The Effects of Urban Violence on Primary Health Care Services: Evidence from Poor Neighborhoods in Rio de Janeiro

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Abstract

We use monthly clinic-level panel data from 204 clinics in Rio de Janeiro between January 2009 and December 2016 to study the effects of violent events on healthcare access, utilization, and quality. Exploiting the proximity of clinics to geocoded episodes of violence related to police operations and drug gang battles, we find that exposure to violence leads to a significant reduction in healthcare utilization. Specifically, each additional police-related shooting is associated with a 12.3% reduction in primary care procedures, primarily driven by decreased access on the day of the event. These effects are more pronounced in neighborhoods with lower average income and socioeconomic status. We provide evidence that while violent events reduce healthcare utilization, they do not significantly impact quality indicators such as employee turnover or hospitalization. Thus, urban violence not only hampers access to health services but also exacerbates inequality in healthcare utilization in affected neighborhoods.

Keywords: urban violence, primary care, health services, utilization, access, quality

JEL codes: R10, D74, I11, I12, I14

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1 Introduction

Violence is often present in favelas[1] where one-third of the world's urban population (one billion people) live (Mc Evoy and Hideg, 2017). The underlying factors associated with rapid urbanization, including inequalities, deprivation, poor public services, irregular and informal housing, and spatial and socioeconomic segregation, are important drivers of violence (Moser and McIlwaine, 2006). Organized crime and drug gangs are additional major contributors, with roughly half of all homicides in the Americas related to organized crime (United Nations Office on Drugs and Crime (UNODC), 2023). These criminal groups often display territorial control and exert criminal governance in poor neighborhoods (Blattman et al., 2024). Moreover, police operations targeting criminal activities often take place in these areas of high violence, increasing the likelihood of shootings and the disruption of citizens' lives.

Urban violence can strain health systems in multiple ways. First, violence can deter the expansion of services in under-served areas due to safety concerns (World Health Organization, 2016; World Health Organization Centre for Health Development, 2010). Second, access and utilization may be reduced; for example if clinics temporarily close, patients are deterred from visiting, or services (e.g. home visits) are reduced (Bellas et al., 2019; Souza et al., 2007). Thirdly, the quality of available care is likely impaired due to violence if staff are absent or there is high turnover, medical supplies are disrupted, or facilities are damaged (Krug et al., 2002).

Understanding how health systems are affected by violence, their responses, and system resilience is vital for strengthening health systems, setting policy priorities, allocating resources more efficiently, and addressing inequalities. The estimation of the causal effects of violence on health systems poses challenges due to significant differences between violent and non-violent areas and hard-to-measure confounding factors related to individual and community characteristics.

This study exploits rich geocoded data on violence and administrative health service records to assess the impact of violent episodes on health service utilization. We also explore mechanisms that explain this relationship in the short run (access indicators) and analyze long-term outcomes (quality indicators). We focus on the city of Rio de Janeiro, Brazil, a city with notorious gang-related violence (Monteiro and Rocha, 2017), high levels of police use of lethal force (Monteiro and Rocha, 2017), and pronounced social inequalities, with a substantial portion of the population living in favelas. Despite these challenges, there is a strong government commitment to expanding health services in under-

[1] We use poor neighborhood or favela interchangeably in the remainder of the paper to refer to Rio de Janeiro's slums.

served areas (Soranz et al., 2016) and high-quality clinic-level data for research (Hone et al., 2023, 2022).

We constructed a monthly clinic-level panel dataset using healthcare data and geocoded information on drug-related violence and police operations shootings in the neighborhoods where clinics operate. We employ a quasi-experimental method that considers temporal and spatial variations in violent events and controls for time-invariant clinic characteristics which may confound the analysis. We estimate the impacts of violence on access, utilization and quality dimensions. For the main outcomes, we consider the total number of appointments and appointments separated by the group of the procedure (primary health care, clinical, diagnostic and surgical), proxies for temporary clinic shutdowns, healthcare professionals' turnover and the effects on hospitalizations due to chronic conditions.

We find that violent events, specifically police operations that involved shootings, are significantly associated with lower rates of PHC utilization. Specifically, police operations are linked to a 7.6% reduction in total procedures ($p < 0.01$), driven by a 12.7% decrease in primary health care procedures ($p < 0.01$), especially home visits. Surgical procedures decreased by 13.3% ($p < 0.05$) and clinical procedures by 7.7% ($p < 0.01$), with a suggestive reduction in diagnostic procedures ($p < 0.1$). Additional episodes of drug gang shootings also resulted in a 7.1% reduction in total procedures ($p < 0.05$). The results were robust across various model and sample specifications and alternative measures of exposure to violence. In terms of mechanisms, we observe a reduction on access to health services in the the day of the violent incident, with a compensation effect in the following days. Health units in areas with below-median average income and low socioeconomic status were more affected.

We also examined the effects of violence on the total number of workers, worker turnover, and the exit rate using CNES data and FHS electronic health records. There was no significant increase in turnover measures at the monthly level due to violence. However, we observe a suggestive increase in the exit rate of physicians with at least one appointment in health units exposed to drug gang-related shootings. No significant effect on chronic conditions hospitalization was found, indicating that while violence impacts service utilization, it does not necessarily affect the quality of care in terms of worker turnover or hospitalization for chronic conditions.

Much of the evidence on PHC and exposure to urban violence comes from qualitative studies or surveys with limited attention to the universe of individuals in poor neighborhoods who suffer the impacts of violence (Lemgruber et al., 2023; Borges et al., 2014). Suggestive evidence indicates that violent events in Brazil have contributed to interruptions in primary health care provision (Lemgruber et al., 2023). This can lead to reductions in health equity and worse health outcomes (Lautharte, 2021). Besides, emerging evidence suggests that populations of lower socioeconomic status, more impacted by urban violence, can benefit more from primary care services (Hone et al., 2023).

The remainder of this paper is organized as follows. Section 2 describes the background and section 3 the data. Section 4 presents and discusses the empirical strategy. In Section 5, we present the results on the effects of episodes of violence on health services and the main robustness checks. In Section 6, we analyze the results. Section 6 concludes.

2 Institutional Context

2.1 Urban Violence

Rio de Janeiro is a city characterized by wide inequalities and gang-related violence. In 2009, there were 2,909 violent deaths in the city - a rate of 46.1 per 100,000 inhabitants (Instituto de Segurança Pública do Estado do Rio de Janeiro (ISP), 2024). However, homicides are unequally distributed varying from 6.6 per 100,000 in affluent southern areas to 60.3 in impoverished northern zones, while life expectancy varies by 13 years across areas (Monteiro and Rocha, 2017). Rio has also ranked among the highest in police killings in Brazil, with the city witnessing an average of two police killings per day in 2009 [2] Between 2009 and 2016, Rio de Janeiro's police were responsible for approximately 20% of the city's violent deaths (Instituto de Segurança Pública do Estado do Rio de Janeiro (ISP), 2024).

The roots of Rio's urban violence relate to the control of the drug markets in the city, engendering the fractionalization of criminal groups and conflict over territory (Penglase, 2009). The conflict between rival drug gangs generates much of the crossfire and gun violence that characterizes the criminal scene in the city. In response, the police often carry out raids to control or interrupt criminal activities. These generally occur in or near favelas (Gonçalves, 2017), and frequently escalate into violent confrontations characterized by shootouts and high mortality rates, particularly among civilians (Hirata and Grillo, 2017), with no effective reduction in crime rates (Monteiro et al., 2020). Beyond the loss of innocent lives and disruption of daily routines, this policing pattern perpetuates inequalities and undermines the legitimacy of law enforcement efforts (Lemgruber et al., 2023). Efforts to address these issues, such as the implementation of Pacifying Police Units (UPPs) in some favelas, aim to reclaim control from drug traffickers and foster a sense of security

[2] In 1995, the police in Rio de Janeiro implemented a policy known as the "Wild West Bonus" (Gratificação Faroeste), which persisted for more than a decade. Under this policy, rewards and promotions for police officers were linked to displays of "bravery," resulting in an increase in the number of police killings during that period (Cano, 1997).

within these communities (Ferraz et al., 2023). This increase in law enforcement in treated favelas caused a rise in the cost of doing drug business in these localities (Felbab-Brown, 2011), and led to a reduction of homicides in these communities, especially police killings.

