Beyond Crime: How Public Safety Programs Improve Mental Health

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Abstract

Peru has one of the highest rates of both victimization and perceived crime in Latin America. This rooted-in-reality feeling of insecurity may harm citizens' mental health. We study the impact of the Safe Neighborhood program, which increased police patrolling, on mental health. We exploit the program's staggered implementation across neighborhoods and find that enhanced crime prevention reduced the incidence of mental health problems. Specifically, the program reduced the prevalence of sleep problems, tiredness, concentration difficulties, suicidal intentions, and feelings of failure. Potential mechanisms for these effects include changes in non-property victimization, crime perception, health service utilization, and labor market conditions.

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1 Introduction

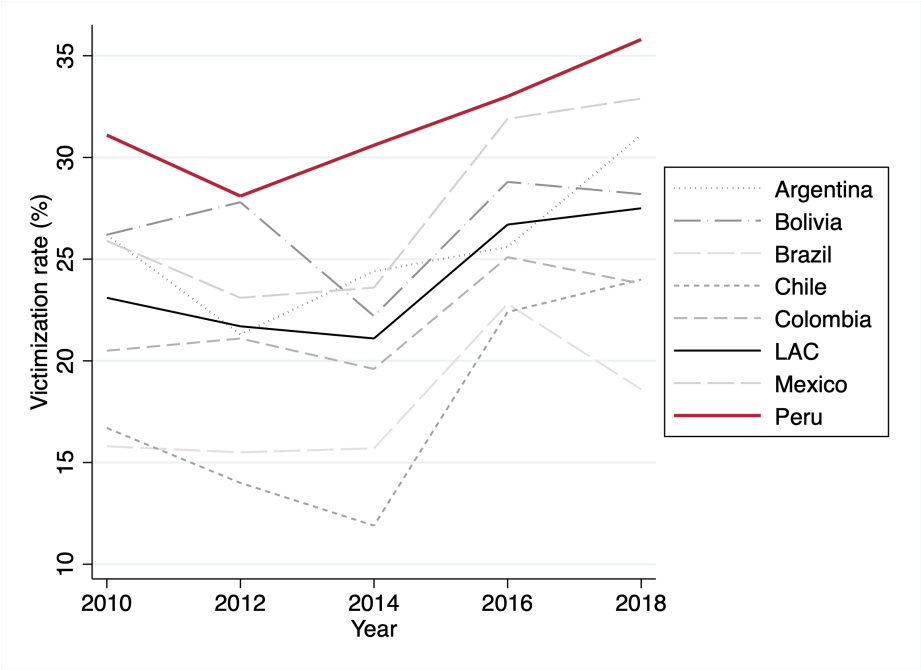
Crime is a complex phenomenon that generates substantial direct and intangible costs to society (Johnston et al., 2018). Peru has one of the highest crime rates in Latin America, and unlike other large countries in the region, crime in Peru has been continuously increasing since 2012 (see Figure 1). In 2023 alone, more than 80% of Peruvian citizens considered crime the country's main problem, and more than 1 in 4 reported having been victims of crime.[1] This prevalence translates into widespread fear and a pervasive sense of insecurity among citizens. Beyond the reduction in life quality caused by feeling threatened or being victimized, the high frequency of these experiences may also harm mental health, with young, females and poor individuals being the most affected (Ridley et al., 2020).

This study analyzes the relationship between public safety and mental health in the context of Peru, a country where both citizens' mental health and safety are pressing challenges. In response to the crime prevalence problem, the Peruvian government implemented the Safe Neighborhood program between 2016 and 2019 in targeted dangerous neighborhoods. The program sought to reduce crime and violence while fostering greater trust in public institutions. Its primary intervention consisted of increased police patrols in targeted neighborhoods. In total, 92 neighborhoods with the highest crime rates were incorporated into the program in a staggered fashion, beginning in 2016. The implementation was interrupted in 2019 due to the onset of the COVID-19 pandemic, halting the addition of new neighborhoods while continuing operations in already treated areas.

To estimate the impact of Safe Neighborhood on mental health, we combined highly detailed datasets from 2013 to 2019. 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

[1] Detailed information is available at `https://www.inei.gob.pe/media/MenuRecursivo/publicaciones_digitales/Est/Lib1962/`.

Figure 1: Proportion of Crime Victims in Latin American 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.

Internal Affairs Minister. We complement this information with individual health and labor data from the Peruvian National Household Survey, individual crime-related data from the National Survey of Public Budget Programs, and novel collected district-level data on mental healthcare centers.

In our analysis, we use a sample of residents from all eventually treated neighborhoods and exploit the staggered implementation of the program across neighborhoods. This approach allows us to compare the mental health trajectories of residents who were exposed at different times. Specifically, we compare the mental health outcomes of residents from not-yet-treated neighborhoods with those from already-treated neighborhoods. The validity of our identification strategy relies on the assumption that citizens treated earlier and later are comparable, as the timing of program implementation is uncorrelated with mental health outcomes or any other factors that may influence them.[2]

[2]A previous study by Hernandez et al. (2023) shows that the program rollout is unrelated to crime and other socioeconomic characteristics. In addition, we show that the timing of program implementation is unrelated to residents' mental health.

Using a two-way fixed effects (TWFE) strategy, we find that the public safety intervention decreases the probability that individuals report experiencing mental health problems. In particular, the Safe Neighborhood program reduces the incidence of mental health problems by 5-6 percentage points. More precisely, the program is effective in reducing the prevalence of sleep problems, tiredness, concentration difficulties, suicidal intentions, and feelings of failure among residents in targeted areas, with all these symptoms decreasing by 3-4 percentage points.

In addition, we find some heterogeneous effects: the impact is stronger among residents of small cities and towns, as well as among less wealthy individuals, suggesting that the effects are concentrated among citizens who experienced lower levels of police patrolling before the intervention and are more vulnerable to crime. Moreover, the impact is stronger among household heads, which is consistent with their greater concern for household safety. We also find that the effect decreases to about 2 percentage points when we account for the possibility that the program may have affected residents within a 500-meter buffer around the targeted area, suggesting the presence of spillover benefits.

The second objective of this paper is to understand the potential mechanisms underlying the main findings. The Safe Neighborhood program may be effective in reducing crime victimization, but it may also generate benefits by increasing residents' perceptions of safety. Our results indicate that the program produced only modest effects on crime, with significant reductions limited to non-property offenses. In addition, the program significantly increased reporting the presence or noticing the presence of police patrols, particularly by the national police patrols, who were directly involved in the program. These findings suggest that both actual reductions in crime and heightened perceptions of safety contribute to the observed improvements in mental health.

On the other hand, we find evidence that the program increases healthcare utilization, and that individuals with health insurance lead the estimated effects. This suggests that

a tangible, health-related behavioral change contributes to the improvement in mental health. Finally, we also find that the program improves the labor market outcomes of residents in targeted neighborhoods, indicating that better economic conditions may also contribute to improvements in mental health.

The main threat to our identification strategy is the potential presence of time-varying unobservables that are correlated with both the timing of the Safe Neighborhood program implementation and changes in mental health outcomes. We conduct several robustness checks to ensure that our results are not driven by selection or unobserved time-varying factors. First, we find no evidence of pre-trends in mental health outcomes, which suggests a non-anticipatory response to the program. Second, all results remain robust when controlling for the implementation of mental healthcare centers, which were partially rolled out during the same period. Third, results are consistent under a more demanding specification with neighborhood-by-year fixed effects. Fourth, we obtain consistent results when conducting a randomization test. Fifth, we present results for placebo outcomes: crime prevention programs have no effect on predetermined characteristics. Finally, given the TWFE strategy does not account for heterogeneous treatment effects, we employ alternative approaches specifically designed for staggered implementation. The estimators proposed by Sun and Abraham (2021), Callaway and Sant'Anna (2021), and Borusyak et al. (2024) yield results consistent with those obtained from our TWFE estimates.

Victimization and fear of crime are well-documented sources of psychological distress. Prior research shows that individuals exposed to crime or living in high-crime areas report significantly worse mental health outcomes (Cornaglia et al., 2014; Dustmann & Fasani, 2016). Importantly, existing studies highlight that not only actual victimization but also the perception of crime imposes substantial psychological burdens, including increased anxiety, stress, and altered daily behaviors (Jackson & Stafford, 2009; Baranyi et al., 2021). These intangible costs are often more widespread than direct harm and affect broader populations through increased fear and behavioral adaptation (Janke et al., 2016;

Johnston et al., 2018). While most of this evidence comes from high-income countries, emerging research from low-and middle-income settings confirms similar relationships, particularly among economically vulnerable populations (Braakmann, 2012; Moya, 2018; Alloush & Bloem, 2022).

Less is known, however, about the extent to which public safety interventions–as opposed to crime itself–can improve mental health. A growing body of work documents the effectiveness of police presence and surveillance in deterring crime (Di Tella & Schargrodsky, 2004; Draca et al., 2011; Blattman et al., 2021; Weisburd, 2021; Ma et al., 2025), but few studies explore whether such programs generate social or psychological spillovers. Some recent work shows that policing interventions can affect outcomes such as birth outcomes (Lautharte, 2021) or school safety (McMillen et al., 2019), yet we are not aware of any existing evidence on mental health outcomes.

Our study fills these gaps by investigating the mental health effects of a public safety intervention–Peru's Safe Neighborhood program–using a quasi-experimental design. We show that policing-based crime prevention can yield measurable improvements in mental well-being, suggesting that such programs generate welfare-enhancing effects beyond crime reduction.

The remainder of this paper is organized as follows. Section 2 describes the institutional background. Section 3 presents the data and describes our sample. Section 4 explains our empirical strategy. Section 5 presents our main results and explores potential mechanisms. Section 6 discusses the robustness of our findings and tests for heterogeneity of the estimated effects. Finally, we conclude in Section 7.

2 Institutional Background

2.1 Mental Health Context

Worldwide, mental well-being remains at its post-pandemic low levels, and there is no sign of recovery (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 global population experienced a mental disorder, and mental disorders accounted for 17% of the total global burden of years lived with disability (Health Metrics and Evaluation, 2024).

Generally, Latin American countries perform better in terms of mental health than other developing regions worldwide, 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. Despite mental health having been 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 to strengthen mental health systems in Latin America and address the region's longstanding crisis. Poverty and extreme poverty-both on the rise-are closely intertwined with mental health as both cause and consequence, while additional threats stem from violence, racial discrimination, and gender inequality (Pan American Health Organization, 2023).

According to the report 'The Burden of Mental Health Disorders in the Americas', mental, neurological, substance use, and suicide (MNSS) disorders are a leading cause of disability and mortality. They account for one-third of total years lived with disability and one-fifth of disability-adjusted life years in Latin America. MNSS is the largest single

contributor to disability in every country of the region, regardless of income level or subregion. In Peru, these disorders represent more than 35% of years lived with disability, above the regional average of 33%. Within this group, depressive disorders impose the heaviest burden, with around 9% of years lived with disability compared to a regional average of 7%, followed by anxiety disorders at 5.3%, slightly 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. The system comprises multiple schemes, including the Integral Health Insurance (SIS) and the Social Health Insurance (EsSalud), each targeting specific population segments and leaving some individuals without coverage (OECD, 2017). SIS mainly serves low-income groups, 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 focuses on primary care, while EsSalud focuses on hospital services, leading to disparities in health service experiences. The coexistence of public, private, and decentralized providers exacerbates systemic fragmentation, highlighting the need for integrative reforms to advance toward universal health coverage (OECD, 2017).

