Crime Prevention Programs Improve Citizen's Mental Health: Evidence from Peru

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Abstract

Among Latin American countries, Peru has one of the highest crime rates, with 9 out of 10 Peruvians reporting feeling unsafe walking the streets at night. This rooted-in-reality feeling of insecurity may harm citizens' mental health. We study the consequences of the Peruvian Safe Neighborhood program, which increased police patrolling in selected neighborhoods, on the mental health of residents. We exploit the program's staggered implementation and use data from the Demographic and Health Survey to precisely geolocate the respondents' residencies. Our results show that enhanced crime prevention reduced the incidence of mental health problems by 6 percentage points. In particular, the program reduced depression, tiredness, concentration problems, suicide intentions, and sense of failure by 3–4 percentage points. The evidence suggests that improvements in mental health are driven by tangible changes in health-related behaviors. Following the implementation of Safe Neighborhood, there is an increase in healthcare utilization.

Keywords: Crime, Police, Mental health, Healthcare, Peru.

JEL codes: K4, I15, I31

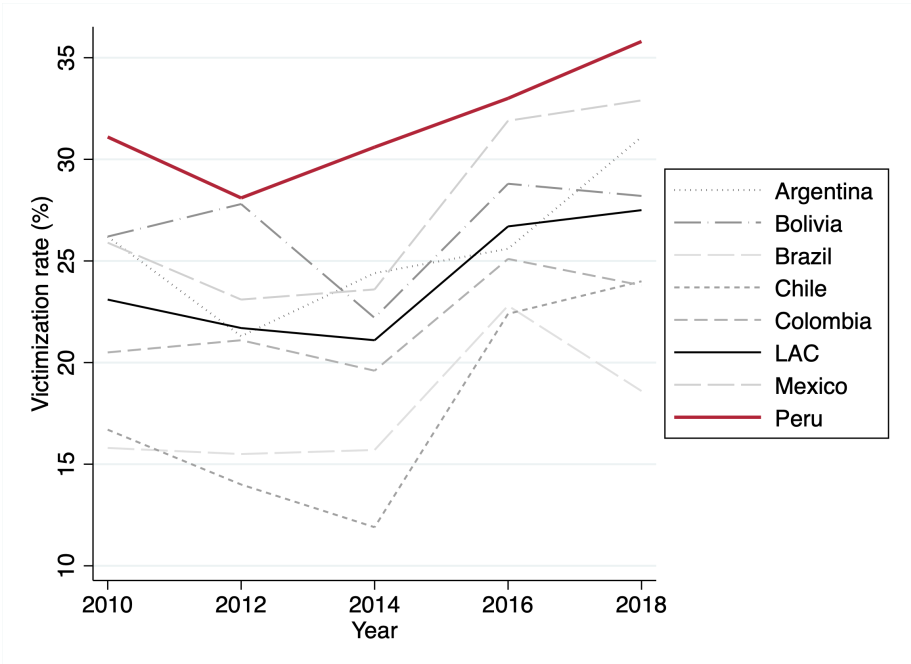
1 Introduction

Crime is a complex phenomenon that generates substantial direct and intangible costs to society (Johnston, Shields, and Suziedelyte [2018]). Among Latin American countries, Peru has one of the highest crime rates, and unlike other large countries in the region, crime in Peru has been continuously increasing since 2012 (see Figure 1). In 2023 alone, more than 80% of Peruvian citizens considered crime the country's main problem, and more than 1 in 4 reported having experienced crime.[1] This prevalence translates into widespread fear and a pervasive sense of insecurity among Peruvian citizens. Beyond the reduction in quality of life caused by feeling threatened or being victimized, the high frequency of these experiences may also harm mental health, with vulnerable individuals being the most affected, as they may fall into the psychological poverty trap (Ridley, Rao, Schilbach, and Patel [2020]). This study analyzes the relationship between crime prevention and mental health, in the context of Peru, a country where both the mental health and the safety of citizens are issues of primary importance, and poverty and socio-economic disparities have amplified the relevance of these issues over recent years.

In response to the crime prevalence problem, the Peruvian government implemented the Safe Neighborhood program between 2016 and 2020 in dangerous targeted neighborhoods. The program aims to reduce crime and violence rates and increase trust in the National Police. The main measure implemented by the program is an increase in police patrolling, but it also includes additional police training, the identification of specific locations with high crime risk, and collaboration with neighborhood associations to recover public spaces and promote the responsible use of public spaces. Unfortunately, qualitative analysis shows that the collaboration with neighborhood associations did not actually take place (Hoyos Arévalo [2020]). The program was implemented in the 92 neighborhoods with the highest crime rates in Peru. Neighborhoods joined the program sequentially, starting in 2016 and ending in 2020, when the pandemic disrupted the program's implementation. Hernandez, Amaya, Cozzubo, and Cueto [2023] show that the

[1] Click here to see the full report.

Figure 1: Proportion of crime victims in Latin America countries (2010-2018)



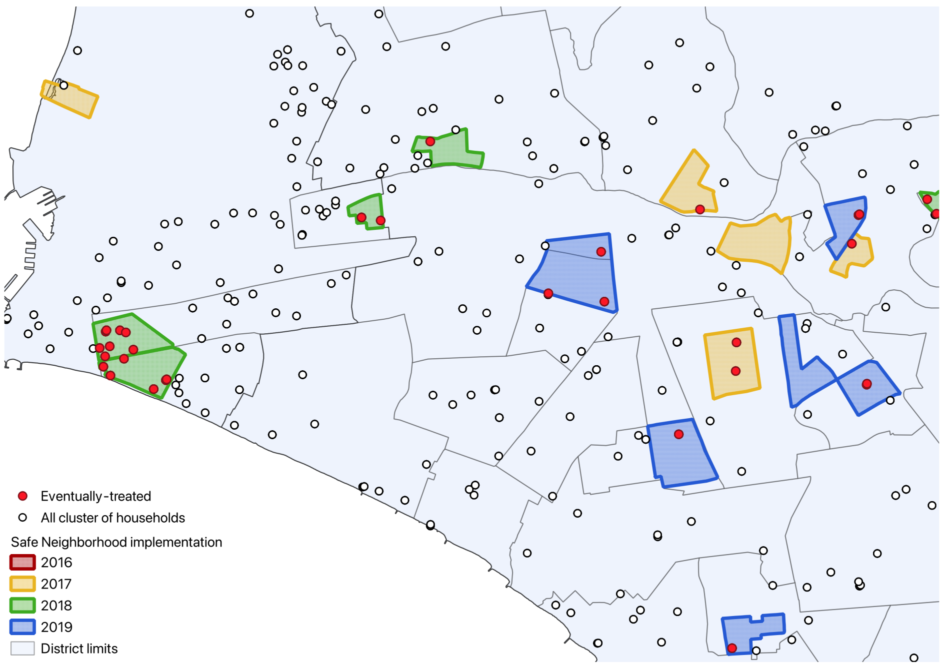
Notes: Survey data from the Latin American Public Opinion Project (LAPOP). The average rate for Latin American countries (LAC) includes Mexico, Colombia, Ecuador, Bolivia, Peru, Paraguay, Chile, Uruguay, Brazil, and Argentina.

order in which neighborhoods joined the program is unrelated to crime or other socioeconomic characteristics. We also show that the timing of program implementation is unrelated to residents' mental health.

We combined highly detailed datasets from 2013 to 2020. We use data from the Peruvian Demographic and Health Survey (DHS). This annual cross-sectional survey allows us to geolocate respondents' residences and includes a battery of questions on respondents' mental health. We also use administrative data of the program implementation provided by the Peruvian Internal Affairs Minister. We complement this information with individual health and life satisfaction data from the Peruvian National Household Survey, and novel collected district-level data from mental healthcare centers.

In our analysis, we use a sample of residents from all eventually treated neighborhoods. For identification, we use information on residents from eventually treated and not-yet-treated neighborhoods as controls for already-treated neighborhoods. Figure 2 provides an example of a zoomed-in area, with interviewed households represented by circles, eventually treated households shown in red, and treated neighborhoods colored according to the year of program implementation. We observe that treated neighborhoods are sparsely distributed across the territory.

Figure 2: Cluster of households exposed to SN Program



Notes: Administrative data from the Peruvian Internal Affairs Minister.

We find that the crime prevention program decreases the probability that individuals declare that they experience mental health problems. In particular, the Safe Neighborhood program reduces the incidence of mental health problems by six percentage points. The program is also effective in reducing depression and suicidal thoughts by four percentage points, and tiredness, concentration problems and feeling of failure by three percentage points, for residents in the protected areas. In addition, we find that the effect is reduced and equals two percentage points when considering that the program may also affect residents in a buffer of 500 meters around the targeted area.

The second focus of this paper is to understand the potential mechanisms behind the main results. We find no evidence that the program improves residents' mental health through enhancements in life satisfaction. This suggests that improvements in mental health are not merely the result of respondents perceiving a positive state (i.e., a good mood). On the other hand, we find evidence that the program increases healthcare utilization, and individuals with health insurance lead the estimated effects. This suggests that a tangible, health-related behavioral change drives the improvement in mental health, given that people feel safer.

The main threat to our identification strategy is the potential for time-varying unobservables that are correlated with both the timing of the Safe Neighborhood program implementation and changes in mental health outcomes. We perform several robustness checks to ensure that our results are not driven by selection or time-varying unobservables. First, we find no evidence of pre-trends on mental health outcomes, which suggests a non-anticipatory response to the program. Second, all results are robust to controlling for the implementation of the mental health reform, which was rolled out during the same period. Third, most results are robust to a more demanding specification, including neighborhood-by-year fixed effects. Finally, we present the results for some placebo outcomes. In particular, crime prevention programs do not impact pre-determined characteristics.

