# Neighborhood Violence, Poverty, and Psychological Well-being*

M. Alloush† Jeffrey R. Bloem‡

January 13, 2021

**Abstract**

We estimate the relationship between neighborhood violence and psychological well-being using nationally representative panel data from South Africa. We use data on household-level perceptions of neighborhood violence as well as reported crimes and local media reports to measure violence. First, we find the poor live in neighborhoods that they perceive to have higher levels of violence and have objectively more violence. Second, higher levels of both perceived and objective violence are strongly linked to elevated depressive symptoms and an increased likelihood of being at risk for clinical depression. Finally, we show that living in urban neighborhoods with high levels of violence while poor is predictive of future poverty in our sample.

**Keywords**: Violence, Psychological Well-being, Depression, Mental Health, Poverty, Neighborhood Effects, South Africa.

**JEL Codes**: I3, O1, D91.

*We thank Luis Mijares for excellent research assistance. We appreciate the team at SALDRU for their commitment to keeping the psychological well-being module in the National Income Dynamics Study of South Africa. We are grateful for constructive feedback from Jason Kerwin, Marc Bellemare, Travis Lybbert, Sunghun Lim, Berenger Djoumessi Tiague, Lindsey Novak, Chris Boyd Leon, and Natalia Ordaz Reynoso. This research was conducted prior to JRB's employment with the USDA. The findings and conclusions in this manuscript are ours and should not be construed to represent any official USDA or US Government determination or policy. All errors are our own.

†Hamilton College, Department of Economics, 198 College Hill Road Clinton, NY 13323. Corresponding author email: malloush@hamilton.edu.

‡United States Department of Agriculture, Economic Research Service, MS9999, Beacon Facility, P.O. Box 419205, Kansas City, MO 64141.

## 1 Introduction

The previous generations of the extremely poor overwhelmingly lived in rural areas in low-income countries. Today most of the poor live in urban settings in countries with fast-growing but increasingly unequal economies (Page and Pande, 2018). Although both the share of the global population and the absolute number of those living in extreme poverty is smaller today than anytime in modern history, important questions remain about how to most effectively alleviate the harsh conditions of those who remain poor. In particular, the poor—especially the urban poor—tend to live in neighborhoods with elevated levels of violence in a variety of contexts around the world.[1] While exposure to violence is universal in its psychological harm, the disproportionate exposure of the poor may be a mechanism through which poverty is reinforced (Ridley et al., 2020). Shedding light on the conditions that may drive the dynamics and persistence of poverty can pave the way for more effective poverty-alleviation policy.

In this paper we investigate the question: What is the relationship between violence within neighborhoods and an individual's psychological well-being? This relationship is important for several reasons. First, psychological well-being is an important outcome as an end in itself. Effects on psychological well-being can be more persistent than effects on economic well-being (Friedman and Thomas, 2009) and, at extreme levels, depression can lead to suicide (Christian, Hensel and Roth, 2019). Second, exposure to violence (Moya and Carter, 2019) and reduced psychological well-being (De Quidt and Haushofer, 2016) may lead to fatalistic beliefs about socioeconomic mobility, which could lead to a psychological poverty trap (Lybbert and Wydick, 2018; Ridley et al., 2020). Third, since adolescents are more likely to suffer from depressive symptoms if one of their parents is also suffering from depression (Eyal and Burns, 2019; Bendini and Dinarte, 2020), psychological disorders can have important inter-generational consequences.

Our primary contribution is to study the relationship between neighborhood violence and psychological well-being using nationally representative panel data from South Africa, a middle-income country with very high levels of violence, economic inequality, and urban poverty. The panel nature of our data allows us to use an empirical approach that includes individual fixed effects and rules out confounding variation between neighborhood violence and psychological well-being due to endogenous sorting of people with low levels of psychological well-being into areas with more or less violence. Additionally, with data on both administrative (e.g., "objective") and perceived violence, we are able to study both the overall relationship between exposure to violence and the more specific relationship

[1] See the World Bank's World Development Report 2011: Conflict, Security, and Development. Available online: `https://doi.org/10.1596/978-0-8213-8439-8`.

between perceived violence on psychological well-being.[2] We also address the important concern of reverse causality and recall bias in the relationship between perceived violence and psychological well-being by using the leave-*i*-out mean of perceived violence within each individual *i*'s primary sampling unit (PSU) as an alternative measure of neighborhood violence.[3] Finally, we study effect heterogeneity across various sub-groups of the population.

We find that depressive symptoms and the likelihood of being at risk for depression increase with higher levels of neighborhood violence. Specifically, the lower end of our estimates show that living in a neighborhood with high levels of violence is associated with a nearly 25 percent increase in the likelihood of being at risk of depression. Moreover, a one standard deviation increase in neighborhood violence is associated with a reduction in psychological well-being that is equivalent to the effect of a 20 percent decrease in income (Haushofer and Shapiro, 2016; Alloush, 2020). To the extent that we are able to rule out confounding factors by (i) controlling for household and individual income, household size, number of children, and neighborhood services, (ii) accounting for district, survey wave, and individual fixed effects, and (iii) addressing endogenous sorting, reverse causality, and recall bias, we show that neighborhood violence can have a large effect on the psychological well-being of individuals. Tests considering selection on observables as an indication of selection on unobservables (Altonji, Elder and Taber, 2005; Oster, 2019) support the credibility of our results. Additional estimation approaches further support the core finding that exposure to violence increases both depressive symptoms and the likelihood of being at risk for depression.[4]

We also find that individuals from the poorest quintile of the wealth distribution who live in a high-violence neighborhood are almost three times more likely to be at risk of clinical depression than individuals from the richest quintile living in a low-violence neighborhood. Given our finding that the poor are disproportionately more likely to live in neighborhoods with high levels of violence, and that low levels of psychological well-being

[2]This distinction is important for at least two reasons. First, although perceiving violence represents an important channel between objective neighborhood violence and an individual's psychological well-being, perceptions of violence do not necessarily align with objective violence (Mawby, 1992; Smith and Torstensson, 1997; Chadee, Austen and Ditton, 2007; Salm and Vollaard, 2018). Second, a relatively large literature investigates the role of *perceived* violence on psychological well-being (Aneshensel and Sucoff, 1996; Ross and Mirowsky, 2009; Steptoe and Feldman, 2001; Latkin and Curry, 2003) and little is known about the extent to which results differ between objective and perceived violence.

[3]This represents the average perceived violence within individual *i*'s PSU excluding individual *i* from the average. We create this variable to break the possible link between an individual's own psychological well-being and their household's measure of perceived violence, as reported by the household respondent for the NIDS survey. PSUs are defined geographic areas. South Africa is divided into 54 districts, on average there are 55 PSUs within each district.

[4]Similar to Currie and Tekin (2012) we find qualitatively similar results using estimation methods that each rely on different assumptions. The uniformity of results, given the different assumptions implicit in the different estimation methods, provides strong support of our core results.

can hinder one's ability to achieve their full earning potential, these results illuminate a mechanism through which poverty may be reinforced. Specifically, increased exposure to violence is a mechanism through which poverty can affect psychological well-being. These dynamics, in turn, can hinder the ability of individuals and households to escape poverty (Haushofer and Fehr, 2014; Haushofer, 2019; Alloush, 2020; Ridley et al., 2020). Finally, we show that living in urban neighborhoods with high levels of violence while poor is predictive of future poverty and lower income growth rates.

Our paper is most closely related to Cornaglia, Feldman and Leigh (2014) and Dustmann and Fasani (2016), who study the effect of crime on mental well-being in Australia and the United Kingdom, respectively. Both of these studies find that exposure to crime reduces mental well-being but examine higher income populations with lower rates of violent crime than we do in our paper. We use a similar research design to investigate the relationship between neighborhood violence and psychological well-being, and add additional analysis using both objective and perceived violence variables.

We add to the previous literature in three important ways. First, and most generally, although much of the previous literature investigates exposure to relatively extreme acts of war, we focus our analysis on exposure to less extreme—but far more common—acts of neighborhood violence.[5] Second, building on the idea that perceptions may importantly mediate the relationship between objective reality and psychological well-being (Kruger, Reischl and Gee, 2007; Curry, Latkin and Davey-Rothwell, 2008), we use both objective data on violent events and perceptions of neighborhood violence. This allows us to compare both the overall effect of exposure to violence and the more specific effect of perceived violence on psychological well-being. Third, our paper is related to the literature on the general effect of neighborhoods on psychological well-being. Much of this literature finds significant and robust correlations between neighborhood characteristics and psychological well-being but are almost entirely based on cross-sectional analysis.[6] Ex-

[5]The previous literature focusing on more extreme acts of war suggests that victims of extreme trauma and violence are more likely to suffer from psychological disorders such as anxiety, depression, and post-traumatic stress disorders. This includes: Cambodians exposed to Pol Pot era trauma (Mollica et al., 1998), internally displaced people (Vinck et al., 2007) and child soldiers (Blattman and Annan, 2010) in Northern Uganda, children exposed to war in Croatia (Ajdukovic and Ajdukovic, 1998), and youth exposed to school shootings in the United States (Rossin-Slater et al., 2020). Additionally, exposure to violence increases risk aversion or preferences for certainty in Afghanistan (Callen et al., 2014), Colombia (Moya, 2018), and Mexico (Brown et al., 2019). Previous literature focusing on less extreme acts of neighborhood violence largely come from the psychological and medical literature which explores the correlation between neighborhood characteristics (including violence) and psychological or mental health (Clark et al., 2007; Dowdall, Ward and Lund, 2017; Fowler et al., 2020; Stockdale et al., 2007; Tomita, Labys and Burns, 2016; Wilson-Genderson and Pruchno, 2013).

[6]For example, previous work suggests that subjective perceptions of neighborhood characteristics are strongly associated with various measures of mental health including depression, anxiety, anger, and lower quality of life (Latkin and Curry, 2003; Ross and Mirowsky, 2009; Yen et al., 2006; Tomita, Labys and Burns, 2016; Dowdall, Ward and Lund, 2017) even after controlling for individual-level observable characteristics

ceptions are studies of the Moving to Opportunity project, which randomly encouraged households to move away from relatively high-crime neighborhoods within cities in the United States and find large improvements in psychological well-being in the short (Katz, Kling and Liebman, 2001), medium (Kling, Liebman and Katz, 2007), and long term (Ludwig et al., 2012). We add to the literature on the neighborhood effects on psychological well-being by focusing more specifically on the role of neighborhood violence, by providing evidence from a new and important context, and by using nationally representative panel data which allows us to account for individual fixed-effects.[7]

The remainder of the paper is organized as follows: In the next section, we discuss the data used in the empirical analysis of this paper and report trends in violence and descriptive results from South Africa. The third section presents the core empirical results with an investigation of effect heterogeneity. Section four tests the robustness and sensitivity of our core results. The fifth section highlights how violence and psychological well-being can influence poverty dynamics. Finally, section six concludes.

## 2 Context and Data

The primary data used in this analysis comes from the panel dataset of the National Income Dynamics Study (NIDS) of South Africa.[8] The first survey wave of this study was conducted in 2008 and households (and individuals) were interviewed again in 2010, 2012, 2014, and 2017. The study began with a nationally representative sample of nearly 27,000 individuals (15,630 completing the adult individual questionnaire) in 6,598 households. Data were collected on many socio-economic variables that include expenditures, labor market participation, economic activity, fertility, mortality, migration, income, education, and anthropometric measures.

NIDS also contains a module on psychological well-being that includes the 10-item Center for the Epidemiological Studies Depression (CES-D) Scale for all adults (at least 16 years old) in all waves. The inclusion of a detailed psychological well-being module in the

such as age, marital status, race, education, and income (Mair, Roux and Galea, 2008). This relationship is often especially strong among children (Cromley, Wilson-Genderson and Pruchno, 2012; Ross and Mirowsky, 2009; McAloney et al., 2009; Bor et al., 2018).

[7]Our paper is also relevant to the literature estimating the consequences of exposure to violence on a host of outcomes (Verwimp, Justino and Bruck, 2019) such as, for example, birth outcomes (Koppensteiner and Manacorda, 2016) and food insecurity (George, Adelaja and Weatherspoon, 2020).

[8]This is panel study conducted by the South Africa Labor and Development Research Unit at the University of Cape Town. An analysis of mental health using the first round of NIDS data can be found in Ardington and Case (2010). Additionally, also using only a single wave of the NIDS data, both Tomita, Labys and Burns (2016) and Dowdall, Ward and Lund (2017) study the relationship between neighborhood characteristics and depressive symptoms. The analysis in our paper builds on this previous analysis in a number of ways. Specifically, Tomita, Labys and Burns (2016) suggest analysis that takes advantage of the longitudinal capabilities of the NIDS data—as we do in this paper—is warranted.

adult questionnaire in every survey wave is unprecedented in a nationally representative panel survey in a low- or middle-income country.[9] The CES-D is a widely used tool for assessing depressive symptoms and screening for depression in the general population (Radloff, 1977; Santor, Gregus and Welch, 2006; Siddaway, Wood and Taylor, 2017).[10]

Waves two through five of the NIDS data include questions at the household-level on the frequency of neighborhood violence. In particular, the survey asks about the frequency of different types of violence in their neighborhood including: violence between different households, violence between members of the same household (e.g., domestic violence), gang violence, and murders, shootings, or stabbings. We create a perceived violence index with these questions using factor analysis. Our core results are based on this standardized index of neighborhood violence created using self-reported perceived frequency of violence measures.

Additional data comes from the South African Police Service's (SAPS) crime database. These data are publicly available on an annual basis and record reported crimes in each police precinct. We match these police precincts to districts in the NIDS data and aggregate violent crimes at the district-year level.[11] With information on the populations in each district, we calculate the rates of reported violent crime within each district over time.

Supplemental data on violent events comes from the Armed Conflict Location and Event Data (ACLED) Project (Raleigh et al., 2010). The ACLED project collects information on conflict events—such as location, date, type of conflict, involved actors, and estimated fatalities—for much of Europe, the Middle East, Asia, and Africa. The entire ACLED dataset includes close to 200,000 individual events spanning from 1997 through the present. We use ACLED data for South Africa from 2008 through 2017, the years associated with each of the five NIDS waves. These data allow us to implement a useful robustness check on our results.

[9] Psychological well-being modules can be found in large nationally representative panel studies for Germany, Australia, UK, and more recently the Indonesia Family Life Survey (IFLS) added a CES-D module in more recent waves of the study.

[10] The score is calculated using answers to 10 questions (in Appendix Table A.1) that ask how often the individual felt certain feelings in the past week. A higher overall score indicates more depressive symptoms and with the 10-item CES-D scale, threshold scores of 10-12 are usually used to indicate a person is at increased risk of depression. The CES-D10 is commonly used in South Africa and has been shown to be internally consistent and verified as an effective screening tool for depression (Baron, Davies and Lund, 2017; Hamad et al., 2008; Myer et al., 2008). The CES-D is similar to another commonly used depression screening tool the PHQ-9. The two are shown to be highly correlated [0.8-0.88] (Pilkonis et al., 2014). Moreover, Baron, Davies and Lund (2017) suggest that the CES-D scale has slightly better positive predictive value than the PHQ-9 in South Africa.

[11] South Africa's nine provinces are divided into 52 districts—the second level of administrative division in the country. As of 2005, all districts are fully within provinces and have an average population of approximately 1 million people.

## 2.1 Descriptive Statistics

South Africa is a middle-income country with the highest level of income and wealth inequality in the world (World Bank, 2018). The mean monthly household income per capita (standard deviation in parenthesis) in the study sample in 2017 is 3,262 ZAR (10,197).[12] This hides significant inequality as the median household income per capita is ZAR 1,437. Moreover, recent analyses estimate that nearly 54 percent of the population is living in poverty and about 20 percent live in extreme poverty (Leibbrandt, Finn and Woolard, 2012).[13] In the balanced panel sample of NIDS, 87 percent of individuals report food expenditure levels that are considered poor in at least one of the five waves. Additionally, 48 percent are poor in at least three out of the five waves and 11 percent are poor in all five waves of the panel.

