effects. Indeed, Figure 3 shows this pattern in the data following the estimation of 900 regressions with different combinations of distance and occupancy ICU bed cutoffs. The impacts gradually decrease whenever the distance to health facilities increases and the ICU-occupied beds' share decreases.

Alternatively, Appendix Figure A.2 shows the estimated coefficients of multiple specifications when varying the 3 km cutoff by 100 meters on both sides (panel A), both the 3km and 15 km cutoffs by 100 meters on both sides (panel B), and the 90% ICU beds cutoff point by one percentage point on both sides (panel C) while estimating equation 1. The vertical red lines represent the baseline point estimates. The point estimates remain positive and statistically significant across multiple alternative values around the original cutoffs.

Figure 3: Sensitivity analysis with multiple cutoff points



Note: This figure reports the estimated coefficient of the interaction term $Group3km_{ih} * Collapse_{ht}$ in equation (1) from 900 regressionswith different combinations of distance and occupancy ICU bed cutoffs. See Table 2 for details about control variates.

4.2 Heterogeneity Analysis

We assess the heterogeneity of the impacts across three important policy variables: age, gender, and socioeconomic status. From an epidemiological standpoint, hospitalizations and excess deaths related to COVID-19 are more prevalent in older people rather than younger ones, men rather than women, and poorer individuals rather than more affluent ones (Siddique et al., 2023; Whitaker et al., 1957). However, the salience of COVID-19 could make younger individuals perceive dramatically higher risks of infections, hospitalizations, and deaths than older ones (Bordalo et al., 2020), as the former is likely to see long-run scarring effects of working prospects. Likewise, women disproportionally stay at home and are responsible for caregiving those who contracted COVID-19, as well as children who missed school days due to extended school closures (Miguel and Mobarak, 2021). Moreover, while remote work was a buffer for more affluent individuals, it might have led to challenges such as burnout and sudden isolation. All these factors can create differential changes in mental health outcomes that do not necessarily correspond with the epidemiological risk burden of specific socio-demographic groups.

Columns 1 and 2 in Table 3 show that the increase in the depression index for individuals near collapsed health facilities is observed only for women (0.81 points) and not for men. Even though the risks and sequels of contracting COVID-19 are disproportionately worse for men than for women, the impacts on men's depression index go in the opposite direction, albeit statistically not significant effects. This result suggests that the sizable changes in the depression index experienced by women (26%) are possibly related to household chores and social norms that consider women as the primary caregivers within the household in Perú. Women disproportionally stayed home and were more likely exposed to the chaos and acoustic noise of neighboring congested health facilities. At the same time, women are the primary responders to the health needs of children, siblings, and partners alike, which could have disproportionally affected their anxiety, stress, and fear levels, particularly in this setting where children missed school days due to extended school closures. Likewise, women in Perú were subject to heightened gender-based domestic violence during the pandemic (Aguero, 2021), all of which may have contributed to higher levels of psychological distress. This result echoes global research showing gender disparities in mental health problems during COVID-19 (Vlassopoulos et al., 2023; Aknin et al., 2022).

Columns 3 and 4 in Table 3 show results by age categories. Since the median age in the sample is 36 years, two age groups are considered from 15 to 36 years and over 36. Our results show that young adults have a substantial (20%) and statistically significant increase in the depression index. The coefficient for the older group is less than half of that and is statistically non-informative. Given that COVID-19 shows higher hospitalization and excess death rates for older people, this result appears counterintuitive. However, it is likely that older people in Perú, who already have experienced collective health shocks in their life trajectories, have different perceived risks than the younger ones (Bordalo et al., 2020), which made them more resilient to COVID-19. Unlike the younger cohort, people older than 36 in 2020 were exposed to cholera epidemics, hyperinflation, and civil war in Perú in the 1980s and early 1990s (Galdo, 2013; Grimard and Laszlo, 2014). These past experiences may have helped older individuals to develop coping mechanisms or psychological resilience. This result is also related to the broader literature about the growth of mental despair among those younger than 30, whose rate of despair has risen dramatically in the past decade or so (Case and Deaton, 2020).

Table 3: Heterogeneous effects by gender, age, and socioeconomic status

	(1)	(2)	(3)	(4)
	Gender		Age	
	Women	Men	Young	Old
Collapse*Group3km	0.806***	-0.118	0.523**	0.21
	(0.300)	(0.246)	(0.262)	(0.270)
N	13697	9890	13404	10183
Mean outcome	3.15	1.7	2.58	2.5
	(5)	(6)	(7)	(8)
	Socioeconomic status			
	Poor	No Poor	No Connected	Connected
Collapse*Group3km	0.277	0.401*	0.303	0.388*
	(0.540)	(0.205)	(0.437)	(0.213)
N	5358	18227	4607	18979
Mean outcome	2.74	2.49	2.27	2.61
Hospital fixed effects	X	X	X	X
Quarter fixed effects	X	X	X	X
Control covariates	X	X	X	X

Note: Clustered standard errors. Young subsample (<36 years old), old subsample (36 years and older), connected (has access to electric grid and water public networks), no connected (has no access to electricity and water public networks). See Table 2 for details on specification and control covariates. *** 1%, **5%, *10%.