Peru has traditionally had one of the smallest health budgets in Latin America. However, over recent decades, the country has tripled its budget for mental health and undertaken a significant transformation of its mental health services, replacing centralized psychiatric hospitals with a network of community-based facilities (Pan American Health Organization, 2023). Despite these reforms, the distribution of mental health services in Peru remains highly unequal, and the prevalence of mental disorders is considerably higher among citizens who cannot meet their basic needs. Moreover, the poorest regions, as well as those most heavily affected by the civil conflict in the 1980s and 1990s, show

a higher prevalence of mental health disorders (Toyama et al., 2017), while underdiagnosis and undertreatment remain persistent challenges. Recent data indicate that MNSS diseases account for between one-third and one-fourth of the total disease burden among individuals aged 10 to 50, the largest share of any disease group during this period (Pan American Health Organization, 2020). Additionally, the country continues to be significantly affected by gender-based violence (National Statistics Office, 2023) and child abuse (UNICEF, 2020), both of which have clear consequences for mental health.

2.2 Safe Neighborhood Program

In 2016, in response to the problem of crime prevalence, the Peruvian Ministry of Internal Affairs launched the country's first hot-spots policing program, called *Barrio Seguro* (Safe Neighborhood). The program targets specific locations within high-crime neighborhoods through increased police patrolling. It followed a staggered implementation, and by 2019 it covered 92 neighborhoods across the country. Between 2016 and 2019, the government spent more than two billion dollars on this program (Ministry of Economy and Finance, 2020).

The intervention increased police resources, including additional officers and patrol units. On average, each police station within targeted neighborhoods received two extra patrol units, a car, and a motorcycle (Ministry of Internal Affairs, 2020), representing a 100% increase in available patrol units.[3] The additional policing was focused on specific areas within the neighborhoods where crimes were more frequent, following routes identified by the police. Police officers and station chiefs received training both before and during the intervention.

By targeting the most dangerous neighborhoods, authorities aimed to reduce crime rates, alleviate fear of crime, and improve citizens' perceptions of the national police. The

[3]Before the intervention, the average police station had 0.72 operational police cars and 2.2 operational motorcycles (Hernandez et al., 2023).

selection of neighborhoods for the program followed a two-step process. First, policymakers created a list of the most dangerous districts using an index of three district-level indicators: homicide rate, reported crimes, and the last residency of the prison population. This step identified 120 districts for potential intervention. Second, a qualitative assessment was conducted, including interviews with local community members and police officers in each district, to identify the most dangerous neighborhoods within the districts.

The Safe Neighborhood program was initially planned to be implemented in all targeted districts, but its rollout was disrupted in early 2020 due to the pandemic. As a result, 92 neighborhoods were officially included in the intervention during our analysis period, all of which were associated with an existing police station. Safe Neighborhood was implemented in a staggered manner, and closely following the priority list. Each change in minister led to a turnover in the program's managerial team. These frequent changes meant that the initial focus on starting with the most dangerous neighborhoods was not strictly followed, which also slowed the rollout process (5 neighborhoods were added in 2016, 17 in 2017, 30 in 2018, and 40 in 2019).

Neither monetary nor non-monetary incentives were provided for participating in the program. Each police station was responsible for only one treated Safe Neighborhood, and these neighborhoods did not border each other. To ensure that the additional police resources were used for increased patrolling, Safe Neighborhood introduced notebooks for citizen monitoring in grocery stores and small businesses throughout the neighborhood. As part of their daily patrol routine, police officers were required to sign these notebooks to indicate that they had patrolled the area. Although never fully enforced, this manual record helped reinforce patrolling and maintain essential community contact.

Formally, Safe Neighborhood is a multisectoral program, which requires ongoing coordination with other programs implemented in the targeted areas, particularly those aimed at preventing crime victimization. A local officer in each neighborhood was re-

sponsible for coordinating with the institutions running these programs. However, the multisectoral component was minimal, as the additional programs were so limited in scope that Safe Neighborhood remained primarily a crime prevention intervention. For example, scholarships were offered to high-risk children to prevent school dropouts, but the reach was extremely limited; in one neighborhood, only a single scholarship was awarded (Hernandez et al., 2023).

3 Data

3.1 Individual-level data

We use several individual-level data sources. First, we use data from the Peruvian Demographic and Health Survey (DHS) for the period 2013-2019. The DHS is a cross-sectional, nationally representative survey with rich information about the health, family structure, and socioeconomic characteristics of respondents from more than 90 emerging countries.[4] DHS data collects 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).[5] In addition, the Peruvian DHS also

[4]The *Encuesta Demográfica y de Salud Familiar* (ENDES) is the Peruvian version of the DHS. This survey is available since 2000 and collected annually on a continuous basis since 2004.

[5]The Peruvian DHS included a mental health questionnaire starting in 2013.

records GPS coordinates for every cluster of households in a certain district, which allows us to identify whether households reside within areas targeted by the program.

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 et al., 2001; Pinto-Meza et al., 2005). The questionnaire assesses the following symptoms: 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), hence 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 minimal, mild, moderate, moderately severe, and severe depression, respectively.

We follow the relevant literature and guidelines to interpret this questionnaire (Kroenke et al., 2001) and analyze the impact of a public safety intervention on several indicators of mental health problems. First, we define individuals as having mental health problems if they report a PHQ-9 score greater than 9 (moderate or severe depression). Second, we define a binary variable indicating mental health problems if individuals fall within the top 10% of the PHQ-9 score distribution. Last, we aggregate all mental health symptoms to create two indices of mental health using Principal Component Analysis and Factor Analysis, and we define two binary variables indicating mental health problems if individuals' scores are at or above the 90th percentile for each index.

To explore potential mechanisms, we use data from the National Survey of Public Budget Programs (ENAPRES) and the Peruvian National Household Survey (ENAHO)

for the period 2013-2019, both conducted by the Peruvian National Statistics Office. Both surveys record GPS coordinates for every cluster of households, and as in the DHS, this allows us to identify whether households are located in areas targeted by the Safe Neighborhood program. The ENAPRES is a cross-sectional, annually conducted, and nationally representative survey that collects information on socioeconomic characteristics, which allows the monitoring of public sector budget programs. For our analysis, we focus on the crime-victimization questionnaire, which is administered to all household members aged 15 or older, and allows us to construct several variables related to crime victimization within districts and even within neighborhoods, as well as variables related to perceptions of crime and police patrolling.

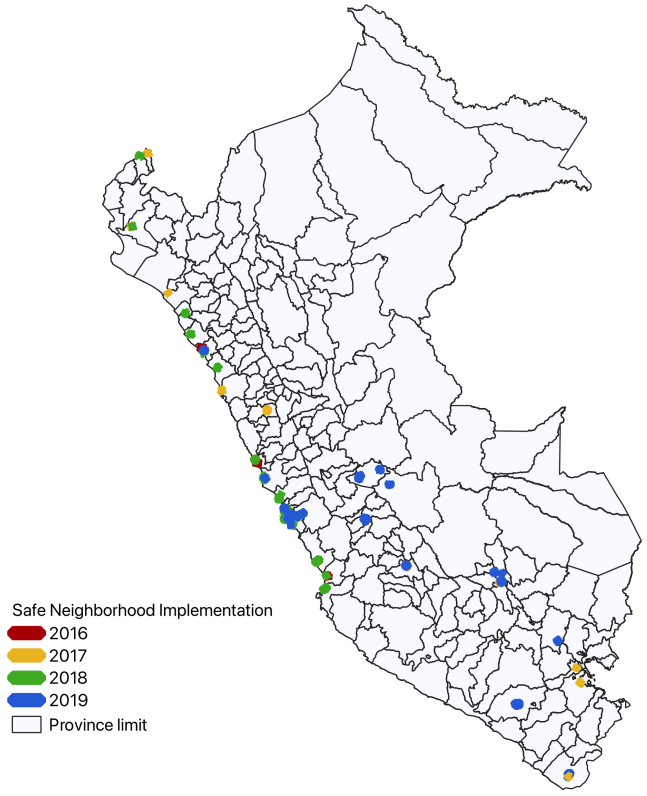
The ENAHO is a cross-sectional, annually conducted, and nationally representative survey that collects information on various welfare dimensions, such as household consumption, educational attainment, health outcomes, and job information, among other characteristics. For the analysis, we are particularly interested in two questionnaires. First, the health questionnaire, which covers all household members, enables the construction of variables related to both general and public healthcare utilization. Second, the labor questionnaire, administered to all household members aged 14 or older, provides information to construct variables related to labor market conditions: employment status, informal employment, primary sector jobs, and wages.

3.2 Neighborhood-level data

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-year), their administrative locations (district-province-state), the names of the police stations in charge, and the spatial boundaries of targeted neighborhoods from 2016 to 2019. 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 92 Safe Neighborhoods im-

plemented by 2019.[6] Figure 2 illustrates the implementation timeline of the Safe Neighborhood program by showing the location of neighborhoods where the program was implemented from 2016 to 2019.

Figure 2: Rollout of Safe Neighborhood Program



Notes: Administrative data from the Peruvian Internal Affairs Minister.

3.3 District-level data

During our period of analysis, a national reform led to the establishment of new community mental health centers (CSMCs) in selected districts.[7] We collected a novel dataset on newly established CSMCs, including their founding dates (month-year) and their administrative locations (district-province-state). This dataset provides information on 131

[6]The implementation of the Safe Neighborhood program was interrupted by the onset of the pandemic, halting the addition of new neighborhoods while continuing operations in those already treated.

[7]Detailed information is available at `https://blogs.worldbank.org/en/health/paradigm-shift-peru-leading-way-reforming-mental-health-services`.

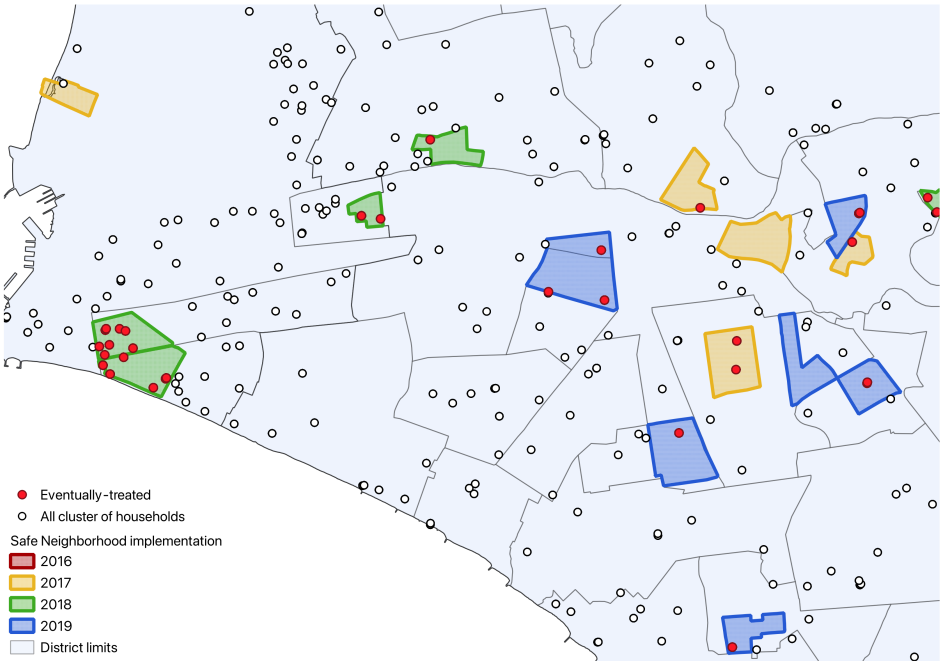
CSMCs implemented between 2015 to 2019. Among the 92 Safe Neighborhoods, only 34 (37%) had a mental health center operating in the same district by 2019. Given the gradual implementation of the CSMCs, only 6% of our sample was exposed to this program. The low overlap is expected, as the focus of Safe 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). Still, we analyze potential interaction effects between the two policies in the results section.

3.4 Measuring exposure to Safe Neighborhood program

The exposure to the Safe Neighborhood program is captured in the DHS data, which records GPS coordinates for every cluster of households within each district. This feature allows us to determine whether clusters of households are located within the boundaries of treated neighborhoods and to identify the timing of treatment. Our DHS clusters overlap with the boundaries of 56 targeted neighborhoods.