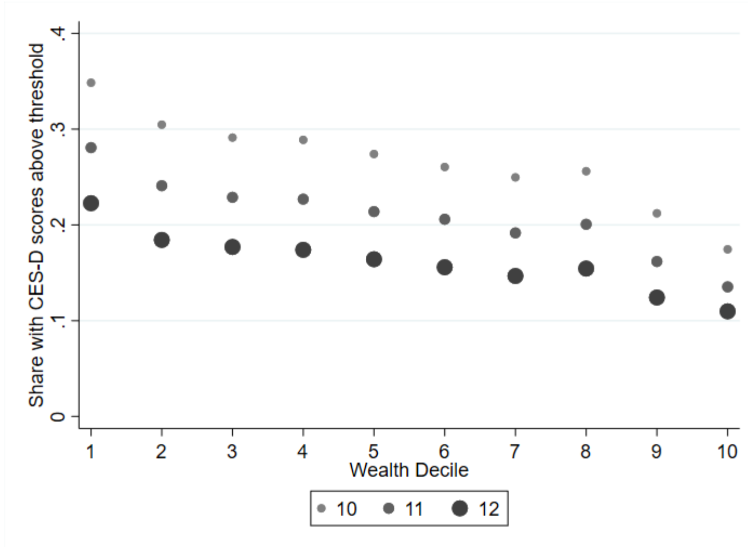
In the study sample, the mean CES-D score (standard deviation) for all five waves is 6.8 (4.4) and shows a decreasing trend where the average score is 8.2 (4.9) in 2008 and 6.62 (4.3) in 2017. The within person standard deviation in the CES-D score is 3.6. Figure A.1 in the Appendix shows the distribution of CES-D scores across all five NIDS waves. The figure highlights the incidence of scores above 10 which exhibit a similar pattern as the means over time and decrease from about 29.3 percent in 2008 to 17.7 percent in 2017. Nearly 54 percent of the panel sample record a CES-D score of 11 or above at least once in all five waves.[14]

Figure 1(A) shows the share of individuals with scores above the thresholds of 10, 11, and 12 by wealth decile. High scores such as these indicate that an individual is experiencing more depressive symptoms and psychologists use thresholds in this range to screen for depression—those with scores above these thresholds are increasingly likely to suffer from what would be clinically diagnosed as depression. Throughout this paper we refer to these variables as measuring an individual's risk of depression. As Figure 1(A) illustrates, the share of individuals with scores above the threshold decreases with wealth whereby the share among the highest wealth decile is nearly half that of the lowest. This figure shows a strong correlation between psychological and economic well-being. Figure 1(B) shows the share of individuals above the CES-D thresholds by an index of perceived vi-

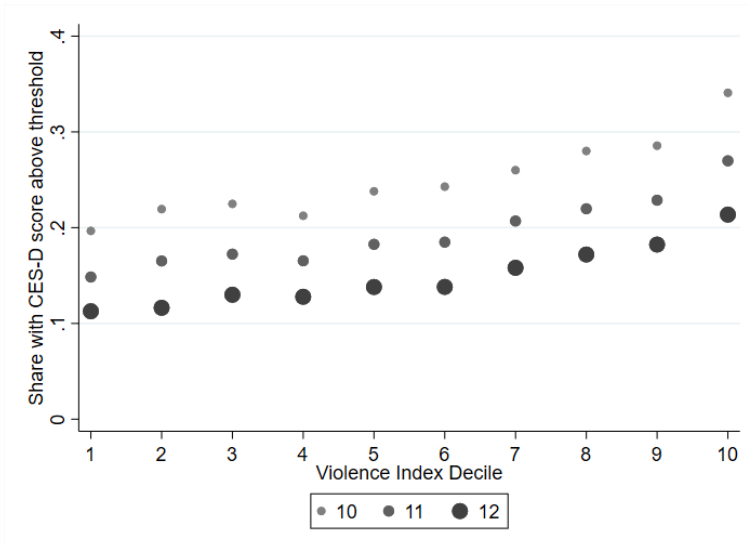
[12] This corresponds to 140 US Dollars or $431 PPP adjusted. The GDP per capita in South Africa in 2017 is $6,160 corresponding to a monthly income per capita of $513. The distribution of income is extremely skewed (a very large standard deviation) and the trimming of the top and bottom extremes in income for our sample brings down the mean and standard deviations reflecting the high levels of inequality in the country. Income and expenditure numbers are adjusted for inflation and are in November 2017 prices.

[13] We use a household income per capita of ZAR 1,138 (official 2017 upper-bound poverty line) to identify individuals as poor and ZAR 531 (official 2017 food poverty line) to identify extremely poor individuals (Lehohla, 2017).

[14] Baron, Davies and Lund (2017) show that scores of 11 and above are appropriate for screening for depression in South Africa among most populations.




(A) Share with elevated depressive symptoms by wealth




(B) Share with elevated depressive symptoms by perceived violence

FIGURE 1: Share of individuals with CES-D scores above 10, 11, and 12 by Wealth Decile. High scores indicate an increasing risk of clinical depression and it is clear (in panel A) that as wealth increases, the share of individuals reporting scores higher than these thresholds is decreasing. Panel (B) shows that this share increases with perceived violence. Figure A.2 in the Appendix displays these shares with a measure of violence that rules out direct reverse-causality that shows a similar pattern.

olence. It is clear that as the level of violence perceived by the household-questionnaire respondent increases, the share of individuals who have elevated depressive symptoms also increases.[15]

[15]This pattern is very similar when using the leave-*i*-out mean of perceived violence within each PSU (see Figure A.2 in the Appendix).

TABLE 1: Psychological Well-Being by Violence and Wealth Quintile

| Panel A: CES-D Score | | | | | | |
|---|---|---|---|---|---|---|
| | | **Wealth Quintile** | | | | |
| | | Poorest | 2 | 3 | 4 | Richest |
| **Violence Index Quintile** | Least Violent | 7.13 | 6.60 | 6.01 | 6.15 | 4.99 |
| | 2 | 7.29 | 6.82 | 6.50 | 6.35 | 5.52 |
| | 3 | 7.24 | 6.95 | 6.66 | 6.68 | 6.10 |
| | 4 | 7.79 | 7.32 | 6.85 | 6.83 | 6.29 |
| | Most Violent | 8.32 | 7.67 | 7.42 | 7.41 | 7.13 |

| Panel B: CES-D $\geq$ 11 | | | | | | |
|---|---|---|---|---|---|---|
| | | **Wealth Quintile** | | | | |
| | | Poorest | 2 | 3 | 4 | Richest |
| **Violence Index Quintile** | Least Violent | 0.21 | 0.18 | 0.16 | 0.16 | 0.11 |
| | 2 | 0.22 | 0.20 | 0.16 | 0.15 | 0.12 |
| | 3 | 0.22 | 0.20 | 0.18 | 0.18 | 0.15 |
| | 4 | 0.26 | 0.22 | 0.20 | 0.20 | 0.17 |
| | Most Violent | 0.31 | 0.26 | 0.24 | 0.23 | 0.21 |

*Note:* Panel A shows average CES-D scores for each bin. Higher scores are associated with more depressive symptoms. Panel B shows the share of individuals with scores above the threshold score of 11 who are at an elevated risk for depression.

Table 1 combines the above two figures and shows the average CES-D scores and share above the depression thresholds by both wealth and violence quintiles. The average CES-D score for the poorest quintile living in a high violence neighborhood is 8.32 with 31 percent of individuals reporting scores above the depression threshold, whereas the average among the wealthiest quintile living in neighborhoods with low levels of perceived violence is 4.99 and 11 percent. The observed patterns in this table suggest that the incidence of violence plays a role in predicting psychological well-being that is not captured by wealth.

### 2.2 Violent Crime in South Africa

South Africa suffers from high levels of violence. In 2017, the yearly homicide rate in the country as a whole was just over 30 per 100,000—the 6th highest rate in the world (Institute for Health Metrics and Evaluation, 2017). The homicide rate is even higher in urban settings: In 2017, the Cape Town metro area had over 2,500 murders making the district's homicide rate 58 per 100,000. With aggravated assault and sexual assault rates of 268 and 78 per 100,000, South Africa has consistently had some of the highest interpersonal violence rates in the world the last 10 years. Table 2 shows violent and property crime

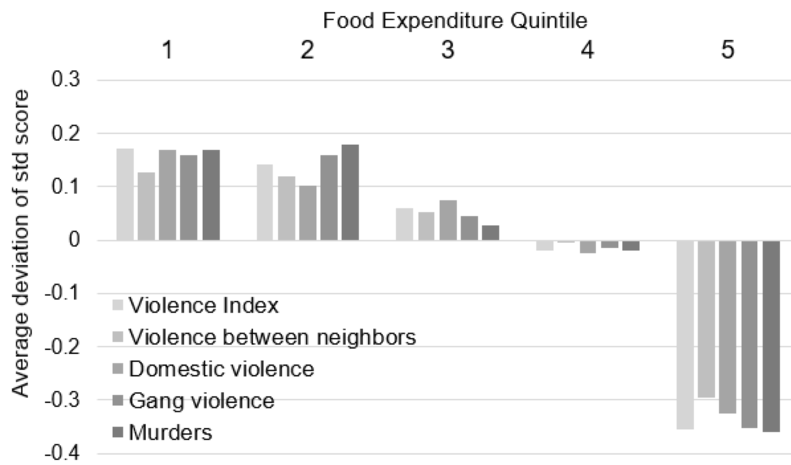
TABLE 2: Crime rates in South Africa and major metro areas.

| Year | 2010 | 2012 | 2014 | 2017 |
|---|---|---|---|---|
| **South Africa** | | | | |
| Homicide rate | 30.0 | 26.7 | 27.9 | 30.3 |
| Sexual assault rate | 120.1 | 109.5 | 101.9 | 78.3 |
| Assault rate | 357.0 | 324.2 | 295.7 | 267.7 |
| Armed robbery rate | 203.1 | 174.7 | 196.9 | 226.6 |
| Property crime rate | 233.1 | 209.1 | 196.0 | 185.3 |
| **Cape Town** | | | | |
| Homicide rate | 37.7 | 39.5 | 52.5 | 57.9 |
| Sexual assault rate | 145.1 | 131.8 | 104.8 | 94.1 |
| Assault rate | 308.7 | 303.5 | 282.2 | 273.5 |
| Armed robbery rate | 274.4 | 277.5 | 379.2 | 457.2 |
| Property crime rate | 430.0 | 401.8 | 408.3 | 434.5 |
| **Durban** | | | | |
| Homicide rate | 47.2 | 35.8 | 36.2 | 42.6 |
| Sexual assault rate | 156.5 | 137.1 | 119.3 | 70.9 |
| Assault rate | 307.1 | 290.4 | 254.4 | 227.8 |
| Armed robbery rate | 364.5 | 267.6 | 275.0 | 293.7 |
| Property crime rate | 322.3 | 201.0 | 175.9 | 160.2 |
| **Johannesburg** | | | | |
| Homicide rate | 24.0 | 22.7 | 24.7 | 30.6 |
| Sexual assault rate | 110.6 | 86.3 | 79.9 | 69.0 |
| Assault rate | 404.0 | 344.6 | 328.9 | 309.7 |
| Armed robbery rate | 396.5 | 297.9 | 344.4 | 450.9 |
| Property crime rate | 342.4 | 274.9 | 259.0 | 256.4 |

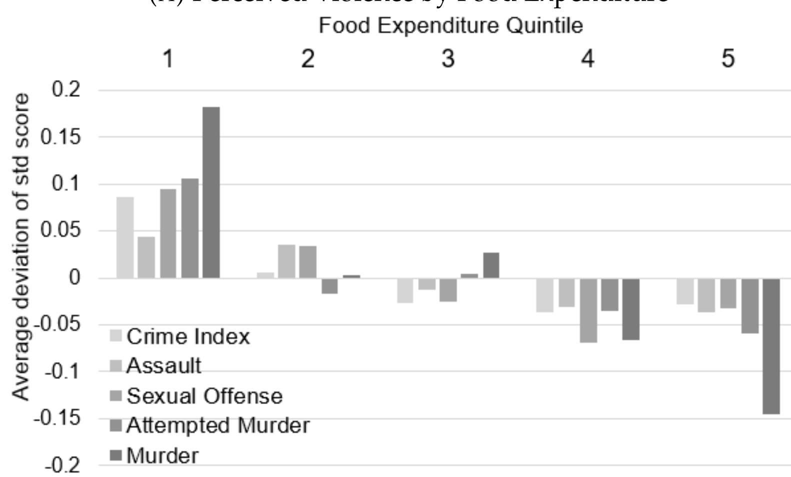
*Note:* Rates reported per 100,000 individuals. South Africa as a whole has high violent crime rates especially in urban areas. The average homicide rate of 30.3 is nearly ten times as high as the average rate in Europe (3.0) and five to six times the average globally (6.1) and in the United States (5.3) (United Nations Office on Drugs and Crime, 2019).

rates in the available years matching the NIDS waves (2010, 2012, 2014, and 2017) in South Africa as a whole as well as in the three largest metro areas: Cape Town, Durban, and Johannesburg. The violent crime rates in Cape Town and Durban (the two largest metro areas) are significantly higher than the country as a whole as well as Johannesburg.

The overall trend in most types of violent crime seems to be decreasing overall, however, homicide rates and armed robberies have seen an uptick recently, especially in Cape Town. While violent crime is more prevalent in urban settings, these areas are also on average better off economically than rural or traditional settings. However within urban settings, the exposure to violence—or perception of it—varies greatly by socio-economic status. The poor are significantly more likely to live in neighborhoods that they perceive to have a lot of violence. Figure 2(A) breaks this down further and shows that greater house-




(A) Perceived Violence by Food Expenditure




(B) Matched SAPS Data on Crime by Food Expenditure

FIGURE 2: Standardized perceived violence scores clearly decreases by economic well-being. District level aggregated crime data show that those in lower food expenditure deciles live in districts with higher crime on average. Figure A.3 in the Appendix also shows that poorer households live in small geographical areas (PSUs) that are perceived by *others* to have more violence.

hold material well-being is associated with lower violence overall. Estimates in the figure show that in urban areas respondents from the highest food expenditure household quintile live in neighborhoods that they perceive to have over 0.5 standard deviations lower violence than those living in the poorest quintile.[16] This pattern looks similar for all the

[16]This difference may be an under or over estimate of the actual difference in violence between the neighborhoods. If the poor are desensitized to the violence while higher income individuals are not, then this difference would be an underestimate of the actual difference in neighborhood violence. If higher income individuals are not exposed to the realities of the neighborhood then this may be an overestimate. This highlights the

components of the perceived violence index.

The relationships between our objective measures of violence and economic well-being are not as strong but still clearly trend in the same manner. Due to confidentiality restrictions, the district is the lowest geographical unit we are able to identify in the NIDS data. Therefore, a limitation of these objective violence data is that we can only link them to the NIDS data at the district level. Nevertheless, Figure 2(B) shows that standardized rates of crime are decreasing overall with household material well-being. Wealthier households live in districts with overall lower levels of violence. The figure shows that households in the lowest quintile of the food expenditure distribution live in districts with overall higher recorded violence rates.[17]

### 2.3 Objective and Perceived Violence

As noted by Dustmann and Fasani (2016), there are at least three channels through which exposure to neighborhood violence may influence psychological well-being: (i) increased fear and anxiety of being directly victimized, (ii) reduced freedom due to limitations on behavior, and (iii) the need to invest in strategies to avoid victimization. Therefore, the relationship between neighborhood violence and psychological well-being depends first on how actual violence influences the perception of violence.