We contribute to the literature on the impact of crime on mental health. Previous studies on the topic include Cornaglia, Feldman, and Leigh [2014], Dustmann and Fasani [2016], and Tsaneva and LaPlante [2024], among others. Our research question differs from the previous papers in that we analyze the impact of a crime prevention program, rather than actual crime, on mental health. Our crime prevention program not only reduced crime but it may have been able to make citizens feel safer, thus amplifying the effects of crime reduction on mental health.

The remainder of this paper is organized as follows. Section 2 reviews related preexisting literature. In Section 3, we describe the institutional background. Section 4 presents the data and describes our sample. Section 5 explains our methodology and Section 6 presents our results. Section 6.1 discusses the robustness of our estimates, explores potential mechanisms, and tests for heterogeneity of the estimated effects. We conclude in Section 7.

2 Literature Review

Victims of crime report significant declines in their mental health (Cornaglia, Feldman, and Leigh [2014]). Beyond direct victimization, actual crime rates elevate fears and anxiety for individuals, who may experience amplified perceptions of their risk of being victimized (Dustmann and Fasani [2016]). Literature from social sciences has shown that fear of crime and perception of crime (in addition to the actual crime itself) impose a substantial burden on individuals' mental health (e.g., Jackson and Stafford [2009]; Foster, Hooper, Knuiman, and Giles-Corti [2016]; and Baranyi, Di Marco, Russ, Dibben, and Pearce [2021] for a meta-analysis). Economists have contributed to this debate by quantifying direct and indirect costs of crime and showing that indirect costs, such as increased fear and anxiety and altered daily routines and behaviors, often exceed direct costs (e.g., Hamermesh [1999]; Janke, Propper, and Shields [2016]; Cornaglia, Feldman, and Leigh [2014]; Dustmann and Fasani [2016]; Johnston, Shields, and Suziedelyte [2018]). Importantly, these intangible costs of crime extend to broader populations, as fear reshapes attitudes and social interactions among many individuals (Cornaglia, Feldman, and Leigh [2014]). As noted in Dustmann and Fasani [2016], high crime in the area of residence amplifies mental distress through anxiety and fear of victimization, reduced freedom, and limitations of individual behaviors (e.g., fear of going out alone and/or at night; not wearing jewelry, etc.). Residents in areas with high crime rates must also adopt precautions and strategies to avoid being victimized (e.g., choosing safer routes to go home at night, repeatedly checking doors and windows before going out, etc.). (Janke, Propper, and Shields [2016]).

A related strand of literature analyses the relationship between neighborhood characteristics and individuals' well-being, showing significant associations between the mental health of residents and aspects of the neighborhood environment, such as socio-economic characteristics, poverty, and risks of crime (e.g., Propper, Jones, Bolster, Burgess, Johnston, and Sarker [2005]; Mair, Roux, and Galea [2008]; Ludwig, Duncan, Gennetian, Katz, Kessler, Kling, and Sanbonmatsu [2012]; among others). We analyze the role of neighborhood satisfaction in our context by estimating the impact of the Safe Neighborhood Program on individuals' neighborhood satisfaction using data from the Peruvian National Household Survey.

Most studies on crime and mental health utilize data from Western developed countries, while evidence from middle and low-income countries is limited and mainly analyses the impact of severe violence or conflicts (Moya [2018]). A notable exception is the study by Alloush and Bloem [2022], who use South African longitudinal data to show that rising neighborhood violence exacerbates depression, with effects disproportionately impacting the poorest quintiles of the wealth distribution. Using the same panel data, Tsaneva and LaPlante [2024] show that a rise in property crime was associated with an increase in the probability of depression for individuals living in South Africa.

A limited number of studies analyze the mechanisms behind the relationship between crime and mental health in the context of low and middle-income countries and show that crime perceptions and safety concerns affect mental health directly through increased stress or indirectly through changes to labor market behaviors (e.g., Braakmann [2012] and Velásquez [2020] for an analysis based on Mexican data; Field [2007] for a study on property crimes in Peru; Lund, Breen, Flisher, Kakuma, Corrigall, Joska, Swartz, and Patel [2010] for a review of studies on food insecurity and mental health in several low and middle-income countries).

Our study is also related to the literature about crime prevention programs and their outcomes, particularly those enhancing police presence or surveillance. Numerous studies have shown that increasing police presence tends to reduce crime rates (e.g., Di Tella and Schargrodsky [2004]; Munyo and Rossi [2020]; Mastrobuoni [2019]; Weisburd [2021]; among many others) through a deterrent effect, and through an increased number of arrests. Some of these studies focus on exogenous changes in police presence driven by special events or terrorist attacks (e.g., Di Tella and Schargrodsky [2004]; Draca, Machin, and Witt [2011]), while others use data on the geographical distribution of police forces (e.g., Blanes i Vidal and Kirchmaier [2018]; Weisburd [2021]). Some of this literature specifically addresses the relationship between crime prevention and crime rates in emerging countries and confirms the effectiveness of crime prevention policies (e.g., Blattman, Green, Ortega, and Tobón [2021]; Gómez, Mejía, and Tobón [2021]; Bellégo and Drouard [2024]).

However, little is known about the impact of crime prevention programs and increased police presence on secondary outcomes. Very few studies have analyzed the impact of crime prevention programs on outcomes other than crime. Remarkable exceptions are those studies that show that specific interventions targeting schools' areas (e.g. increase in school police) improve students' outcomes such as absenteeism and school discipline (Owens [2017]; McMillen, Sarmiento-Barbieri, and Singh [2019]; Weisburst [2019]).

Our study contributes to the literature mentioned above in several ways. First of all, we shed some light on the importance of targeting crime to improve mental health in Peru, a country where crime remains a significant cause of concern for policymakers and mental health has gained importance in policies and regulations in recent years. Second, we establish a causal link between a crime prevention program (rather than the crime itself) and psychological well-being, filling a critical gap in the research. Our work expands the focus beyond crime rates to secondary outcomes, emphasizing the broader social implications of crime prevention strategies.

3 Institutional Background

Worldwide, mental well-being remains at its post-pandemic low levels, and there is no sign of movement towards pre-pandemic levels (Sapien Labs [2024]). Younger generations remain the most severely affected, raising important questions about the lasting impact of the pandemic and how changes in individuals' lifestyles and work have pushed society into poorer mental well-being (Sapien Labs [2024]). In 2021, 14% of the world's population experienced mental disorders, and 17% of total years lived with disability were due to mental disorders (Health Metrics and Evaluation [2024]).

Generally, Latin American countries perform better in terms of mental health than countries with similar levels of development in other areas of the world, but they also exhibit rising levels of mental illnesses, such as depression and anxiety disorders (Guzman Ruiz [2023]). Further, Latin Americans are reluctant to discuss mental health issues unless they severely interfere with their everyday life, and this leads to a severe percentage of untreated individuals (Pan American Health Organization [2023]). Despite mental health being an important topic of discussion among Latin American policymakers and public health officials for several decades, people with mental health conditions still experience widespread stigma and discrimination, abuse, and denial of their basic human rights (Pan American Health Organization [2023]). In 2022, the Pan American Health Organization established the High-Level Commission on Mental Health and COVID-19. Its primary objective was to strengthen mental health systems across Latin America in the aftermath of the pandemic, while advancing a new agenda to address the longstanding mental health crisis in the region. Latin America is marked by high rates of poverty and extreme poverty, which has been rising in recent years, and mental health conditions can be both a cause and a consequence of poverty, generating a vicious circle. Other key threats to mental health in the region include a high incidence of violence, racial discrimination, and gender inequality (Pan American Health Organization [2023]).

According to the latest report on "The Burden of Mental Health Disorders in the America", mental, neurological, substance use, and suicide (MNSS) form a subgroup of diseases and conditions that are a major cause of disability and mortality and give rise to a third of total years lived with disability and a fifth of total disability-adjusted life years in Latin America. Further, MNSS constitutes the largest subgroup cause of disability in every country in the region, regardless of income level or subregion. In Peru, MNSS diseases cause over 35% of years lived with disability, just above the regional average of 33%. In particular, depressive disorders account for one of the highest percentages in the country (around 9% of total years lived with disability, with a regional average of 7%), followed by anxiety disorders (5.3% of total years lived with disability, just above the regional average of 4.7%) (Pan American Health Organization [2018]).

The Peruvian health system has developed rapidly in recent decades but remains characterized by significant fragmentation in financing and service delivery (OECD [2017]). The system comprises multiple schemes, including the Integral Health Insurance (SIS) and the Seguro Social de Salud (EsSalud), each targeting specific population segments and leaving some individuals without coverage (OECD [2017]). SIS mainly serves low-income groups, focusing on maternal and child health, offering both fully funded and subsidized regimes. EsSalud provides mandatory social insurance for employees and their families, with variable contribution rates and options for private insurance supplements. Additional insurance arrangements exist for specific groups, like police and armed forces, alongside a small private insurance market. Despite efforts to provide comprehensive care, SIS predominantly funds primary care, while EsSalud emphasizes hospital services, leading to disparities in health service experiences. The coexistence of public, private, and decentralized providers further exacerbates systemic fragmentation, underscoring the need for integrative reforms to achieve universal health coverage (OECD [2017]).

Peru has traditionally had one of the smallest health budgets in Latin America. However, over the recent decades, Peru has tripled its budget for mental health and has engaged in an important transformation of mental health services, replacing centralized psychiatric hospitals with a network of community-based mental health services (Pan American Health Organization [2023]). However, the distribution of mental health in Peru is still very unequal, and the prevalence of mental disorders is much higher among citizens who can't cover their basic needs (Toyama, Castillo, Galea, Brandt, Mendoza, Herrera, Mitrani, Cutipé, Cavero, Diez-Canseco, et al. [2017]). Further, the poorest regions, or those who were most heavily affected by conflicts in the 1980s and 1990s, show a particularly high prevalence of mental health disorders (Toyama, Castillo, Galea, Brandt, Mendoza, Herrera, Mitrani, Cutipé, Cavero, Diez-Canseco, et al. [2017]), and the issue of lack of diagnosis or under treatment remains particularly important. Recent data shows that MNSS diseases account for a third to a fourth of the total burden between 10 and 50 years of age, the largest burden of all disease groups during this period (Pan American Health Organization [2020]). Further, the country remains significantly affected by issues such as gender-based violence (National Statistics Office [2023]) and child abuse (around 70% of children 9-15 have suffered psychological or physical abuse at least once in their lives, according to the UNICEF [2020] report), which have clear consequences on mental health.