In addition to the potential direct and indirect impacts on health (Lemgruber et al., 2023; Borges et al., 2014), urban violence also places a huge burden on local public services, including education (Monteiro and Rocha, 2017; Ministério Público do Estado do Rio de Janeiro, 2024; Lemgruber et al., 2022; Pecanha, 2023), policing (Monteiro et al., 2020; Ferraz et al., 2023), and birth outcomes (Lautharte, 2021).

2.2 Health System

Brazil operates the largest community primary care system (the Family Health Strategy (FHS)) in the World, being that is the cornerstone of its public health system and foundation for Universal Health Coverage (Macinko and Harris, 2015). It is a multidisciplinary model of PHC that includes doctors, nurses, and community health workers, providing a comprehensive range of services to local populations.

Coverage of the FHS in Rio lagged relative to other parts of the country. In 2008, the city had the lowest public health spending among state capitals; over 80% of the city's health budget was allocated to hospitals and 40% of FHS teams lacked doctors (Soranz et al., 2016). However, investments since then have led to a significant expansion of FHS in Rio with coverage increasing from around 30% in 2010 to almost 70% in 2016, reaching about 2.6 million inhabitants (Instituto de Estudos para Políticas de Saúde (IEPS), 2024). As of 2024, the municipality of Rio has 241 PHC units, which include family clinics (37%) and municipal health centers (32%) (Instituto Municipal de Urbanismo Pereira Passos, 2024). FHS expansion occurred mainly in poorer areas (Almeida et al., 2018), and FHS usage in these poorer populations was associated with reductions in mortality, avoidable hospitalizations, and improved infant health (Hone et al., 2020, 2022, 2023).

Despite improvements, the Rio FHS system still faces significant challenges. Over 50% of patients still lack access to primary care, the adjusted mortality rate for conditions amenable to primary healthcare remains above the national average (Instituto de Estudos para Políticas de Saúde (IEPS), 2024), and there is a demand for health services concentrated on emergency department access (Bhalotra et al., 2023). Additionally, episodes of violence can lead to the closure of health facilities and worsen health conditions, further overburdening healthcare services (Lemgruber et al., 2023; Silva et al., 2021).

3 Data

This study is a longitudinal (panel) analysis of 204 health clinics covering the period from January 2009 to December 2016. The unit of analysis is the health clinic. We undertake a quasi-experimental approach to causally estimate the effects of episodes of violence on health services. We account for confounders that may be associated with both violent episodes and outcomes and we exploit temporal and spatial variations in violent events while controlling for time-invariant characteristics in two-way fixed effects panel regression models. The identification strategy relies on the unpredictability and randomness of the timing of episodes of violence, conditional on the covariates – an assumption that has been validated in previous studies in Rio de Janeiro (Monteiro and Rocha, 2017).

We focus this study on 2,221 poor neighborhoods in the city of Rio de Janeiro, which cover more than 2.5 million inhabitants, including both officially designated favelas (1,093) and other non-favela-poor areas. This aims to capture all areas predominantly affected by violence in the city and populations most reliant on the public health system for their healthcare needs (Silva et al., 2021)

Multiple datasets from various sources were compiled for this analysis. Two publicly available datasets from 2009 to 2016 were utilized: i) the National Registry of Health Establishments (CNES) was consulted for data on the numbers of human resources and health unit characteristics; ii) the Ambulatory Information System (SIA) was used to obtain all ambulatory records for emergency care. The data was supplemented with an administrative and restricted dataset of municipal FHS electronic records including individuals' date of registration and utilization of health services for the period from 2011 to 2016, which was linked to publicly funded hospital admissions records from the Hospital Information System (SIH) (Coeli et al., 2021). Both datasets were obtained from the Rio de Janeiro Municipal Health Secretariat. To define the address of each health clinic, we used publicly available data from the Rio de Janeiro City Hall[3] for units that were open in 2024. For clinics that had already closed, we supplemented this information with addresses obtained from the CNES.These datasets were used to construct outcome measures, include information on clinic characteristics, and geocode the episodes of violence.

Detailed information on the locations and timing of shootings is not publicly available. Official crime data provided by the Public Security Institute (ISP) lacks sufficient precision on episodes of violence and only captures homicides, which is a crude measure of these conflicts. To overcome the lack of data on episodes of violence, we created a novel approach to measure exposure to violence by combining information from different sources. To construct the measure of drug battles, we leveraged data on drug-gang shootings reg-

[3] `https://datariov2-pcrj.hub.arcgis.com/`. Accessed in July 2024.

istered between 2009 and 2016 in the city of Rio de Janeiro, assembled by (Monteiro and Rocha, 2017) using information from Disque-Denúncia[4]. We expanded the time range and improved the geocoding of their data by using a broader definition of poor neighborhoods. Disque-Denúncia is a non-profit civil organization that developed a crime hotline where the public can anonymously report security or public order issues that require government intervention. We gathered from Disque-Denúncia (DD) all reports classified as 'gunfights between drug-gangs' (*tiroteio entre facções*). Each report includes the date, location, and description of the event.

To supplement the drug-gang battle data, we used data on police operations collected by the research group *Novos Ilegalismos* from the Federal University Fluminense (GENI/UFF) through news scraping techniques (Hirata and Grillo, 2019), which is available for request on the GENI/UFF website[5]. The database was constructed from news coverage of armed incursions conducted by law enforcement in "risk areas," particularly favelas and impoverished neighborhoods of Rio de Janeiro Metropolitan area (Hirata and Grillo, 2019). The search was limited to major crime-focused newspapers: O Dia, Extra, and Meia Hora. There is a risk of underreporting these incidents since the data relies solely on news reports, potentially biased towards capturing only significant operations. By focusing our analysis on Rio de Janeiro and operations involving shootings, which are more frequently reported, we mitigated this bias to some extent.

To geocode events within poor neighborhood borders, we used a free online map resource provided by the Public Prosecutor's Office of the State of Rio de Janeiro (MPRJ em Mapas[6]), covering poor neighborhoods in the city of Rio de Janeiro. We constructed a dictionary of poor neighborhoods names and compared them with the address and neighborhood information provided in the Disque-Denúncia and Geni/UFF databases. If a neighborhood could not be identified directly, we used the reported address to determine if it was inside any poor neighborhood polygon. For these cases, we conducted searches using the same sources used by the Public Prosecutor's Office of the State of Rio de Janeiro (MPRJ), informal and low-income settlements system (SABREN[7]), information of favelas boundaries and housing projects, provided by the Municipality of Rio de Janeiro (Data.Rio/IPP), and Wikimapia data, an open-content collaborative mapping platform, as well as Google searches to identify the reported locations. This process corrected and standardized community names in the violence databases, enabling them to be merged with the MPRJ spatial data.

[4] `https://disquedenuncia.org.br/`. Accessed in July 2024.
[5] `https://geni.uff.br/category/dados/`. Accessed in July 2024.
[6] `https://apps.mprj.mp.br/sistema/rjinloco/`. Accessed in July 2024.
[7] `https://sabren-pcrj.hub.arcgis.com/`. Accessed in July 2024.

Violence measures (exposure variable)

We linked episodes of violence to poor neighborhood areas by matching the poor neighborhoods' information from the episodes of violence sources to the names in the dictionary we described above. Events outside poor neighborhoods and cases that did not specify the address and/or neighborhood for geocoding were disregarded. For drug-gang related shootings, we could geocode 91% of the observations. In the case of police operations, we were able to associate the event with a poor neighborhood in almost 90% of cases provided by Geni/UFF. Given the broad scope of these police operations, we focus exclusively on those involving shootings (87%). Therefore, our measures of violent episodes are based solely on shootings. We removed duplicated observations for the same neighborhood-day for each dataset.