In our analysis, we use a sample of residents from all eventually treated neighborhoods (i.e., the 56 neighborhoods which contain at least one DHS cluster), comparing information on the mental health of residents in already-treated and not-yet-treated neighborhoods. Figure 3 provides an example of a zoomed-in area, where interviewed cluster of households are represented by dots and eventually treated clusters are shown in red (i.e., our effective sample of interest). Polygons of treated neighborhoods are colored according to the year of program implementation. We observe that treated neighborhoods are sparsely distributed across the territory.

Figure 3: DHS Clusters Exposed to Safe Neighborhood Program



Notes: Administrative data from the Peruvian Internal Affairs Minister.

We take advantage of the rich information available in the DHS and, in addition to using data on mental health, date of exposure, and neighborhood 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, and household composition. Table 1 describes the characteristics of the estimation sample. In general, 7% of surveyed individuals suffer from moderate to severe depression, and the average PHQ-9 score is 2.6 points. The proportion of affected individuals varies across symptoms. From 3% of individuals experiencing feelings of failure or 4% of individuals who have concentration difficulties, the proportion reaches 9% for lack of sleep and depressive feelings. Regarding exposure to the Safe Neighborhood Program, 26% of the sample comprises residents already affected by the program. In terms of sociodemographic characteristics, females are slightly overrepresented in our sample and the average individual in our sample is 40 years old. Overall, 44% of respondents have secondary education, while 42% have a tertiary education diploma. On average, households include at least one person aged 15 to 29, an age group with a higher likelihood of

being a victim of crime (National Statistics Office, 2023).

Table 1: Descriptive Statistics - Estimation Sample

	Mean	SD	Min	Max	N
Mental Health Indexes					
PHQ9>moderate	0.066	0.249	0	1	3,758
Index of mental health	2.619	4.026	0	27	3,758
Index>p90	0.086	0.280	0	1	3,758
PCA>p90	0.100	0.299	0	1	3,757
FA>p90	0.100	0.299	0	1	3,757
Mental Health Symptoms					
Lack of motivation	0.088	0.283	0	1	3,758
Feel depressed	0.097	0.296	0	1	3,758
Lack of sleep	0.094	0.292	0	1	3,758
Tiredness and fatigue	0.065	0.247	0	1	3,758
Loss of appetite	0.061	0.240	0	1	3,758
Poor concentration	0.043	0.204	0	1	3,757
Restless or slowed movements	0.047	0.211	0	1	3,758
Suicide intent	0.072	0.258	0	1	3,758
Feeling of failure	0.034	0.181	0	1	3,758
Main Treatment					
Safe Neighborhood	0.260	0.439	0	1	3,758
Early exposure (for sample before 2016)	0.477	0.500	0	1	1,332
Demographic Characteristics					
Male	0.436	0.496	0	1	3,758
Age	39.935	16.880	15	97	3,758
Primary	0.131	0.337	0	1	3,758
Secondary	0.442	0.497	0	1	3,758
Tertiary	0.417	0.493	0	1	3,758
Household members 15-29	0.963	1.010	0	7	3,758

Notes: The data come from the 2013-2019 Peruvian DHS. The sample includes all surveyed residents in the neighborhoods where Safe Neighborhood was implemented.

4 Methodology

We estimate the effect of the Safe Neighborhood 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 implementation is independent of the neighborhood's residents' mental health, or any factor that influences mental health.[8] We support this assumption by providing balance tests comparing the average mental health of residents in the earliest-treated half of neighborhoods with that of residents in the latest-treated half, using data from before the implementation of the Safe Neighborhood program (i.e., respondents interviewed between 2013 and 2015). Figure 4 shows the results of these tests that indicate that there are no significant pre-existing differences in mental health across neighborhoods by treatment time.

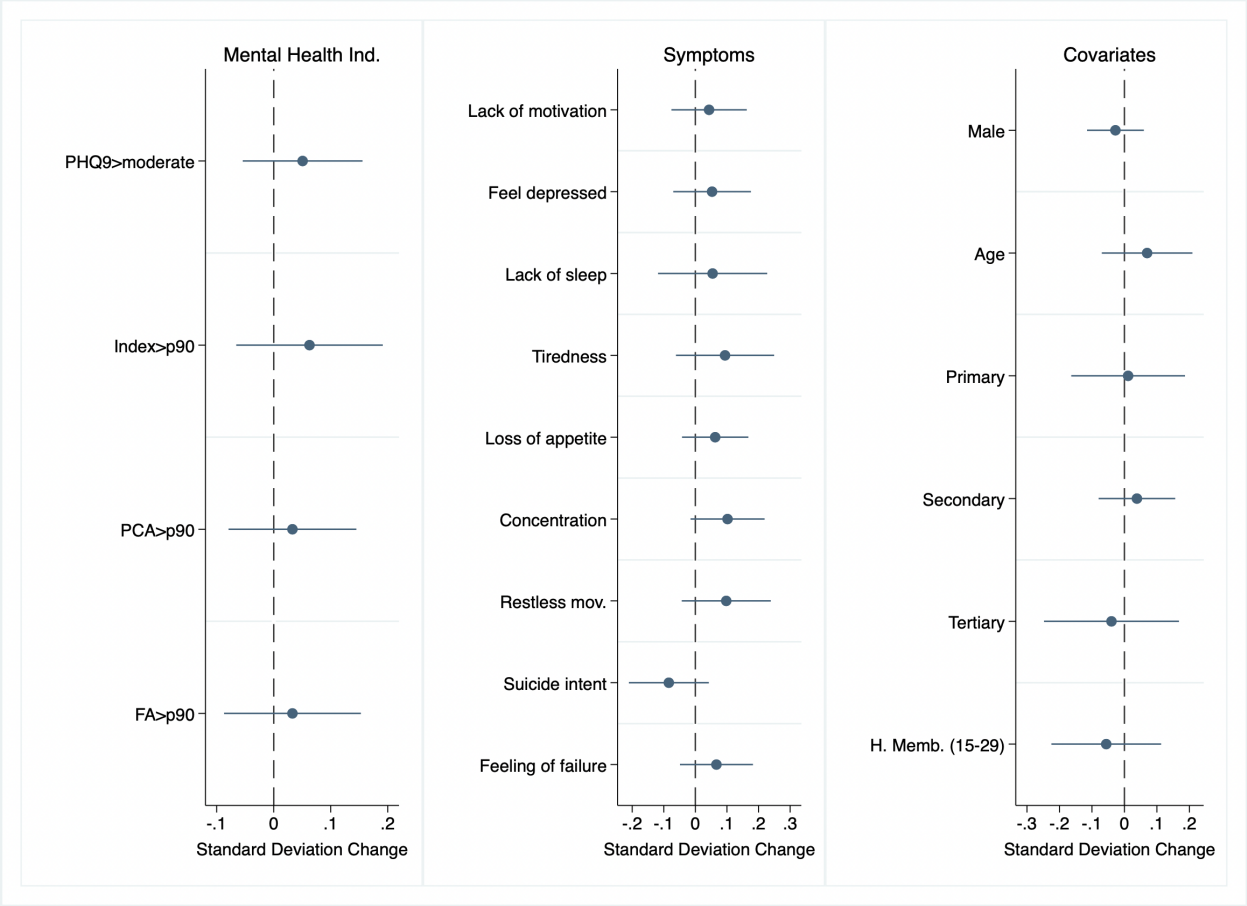
Under the assumption that the timing of the public safety program implementation is quasi-random, we can estimate the impact of the Safe Neighborhood program on mental health as follows:

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

where MH_{int} indicates mental health problems (defined as explained above according to various measures) or one of the mental health symptoms experienced by individual 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. The vector C_{int} includes a set of individual characteristics, including sex, age, education, and the number of high-risk crime victimization individuals (from 15 to 29 years old) in the household. We control for neighborhood characteristics using

[8] Hernandez et al. (2023) also shows the quasi-random assignment of the Safe Neighborhood program with respect to crime, and we provide evidence of the lack of correlation between program implementation and crime in the event-study plots presented in the mechanism section.

Figure 4: Balance Test - Early vs Late Adopters



Notes: These graphs plot the coefficients of a linear model and the corresponding 95% confidence intervals. For each case, the dependent variable is mental health or sociodemographic characteristic, and the independent variable is the early exposure to the program. All regressions include survey-year and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2015 Peruvian DHS.

a vector of neighborhood fixed effects, D_n, and survey-year fixed effects, D_t. We cluster standard errors at the neighborhood level, which corresponds to the level of program implementation (Abadie et al., 2023). We interpret the estimate of the coefficient β_1 as the effect of the Safe Neighborhood program on residents' mental health.

We also explore the dynamic effects of the Safe Neighborhood program on mental health using an event study. In particular, we estimate the following equation:

$$MH_{int} = \beta_0 + \gamma_{-3} SN_{nt,\tau-3} + \gamma_{-2} SN_{nt,\tau-2} + \gamma SN_{nt,\tau} + \gamma_1 SN_{nt,\tau+1} + \beta_1 C_{int} + \beta_2 D_n + \beta_3 D_t + \varepsilon_{int} \tag{2}$$

where τ denotes the year in which an individual starts to be exposed to the program. The coefficients are measured relative to the omitted category $\tau - 1$, and therefore $SN_{nt,\tau-3}$, $SN_{nt,\tau-2}$ are indicators for three or more periods and two periods before the adoption of the program in neighborhood n. Similarly, $SN_{nt,\tau}$ and $SN_{nt,\tau+1}$ are binary variables indicating the year-of-implementation and at least one period after the adoption of the program. Again, we cluster standard errors at the neighborhood level.

While our main specification relies on a standard TWFE estimator, recent literature has highlighted that TWFE estimates may be biased in the occurrence of heterogeneous treatment effects due to the presence of negative weights (Roth et al., 2023). To address these concerns, we also implement alternative estimators proposed by Sun and Abraham (2021), Callaway and Sant'Anna (2021) and Borusyak et al. (2024), all of them robust to the presence of heterogeneous treatment effects.

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, as close residential areas may be only marginally affected by the positive externalities of additional police patrolling.

5 Results

5.1 Baseline results

A growing body of literature examines the impact of crime victimization on mental health outcomes. In contrast, our contribution focuses on evaluating the effect of a public safety intervention on the mental health of residents in the affected neighborhoods. We begin by estimating the impact of the Safe Neighborhood program on the incidence of mental health problems, first using comprehensive indices and then considering nine specific mental health symptoms.

Table 2 shows the effects of the Safe Neighborhood program on mental health indices. Findings are consistent across columns and indicate that the Safe Neighborhood Program reduces the probability of suffering from mental health problems. The magnitude of the effect is 5-6 percentage points, representing a decrease of between 50% and 81%. Table A.1 in the Appendix presents the results for the continuous variables from which we constructed the discrete measures of mental health problems. These findings are consistent with those in Table 2, although significance levels are lower.

