Neighborhood Violence, Poverty, and Psychological Well-being*

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Abstract

In this paper we explore the psychological consequences of heightened levels of exposure to neighborhood violence among the poor. Using a nationally representative panel dataset from South Africa—a country with high levels of interpersonal violence, urban poverty, and inequality—we estimate the relationship between neighborhood violence and psychological well-being. Specifically we use household-level perception of neighborhood violence that we validate using objective data from the the South African Police Service and the Armed Conflict Location and Event Data project. With this data, we first show that the poor live in neighborhoods that they perceive to have higher levels of violence and live in districts that have objectively more violence. Second, by controlling on observable characteristics and using a propensity score matching method, we find that higher levels of perceived violence are strongly linked to elevated depressive symptoms and an increased likelihood of being at risk for clinical depression. Finally, we find that this link is strongest among the poor and that living in urban neighborhoods with a lot of violence while poor is predictive of future poverty in our sample. We posit that this relationship may be a mechanism through psychological poverty traps may operate.

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

JEL Codes: I3, O1, D91.

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1 Introduction

The previous generations of the extremely poor mainly lived in rural areas in low-income countries. Today the majority of those living in extreme poverty 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 different contexts around the world. While exposure to violence is universal in its harm, the disproportionate exposure of the poor may be a mechanism through which poverty persists. Shedding light on the conditions confounding the dynamics of poverty may pave the way for more effective poverty-alleviation policy.

In this paper we investigate the question: What is the relationship between violence and crime within neighborhoods and individual-level psychological well-being? Using nationally representative panel data from South Africa, an upper middle-income country with high levels of violence and urban poverty, we find that higher levels of neighborhood violence increase depressive symptoms and the likelihood being being at risk for depression. In addition, we show that the poor are more likely to live in neighborhoods with high levels of violence. Taken together, these results show that 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 (Alloush, 2019; Haushofer and Fehr, 2014). We show that living in poverty and in a neighborhood with high levels of violence is predictive of future poverty in South Africa.

Previous work suggests that subjective perceptions of neighborhood characteristics are strongly associated with depression, anxiety, anger, and lower quality of life (Latkin and Curry, 2003; Ross and Mirowsky, 2009; Yen et al., 2006) even after controlling for individual-level observable characteristics 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). Much of this previous research, however, struggles to identify the specific neighborhood characteristics that most strongly affect psychological well-being and mental health (Wilson-Genderson and Pruchno, 2013). Some evidence suggests that the presence of violence and crime strongly affects psychological well-being (Aneshensel and Sucoff, 1996; Ross and Mirowsky, 2001; Steptoe and Feldman, 2001; Latkin and Curry, 2003), however, each of these studies use subjective reports of the perception of neighborhood violence or crime. More recent studies suggest that subjective perceptions of neighborhood characteristics mediate the relationship between objective neighborhood measures and psychological outcomes (Kruger, Reischl and Gee, 2007; Curry, Latkin and Davey-Rothwell, 2008). However, failing to account for the individual characteristics that determine how individuals perceive neighborhood characteristics may bias estimates of the relationship between perceptions and psychological well-being (Elliott, 2000). Moreover, objective neighborhood characteristics may have a direct effect on psychological well-being that is independent of their perceptions (Wilson-Genderson and Pruchno, 2013; Parra et al., 2010; Curry, Latkin and Davey-Rothwell, 2008).

Other related work 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). Additionally, exposure to violence and crime increases risk aversion or preferences for certainty in Afghanistan (Callen et al., 2014), Colombia (Moya, 2018), and Mexico (Brown et al., 2019).

The relationship between violence and crime within neighborhoods and psychological well-being is important for several reasons. First, psychological well-being is an important outcome as an end in itself and, at extreme levels, depression can lead to suicide (Christian, Hensel and Roth, 2019). Second, exposure to violence may lead to fatalistic beliefs about socioeconomic mobility (Moya and Carter, 2019), which could lead to a psychological poverty trap (Lybbert and Wydick, 2018). 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), psychological disorders can have important inter-generational consequences.

We add to this previous literature in three important ways. First, and most generally, although much of the previous literature estimating the relationship between violence and psychological well-being investigates exposure to relatively extreme acts of war, we focus our analysis on exposure to less extreme—but more common—acts of neighborhood violence and crime. This is important for at least two reasons: (i) Although understanding the consequences of extreme acts of war is undoubtedly important, war is in relative decline (Blattman and Annan, 2010). (ii) Far less is known about the psychological consequences of exposure to less extreme—but far more common—acts of violence and crime. Second, building on the idea that perceptions may importantly mediate the relationship between objective reality and psychological well-being, we use both administrative (i.e., "objective") data on conflict and crime events and individual's subjective perceptions of neighborhood violence. This allows us to validate the accuracy of the subjective perception data. Third, our analysis makes use of a nationally representative panel survey data set. This allows us to draw inferences on the entire national population of South Africa and account for important and often unobservable individual-level characteristics.

The results show that the perception of violence is strongly associated with higher levels of depressive symptoms and an increased likelihood of being at risk to depression. Living in a neighborhood with high levels of violence increases the likelihood of being at risk to depression by 25%. To the extent that we are able to control for confounding factors by controlling for a number of different variables while taking into account individual fixed effects and ruling out the direct reverse causality, we show that neighborhood violence can have significant effects on the psychological well-being of individuals. Additional approaches using propensity score matching and instrumental variables find similar results.

Given that the poor are disproportionately more likely to live in neighborhoods with high levels of violence and crime and that that low levels of psychological well-being are shown to hinder one's ability to achieve their full earning potential, these results illuminate an additional mechanism through which poverty can persist and psychological poverty traps may arise.

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 crime in South Africa and discussing the context for this study. The third section presents the core empirical results. Finally, Section four concludes.

2 Data

2.1 Data Sources

The main data used in this analysis comes from the panel dataset of the National Income Dynamics Study (NIDS) of South Africa.[1] 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 was collected on many socio-economic variables that include expenditure, labor market participation and economic activity, fertility and 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. This is unprecedented in a nationally representative panel survey in a developing country. The CES-D is a widely used tool used to assess depressive symptoms and screen for depression in the general population (Radloff, 1977; Santor, Gregus and Welch, 2006; Siddaway, Wood and Taylor, 2017).[2] In addition, NIDS has a measure of life satisfaction in every wave asking individuals to rate their overall satisfaction with their life on a scale of one to ten. This is a common tool used to measure subjective well-being (Snyder and Lopez, 2001).

The NIDS surveys also include questions asked at the household-level on the frequency of neighborhood violence, crime, and conflict events. In particular, the survey asks specifically about the frequency of different types of violence in their neighborhood including: violence between different households, violence between members of the same household (domestic violence), gang violence, and murder, shootings, or stabbings. We create a perceived violence index using these questions using factor analysis. Our core results are based on these self-reported measures to

[1] 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 data of this study can be found in Ardington and Case (2010).

[2] 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-D scale has been validated for use in South Africa in several studies (Baron, Davies and Lund, 2017; Hamad et al., 2008; Myer et al., 2008).

indicate the perceived prevalence of violence and data from all five waves of NIDS. As we describe in more detail below, we validate these measures with objective data on conflict and crime.

Supplemental data on conflict events comes from the Armed Conflict Location and Event Data (ACLED) Project. The ACLED Project collects information on conflict events—such as location, date, type of violence, involved actors, etc.—for much of Europe, the Middle East, Asia, and Africa. We use ACLED data from South Africa from 2007 through 2017, the years associated with each of the five NIDS waves.