To construct our measure of exposure to violence at the health unit level, we considered all events that happened in poor neighborhoods that are within a 250m buffer around the health unit. In the case of multiple nearby communities, we considered all poor neighborhoods within a 250-meter buffer around each health unit. We counted the episodes of violence occurring in these neighborhoods to define the exposure variable at the health unit level.

Health services and other variables

To evaluate the impact of violence on healthcare service provision, we examined primary outcomes in three dimensions: access, utilization, and proxies of quality, aggregated at the health unit level. The utilization outcomes were derived from the Ambulatory Information System (SIA) and were built at the monthly level. We divide the health units' procedures into four main groups: i) PHC procedures, encompassing low-complexity tasks, mainly home visits; ii) diagnostic procedures, including material collection, radiology diagnostics, ultrasonography, and rapid tests; (iii) clinical procedures, such as appointments and dental consultations; and (iv) surgical procedures, covering minor surgeries and maxillofacial procedures. Only the first group refers to procedures performed outside the health unit.

We use FHS electronic records to create monthly and daily measures of access to health services. In this data, we observe the daily number of appointments in a health unit. We explore the daily effects of violence exposure on the daily number of appointments to test if there is a contemporaneous reduction of appointments on the same day of a shooting or a police operation or in the next few days. Moreover, we construct other variables to shed light on the effects of violence on access: the number of weekdays with zero appointments, a dummy if the number of days with zero appointments in the month is below the median value of zero appointments in that clinic, and the number of weekdays in a month in which the daily number of procedures was below the health unit's median of daily appointments (or below the 20th percentile).

Outcomes related to the quality of health service include healthcare professionals' exit rate, and hospitalizations for selected chronic conditions (asthma, chronic obstructive pulmonary disease, congestive heart failure, hypertension, and diabetes). The exit rate, a measure of turnover, is defined as the number of employees who left clinic i in month m divided by the number of employees in the previous month $m-1$. We also consider the number of exits as an indicator by itself. We define that an employee leaves the health unit in month m if the person has a job in clinic i and month m, but did not have a job connection with the same health unit i in the next three months. To measure turnover, we utilize two data sources: the National Registry of Health Establishments (CNES) and FHS Electronic Records. CNES provides monthly records of individuals employed at each health unit, while FHS Electronic Records detail the number of physicians who had at least one appointment at the health unit each month. Note that each indicator sheds light on a different aspect of the phenomena. For example, it is possible that a physician is registered but holds zero appointments in the month. The number of hospitalizations per condition was determined by linking individuals' registries at a FHS unit with monthly hospitalization data (SIH). Thus, we calculate the number of individuals registered to an FHS unit i hospitalized in the month m.

Covariates were included to account for health clinic characteristics. Health unit-level covariates included the number of teams as a proxy for the size of the covered population, the number of consulting rooms by type (basic care, specialized, dental), the number of dental teams, and available services within the clinic (support, social services, pharmacy, sterilization). We also included a dummy variable indicating the presence of a Pacifying Police Unit (UPP) in the nearby community to address the potential effect of this program on our violence indicators. The inequality analysis uses the average income in the neighborhood retrieved from the Social Development Index provided by Data.Rio/IPP to define the community's Socioeconomic Status (SES), composed of eight indicators that characterize household and individual conditions based on data from the 2010 Demographic Census (IBGE). We also performed this exercise with the SES index itself.

Sample

A monthly clinic-level unbalanced panel dataset was constructed. The panel included 204 primary care health units that had at least one active PHC team between 2009 and 2016 and were located within a 250-meter buffer from a poor neighborhood. Notably, 78%

of these units are within 100-meter distance from at least one low-income neighborhood. We excluded hospitals, polyclinics, and prison units, health units without an associated address, and those established after 2016. Our panel dataset is unbalanced since health units may have opened or closed during our analysis during this period. For clinics that opened after 2009, we define the entry date as the first month in which a health team was registered. Similarly, the closing date is defined as the last month in which a health team was registered, up until 2016. In our sample, 151 clinics were opened after 2009 and 23 were closed before 2016.

We mapped the data of drug-gang shootings and police operations onto our monthly clinic-level dataset to compute monthly exposure to violence for each clinic. We used a linear distance buffer to define a 250m radius around clinics and aggregated the number of monthly violence events in neighborhoods within this radius. Thus, for each month and clinic, we calculated the number of violent events in all neighborhoods within 250m distance from the clinic. In the main empirical model, we only considered health units that are near poor neighborhoods.

Descriptive analysis

From January 1, 2009, to December 31, 2016, there were 204 health clinics with at least one active PHC team located within a 250m linear distance from a poor neighborhood (Table 1). These clinics are large, with an average of 79 employees and a maximum of 331 per unit. Considering only healthcare professionals, the mean is 20, with a maximum of 101. Each clinic has an average of 4.1 health teams (maximum 18), and each team covers a maximum of 4,000 people. In terms of infrastructure, clinics have around 10 consulting rooms, most of which are used in the provision of basic care. Almost all units have their own patient support services (84% on average), providing pharmaceutical and sterilization support as well. The clinics in the sample are well-distributed throughout the city (Figure 1), with 78% located within 100 meters of a poor neighborhood. However, only 36 units are located close to the favelas that received the Pacification Police Units program.

Regarding the economic profile of the population served, 35% earn less than two minimum wages, with one clinic reaching 90%. Few clinics serve populations earning more than ten minimum wages. The average income in the health unit's catchment area is 2.77 times the minimum wage. Since our sample focuses exclusively on poor neighborhoods, there is little variation in the SES index. The maximum value is related to a single unit located in an affluent part of the city. The results are robust even when excluding this unit from the analysis.

On average, the health units experienced 0.18 episodes of police operation shootings and 0.07 drug-gang shootings per month, with maximums of 10 and 21 per unit-month, respectively. The distribution is right-skewed in both cases. Police operations were more frequent, occurring twice as often between 2009 and 2016, with a total of 4,587 police operations and 2,008 drug-related shootings. During the analyzed period, the trajectory of police operation was more erratic than that of drug-gang shootings. After a decline between 2009 and 2011, the number grew until 2014, peaking at 776, followed by a reduction in subsequent years (figure A1). Of 2,221 communities, only 266 experienced at least one police operation between 2009 and 2016, and 90 had more than 10 episodes. There is considerable variation over time in the exposure to violence within the studied period, but it is concentrated in a few neighborhoods (figure 1).

These clinics handle a high volume of patients, with an average of 11,929 monthly procedures per neighborhood and a maximum of 320,414 procedures. The volume of PHC procedures is significantly lower, averaging 3.85 and peaking at 22.68, with home visits accounting for almost half of them. Diagnostic procedures average 2.50 per clinic per month, with a maximum of 305.62, while clinical procedures, mainly appointments, average 5.40, with a maximum of 118,496. There is significant variation in the number of all types of procedures, reflected in a high standard deviation. Additionally, the variables exhibit outliers, as seen by the large difference between the 90th percentile and maximum values.

4 Empirical Strategy

Our identification relies on the assumption that conditional on health clinic and time-fixed effects, as well as on neighborhood and health clinic observed characteristics, the timing of police operations and conflicts between drug gangs within neighborhoods cannot be predicted ex-ante, i.e., the timing is arguably exogenous. If this assumption holds, we can identify the causal impact of violence on health services given that our variable of exposure to violence should be orthogonal to the error term in equation (1) below. Thus, we exploit the variation of violent events over time and space, rather than their levels.