4 Data and Descriptive Statistics

We use several data sources. First, we use data from the Peruvian Demographic and Health Survey (DHS) for the period 2013-2020. The DHS is a cross-sectional, nationally representative survey with rich information about the health, family structure, and economic and social characteristics of respondents from more than 90 emerging countries. The first round of DHS surveys was administered in the mid-1980s, and the surveys have been collected approximately every 5 years since. DHS data collect information based on a set of questions to representative samples of adult women of reproductive age (15-49 years old).

The Peruvian DHS is made of three questionnaires. The first is about the household and its members, the second is specifically addressed to all women of childbearing age, and the last is a health questionnaire directed to a one random-selected person within the household aged 15 years and older. The household questionnaire includes information about the essential socio-economic characteristics of all household members and participation in several social programs. The second questionnaire contains specific information about women, including their fertility and reproductive history and some questions about infant health. The health questionnaire includes information about treatment and prevention for several diseases (e.g., cancer, diabetes, oral health, HIV) and some questions about mental health (DHS Program [2015]).[2]

Further, the health questionnaire includes the Patient Health Questionnaire (PHQ-9), which is an established tool for supporting medical practitioners in diagnosing depressive and other mental health disorders commonly observed in primary care (Kroenke, Spitzer, and Williams [2001]). The questionnaire assesses symptoms such as lack of motivation, feelings of depression, lack of sleep, tiredness and fatigue, loss of appetite, poor concentration, restless or slowed movements, suicidal thoughts, and sense of failure. We reproduce the complete PHQ-9 questionnaire in Section A.1 in the Appendix. Respondents indicate whether they have experienced these symptoms in the past two weeks using a 4-point scale: not at all, several days, more than half the days, nearly every day. Responses are scored from 0 (not at all) to 3 (nearly every day), with higher scores indicating greater symptom severity. The PHQ-9 score ranges from 0 to 27, and the total score is calculated by adding the scores for each symptom. The PHQ-9 score is commonly categorized into five severity levels: 1 to 4, 5 to 9, 10 to 14, 15 to 19, 20 or greater, indicating respectively minimal, mild, moderate, moderately severe, and severe depression.

We follow the relevant literature and the guidelines to interpret this questionnaire (Kroenke, Spitzer, and Williams [2001]) and analyze the impact of the Safe Neighborhood program on several indicators of mental health problems. First, we define an individual with mental health problems if she/he reports a PHQ-9 score greater than 9 (moderate or

[2]Questions on mental health are available since 2013.

severe depression). Second, we define a binary variable indicating mental health problems if an individual is in the top 90% of the distribution of the PHQ-9 score (i.e., in the worst 10% of the mental health distribution). Last, we aggregate all mental health symptoms and create two indexes of mental health using Principal Component Analysis and Factor Analysis, and we define two binary variables indicating mental health problems if the individual's score is in a percentile equal to or greater than the 90th for each index.

Second, we use administrative data on the implementation of the Safe Neighborhood program provided by the Peruvian Ministry of Internal Affairs. This dataset contains the names of the Safe Neighborhoods, their founding dates (month and year), their administrative locations (district, province, state), the names of the local police stations in charge, and the spatial boundaries of targeted neighborhoods from 2016 to 2020. This administrative data includes both the exact GPS locations and the boundaries (polygons) planned to be covered by the program. The dataset provides information on 91 Safe Neighborhoods implemented by early 2020.[3]

Third, to explore some potential mechanisms, we use data from the National Household Survey (ENAHO) for the period 2013-2020, conducted by the Peruvian National Statistics Office. This survey is a cross-sectional, annually conducted, and nationally representative survey that collects information on various welfare dimensions, such as household consumption, educational attainment, health outcomes, and job information, among other characteristics. For the analysis, we are particularly interested in two questionnaires. The health questionnaire, which addresses all household members, allows us to construct variables related to general and public healthcare utilization. The subjective well-being questionnaire is directed to one randomly selected person aged 15 years and older and allows us to construct several variables related to subjective perceptions of the neighborhood and life satisfaction.

[3] The implementation of the last Safe Neighborhood in the first wave was interrupted by the beginning of the pandemic.

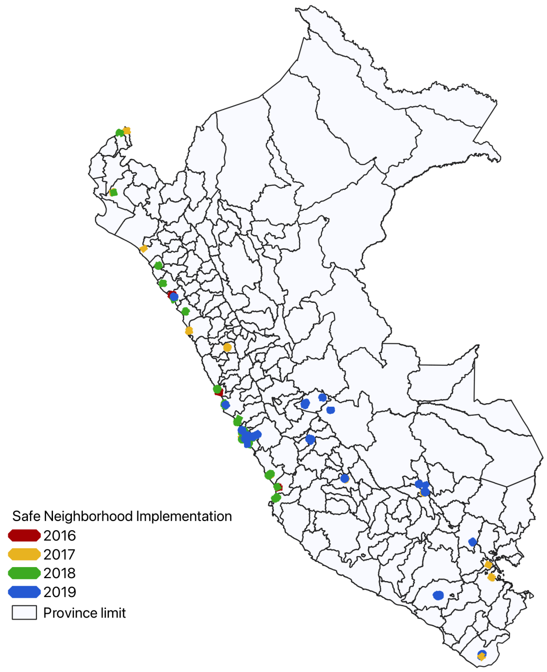
During the analysis period, a national reform led to the establishment of new community mental health centers (CSMCs) in selected Peruvian districts.[4] We collected a novel dataset on newly established CSMCs, including their founding dates (month and year) and their administrative locations (district, province, state) from 2015 to 2020. This dataset provides information on 97 CSMCs implemented by mid-2020. Among the 91 Safe Neighborhoods, only 34 had a mental health center operating in the same district (37%) by 2020. Given the gradual implementation of the CSMCs, only 7% of our sample was exposed to this program. The low overlap is expected, as the focus of Safe Neighborhoods is based on crime-related criteria, whereas CSMCs are established based on the availability of health infrastructure (e.g., districts with large hospitals and a significant supply of specialized physicians). However, we analyze potential interaction effects between the two policies in the results section.

Exposure to the Safe Neighbourhood program is captured in DHS data as the dataset records geolocation for every cluster of households within a given district. This feature allows us to determine both whether households reside within the boundaries of treated neighborhoods and the timing of the treatment. Figure 3 illustrates the implementation timeline of the Safe Neighborhood program across different neighborhoods.

We take advantage of the rich information available in DHS and, in addition to leveraging information on mental health and district of residence, we control for a vector of sociodemographic characteristics at both the individual and household levels. Sociodemographic characteristics include information about individual age, sex, education level, marital status, household composition, and family wealth. Table 1 describes the characteristics of the estimation sample. The prevalence of mental health problems is very similar across different measures: 7% of surveyed individuals suffer from moderate to severe depression, and 9-10% of individuals in our sample are among the 10% with worse health according to the PHQ-9 index, and the indexes constructed using Factor and the Principal Component Analyses. The proportion of affected individuals varies across symptoms.

[4]See detailed information on this expansion here.

Figure 3: Rollout of Safe Neighborhood program



Notes: Administrative data from the Peruvian Internal Affairs Minister.

From 3% of individuals experiencing feelings of failure or 4% of individuals who have concentration difficulties, the proportion reaches 10% for lack of sleep and depression feelings. Regarding exposure to the Safe Neighborhood Program, 28% of the sample's observations refer to residents already affected by the program. Regarding sociodemographic characteristics, females are slightly overrepresented in our sample. The average individual in our sample is 40 years old. 44% of respondents have secondary education, and 41% have a tertiary education diploma. Most respondents are married (61%). Most households belong to the poorest (30%) or second poorest (29%) income quintile. Individuals from 15 to 29 years old have a higher likelihood of becoming crime victims (National Statistics Office [2023]). 97% of households include at least one of these high-risk individuals.

Table 1: Descriptive Statistics: Estimation Sample

	Mean	SD	Min	Max	N
Mental Health Indexes					
PHQ9>moderate	0.066	0.249	0	1	3,857
Index of mental health	2.626	4.032	0	27	3,857
Index>p90	0.086	0.280	0	1	3,857
PCA>p90	0.100	0.300	0	1	3,856
FA>p90	0.100	0.299	0	1	3,856
Mental Health Symptoms					
Lack of motivation	0.087	0.282	0	1	3,857
Feel depressed	0.098	0.297	0	1	3,857
Lack of sleep	0.095	0.293	0	1	3,857
Tiredness and fatigue	0.066	0.248	0	1	3,857
Loss of appetite	0.062	0.241	0	1	3,857
Poor concentration	0.044	0.204	0	1	3,856
Restless or slowed movements	0.047	0.211	0	1	3,857
Suicide intent	0.072	0.258	0	1	3,857
Feeling of failure	0.034	0.181	0	1	3,857
Main Treatment					
Safe Neighborhood	0.280	0.449	0	1	4,087
Early exposure (using median)	0.476	0.500	0	1	1,413
Demographic Characteristics					
Male	0.434	0.496	0	1	3,857
Age	39.824	16.859	15	97	3,857
Primary	0.130	0.337	0	1	3,857
Secondary	0.443	0.497	0	1	3,857
Tertiary	0.416	0.493	0	1	3,857
Married	0.607	0.488	0	1	3,857
Quintile 1 (poorest)	0.016	0.126	0	1	4,087
Quintile 2	0.154	0.361	0	1	4,087
Quintile 3	0.243	0.429	0	1	4,087
Quintile 4	0.290	0.454	0	1	4,087
Quintile 5 (richest)	0.297	0.457	0	1	4,087
Household members 15-29	0.968	1.013	0	7	3,857

Notes: Data is from the Peruvian Demographic and Health Survey (DHS) for the years 2013-2020. The sample includes all residents in the neighborhoods where Safe Neighborhood was implemented.