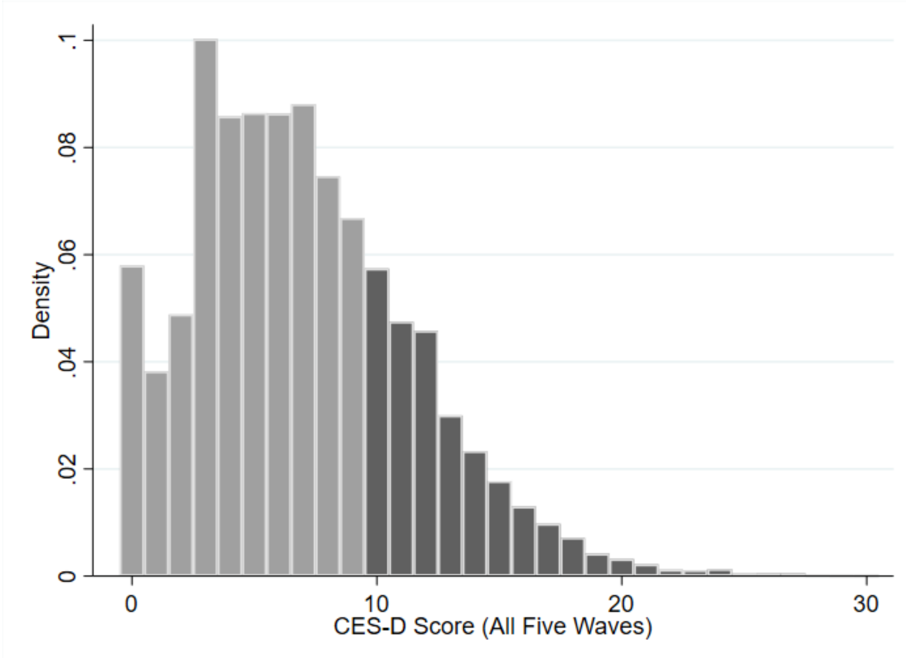
Additional data comes from the South African Police Service's (SAPS) crime database. This data is publicly available yearly on reported crimes in each police precinct. We matched these police precincts to districts in the NIDS data and aggregated crimes at the district-year level. With information on the populations in each district, we are able to calculate the rates of reported crime within each district over time for many crimes such as murder, attempted murder, aggravated assault, sexual assault, arson, drug dealing, robbery, and burglary.

These data from ACLED and SAPS are useful in validating the accuracy of the self-reported measures of the frequency of neighborhood violence. Despite the importance of the perception of violence in its own right, it is important to show that these perceptions reflect the reality of the existence of violence in these areas. We discuss these validation results in Section 3.2.

2.2 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 brackets) in the study sample in 2017 was 3,262 ZAR (10,197).[3] This hides significant inequality as the median household income per capita is ZAR 1,437. Moreover, recent analyses estimate that nearly 54% of the population is living in poverty and about 20% live in extreme poverty (Leibbrandt, Finn and Woolard, 2012). In the balanced panel sample of NIDS, 87% of

[3] 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.



(A) Histogram of CES-D Scores

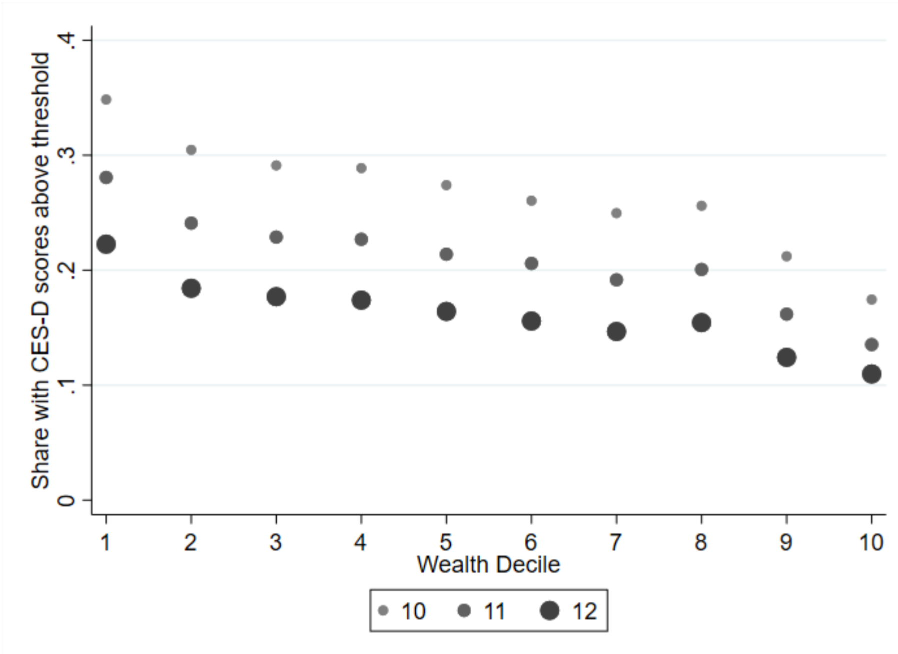
FIGURE I: Distribution of CES-D Scores and Changes between waves: Histogram of the CES-D scores shows that a significant portion of the population have scores above the threshold of 10 used by psychologists to screen for depression.

individuals report food expenditure levels that are considered poor in at least one of the five waves. 48% are poor in at least three out of the five waves and 11% are poor in all five waves of the panel.

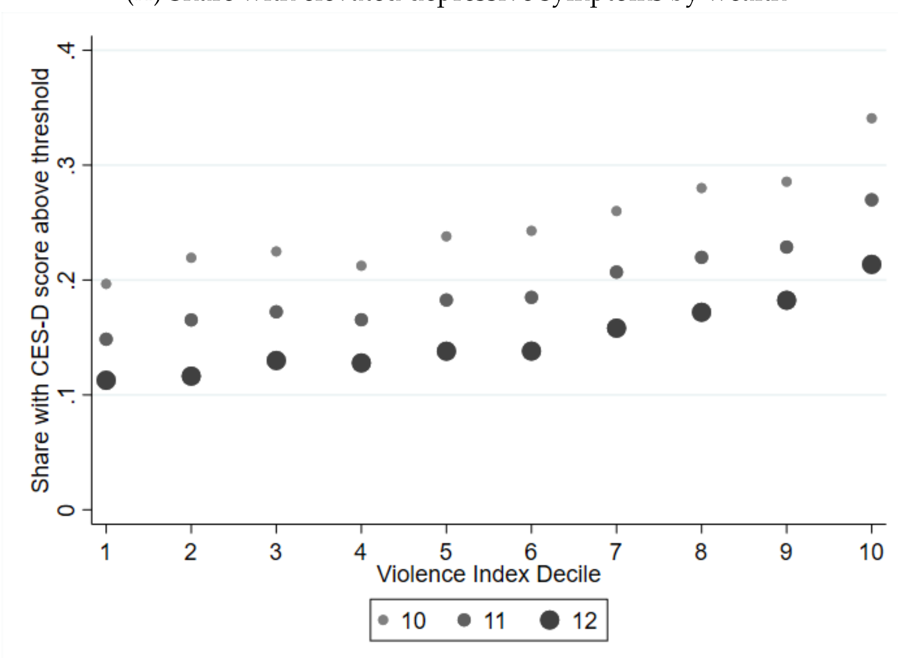
In the study sample, the mean CES-D score (standard deviation) for all five waves is 6.8 (4.4) and shows a decreasing trend where the average score is 8.2(4.9) in 2008 and 6.62(4.3) in 2017. The within person standard deviation in the CES-D score is 3.6. The distribution of CES-D scores across all five waves is shown in Figure I. 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% in 2008 to 17.7% in 2017.[4] Nearly 54% of the panel sample record a CES-D score of 11 or above at least once in all five waves.