We employ a two-way fixed effects estimator. The empirical specification is:

$$\log y_{iam} = \alpha_{ia} + \delta_{am} + \beta_1 D^{(1)}_{iam} + \beta_2 D^{(2)}_{iam} + \Gamma X_{iam} + \epsilon_{iam} \tag{1}$$

where, Y_{iam} represents the outcome variables, which include healthcare services indicators in each PHC clinic i in the year a in month m between 2009 and 2016. Access and utilization are measured by the number of procedures and appointments as discussed above. The secondary outcomes are quality proxies, employee turnover, and hospitalization for chronic conditions. We employ log transformation in all variables to deal with skewed data (see table 1). α_i is the health clinic fixed effect and δ_{am} is the month fixed effect. ΓX_{ima} represents the covariates at the clinic level: number of health teams, clinics, available services, and presence of UPP in the nearby poor neighborhood. The number of health teams is a proxy for the size of the covered population. ϵ_{iam} is the error term, clustered at the health unit level. D_{iam} captures exposure to violence. It is a dummy that turns one if the sum of episodes of violence close to the health unit i is greater than a threshold n in year a and month m. Formally, we define this variable as:

$$D_{iam} = \begin{cases} 1, & \text{if } \sum_j [(\mathbb{1}(dist_{ij} \leq B) v_{jam}] \geq n \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where, i identifies the health unit and j poor neighborhoods. The term $dist_{ij} < B$ indicates whether the linear distance $dist_{ij}$ between the health unit and the poor neighborhood j's border is less than B meters. v_{jam} captures the number of violent events in poor neighborhood j in that period of time. If the sum of episodes of violence close to the health unit is greater than n, then, D_{iam} turns one. In our benchmark specification, we set the parameter B to be 250 meters and n to 2 episodes of violence. By defining $n = 2$, we exclude isolated shootings that may add noise to our analysis. Formula (2) is a straightforward and flexible way of measuring violence (Monteiro and Rocha, 2017). We split the episodes of violence into two separate categories, both related to shootings: police operations and drug gang battles. Arguably, the dynamics of these events are different from each other (Monteiro et al., 2020), leading to potentially different effects on health services.

We also explore high-frequency data from FHS electronic health records to estimate within-month effects on access. We ran a slightly modified version of equation (1) at the daily level. The empirical specification is:

$$\log y_{iamd} = \alpha_{ia} + \delta_{am} + \sum_{\tau=-2}^{2} (\beta_{1\tau} D^{(1)}_{iamd-\tau} + \beta_{2\tau} D^{(2)}_{iamd-\tau}) + \Gamma X_{iam} + \epsilon_{iam} \tag{3}$$

For this purpose, we calculated the number of police operations and drug-gang battles per day, with the same restriction of $B = 250$ but setting n to 1. Thus, the exposure variable was defined as a dummy that turns one if the sum of daily violent events in poor neighborhoods close to the health unit i is greater or equal than one[8]. The outcome is the

[8]Only 54 observations (out of 3,076 observations of clinics with daily reports of violent episodes) had

number of appointments on that day d in clinic i. Given that police operations mostly occur on weekdays (Monteiro et al., 2020), we restrict our observations to weekdays for this exercise. We control the same covariates as before. Since these covariates are at the monthly level, we also perform a robustness exercise in which we include health unit x year x month fixed effects to address possible unobservable changes that happen at the monthly level in the clinic instead of using the covariates. Both empirical exercises include health units and calendar days as fixed effects. To test for the potential temporal displacement of the episodes of violence on health services, we estimated $D_{iamd-\tau}$ for τ, where $0 \leq \tau \leq 2$. We also estimate placebo effects as robustness for $\tau < 0$.

Robustness

To test the robustness of our main results we perform three empirical exercises. First, we run different model specifications for equation (1), varying the controls and fixed effects. The results are in table A1. Second, we use different sample restrictions. In A2, we drop units that closed during the analysis period and we also drop units that open in the last year of the panel. The idea is to mitigate concerns about endogenous closures or entries and create a more balanced panel. In the next exercise shown in table A3, we consider only health units that experienced at least one episode of violence between 2009 and 2016. Our goal is to create a more comparable sample by dropping units that were never exposed to violence. Third, we analyze the robustness of the results in different exposure variable specifications. Table A4 uses the count of episodes of violence, table YA5 evaluates the gradient of exposure, and table A6 the interaction of police operations and drug gang-related shootings.

Heterogeneity

The heterogeneity analysis employs socioeconomic variables constructed at the health unit's catchment area level. We utilized the Socioeconomic Status Index (SES) developed by the Pereira Passos Institute (IPP), which includes various socioeconomic indicators from the 2010 Brazilian Census at the census tract level, such as average income. We intersected the catchment areas of the health teams provided by the Municipal Secretary of Health with the centroids of the census tracts. A census tract is considered part of a health unit's catchment area if its centroid lies within it. Then, we calculated the average value of these variables for each health unit.

We created a dummy variable that equals one if the average income of a health unit's sur-

two episodes of violence. The results do not change if we run using the levels.

rounding area is below the median income of the health units in the sample[9]. Then, we interacted the exposure variables with this dummy. The coefficient of the interaction indicates the differential impact of episodes of violence on health units with incomes below the median compared to those above it. We also do the same exercise using the SES index. Tables 3 and A9 display the results for average income and SES index, respectively.

5 Results

The impacts of violence on primary health care services in poor neighborhoods

Police operations are significantly associated with a reduction in the number of procedures conducted in health units located within 250m of poor neighborhoods. In table 2, we show that the occurrence of a police operation is associated with a 7.6% reduction in the total number of procedures ($p < 0.01$). This reduction is primarily driven by a 12.7% decrease in primary health care procedures ($p < 0.01$), especially home visits (table A7). Among other types of procedures, the impact is greatest among surgical procedures (13.3%, $p < 0.05$), followed by clinical procedures (7.7%, $p < 0.01$). We find a suggestive reduction in diagnostic procedures ($p < 0.1$). Additional episodes of drug gang shootings have a less clear impact, although we observe a decrease in the total number of procedures, with a 7.1% reduction ($p < 0.05$). In all cases, we used fixed effects for months, CNES x year, and controlled for the number of health teams, clinics, available services, and the presence of a UPP nearby. The main results are robust to different model and sample specifications (tables A1, A3 and A2) and alternative measures of exposure to violence (tables A4, A6 and A5). It is suggestive that health units located in areas with average income below the median and with low socioeconomic status are more affected (tables 3 and A9).

To check if the effect is temporally concentrated around the event, we measured the impacts of episodes of violence at the daily level using the number of daily appointments held by a health unit from the FHS electronic records data. The analysis of temporally lagged effects shows that the impact was driven mainly by short-run consequences on access, with most of the impact happening on the first day for police operations and on the first and second days for drug gang shootings after the episode of violence. Importantly, there is a compensation effect in the following days, with an increase in the number of appointments held by the clinic (figure 2).

[9]We only consider poor neighborhoods in the sample. The average income relative to the minimum wage in our sample is 59% of the mean income of the city.

Table A8 analyzes other measures of access aggregated at the monthly level. First, we discuss the effects of episodes of violence on the number of weekdays with zero appointments and whether this number is below the clinic's median value. The results are not statistically different than zero. However, there is indicative evidence that the number of days in a month with procedures below the median or the 20th percentile increases. These findings suggest that although episodes of violence reduce utilization, the clinic does not fully close. Instead, access is reduced by decreasing the number of procedures conducted on those days. This aligns with anecdotal evidence of how health units respond after episodes of violence, often stopping home visits but not fully interrupting activities within the clinic[10].

Outcomes related to quality of care

Tables A10 and A11 display the results for various quality proxies. It examines how episodes of violence affect the total number of workers, the number of workers leaving the clinic, and the exit rate. We focus on the monthly number of employees, health professionals, and physicians using CNES data. We complement his analysis with information from FHS electronic health records, which allow us to identify physicians who actually conducted at least one appointment in the health unit within a month. Together, these variables offer insights into different turnover measures.