Table 2: The Impact of Safe Neighborhood Program on Mental Health Indices

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.059***	-0.062***	-0.053**	-0.055**
	(0.016)	(0.019)	(0.023)	(0.022)
Dep. Var. Mean	0.072	0.093	0.106	0.107
Observations	3758	3758	3757	3757
R^2	0.04	0.04	0.04	0.04
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

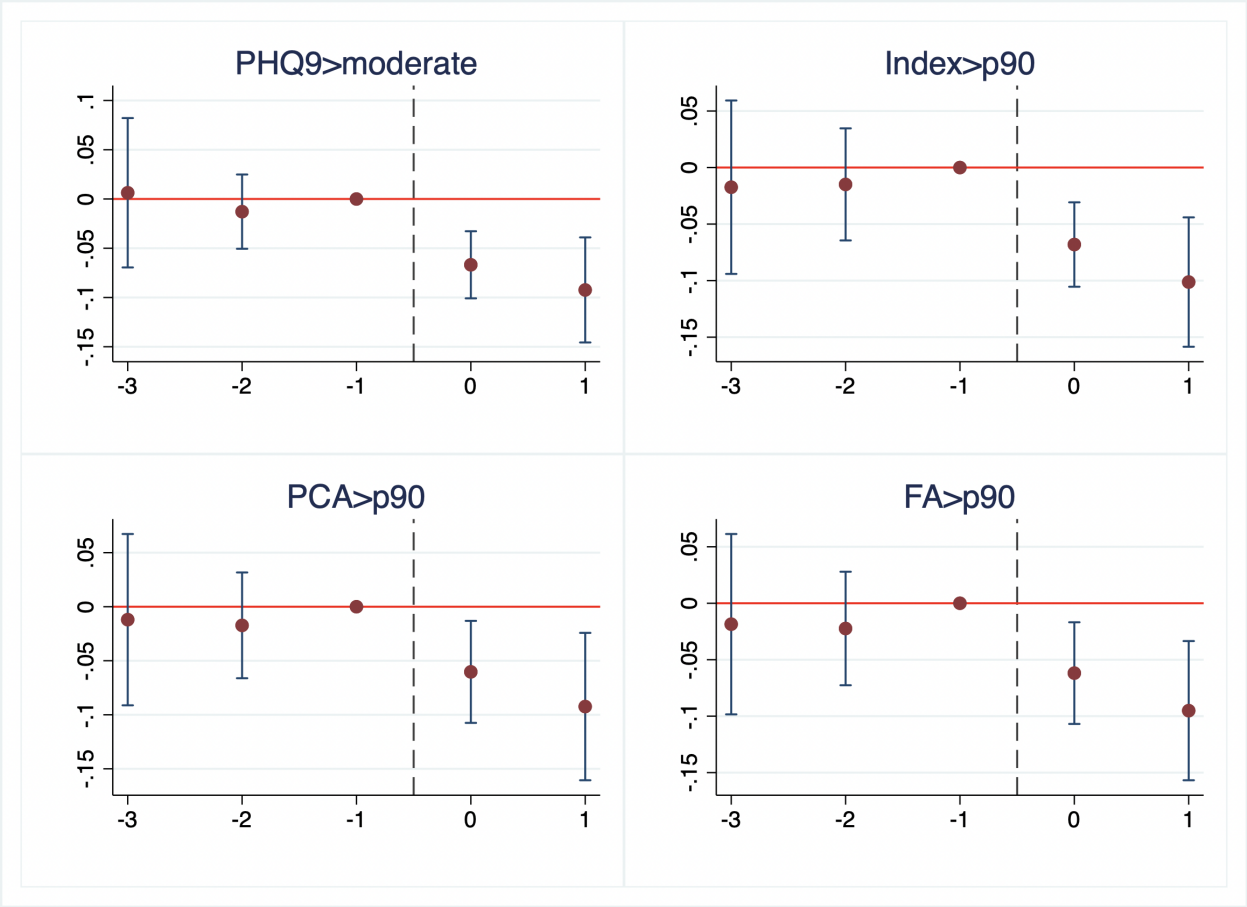
The magnitude of our estimated effect is large. Since our empirical strategy identifies a treatment effect for the subpopulation affected by the timing of the program's rollout, the estimated coefficients primarily capture the impact on individuals whose exposure to crime risk or perception of insecurity changed as a direct consequence of the program. These individuals plausibly faced higher-than-average risks of mental health problems prior to the intervention. Consequently, our estimates should be interpreted as reflecting the response of high-risk individuals whose mental well-being was particularly sensitive to changes in public safety.

We shed additional light on the impact of the Safe Neighborhood program on mental health by estimating how the effect is distributed across time through an event study. In Figure 5, the pre-treatment estimates show no significant differences in mental health prior to the program's implementation. The post-treatment estimates reveal a negative effect that grows over time. Unfortunately, we cannot present estimates beyond two periods due to the small number of observations affected by the program for more than two years.

To address concerns about potential biases in the standard TWFE and event study strategies, we complement our baseline results with alternative estimators proposed by Sun and Abraham (2021), Callaway and Sant'Anna (2021), and Borusyak et al. (2024). The results from these methods are consistent with our main specifications, suggesting that potential biases due to treatment effect heterogeneity are not consequential in our context. Figures A.1, A.2, and A.3 in the Appendix show the event study plots for each of the dynamic approaches mentioned, and the pattern is the same: no pre-trends and negative, growing effects after the implementation of the policy.

Table 3 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 more than half-days in the last two weeks. We find negative, sizable, and significant effects on the prevalence of sleep problems (column 3), the likelihood of being tired or having little energy (column 4), on the incidence of having trouble 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 3-4 percentage points, equivalent to a decrease between 52% to 66%. The corresponding event study in Figure 6 is consistent with the estimated coeffficents in Table 3.

Figure 5: Event Study - Impact of the Safe Neighborhood Program on Mental Health Indices



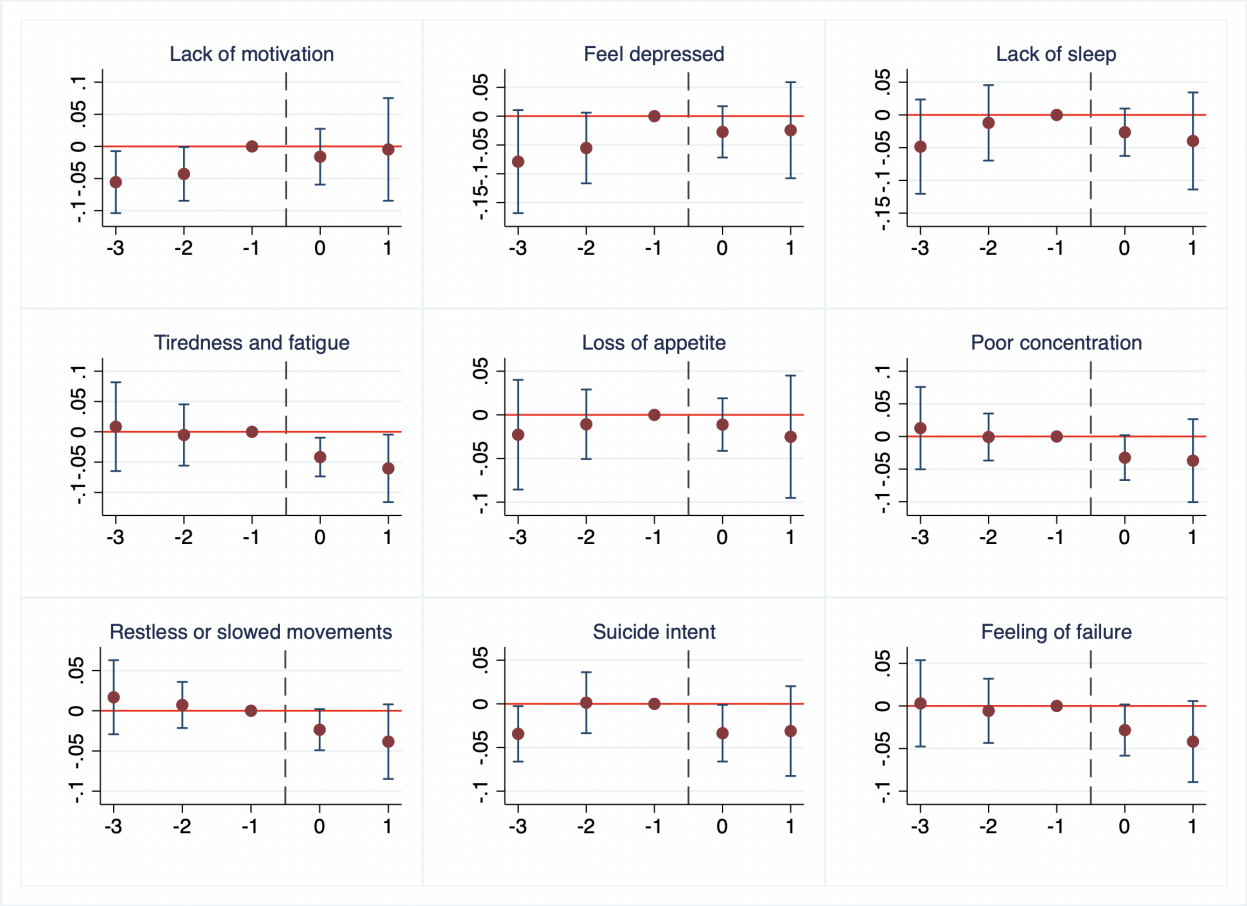
Notes: These graphs plot the coefficient obtained from Eq. (2). Each dot represents the estimated coefficients, and the vertical segment shows the estimated 95% confidence interval. The survey year $t-1$ is the reference period. Covariates include sex, age, level of education, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 Peruvian DHS.

Table 3: The Impact of Safe Neighborhood Program on Mental Health Symptoms

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.021	-0.032	-0.030*	-0.036**	-0.010	-0.029*	-0.019	-0.040**	-0.024*
	(0.020)	(0.022)	(0.017)	(0.017)	(0.016)	(0.015)	(0.012)	(0.017)	(0.014)
Dep. Var. Mean	0.088	0.101	0.100	0.068	0.062	0.045	0.048	0.074	0.036
Observations	3758	3758	3758	3758	3758	3757	3758	3758	3758
R^2	0.03	0.05	0.03	0.04	0.03	0.02	0.02	0.06	0.02
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure 6: Event Study - Impact of Safe Neighborhood Program 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, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 Peruvian DHS.

5.2 Potential Mechanisms

In this section, we provide evidence on the mechanisms behind the reduction in mental health problems. The program could potentially influence mental health either by reducing actual victimization or by improving perceptions of safety. We explore this mechanism by assessing the program's impact on crime rates and citizens' perceptions of security. The results in Tables 4 and 5 show that the Safe Neighborhood program significantly reduces non-property crime within the district and even within the neighborhood, both by 1.4 percentage points. However, there are no detectable effects on other types of crime. This limited impact suggests that changes in crime victimization alone may not be suffi-

cient to generate meaningful improvements in mental health.

Table 4: The Impact of Safe Neighborhood Program on Victimization within Districts

	(1) Vict. District	(2) Vict. Dist. Property	(3) Vict. Dist. Non-Property
Safe Neighborhood	-0.016	-0.002	-0.014*
	(0.021)	(0.020)	(0.008)
Dep. Var. Mean	0.266	0.228	0.038
Observations	15112	15112	15112
R^2	0.03	0.03	0.01
Covariates	Yes	Yes	Yes
FE	Yes	Yes	Yes

Notes: The data come from the 2013-2019 ENAPRES. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: The Impact of Safe Neighborhood Program on Victimization within Neighborhoods

	(1) Vict. Neighborhood	(2) Vict. Neigh. Property	(3) Vict. Neigh. Non-Property
Safe Neighborhood	-0.026	-0.012	-0.014*
	(0.019)	(0.017)	(0.008)
Dep. Var. Mean	0.174	0.144	0.030
Observations	13811	13811	13811
R^2	0.02	0.02	0.01
Covariates	Yes	Yes	Yes
FE	Yes	Yes	Yes

Notes: The data come from the 2013-2019 ENAPRES. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

In line with the perception of safety mechanism, the results in Table 6 show that the Safe Neighborhood program leads to a significant increase of 4.3 percentage points in perceived patrolling by the national police, the law enforcement body whose patrol activity was directly intensified by the program. The event study plots in Figure A.4 show the

absence of pre-trends for non-property victimization and perception-of-police-patrolling mechanisms.