Figure II(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

[4] Baron et al. 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 II: Share of individuals with CES-D scores above 10, 11, and 12 by Wealth Decile. High scores indicate an increasing likelihood of clinical depression and it is clear that as wealth increases, the share of individuals reporting scores higher than these thresholds is decreasing.

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. As Figure II(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 show a strong correlation between psychological and economic well-being. Figure II(B) shows the share of individuals above the CES-D thresholds by an index of perceived violence. It is clear that as the level of violence perceived by the household-questionnaire respondent increase, the share of individuals who have elevated depressive symptoms also increases.[5]

2.3 Violence in South Africa

South Africa suffers from high levels of violence and crime. 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 in the last 10 years. Table I shows violent and property crime 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. Linking our two datasets allows us to show that crime is overall higher in districts with higher levels of inequality.[6] 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

[5] This pattern is very similar when excluding the household-level questionnaire respondent (see Figure A.1 in the Appendix). As discussed in Section 2.1, the perceived neighborhood violence questions are part of the household questionnaire. To minimize direct reverse causality (those who have more depressive symptoms may perceive higher levels of violence), we exclude the household-level questionnaire respondent and find a very similar pattern for elevated depressive symptoms and neighborhood violence.

[6] An increase in 0.1 in the gini coefficient within a district is associated with a 0.07 standard deviation increase in violent crime.

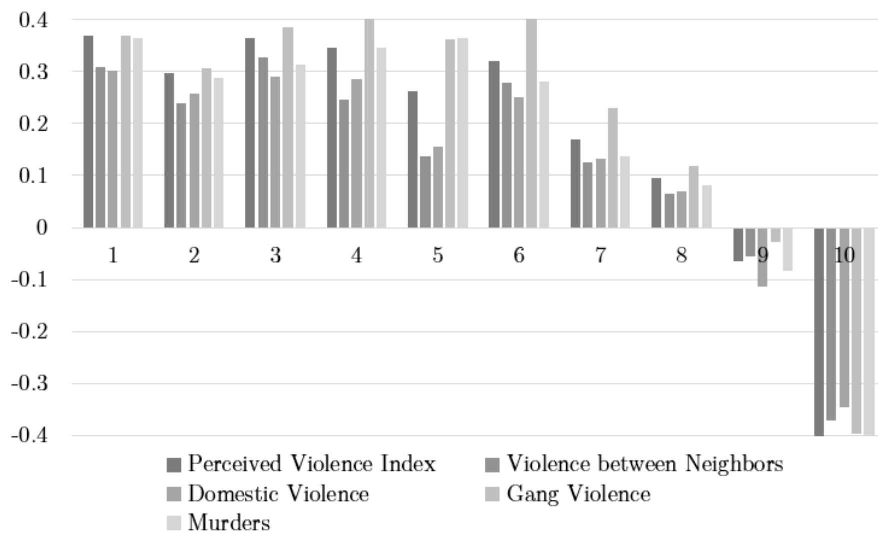
TABLE I: Crime rates in South Africa and major metro areas.

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	3220.3	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

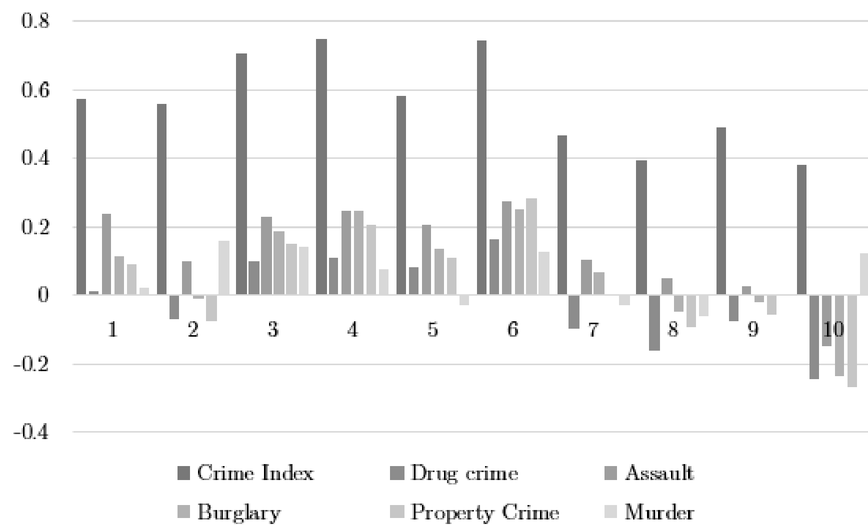
violence (or perception of it) varies greatly by socio-economic status. The poor are significantly more likely to live in neighborhoods that they perceive to have a lot of violence—the poor live in neighborhoods that they perceive to have 0.29 standard devations more violence. Figure III(A) breaks this down further and shows that the wealth of households is associated with lower violence overall. Estimates in the figure show that in urban areas respondents from the wealthiest household decile live in neighborhoods that they perceive to have over 0.8 standard deviations lower violence than those living in the poorest decile.[7] This pattern looks similar for all the components of the perceived violence index.

When it comes recorded violence or the objective measures of violence we use

[7]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 the rich are not, then this difference would be an underestimate of the actual difference in neighborhood violence. If the rich are not exposed to the realities of the neighborhood then this may be an overestimate. When it comes to psychological well-being, however, the perception of violence is likely more important.



(A) Standardized Perceived Violence scores by Wealth Decile



(B) Matched district-level SAPS Data on Crime

FIGURE III: Perceived violence clearly decreases by wealth decile. District level aggregated crime data show that those in lower wealth deciles live in districts with higher crime on average.

in our analysis, the patterns when it comes to poverty are less clear. This is possibly due to the level of aggregation of the ACLED and crime data. One drawback of this objective crime and violence data is that the lowest geographical unit we are able to connect it to in the NIDS dataset is the district.[8] Still, in Figure III(B) it can be

[8]Due to privacy concerns, the publicly available NIDS data only indicates which district a house-

seem that standardized rates of crime are overall decreasing with wealth. Wealthier households live in districts with overall lower levels of crime. The figure shows that households in lower half (or 2/3) of the wealth distribution live in districts with overall higher recorded crime rates.[9]

2.4 Data Validation

Violence is a multi-dimensional concept and can be difficult to define. Therefore, one may have concerns with the self-reported nature of our measure of the frequency of violence. However, it is worth noting that the perception of violence is likely the most important mechanism through which actual violence in the neighborhood affects individuals and—for the purposes of this study—their mental health. Despite this, it is key to see if objective measures of violence are predictive of higher perceptions of violence in the NIDS sample.

The main data we use to validate the perceived violence measures comes from the South African Police Service (SAPS) that provides yearly records of crimes recorded in each police precinct in South Africa. We collected information on violent and property crimes for years that coincide with the NIDS waves and aggregated this data at the lowest geographical unit we are able to match in the NIDS dataset—the district. It is likely that this data underreports the actual amount of crime committed in each of these district with higher rates of underreporting in poorer areas.

ACLED data provides information on conflict events using information available from secondary sources, such as 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. Although ACLED data are not perfect, at the present time they represent the most accurate and detailed quantitative information on the prevalence of conflict, violence, and crime available.