We observe that violence does not increase turnover measures for outcomes at the monthly level. However, we do find a suggestive increase in the exit rate of physicians with at least one appointment conducted in health units exposed to drug gang-related shootings. Finally, we do not observe any significant effect on chronic conditions hospitalization.

6 Discussion

Our study shows that episodes of urban violence significantly impact the utilization of primary healthcare (PHC) services in Rio de Janeiro's poor neighborhoods. The findings show that violent events, particularly police operations involving shootings, lead to a significant decrease in health service utilization, particularly primary care procedures and home visits.

The short-term nature of these effects is evident. The reduction in access is most pronounced on the day of the violent event, but it dissipates in the following days. It suggests

[10] `https://g1.globo.com/rj/rio-de-janeiro/noticia/2024/07/03/operacao-policia-militar-cidade-de-deus.ghtml` and `https://odia.ig.com.br/rio-de-janeiro/2024/07/6886577-criminosos-colocam-fogo-em-barricadas-durante-operacao-na-vila-alianca.html`. Accessed in July, 2024.

a rapid system response, where health services attempt to compensate for the disruption in the next days after the episode of violence. However, this compensation may be insufficient to offset the immediate drop in utilization, indicating a vulnerability in the health system's resilience to violence.

The study's focus on low-income areas highlights the disproportionate burden of violence on the most vulnerable populations. The greater impact of violence in poorer neighborhoods highlights the need for targeted interventions to protect and improve health service delivery in these areas.

Furthermore, while our analysis did not find significant long-term impacts on hospitalization rates or overall quality of care measures such as employee turnover, there is suggestive evidence of increased physician exit rates associated with drug gang-related shootings. This indicates potential long-term impacts on the stability and quality of health care provision, which demands further investigation.

In conclusion, our research emphasizes the critical need for policies and interventions that can mitigate the effects of urban violence on health services. Strengthening the resilience of health systems in violence-prone areas is important to ensure uninterrupted access to care for vulnerable populations in low- and middle-income countries.

Future research should aim to address the limitations of this study, including exploring the long-term health impacts of living in consistently violent environments and developing better measures for capturing the chronic effects of violence on health outcomes, particularly on mental health. Investigating the broader psychological and social stressors associated with chronic exposure to violence will provide a more comprehensive understanding of its impact on citizens' lives.

7 Conclusion

The violent events that occurred between 2009 and 2016 in poor urban neighborhoods were associated with a reduction in the utilization of primary health care (PHC) services, especially in lower-income areas and those that experienced more shooting episodes. The results are driven mainly by short-run effects; however, there is suggestive evidence that it may impact the turnover of health professionals. This evidence contributes to the understanding that accounting for the impact of violence in PHC is important for strengthening health systems and delivering health gains to vulnerable populations in low- and middle-income countries (LMICs).

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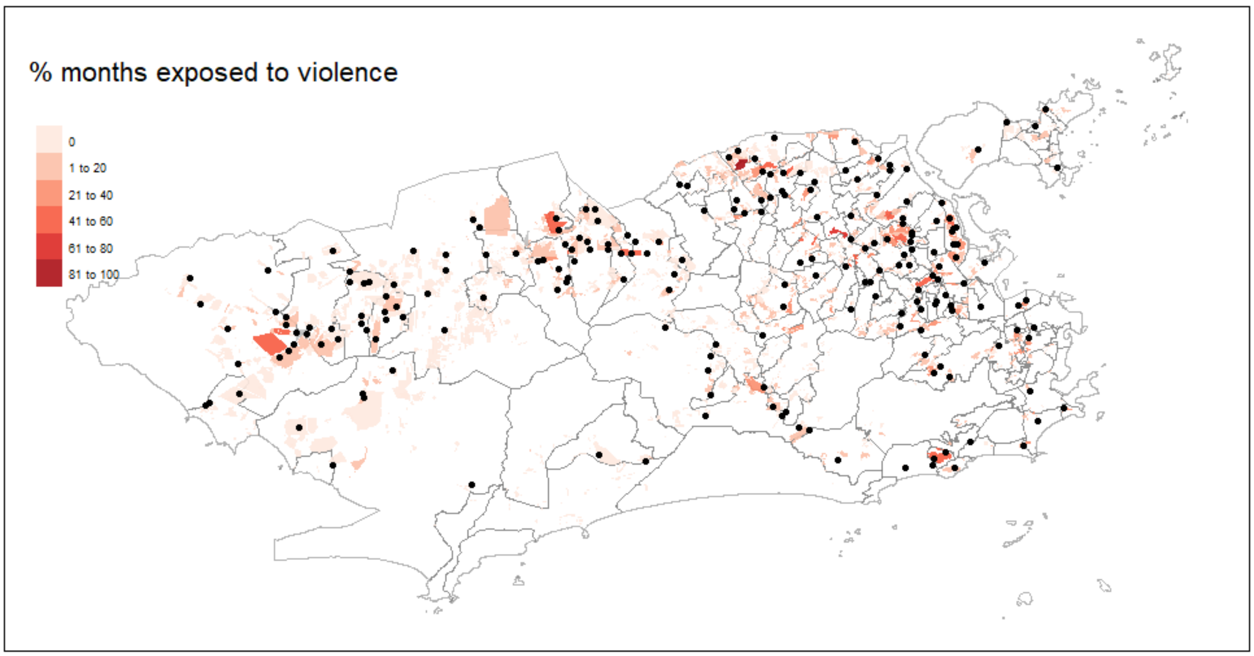
Figures and tables

Table 1: Descriptive statistics

Variables	Mean	sd	p50	p90	max
Health unit characteristics					
Employees	78.63	49.07	72.00	141.00	331.00
Health professionals	19.79	15.60	16.00	40.00	101.00
Health teams	4.12	2.11	4.00	7.00	18.00
Dental teams	0.82	1.43	0.00	3.00	12.00
Consulting rooms	10.47	6.90	10.00	48.00	
Basic care	5.08	3.16	5.00	9.00	22.00
Specialized care	0.65	1.75	0.00	2.00	13.00
Dental	0.03	0.19	0.00	0.00	2.00
Available services					
Own patients' support service	0.84	0.36	1.00	1.00	1.00
Own social service	0.27	0.45	0.00	1.00	1.00
Own pharmacy service	0.90	0.30	1.00	1.00	1.00
Own sterilization service	0.78	0.41	1.00	1.00	1.00
Health services outcomes					
Procedures	11,930	9,796	10,006	23,104	320,414
PHC procedures	3,848	3,277	3,197	7,639	56,742
Home visits	1,908	1,938	1,536	4,411	22,680
Diagnostic procedures	2,499	4,572	1,102	6,296	305,620
Clinical procedures	5,402	4,490	4,574	10,312	119,752
Appointments	5,026	4,320	4,182	9,725	118,496
Zero appointments (weekdays)	3.01	4.94	2.00	7.00	23.00
Surgical proc.	180.20	267.65	99.50	426.00	6,196.00
Hospitalization chronic	0.47	0.87	0.00	2.00	19.00
Exit rate	0.03	0.12	0.01	0.06	11.00
Exit rate health professionals	0.04	0.09	0.00	0.13	2.00
Violence exposure					
n police operations < 250m	0.04	0.20	0.00	0.00	1.00
n drug battle shootings < 250m	0.01	0.11	0.00	0.00	1.00
2+ police operations < 250m	0.18	0.66	0.00	1.00	10.00
2+ drug battle shootings < 250m	0.07	0.52	0.00	0.00	21.00
Territorial and socioeconomic					
100m dist. to a poor neighborhood	0.78	0.41	1.00	1.00	1.00
UPP < 250m	0.14	0.35	0.00	1.00	1.00
SES index	0.55	0.05	0.55	0.61	0.77
% income < 2 min. wages	0.35	0.15	0.34	0.57	0.90
% income > 10 min. wages	0.03	0.07	0.01	0.08	0.56
Avg. income (relative to min. wage)	2.78	2.00	2.17	5.09	16.52

Note: This table presents the descriptive statistics for the main variables discussed in the paper. PHC stands for Primary Health Care; UPP refers to Pacifying Police Units; Socioeconomic Status index is calculated from *Índice de Desenvolvimento Social* developed by Instituto Pereira Passos (IPP/RJ). All statistics are based on the monthly-level health unit panel (N = 11,391).