Our main objective violence data come from the South African Police Service (SAPS) that provide yearly records of crimes in each police precinct in South Africa. We use information on violent crimes for years that coincide with the NIDS waves and aggregate these data at the lowest geographical unit we are able to match in the NIDS dataset—the district. A secondary source for objective violence data come from the ACLED Project, which provides information on conflict events using information available from media and news reports. On a weekly basis ACLED are coded based on available reports. This coding is then scrutinized and crossed-checked by two reviewers to ensure comparability and accuracy.

We use these two supplementary data sources to demonstrate the relationship between our objective and perceived violence variables. To do this we compare the number of different types of events in the calendar year prior to the NIDS interview (as reported by SAPS and ACLED) to the main self-reported index measure of perceived violence (as recorded in the NIDS). Table 3 reports these results with household-level regressions between our objective violence measures and our perceived violence index.[18] All of the coefficient es-

importance of considering *perceived* violence and the relationship with psychological well-being.

[17]This pattern can be observed with other definitions of economic well-being; for example using a wealth index or household income per capita, it is clear that poorer households live in districts with higher levels of crime and violence events.

[18]Note that only one person within each household responds to the perceived violence survey question.

Table 3: Predictive Value of Objective Violence Measures

| *Dep Var: Perceived Violence Index* | | | Urban Sample | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Crime index (SAPS) | 0.169*** | 0.202*** | 0.210*** | 0.235*** | |
| | (0.044) | (0.044) | (0.062) | (0.060) | |
| # of conflict events (ACLED) | | | | | 0.075*** |
| | | | | | (0.019) |
| District fixed effects | ✓ | ✓ | ✓ | ✓ | ✓ |
| Wealth controls | | ✓ | | ✓ | |
| $N$ | 20,804 | 20,320 | 12,469 | 12,168 | 12,469 |

*Note:* Standard errors clustered at the PSU level are in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. There is a high level of correlation between district-level objectively measured violent crime and perceived crime—especially in urban areas.

timates of the predictive value of the objective measures for the perceived violence index are positive and statistically significant at the 1 percent level. The reported standard errors are clustered at the PSU level.[19]

Despite the aggregation levels of the objective measures of violence, they have strong predictive value with the perceived violence index. For example, results in Column (2) of Table 3 show that after controlling for district-fixed effects and wealth of the respondent a one SD change in the objective crime index increases the perceived violence index by 0.2 standard deviations. These estimated magnitudes are meaningful and show a strong correlation between objective violence and perceived violence.[20]

## 3 Empirical Approach and Results

We estimate the relationship between neighborhood violence and psychological well-being with the following linear regression specification:

$$PW_{ihdt} = \alpha_0 V_{hdt} + \boldsymbol{X'_{hdt}\beta_0} + \boldsymbol{Y'_{hdt}}\gamma_0 + \boldsymbol{Z'_{ihdt}}\delta_0 + \rho_i + \theta_t + \tau_d + \epsilon_{ihdt} \tag{1}$$

In equation (1) $PW_{ihdt}$ represents measures of psychological well-being: the score on the full CES-D scale and a binary variable for having a CES-D score of 11 or above for individual $i$ in household $h$ in district $d$ at time $t$.[21] The variable $V_{hdt}$ represents various

[19] PSUs are defined geographic areas on which the sampling for NIDS took place. All standard errors reported in this paper are clustered at the PSU level.

[20] We expect that if the objective crime variables were aggregated at a smaller geographical unit, its predictive value would likely be larger. The smallest identifiable geographical unit in the publicly available NIDS data is the district. The PSUs are significantly smaller geographical areas but are de-identified.

[21] Although subjective and self-reported psychological well-being data have some well-documented limitations, they do contain relevant information about an individual's well-being (Di Tella, MacCulloch and Oswald, 2003).

measures of household-level neighborhood violence, which takes one of three forms in our analysis: (i) perceived violence as reported by the household respondent, (ii) the PSU-level leave-*i*-out-mean of perceived violence, and (iii) district level objective violent crime. $\boldsymbol{X_{hdt}}$ and $\boldsymbol{Y_{hdt}}$ are household-level controls while $\boldsymbol{Z_{ihdt}}$ are individual-level control variables. $\boldsymbol{X_{hdt}}$ are household-level controls that include: household size, number of children, and neighborhood services such as electricity, trash collection, and streetlights. $\boldsymbol{Y_{hdt}}$ are household-level controls that proxy for time-variant economic characteristics including household income, a wealth index, and food expenditure per capita. $\boldsymbol{Z_{ihdt}}$ are individual controls that include: individual income, sex, ethnicity, age (cubic polynomial), and educational attainment dummy variables. $\rho_i$ is the individual fixed effect, $\theta_t$ is a time or survey wave fixed effect, and $\tau_d$ is a district fixed effect.[22] Finally, $\epsilon_{ihdt}$ is the error term.

In addition, we estimate a similar equation that takes into account lagged values of the dependent variables and measures of economic well-being at the household level.

$$\begin{aligned} PW_{ihdt} = \alpha_1 V_{hdt} + \sigma_1 PW_{ihd(t-1)} + \boldsymbol{Y'_{h,d,t}}\boldsymbol{\gamma_1} + \boldsymbol{Y'_{hd(t-1)}}\boldsymbol{\gamma_2} \\ + \boldsymbol{X'_{hdt}}\boldsymbol{\beta_1} + \boldsymbol{Z'_{ihdt}}\boldsymbol{\delta_1} + \rho_i + \theta_t + \tau_d + \epsilon_{ihdt} \end{aligned} \tag{2}$$

We estimate equation (2) to take advantage of the panel nature of these data and better control for income which is an important confounder. Taking into account both current and prior income is an important robustness test for the credibility of our results. This effectively accounts for the way time-variant economic conditions (e.g., income or poverty dynamics) can drive both violence (Demombynes and Ozler, 2005) and mental health status (Haushofer and Fehr, 2014; Haushofer, 2019; Ridley et al., 2020; Alloush, 2020).

Three empirical challenges arise when estimating the relationship between neighborhood violence and psychological well-being. First, and specifically when using our perceived violence variable, psychological well-being could influence perceived violence leading to reverse causality or recall bias. Second, if individuals or households endogenously sort themselves into neighborhoods specifically due to neighborhood violence, then our estimates may be biased. Third and finally, although our estimation approach aims to account for many sources of unobservable heterogeneity we do not have the benefit of a perfect natural experiment and therefore, unobserved time-varying neighborhood characteristics influencing both violence and psychological well-being could bias our estimates.

Our research design addresses each of these challenges. First, on reverse causality and recall bias, we construct an alternative perceived violence variable that represents the leave-*i*-out mean of perceived violence within individual *i*'s PSU. We create this variable to break the possible link between an individual's own psychological well-being and their

[22]Including individual fixed effects accounts for the inter-generational effect of parental depression on children (Eyal and Burns, 2019).

household respondent's perception of violence in their neighborhood and use this variable as an alternative violence indicator throughout our analysis.[23] One downside of using this variable is that PSUs are defined in the initial 2008 NIDS sample and are not updated for households that move. Therefore, we restrict our analysis with this variable to the non-mover sub-sample which is approximately half of the full sample.

Second, on the challenge of endogenous sorting, if individuals and households never move across district boundaries then conditioning on district and individual fixed effects (e.g., $\rho_i$ and $\tau_d$) estimates effects based on within-district and within-individual variation and rules out bias due to endogenous sorting. If, on the other hand, individuals and households do sometimes move across district boundaries—which occurs very infrequently in our data, only about 3.2 percent of respondents move across districts between each round—then bias from this endogenous sorting could still persist. To address this concern, we follow Dustmann and Fasani (2016) and consider each individual in our data as a different individual in each district with a different individual fixed effect and discuss these results in Section 4.1.[24]

Finally, on the possibility of unobserved heterogeneity biasing our results, we test the robustness and sensitivity of our results to several alternative estimation approaches. In Section 4.1, in addition to addressing the concern of endogenous sorting, we present several robustness and sensitivity tests by considering selection on observables as an indication of selection on unobservables (Altonji, Elder and Taber, 2005; Oster, 2019) and showing alternative results using ACLED data to measure violence (Raleigh et al., 2010). In Section 4.2, we test for pre-trend effects, which may highlight problematic bias in our estimates (Koppensteiner and Manacorda, 2016). In Section 4.3 we show results using matching methods (Imbens, 2015; Rosenbaum and Rubin, 1983; LaLonde, 1986; Heckman, Ichimura and Todd, 1998; Dehejia and Wahba, 2002). Each of these robustness and sensitivity tests, which crucially rely on different assumptions, point to results that are consistent with our core finding that exposure to violence increases both depressive symptoms and the likelihood of being at risk for depression. As discussed by Currie and Tekin (2012), the uniformity of results across estimation approaches relying on different assumptions provides strong support for the credibility of our core results.

[23] This type of constructed variable is most commonly used in the peer effects literature—for example in Fruehwirth, Iyer and Zhang (2019). In our data, the raw correlation between the leave-$i$-out PSU mean of perceived violence and individual $i$'s perceived violence is 0.53, which shows a strong correlation between these two measures of perceived violence.

[24] If and when an individual moves to a different district, they are considered a different individual in our fixed effects estimation approach. Our core results are robust to this alternative estimation approach.

### 3.1 Main Results

Table 4 shows the results for different specifications of equations (1) and (2). Each panel shows a different variation of our violence variable. Panel A reports results when using the household-level violence index. The coefficient on the perceived violence index is consistently statistically significant and decreases in magnitude only slightly when individual fixed effects and a litany of other variables are controlled for such as age, marital status, education levels, and income controls (both levels and lags). The estimate in column (5) suggest that a 1 standard deviation increase in the perceived violence index is associated with a 0.39-point increase in an individual's CES-D score. This corresponds to approximately a 0.13 SD increase in depressive symptoms.[25] As we show in Table A.2 in the Appendix, the estimated coefficient is also positive and statistically significant for the probability of being at risk of depression (e.g., CES-D score greater than or equal to 11). A one standard deviation increase in the perceived violence index is associated with a 3.3 percentage point increase in the likelihood of being at high risk of depression—with baseline probabilities near 20 percent, this is a 17 percent increase.[26]

Given the sensitivity of violence and the effects of depression on perceptions, we may encounter issues related to reverse causality and recall bias. In particular, it may be that changes in psychological well-being change one's perception of violence. Alternatively, it may be that those prompted to recall violence in a survey questionnaire can have an effect on psychological well-being measures.

We address the issue of reverse causality and recall bias in two ways. First, we exploit a characteristic of the survey methodology which asks perceived violence questions as part of the household questionnaire, a part of the survey answered by one person in the household.[27] In Table A.3 in the Appendix, we remove the person who answered the household questionnaire from the sample. These results show that the magnitude of the coefficient estimates decrease only slightly and remain both statistically and psychologically significant.[28] While removing the direct respondent from the sample can rule out direct reverse causality and recall bias, it does not rule out reverse causality through within-household correlations in psychological well-being (Das et al., 2009). It could be that the household respondent's low levels of psychological well-being affects other members directly in ad-

[25]The violence index is standardized across individuals. There is significant variation within respondents across waves as well. The change between waves is centered around zero but has a standard deviation of nearly one.

[26]The results are similar for the different commonly used thresholds of 10 or 12.

[27]In NIDS, this questionnaire is usually responded to by the oldest female in the household who is familiar with day-to-day expenditures of the household.

[28]Specifically, the fixed effects regressions suggests that a one SD increase in the perceived violence of the household respondent is associated with a 0.31-point increase in CES-D scores—this corresponds to approximately a 0.1 SD increase in depressive symptoms for other members of the household.

TABLE 4: Violence and Psychological Well-being—CES-D Score

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Panel A**: Household-Level Perceived Violence | | | | |
| Violence Index$_{hdt}$ | 0.580$^{***}$ | 0.541$^{***}$ | 0.476$^{***}$ | 0.472$^{***}$ | 0.386$^{***}$ |
| | (0.046) | (0.043) | (0.038) | (0.044) | (0.049) |
| $N$ | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |
| | **Panel B**: Leave-$i$-Out PSU Means (Non-Movers) | | | | |
| Average Violence Index$_{hdt}{}^{(-i)}$ | 0.520$^{***}$ | 0.442$^{***}$ | 0.389$^{***}$ | 0.343$^{***}$ | 0.299$^{***}$ |
| | (0.066) | (0.060) | (0.052) | (0.063) | (0.100) |
| $N$ | 32,725 | 32,725 | 32,725 | 20,667 | 32,725 |
| | **Panel C**: Violent Crime Index (District-Level) | | | | |
| Violent Crime Index$_{dt}$ | 0.024 | 0.136$^{**}$ | 0.431$^{***}$ | 0.510$^{***}$ | 0.496$^{***}$ |
| | (0.061) | (0.057) | (0.154) | (0.174) | (0.165) |
| $N$ | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |
| Indiv & HH Characteristics | | ✓ | ✓ | ✓ | ✓ |
| Neighborhood Services | | ✓ | ✓ | ✓ | ✓ |
| Income Controls | | ✓ | ✓ | ✓ | ✓ |
| District-Wave Fixed Effect$^{\dagger}$ | | | ✓ | ✓ | ✓ |
| Lagged Controls | | | | ✓ | |
| Lagged Dependent | | | | ✓ | |
| Individual Fixed Effect | | | | | ✓ |

*Note:* Standard errors clustered at the PSU level are in the parentheses.$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. † Fixed effects regressions in column (5) and Panel C control for district fixed effects and wave fixed effects independently. Our main results show a robust link between the perceived violence index and depressive symptoms.

dition to how they respond to the frequency of neighborhood violence questions. If this occurs, then the main estimates would falsely attribute intra-household effects to neighborhood violence. This leads to our second approach. As previously discussed, we calculate leave-*i*-out means for the violence index at the PSU level.[29] This variable breaks the possible link between an individual's own psychological well-being and their measure of perceived violence. For this possible link to persist, an individual's psychological well-being would need to directly influence the average perception of violence of household respondents within their PSU. Given that individuals are unlikely to personally know most members of their PSU, we argue that this variable rules out the effect of reverse causality, recall bias, and any intra-household correlation in psychological well-being while still capturing neighborhood violence.

In Panel B of Table 4 we re-estimate equations (1) and (2) but instead of the household-level violence index, we use the leave-*i*-out mean of the violence index for other house-

[29]The PSUs in NIDS are formed by dividing up districts into geographically proximate areas.

holds who are in individual *i*'s PSU. We estimate these results on the non-mover sub-sample—which is about half the size of the full sample—because PSUs are only defined for the initial 2008 NIDS sample and not updated when individuals and households move. Nevertheless, these alternative results also support our core finding that exposure to violence increases depressive symptoms. The estimate in column (5) suggests that a 1 standard deviation increase in the leave-*i*-out mean of perceived violence is associated with a 0.30-point increase in an individual's CES-D score. Panel B of Table A.2 shows that a one standard deviation increase in the leave-*i*-out mean of perceived violence is associated with a 2.5 percentage point increase in the likelihood of being at high risk of depression—with baseline probabilities near 20 percent, this is a 13 percent increase.

Finally, in Panel C of Table 4 we again re-estimate equations (1) and (2) with another alternative variable measuring violence: an objective violent crime index aggregated to the district level based on the SAPS data. These alternative results again support our core finding that exposure to violence increases depressive symptoms. In fact, the estimated coefficients in columns (4) and (5) are slightly larger than the corresponding estimated coefficients in Panels A and B. The estimate in column (5) suggests that a one standard deviation increase in district level violent crime is associated with a 0.50-point increase on an individual's CES-D score. Panel C of Table A.2 show similar results. Specifically, a one standard deviation increase in district level violent crime is associated with a 2.9 percentage point increase in the likelihood of being at risk of depressing—corresponding to a 15 percent increase.[30]

In Section 4, we show several falsification and robustness checks on these core results. These include tests of pre-trends, coefficient stability tests (Altonji, Elder and Taber, 2005; Oster, 2019), alternative estimation approaches using matching methods, tests addressing if our results are driven by endogenous migration across district boundaries (Dustmann and Fasani, 2016), and the use of another alternative violence variable using data from the ACLED Project (Raleigh et al., 2010). Each of these tests support the validity of our core finding that exposure to violence increases both depressive symptoms and the likelihood of being at risk for depression.