We use these data to validate the self-reported measures of violence available in the NIDS data. To do this we compare the number of different types of events in the calendar year prior to the NIDS interview (as reported by ACLED and SAPS)

hold resides in.

[9]This pattern can be observed with other definitons of economic well-being; for example using food expenditure per capita, it is clear that households with lower food expenditure per capita live in districts with higher levels of crime and conflict events.

TABLE II: Predictive value of objective crime measures

Dep Var: Violence Index (perceived)			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	12,168	12,469	12,469

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to the main self-reported index measure of perceived violence (as recorded in the NIDS). These validation results are shown in Table II. In general, all of the coefficient estimates of the predictive value of the objective measures for the perceived violence index are positive and statistically significant at the 1% level.

Despite the aggregation levels of the objective measures of violence, they have strong associations with the perceived violence measures. For example, results in Column (3) that control for district-fixed effects and wealth decile of the respondent suggest that a one SD change in the objective crime index increases the perceived violence index by 0.23 standard deviations. These estimated associations could be quite meaningful. The coefficient estimates represent the standard deviation change in the self-reported frequency of various types of conflict associated with one additional conflict event in the previous calendar year within each South African district. Although some districts in some years are quite peaceful, with zero recorded conflict events, some districts can experience a relatively large number of events. For example, when considering all types of conflict aggregated together, the average South African district experienced over 17 events (median of 5). These measures of the central tendency, however, somewhat hide the large variation in the prevalence of conflict across South Africa. Some districts hardly experience any conflict while others experience almost one conflict event each day.

It is important to note again that the objective crime and violence measures we have are at the district level. If these variables were aggregated instead at a smaller geographical unit, we expect the coefficients on these regressions to be even larger.

3 Results

3.1 Econometric Approach

We estimate the effect of neighborhood violence on psychological well-being with the following linear regression specification:

$$pw_{ihdt} = \alpha V_{hdt} + \boldsymbol{Y'_{hdt}}\gamma + \boldsymbol{X'_{hdt}}\boldsymbol{\beta} + \boldsymbol{Z'_{ihdt}}\delta + \rho_i + \theta_t + \tau_d + \epsilon_{ihdt} \tag{1}$$

In equation (1) pw_{ihdt} represents measures of psychological well-being: depression and an indicator variable for having a CES-D score over the threshold of 11 for individual i in household h in district d at time t. The variable V_{hdt} represents various measures of household-level neighborhood violence. $\boldsymbol{X_{hdt}}$ 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 and number of children. $\boldsymbol{Y_{hdt}}$ are household-level controls that proxy economic well-being including household income, a wealth index, and food expenditure per capita. Individual controls include: individual income, sex, ethnicity, age, and educational attainment. ρ_i is the individual fixed effect, θ_t is a time or survey wave fixed effect, and τ_d is a district fixed effect. Finally, ϵ_{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.

$$\begin{aligned} pw_{ihdt} = \alpha_1 V_{hdt} + \alpha_2 V_{hd(t-1)} + pw_{ihd(t-1)}\sigma + \boldsymbol{Y'_{h,d,t}}\boldsymbol{\gamma_1} + \boldsymbol{Y'_{hd(t-1)}}\boldsymbol{\gamma_2} \\ + \boldsymbol{X'_{hdt}}\boldsymbol{\beta} + \boldsymbol{Z'_{ihdt}}\delta + \rho_i + \theta_t + \tau_d + \epsilon_{ihdt} \end{aligned} \tag{2}$$

We estimate this equation to take advantage of the panel nature of this data and better control for income which is likely an important confounder. Taking into account both current and prior income would lead to more robust results. Estimating a fixed effects regression with lagged dependent variables leads to Nickel bias, so when individual fixed effects are taken into account, we estimate the above equation using Arellano and Bond (1991) -type methods where the violence index is assumed to be exogenously determined.[10]

[10] These panel data methods were introduced by Anderson and Hsiao (1981) and Holtz-Eakin, Newey and Rosen (1988) and later refined and popularized by Arellano and Bond (1991). Under certain assumptions such as sequential exogeneity, lagged levels are used as instruments for first

TABLE III: Perceived Violence and Psychological Well-being

	CES-D Score				
	(1)	(2)	(3)	(4)	(5)
Violence Index$_t$	0.58***	0.54***	0.53***	0.49***	0.48***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.12)
Violence Index$_{t-1}$			0.13***	0.13***	0.29***
			(0.05)	(0.04)	(0.06)
	Dummy variable: CES-D≥11				
	(6)	(7)	(8)	(9)	(10)
Violence Index$_t$	0.039***	0.034***	0.034***	0.032***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
Violence Index$_{t-1}$			0.007*	0.007*	0.017***
			(0.004)	(0.004)	(0.005)
Indiv & HH Characteristics		✓	✓	✓	✓
Income Controls		✓	✓	✓	✓
Lagged Income Controls			✓	✓	✓
Lagged CES-D Score			✓	✓	✓
Urban Dummy				✓	✓
District Fixed Effect				✓	
Individual Fixed Effect					✓
N	65,536	65,530	32,482	32,482	9,294

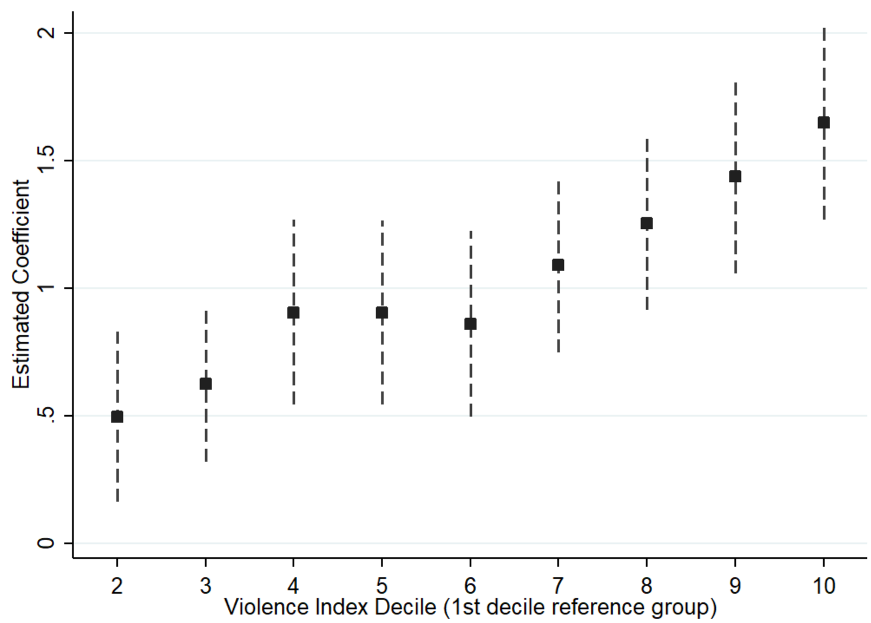
Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.2 Main results

Table III shows the results for different specifications of equations (1) and (2). 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). Interpreting the results from column (6) suggest that a 1 standard deviation (SD) increase in the perceived violence index is associated with a 0.44 increase in an individual's CES-D score. This corresponds to approximately a 0.1 SD increase in depressive symptoms (results using standardized CES-D scores are shown in Appendix Table A.2).[11] The estimated coefficient is also positive and statistically significant for the probability of having a high CES-D

differenced endogenous variables.