Figure 1: Health units and exposure to violence



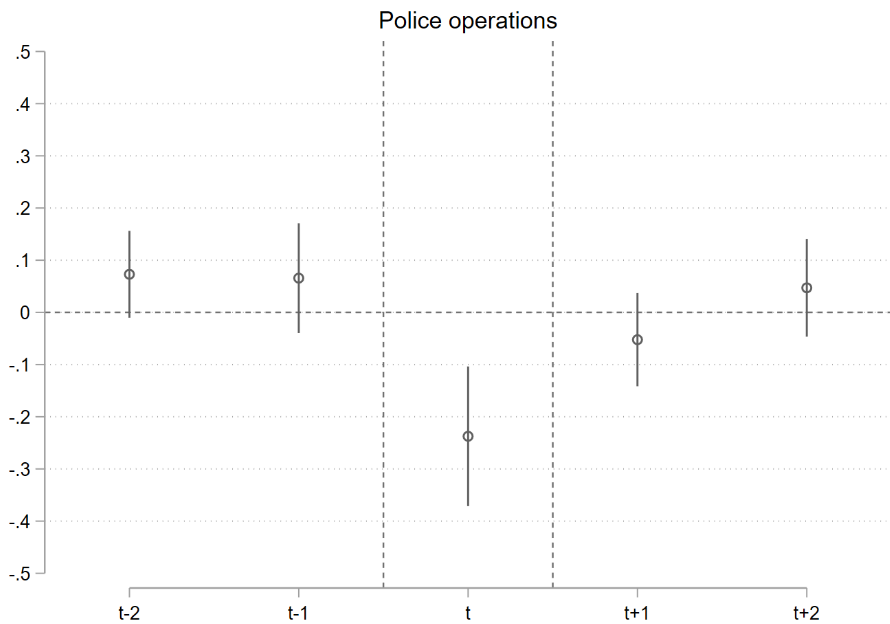
Notes: The dots represent the health units in our main sample. The polygons delineate the poor neighborhoods in Rio de Janeiro. Each polygon is shaded to indicate the percentage of months during the study period (96 months) that the neighborhood experienced at least one violent incident.

Table 2: Results from two-way fixed effects regression models on procedures by type.

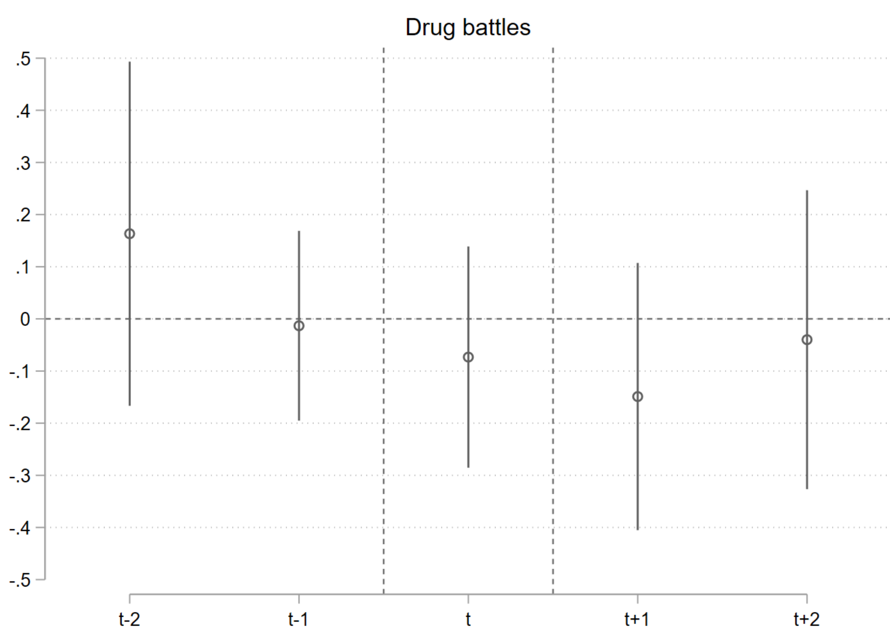
	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.076	-0.127	-0.064	-0.077	-0.133
	(0.027)***	(0.044)***	(0.035)*	(0.037)**	(0.063)**
Drug battles	-0.071	-0.118	-0.080	-0.130	-0.117
	(0.034)**	(0.106)	(0.083)	(0.080)	(0.086)
Observations	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12,132	3,960	2,667	5,348	156

Notes: Table shows the results of regression (1). Dependent variables are the log plus one of levels. The variables that define exposure to episodes of violence are dummies that turn one if there were two or more events within a 250m buffer around the health units in a month. Controls include covariates at the clinic level: number of health teams, clinics, available services, and presence of UPP in the nearby poor neighborhood. Standard errors are clustered at the health unit level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 2: Effects of episodes of violence on access



(a) Police operations



(b) Drug battles

Notes: This figure illustrates the dynamic effects of violent incidents on access using daily appointments data from FHS electronic records. It plots the coefficients from equation (3), including three lagged terms of the exposure variables. The dots are the point estimate for the exposure variables and the vertical lines represent the 95% confidence interval for each coefficient.

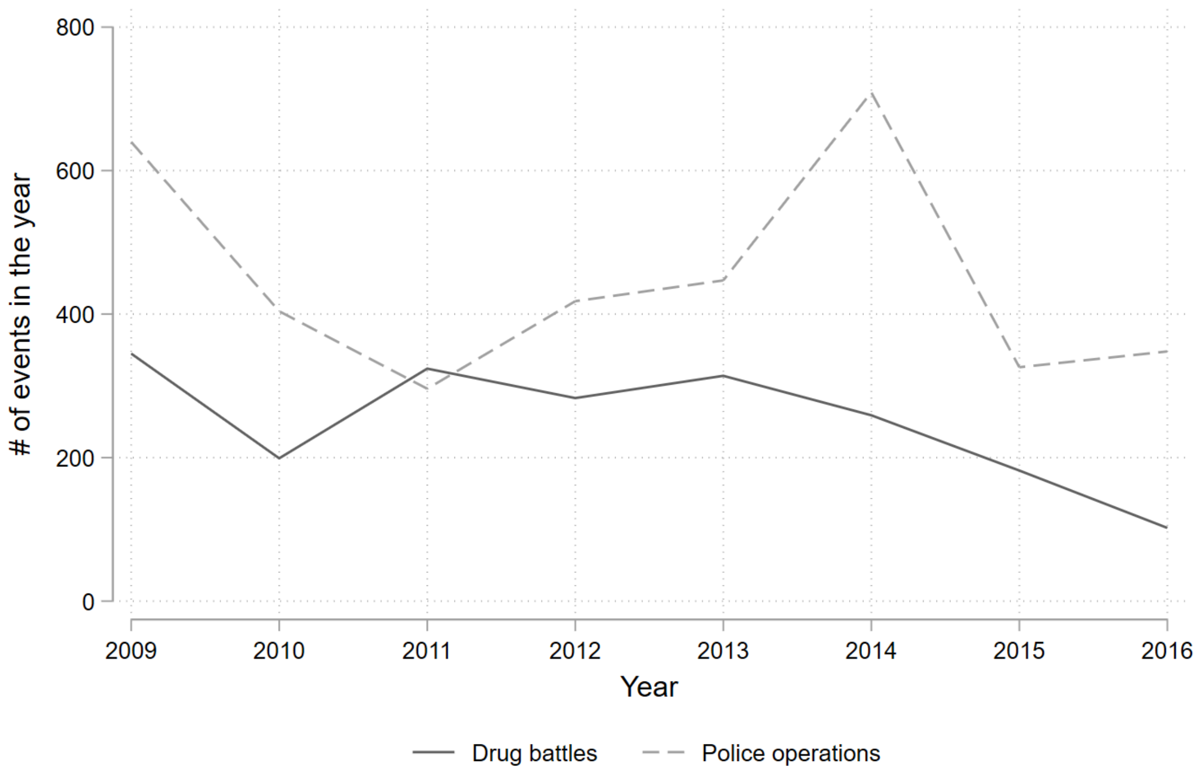
Table 3: Inequality analysis – average income