### 3.2 Effect Heterogeneity

The results reported in Table 4 show average effects, and obscures any potential effect heterogeneity or effect non-linearity at different levels of violence or depression. In this

[30] As indicated by Figure 2, the frequency of perceived violence tends to be lower than the frequency of objective violence. Therefore, these measures of violence are distinct and not directly comparable since a one standard deviation change in objective violence may be a more extreme change in actual violence relative to a one standard deviation change in perceived violence.

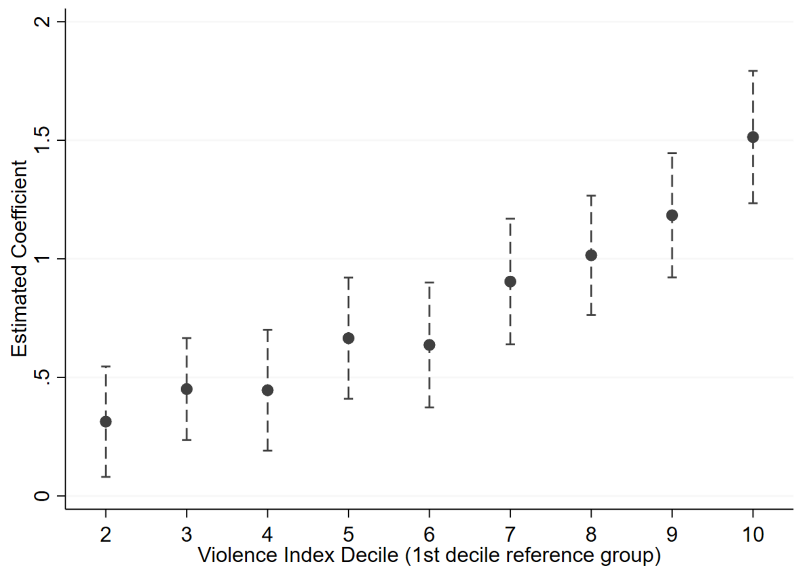
sub-section, we explore potential effect non-linearity and heterogeneity in a variety of dimensions.

*Non-Linearity*—In Figure 3(A) we show results when using a more flexible estimation approach. To do so, we use the same specification shown in regression (4) in Panel A of Table 4 but with nine violence index decile dummies. These results show that compared to those who live in neighborhoods with the lowest levels of perceived violence, those living in neighborhoods with higher levels of perceived violence have consistently more depressive symptoms. Individuals in the highest decile of perceived neighborhood violence have CES-D scores that are, on average, 1.5 points higher than do those in the lowest violence neighborhoods.

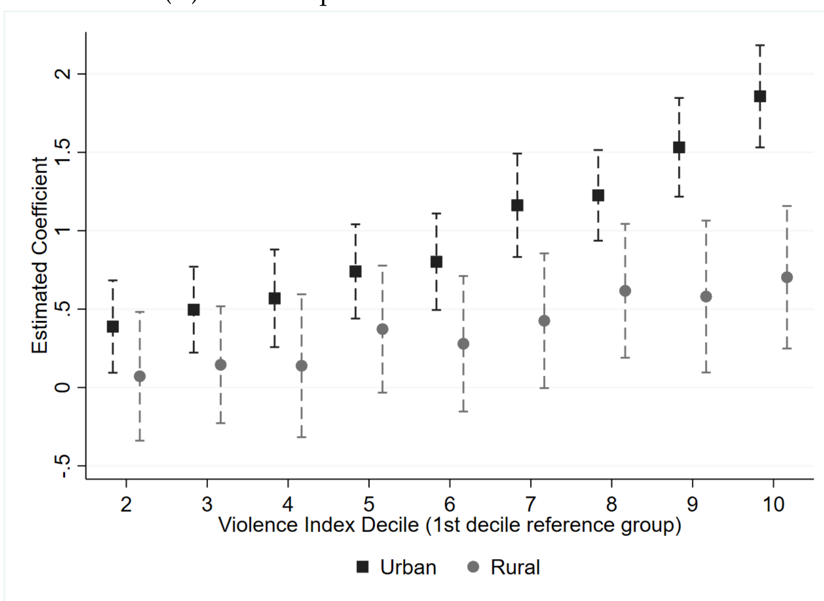
*Urban vs. Rural*—We also investigate how the relationship between perceived violence and psychological well-being differs between urban and rural areas. To do this, we re-run the specification used in Figure 3(A) separately for urban and rural households. The outcome variable is the full CES-D score and we show coefficient estimates on each violence index decile with the first decile omitted for reference.

Figure 3(B) shows that the relationship between perceived violence and psychological well-being differ between urban and rural areas. The estimated effects on each violence index decile are always at least as large, and often larger, in urban areas compared to rural areas. Specifically, the estimated coefficient on the highest violence index decile is almost twice as large in urban areas compared to rural areas. Although the effect estimates are still statistically and psychologically significant in rural areas, violence in South Africa's urban areas seem to be more detrimental to psychological well-being. In fact, the gradient of the estimated effects also seem to differ. Moving from one violence index decile to a higher decile nearly always implies a larger change in the estimated coefficient in urban areas compared to rural areas. This urban-rural heterogeneity can be explained in part because urban areas have a higher population density than rural areas. Therefore, those exposed to higher levels of violence in urban areas are likely physically closer to the violence and are potentially less able to (psychologically) escape it. This is consistent with existing evidence suggesting that neighborhood violence can influence mental health even for those who are not directly involved in the violence itself (Clark et al., 2007) and existing evidence on the importance of stress-buffering mechanisms (Stockdale et al., 2007). Figure A.4 in the Appendix, shows that this same pattern holds when using our alternative perceived violence variable of the leave-$i$-out mean within each PSU.

*Level of Depressive Symptoms*—Many studies on depression find that individuals with higher CES-D scores are prone to depression and are experiencing relatively high depressive symptoms. It is plausible, therefore, that neighborhood violence can have a different effect on CES-D scores for those on the lower end of the CES-D scale than for those at the




(A) Flexible Specification for Violence Index




(B) Differentiating Urban and Rural settings

FIGURE 3: Flexible estimation approach. Estimated coefficients are increasing by Violence Index Deciles and differences for higher deciles are larger in Urban areas. In Panel B, we differentiate between Urban and Rural Area. Figure A.4 in the Appendix shows similar results for the Leave-*i*-out violence index.

higher end. This, therefore, raises the question: Does violence affect psychological well-being in the same way at all levels of psychological well-being? To explore this question further, we conduct quantile regression analysis using the same specification as in Column

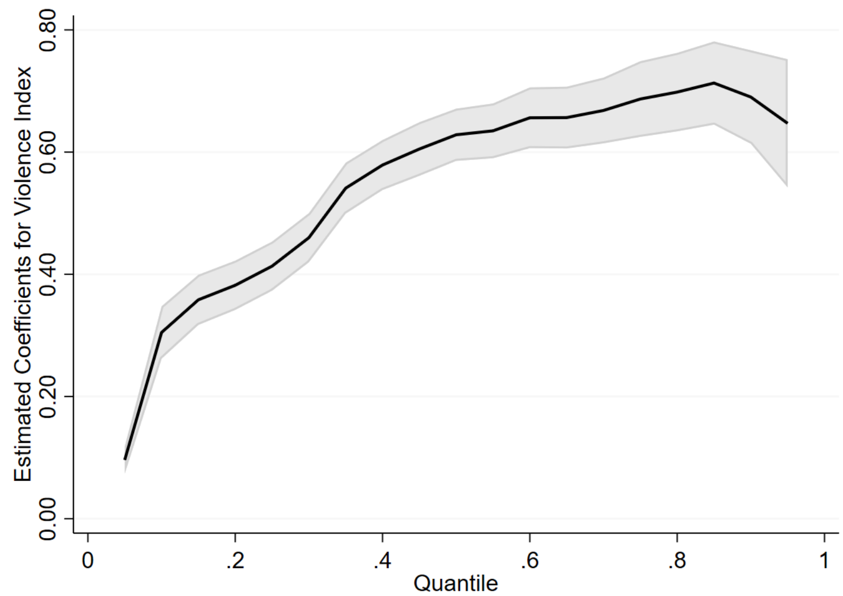



FIGURE 4: Quantile regression results show that the estimated link between violence and psychological well-being is higher for those with more depressive symptoms who are on the higher end of the CES-D score. Figure A.5 in the Appendix shows similar results for the Leave-i-out mean violence index and the district level objective crime index.

(3) in Table 4.

Figure 4 plots these quantile regression results where we estimate effects at each quantile of the distribution in psychological well-being. The results suggest that the link between violence and psychological well-being is larger for those on the higher end of the CES-D score. The median CES-D score is roughly 7 and the quantile regression results show that the effect of violence peaks just above the median. Consistent with other empirical studies on depression (Fruehwirth, Iyer and Zhang, 2019), this suggests that those already experiencing depressive symptoms are more susceptible to experiencing larger changes in their depressive symptoms when perceiving increased violence in their neighborhoods. Additionally, those already at risk—due to factors such as poverty—may experience larger increases in their CES-D score when neighborhood violence increases. This finding is also consistent with research highlighting the importance of environmental mechanisms that can shield individuals from the psychological effects of neighborhood violence (Stockdale et al., 2007). Figure A.5 in the Appendix, show that this same pattern holds when using our alternative perceived violence variable of the leave-*i*-out mean of perceived violence within each PSU (in Panel A) and the district-level violent crime index (in Panel B).

*Types of Violence*—The NIDS data provide information on perceptions of different types

TABLE 5: Types of Violence and Crime

| | | CES-D Score | |
|---|---|---|---|
| | *Standardized Variable* | (1) | (2) |
| **Panel A:** Perceived Violence | Frequency of Violence between Households | 0.422*** (0.054) | 0.379*** (0.05) |
| | Frequency of Domestic Violence | 0.459*** (0.044) | 0.352*** (0.055) |
| | Frequency of Gang Violence | 0.296*** (0.038) | 0.221*** (0.057) |
| | Frequency of Murder | 0.109*** (0.036) | 0.058 (0.056) |
| *N* | | 64,651 | 64,651 |
| **Panel B:** Leave-*i*-out PSU Means of Perceived Violence (Non-Movers) | Frequency of Violence between Households | 0.392*** (0.051) | 0.295*** (0.083) |
| | Frequency of Domestic Violence | 0.390*** (0.051) | 0.282*** (0.088) |
| | Frequency of Gang Violence | 0.338*** (0.052) | 0.292*** (0.100) |
| | Frequency of Murder | 0.221*** (0.052) | -0.013 (0.096) |
| *N* | | 32,725 | 32,725 |
| **Panel C:** Violent Crime Index (District-Level) | Murder Rate | 0.661*** (0.188) | 0.761*** (0.206) |
| | Attempted Murder Rate | 0.308*** (0.108) | 0.351*** (0.118) |
| | Sexual Assault Rate | 0.185* (0.110) | 0.208* (0.120) |
| | Armed Robbery Rate | 0.360** (0.182) | 0.455** (0.203) |
| *N* | | 64,651 | 64,651 |
| Indiv & HH Characteristics | | ✓ | ✓ |
| Neighborhood Services | | ✓ | ✓ |
| Income Controls | | ✓ | ✓ |
| District Fixed Effect | | ✓ | ✓ |
| Individual Fixed Effect | | | ✓ |

*Note:* Standard errors clustered at the PSU level are in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table shows results that differentiate by the different components of the perceived violence index.

of violent events. These types include violence between households, domestic violence, gang violence, and murder. In the results discussed so far, we use an aggregated index which includes all of these types of perceived violence together. In Table 5 we pull apart these various types of perceived violence and estimate their relationship with psychological well-being. In Panel A we use our primary measure of perceived violence and in Panel B we use our leave-*i*-out mean of perceived violence at the PSU level. In each of the top two panels, both violence between households and domestic violence are highly associated with depressive symptoms. The effect of gang violence is also statistically significant but coefficient estimates are generally smaller. Finally, the frequency of murders does not have a statistically significant effect on CES-D scores. Most generally, these results show that the effect of violence on psychological well-being is not driven by exposure to any one particular type of violence. Instead, exposure to multiple different types of violence are associated with increased symptoms and risk of depression. This general finding holds in Panel C where we show similar results using different types of violent crime recorded in the SAPS data.[31]

In Table A.4 in the Appendix we also show effect heterogeneity between men and women and by age group. Perhaps surprisingly, these results show no statistically significant difference in the effect of neighborhood violence on psychological well-being between these different groups.

# 4 Robustness, Falsification, and Alternative Estimations

Our results are, so far, robust to including a rich set of control variables (e.g., household and individual income, household size, number of children, and neighborhood services), including lagged controls and outcome variables, and individual fixed effects, the use of two alternative violence variables (e.g., the leave-*i*-out mean of perceived violence within PSUs and a district level objective violent crime index), and are also robust to excluding the household respondent (Table A.3). Robustness to this wide variety of specifications lends considerable credence to the credibility of our central finding that violence increases depressive symptoms and the risk of depression. Nevertheless, alternative estimation approaches allow for additional robustness and sensitivity tests. In this section we present robustness and sensitivity tests on our core specification, pre-trend falsification tests, and results using alternative estimation methods.

## 4.1 Robustness and Sensitivity Tests

We show three sets of robustness and sensitivity tests: (i) testing robustness by accounting for endogenous sorting (Dustmann and Fasani, 2016), (ii) testing sensitivity with unobservable selection and coefficient stability tests (Altonji, Elder and Taber, 2005; Oster, 2019),

[31]Note that the categories of different types of violence do not exactly overlap between the NIDS and SAPS data.

and (iii) testing robustness to an additional alternative violence variable derived from the ACLED Project (Raleigh et al., 2010).

First, following the methods of Dustmann and Fasani (2016) we re-estimate question (1) but include individual by district fixed effects. In doing this we effectively consider each individual in our data as a different individual if they moved across a district boundary. This robustness test aims to account for bias driven by endogenous sorting—the possibility that our estimated effects are driven by individuals (and households) that move because of violence in their neighborhood. As Dustmann and Fasani (2016) discuss, this approach is not perfect—it may induce both across-individual correlation within the error term and selection bias. Despite these concerns, as shown in Table A.6 in the Appendix, the effects estimated with this alternative approach are qualitatively consistent with our core results reported in Table 4. These results support the credibility of our core results by highlighting that our estimated coefficients are not driven by endogenous sorting.

Second, following the insights of Altonji, Elder and Taber (2005) and the methods of Oster (2019), we consider selection on observables as an indication of selection on unobservables. In doing so this method generates bounds on the effect estimate by first estimating a "short" regression without additional control variables and then estimating a "long" regression including additional control variables. The intuition of this approach is relatively straightforward. If the coefficient of interest—in our case the effect of neighborhood violence on psychological well-being—remains stable relative to the $R^2$ when additional controls are added to the regression, then this lends credence to the credibility of the effect estimates.

These results rely on an assumption about the maximum possible $R^2$ of the specification, $R_{Max}$. It is clear that the smallest possible value of $R_{Max}$ is simply the $R^2$ from the "short" regression and the largest possible value is one. In the present setting, however, where we use household survey data to measure psychological well-being, it is well-known that such variables can be measured with considerable error (McKenzie, 2012). Therefore, assuming $R_{Max}$ to have a value of one is likely overly conservative. We use the approach suggested by Oster (2019), which sets $R_{Max}$ equal to $1.3 \times$ the $R^2$ from the "long" regression.