[11]The violence index is standardized across individuals. There is significant variation within respondents across waves as well. The change between waves is centered around 0 but has a standard deviation of nearly 1.



(A) Flexible Specification

FIGURE IV: Coefficients on violence index decile dummies. Using the same specification as that in regression (4) in Table III, we estimate the equation with nine violence index decile dummies to allow for a more flexible specification (vs linear). Compared to those who live in neighborhoods with the lowest perceived violence levels, those living in neighborhoods with higher levels of perceived crime have consistently more depressive symptoms. Individuals in the highest decile of perceived neighborhood crime have CES-D scores that are, on average, 1.6 points (0.3 SD) higher than do those in the lowest violence neighborhoods.

score (greater than or equal to 11). A 1 standard deviation increase in the perceived violence index is associated with a 3.2 percentage point increase in the likelihood of being at high risk for depression—with baseline probabilities near 20%, this is a 15% increase.[12]

Notably, lagged perceived violence also seems to be a good predictor of depressive symptoms even when controlling for current and lagged socioeconomic variables.

The perceived violence variable is composed of survey questions that are asked at the household level; this household questionnaire is answered by one person in the household.[13] In Table IV, we remove the person who answered the household

[12]Restricting the sample to only the household respondent gives very similar results.

[13]In NIDS, this questionnaire is usually responded to by the oldest female in the household who is

TABLE IV: Perceived Violence and Psychological Well-being–Excluding household respondent

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
Violence Index$_t$	0.357***	0.688***	0.023***	0.051***
	(0.066)	(0.160)	(0.006)	(0.015)
Violence Index$_{t-1}$	0.126**	0.352**	0.007	0.033**
	(0.053)	(0.144)	(0.005)	(0.014)
Indiv & HH Characteristics	✓	✓	✓	✓
Income Controls	✓	✓	✓	✓
Lagged Income Controls	✓	✓	✓	✓
Lagged CES-D Score	✓	✓	✓	✓
Urban Dummy	✓	✓	✓	✓
District Fixed Effect	✓		✓	
Individual Fixed Effect		✓		✓
N	16,562	16,562	16,562	16,562

Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

questionnaire from the study sample. We do so to rule out direct reverse causality i.e. it rules out that those with more depressive symptoms will likely indicate that there is more violence in the neighborhood than there actually is. This fits in with the literature on the effects of depression on perception. This does not, however, rule out reverse causality through within-household correlations in psychological well-being. In Table IV, we can see that the magnitude of the coefficient decreased slightly for the OLS regression yet it is still statistically significant. The results from the fixed effects regression show a similar, albeit slightly larger, coefficient for violence index with both dependent variables. A one SD increase in the perceived violence of the household respondent is associated with a 0.69-point increase in CES-D scores–nearly 0.16 SD increase in depressive symptoms for other members of the household.[14]

Table V shows the various components of perceived violence and their associations with psychological well-being. The main components of perceived violence that highly associated with higher depressive symptoms are violence between households and domestic violence. Gang violence is also statistically significant. Notably, the frequency of murders does not seem to be statistically significant

familiar with day-to-day expenditures of the household.

[14]Controlling for the respondent's CES-D score may alleviate concerns regarding intra-household correlation in depressive symptoms, however this takes away one of the mechanisms through which neighborhood violence can affect individuals. Results in Appendix Table A.3 show that the coefficient on the violence index remains statistically significant yet it is smaller in magnitude.

TABLE V: Components of Perceived Violence

	CES-D Score		
		Exclude HH respondent	
	(1)	(2)	(3)
Panel A: Frequency of Violence between Households	0.394***	0.331***	0.333***
	(0.054)	(0.052)	(0.084)
R^2	0.155	0.092	0.175
Panel B: Frequency of Domestic Violence	0.380***	0.381***	0.315***
	(0.059)	(0.059)	(0.091)
R^2	0.152	0.094	0.171
Panel C: Frequency of Gang Violence	0.252***	0.205***	0.208**
	(0.063)	(0.050)	(0.094)
R^2	0.151	0.087	0.170
Panel D: Frequency of Murder	0.060	0.016	-0.113
	(0.057)	(0.048)	(0.083)
R^2	0.148	0.086	0.168
Indiv & HH Characteristics	✓	✓	✓
Income Controls	✓	✓	✓
Lagged Income Controls	✓	✓	✓
Lagged CES-D Score	✓	✓	✓
Urban Dummy	✓	✓	✓
District Fixed Effect	✓	✓	✓
Individual Fixed Effect		✓	✓
N	33,160	16,840	16,840

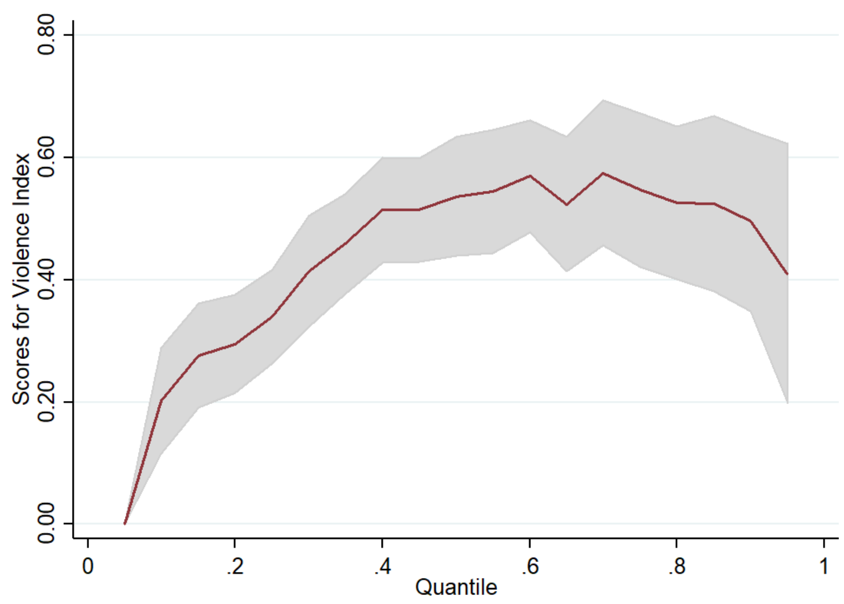
Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in predicting CES-D scores.

3.3 Quantile Regressions

Does violence affect psychological well-being in the sample way at all levels of psychological well-being? As discussed earlier, individuals with higher CES-D scores are prone to depression and are experiencing relatively high depressive symptoms. It is plausible 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 higher end. To explore this further, we conduct quantile regression analysis using the same specification as in Column (1) in Table IV.

A plot of the quantile regression results is shown in Figure IV. The results suggest that violence has a bigger effect for those on the higher end of the CES-D score. The median CES-D score is 7 and the quantile regression results show that the effect of violence peaks just above the median. It may be that those already experiencing



(A) CES-D

FIGURE V: Quantile regression results.

depressive symptoms are more susceptible to experiencing larger changes in their depressive symptoms when perceiving increased violence in their neighborhoods. Those already at risk due to a multitude of factors (such as poverty) may experience even bigger increases in their CES-D score when neighborhood violence increases.

3.4 Heterogeneity by Wealth

Do the poor who, on average, exhibit more depressive symptoms and higher exposure to violence respond to changes in perceived violence differently? Or do the wealthy whose exposure to violence in the first place is lower show larger changes in depressive symptoms when their perception of neighborhood violence increase? To explore this question, we ran five separate regressions by wealth quintile. These regressions look at the effect of perceived violence on the likelihood of having a CES-D score over 11 which is considered at risk for clinical depression. These regressions had the same specification as that in Column (4) of Table IV, however, they are restricted to urban settings for each of wealth comparisons.[15]

It is clear from the results that individuals in poorer households are affected

[15]Wealth is less comparable across urban and rural areas than within each area.