Columns 5-8 show results for socioeconomic status according to two indicators: income poverty and connection to electricity and water public networks, a proxy for long-run poverty. The pattern that emerges from these results is that individuals from more affluent households show higher adverse changes in their depression index. More affluent household members are likely to work remotely from home during the health crisis because of their occupations, which could imply more chaos and noise pollution exposure for those living near the health facilities. Affluent individuals, often expected to fare better, may have a lower threshold for coping with acute disruptions, given relatively higher insulation from typical chronic stressors. Unlike the heterogenous impacts on gender or age, differences in mental health changes between individuals of higher and lower socioeconomic status are, however, relatively small and statistically significant only at the 10% level. In general, the literature shows disproportional adverse mental health effects of COVID-19 on disadvantaged households, the ones more economically vulnerable to the pandemic (Gibson et al., 2021; Green et al., 2021).

4.3 Assessing the Identification Assumption

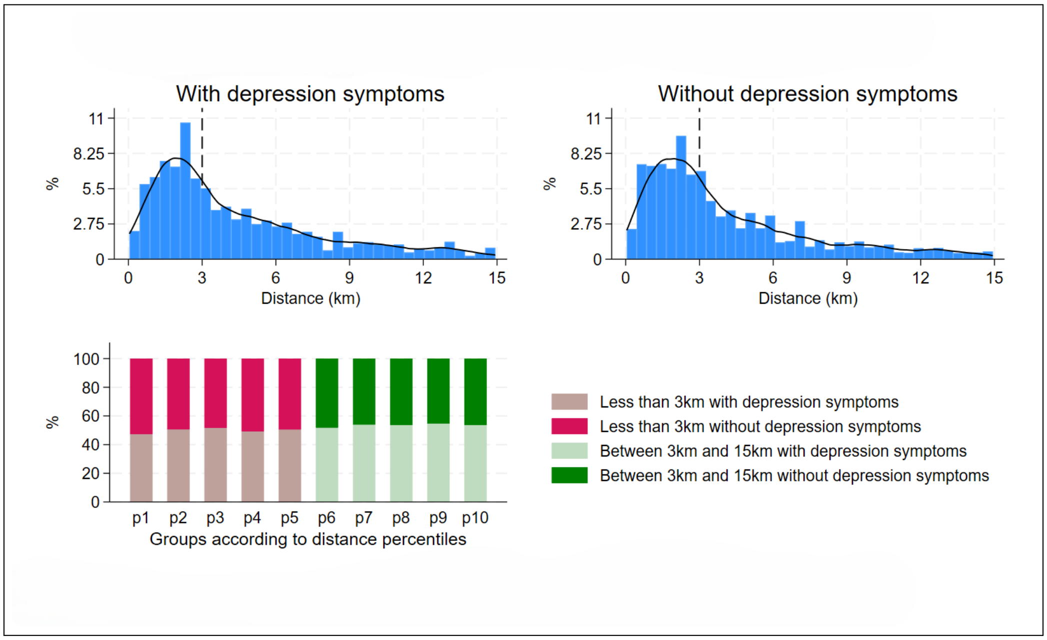
The internal validity of our results depends on the plausibility of the difference-in-differences approach assumptions in the context of institutions and data at hand. In the absence of COVID-19, one expects that changes in the depression index of individuals living within 3 km of health facilities are, on average, the same as the changes in the depression index of individuals between 3 km and 15 km. This identification assumption does not hold if, for example, individuals with more prevalent mental health problems tend to live closer to hospitals (Skinner et al., 2023), leading to spatial sorting problems that threaten the identification of causal effects in this type of setting. In addition, some unobserved factors correlated with the outcome of interest may have changed unevenly in neighborhoods adjacent to and farther away from hospitals in response to the coronavirus epidemic. For example, police surveillance might have increased in the areas near health facilities, leading to decreased street crimes, a potential psychological factor of stress and anxiety. Although we cannot reject the violation of the identification assumption directly, we can implement a battery of empirical analyses and statistical tests that lend credibility to our estimated causal effects.

First, we graphically describe the spatial ordering in the data to assess whether individuals with symptoms of depression before the collapse of health facilities amid COVID-19 tend to reside closer to health facilities. Figure 4 shows the density of the distance between dwelling units and the nearest health facility for those with symptoms of depression vis-à-vis those without symptoms of depression. The graphs show that the density distribution follows remarkably similar patterns and structures between the two groups. We also assess the same information according to distance deciles at the bottom of Figure 4. It shows a similar distribution for those who have and those who do not have symptoms of depression in each decile of the distance distribution before COVID-19.

Second, Figure 5 draws the unconditional depression index profiles for those living less than 3 km and between 3 km and 15 km from the health facilities before and after COVID-19. Figure 5 shows similar trends between both groups in 2018 and 2019. We no longer observe these parallel trends in 2020 and up until 2022. Moreover, the data suggest a reversal of trends to pre-pandemic levels in 2023. All in all, these patterns in the data imply that, in the absence of overburdened health facilities, it is plausible to observe similar changes in the prevalence of the depression index between individuals residing closer and further away from the health facilities. Furthermore, a formal test that evaluates the mean equality of the depression index before 2020 does not reject the null. We observe similar unreported results when assessing each component of the depression index separately.