5 Methodology

We estimate the effect of the Safe Neighborhood crime prevention program on the mental health of residents in the selected neighborhoods by restricting our sample to the eventually-treated neighborhoods and exploiting differences in the time of the program's implementation. This allows us to compare similar neighborhoods that were treated at different times. The validity of our estimation strategy relies on the assumption that early and late adopters are comparable because the timing of the policy's implementation is independent of the neighborhood's residents' mental health, crime[5], or any factor that influences mental health and crime. We support this assumption by providing balance tests that compare the average mental health of residents in the half-earliest-treated neighborhoods to that of the half-latest-treated neighborhoods before implementing the Safe Neighborhood Program. Table 2 shows the results of these tests that indicate that there are no significant pre-existing differences in mental health across neighborhoods by treatment time.

Under the assumption of quasi-random allocation of the timing of the crime prevention program implementation, we can estimate the impact of the Safe Neighborhood program on mental health as follows:

$$MH_{int} = \beta_0 + \beta_1 SN_{nt} + \beta_2 C_{int} + \beta_3 D_n + \beta_4 D_t + \varepsilon_{int} \tag{1}$$

where MH_{int} indicates mental health problems (defined as explained above according to the various indexes we created) or one of the mental health symptoms experienced by subject i residing in neighborhood n at time t, the variable SN_{nt} equals one if the crime prevention program has been implemented in the neighborhood and zero if it has not been implemented yet. We interpret the estimate of the coefficient β_1 as the effect of the crime prevention program on residents' mental health. The vector C_{int} includes a set of individual characteristics, including sex, age, education, marital status, household wealth

[5]As DHS does not have data on crime victimization, we rely on the previous results from Hernandez, Amaya, Cozzubo, and Cueto [2023]

Table 2: Balance Test: Early vs. Late Adopters

	Early = 0	Early = 1	Difference	SE
Mental Health Indexes				
PHQ9>moderate	0.065	0.077	-0.013	0.013
Index>p90	0.083	0.101	-0.018	0.017
PCA>p90	0.099	0.109	-0.010	0.016
FA>p90	0.099	0.109	-0.010	0.017
Mental Health Symptoms				
Lack of motivation	0.077	0.09	-0.012	0.015
Feel depressed	0.096	0.112	-0.016	0.018
Lack of sleep	0.099	0.115	-0.016	0.024
Tiredness and fatigue	0.060	0.083	-0.023	0.018
Loss of appetite	0.057	0.072	-0.015	0.012
Poor concentration	0.034	0.055	-0.021*	0.012
Restless or slowed movements	0.034	0.055	-0.021	0.014
Suicide intent	0.085	0.063	0.022	0.016
Feeling of failure	0.027	0.039	-0.012	0.010
Demographic Characteristics				
Male	0.44	0.427	0.014	0.020
Age	40.554	41.734	-1.18	1.116
Education	2.215	2.198	0.017	0.079
Married	0.595	0.584	0.011	0.029
Wealth Index	3.737	3.935	-0.198	0.183
Household members 15−29	1.019	0.962	0.056	0.082

Notes: Column 1 reports the characteristics of late adopters. Column 2 reports the characteristics of early adopters. Column 3 reports the difference between early−late adopters. Column 4 presents the clustered standard errors at the district level from an OLS regression.

(in quintiles), and the number of high-risk crime victimization individuals (from 15 to 29 years old) in the household. We control for neighborhood characteristics using a vector of neighborhood fixed effects, D_n, and time (quarter and survey-year) fixed effects, D_t. We cluster standard errors at the district level.

We also explore the dynamics of the effects of the crime prevention program on mental health using an event study. In particular, we estimate the following equation:

$$\begin{aligned} MH_{int} = \beta_0 + \beta_{-4}SN_{nt,\tau-4} + \beta_{-3}SN_{nt,\tau-3} + \beta_{-2}SN_{nt,\tau-2} + \beta_{-1}SN_{nt,\tau-1} \\ +\beta_1 SN_{nt,\tau+1} + \beta_2 SN_{nt,\tau+2} + \beta_4 C_{int} + \beta_4 D_n + \beta_6 D_t + \varepsilon_{int} \end{aligned} \tag{2}$$

where τ is normalized time such that τ equals zero at the time of the adoption of the program and therefore $SN_{nt,\tau-4}$, $SN_{nt,\tau-3}$, $SN_{nt,\tau-2}$, $SN_{nt,\tau-1}$ are indicators for four, three, two, one periods before the adoption of the program in neighborhood n. Similarly, $SN_{nt,\tau+1}$ and $SN_{nt,\tau+2}$ are binary variables indicating one and two periods after the adoption of the program. Again, we cluster standard errors at the district level.

In alternative regressions, we change the definition of n and consider the original neighborhood plus a 500-meter buffer around it. In this specification, we expect the magnitude of the effects to be smaller.

6 Results

In this section, we describe the results of our estimations of the crime prevention program's effect on the incidence of mental health problems as measured by several indices first and on nine mental health symptoms later. We consider an individual with mental health problems if she/he reports a PHQ-9 score greater than 9 (moderate or severe depression) or if their overall PHQ-9 score is in the top 90% of the score distribution. We also consider two additional indices of mental health, aggregating all symptoms using Principal Component Analysis and Factor Analysis and then defining two binary indicators of mental health problems if the individual's score is in a percentile equal to or greater than the 90th for each one.

Table 3 shows the impact of the crime prevention program on the frequency of mental health problems measured by various indices. Results are consistent across columns and show that the Safe Neighborhood Program reduces the probability of suffering mental health problems. The magnitude of the effect equals six percentage points, equivalent to one-fifth of a standard deviation. Table A.1 in the Appendix shows the results on the corresponding index from which we created the variables on the incidence of mental health problems. Results align with Table 3, but significance levels are lower.

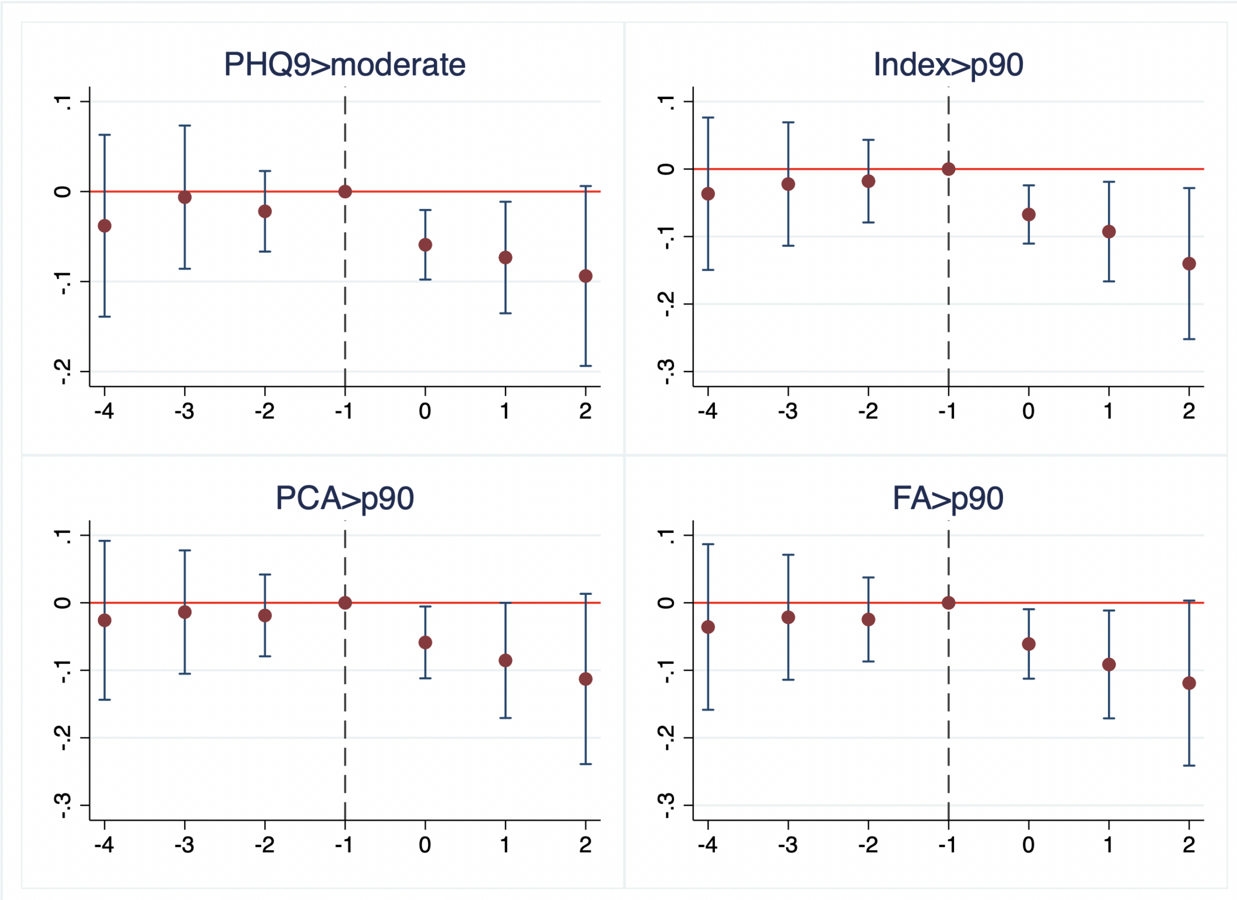
Table 3: The Effect of Crime Prevention Programs on Mental Health Problems

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.058***	-0.062***	-0.056**	-0.058***
	(0.014)	(0.019)	(0.022)	(0.021)
Observations	3,857	3,857	3,856	3,856
R^2	0.04	0.04	0.04	0.04
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

We shed additional light on the Safe Neighborhood Program's effect on mental health by estimating how the effect is distributed across time through an event study. In Figure 4, the pre-treatment estimates indicate no significant differences in mental health before the program's implementation. The post-treatment estimates reveal a negative effect that grows over time but becomes less precise. Unfortunately, we cannot present estimates beyond two periods after the program's implementation because the pandemic affected

Figure 4: Event Study of the Effect of Crime Prevention Programs on Mental Health Problems



Notes: These graphs plot the coefficient obtained from Eq. (2). Each dot represents the estimated coefficients, and the vertical segment shows the estimated 95% confidence interval. The survey year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood fixed effects.

the neighborhoods in our sample and interrupted the program's implementation by early 2020.