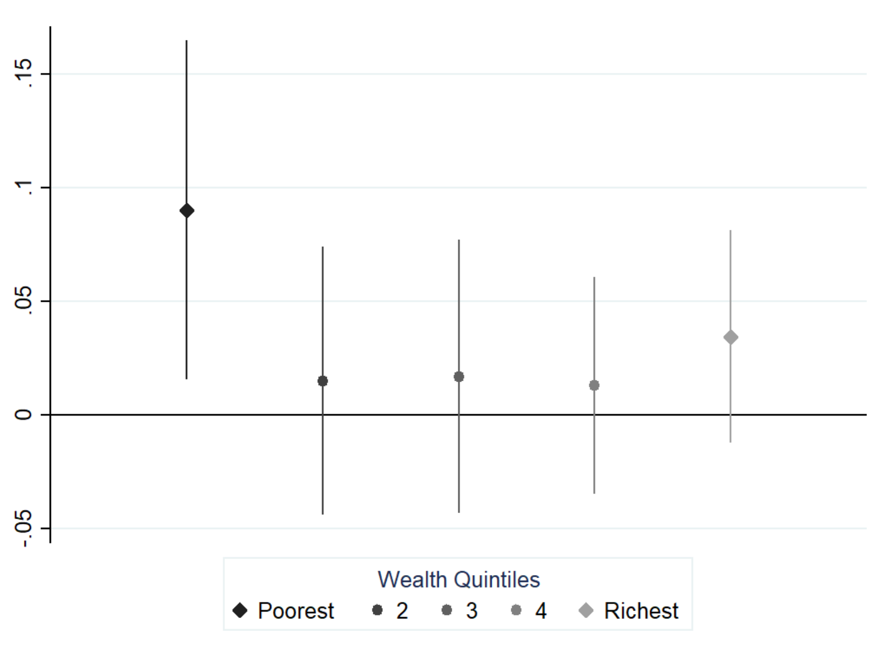


FIGURE VI: Effect on likelihood of CES-D greater than 11 by wealth quintile

differently. While the difference in the coefficients is not statistically significant, the pattern in the figure is clear showing a larger effect amongst the poorest quintile. The estimated coefficients are still positive for the other four quinitles, however, they are not statistically significant. This may be due to the lower sample size among this cohort. The figure where the dependent variable the CES-D continuum looks similar, however the effects are larger for quintiles four and five suggesting that individuals in wealthier households may also be affected in an elevated way by changes in violence in their neighborhoods.

These results suggest that at least for pushing individuals into CES-D scores that are above the threshold used to screen for depression, violence has a bigger effect among the poor—possibly because the poor have more depressive symptoms and thus higher average CES-D scores to begin with.[16]

[16]This can clearly been seen in Figure II(A).

4 Causal Effects of Perceived Violence

4.1 Propensity Score Matching

An alternative method to get at the causal impacts of violence on depressive symptoms with this observational data is through propensity score matching methods (Imbens, 2015; Rosenbaum and Rubin, 1983; LaLonde, 1986; Heckman, Ichimura and Todd, 1998; Dehejia and Wahba, 2002).[17] While randomization would be ideal in estimating causal impacts of violence from a research perspective, this is the type of question that should to be answered retroactively with other methods quasi-experimental or otherwise. In the analysis above, we attempt to control a litany of observable variables, in this section we use propensity score matching to improve the credibility of the estimates.

Propensity score matching methods assumes exposure to neighborhood violence is involves some selection but also has a lot of randomness to it. Individual, household, and region-level observable and unobservable characteristics determine the probability that a person lives in a neighborhood with high levels of violence. After this probability is determined, it is based on chance whether the individual experiences high levels of violence in their neighborhood or not. Two individuals could have very similar characteristics and thus propensity scores (probability of being in neighborhoods with high levels of violence) while they have different realizations of exposure. In theory, if we compare the CES-D scores of these two individuals we should get the causal impact of living in a high-violence neighborhood.[18] In theory, this method should produce unbiased estimates of the causal effects of living in perceived-violent neighborhoods if we can assume that we have *strongly ignorable exposure assignment*.[19] Richer pre-exposure information makes this more plausible. Moreover, various sensitivity analyses can be conducted to test the robustness of the results to violations of these assumptions.

To conduct this analysis we create a treatment variable of *high violence* (in the

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

[18] 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.

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

TABLE VI: Propensity Score Matching

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
High Violence	1.16***	0.91***	.066***	0.047*
	(0.09)	(0.13)	(.009)	(0.014)
Excluding Household Respondent		✓		✓
Matching Variables				
Indiv & HH Characteristics	✓	✓	✓	✓
Region (District & Urban)	✓	✓	✓	✓
Lagged Income Controls	✓	✓	✓	✓
Lagged Violence Index	✓	✓	✓	✓
Lagged CES-D Score	✓	✓	✓	✓
Lagged respondent CES-D Score		✓		✓
N	20,102	9,823	20,102	9,823

Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

top quintile of perceived violence vs the other four quintiles).[20] We match individuals on a large number of individual and household-level controls including the lagged CES-D score and of the individual and the CES-D score of the excluded (when excluded) household-questionnaire respondent. We calculate the propensity score with variables that are plausibly already determined such as regional variables (district fixed effects, urban dummy, population densities), individual and household characteristics (that are not possibly outcome), lagged income variables (concurrent might be actual outcomes of violence).

The results in Table VI show that this method gives fairly similar results to the other empirical methods used in this paper.[21] Living in a high violence neighborhood on average increases CES-D scores by approximately 1 point (0.2 SD) and the likelihood of having a score above 11 by about 5 percentage points (nearly 25%).

There are two strong assumptions needed to get unbiased results using these methods. First, the overlap assumption—this assumption is testable and Figure A.2 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 other assumption is regarding the unconfoundedness of the treatment—this assumption is not directly testable, however, we can assess the plausibility of this assumption by estimating the causal effect of the treatment on a pseudo outcome

[20]The average violence index in the top quintile is 1.4 vs -.34 in the other four (-1.19, -0.58, -0.06, & 0.45)

[21]Nearest neighbor matching requiring the matched observations to be in the same province give very similar results.

TABLE VII: Instrumental Variables Regressions–
Excluding household respondent

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
Violence Index	2.022***	1.360***	0.109***	0.065*
	(0.438)	(0.396)	(0.034)	(0.034)
Excluding Household Respondent		✓		✓
Respondent CES-D Score		✓		✓
Indiv & HH Characteristics	✓	✓	✓	✓
Income Controls	✓	✓	✓	✓
Lagged Controls	✓	✓	✓	✓
Province Fixed Effect	✓		✓	
N	40,041	14,325	40,041	14,325
Hansen J Statistic (p-value)	0.495	0.208	0.184	0.264

Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(Imbens, 2015). This outcome is a pseudo outcome because it is known to be unaffected by the treatment usually because it is determined prior to the treatment.[22] If the estimated effects on these pseudo outcomes is different from zero, it is less plausible that the unconfoundedness assumption holds. In Table A.4 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.