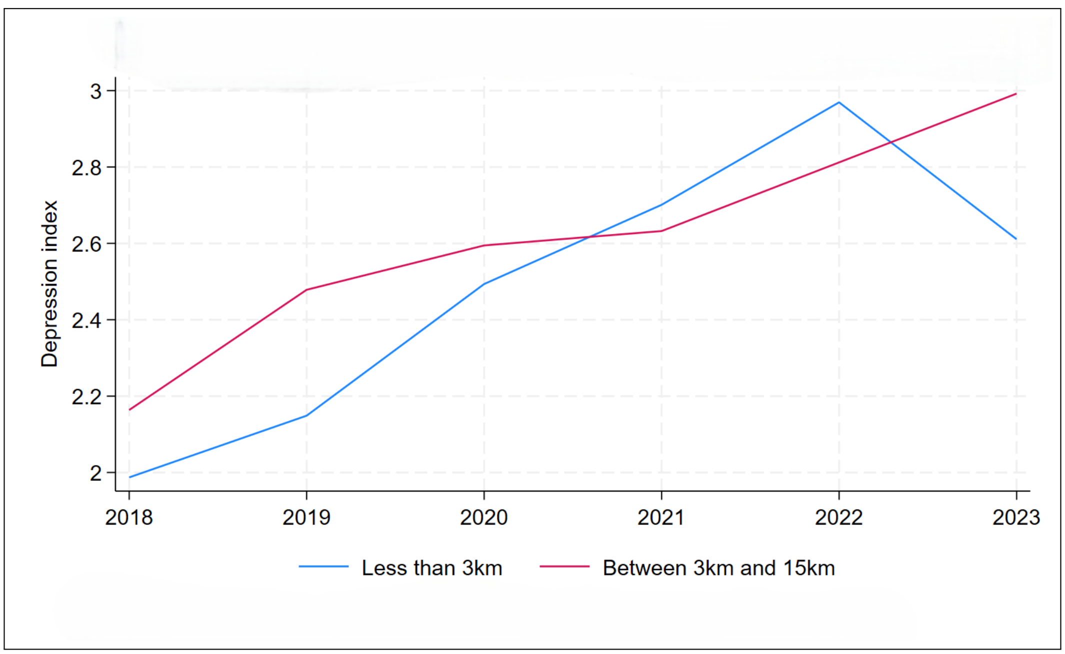
Third, we implement two econometric models to evaluate the assumption of parallel trends. The first model uses information only from the pre-pandemic years 2018 and 2019 and estimates

Figure 4: Data sorting before the COVID-19 pandemic



Note: Authors' elaboration. Source: DHS and SUSALUD datasets from January 2018 to March 2020.

Figure 5: Unconditional average of depression index by time period



Note: Unconditional means for the depression index (PHQ9). Source: 2018-2023 DHS datasets.

the standard difference-in-differences estimator after falsely assigning the occurrence of ICU bed collapse to the year 2019. Table 4 shows these results under two scenarios: when falsely assigning hospital collapse to all months of 2019 (panel A), and when falsely assigning hospital

Table 4: Placebo tests for the timing of health facility collapse

	(1)	(2)	(3)	(4)
	Panel A. Collapse is 2019			
FalseCollapse*Group3km	-0.184	-0.150	-0.150	-0.150
	(0.193)	(0.194)	(0.194)	(0.194)
N	8785	8785	8785	8785
Average	2.20	2.20	2.20	2.20
	Panel B. Collapse is May-August 2019			
FalseCollapse*Group3km	0.001	0.001	0.001	0.001
	(0.308)	(0.310)	(0.315)	(0.315)
N	8785	8785	8785	8785
Average	2.20	2.20	2.20	2.20
Quarter fixed effect	X	X	X	X
Control covariates	X	X	X	X
Hospital fixed effects	X			
Diresa fixed effect		X		
City fixed effect			X	
Department fixed effect				X

Note: Clustered standard errors. See Table 2 for details on control covariates. *** 1%, **5%, *10%.

collapse only to May to August 2019 (panel B). Unlike the main estimates reported in Table 2, these fake estimates show negative signs or zero effects and are statistically not informative in all cases. These results support the assumption of parallel trends.

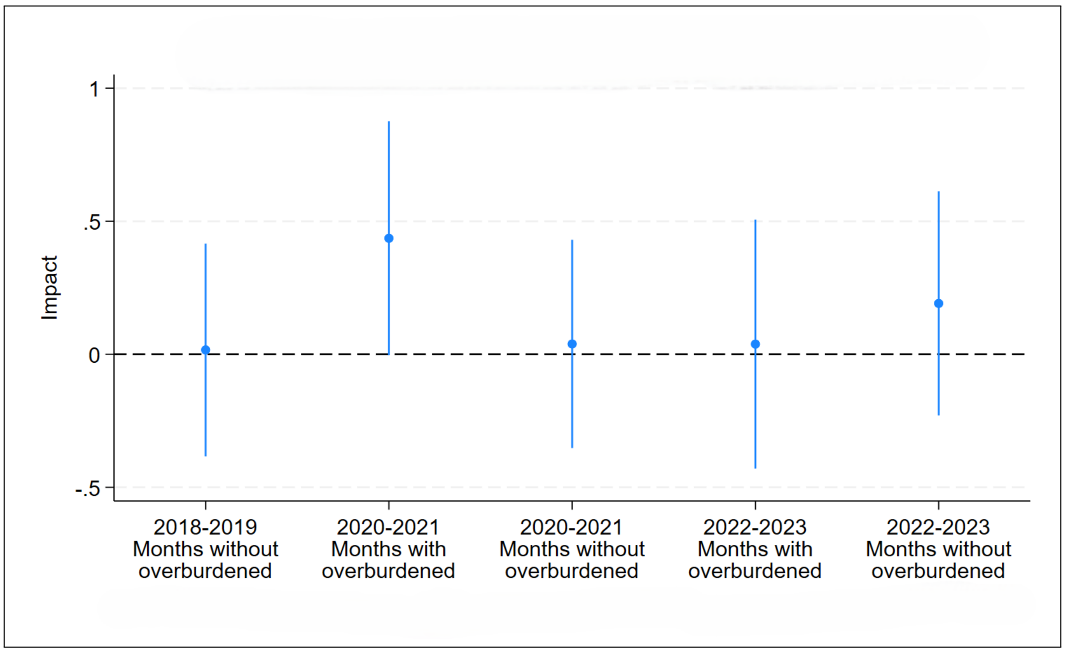
A second econometric approach considers an event-study design where we consider six periods of interest. Given that health facilities collapse in May-August 2020 and January-June 2021, we consider three pair of years: 2018-2019, 2020-2021, and 2022-2023, and within each pair of years, we consider two periods corresponding to the months of health facility collapse (May-August of year ‘t’ and January-June of year ‘t+1’). That is, we fictitiously assigned the occurrence of the collapse to May-August 2018, January-June 2019, May-August 2022, and January-June 2023. Thus, the $Period_t$ variable takes 1 for the months of health facility collapse and 0 otherwise. Following the same definitions as before, equation (2) describes the event study:

$$index_{iht} = \alpha_1 Group3km_{ih} + \sum_j \theta_j 1(Period_t = j) * Group3km_{ih} + \gamma' X_{it} + \delta_h + \delta_a + \varepsilon_{iht} \quad (2)$$

Where the coefficients of interest are θ_j. We also include health facility fixed effect (δ_h), time (quarter) fixed effect (δ_t), and the same control covariates (X). The omitted category is the months of health collapse in 2018-2019. We test the assumption of parallel trends by examining the estimated coefficient associated with the months of no health facility collapse in 2018-2019. The standard errors are estimated with cluster corrections at the cluster sampling survey.

Figure 6 shows three noteworthy results. First, a coefficient equal to zero is observed for the months without health facility collapse in 2018-2019, which indicates the absence of non-parallel trends. Second, a positive (0.49) and statistically significant effect on the depression index is associated with the months of health facility collapse in 2020-2021. Finally, we observe positive but statistically insignificant coefficients for all the remaining 2021, 2022, and 2023 periods. This last result indicates that the increased depression symptoms index follows a short-run pattern and fades over time once the strain on the health system lessens.

Figure 6: Dynamic Difference-in-Difference placebo test

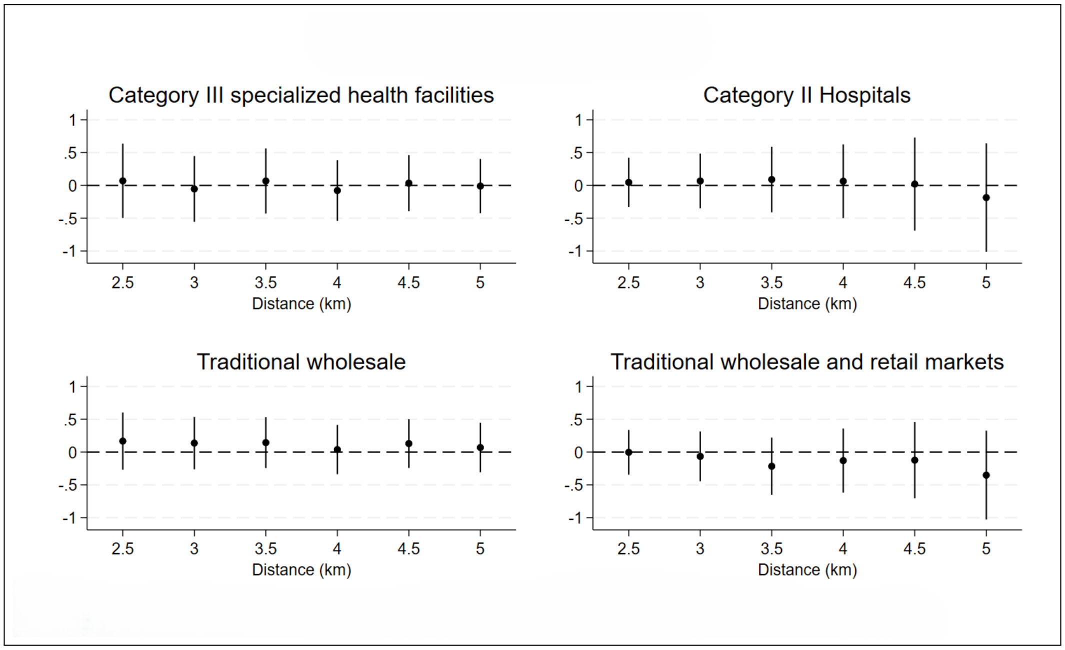


Note: Clustered standard errors at the DHS cluster survey level. See Table 2 for a description of control covariates.

Finally, we implement two placebo tests to show that the adverse changes in the depression index are not linked mechanically to geographic proximity to bustling urban areas. For that, we consider proximity to traditional wholesale and retail markets, typical spaces of agglomeration, acoustic noise, and chaos in developing settings. We also consider other types of health facilities that, by constitution and infrastructure, do not face the demand for COVID-19 hospitalizations. We thus consider Category III specialized health facilities, primarily research health facilities that attend demand for specialized and complex health care (e.g., The Heart Instituto), and Category II hospitals that do not absorb the hospitalization demand from patients with COVID-19 due to infrastructure restrictions.