Table 6 presents the results of these unobservable selection and coefficient stability tests. Similar to Table 4, each panel shows results using a different violence variable. The first three columns apply this method to simple OLS results from Table 4. The "short" regression, in column (1) of Table 6, are the same results from column (1) in Table 4 with no fixed effects or control variables. The "long" regression, in column (2) of Table 6, are the same results from column (3) in Table 4, with controls for individual and household characteristics, neighborhood services, income, and district-wave fixed effects. Column

TABLE 6: Unobservable Selection and Coefficient Stability

| | OLS | | | Fixed Effects | | |
|---|---|---|---|---|---|---|
| | Short | Long | $\delta$ | Short | Long | $\delta$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | **Panel A:** Household-Level Perceived Violence | | | | | |
| Violence Index$_{hdt}$ | 0.58*** | 0.48*** | 7.91 | 0.42*** | 0.39*** | 14.83 |
| | (0.046) | (0.044) | | (0.054) | (0.049) | |
| $R^2$ | 0.015 | 0.094 | | 0.007 | 0.092 | |
| $N$ | 64,651 | 64,651 | | 64,651 | 64,651 | |
| | **Panel B:** Leave-$i$-Out PSU Means (Non-Movers) | | | | | |
| Average Violence Index$_{hdt}{}^{(-i)}$ | 0.52*** | 0.39*** | 4.22 | 0.32*** | 0.30*** | 6.32 |
| | (0.066) | (0.052) | | (0.081) | (0.10) | |
| $R^2$ | 0.013 | 0.103 | | 0.003 | 0.096 | |
| $N$ | 32,725 | 32,725 | | 32,725 | 32,725 | |
| | **Panel C:** Violent Crime Index (District-Level) | | | | | |
| Violence Crime$_{dt}$ | 0.024 | 0.43*** | -13.16 | 0.31** | 0.50*** | 13.30 |
| | (0.046) | (0.154) | | (0.12) | (0.052) | |
| $R^2$ | 0.000 | 0.084 | | 0.001 | 0.007 | |
| $N$ | 64,651 | 64,651 | | 64,651 | 64,651 | |

*Note:* Controls in the long regressions include individual and household characteristics, current and lagged income controls, lagged CES-D scores, urban dummy, and district fixed effects. Standard errors clustered at the PSU level are in the parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

(3) reports the proportional selection coefficient or "Oster's $\delta$." The proportional selection coefficient estimates how much more important selection on unobservables would need to be, relative to selection on observables, to produce an estimated effect of zero. In Panels A and B, Oster's $\delta$ suggests that any omitted unobservables would need to be 7.9 and 4.2 times, respectively, more important than the included control variables to explain away the result. Oster (2019) argues that $\delta$ values greater than one are robust to potential unobservable selection, and therefore, these results support the credibility of our core results. In Panel C, adding control variables only makes the estimated coefficient move farther away from zero, resulting in a negative value for Oster's $\delta$, and is trivially robust.

The last three columns of Table 6 apply this method to a more rigorous fixed effects regression. The "short" regression, in column (4) of Table 6, are not reported elsewhere in this paper and only include individual fixed effects. The "long" regression, in column (5) of Table 6, are the same results from column (5) in Table 4, with controls for individual and household characteristics, neighborhood services, income, district-wave fixed effects, and individual fixed effects. In each panel, Oster's $\delta$ suggests that any omitted unobservables would need to be at least 6.3 and at most 14.8 times more important than included control variables to explain away the result. Again, based on Oster (2019), which argues that $\delta$ values greater than one are robust to potential unobservable selection, these results again support the credibility of our core results.

Finally, we construct another alternative violence variable using data from the ACLED Project (Raleigh et al., 2010). These data are compiled by encoding information from local media reports about conflict and violence and provides an additional objective violence variable. In particular, it may be that an individual's perception of violence is driven more by the type of violence that gets reported by the local media rather than the type of violence that gets reported to the local South African police precinct. Table A.7 in the Appendix shows that our core finding that neighborhood violence increases depressive symptoms is robust to the use of this alternative violence variable. In fact, the overall magnitude of these results are well within the range of results reported in Table 4.

### 4.2 Pre-Trend Tests

A threat to the credibility of our results are potential unobservable individual, household, or neighborhood characteristics that affect responses to the neighborhood violence questions and are also important in determining psychological well-being. If such characteristics persist systematically in our data the main results may be biased. We further exploit the panel nature of the NIDS data to investigate the possibility of systematic pre-trends biasing our estimates. Specifically, we estimate the following equation four times with $j = 0, 1, 2, 3$:

$$\begin{aligned} PW_{ihd(t-j)} = \alpha_2 V_{hdt} + \alpha_3 V_{hd(t-j)} + \sigma_2 PW_{ihd(t-j-1)} + \boldsymbol{Y'_{hd(t-j)}}\boldsymbol{\gamma_3} \\ + \boldsymbol{X'_{hd(t-j)}}\boldsymbol{\beta_2} + \boldsymbol{Z'_{ihd(t-j)}}\boldsymbol{\delta_2} + \theta_{t-j} + \tau_d + \epsilon_{ihd(t-j)} \end{aligned} \tag{3}$$

With these specifications, we test for pre-trend effects of present violence on the CES-D score in previous time periods. If our results show that perceived violence in wave $t$ is associated with psychological well-being in previous waves, conditional on violence in previous waves, then we may suspect our main results are systematically biased due to unobserved factors that affect both the perception of violence and psychological well-being. Any association between current violence levels $V_{hdt}$ and lagged levels of psychological well-being $PW_{ihd(t-j)}$ should be through contemporaneous levels of violence and thus controlling for previous levels of perceived violence should ensure that current perceived violence is not associated with past levels of psychological well-being. This approach is similar to that used by Koppensteiner and Manacorda (2016) when testing the robustness of their estimates of the relationship between in-utero exposure to violence on birth outcomes.

Figure 5 presents these results. When $j = 0$ we simply replicate the result from Column 4 in Table 4. When $j > 0$ we estimate the effect of present day violence on lagged psychological well-being and, conditional on contemporaneous levels of violence, expect

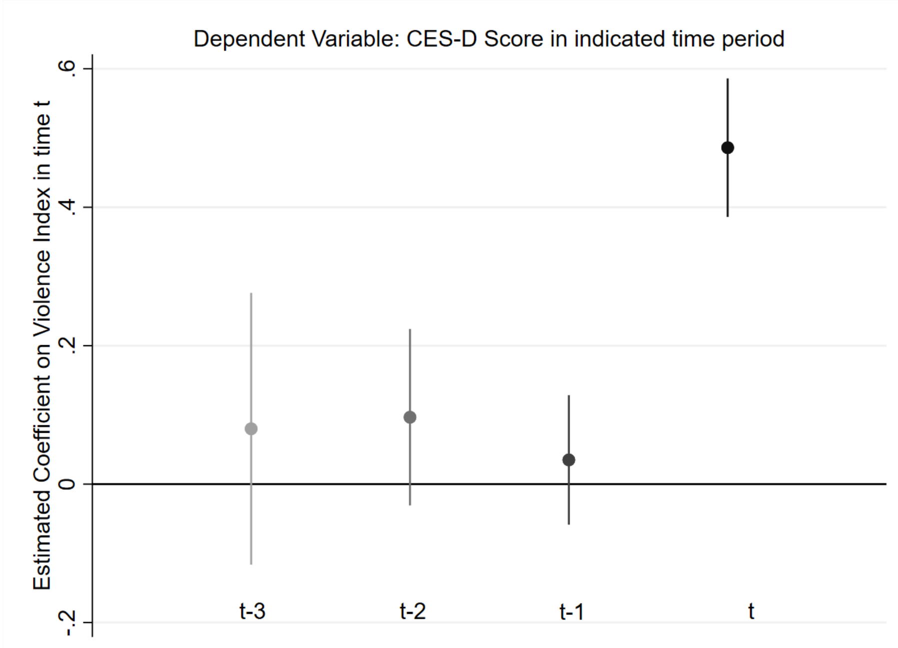



FIGURE 5: Coefficients on Violence Index in time t on CES-D scores in time periods t, t-1, t-2, and t-3. This falsification tests shows no evidence of pre-trend effects of present violence on the CES-D score in previous periods.

to see estimates that are statistically indistinguishable from zero. Indeed, the effect of $V_{hdt}$ on $PW_{ihd(t-j)}$ for $j = 1, 2, 3$ are each statistically indistinguishable from zero. Therefore, we find no evidence of pre-trend effects that potentially bias our main results.

Although the results in Figure 5 show that there are no pre-trend effects of present violence on present violence on psychological well-being in the previous year, it may still be possible that within a given year psychological well-being declines and this causes higher perceptions of violence. Our alternative violence variable measuring the leave-*i*-out PSU mean of perceived violence accounts for this possibility. By removing individual *i* from the PSU mean of perceived violence, we effectively remove the possibility that an individual's own psychological well-being could influence our measure of neighborhood violence. Figure A.6 in the Appendix shows similar falsification tests for the leave-*i*-out PSU mean of perceived violence and the district-level objective violence results.

### 4.3 Alternative Estimation Methods

An alternative method to estimate the relationship between neighborhood violence and depressive symptoms with these observational data is through matching methods (Imbens, 2015; Rosenbaum and Rubin, 1983; LaLonde, 1986; Heckman, Ichimura and Todd, 1998; Dehejia and Wahba, 2002).[32] Although randomization would be ideal in estimating unbiased effects of violence from a research perspective, there are clear ethical barriers that prevent randomization of exposure to violence. In the analysis above, we attempt to control a litany of observable variables, in this section we use propensity score and nearest neighbor matching to test the credibility of our core estimates.

Propensity score matching assumes exposure to neighborhood violence involves some selection but, conditional on a set of characteristics, this selection process is plausibly random. Specifically in the context of this empirical setting individual, household, and region-level observable and unobservable characteristics determine the probability that an individual lives in a neighborhood with high levels of violence. After this probability is determined, random chance plausibly determines whether the individual experiences high levels of violence in their neighborhood. Two individuals could have very similar characteristics and thus propensity scores of their probability of being in neighborhoods with high levels of violence while they have different realizations of exposure. This being the case, if we compare the CES-D scores of these two individuals we can credibly estimate the effect of living in a high-violence neighborhood.[33] In theory, this method should produce unbiased estimates of the effects of living in perceived-violent neighborhoods if we can assume that we have strongly ignorable exposure assignment.[34] Richer pre-exposure information makes this assumption more plausible. Moreover, various sensitivity analyses can test the robustness of the results to violations of these assumptions.

We create a treatment variable of "high violence" (e.g., in the top quintile of perceived violence vs the other four quintiles).[35] We match individuals on a large number of individual and household-level controls including the contemporaneous and lagged CES-D score. We calculate the propensity score with variables that are plausibly already determined such as regional variables (e.g., district fixed effects, urban dummy, population densities), individual and household characteristics that are not possibly outcomes, and lagged income variables.

Table 7 shows results using two approaches to matching: propensity score matching (in columns 1 and 3) and nearest neighbor matching (in columns 2 and 4).[36] Again, each

[32] An application of matching methods on the effect of exposure to gun violence can be found in Bingenheimer, Brennan and Earls (2005).

[33] The approach starts with using all available pre-treatment information to estimate the probability of treatment (the propensity score); match individuals based on these probabilities; ensure that in a wide range of probabilities there are individuals who have been treated and others who have not; calculate the difference in the outcome of interest between the two groups.

[34] This effectively means that no observable or unobservable variable affects both neighborhood violence and depressive symptoms outside of the estimated propensity score.

[35] The average violence index in the top quintile is 1.4 vs -.34 in the other four quintiles. The other four quintiles have average violence index scores of -1.19, -0.58, -0.06, & 0.45.

[36] See King and Nielsen (2019) for a discussion of the substantive difference between propensity score match-

TABLE 7: Matching Results

| | CES-D Score | | Dummy CES-D≥11 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Panel A**: High Violence$_t$ | 1.041*** | 1.171*** | 0.076*** | 0.080*** |
| | (0.098) | (0.093) | (0.009) | (0.009) |
| *N* | 20,465 | 16,316 | 20,465 | 16,316 |
| **Panel B**: Leave-*i*-out Mean High Violence$_t$ (Non-Movers) | 0.785*** | 0.856*** | 0.057*** | 0.058*** |
| | (0.122) | (0.129) | (0.011) | (0.012) |
| *N* | 10,018 | 7,454 | 10,018 | 7,454 |
| **Panel C**: High Violent Crime$_t$ (District-level) | 0.483*** | 0.539** | 0.021** | 0.029** |
| | (0.121) | (0.111) | (0.011) | (0.010) |
| *N* | 20,465 | 16,316 | 20,465 | 16,316 |
| **Matching Variables** | | | | |
| *Indiv & HH Characteristics* | ✓ | ✓ | ✓ | ✓ |
| *Region (District & Urban)* | ✓ | ✓ | ✓ | ✓ |
| *Lagged Income Controls* | ✓ | ✓ | ✓ | ✓ |
| *Lagged Violence Index and CES-D Score* | ✓ | ✓ | ✓ | ✓ |

*Note:* Columns (1) and (3) present propensity score matching results, columns (2) and (4) show nearest neighbor matching results. Standard errors clustered at the PSU level are in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Matching methods show results that are qualitatively similar to the main results. Table A.5 and Figure A.3 in the Appendix show supporting evidence for unconfoundedness and overlap of the propensity scores.

panel reports results when using each of our three violence variables. In Panel A, we find that both approaches estimate qualitatively similar, albeit slightly larger, results to the core results reported in Table 4. Specifically, living in a high violence neighborhood on average increases CES-D scores by between 1 and 1.2 points and the likelihood of being at risk of depression by about 8 percentage points, this is nearly a 35 percent increase. The larger effect estimates are likely due to the different violence variable, which here is a binary variable indicating is an individual lives in a "high violence" neighborhood and is consistent with the results in the highest deciles of the violence index reported in Figure 3(A). Panels B and C are also qualitatively consistent with the core results reported in Table 4. These results support the core credibility of the core finding that exposure to violence increase depressive symptoms and the likelihood of being at risk of depression.

Two strong assumptions are necessary to estimate unbiased results using matching methods. First, the overlap assumption—this assumption is testable and Figure A.7 in the Appendix shows that there is considerable overlap the in the propensity scores of those who have different realizations of the "high violence" variable. The second assumption is the unconfoundedness of treatment—this assumption is not directly testable, however, we

ing and nearest neighbor matching.

can assess the plausibility of this assumption by estimating the causal effect of the treatment on a pseudo outcome (Imbens, 2015). This outcome is a pseudo outcome because it is plausibly unaffected by the treatment usually because it is determined prior to the treatment.[37] If the estimated effects on these pseudo outcomes are different from zero, it is less plausible that the unconfoundedness assumption holds. One strength of having panel data is that we are able to use lagged-psychological well-being as a pseudo-outcome to test the unconfoundedness assumption—a lack of effect on lagged psychological well-being suggests unconfoundedness (Imbens, 2015) an intuition similar to our falsifcation test in Section 4.1. In Table A.5 in the Appendix, we show results for these pseudo outcomes where the estimated effect of perceived neighborhood violence is not statistically significant suggesting plausibility of the unconfoundedness assumption.

# 5 Urban Neighborhood Violence and Future Poverty

The strong association between poverty, the perception of violence, and lower levels of psychological well-being raises an important question: Can current exposure to violence and elevated depressive symptoms add to the predictive value of current poverty on future poverty? This question is important for at least two reasons. First, as Figure 2(B) highlights, the poor tend to live in neighborhoods with higher levels of violence. Second, although exposure to violence is universal in its psychological harm, the unequal exposure of the poor to violence may be a mechanism that leads to the existence of persistent poverty and, in some cases, poverty traps (Ridley et al., 2020).