4.2 Instrumental Variables

There is an active debate within the literature on if objective measures of violence have an effect on individuals only through their perception of this violence or also through other means (Wilson-Genderson and Pruchno, 2013; Parra et al., 2010). When it comes to psychological well-being, the most important mechanism through which objective measures of violence affect an individual is through their perception of it, however, it is plausible that high levels of violence objectively measured could affect psychological well-being through decreased public services in the neighborhood for example.

If we are able to control for a multitude of these potential mechanisms, it is

[22]We can use time-invariant outcomes for this pseudo outcome, but as Imbens (2015) suggest, using a lagged outcome is a more interesting and convincing illustration of unconfoundedness—the more closely related the pseudo outcomes are to the actual outcome of interest, the more convincing the test.

plausible to use objective measures of crime and violence as instrumental variables for the perception of violence in the neighborhood. Table VII shows results that use this approach to get estimates of the effect of perception of violence on psychological well-being. For these results we use objective rates of murder, attempted murder, and armed robberies at the district level as instruments for the perceived violence index. The results suggest that the effects of neighborhood violence on CES-D is larger than what we estimated using the OLS and fixed effects approaches.[23]

4.3 Poverty Dynamics: Long-run Predictions

Given the strong associations between poverty, perception of violence, and psychological well-being illustrated above, a logical question comes out: Can current exposure to violence and elevated depressive symptoms add to the predictive value of current poverty on future poverty?

To investigate this, we estimate the following equation:

$$\begin{aligned} LowWealth_{ihdt} = \alpha_1 LowWealth_{hd(t-1)} + \alpha_2 HighViolence_{hd(t-1)} + \alpha_3 CESD11_{ihd(t-1)} \\ + \gamma_1 LowWealth_{hd(t-1)} * HighViolence_{hd(t-1)} \\ + \gamma_2 LowWealth_{hd(t-1)} * CESD11_{ihd(t-1)} \\ + \gamma_3 HighViolence_{hd(t-1)} * CESD11_{ihd(t-1)} \\ + \boldsymbol{X'_{hdt}\beta} + \boldsymbol{Z'_{ihdt}}\delta + \theta_t + \tau_d + \epsilon_{ihdt} \end{aligned} \tag{3}$$

where we estimate the predictive power of dummy variables for lagged low wealth (1st wealth quintile), high neighborhood violence (highest wealth quintile—as in the propensity score matching results), and a dummy variable for being at risk of depression (CES-D scores above 11) on poverty and depression risk today. We also include interaction terms for each pair and control for individual and household characteristics as well as district and wave fixed effects. The results are shown in Table VII.

In Column (1) we see that lagged wealth, violence, and high levels of depressive symptoms all predict wealth today even when district fixed effects, and individual and household time varying controls are taken into account. When interaction

[23]Table in the appendix shows results for the same instruments for fixed effects instrumental variable regressions and using ACLED variables as instruments. All the results are similar in magnitude to those presented in Table VII.

TABLE VIII: Violence and Prediction of Future Poverty and Depressive Symptoms

	Low Wealth		CES-D≥11	
	(1)	(2)	(3)	(4)
Low Wealth$_{t-1}$	0.352***	0.333***	0.028**	0.005
	(0.017)	(0.020)	(0.011)	(0.013)
High Violence$_{t-1}$	0.019**	0.008	0.014	0.004
	(0.009)	(0.009)	(0.010)	(0.012)
CES-D≥11$_{t-1}$	0.016*	0.018**	-0.001	-0.011
	(0.008)	(0.008)	(0.010)	(0.011)
Low Wealth$_{t-1}$*High Violence$_{t-1}$		0.073**		0.046*
		(0.034)		(0.024)
Low Wealth$_{t-1}$*CES-D≥11$_{t-1}$		-0.009		0.044*
		(0.033)		(0.027)
High Violence$_{t-1}$*CES-D≥11$_{t-1}$		-0.003		0.008
		(0.018)		(0.020)
Constant	0.137***	0.141***	-0.086	-0.080
	(0.053)	(0.053)	(0.068)	(0.068)
Indiv & HH Characteristics	✓	✓	✓	✓
N	16,466	16,466	16,373	16,373
R^2	0.184	0.185	0.040	0.041

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

terms are introduced, violence still plays a role, however, only when it coincides with poverty as well. The interaction term of low wealth and high violence is statistically significant. Being poor two years ago increases the probability of being poor today by 0.33. Being poor and living in a neighborhood with high levels of violence adds another 0.07 in probability to that. Similarly for CES-D scores above 11 the lagged interaction of violence and low wealth has a statistically significant predictive value.

5 Conclusion

The poor in South Africa, especially in urban areas, live in neighborhoods that exhibit more violence. They also, predictably, perceive higher levels of violence than do the rich; individuals in the lowest wealth quintile perceive violence to be 0.8 standard deviations higher than those in the richest wealth quintile. We use objective data from the South African Police Service and ACLED to show that objective data on violent crimes and events are strong predictors of the subjective perception of crime variables in the NIDS dataset.

We then show that perceived violence is very strongly linked to higher levels of depressive symptoms and and increased likelihood of being at risk for clinical depression. This relationship is especially strong for the poor and among those who have more depressive symptoms. We then attempt to isolate the causal effects that neighborhood violence has on psychological well-being through an instrumental variables approach where objective measures of violent crime are used as instruments for perceived neighborhood violence in addition to a propensity score matching approach. We find evidence of strong effects of neighborhood violence on psychological well-being in as much as our assumptions hold. Finally, we show that the interaction of high levels of violence and poverty are predictive of future poverty and depression risk in our nationally representative sample.

This paper shows that elevated exposure to violence among the poor, at least in the very urbanized context of South Africa which exhibits high levels of violence, can possibly be a mechanism through which psychological poverty traps could operate.

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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 donâĂŹt bother me	0	1	2	3
2	I did not feel like eating; my appetite was poor	0	1	2	3
3	I felt that I was just as good as other people	3	2	1	0
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 âĂIJget goingâĂİ	0	1	2	3

TABLE A.2: Standardized Elements of the Neighborhood Violence Index and Standardized CES-D Scores

	(1)	(2)	(3)	(4)
Panel A: Frequency of Any Violence				
Frequency of any violence	0.106***	0.0994***	0.0958***	0.0810***
	(0.00921)	(0.00869)	(0.00832)	(0.00983)
Observations	46,162	43,930	43,930	28,123
R-squared	0.012	0.064	0.095	0.103
Panel B: Frequency of Domestic Violence				
Frequency of domestic violence	0.111***	0.105***	0.100***	0.0857***
	(0.00988)	(0.00953)	(0.00910)	(0.0109)
Observations	46,186	43,951	43,951	28,148
R-squared	0.013	0.065	0.096	0.104
Panel C: Frequency of Gang Violence				
Frequency of gang violence	0.0901***	0.0826***	0.0701***	0.0566***
	(0.00995)	(0.00949)	(0.00862)	(0.0101)
Observations	46,154	43,930	43,930	28,144
R-squared	0.009	0.061	0.090	0.100
Panel D: Frequency of Drug Violence				
Frequency of drug violence	-0.0367***	-0.0462***	-0.0417***	-0.0449***
	(0.0106)	(0.00951)	(0.00898)	(0.0104)
Observations	46,039	43,823	43,823	28,037
R-squared	0.001	0.056	0.086	0.098
Panel E: Frequency of Murder				
Frequency of murder	0.0575***	0.0468***	0.0336***	0.0212**
	(0.00994)	(0.00932)	(0.00831)	(0.00991)
Observations	46,321	44,088	44,088	28,220
R-squared	0.003	0.056	0.086	0.097
Panel F: Frequency of Theft				
Frequency of theft	0.0161	0.0136	0.00303	-0.00968
	(0.0107)	(0.00989)	(0.00902)	(0.0107)
Observations	46,362	44,124	44,124	28,248
R-squared	0.000	0.054	0.085	0.097
Household controls	No	Yes	Yes	Yes
Individual controls	No	Yes	Yes	Yes
Wave fixed effects	No	No	Yes	Yes
District fixed effects	No	No	Yes	Yes