Table 4 shows the estimated effects of the Safe Neighborhood program on mental health symptoms. The dependent variables equal one if the respondent declares to have suffered from each of the mental health symptoms over the last two weeks more than half the days or nearly every day. We find negative, sizable, and significant effects on the probability of declaring to feel down, depressed, or hopeless (column 2), on the likelihood of being tired or having little energy (column 4), on the incidence of having trouble

Table 4: The Effect of Crime Prevention Programs on Mental Health Symptoms

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.029	-0.042**	-0.017	-0.032*	-0.008	-0.029*	-0.014	-0.036**	-0.026*
	(0.020)	(0.020)	(0.016)	(0.016)	(0.015)	(0.015)	(0.012)	(0.018)	(0.013)
Observations	3,857	3,857	3,857	3,857	3,857	3,856	3,857	3,857	3,857
R^2	0.03	0.05	0.04	0.04	0.03	0.02	0.02	0.06	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

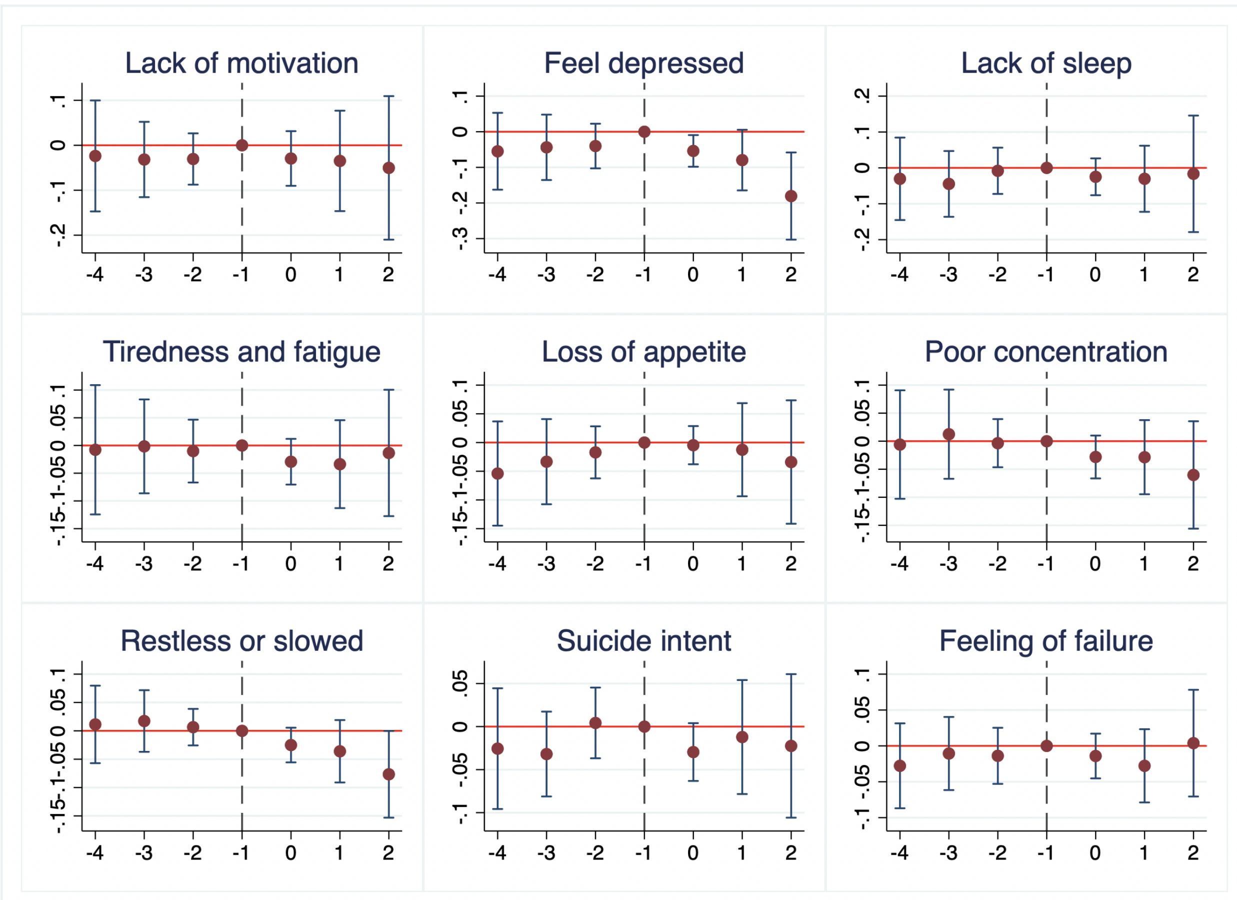
concentrating on things (column 6), on suicide intentions (column 8), and on experiencing negative feelings about oneself (column 9). The magnitudes of the effects range from three to four percentage points, equivalent to $0.13 - 0.14$ standard deviations. The corresponding event study in Figure 5 is coherent with the estimated impacts in Table 4, but the estimates are noisier.

6.1 Robustness Checks, Extensions, and Heterogeneity Analysis

In this section, we first test the robustness of our results to a change in the identification strategy. In our primary estimation, we use district- and time-fixed effects, comparing mental health in the district before and after the program's implementation net of all time-variant factors common to all neighborhoods. In a more demanding specification, we include neighborhood-by-year fixed effects to identify the impact using changes in residents' mental health within a neighborhood and a year before and after the introduction of Safe Neighborhood program. Results shown in Table A.2 align with those in the baseline estimation regarding sign but are higher in magnitude and less precise for the Principal Component and Factor Analysis outcomes. The same happens for the symptoms in Table A.3.

We also extend our analysis by defining the treated households as those residing in the affected neighborhoods and those 500 meters or less from the border of the targeted

Figure 5: Event Study of the Effect of Crime Prevention Programs on Mental Health Symptoms



Notes: These graphs plot the coefficient obtained from Eq. (2). Each dot represents the estimated coefficients, and the vertical segment shows the estimated 95% confidence interval. The survey year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood fixed effects.

Table 5: The Effect of Crime Prevention Programs on Healthcare Utilization

	(1) Health Care Utilization	(2) Public Healthcare Util.
Safe Neighborhood	0.046**	0.010
	(0.019)	(0.012)
Observations	15,844	15,844
R^2	0.04	0.05
Controls	Yes	Yes
FE	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, poor condition, number of members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood-fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

neighborhoods. As a result of this exercise, the estimated effects become smaller in magnitude (less than half of the original size) but are still sizable and significant. See Tables A.4 and A.5 in the Appendix.

A potential explanation behind our estimated effects of Safe Neighborhood on mental health is that residents in protected areas may increase healthcare services utilization because they feel safer visiting healthcare centers at any location and time of the day. We explore this possibility using healthcare utilization as an alternative dependent variable in Eq. (1). One-third of individuals in our sample declare that they used healthcare services the previous month. Results in Table 5 show that the Safe Neighborhood program increased this prevalence by five percentage points. Private healthcare could drive the effect as we find no effect on public healthcare. Hence, an increase in healthcare utilization is a potential mechanism behind the estimated positive impact of Safe Neighborhood on mental health.

The Peruvian health system leaves a significant part of the population uncovered because these individuals have no access to either the public or private systems. According to ENAHO data, almost one-fourth of the population did not have access to insurance during our period of interest (see also OECD [2017]). In our sample, these individuals represent almost 30%. We perform our analysis separately for individuals covered by and uncovered by the Peruvian health system. The results of this exercise are shown in

Table 6: The Effect of Crime Prevention Programs on Mental Health Problems by Health Insurance Coverage

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Sample A: No Insurance Coverage				
Safe Neighborhood	-0.035	-0.030	-0.022	-0.025
	(0.022)	(0.027)	(0.030)	(0.030)
Observations	1,132	1,132	1,132	1,132
R^2	0.09	0.11	0.10	0.11
Sample B: Insurance Coverage				
Safe Neighborhood	-0.073***	-0.078***	-0.074***	-0.075***
	(0.016)	(0.022)	(0.024)	(0.023)
Observations	2,724	2,724	2,723	2,723
R^2	0.05	0.05	0.05	0.05
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table 6 and reveal that individuals with health insurance lead the estimated effect. These results constitute additional evidence that an increase in healthcare utilization may be one of the mechanisms behind the positive impact of Safe Neighborhood on mental health.