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.004	0.014	0.035	0.031	-0.030
	(0.036)	(0.075)	(0.037)	(0.036)	(0.089)
Drug battles	-0.042	-0.226	-0.137	-0.211	-0.283
	(0.054)	(0.200)	(0.100)	(0.185)	(0.110)**
Police operations $\times$ below median income	-0.078	-0.164	-0.133	-0.124	-0.172
	(0.051)	(0.094)*	(0.057)**	(0.062)**	(0.124)
Drug battles $\times$ below median income	-0.060	0.118	0.058	0.111	0.218
	(0.077)	(0.224)	(0.168)	(0.192)	(0.171)
Observations	10,534	10,534	10,534	10,534	10,534
Time FE	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12,715	4,126	2,829	5,596	163

Notes: Table shows the results of regression (1). Dependent variables are the log plus one of levels. The variables that define exposure to episodes of violence are dummies that turn one if there were two or more events within a 250m buffer around the health units in a month. Controls include covariates at the clinic level: number of health teams, clinics, available services, and presence of UPP in the nearby poor neighborhood. Standard errors are clustered at the health unit level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Additional figures and tables

Figure A1: Time series of violent events in the city of Rio de Janeiro, 2009–2016



Notes: Each line represents the annual number of events for each category. The dashed gray line shows the number of shootings related to police operations, and the solid black line for shooting related to drug battles.

Table A1: Robustness – main model with different specifications

	(1)	(2)	(3)
Panel A: Total procedures			
Police operations	-0.076	-0.077	-0.067
	(0.027)***	(0.026)***	(0.032)**
Drug battles	-0.071	-0.070	-0.061
	(0.034)**	(0.034)**	(0.076)
Panel B: PHC procedures			
Police operations	-0.127	-0.125	-0.101
	(0.044)***	(0.044)***	(0.054)*
Drug battles	-0.118	-0.118	-0.107
	(0.106)	(0.104)	(0.159)
Panel C: Diagnostic procedures			
Police operations	-0.064	-0.059	-0.033
	(0.035)*	(0.037)	(0.061)
Drug battles	-0.080	-0.076	-0.176
	(0.083)	(0.083)	(0.122)
Panel D: Clinical procedures			
Police operations	-0.077	-0.077	-0.059
	(0.037)**	(0.037)**	(0.046)
Drug battles	-0.130	-0.130	-0.052
	(0.080)	(0.078)*	(0.087)
Panel E: Surgical procedures			
Police operations	-0.133	-0.135	-0.127
	(0.063)**	(0.065)**	(0.065)*
Drug battles	-0.117	-0.119	-0.001
	(0.086)	(0.086)	(0.147)
Observations	11,391	11,391	11,405
Time FE	Yes	Yes	Yes
CNES	Yes	Yes	Yes
CNES x Year	Yes	Yes	No
Controls	Yes	No	No

Notes: This table presents the results of different empirical specifications to assess robustness. Panel A through E show results for various types of procedures: Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures, respectively. The preferred specification is in column (1), which includes fixed effects for time, interactions between CNES and year, as well as controls. Columns (2) and (3) show results excluding controls and the CNES x year fixed effects, respectively. The dependent variables are the log of the number of procedures plus one. Exposure to violence is measured as the number of violent incidents occurring within a 250m buffer around the health units in a given month. Controls include covariates at the clinic level, such as the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A2: Robustness – balanced sample

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.066	-0.111	-0.056	-0.070	-0.141
	(0.028)**	(0.044)**	(0.033)*	(0.040)*	(0.065)**
Drug battles	-0.077	-0.154	-0.097	-0.140	-0.155
	(0.036)**	(0.104)	(0.087)	(0.086)	(0.091)*
Observations	10,535	10,535	10,535	10,535	10,535
Time FE	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean_DepVar	12,627	4,103	2,802	5,558	162

Notes: This table presents the results of regressions from the model in equation (1) using a more balanced sample by excluding units that left the panel or entered in 2016. The dependent variables are the log of the number of procedures plus one, categorized by type: Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures. Exposure to violence is defined as having two or more incidents within a 250m buffer around the health units in a given month. All regressions include fixed effects for time, CNES, and interactions between CNES and year. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows:* p<0.10; ** p<0.05.

Table A3: Robustness – ever-exposed to violence sample

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.079	-0.132	-0.070	-0.079	-0.137
	(0.027)***	(0.044)***	(0.033)**	(0.038)**	(0.063)**
Drug battles	-0.069	-0.105	-0.096	-0.123	-0.114
	(0.032)**	(0.106)	(0.081)	(0.079)	(0.083)
Observations	6,147	6,147	6,147	6,147	6,147
Time FE	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	11,028	3,633	2,383	4,876	136

Notes: This table presents the results of regressions from the model in equation (1) using a sample restricted to units that have ever been exposed to violence. The dependent variables are the log of the number of procedures plus one, categorized into Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures. Exposure to violence is defined as having two or more violent incidents within a 250m buffer around the health units in a given month. All regressions include fixed effects for time, CNES, interactions between CNES and year, and controls. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A4: Effects of violent episodes count

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.016	-0.031	-0.015	-0.017	-0.030
	(0.007)**	(0.013)**	(0.011)	(0.011)	(0.016)*
Drug battles	-0.006	-0.029	-0.004	-0.008	-0.022
	(0.013)	(0.027)	(0.017)	(0.022)	(0.023)
Observations	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12,232	3,978	2,710	5,386	157

Notes: This table presents the results of regressions from the model in equation (1) examining the effects of the count of episodes of violence on various types of procedures. The dependent variables are the log of the number of procedures plus one, categorized into Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures. The exposure to violence is measured as the number of violent incidents occurring within a 250m buffer around the health units during the specified period. All regressions include fixed effects for time, CNES, and interactions between CNES and year. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.05; ** p<0.01.

Table A5: Effects of the intensity of exposure to violence

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
1 police operation	0.020	0.018	0.070	0.018	0.016
	(0.021)	(0.041)	(0.035)**	(0.038)	(0.039)
2+ police operations	-0.067	-0.114	-0.037	-0.071	-0.125
	(0.027)**	(0.044)**	(0.036)	(0.036)**	(0.063)**
1 Drug battles	-0.034	-0.115	-0.018	0.021	-0.039
	(0.032)	(0.071)	(0.069)	(0.053)	(0.066)
2+ Drug battles	-0.079	-0.145	-0.085	-0.125	-0.127
	(0.038)**	(0.112)	(0.074)	(0.081)	(0.090)
Observations	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12,232	3,978	2,710	5,386	157

Notes: This table presents the results of regressions from the model in equation (1) analyzing the effects of the intensity of exposure to violence. The dependent variables are the log of the number of procedures plus one, categorized into Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures. Exposure to violence is measured as the number of police operations or shootings occurring within a 250m buffer around the health units in a given month, with distinctions between having one versus two or more events. All regressions include fixed effects for time, CNES, and interactions between CNES and year, as well as controls. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A6: Effects of the interaction of police shootings and shooting events