Notes: The measure of depression and the frequency variables are standardized to have a mean of zero and a standard deviation of one. Columns (1) through (3) include the full sample of all respondents. Column (4) excludes the respondent to the household questionnaire. Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1

TABLE A.3: Validating the Self-Reported Measues of Violence

	Any violence	Domestic violence	Gang violence	Drug violence	Murder	Theft
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All Conflict Events						
Number of events	0.00227***	0.00231***	0.00295***	0.00202***	0.00289***	0.00291***
	(0.000379)	(0.000334)	(0.000660)	(0.000283)	(0.000527)	(0.000362)
Observations	77,853	77,897	77,799	77,603	78,064	78,154
R-squared	0.009	0.009	0.015	0.007	0.015	0.015
Panel B: Violence Against Civilians						
Number of events	0.0149**	0.0167**	0.0253	0.0218***	0.0311***	0.0292***
	(0.00724)	(0.00686)	(0.0152)	(0.00805)	(0.00977)	(0.0106)
Observations	77,853	77,897	77,799	77,603	78,064	78,154
R-squared	0.002	0.002	0.005	0.004	0.007	0.007
Panel C: Riots						
Number of events	0.00561***	0.00576***	0.00767***	0.00556***	0.00747***	0.00763***
	(0.00132)	(0.00106)	(0.00227)	(0.000955)	(0.00166)	(0.00140)
Observations	77,853	77,897	77,799	77,603	78,064	78,154
R-squared	0.008	0.008	0.015	0.008	0.014	0.015
Panel D: Protests						
Number of events	0.00400***	0.00401***	0.00494***	0.00320***	0.00479***	0.00481***
	(0.000546)	(0.000548)	(0.000875)	(0.000414)	(0.000844)	(0.000468)
Observations	77,853	77,897	77,799	77,603	78,064	78,154
R-squared	0.010	0.010	0.015	0.006	0.014	0.014
Panel E: Battles						
Number of events	0.0756	0.0495	0.261	0.300***	0.337***	0.361***
	(0.121)	(0.103)	(0.159)	(0.0427)	(0.0931)	(0.0704)
Observations	77,853	77,897	77,799	77,603	78,064	78,154
R-squared	0.000	0.000	0.002	0.003	0.004	0.004

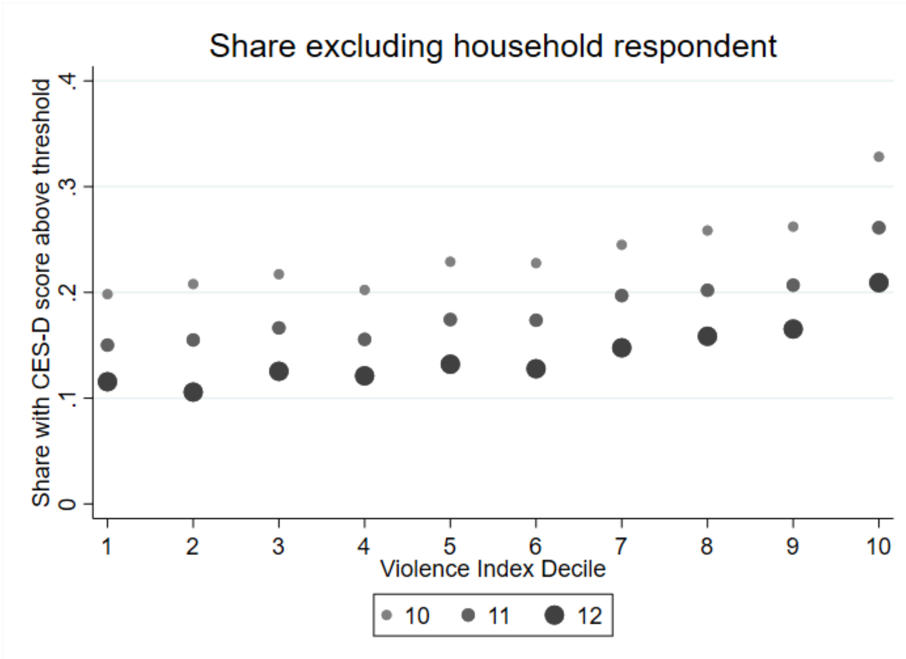
Notes: Each panel represents a different type of conflict, as recorded in the ACLED database. Each column is a different self-reported violence measure, as recorded in the NIDS. These self-reported measures are standardized to have a mean of zero and a standard deviation of one. Standard errors clustered at the district level are shown in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

TABLE A.4: Propensity Score Matching—Tests of Unconfoundedness

	Lagged CES-D Score	Primary Education	Lagged Married	Male 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	✓	✓	✓	✓
Lagged respondent CES-D Score	✓	✓	✓	✓
N	11,075	11,075	11,075	11,075

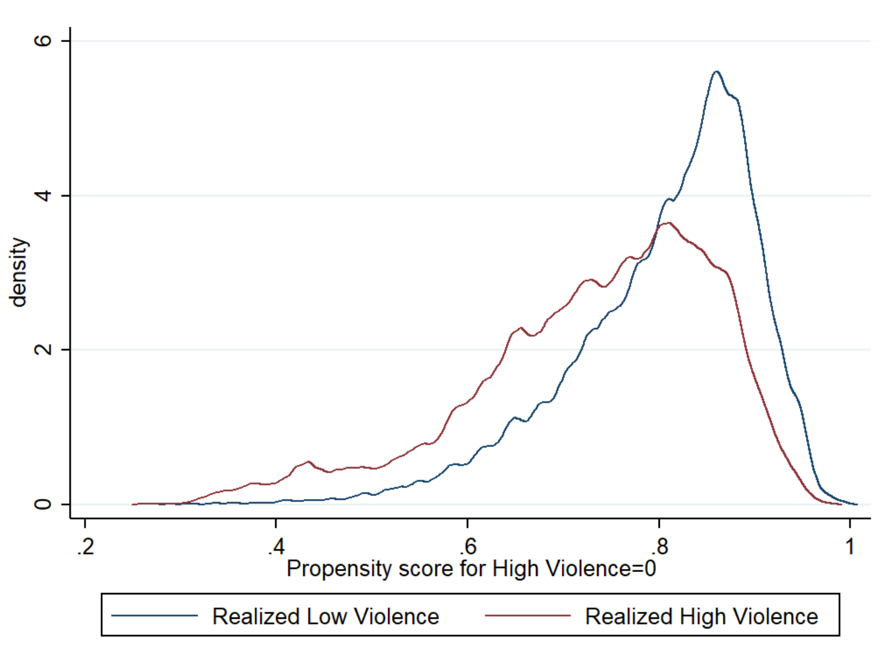
Cluster robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Figures



(A) Histogram of CES-D Scores

FIGURE A.1: Distribution of CES-D Scores and Changes between waves: 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) Overlap of propensity scores

FIGURE A.2: Distribution of propensity scores (for low violence) shows significant overlap between the two groups; those who live in neighborhoods with high violence and others with low violence.