To this end, we implement the same estimation model (equation 1), with the only change that variable ‘Group3km’ now reflects the distance to the nearest traditional food market or new health facilities. Figure 7 shows these placebo results. We observe negligible and statistically insignificant effects in each of the panels. This placebo exercise suggests that living near health facilities or traditional wholesale and retail markets during the same analysis period is not mechanically related to adverse changes in depression symptoms in Peru. Indeed, we observe adverse changes in depression symptoms only when we consider geographic proximity to overburdened health facilities.

Figure 7: Placebo tests



Note: Point estimates and confidence intervals from equation (1) specification. See Table 2 for specification details.

4.4 What does administrative data reveal?

Because self-reported survey information can be subject to measurement errors, we use administrative microdata to assess our estimates’ robustness regardless of the data production type. To this end, we use the administrative data of the Registry of Health Establishments of the National Superintendence of Health (SuSalud). Unlike the self-reported survey data, the available administrative dataset does not have geo-referenced information at the household or individual level. Therefore, defining households’ proximity to health facilities is impossible; thus, we do not follow the equation (1) specification. Instead, the administrative data allows us to identify the total number of people treated for depression in category III health facilities in each month between 2018 and 2023. The following specification is estimated for hospital ‘h’ in month ‘m’ and year 't':

$$depress_{hmt} = \alpha_1 monthcollapse_m + \alpha_2 year2020\_2021_t + \\ \beta monthcollapse_m * year2020\_2021_t + \lambda_m + \lambda_t + \lambda_h + \varepsilon_{hmt} \tag{3}$$

Where depression refers to the proportion of users treated for depression, monthcollapse takes the value 1 for the specific months of hospital collapse and 0 otherwise within each year, $year2020\_2021_t$ is a binary indicator for the years 2020 and 2021. β is the parameter of interest as it captures depression care cases before and after hospital collapse. Fixed effects are added at the level of health facilities (λ_h), and year (λ_t). Standard errors are clustered at the health facility level because we use administrative data at that level for each month.

Table 5 shows the point estimates emerging from equation (3). We consider two groups since category III health facilities include overburdened hospitals (Panel A) and specialized institutes that did not meet the demand for COVID-19 hospitalizations (Panel B). Looking at columns 1 to 2 in Panel A, we observe positive and significant changes in the proportion of people treated for depression during the months of health facilities collapse due to COVID-19. These changes equal a 16% increase, statistically significant at the 5% levels. On the other hand, Panel B shows results for the specialized health institutes. We observe negative and uninformative coefficients that, depending on the specification, take positive or negative values.

Comparing Table 5 (administrative data) with Table 2 (household survey effects) shows one clear result: relative to the pre-pandemic situation, we observe a higher prevalence of depression symptoms in Perú caused by the emergence of COVID-19, regardless of the nature of the data production used.

4.5 Mechanisms

This section analyzes the channels that help explain the increase in the depression index for individuals living near strained health facilities during the COVID-19 pandemic. Proximity to overburned facilities likely amplifies stressors through direct and indirect pathways, including heightened exposure to visible suffering, noise pollution, and disruption in daily life. These stressors can create an acute psychological burden that extends beyond those directly affected by the coronavirus. Thus, we focus on negative externalities such as acoustic pollution and congestion (Brueckner, 2011), which are particularly salient during crises and may impose an uncompensated cost on people living near health facilities, potentially leading to a more rapid mental health deterioration (Murphy and King, 2022; Alexander and Currie., 2017)[5]. Acoustic

[5]Hospitals typically generate high noise levels exceeding 70 decibels, well above the World Health Organizationâs recommended 35 decibels daytime and 30 decibels nighttime thresholds. During health crises, the hospital's acoustic pollution can easily exceed 70 decibels due to the increased use of ambulances, alarms, and heightened foot and vehicular traffic. This acoustic pollution can spill over to nearby residents, leading to sleep disturbance, stress, and adverse mental health outcomes (Coiado et al., 2022).

Table 5: Effects on inpatient depression care (administrative data)

	(1)	(2)
	% users treated for depression	
	Panel A. Hospitals	
Collapse*Year20-21	0.381**	0.352**
	(0.177)	(0.156)
N	1856	1856
Average	2.33	2.33
	Panel B. Institutes	
Collapse*Year20-21	-0.222	-0.026
	(0.668)	(0.500)
N	536	536
Average	3.72	3.72
Hospital fixed effect	X	X
Year fixed effect	X	
Biannual fixed effects		X