To investigate how exposure to violence may influence poverty dynamics, we use the following specification:

$$\begin{aligned} y_{ihdt} = {} & \alpha_1 LowWealth_{hd(t-1)} + \alpha_2 HighViolence_{hd(t-1)} \\ & + \gamma_1 LowWealth_{hd(t-1)} * HighViolence_{hd(t-1)} \\ & + \boldsymbol{X'_{hdt}\beta} + \boldsymbol{Z'_{ihdt}}\delta + \theta_t + \tau_d + \epsilon_{ihdt} \end{aligned} \tag{4}$$

In this equation, we estimate the predictive power of dummy variables for lagged low wealth (= 1 if the household is in the first wealth quintile in the previous period) and high neighborhood violence (= 1 if the household is in the highest violence index quintile) on current low wealth (= 1 if the household is in the first wealth quintile in the current period) or household income growth.

[37] We can use time-invariant outcomes for this pseudo outcome, but as Imbens (2015) suggest, using a lagged outcome is a more convincing illustration of unconfoundedness. This conclusion rests on the idea that the more closely related pseudo outcomes are to the actual outcome of interest, the more convincing the test.

TABLE 8: Predicting Future Poverty

| | Low Wealth$_t$ | | Growth | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low Wealth$_{t-1}$ | 0.255*** | 0.248*** | 0.056* | 0.065* |
| | (0.017) | (0.017) | (0.0033) | (0.033) |
| High Violence$_{t-1}$ | 0.016* | 0.004 | -0.012 | 0.005 |
| | (0.009) | (0.010) | (0.023) | (0.024) |
| Low Wealth$_{t-1}$*High Violence$_{t-1}$ | | 0.059* | | -0.113* |
| | | (0.031) | | (0.063) |
| Individual Characteristics | ✓ | ✓ | ✓ | ✓ |
| Household Characteristics | ✓ | ✓ | ✓ | ✓ |
| Neighborhood Services | ✓ | ✓ | ✓ | ✓ |
| Wave and District Fixed Effects | ✓ | ✓ | ✓ | ✓ |
| *N* | 17,144 | 17,144 | 17,144 | 17,144 |

*Note:* Cluster robust standard errors in parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The results in this table show that conditional on many individual, household, and neighborhood characteristics, past levels of low wealth predict current levels of low wealth today even after controlling for wave and district fixed effects. While high violence on its own does not predict poor wealth, the mix of past violence and low levels of wealth predict higher levels of poverty today. In addition, the combination of high violence and low wealth predict significantly levels of growth between waves.

We estimate two versions of equation (4) for each of the two outcome variables of interest. First, we omit the interaction term. Second, we include the interaction between low wealth and high violence. In column (1) of Table 8 we see that lagged low wealth predicts current low wealth even when controlling for district fixed effects, and individual and household time varying controls. Reinforcing previous research on poverty dynamics in South Africa specifically (Adato, Carter and May, 2006), this indicates that poverty exhibits some persistence in our sample. In column (2) when we include the interaction term, we see that violence plays a role predicting future low wealth when it coincides with low wealth. The interaction term of low wealth and high violence is statistically significant. Specifically, being poor two years ago increases the probability of being poor today by 25 percentage points. Being poor and living in a neighborhood with high levels of violence two years ago adds another 6 percentage points to the probability of being poor today.

Moreover, in column (3) and (4), we see that while poorer households experience more growth when compared to wealthier households—as we expect under convergent income dynamics—this higher rate of growth is completely negated for poor households living in neighborhoods with high levels of violence. While these results do not speak to the mechanisms explaining this finding, it reinforces the importance of considering the role that exposure to violence may play in the dynamics of poverty.

## 6 Conclusion

Using nationally representative panel data from South Africa, along with data on both objective and perceived measures of violence, we investigate the relationship between neighborhood violence and psychological well-being. Exploiting the panel nature of our data with lagged variables and individual fixed effects, conditioning on a rich set of controls, and using various alternative violence variables, we find three results.

First, the poor in South Africa, especially in urban areas, live in neighborhoods both with objectively more violence and where they perceive relatively high levels of violence. Specifically, we find that individuals in the poorest decile perceive violence to be 0.5 standard deviations higher than those in the richest decile.

Second, we show that both perceived and objective violence is strongly linked to higher levels of depressive symptoms and increased likelihood of being at risk for clinical depression. This relationship is especially strong for those who live in urban areas and those who already express more depressive symptoms. In terms of the magnitude of our estimates, the psychological distress associated with a one standard deviation change in violence is equivalent to a 20 percent decrease in income (Alloush, 2020; Haushofer and Shapiro, 2016).

Finally, we show that the interaction of high levels of violence and poverty are predictive of future poverty in our nationally representative sample. Our results highlight that elevated exposure to violence among the poor, at least in urban areas within South Africa, can possibly be a mechanism through which persistent poverty or psychological poverty traps could operate.

Taken together our results underscore the importance of considering the conditions and experiences of poverty that may hinder both psychological and economic well-being. At a micro-level, the psychological toll of exposure to neighborhood violence may have a lasting effect on those living in poverty in South Africa. On a more macro-level, our results suggest an indirect pathway by which violent conflict and crime may influence national-level economic growth indicators.

## References

**Adato, M., Michael Carter, and Julian May.** 2006. "Exploring poverty traps and social exclusion in South Africa using qualitative and quantitative data." *Journal of Development Studies*, 42(2): 226—247.

**Ajdukovic, Marina, and Dean Ajdukovic.** 1998. "Impact of displacement on the psychological well-being of refugee children." *International Review of Psychiatry*, 10(3): 186–195.

**Alloush, M.** 2020. "Income, Psychological Well-being, and the Dynamics of Poverty." *Working Paper*.

**Altonji, Joseph G, Todd E Elder, and Christopher R Taber.** 2005. "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools." *Journal of political economy*, 113(1): 151–184.

**Aneshensel, Carol S., and Clea A. Sucoff.** 1996. "The Neighborhood Context of Adolescent Mental Health." *Journal of Health and Social Behavior*.

**Ardington, C., and A. Case.** 2010. "Interactions between mental health and socioeconomic status in the South African National Income Dynamics Study." *Journal for Studies in Economics and Econometrics*, 34(3): 69–85.

**Baron, Emily Claire, Thandi Davies, and Crick Lund.** 2017. "Validation of the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa." *BMC Psychiatry*, 17(6): 1–14.

**Bendini, M., and L. Dinarte.** 2020. "Does Maternal Depression Undermine Childhood Cognitive Development? Evidence from the Young Lives Survey in Peru." *World Bank Policy Research Working Paper, No. 9479*.

**Bingenheimer, Jeffrey B, Robert T Brennan, and Felton J Earls.** 2005. "Firearm violence exposure and serious violent behavior." *Science*, 308(5726): 1323–1326.

**Blattman, Christopher, and Jeannie Annan.** 2010. "The consequences of child soldiering." *The Review of Economics and Statistics*, 92(4): 882–898.

**Bor, Jacob, Atheendar S. Venkataramani, David R. Williams, and Alexander C. Tsai.** 2018. "Police killings and their spillover effects on the mental health of black Americans: a population-based, quasi-experimental study." *The Lancet*, 392(10144): 302–310.

**Brown, Ryan, Verónica Montalva, Duncan Thomas, and Andrea Velásquez.** 2019. "Impact of Violent Crime on Risk Aversion: Evidence from the Mexican Drug War." *The Review of Economics and Statistics*, 101(5): 892–904.

**Callen, Michael, Mohammad Isaqzedeh, James D. Long, and Charles Sprenger.** 2014. "Violence and risk preference: Experimental evidence from Afghanistan." *American Economic Review*, 104(1): 123–148.

**Chadee, D., L. Austen, and J. Ditton.** 2007. "The relationship between likelihood and fear of criminal victimization: evaluating risk sensitivity as a mediating concept." *British Journal of Criminology*, 47(1): 133–153.

**Christian, Cornelius, Lukas Hensel, and Christopher Roth.** 2019. "Income Shocks and Suicides: Causal Evidence From Indonesia." *The Review of Economics and Statistics*, 101(5): 905–920.

**Clark, C., L. Ryan, I. Kawachi, M.J. Canner, L. Berkman, and R.J. Wright.** 2007. "Witnessing Community Violence in Residential Neighborhoods: A mental Health Hazard for Urban Women." *Journal of Urban Health*, 85(1).

**Cornaglia, F., N.E. Feldman, and A. Leigh.** 2014. "Crime and Mental Well-Being." *Journal of Human Resources*, 49(1): 110–140.

**Cromley, Ellen K., Maureen Wilson-Genderson, and Rachel A. Pruchno.** 2012. "Neighborhood characteristics and depressive symptoms of older people: Local spatial analyses." *Social Science and Medicine*, 75(12): 2307–2316.

**Currie, Janet, and Erdal Tekin.** 2012. "Understanding the cycle childhood maltreatment and future crime." *Journal of Human Resources*, 47(2): 509–549.

**Curry, Aaron, Carl Latkin, and Melissa Davey-Rothwell.** 2008. "Pathways to depression: The impact of neighborhood violent crime on inner-city residents in Baltimore, Maryland, USA." *Social Science and Medicine*, 67(1): 23–30.

**Das, Jishnu, Quy-Toan Do, Jed Friedman, and David McKenzie.** 2009. "Mental Health Patterns and Consequences: Results from Survey Data in Five Developing Countries." *World Bank Economic Review*, 23(1): 31—55.

**Dehejia, Rajeev H, and Sadek Wahba.** 2002. "Propensity score-matching methods for nonexperimental causal studies." *Review of Economics and statistics*, 84(1): 151–161.

**Demombynes, G., and B. Ozler.** 2005. "Crime and local inequality in South Africa." *Journal of Development Economics*, 76(2): 265—292.

**De Quidt, Jonathan, and Johannes Haushofer.** 2016. "Depression for Economists." *NBER Working Paper Series No. 22973*, 1–33.

**Di Tella, Rafael, Robert MacCulloch, and Andrew Oswald.** 2003. "The Macroeconomics of Happiness." *Review of Economics and Statistics*, 85(4): 809–827.

**Dowdall, Nicholas, Catherine Ward, and Crick Lund.** 2017. "The Association Between Neighborhood-Level Deprivation and Depression: Evidence From the South African National Income Dynamics Study." *BMC Psychiatry*, 17(1): 1—10.

**Dustmann, C., and F. Fasani.** 2016. "The Effect of Local Ara Crime on Mental Health." *Economic Journal*, 126: 978–1017.

**Eyal, Katherine, and Justine Burns.** 2019. "The parent trap: Cash transfers and the intergenerational transmission of depressive symptoms in South Africa." *World Development*, 117: 211–229.

**Fowler, P.J., C.J. Tompsett, J.M. Braciszewski, A.J. Jacques-Tiura, and B.B. Baltes.** 2020. "Community violence: A meta-analysis on the effect of exposure and mental health outcomes of children and adolescents." *Development and Psychopathology*, 21: 227—259.

**Friedman, Jed, and Duncan Thomas.** 2009. "Psychological Health Before, During, and After an Economic Crisis: Results from Indonesia, 1993-2000." *World Bank Economic Review*, 23(1): 57—76.

**Fruehwirth, Jane Cooley, Sriya Iyer, and Anwen Zhang.** 2019. "Religion and Depression in Adolescence." *Journal of Political Economy*, 127(3): 1178–1209.

**George, J., A. Adelaja, and D. Weatherspoon.** 2020. "Armed Conflicts and Food Insecurity: Evidence from Boko Haram's Attacks." *American Journal of Agricultural Economics*, 102(1): 114–131.

**Hamad, R, L C H Fernald, D S Karlan, and J Zinman.** 2008. "Social and economic correlates of depressive symptoms and perceived stress in South African adults." *Journal of epidemiology and community health*, 62(6): 538–544.

**Haushofer, Johannes.** 2019. "Is there a Psychological Poverty Trap?" *Working Paper*.

**Haushofer, Johannes, and Ernst Fehr.** 2014. "On the psychology of poverty." *Science*, 344(6186): 862–7.

**Haushofer, Johannes, and Jeremy Shapiro.** 2016. "The short-term impact of unconditional cash transfers to the poor: Experimental evidence from kenya." *Quarterly Journal of Economics*, 131(4): 1973–2042.

**Heckman, James J, Hidehiko Ichimura, and Petra Todd.** 1998. "Matching as an econometric evaluation estimator." *The review of economic studies*, 65(2): 261–294.

**Imbens, Guido W.** 2015. "Matching methods in practice: Three examples." *Journal of Human Resources*, 50(2): 373–419.

**Institute for Health Metrics and Evaluation.** 2017. "Global Burdern of Disease Study." data retrieved from Global Health Data Exchange, `http://ghdx.healthdata.org/gbd-results-tool`.

**Katz, L., J.R. Kling, and J.B. Liebman.** 2001. "Moving to opportunity in Boston: early results of a randomized mobility experiment." *Quarterly Journal of Economics*, 116(2): 607–654.

**King, Gary, and Richard Nielsen.** 2019. "Why Propensity Scores Should Not Be Used for Matching." *Political Analysis*, 27(4): 1—20.

**Kling, J.R., J.B. Liebman, and L. Katz.** 2007. "Experimental analysis of neighbourhood effects." *Econometrica*, 75(1): 89–119.

**Koppensteiner, M.K., and M. Manacorda.** 2016. "Violence and birth outcomes: Evidence from homicides in Brazil." *Journal of Development Studies*, 119: 16–33.

**Kruger, Daniel J., Thomas M. Reischl, and Gilbert C. Gee.** 2007. "Neighborhood social conditions mediate the association between physical deterioration and mental health." *American Journal of Community Psychology*.

**LaLonde, Robert J.** 1986. "Evaluating the econometric evaluations of training programs with experimental data." *The American economic review*, 604–620.

**Latkin, Carl, and Aaron D Curry.** 2003. "Stressful Neighborhoods and Depression: A Prospective Study of the Impact of Neighborhood Disorder." *Journal of Health and Social Behavior*, 44(1): 34–44.

**Lehohla, Pali.** 2017. "Poverty Trends in South Africa." Pretoria, South Africa:Statistics South Africa.

**Leibbrandt, Murray, Arden Finn, and Ingrid Woolard.** 2012. "Describing and decomposing post-apartheid income inequality in South Africa." *Development Southern Africa*, 29(1): 19–34.

**Ludwig, J., G.J. Duncan, L.A. Gennentian, L. Katz, R.C. Kessler, J.R. Kling, and L. Sanbonmatsu.** 2012. "Neighborhood effects on the long-term well-being of low-income adults." *Science*, 337: 1505–1510.

**Lybbert, Travis J., and Bruce Wydick.** 2018. "Poverty, Aspirations, and the Economics of Hope." *Economic Development and Cultural Change*, 66(4).

**Mair, C, A V Diez Roux, and S Galea.** 2008. "Are neighbourhood characteristics associated with depressive symptoms? A review of evidence." *Journal of Epidemiology & Community Health*, 62(11): 940–946.

**Mawby, R.** 1992. "Crime and the elderly: a review of British and American research." *Current Psychological Reviews*, 2(3): 301–310.

**McAloney, Kareena, Patrick McCrystal, Andrew Percy, and Claire McCartan.** 2009. "Damaged Youth: Prevalence of Community Violence Exposure and Implications for Adolescent Well-being in Post-Conflict Northern Ireland." *Journal of Community Psychology*, 37(5): 635–648.

**McKenzie, David.** 2012. "Beyond baseline and follow-up: The case for more T in experiments." *Journal of Development Economics*, 99(2): 210–221.

**Mollica, Richard F., Keith McInnes, Charles Pool, and Svang Tor.** 1998. "Dose-effect relationships of trauma to symptoms of depression and post-traumatic stress disorder among Cambodian survivors of mass violence." *British Journal of Psychiatry*, 173(6): 482–488.

**Moya, Andrés.** 2018. "Violence, psychological trauma, and risk attitudes: Evidence from victims of violence in Colombia." *Journal of Development Economics*, 131(November 2017): 15–27.

**Moya, Andrés, and Michael R. Carter.** 2019. "Violence and the formation of hopelessness: Evidence from internally displaced persons in Colombia." *World Development*, 113: 100–115.