The Peruvian mental healthcare system expanded significantly during the period of analysis (Marquez and Bayona Garcia [2019], Toyama, Castillo, Galea, Brandt, Mendoza, Herrera, Mitrani, Cutipé, Cavero, Diez-Canseco, et al. [2017]). The Peruvian mental health reform was approved in 2012. It introduced several changes to the delivery of mental healthcare, including new service delivery at the primary and secondary care levels and the introduction of supporting services to facilitate patient recovery and reintegration into society. We first examined whether the creation of new community mental health centers (CSMC) was correlated with the timing of the Safe Neighborhood program but found no such correlation (see Table A.6 in the Appendix). Nevertheless, we replicated our baseline estimates by including a dummy variable for exposure to CSMC at the district level and their interaction with the implementation of the Safe Neighborhood Program as covariates. The results in Table 7 indicate that our coefficient of interest remains unchanged and that both the CSMC coefficient and the interaction term for the availability of CSMC are

Table 7: The Effect of Crime Prevention Programs Interacted with New Mental Healthcare Centers on Mental Health Problems

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.058***	-0.058***	-0.053**	-0.053**
	(0.015)	(0.020)	(0.023)	(0.022)
CSMC	-0.006	0.020	0.032	0.032
	(0.029)	(0.028)	(0.027)	(0.028)
SN × CSMC	0.005	-0.028	-0.042	-0.037
	(0.030)	(0.033)	(0.033)	(0.034)
Observations	3,822	3,822	3,821	3,821
R^2	0.04	0.04	0.04	0.04
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

statistically insignificant. These findings suggest that the implementation of this contemporary mental health policy is not a confounding factor, supporting the validity of our research design.

Individuals living in areas with high crime rates may experience dissatisfaction with their social position and lower levels of life satisfaction. Consequently, we explore whether the Safe Neighborhood program improved residents' mental health by enhancing their life satisfaction and subjective well-being. However, the results presented in Table 8 provide evidence against this hypothesis. This finding suggests that improvements in mental health are not attributable to positive, transitory affective perceptions (i.e., temporary good mood).

We expect that certain population groups may be particularly affected by this policy, so we conduct additional heterogeneous analyses. First, when splitting the sample between individuals living in capital cities and those residing in small cities or towns, we find that the impact of the Safe Neighborhood program on mental health is concentrated in the sub-sample of individuals living in small cities or towns (see Tables A.7 and A.8 in the Appendix). These findings are expected, as small towns may have experienced a shift

Table 8: The Effect of Crime Prevention Programs on Life Satistaction

	(1) Better Neighborhood	(2) Subjetive (ladder)	(3) Ladder>5
Safe Neighborhood	-0.016	0.052	0.005
	(0.038)	(0.097)	(0.032)
Observations	4,241	4,241	4,241
R^2	0.07	0.24	0.16
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, poor condition, number of members between 15 and 29, quarter-fixed effects, survey-year fixed effects, and neighborhood-fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

from having little to no police patrol presence to a high supply of police patrolling, which is reflected in a greater reduction of mental health problems. Second, when splitting the sample between household heads and other members, we find a greater reduction in mental health problems within the sub-sample of household heads (see Tables A.9 and A.10 in the Appendix). These findings are also expected, as household heads are more concerned about the safety of all household members. Consequently, living in a less dangerous neighborhood could significantly reduce their stress levels.

Our final robustness check consists of re-estimating the baseline specification using the set of covariates as outcome variables (placebo test). Table A.11 in the Appendix shows that the crime prevention program does not affect any of the pre-determined characteristics, giving us greater confidence that our results are not spurious.

7 Discussion

We study the impact of Safe Neighborhood, a crime prevention program that mainly consists of increased police patrolling in specific Peruvian neighborhoods, on residents' mental health. The chosen neighborhoods had the highest crime rates in Peru, but the program implementation timing at different points between 2016 and 2019 was as good as random. We exploit the randomness of the timing of implementation to obtain estimates of the effect of the program on mental health by comparing the mental health of residents in already-treated neighborhoods to those in yet-to-be-treated neighborhoods.

We use data from the Peruvian Demographic and Health Survey, which provides wide information on mental health and allows us to geolocate households precisely. We obtain information on mental health and other individual and household characteristics for 3,857 individuals in 91 neighborhoods.

Our results show that the Safe Neighborhood Program reduced the incidence of mental health problems by six percentage points. Reductions of three to four percentage points in depression, tiredness, concentration problems, and a sense of failure lead these effects. Our results are robust when using a more demanding estimation with neighborhood-by-year fixed effects. Though smaller in magnitude, the effects are also present when considering residents in an extended area around the neighborhood as treated.

We find suggestive evidence that a tangible change in healthcare utilization may have driven the improvements in mental health induced by the crime prevention program: healthcare utilization increased significantly following the implementation of Safe Neighborhood, and the effect of our crime prevention program on mental health is driven by individuals covered by (public or private) health insurance. Instead, we rule out that life satisfaction improvements resulting from living in safer neighborhoods could be behind the estimated effect of Safe Neighborhood on mental health.

Our estimated effects of the crime prevention program on mental health are most substantial in small cities or towns, where the low level of pre-existing police patrolling may have rendered the increase in police patrolling more noticeable. Household heads' mental health experienced the most remarkable improvement following the implementation of the Safe Neighborhood program. This can be explained because the household head may feel responsible for the safety of other household members in addition to their safety.

Overall, our results imply that policymakers in developing countries with high crime rates should consider the improvements in mental health following crime prevention programs when studying the convenience of investing public resources in those programs. Thus, mental health becomes an additional argument favoring investing more resources in crime prevention in contexts in which citizens often declare feeling unsafe.

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A Appendix

A.1 Mental Health Questionnaire

In this subsection, we reproduce the mental health questionnaire included in the DHS data:

Question: Over the last 2 weeks, how often have you been bothered by any of the following problems?

1. Little interest or pleasure in doing things
2. Feeling down, depressed, or hopeless
3. Trouble falling or staying asleep, or sleeping too much
4. Feeling tired or having little energy
5. Poor appetite or overeating
6. Trouble concentrating on things, such as reading the newspaper or watching television
7. 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
8. Thoughts that you would be better off dead or hurting yourself in some way
9. Feeling bad about yourself or that you are a failure or have let yourself or your family down

A.2 Tables and Figures

Table A.1: The Effect of Crime Prevention Programs on Mental Health: Continuous version of Indexes

	(1) S.Accumulated	(2) Dep. Disorder	(3) Dep. Major	(4) PHQ9	(5) Index-27	(6) PCA	(7) FA
Safe Neighborhood	-0.234***	-0.028*	-0.043***	-0.080*	-0.521**	-0.291**	-0.127**
	(0.088)	(0.015)	(0.014)	(0.046)	(0.258)	(0.135)	(0.061)
Observations	3,857	3,857	3,857	3,857	3,857	3,856	3,856
R^2	0.05	0.03	0.03	0.06	0.08	0.08	0.08
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

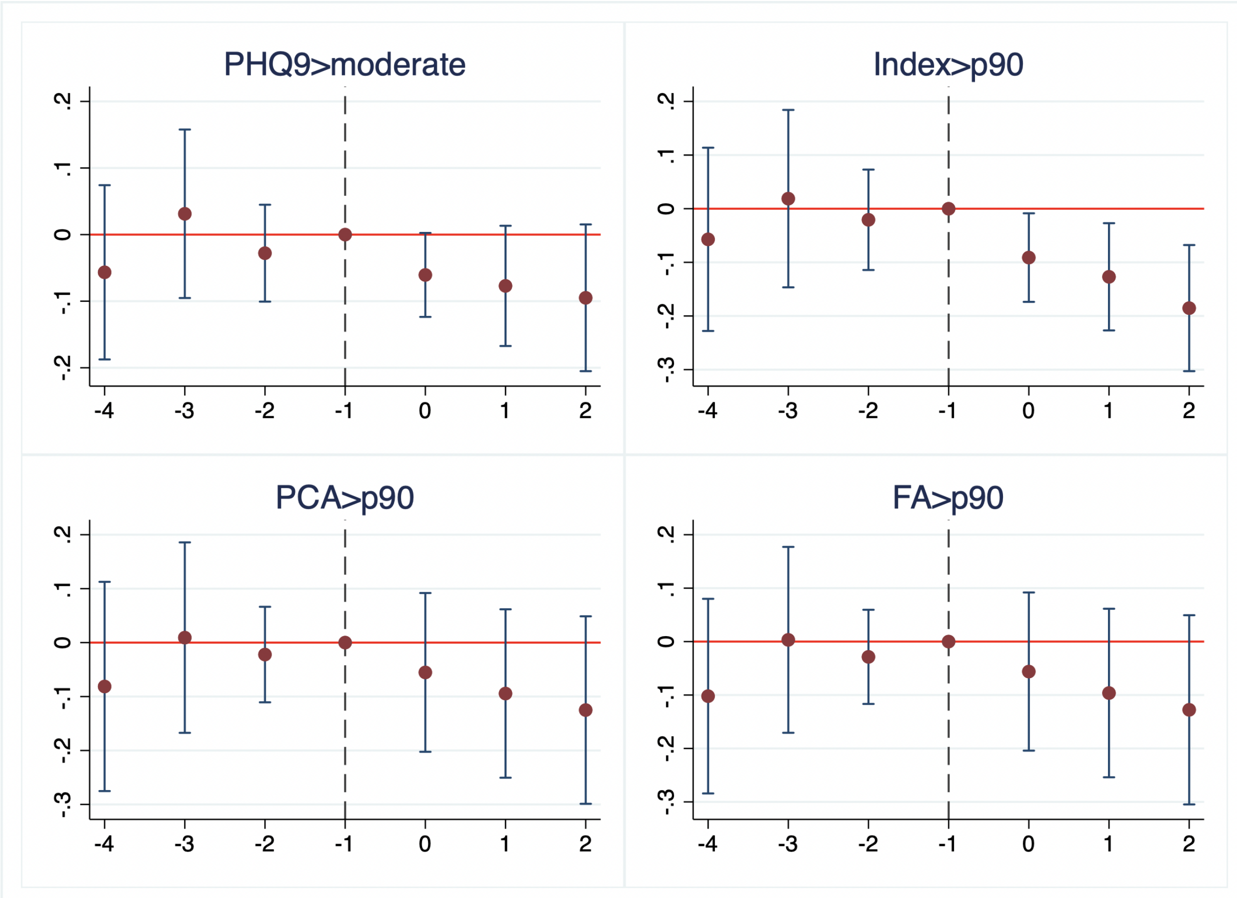
Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.2: The Effect of Crime Prevention Programs on Mental Health Problems. Neighborhood by year fixed effects

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.060***	-0.111***	-0.095	-0.097*
	(0.014)	(0.035)	(0.057)	(0.058)
Observations	3,856	3,856	3,855	3,855
R^2	0.06	0.06	0.06	0.06
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, and neighborhood by year fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Figure A.1: Event Study with Neighbourhood by Year Fixed Effects



Notes: These graphs plot the coefficient obtained from Eq. (2). Each bar represents the estimated coefficients and the capped, vertical line shows the estimated 95% confidence interval. The survey-year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, and neighborhood by year fixed effects.