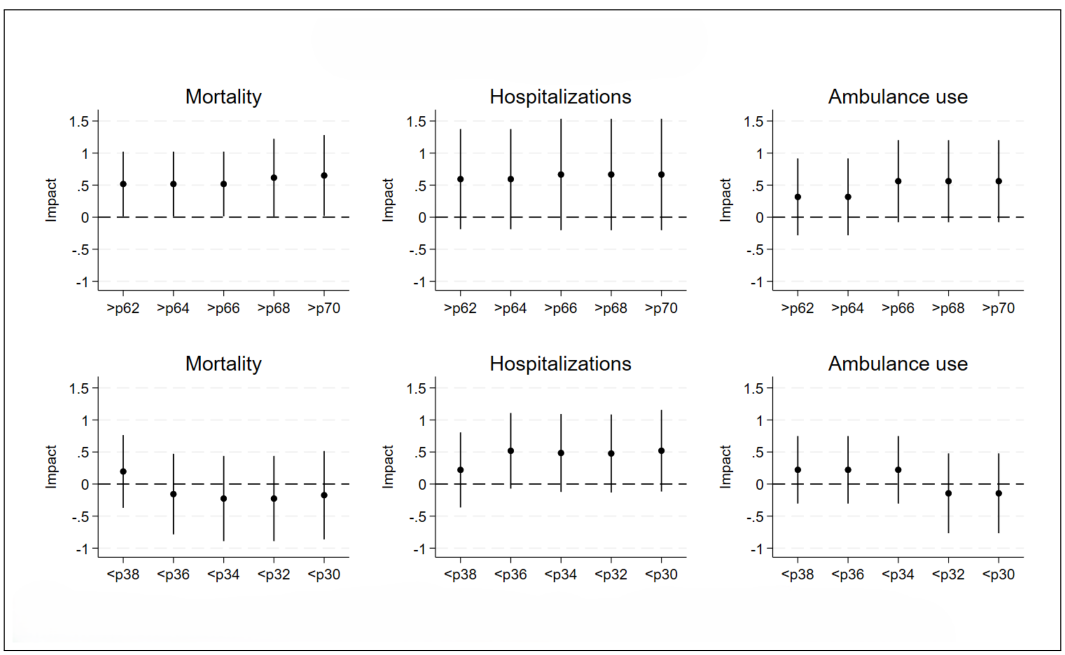
Note: Clustered standard errors at the health facility level. Panel A refers to overburdened health facilities, and Panel B refers to Health Institutes that did not face the demand for hospitalization for COVID-19. *** 1%, **5%, *10%.

pollution, for instance, may cause sleep disturbance, a driver of mental health problems such as anxiety and depression (Alvaro et al., 2013; Tortorella et al., 2022). Likewise, congestion-related stress is associated with adverse psychological outcomes, which, in the context of isolation, can heighten the risk of depressive symptoms (Novaco et al., 1990).

To this end, we make use of the administrative data of the Registry of Health Establishments of the National Superintendence of Health (SuSalud) that allows us to identify proxy variables for chaos and congestion in hospitals, as well as acoustic pollution and the visual nonstop operation of hospital crematoriums. We select three variables: the number of in-hospital deaths, in-hospital hospitalizations, and ambulance rides entering and leaving hospitals. These variables are identified monthly for each health facility from 2018 to 2023. We then rank health facilities according to the "excess" of mortality, hospitalizations, and ambulance use when health facilities collapsed relative to the same months in previous years. That is, the ordering of hospitals follows a ratio where the numerator is the total number of in-hospital deaths in the months of May-August 2020 and January-July 2021, and the denominator is the total number of in-hospital deaths in the same months of May-August 2018 and January-June 2019. Next, this ordering ranking of health facilities for each of the three variables considered is linked to each observation of the demographic health survey using the geographic coordinates of the nearest health facility as a connector. Finally, we estimate equation 1 across different subsamples according to the percentiles of the nearest health facilities (e.g., top 70th percentile vs bottom 30th percentile). We aim to show that the change in the depression index is, for instance, driven by individuals living near hospitals with the highest excess mortality during the COVID-19 health collapse vis-à-vis the change in the depression index for individuals living near hospitals with the lowest excess mortality during the COVID-19.

Figure 8 shows the results with the top (bottom) panels showing the impacts for individuals residing near health facilities with higher (lower) excess mortality, hospitalizations, and ambulance use. The graphs on the left show that individuals living near hospitals with the highest excess mortality during COVID-19 show a statistically significant increase in the depression index. On the contrary, those residing near hospitals with the lowest excess mortality during COVID-19 show negative and statistically non-informative impacts on the depression index. We also observed a similar pattern in the case of the excess hospitalization variable by looking at the middle panels. However, the differences are minor; thus, we do not observe statistically significant results for those in the top and bottom tercile of the excess hospitalizations distribution. Finally, the panels on the right show that individuals living near hospitals with the highest ambulance excess use have a statistically meaningful increase in the depression index. On the contrary, those living close to health facilities with the lowest acoustic contamination show negligible and not statistically significant effects. Among the three variables considered, ambulance excess use is the channel with the highest salience, a persistent reminder of the health crisis, compounding stress level and sleep disturbance.

Figure 8: Mechanisms



Note: Point estimates and confidence intervals from equation (1) specification. See Table 2 for specification details.

5 Conclusions

This research shed light on the mental health costs of living near overburdened health facilities during COVID-19 in Perú. Our main result shows that, relative to a pre-pandemic situation, people who live near overburdened health facilities showed an increase of 15% in a standard self-reported depression index that is mirrored by a rise of 16% in the share of patients treated with depression according to administrative data. Congestion and chaos around health facilities, proxied by in-hospital excess deaths, excess hospitalizations, and ambulance trips, contributed to a heightened perception of danger and helplessness, leading to anxiety, stress levels, and depression. These findings align with established theories in health and geography economics and point to the multifaceted nature of the mental health impact during health crises where environmental and institutional stressors intersect with individual vulnerabilities.