Table 6: The Impact of Safe Neighborhood Program on Perceived Crime

	(1) Fear to Walk	(2) Presence National Police	(3) Presence Local Police
Safe Neighborhood	-0.000	0.043*	0.007
	(0.023)	(0.026)	(0.028)
Dep. Var. Mean	0.623	0.250	0.348
Observations	15111	15111	15111
R^2	0.05	0.10	0.12
Covariates	Yes	Yes	Yes
FE	Yes	Yes	Yes

Notes: The data come from the 2013-2019 ENAPRES. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Another potential explanation behind the decrease in mental health problems 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. The results in Table 7 shows that the Safe Neighborhood program increased healthcare utilization by 5 percentage points. Private healthcare could drive the effect as we find no effect on public healthcare. The event study plots in Figure A.5 show no anticipatory response in the healthcare utilization measure. Hence, an increase in healthcare utilization is an additional potential mechanism behind the estimated positive impact of crime prevention on mental health.

Table 7: The Impact of Safe Neighborhood Program on Healthcare Utilization

	(1) Healthcare Utilization	(2) Public Healthcare Util.
Safe Neighborhood	0.050***	-0.001
	(0.018)	(0.010)
Dep. Var. Mean	0.332	0.129
Observations	18025	18025
R^2	0.03	0.04
Covariates	Yes	Yes
FE	Yes	Yes

Notes: The data come from the 2013-2019 ENAHO. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The Peruvian health system leaves a significant part of the population uncovered because many 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 8 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 crime prevention on mental health.

Table 8: The Impact of Safe Neighborhood Program on Mental Health by Health Insurance Coverage

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Sample A: No Insurance Coverage				
Safe Neighborhood	-0.021	-0.028	-0.016	-0.021
	(0.021)	(0.026)	(0.029)	(0.030)
Dep. Var. Mean	0.057	0.076	0.092	0.092
Observations	1100	1100	1100	1100
R^2	0.09	0.10	0.10	0.10
Sample B: Insurance Coverage				
Safe Neighborhood	-0.079***	-0.079***	-0.073***	-0.072***
	(0.018)	(0.022)	(0.027)	(0.027)
Dep. Var. Mean	0.079	0.100	0.112	0.113
Observations	2657	2657	2656	2656
R^2	0.05	0.04	0.05	0.05
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Finally, given the increased perception of safety in targeted areas, it is plausible that residents are more inclined to engage in economic activities outside the home, which in turn may contribute to improved labor market outcomes. We explore this potential mechanism by assessing the impact of the program on labor market outcomes. The results in Table 9 show that the Safe Neighborhood program increases labor force participation by 3.3 percentage points and, for those who are employed, shifts the composition of jobs, promoting employment outside the primary sector (i.e., agriculture, fishing, and mining) by 1.9 percentage points. The event study plots in Figure A.6 also show no pre-trends in labor force participation and primary sector jobs measures. These findings suggest that improvements in labor market conditions are potential mechanisms behind the observed improvements in residents' mental health.

Table 9: The Impact of Safe Neighborhood Program on Labor Market Outcomes

	(1) Employment	(2) Informality	(3) Primary Sector	(4) Log-wages
Safe Neighborhood	0.033**	-0.006	-0.019**	-0.022
	(0.015)	(0.022)	(0.008)	(0.039)
Dep. Var. Mean	0.741	0.612	0.050	6.927
Observations	11782	8799	8799	8426
R^2	0.09	0.18	0.14	0.22
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 ENAHO. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. According to the Peruvian National Statistics Office, informal employment refers to workers who meet at least one of the following conditions: (i) Employers and self-employed workers whose firm belongs to the informal sector; (ii) Workers without social security covered by the firms; (iii) Unpaid family workers (INEI, 2022). According to the ISIC Revision 4, employment in the primary sector includes individuals who work in agriculture, fishing or mining.

We conclude that the relatively large magnitude of the estimated effect of Safe Neighborhood program on mental health reflects the presence of multiple, mutually reinforcing mechanisms through which the program operated. In addition to reducing non-property crime, the program improved several aspects of well-being that are closely tied to mental health. First, residents reported a 4.3 percentage point increase in perceived police presence, suggesting a substantial improvement in feelings of safety. Second, healthcare utilization rose by 5 percentage points, indicating that individuals may have felt more secure accessing medical services and more willing to invest in their health. Third, labor market outcomes improved, with employment increasing by 3.3 percentage points and the share of workers in primary-sector jobs declining by 1.9 percentage points. These concurrent improvements in perceived security, access to healthcare, and economic conditions likely reinforced one another, amplifying the program's overall impact on mental health.

6 Robustness Checks and Heterogeneity Analysis

In this section, we first test the robustness of our results and then provide evidence of heterogeneous effects. Our first robustness check consists of using 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 year before and after the introduction of the Safe Neighborhood program. Results in Table A.2 align with those in the baseline estimation in terms of sign and magnitude, but are less precise for the Principal Component and Factor Analysis outcomes. Regarding the symptoms, Table A.3 shows that the signs are preserved when adding neighborhood-by-year fixed effects, but only the suicide intention symptom is statistically significant.

We also extend our analysis by defining the treated clusters of households as those residing in the affected neighborhoods and within 500 meters of the border of the targeted neighborhoods. As a result of this exercise, the estimated effects become smaller in magnitude (less than half of the original size) but remain sizable and statistically significant. Table A.4 shows that the Safe Neighborhood Program reduces mental health problems in the extended areas (within 500 meters) by 2-3 percentage points, and Table A.5 shows that the Safe Neighborhood program improves symptoms such as depression, sleep problems, concentration difficulties, movement problems, and feelings of failure even up to 500 meters beyond the boundaries of program implementation.

The Peruvian mental healthcare system expanded considerably during the period under analysis (Marquez & Bayona Garcia, 2019; Toyama et al., 2017). The mental health reform, approved in 2012, introduced multiple changes to the delivery of care, including the establishment of new services at the primary and secondary care levels (i.e., within health facilities with improved infrastructure) and the implementation of supporting services to facilitate patient recovery and reintegration into society. We first investigated whether the creation of new community mental health centers (CSMCs) was correlated with the timing of the Safe Neighborhood Program, but found no such correlation (see

Table A.6 in the Appendix). This lack of association is expected, as the two programs follow different implementation criteria: while Safe Neighborhood targets areas based on crime criteria, CSMC placement is determined by the availability of health infrastructure.

We replicated our baseline estimates by including a district-level dummy for exposure to CSMCs and its interaction with the Safe Neighborhood program as covariates. Table 10 shows that our coefficient of interest remains unchanged, while both the CSMC coefficient and the interaction term are statistically insignificant. These results indicate that the contemporaneous mental health policy does not confound our estimates, supporting the validity of our research design.

Table 10: The Impact of Safe Neighborhood Interacted with Mental Healthcare Centers on Mental Health

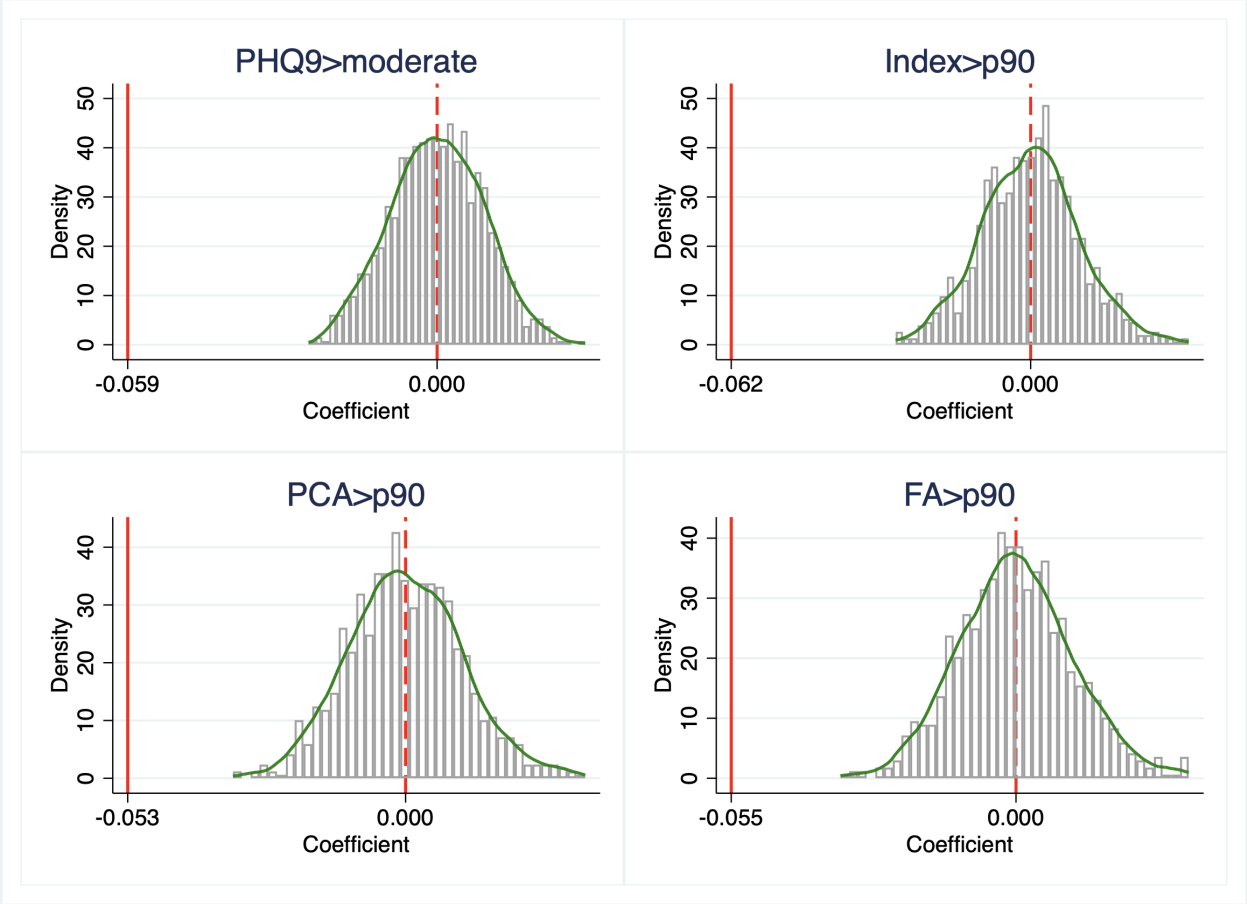
	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.059***	-0.058***	-0.049**	-0.049**
	(0.017)	(0.019)	(0.023)	(0.023)
CSMC	-0.007	0.018	0.032	0.033
	(0.027)	(0.027)	(0.027)	(0.027)
SN × CSMC	-0.001	-0.033	-0.052	-0.051
	(0.028)	(0.031)	(0.032)	(0.032)
Dep. Var. Mean	0.072	0.092	0.105	0.106
Observations	3724	3724	3723	3723
R^2	0.04	0.03	0.04	0.04
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

We also conduct a randomization test. We randomly reassign the treatment status 1000 times, preserving the sample structure, and re-estimate the baseline specification using these placebo assignments. Figure 7 shows the distribution of estimated treatment effects under random assignment. The actual coefficients from the true data lie at the far

tail of these distributions, indicating that the likelihood of obtaining our results by chance is extremely low. This reinforces the causal interpretation of our findings.

Figure 7: Randomization test



Notes: We randomly assigned exposure to the Safe Neighborhood program. The graphs show the distribution of coefficients obtained by estimating the baseline specification 1000 times for each mental health outcome using the random reassignments. The solid red line represents the true effect, while the dashed red line indicates the average value of the simulated coefficients. The data come from the 2013-2019 Peruvian DHS.

Our final robustness check consists of re-estimating the baseline specification using the set of covariates as outcome variables (placebo test). Table A.7 in the Appendix shows that the crime prevention program does not affect any of the pre-determined characteristics. These results suggest that the composition of neighborhoods does not change as a result of the program.