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Only police operations	-0.084	-0.158	-0.073	-0.091	-0.161
	(0.029)***	(0.047)***	(0.037)**	(0.039)**	(0.068)**
Only drug battles	-0.105	-0.259	-0.121	-0.192	-0.246
	(0.049)**	(0.142)*	(0.083)	(0.112)*	(0.109)**
Both	-0.068	0.084	-0.049	-0.060	0.050
	(0.039)*	(0.109)	(0.125)	(0.042)	(0.112)
Observations	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12,132	3,960	2,667	5,348	156

Notes: This table presents the results of regressions from the model in equation (1) evaluating the effects of different types of violence exposure on various types of procedures. The dependent variables are the log of the number of procedures plus one, categorized into Total procedures, PHC procedures, Diagnostic procedures, Clinical procedures, and Surgical procedures. Exposure to violence is categorized into three groups: (1) only police operations, (2) only shootings, and (3) both types of violence. The regressions include fixed effects for time, CNES, and interactions between CNES and year, as well as controls. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A7: Results by subgroups in SIA (home visits and procedures)

		PHC procedures			Clinical procedures		
	(1) Total proc.	(2) PHC total	(3) Home visits	(4) Non-home visits	(5) Clinical total	(6) Appointments	(7) Non-appointments
Police operations	-0.076	-0.127	-0.154	-0.116	-0.077	-0.090	-0.051
	(0.027)***	(0.044)***	(0.064)**	(0.053)**	(0.037)**	(0.042)**	(0.067)
Drug battles	-0.071	-0.118	-0.166	-0.072	-0.130	-0.132	-0.061
	(0.034)**	(0.106)	(0.137)	(0.103)	(0.080)	(0.082)	(0.113)
Observations	11,391	11,391	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean y	12132	3960	2162	1799	5348	4973	375.1

Notes: This table presents the results of regression (1) for different subgroups of procedures and home visits. The dependent variables include Total procedures, PHC procedures, Home visits, Clinical procedures, and Appointments. Exposure to violence is measured by dummies indicating whether there were two or more violent events within a 250m buffer around the health units in a given month. The regressions include fixed effects for time, CNES, and interactions between CNES and year, as well as controls at the clinic level, which include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A8: Effects of episodes of violence on access – FHS electronic records

	(1) # Zero appoint.	(2) Median zero appoint.	(3) # Below median	(4) # Below p20
Police operations	0.034	0.031	0.584	0.100
	(0.037)	(0.031)	(0.336)*	(0.177)
Drug battles	-0.043	-0.024	-0.008	0.517
	(0.035)	(0.035)	(0.393)	(0.311)*
Observations	8,280	8,280	8,280	8,280
Time FE	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean y	0.959	0.494	10.95	4.798

Notes: This table presents the results of regression (1) using data from FHS electronic records. The dependent variables include: the number of weekdays with zero appointments in a month, a binary indicator for whether the number of zero-appointment days is below the historical median for the health unit, the number of days with appointments below the historical daily median, and the number of days in a month with appointments below the 20th percentile of daily appointments. Exposure to episodes of violence is represented by dummies that equal one if there were two or more violent events within a 250m buffer around the health units in a given month. Controls are included for clinic-level covariates such as the number of health teams, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. * indicates significance at the 10% level; ** at the 5% level; *** at the 1% level.

Table A9: Inequality analysis – SES index

	(1) Total proc.	(2) PHC proc.	(3) Diagnostic proc.	(4) Clinical proc.	(5) Surgical proc.
Police operations	-0.011	0.000	0.024	0.018	-0.048
	(0.032)	(0.065)	(0.034)	(0.033)	(0.086)
Drug battles	-0.082	-0.300	-0.186	-0.280	-0.169
	(0.023)***	(0.187)	(0.096)*	(0.168)*	(0.110)
Police operations $\times$ below median income	-0.078	-0.164	-0.133	-0.124	-0.172
	(0.051)	(0.094)*	(0.057)**	(0.062)**	(0.124)
Shootings $\times$ below median income	0.006	0.227	0.132	0.213	0.024
	(0.062)	(0.213)	(0.160)	(0.180)	(0.171)
Observations	10,534	10,534	10,534	10,534	10,534
Time FE	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Mean y	12715	4126	2829	5596	163.4

Notes: Table shows the results of regression (1). Dependent variables are the log plus one of levels. The variables that define exposure to episodes of violence are dummies that turn one if there were two or more events within a 250m buffer around the health units in a month. Controls include covariates at the clinic level: number of health teams, clinics, available services, and presence of UPP in the nearby poor neighborhood. Standard errors are clustered at the health unit level. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table A10: Effects on number of employees, exit and turnover

	CNES									FHS		
	Employees			Health Professionals			Doctors					
	(1) Level	(2) Exit	(3) Rate	(4) Level	(5) Exit	(6) Rate	(7) Level	(8) Exit	(9) Rate	(10) Level	(11) Exit	(12) Rate
Police operations	-0.003	0.005	-0.002	-0.005	-0.021	-0.007	-0.001	-0.004	-0.006	0.005	0.021	0.004
	(0.003)	(0.040)	(0.002)	(0.005)	(0.028)	(0.003)**	(0.007)	(0.021)	(0.004)	(0.011)	(0.029)	(0.007)
Drug battles	0.012	0.093	0.008	0.001	0.031	0.007	-0.012	-0.039	-0.004	0.008	0.093	0.036
	(0.009)	(0.085)	(0.006)	(0.011)	(0.051)	(0.007)	(0.015)	(0.038)	(0.011)	(0.030)	(0.048)*	(0.018)**
Observations	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	11,320	7,682	7,682	7,682
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean_DepVar	80.69	1.755	0.0237	19.20	0.685	0.0414	8.995	0.391	0.0508	5.553	0.350	0.0622

Notes: This table presents the results of regressions from the model in equation (1) examining the impact of violent incidents on the number of employees, exits, and exit rates. Each cell reports the coefficient for the indicated variable, with standard errors in parentheses. The dependent variables are the log of the number of employees, exits, or exit rate plus one. Exposure to violence is defined as having two or more incidents within a 250m buffer around the health units in a given month. All regressions include fixed effects for time, CNES, and interactions between CNES and year. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.

Table A11: Effects of episodes of violence on hospitalization

	(1) Hosp. chronic	(2) Hosp. asthma	(3) Hosp. copd	(4) Hosp. chf	(5) Hosp. ht	(6) Hosp. diab
Police operations	-0.034	-0.020	0.013	-0.002	-0.013	-0.019
	(0.019)*	(0.012)	(0.012)	(0.007)	(0.010)	(0.015)
Drug battles	0.001	0.020	0.004	0.006	-0.003	-0.030
	(0.033)	(0.019)	(0.013)	(0.011)	(0.018)	(0.031)
Observations	11,391	11,391	11,391	11,391	11,391	11,391
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
CNES	Yes	Yes	Yes	Yes	Yes	Yes
CNES x Year	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean y	0.519	0.0671	0.0526	0.0307	0.114	0.254

Notes: This table presents the results of regressions from the model in equation (1) examining the impact of episodes of violence on hospitalizations for various chronic conditions: asthma, chronic obstructive pulmonary disease (copd), congestive heart failure (chf), hypertension (ht), and diabetes (diab). Each cell reports the coefficient for the indicated variable, with standard errors in parentheses. Hospitalization for a specific condition is measured as the number of admissions due to that condition for individuals registered in the health unit. The dependent variables are the log of the number of hospitalizations plus one. Exposure to violence is defined as having two or more incidents within a 250m buffer around the health units in a given month. All regressions include fixed effects for time, CNES, and interactions between CNES and year. Controls at the clinic level include the number of health teams, clinics, available services, and the presence of UPP in nearby poor neighborhoods. Standard errors are clustered at the health unit level. Significance levels are denoted as follows: * p<0.10; ** p<0.05; *** p<0.01.