This research showed that the adverse effects on mental health in people who live near collapsed health facilities do not particularly strike people at higher risk of infection, hospitalization, or death from COVID-19. On the contrary, women, young adults, and relatively more affluent individuals are the demographic groups most affected. Older people were directly affected by the civil war in the 1980s, hyperinflation and economic crisis during 1987-92, and the cholera epidemic in 1991. Poor households were disproportionally affected by these past adverse shocks. Thus, it is likely that older and poorer individuals have developed higher levels of psychological resilience over the years, which may help them build an adaptative capacity to face contemporary adverse shocks. For women, on the other hand, it is likely that the weight of entrenched social norms and cultural factors, which make them the primary caregivers of household members, might explain the higher prevalence of anxiety and depression during crises. Acknowledging these heterogeneous responses reveals a role for public policies to target and focus on communication, prevention, and treatment of mental health for the most at-risk groups.

This research provided an opportunity to emphasize the issues of mental health affecting developing countries that are generally missing in public discourse and economics research. Our results revealed that in times of health system crises, the costs to mental health could challenge traditional assumptions about the net benefits of living near health facilities, particularly in urban and densely populated areas. Thus, the design of specific public policies that seek to reduce the source of these costs would be needed. Specific measures for mitigating environmental stressors such as addressing the management of acoustic pollution, the hours of operation of in-hospital crematory services, the management of the flow of visitors, the establishment of control areas, and the immediate expansion of a minimum number of ICU beds following the recommendations of the World Health Organization emerge as leading candidates. Amid growing environmental and public health challenges, including climate change and potential future pandemics, this research underscores the need for proactive policies integrating mental health considerations into emergency response planning. Specific measures for promoting mental health policies might include expanding public investment in community-based virtual programs such as Anímate Perú, which can expand its operations due to its relatively low costs associated with mental health online interventions. Strengthening specialized online community-based mental health centers and promoting adaptative capacity at the community level is critical for mitigating the consequences of pandemics and other health crises.

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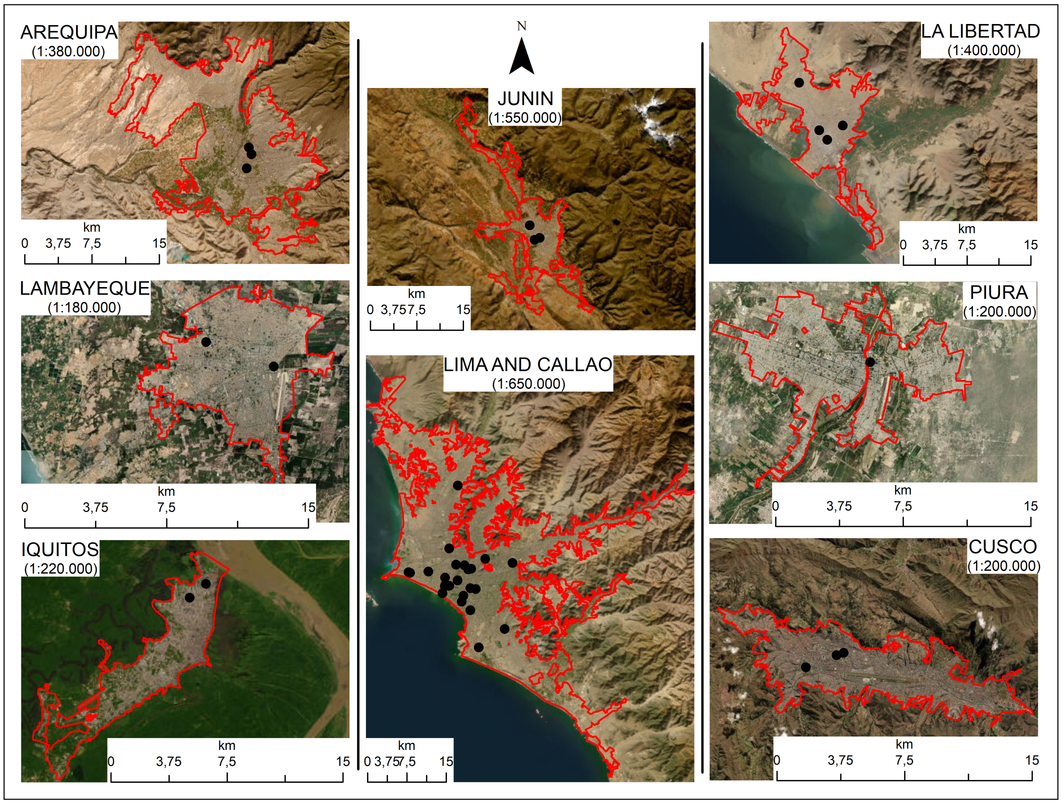
Figure A.1: Study area (urban centers)



Note: Authors' elaboration. Source: Administrative data from SUSALUD and cartographic maps from Perú.