Table A.3: The Effect of Crime Prevention Programs on Mental Health Symptoms. Neighborhood by year fixed effects

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.059^{**}	-0.038	-0.014	-0.004	-0.017	-0.019	0.010	-0.062	-0.022
	(0.028)	(0.054)	(0.043)	(0.042)	(0.030)	(0.037)	(0.026)	(0.040)	(0.018)
Observations	3,856	3,856	3,856	3,856	3,856	3,855	3,856	3,856	3,856
R^2	0.06	0.08	0.06	0.07	0.05	0.05	0.05	0.09	0.06
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

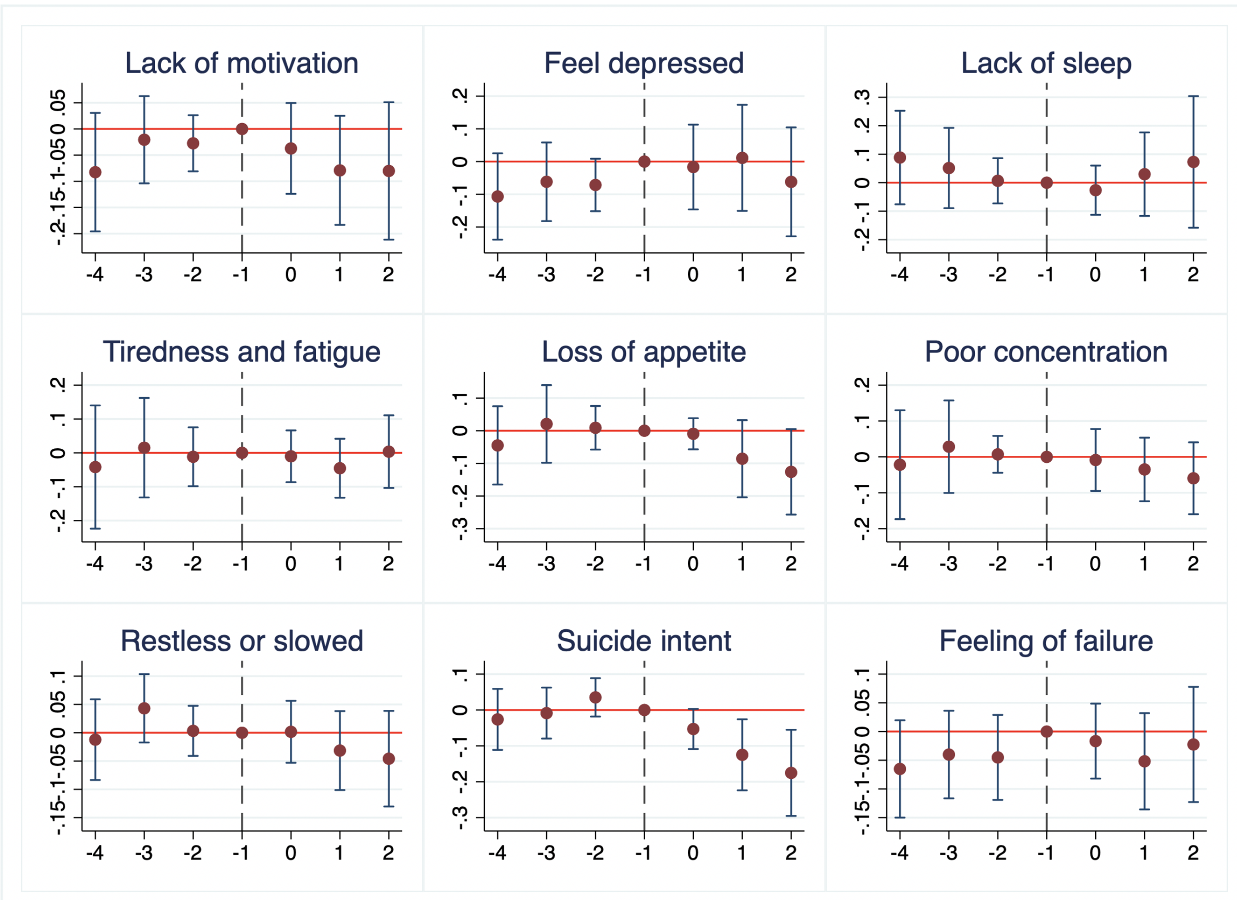
Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, and neighborhood by year fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.4: The Effect of Crime Prevention Programs on Mental Health. Plus 500 m buffer

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.024^{***}	-0.024^{***}	-0.023^{**}	-0.024^{**}
	(0.009)	(0.009)	(0.010)	(0.010)
Observations	15,509	15,509	15,506	15,506
R^2	0.03	0.04	0.04	0.04
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

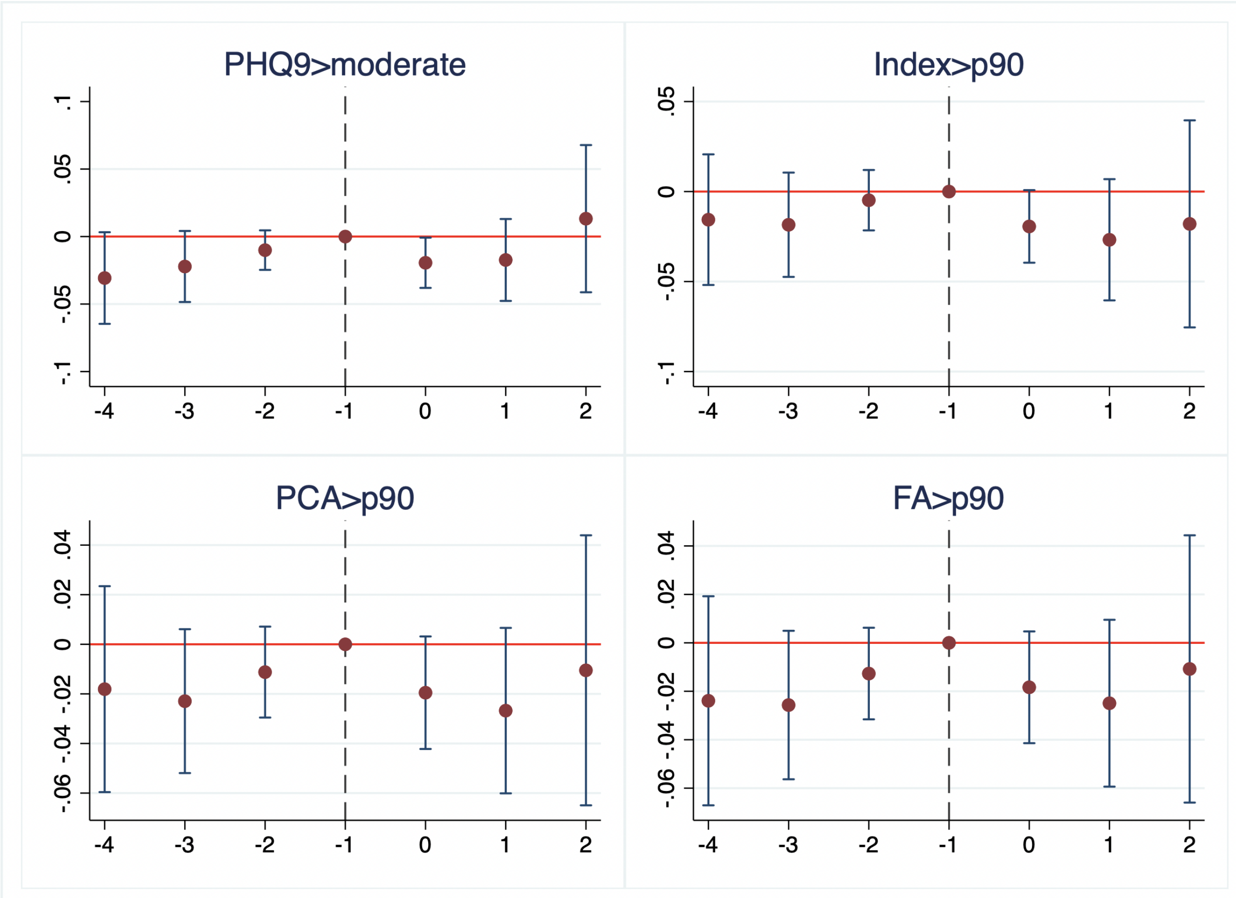
Notes: Standard errors clustered at district level are shown in parentheses. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Figure A.2: Event Study with Neighbourhood by Year Fixed Effects



Notes: These graphs plot the coefficient obtained from Eq. (2). Each bar represents the estimated coefficients and the capped, vertical line shows the estimated 95% confidence interval. The survey-year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, and neighborhood by year fixed effects.