We explore heterogeneous effects of the Safe Neighborhood Program across different

population groups. First, the impact on mental health is concentrated among individuals living in small cities or towns, likely reflecting a shift from minimal to substantial police presence in these areas (see Table A.8 in the Appendix). Second, household heads experience larger reductions in mental health problems than other members, consistent with their greater concern for household safety and consequent stress reduction (see Table A.9 in the Appendix). Third, less-wealthy individuals benefit more from the program, as they are more likely to be victims of crime; splitting the sample by wealth index confirms that households in the lower terciles experience larger mental health gains compared to wealthier households (see Table A.10 in the Appendix). These findings highlight that the mental health improvements induced by the program are particularly pronounced among the most vulnerable groups.

7 Conclusion

We study the impact of Safe Neighborhood, a public safety program that mainly consists of increased police patrolling in targeted neighborhoods, on residents' mental health. The selected neighborhoods had the highest crime rates in Peru, but the program's staggered rollout between 2016 and 2019 was plausibly exogenous with respect to mental health outcomes. We exploit this feature to estimate the effect of the program on mental health by comparing the mental health of residents in already-treated neighborhoods to those in not-yet-treated neighborhoods.

We use individual-level data from the Peruvian Demographic and Health Survey, which provides extensive information on mental health and allows us to geolocate households precisely. Our sample includes 3,858 individuals across 56 neighborhoods, for whom we also observe a wide range of individual and household characteristics.

Our results show that the Safe Neighborhood program reduced the incidence of mental health problems by 5-6 percentage points, depending on the mental health measure used. The largest reductions, ranging from 3 to 4 percentage points, are observed for

symptoms such as tiredness, concentration difficulties, suicidal intentions, and feelings of failure. These results are robust to a wide set of robustness checks, including alternative estimation methods specifically designed for staggered program implementations (Sun & Abraham, 2021; Callaway & Sant'Anna, 2021; Borusyak et al., 2024).

Potential mechanisms for these effects include changes in crime victimization, perceptions of safety, healthcare utilization, and labor market conditions. Following the implementation of the program, we document a small decrease in non-property crimes at both the district and neighborhood levels, an increase in perceived national police patrolling, higher labor force participation, and greater healthcare utilization, effects that are particularly pronounced among individuals covered by public or private health insurance.

Our estimated effects of the public safety intervention on mental health are strongest in small cities and towns, where the initially low levels of police patrolling may have made the subsequent increase more salient. The mental health of household heads experienced the most notable improvement, consistent with their greater concern for household safety. Finally, the program proved particularly beneficial for less-wealthy individuals, who are more likely to be victims of crime.

Overall, our results suggest that policymakers in developing countries with widespread crime victimization should take into account the improvements in mental health generated by public safety programs when assessing the allocation of public resources. In this context, mental health provides an additional rationale for investing more in crime prevention, particularly in settings where citizens frequently report 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

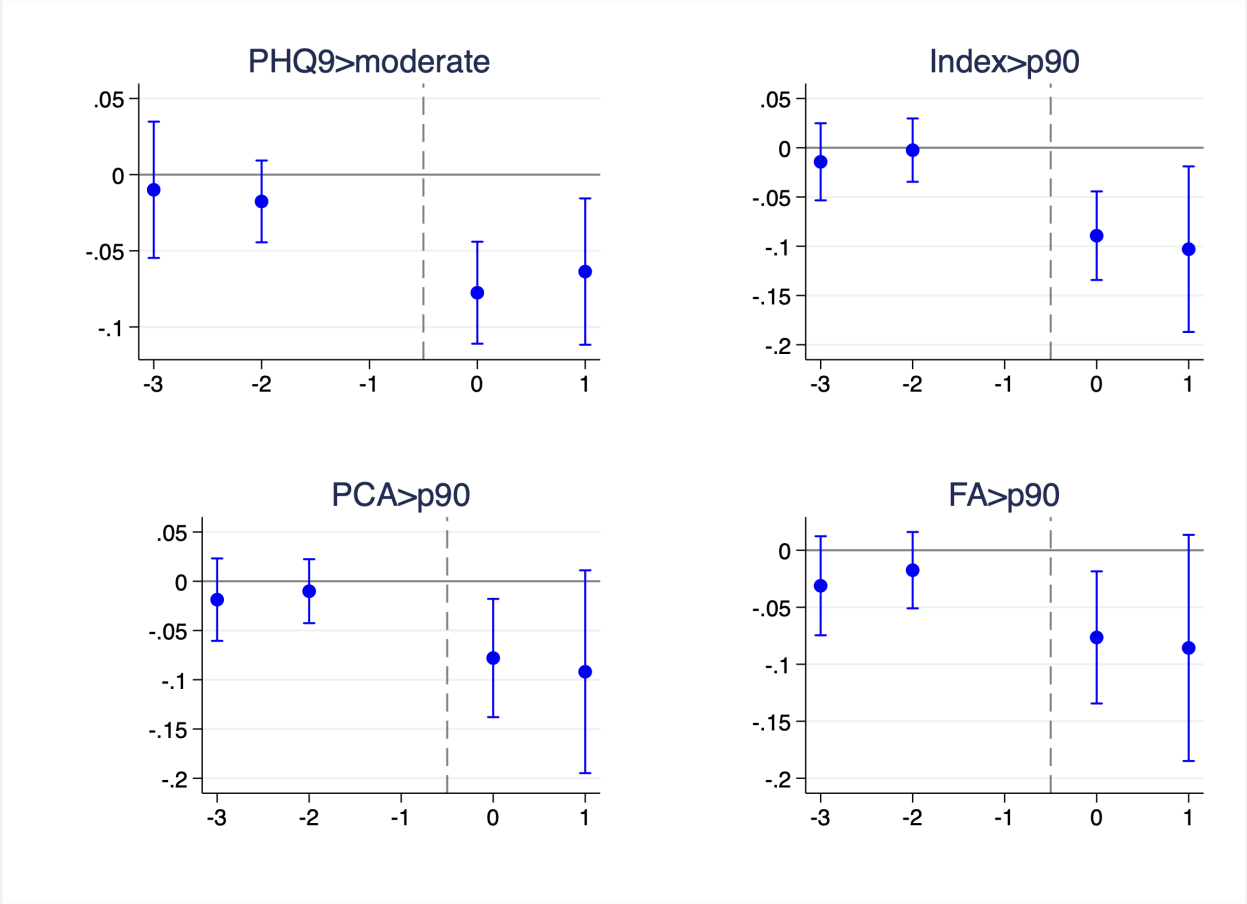
A.2 Tables and Figures

Table A.1: The Impact of Safe Neighborhood Program on Mental Health - Continuous Indices

	(1) Symptoms (1-9)	(2) Depression Disorder	(3) Index-27	(4) PCA	(5) FA
Safe Neighborhood	-0.241**	-0.024	-0.458	-0.256*	-0.112
	(0.092)	(0.015)	(0.291)	(0.152)	(0.069)
Dep. Var. Mean	0.621	0.040	2.697	0.037	0.016
Observations	3758	3758	3758	3757	3757
R^2	0.05	0.03	0.07	0.07	0.07
Covariates	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes

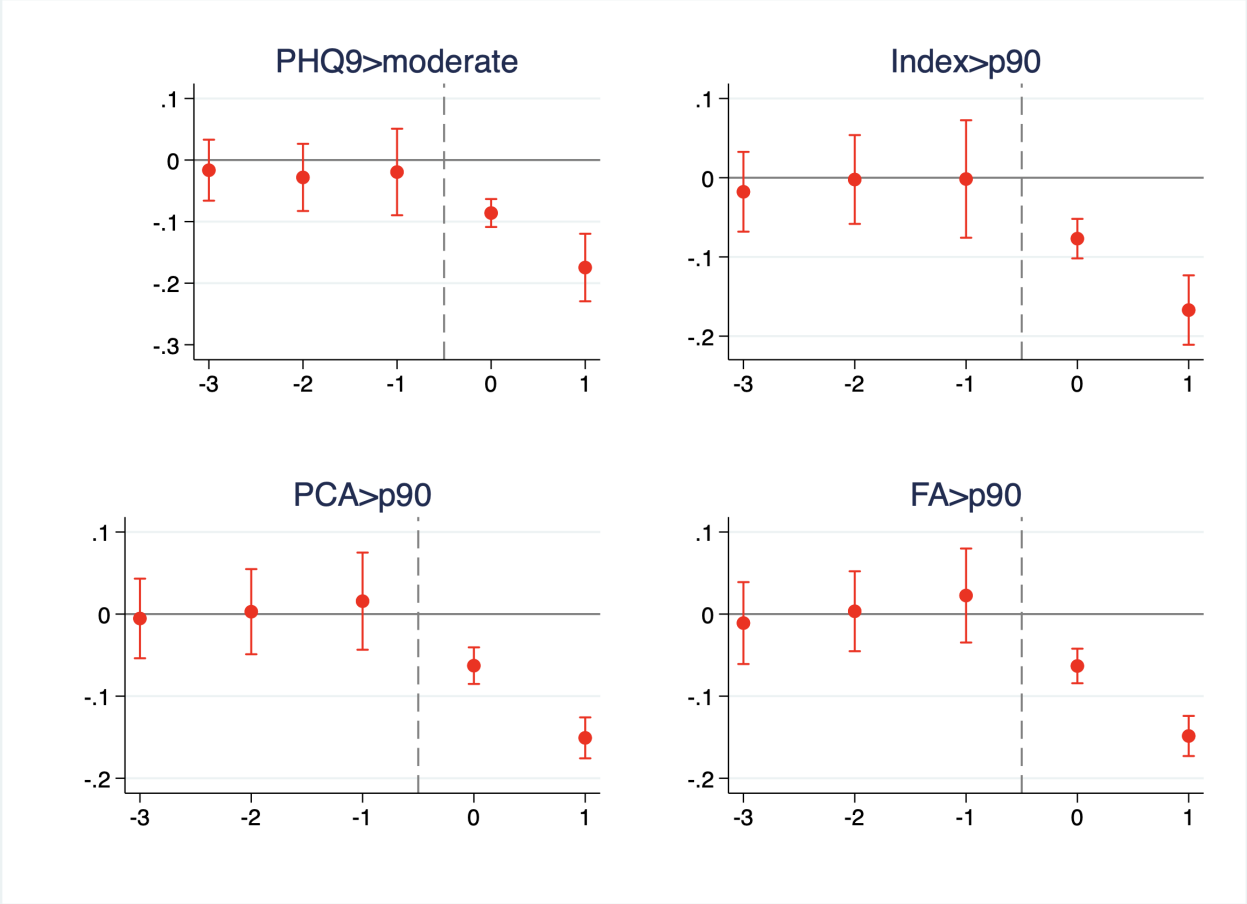
Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure A.1: Event Study - Sun and Abraham (2021) Approach