**Myer, Landon, Joalida Smit, Liezel Le Roux, Siraaj Parker, Dan J Stein, and Soraya Seedat.** 2008. "Common mental disorders among HIV-infected individuals in South Africa: prevalence, predictors, and validation of brief psychiatric rating scales." *AIDS patient care and STDs*, 22(2): 147–158.

**Oster, Emily.** 2019. "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business & Economic Statistics*, 37(2): 187–204.

**Page, Lucy, and Rohini Pande.** 2018. "Ending Global Poverty: Why Money Isn't Enough." *Journal of Economic Perspectives*, 32(4): 173–200.

**Pilkonis, Paul A., Lan Yu, Nathan E. Dodds, Kelly L. Johnston, Catherine C. Maihoefer, and Suzanne M. Lawrence.** 2014. "Validation of the depression item bank from the Patient-Reported Outcomes Measurement Information System (PROMIS ®) in a three-month observational study." *Journal of Psychiatric Research*, 56: 112–119.

**Radloff, Lenore Sawyer.** 1977. "The CES-D Scale: A Self-Report Depression Scale for Research in the General Population." *Applied Psychological Measurement*, 1(3): 385–401.

**Raleigh, Clionadh, Andrew Linke, Havard Hegre, and Joakim Karlsen.** 2010. "Introducing ACLED: An Armed Conflict Location and Event Dataset." *Journal of Peace Research*, 47(5): 651–660.

**Ridley, Matthew W., Gautam Rao, Frank Schilbach, and Vikram H. Patel.** 2020. "Poverty, Depression, and Anxiety: Causal Evidence and Mechanisms." *Science*, 370: 1–12.

**Rosenbaum, Paul R, and Donald B Rubin.** 1983. "The central role of the propensity score in observational studies for causal effects." *Biometrika*, 70(1): 41–55.

**Ross, Catherine E., and John Mirowsky.** 2009. "Neighborhood disorder, subjective alienation, and distress." *Journal of Health and Social Behavior*.

**Rossin-Slater, Maya, Molly Schnell, Hannes Schwandt, Sam Trejo, and Lindsey Uniat.** 2020. "Local Exposure to School Shootings and Youth Antidepressant Use." *Proceedings of the National Academy of Sciences of the United States of America*, 117(38).

**Salm, M., and B. Vollaard.** 2018. "Perceptions follow experiences: Assessment of local crime risk." *Working Paper*, CentER Discussion Paper No. 2014-072.

**Santor, Darcy A., Michelle Gregus, and Andrew Welch.** 2006. "Eight Decades of Measurement in Depression." *Measurement: Interdisciplinary Research & Perspective*, 4(3): 135–155.

**Siddaway, Andy P., Alex M. Wood, and Peter J. Taylor.** 2017. "The Center for Epidemiologic Studies-Depression (CES-D) scale measures a continuum from well-being to depression: Testing two key predictions of positive clinical psychology." *Journal of Affective Disorders*, 213: 180–186.

**Smith, W.R., and M. Torstensson.** 1997. "Gender differences in risk perception and neutralizing fear of crime: Toward resolving the paradoxes." *British Journal of Criminology*, 37(4): 608–634.

**Steptoe, Andrew, and Pamela J. Feldman.** 2001. "Neighborhood problems as sources of chronic stress: Development of a measure of neighborhood problems, and associations with socioeconomic status and health." *Annals of Behavioral Medicine*.

**Stockdale, S.E., K.B. Wells, L. Tang, T.R. Belin, L. Zhang, and C.D. Sherbourne.** 2007. "The importance of social context: Neighborhood stressors, stress-buffering mechanisms, and alcohol, drug, and mental health disorders." *Social Science & Medicine*, 65(9): 1867—1881.

**Tomita, Andrew, Charlotte Labys, and Jonathan Burns.** 2016. "A multilevel analysis of the relationship between neighborhood social disorder and depressive systems: Evidence from the South African National Income Dynamics Study." *American Journal of Orthopsychiatry*, 85(1): 56—62.

**United Nations Office on Drugs and Crime.** 2019. "Glonal Study on Homocide."

**Verwimp, P., P. Justino, and T. Bruck.** 2019. "The microeconomics of violent conflict." *Journal of Development Economics*, 141.

**Vinck, Patrick, Phuong N. Pham, Eric Stover, and Harvey M. Weinstein.** 2007. "Exposure to war crimes and implications for peace building in northern Uganda." *Journal of the American Medical Association*, 298(5): 543–554.

**Wilson-Genderson, Maureen, and Rachel Pruchno.** 2013. "Effects of neighborhood violence and perceptions of neighborhood safety on depressive symptoms of older adults." *Social Science and Medicine*.

**World Bank.** 2018. "Gini Index." data retrieved from World Development Indicators–Poverty and Equity Data Portal, `http://povertydata.worldbank.org/poverty/country/ZAF`.

**Yen, Irene H., Edward H. Yelin, Patricia Katz, Mark D. Eisner, and Paul D. Blanc.** 2006. "Perceived neighborhood problems and quality of life, physical functioning, and depressive symptoms among adults with asthma." *American Journal of Public Health*.

# A Appendix

## A.1 Tables

TABLE A.1: CES-D 10 Questionnaire

| | *In the past week* | Rarely or none of the time (Less than 1 day) | Some or little of the time (1-2 days) | Occasionally or a moderate amount of the time (3-4 days) | Most or all of the time (5-7 days) |
|---|---|---|---|---|---|
| 1 | I was bothered by things that usually don't bother me | 0 | 1 | 2 | 3 |
| 2 | I felt lonely | 0 | 1 | 2 | 3 |
| 3 | I felt depressed | 0 | 1 | 2 | 3 |
| 4 | I had trouble keeping my mind on what I was doing | 0 | 1 | 2 | 3 |
| 5 | I felt that everything I did was an effort | 0 | 1 | 2 | 3 |
| 6 | I felt hopeful about the future | 3 | 2 | 1 | 0 |
| 7 | I felt fearful | 0 | 1 | 2 | 3 |
| 8 | My sleep was restless | 0 | 1 | 2 | 3 |
| 9 | I was happy | 3 | 2 | 1 | 0 |
| 10 | I could not "get going" | 0 | 1 | 2 | 3 |

TABLE A.2: Violence and Psychological Well-being—CES-D $\geq$ 11

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | **Panel A**: Household-Level Perceived Violence | | | | |
| Violence Index$_{hdt}$ | 0.039*** | 0.037*** | 0.035*** | 0.035*** | 0.033*** |
| | (0.004) | (0.003) | (0.003) | (0.004) | (0.004) |
| *N* | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |
| | **Panel B**: Leave-*i*-Out PSU Means (Non-Movers) | | | | |
| Average Violence Index$_{hdt}{}^{(-i)}$ | 0.031*** | 0.028*** | 0.029*** | 0.033*** | 0.025*** |
| | (0.005) | (0.005) | (0.004) | (0.005) | (0.008) |
| *N* | 32,725 | 32,725 | 32,725 | 20,667 | 32,725 |
| | **Panel C**: Violent Crime Index (District-Level) | | | | |
| Violent Crime Index$_{dt}$ | 0.012*** | 0.019*** | 0.022* | 0.025* | 0.029** |
| | (0.004) | (0.004) | (0.012) | (0.014) | (0.013) |
| *N* | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |
| | **Panel D**: ACLED Conflict Events (District-Level) | | | | |
| Standardized ACLED Conflict$_{dt}$ | 0.008*** | 0.014*** | 0.021*** | 0.020** | 0.025*** |
| | (0.003) | (0.003) | (0.006) | (0.008) | (0.008) |
| *N* | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |
| Indiv & HH Characteristics | | ✓ | ✓ | ✓ | ✓ |
| Neighborhood Services | | ✓ | ✓ | ✓ | ✓ |
| Income Controls | | ✓ | ✓ | ✓ | ✓ |
| District-Wave Fixed Effect† | | | ✓ | ✓ | ✓ |
| Lagged Controls | | | | ✓ | |
| Lagged Dependent | | | | ✓ | |
| Individual Fixed Effect | | | | | ✓ |

*Note:* Standard errors clustered at the PSU level are in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. † Fixed effects regressions (5) and Panel C control for district fixed effects and wave fixed effects independently. Our main results show a robust link between the perceived violence index and depressive symptoms.

TABLE A.3: Perceived Violence and Psychological Well-being—Excluding the household respondent

| | CES-D Score | | Dummy CES-D≥11 | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Violence Index$_t$ | 0.419$^{***}$ | 0.318$^{***}$ | 0.031$^{***}$ | 0.027$^{***}$ |
| | (0.047) | (0.071) | (0.004) | (0.005) |
| Indiv & HH Characteristics | ✓ | ✓ | ✓ | ✓ |
| Neighborhood Services | ✓ | ✓ | ✓ | ✓ |
| Income Controls | ✓ | ✓ | ✓ | ✓ |
| Urban Dummy | ✓ | ✓ | ✓ | ✓ |
| District Wave Fixed Effect | ✓ | ✓ | ✓ | ✓ |
| Individual Fixed Effect | | ✓ | | ✓ |
| $N$ | 42,653 | 42,653 | 42,653 | 42,653 |

*Note:* Standard errors clustered at the PSU level are in the parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. Excluding the household respondent aims to weed out direct reverse causality. The results are similar to the main results in Table III.

TABLE A.4: Lack of Observable Heterogeneity by Sex and Age

| | Male | Female | Age Under 30 | Age 30-50 | Age 50+ |
|---|---|---|---|---|---|
| *Dep Var: CES-D Score* | (1) | (2) | (3) | (4) | (5) |
| Violence Index$_t$ | 0.396*** | 0.495*** | 0.449*** | 0.532*** | 0.450*** |
| | (0.075) | (0.051) | (0.060) | (0.060) | (0.069) |
| Controls | ✓ | ✓ | ✓ | ✓ | ✓ |

*Note:* Standard errors clustered at the PSU level are in the parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. The estimated results for different groups are very similar suggesting a lack of heterogeneity in the average effects of violence on the psychological well-being of individuals in these different groups.

TABLE A.5: Propensity Score Matching—Tests of Unconfoundedness

| | Lagged CES-D Score | Primary Education | Lagged Married | Male |
|---|---|---|---|---|
| High Violence | -0.026 | -0.001 | 0.009 | -0.004 |
| | (0.080) | (0.005) | (0.008) | (0.011) |
| **Excluding Household Respondent** | ✓ | ✓ | ✓ | ✓ |
| Matching Variables | | | | |
| *Indiv & HH Characteristics* | ✓ | ✓ | ✓ | ✓ |
| *Region (District & Urban)* | ✓ | ✓ | ✓ | ✓ |
| *Lagged Income Controls* | ✓ | ✓ | ✓ | ✓ |
| *Lagged Violence Index* | ✓ | ✓ | ✓ | ✓ |
| *Lagged CES-D Score* | | ✓ | ✓ | ✓ |
| $N$ | 20,470 | 20,470 | 20,470 | 20,470 |

Cluster robust standard errors in parentheses: $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. A test of unconfoundedness of the treatment shows no statistically significant coefficient of violence on the pseudo-outcomes (Imbens, 2015). Specifically, the first column uses the lagged outcome variable as a pseudo-outcome which Imbens (2015) suggests is likely the best variable to test for unconfoundedness if available—something we are able to use this panel dataset to do.

Table A.6: Violence and Psychological Well-being—Individual × District Fixed Effects

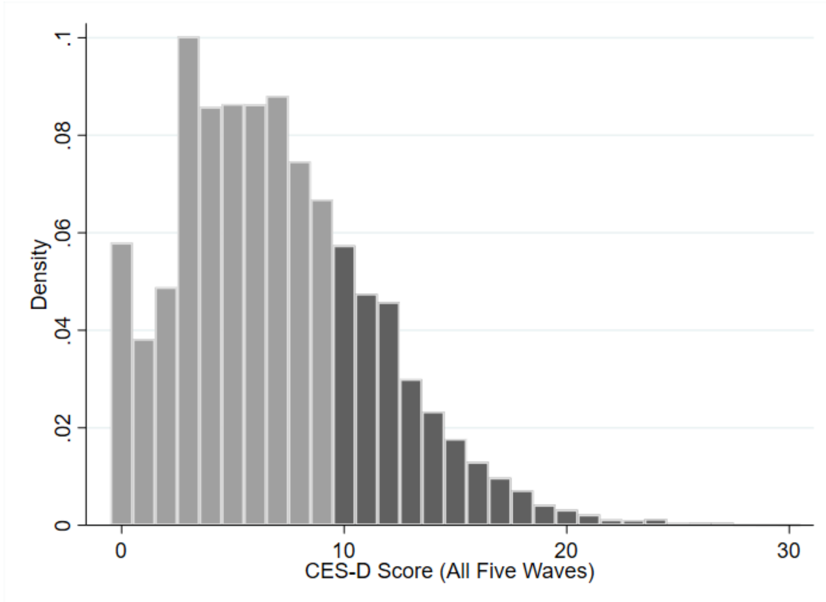
| | (1) |
|---|---|
| **Panel A**: Household-Level Perceived Violence | |
| Violence Index$_{hdt}$ | 0.379$^{***}$ |
| | (0.052) |
| $N$ | 64,651 |
| **Panel B**: Leave-$i$-Out PSU Means (Non-Movers) | |
| Average Violence Index$_{hdt}{}^{(-i)}$ | 0.299$^{***}$ |
| | (0.099) |
| $N$ | 32,725 |
| **Panel C**: Violent Crime Index (District-Level) | |
| Violent Crime Index$_{dt}$ | 0.515$^{***}$ |
| | (0.169) |
| $N$ | 64,651 |
| **Panel D**: ACLED Conflict Events (District-Level) | |
| Standardized ACLED Conflict$_{dt}$ | 0.327$^{***}$ |
| | (0.101) |
| $N$ | 64,651 |
| Indiv & HH Characteristics | ✓ |
| Neighborhood Services | ✓ |
| Income Controls | ✓ |
| Wave Fixed Effect† | ✓ |
| Individual Fixed Effect | ✓ |

*Note:* Standard errors clustered at the PSU level are in the parentheses.$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. † Fixed effects regressions (5) and Panel C control for district fixed effects and wave fixed effects independently. Our main results show a robust link between the perceived violence index and depressive symptoms.

TABLE A.7: ACLED Conflict and Psychological Well-being.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | District-Level ACLED Conflict Events. | | | | |
| Standardized ACLED Conflict$_{dt}$ | 0.113$^{***}$ | 0.218$^{***}$ | 0.252$^{***}$ | 0.274$^{***}$ | 0.323$^{***}$ |
| | (0.038) | (0.035) | (0.078) | (0.091) | (0.096) |
| Indiv & HH Characteristics | | ✓ | ✓ | ✓ | ✓ |
| Neighborhood Services | | ✓ | ✓ | ✓ | ✓ |
| Income Controls | | ✓ | ✓ | ✓ | ✓ |
| District-Wave Fixed Effect$^{\dagger}$ | | | ✓ | ✓ | ✓ |
| Lagged Controls | | | | ✓ | |
| Lagged Dependent | | | | ✓ | |
| Individual Fixed Effect | | | | | ✓ |
| $N$ | 64,651 | 64,651 | 64,651 | 39,997 | 64,651 |

*Note:* Standard errors clustered at the PSU level are in the parentheses.$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. † Fixed effects regressions (5) and Panel C control for district fixed effects and wave fixed effects independently. Our main results show a robust link between the perceived violence index and depressive symptoms.




Histogram of CES-D Scores

FIGURE A.1: Distribution of CES-D Scores: Histogram of the CES-D scores shows that a significant portion of the population have scores above the threshold of 10 used by psychologists to screen for depression.