Table A.1: Typology of health facilities in Perú

LEVELS OF CARE	Category I	Category II	Category III
NUMBER	20558	560	58
CATEGORIES	I-1, I-2, I-3, I-4	II-1, II-2	III-1, III-2
DENOMINATION	Health Post or Health PostMedical OfficeHealth CenterMedical CenterPolyclinic	Hospitals	Hospital (41) and Specialized Institute (17)
SERVICES	Outpatient consultation, clinical pathology, pharmacy	Equal to type I plus: Emergency rehabilitation medicine, pathological anatomy, central sterilization, obstetrical center, surgical center, blood bank, dietary nutrition.	Same as type II plus: Intensive Care Unit (General, neonatal, and other specialties), Nuclear Medicine, Hemodialysis Radiotherapy, Nuclear Medicine
SPECIALTIES	General Medicine and some specialties (Gynecology and Pediatrics as a priority)	Equal to type I plus Internal Medicine, Obstetrics, General Surgery, and Anesthesiology.	All Specialties & Subspecialties
PROFESSIONAL	Doctors, laboratory technician, pharmacy, nursing, bachelor's degree in nursing, obstetrics, dentistry	Internist, pediatrician, obstetrician-gynecologist, general surgeon, anesthesiologist, dentist, pharmaceutical chemist. Bachelor's degree in obstetrics, nursing, psychology, social work, nutrition. Medical technologist. Nursing technician, laboratory, pharmacy, statistics, general services.	Specialist doctor: Hematologist, Infectologist, Oncologist, Oncologist Surgeon, Thoracic and Cardiovascular Surgeon, Plastic Surgeon, Head and Neck Surgeon, Neurosurgeon, Neonatologist, Nephrologist, Emergency Physician, Intensivist, Geriatrician, Surgeon, Pediatrician, Specialized Dentist. Professional trained in research.

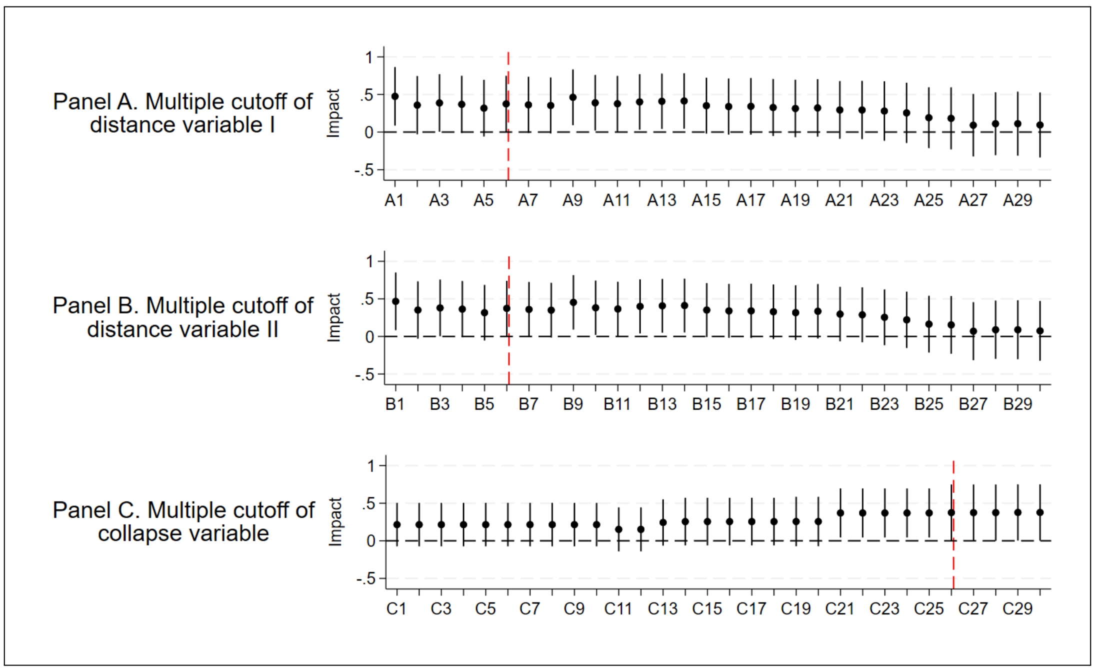
Note: Authors' elaboration. Source: Ministry of Health of Perú.

Table A.2: Main results using alternative specifications

	(1)	(2)	(3)	(4)
	Panel A. Average Depression Index			
Collapse*Group3km	0.042**	0.041*	0.042**	0.042**
	(0.022)	(0.022)	(0.022)	(0.022)
N	23587	23587	23587	23587
Average	0.28	0.28	0.28	0.28
	Panel B. Standardized Depression Index			
Collapse*Group3km	0.088*	0.086*	0.08*	0.088*
	(0.047)	(0.047)	(0.047)	(0.047)
N	23587	23587	23587	23587
Average	-0.07	-0.07	-0.07	-0.07
	Panel C. Poisson Specification			
Collapse*Group3km	0.170**	0.141*	0.142*	0.147*
	(0.076)	(0.079)	(0.079)	(0.079)
N	23587	23587	23587	23587
Average	2.54	2.54	2.54	2.54
	Panel D. Average Depression Index with Poisson Specification			
Collapse*Group3km	0.147*	0.141*	0.142*	0.147*
	(0.079)	(0.079)	(0.079)	(0.079)
N	23587	23587	23587	23587
Average	0.28	0.28	0.28	0.28
Quarter fixed effect	X	X	X	X
Control covariates	X	X	X	X
Hospital fixed effects	X			
Diresa fixed effects		X		
City fixed effects			X	
Department fixed effects				X

Note: Clustered standard errors are at the survey cluster level. See notes in Table 2 for specification details. ***1%, **5%, *10%.

Figure A.2: Multiple cutoff sensitivity checks



Note: Point estimates and confidence intervals from equation (1) specification. See Table 2 for specification details. The vertical red line represents the main point estimate presented in Table 2.