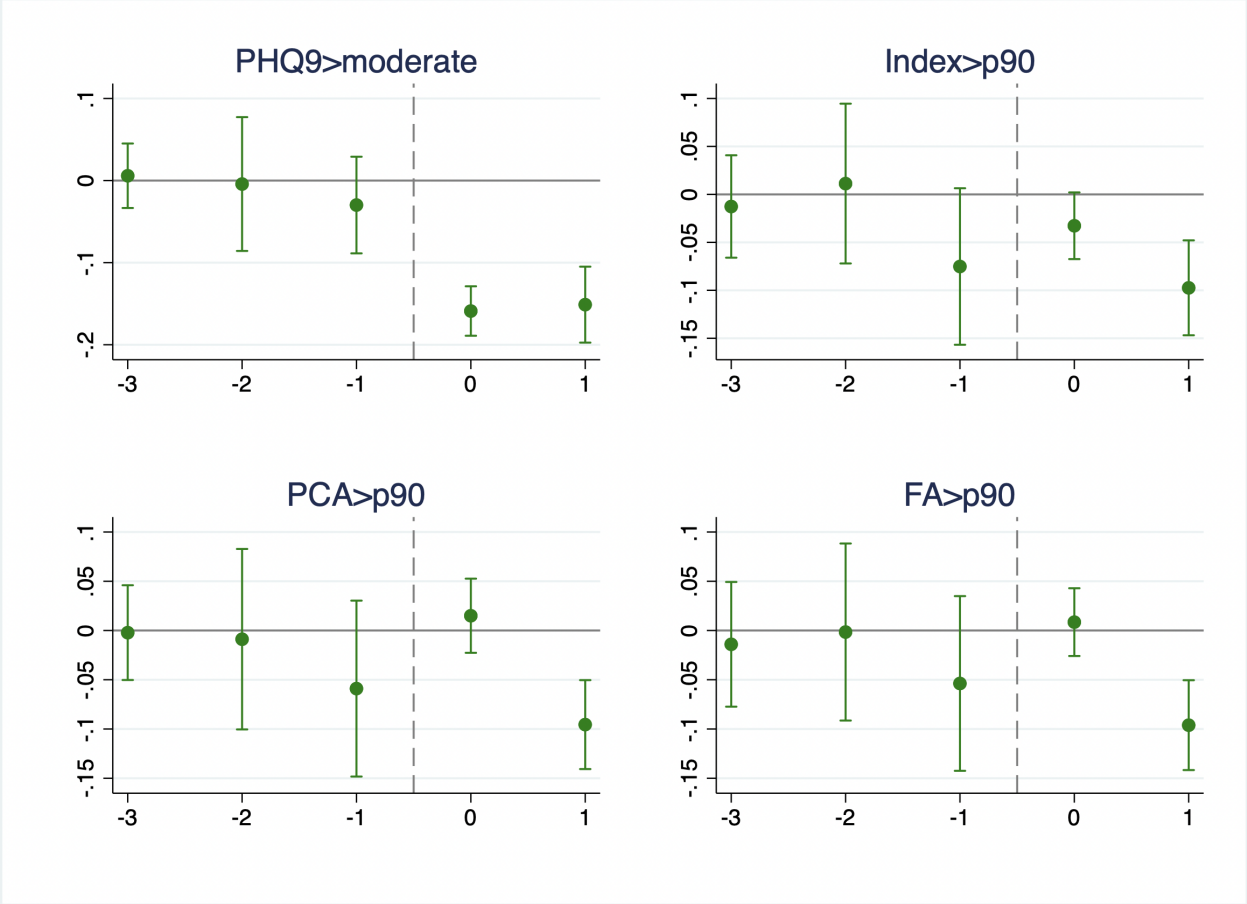
Notes: These graphs plot an event-study specification based on Sun and Abraham (2021). Each dot represents an estimated coefficient, and the vertical segment shows the corresponding 95% confidence interval. Covariates include sex, age, level of education, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. This approach requires a never-treated group, so we use neighborhoods where the program was implemented after July 2019 as the never-treated units. The data come from the 2013-2019 Peruvian DHS.

Figure A.2: Event Study - Borusyak et al. (2024) Approach



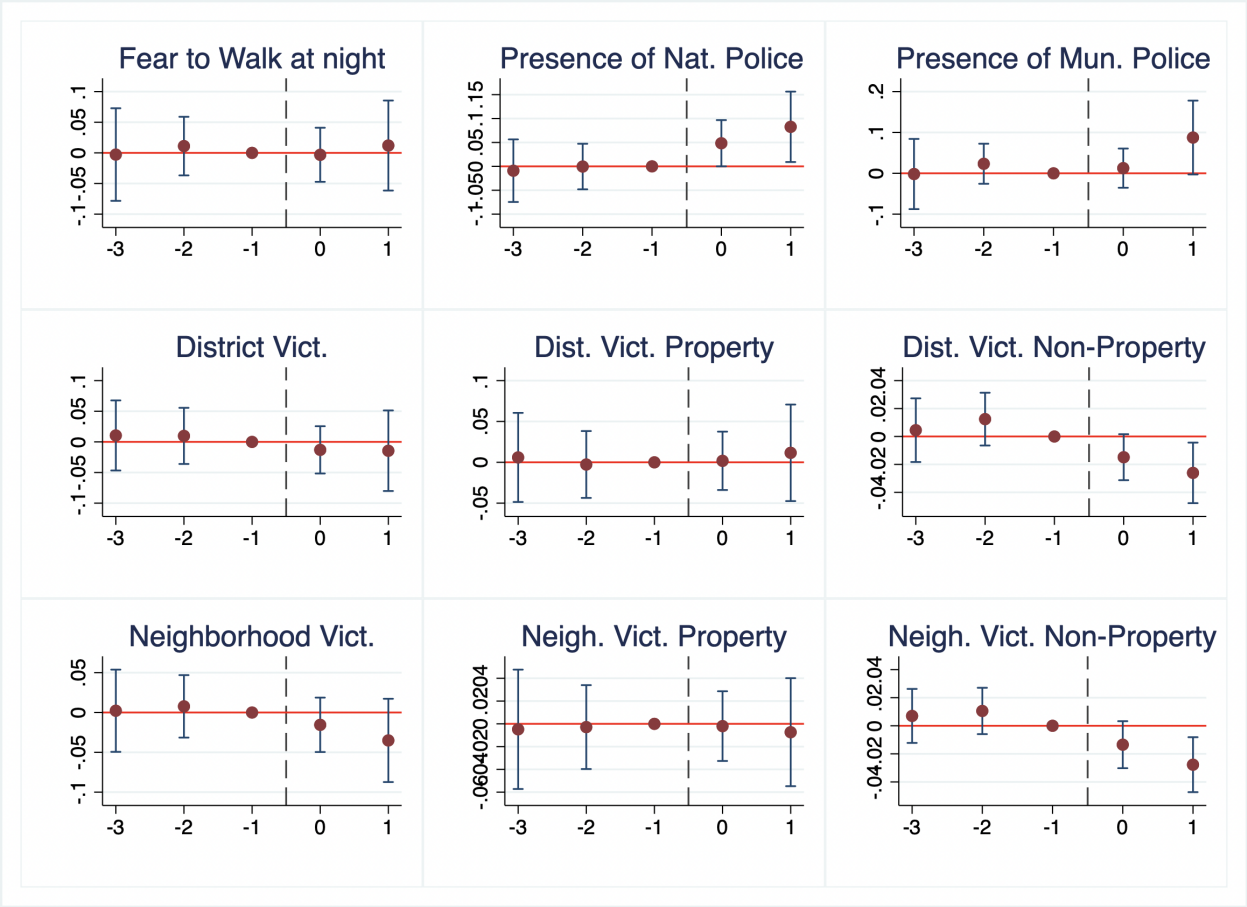
Notes: These graphs plot an event-study specification based on Borusyak et al. (2024). Each dot represents an estimated coefficient, and the vertical segment shows the corresponding 95% confidence interval. Covariates include sex, age, level of education, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. This approach requires a never-treated group, so we use neighborhoods where the program was implemented after July 2019 as the never-treated units. The data come from the 2013-2019 Peruvian DHS.

Figure A.3: Event Study - Callaway and Sant'Anna (2021) Approach



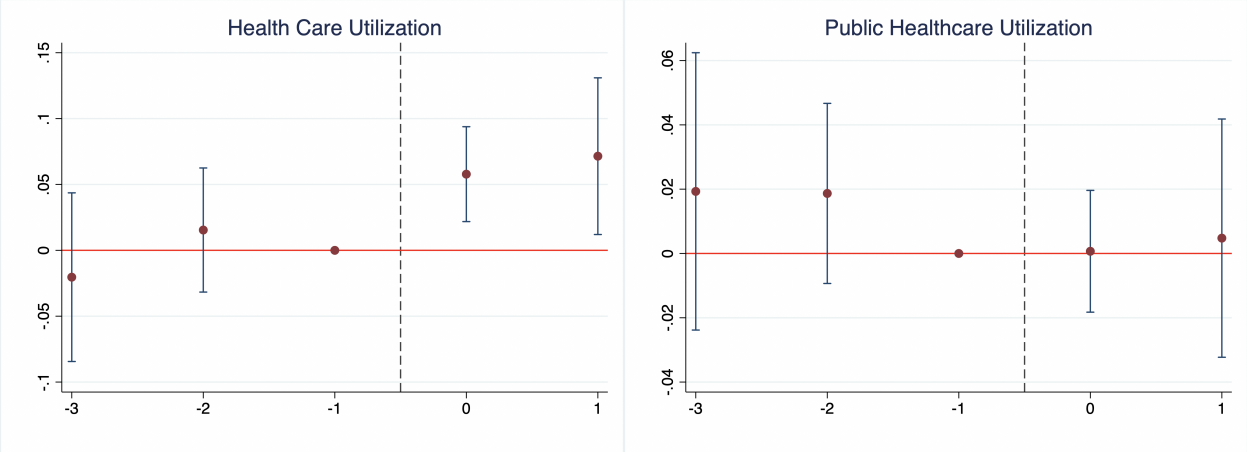
Notes: These graphs plot an event-study specification based on Callaway and Sant'Anna (2021). Each dot represents an estimated coefficient, and the vertical segment shows the corresponding 95% confidence interval. Covariates include sex, age, level of education, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. To compare with the other dynamic methods, we use neighborhoods where the program was implemented after July 2019 as the never-treated units. The data come from the 2013-2019 Peruvian DHS.

Figure A.4: Event Study - Impact of Safe Neighborhood Program on Perceived Crime and Victimization



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, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 ENAPRES.

Figure A.5: Event Study - Impact of Safe Neighborhood Program on Healthcare Utilization



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, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 ENAHO.

Figure A.6: Event Study - Impact of Safe Neighborhood Program on Labor Market Outcomes



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, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 ENAHO.

Table A.2: The Impact of Safe Neighborhood Program on Mental Health - Neighborhood-by-year FE

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.061**	-0.093**	-0.058	-0.058
	(0.029)	(0.042)	(0.077)	(0.077)
Dep. Var. Mean	0.072	0.093	0.106	0.107
Observations	3758	3758	3757	3757
R^2	0.06	0.06	0.06	0.05
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, and neighborhood-by-year fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.3: The Impact of Safe Neighborhood Program on Mental Health Symptoms - Neighborhood-by-year FE

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.026	0.002	-0.017	-0.015	-0.008	-0.004	-0.005	-0.046*	-0.022
	(0.043)	(0.066)	(0.042)	(0.038)	(0.019)	(0.043)	(0.024)	(0.025)	(0.032)
Dep. Var. Mean	0.088	0.101	0.100	0.068	0.062	0.045	0.048	0.074	0.036
Observations	3758	3758	3758	3758	3758	3757	3758	3758	3758
R^2	0.06	0.07	0.05	0.06	0.05	0.04	0.04	0.08	0.05
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