## A.2 Figures

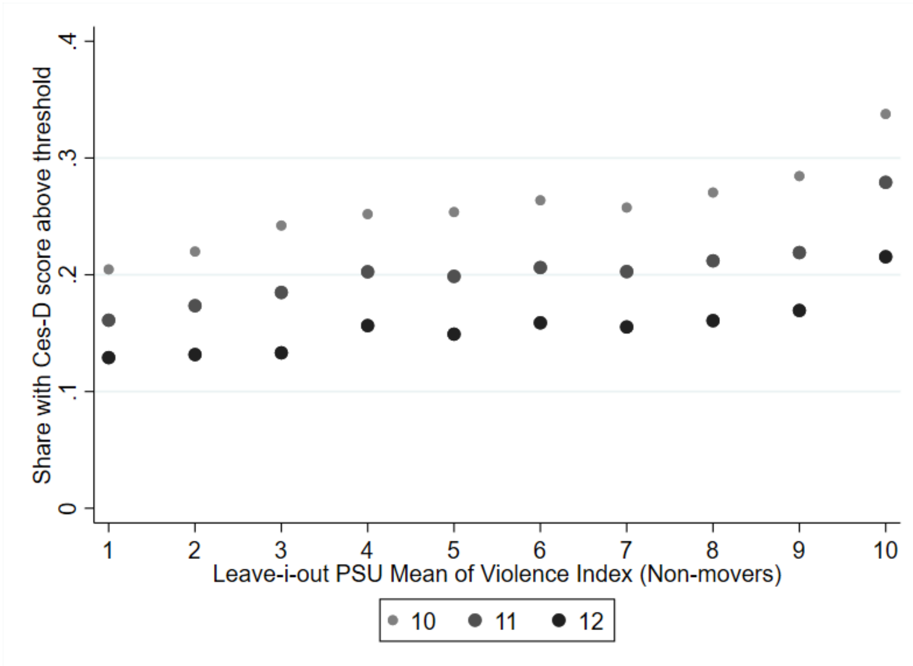



FIGURE A.2: Share above depression thresholds by Wealth Decile. This figure shows these shares when excluding the household respondent who completed the frequency of violence questions. The pattern is very similar to the full sample in Figure II(b).

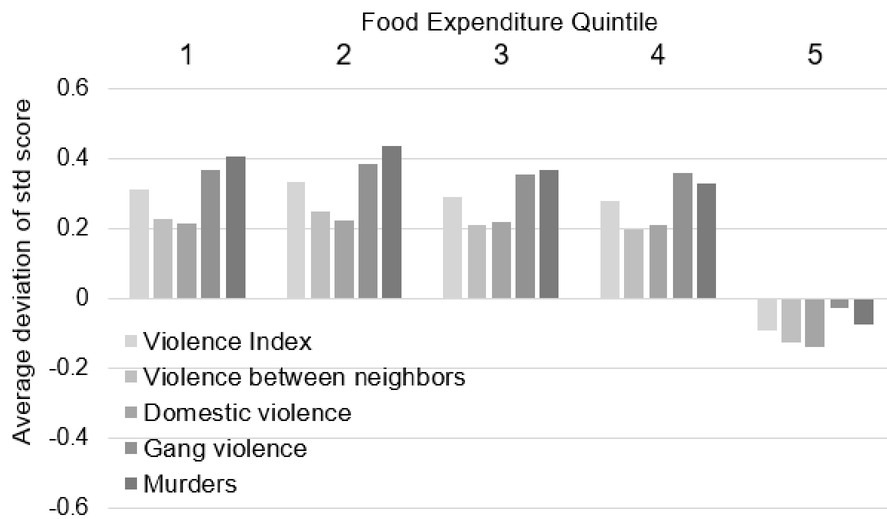
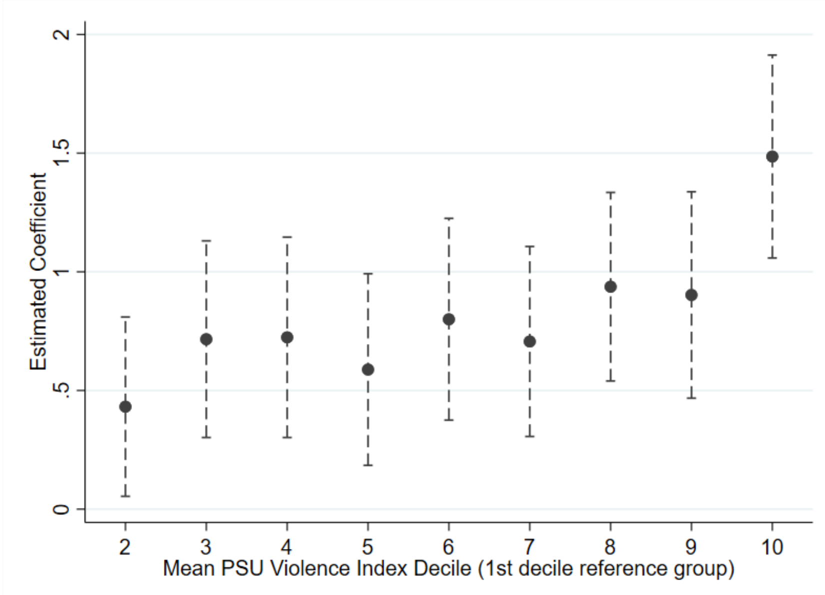
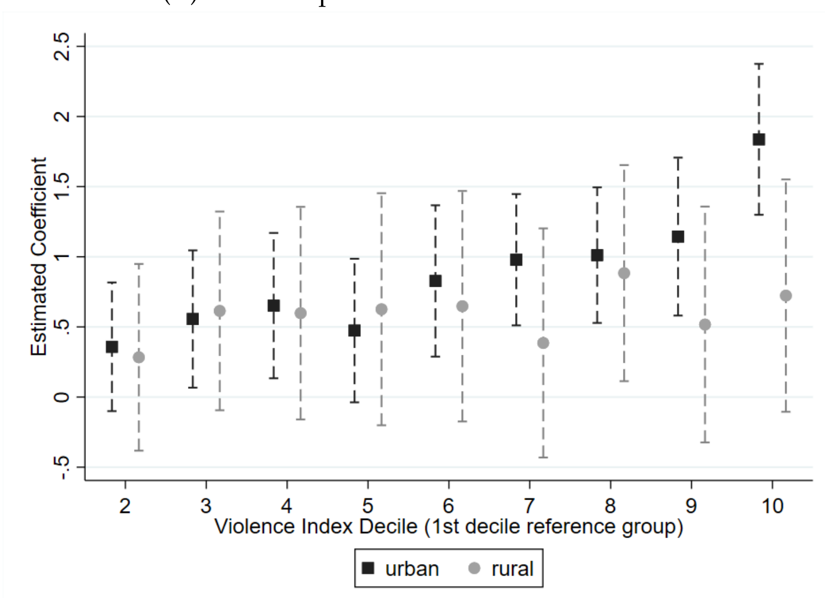



FIGURE A.3: Leave-i-out Mean PSU perceived violence also shows a similar pattern where poorer households are more likely to live in geographical areas that on average people perceive more violence.

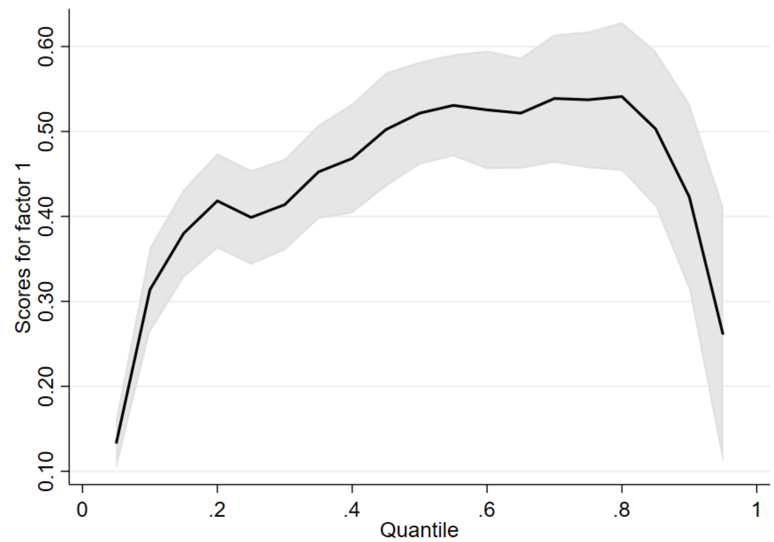



(A) Flexible Specification for Violence Index

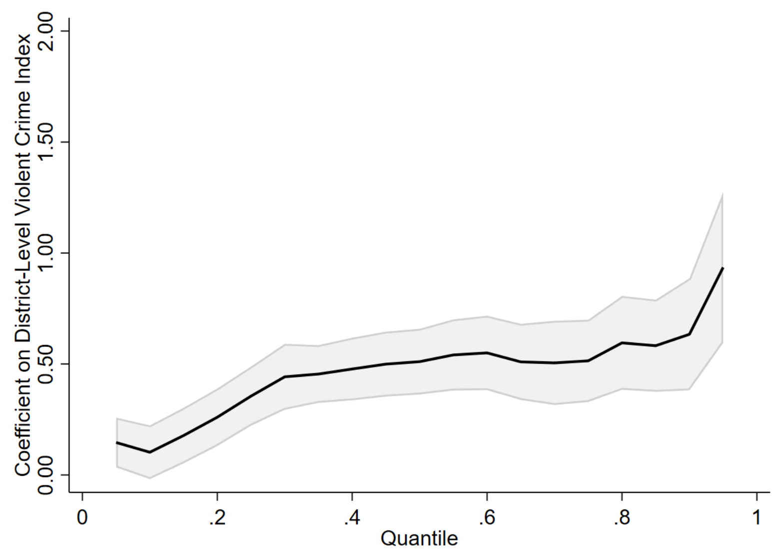



(B) Differentiating Urban and Rural settings

FIGURE A.4: Flexible estimation approach. Estimated coefficients are increasing by Violence Index Deciles and differences for higher deciles are larger in Urban areas. These results are for non-movers only.

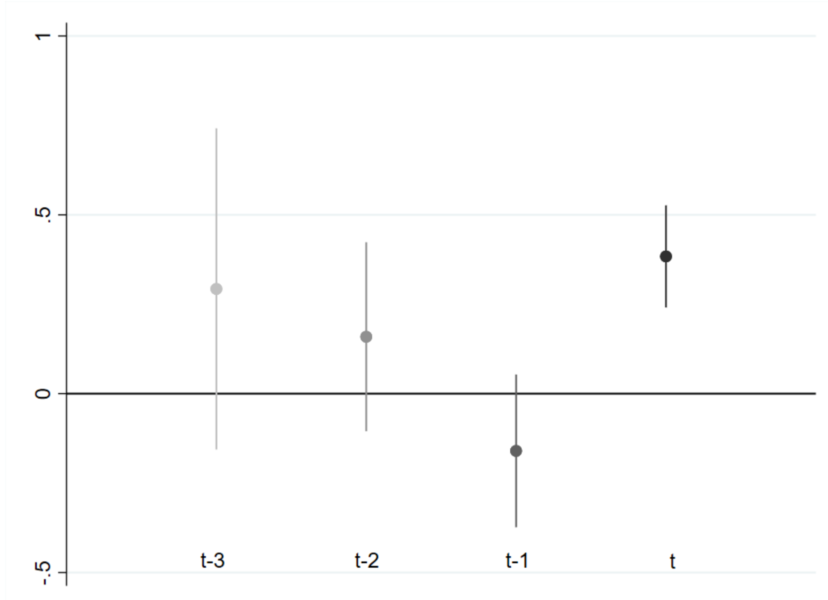



(A) Quantile regression: Leave-*i*-out PSU means of perceived violence.

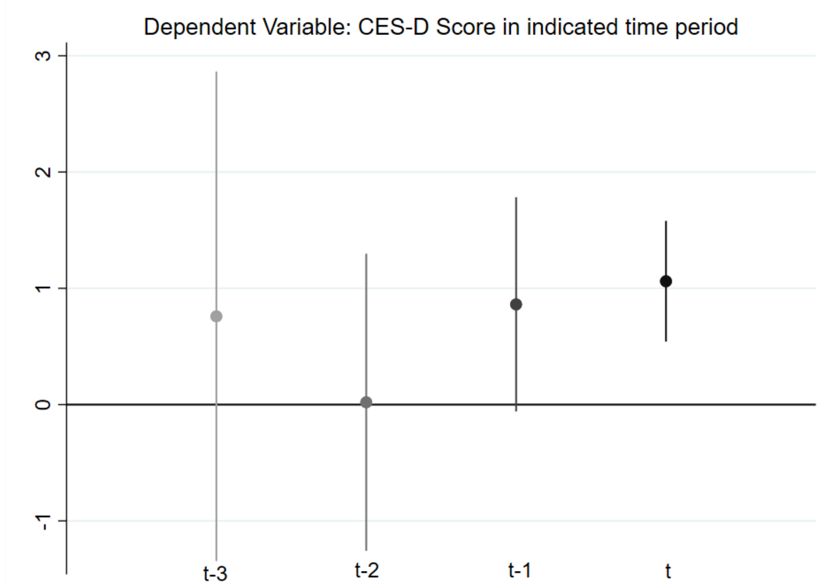



(B) Quantile Regression: District level violent crime.

FIGURE A.5: Similar to Figure 4, these quantile regression results show that the estimated link between violence and psychological well-being is higher for those with more depressive symptoms who are on the higher end of the CES-D score.




(A) PSU-Level Leave-i-out Mean




(B) District-Level Violent Crime Index

FIGURE A.6: Similar to Figure 5, these results attempt to show predictive value for current violence on past psychological well-being controlling for past violence for our two other measures of violence. Similar to household-level perceived violence, these results do not show a statistically significant predictive value for current violence of past psychological well-being.

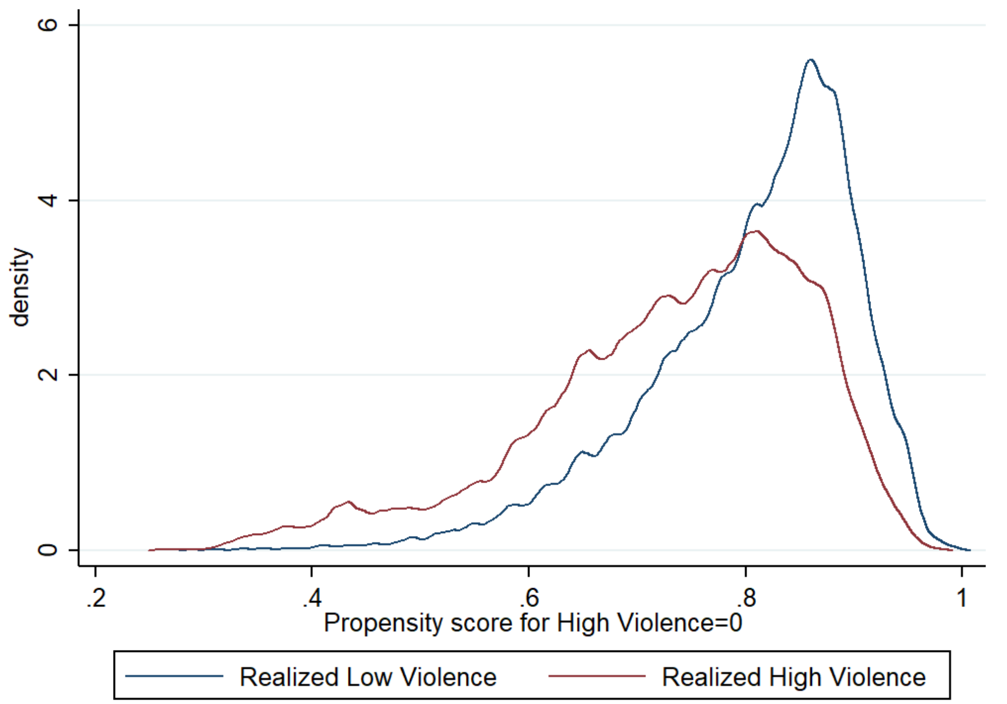



FIGURE A.7: The distributions of the propensity scores for living in neighborhoods that are not violent show significant overlap.