Figure A.3: Event Study of the Effect of Crime Prevention Programs on Mental. Plus 500 m buffer



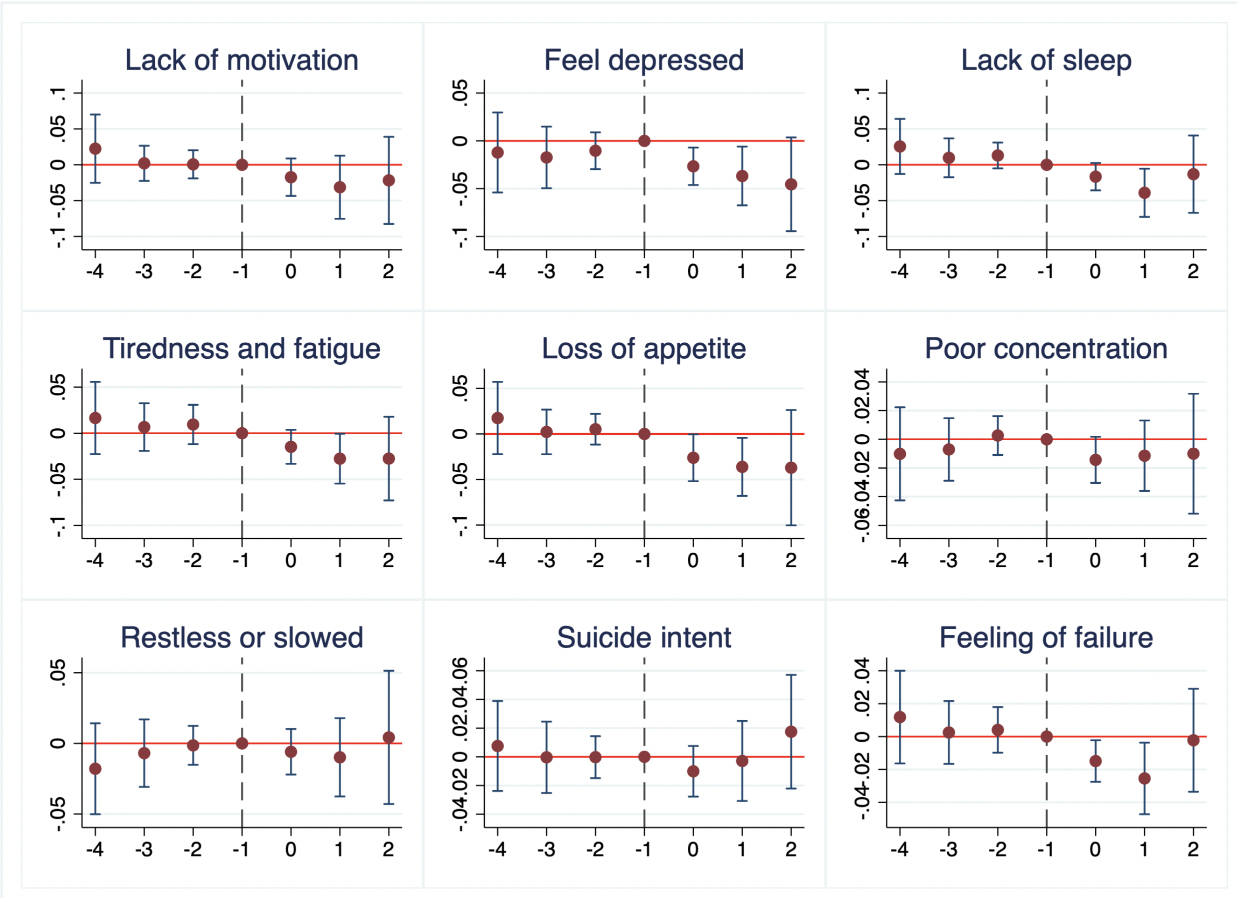
Notes: These graphs plot the coefficient obtained from Eq. (2). Each bar represents the estimated coefficients and the capped, vertical line shows the estimated 95% confidence interval. The survey-year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects.

Table A.5: The Effect of Crime Prevention Programs on Mental Health Symptoms. Plus 500 m buffer

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.019	-0.029***	-0.011	-0.018*	-0.023**	-0.012	-0.003	-0.006	-0.014**
	(0.012)	(0.009)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.007)
Observations	15,509	15,509	15,508	15,509	15,508	15,508	15,509	15,509	15,509
R^2	0.02	0.05	0.03	0.03	0.02	0.02	0.02	0.04	0.02
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at district level are shown in parentheses. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Figure A.4: Event Study of the Effect of Crime Prevention Programs on Mental Symptoms. Plus 500 m buffer



Notes: These graphs plot the coefficient obtained from Eq. (2). Each bar represents the estimated coefficients and the capped, vertical line shows the estimated 95% confidence interval. The survey-year $t-1$ is the reference period. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects.

Table A.6: Association between implementation of CSMC and Safe Neighborhood

	(1)
	Implementation of CSMC
Safe Neighborhood	-0.047
	(0.082)
Male	-0.004
	(0.005)
Age	-0.000*
	(0.000)
Primary	0.000
	(0.017)
Secundary	-0.008
	(0.015)
Tertiary	-0.010
	(0.018)
Married	0.000
	(0.007)
Quintil 2	0.008
	(0.018)
Quintil 3	0.034*
	(0.018)
Quintil 4	0.022
	(0.020)
Quintil 5	0.029
	(0.023)
Household members 15-29	-0.003
	(0.002)
Observations	3,822
R^2	0.60
FE	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.7: The Effect of Crime Prevention Programs on Mental Health Problems by Type of city

	(1)	(2)	(3)	(4)
	PHQ9>moderate	Index>p90	PCA>p90	FA>p90
Sample A: Small cities and towns				
Safe Neighborhood	-0.060***	-0.067***	-0.066**	-0.067***
	(0.021)	(0.024)	(0.025)	(0.023)
Observations	2,268	2,268	2,267	2,267
R^2	0.05	0.05	0.05	0.05
Sample B: Capital city				
Safe Neighborhood	-0.049*	-0.057	-0.044	-0.044
	(0.025)	(0.041)	(0.052)	(0.054)
Observations	1,589	1,589	1,589	1,589
R^2	0.04	0.04	0.05	0.05
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.8: The Effect of Crime Prevention Programs on Mental Health Symptoms by Type of city

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Sample A: Small cities and towns									
Safe Neighborhood	-0.041	-0.060**	-0.017	-0.030*	-0.005	-0.046***	-0.043***	-0.036	-0.038**
	(0.028)	(0.026)	(0.019)	(0.017)	(0.021)	(0.017)	(0.014)	(0.024)	(0.017)
Observations	2,268	2,268	2,268	2,268	2,268	2,267	2,268	2,268	2,268
R^2	0.04	0.06	0.05	0.05	0.05	0.03	0.03	0.08	0.04
Sample B: Capital city									
Safe Neighborhood	0.001	-0.005	-0.006	-0.010	-0.008	-0.004	0.026	-0.029	-0.003
	(0.035)	(0.045)	(0.036)	(0.032)	(0.025)	(0.031)	(0.020)	(0.031)	(0.022)
Observations	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589	1,589
R^2	0.04	0.07	0.03	0.05	0.03	0.03	0.02	0.06	0.04
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.9: The Effect of Crime Prevention Programs on Mental Health Problems by Household Head

	(1)	(2)	(3)	(4)
	PHQ9>moderate	Index>p90	PCA>p90	FA>p90
Sample A: Any member				
Safe Neighborhood	-0.061*	-0.046	-0.017	-0.023
	(0.035)	(0.041)	(0.046)	(0.045)
Observations	1,166	1,166	1,166	1,166
R^2	0.10	0.09	0.11	0.10
Sample B: Household head				
Safe Neighborhood	-0.060***	-0.074***	-0.078**	-0.077**
	(0.020)	(0.026)	(0.030)	(0.029)
Observations	2,691	2,691	2,690	2,690
R^2	0.05	0.05	0.05	0.05
Controls	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.10: The Effect of Crime Prevention Programs on Mental Health Symptoms by Household Head

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Sample A: Any member									
Safe Neighborhood	-0.011	-0.029	0.020	-0.004	-0.035	-0.049*	-0.022	-0.005	-0.018
	(0.027)	(0.032)	(0.032)	(0.031)	(0.023)	(0.028)	(0.035)	(0.040)	(0.028)
Observations	1,166	1,166	1,166	1,166	1,166	1,166	1,166	1,166	1,166
R^2	0.06	0.10	0.08	0.09	0.08	0.07	0.06	0.13	0.06
Sample B: Household head									
Safe Neighborhood	-0.045*	-0.056**	-0.036	-0.045**	0.005	-0.022	-0.012	-0.058***	-0.035**
	(0.027)	(0.023)	(0.023)	(0.020)	(0.020)	(0.019)	(0.014)	(0.020)	(0.015)
Observations	2,691	2,691	2,691	2,691	2,691	2,690	2,691	2,691	2,691
R^2	0.05	0.07	0.05	0.05	0.04	0.03	0.03	0.07	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include sex, age, level of education, marital status, wealth index, number of household members between 15 and 29, quarter fixed effects, survey-year fixed effects, and neighborhood fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.11: The Effect of Crime Prevention Programs on Pre-determined characteristics

	(1) Male	(2) Age	(3) Education	(4) Married	(5) Wealth Index	(6) Members 15-29
Safe Neighborhood	0.016	0.265	-0.040	0.051	-0.026	0.083
	(0.028)	(0.996)	(0.076)	(0.033)	(0.098)	(0.058)
Observations	3,857	3,857	3,857	3,857	4,087	3,857
R^2	0.02	0.03	0.07	0.02	0.25	0.04
FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors clustered at the district level are shown in parentheses. Covariates include quarter-fixed effects, survey-year fixed effects, and neighborhood-fixed effects. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.