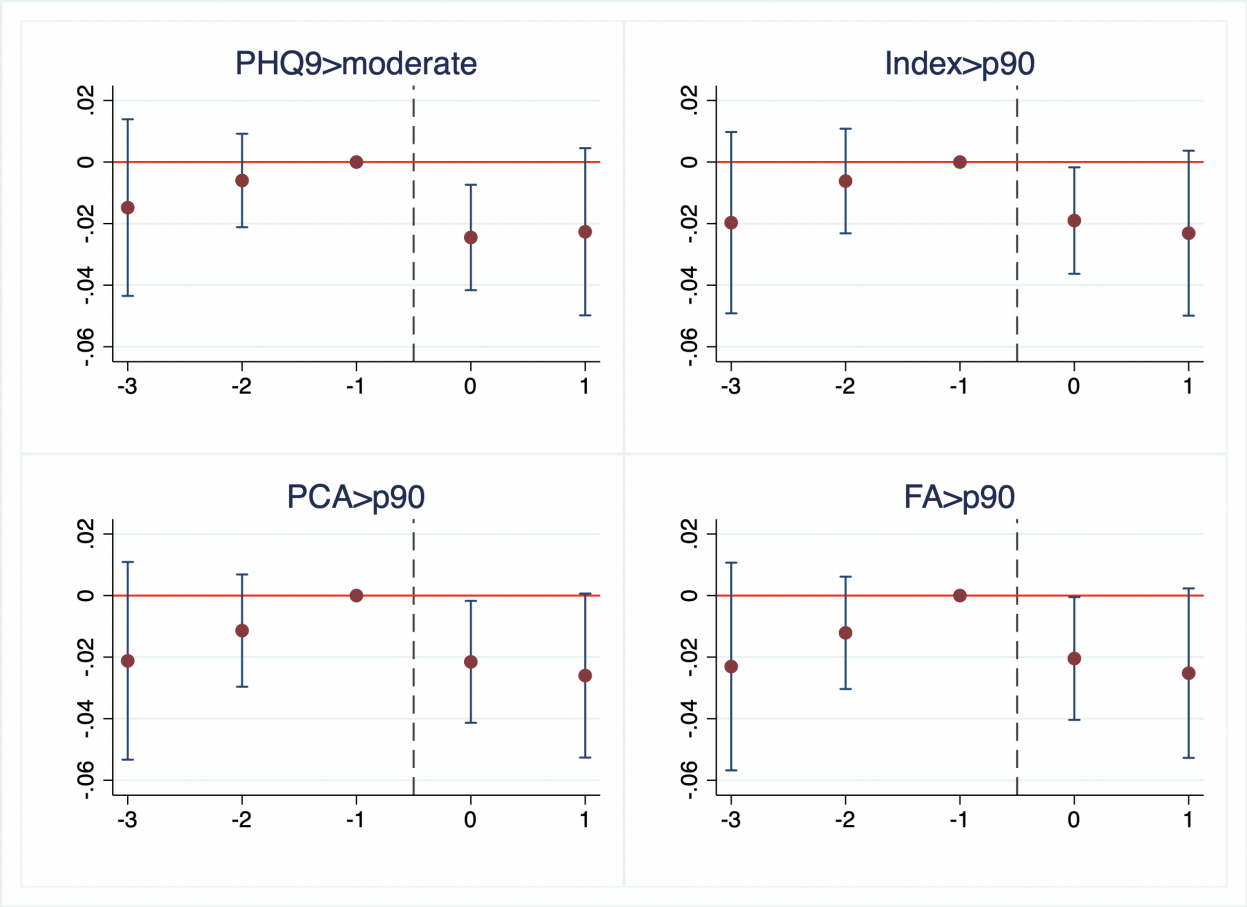
Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, and neighborhood-by-year fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.4: The Impact of Safe Neighborhood Program on Mental Health Indices (500m Buffer)

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Safe Neighborhood	-0.025***	-0.021**	-0.023**	-0.022**
	(0.009)	(0.009)	(0.010)	(0.010)
Dep. Var. Mean	0.068	0.086	0.103	0.103
Observations	15191	15191	15188	15188
R^2	0.03	0.03	0.03	0.04
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure A.7: Event Study - Impact of Safe Neighborhood Program on Mental Indices (500m Buffer)



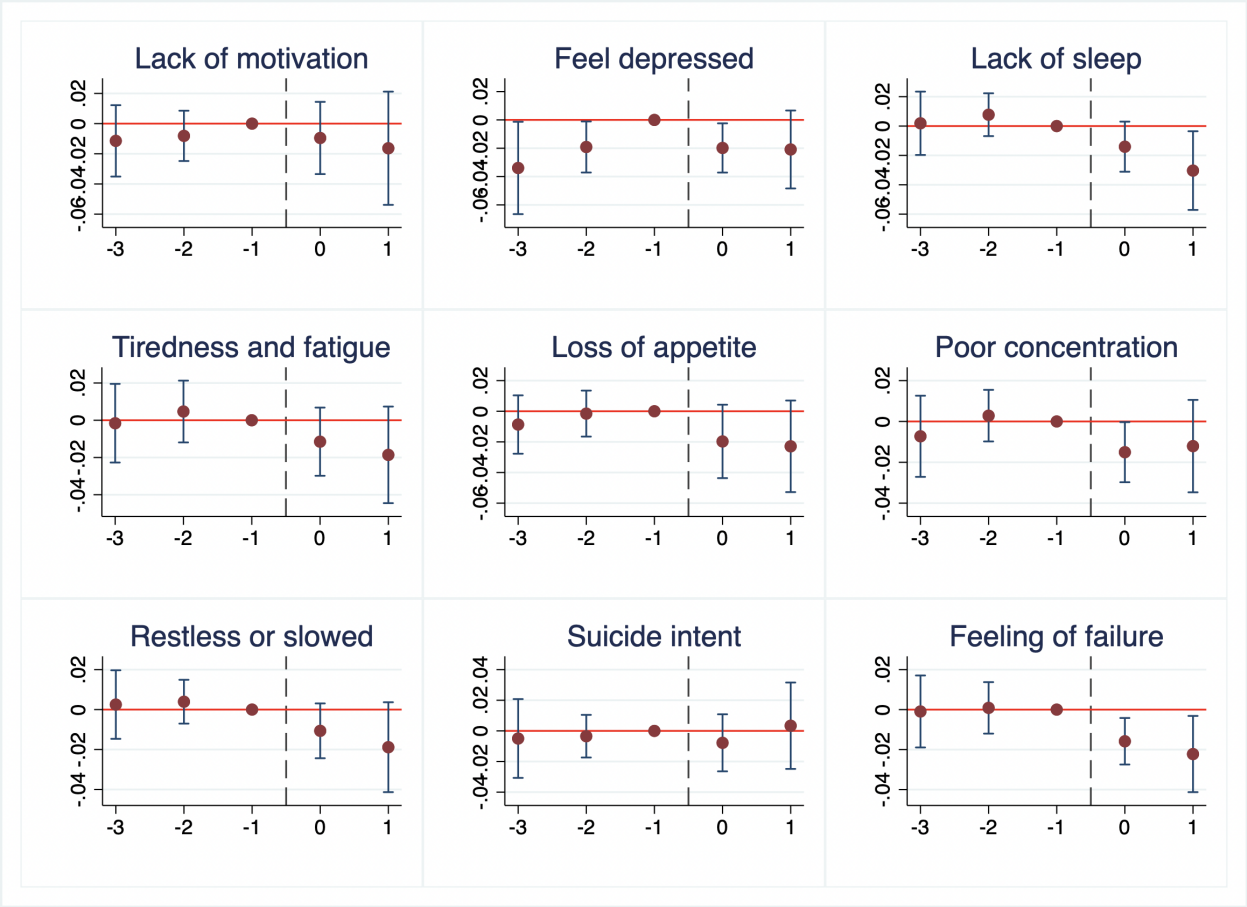
Notes: These graphs plot the coefficient obtained from Eq. (2). Each bar represents the estimated coefficients and the capped, vertical line shows the estimated 95% confidence interval. The survey-year $t-1$ is the reference period. Covariates include sex, age, level of education, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 Peruvian DHS.

Table A.5: The Impact of Safe Neighborhood Program on Mental Health Symptoms (500m Buffer)

	(1) Motivation	(2) Depression	(3) Sleep	(4) Tiredness	(5) Appetite	(6) Concentration	(7) Move	(8) Suicide	(9) Failure
Safe Neighborhood	-0.010	-0.021**	-0.016*	-0.013	-0.021*	-0.017**	-0.011*	-0.007	-0.016***
	(0.012)	(0.009)	(0.008)	(0.009)	(0.012)	(0.007)	(0.007)	(0.009)	(0.006)
Dep. Var. Mean	0.083	0.093	0.084	0.063	0.063	0.050	0.048	0.074	0.033
Observations	15191	15191	15190	15191	15190	15190	15191	15191	15191
R^2	0.02	0.04	0.02	0.02	0.02	0.02	0.02	0.04	0.01
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure A.8: Event Study - Impact of Safe Neighborhood Program on Mental Symptoms (500m 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, number of household members between 15 and 29, survey-year fixed effects, and neighborhood fixed effects. The standard errors are clustered at the neighborhood level. The data come from the 2013-2019 Peruvian DHS.

Table A.6: Association Between Implementation of CSMC and Safe Neighborhood

	(1) Implementation of CSMC
Safe Neighborhood	-0.066
	(0.086)
Male	-0.005
	(0.005)
Age	-0.000
	(0.000)
Primary	-0.001
	(0.016)
Secundary	-0.009
	(0.016)
Tertiary	-0.011
	(0.017)
Household members 15-29	-0.002
	(0.002)
Observations	3,724
R^2	0.55
FE	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. Covariates include survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: The Impact of Safe Neighborhood Program on Pre-determined Characteristics

	(1) Male	(2) Age	(3) Education	(4) Members 15-29
Safe Neighborhood	0.021	-0.519	-0.035	0.084
	(0.032)	(1.051)	(0.079)	(0.061)
Dep. Var. Mean	0.437	40.223	2.277	0.952
Observations	3758	3758	3758	3758
R^2	0.02	0.03	0.07	0.03
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.8: The Impact of Safe Neighborhood Program on Mental Health by Type of City

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Sample A: Small cities and towns				
Safe Neighborhood	-0.064***	-0.067***	-0.069***	-0.069***
	(0.020)	(0.023)	(0.022)	(0.021)
Dep. Var. Mean	0.082	0.103	0.116	0.116
Observations	2198	2198	2197	2197
R^2	0.04	0.04	0.04	0.04
Sample B: Capital cities				
Safe Neighborhood	-0.043	-0.049	-0.022	-0.024
	(0.031)	(0.038)	(0.059)	(0.058)
Dep. Var. Mean	0.061	0.081	0.095	0.095
Observations	1560	1560	1560	1560
R^2	0.04	0.04	0.04	0.04
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Capital cities are those with more than 1 million inhabitants, small cities are those with a population above 50,000 but below 1 million, and towns include the remaining urban areas.

Table A.9: The Impact of Safe Neighborhood Program on Mental Health by Household Head

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Sample A: Non Household Head				
Safe Neighborhood	-0.060*	-0.054	-0.004	-0.010
	(0.034)	(0.037)	(0.048)	(0.046)
Dep. Var. Mean	0.065	0.080	0.091	0.090
Observations	1126	1126	1126	1126
R^2	0.09	0.08	0.10	0.09
Sample B: Household head				
Safe Neighborhood	-0.059***	-0.067**	-0.074**	-0.073**
	(0.020)	(0.025)	(0.029)	(0.028)
Dep. Var. Mean	0.076	0.098	0.112	0.114
Observations	2632	2632	2631	2631
R^2	0.05	0.04	0.05	0.05
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.10: The Impact of Safe Neighborhood Program on Mental Health by Wealth Status

	(1) PHQ9>moderate	(2) Index>p90	(3) PCA>p90	(4) FA>p90
Sample A: Wealth index $\leq 3(poorest)$				
Safe Neighborhood	-0.071***	-0.067**	-0.075**	-0.072**
	(0.026)	(0.029)	(0.031)	(0.030)
Dep. Var. Mean	0.084	0.110	0.126	0.127
Observations	1550	1550	1549	1549
R^2	0.05	0.05	0.06	0.06
Sample B: Wealth index $\geq 4(richest)$				
Safe Neighborhood	-0.056***	-0.060**	-0.034	-0.037
	(0.020)	(0.025)	(0.032)	(0.032)
Dep. Var. Mean	0.065	0.082	0.094	0.094
Observations	2207	2207	2207	2207
R^2	0.06	0.06	0.06	0.06
Covariates	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes

Notes: The data come from the 2013-2019 Peruvian DHS. The dependent variable mean corresponds to the average value for non-exposed individuals ($SN = 0$). Covariates include sex, age, level of education, number of household members aged 15-29, survey-year fixed effects, and neighborhood fixed effects. Standard errors are clustered at the neighborhood level and shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.