Neighborhood Violence, Poverty, and Psychological Well-being*

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Abstract

We estimate the relationship between neighborhood violence and psychological well-being using nationally representative panel data from South Africa. We use household-level perceptions of neighborhood violence that we validate using reported crimes and local media reports. 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 perceived 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. We posit that this relationship may be a mechanism through which psychological poverty traps 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 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 different contexts around the world. 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. Shedding light on the conditions that may be confounding 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 individual-level psychological well-being? Using nationally representative panel data from South Africa, a low- or middle-income country with very high levels of violence and urban poverty, we find that depressive symptoms and the likelihood of being at risk for depression increase with higher levels of neighborhood violence. In addition, using subjective and objective measures, we show that the poor are more likely to live in neighborhoods and districts with higher levels of violence. Taken together, these results suggest that increased exposure to violence is a mechanism through which poverty can affect psychological well-being and mental health. 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). We show that living in poverty, in an urban neighborhood with high levels of violence, is predictive of future poverty and lower income growth rates in South Africa.

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 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 strongly affects psychological well-being (Aneshensel and Sucoff, 1996; Ross and Mirowsky, 2009; Steptoe and Feldman, 2001; Latkin and Curry, 2003), however, each of these studies only use subjective reports of the perception of neighborhood violence. 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), and youth exposed to school shootings in the United States (Rossin-Slater et al., 2019). 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).

The relationship between violence within neighborhoods and psychological well-being is important for several reasons. First, psychological well-being, and specifically mental health, 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 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 that estimates 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. 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.[1] 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 violent 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.[2]

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 of depression. The lower end of our estimates show that living in a neighborhood with high levels of violence is associated with a nearly 25% increase in the likelihood of being at risk of depression. 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 recall bias, we show that neighborhood violence can have significant effects 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 approaches using matching methods and instrumental variables further support our findings.

We 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 that the poor are disproportionately more likely to live in neighborhoods with high levels of violence, and that that low levels of psychological well-being can hinder one's ability to achieve their full earning potential, these results illuminate a mechanism through which poverty may be reinforced. Exposure to violence can contribute to a vicious cycle possibly leading to persistent poverty or, more specifically, a psychological poverty trap.

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 in South Africa. The third section presents the core empirical results. Section four tests the robustness of our core results. The fifth section highlights and discusses how violence and psychological well-being can influence poverty dynamics. Finally, section six concludes.

[1] Exceptions to this include some of the psychological and medical literature which explores the simple correlation between neighborhood 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).

[2] Our analytical framework is akin to that of McDool et al. (2020) who study the effect of neighborhood access to broadband internet and the psychological well-being of adolescent children in England.

2 Data

The main data used in this analysis comes from the panel dataset of the National Income Dynamics Study (NIDS) of South Africa.[3] 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 adult questionnaire in every survey wave is unprecedented in a nationally representative panel survey in a low- or middle-income country.[4] 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).[5]

The NIDS surveys (waves 2-5) 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 (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

[3]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.

[4]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.

[5]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.

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 matched these police precincts to districts in the NIDS data and aggregated violent crimes at the district-year level.[6] With information on the populations in each district, we are able to calculate the rates of reported violent crime within each district over time.[7]

Supplemental data on conflict 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 2007 through 2017, the years associated with each of the five NIDS waves.

These data from SAPS and ACLED 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 useful to show that these perceptions reflect the reality of the objective existence of violence in these areas. We discuss these validation results in Section 2.3.

2.1 Descriptive Statistics

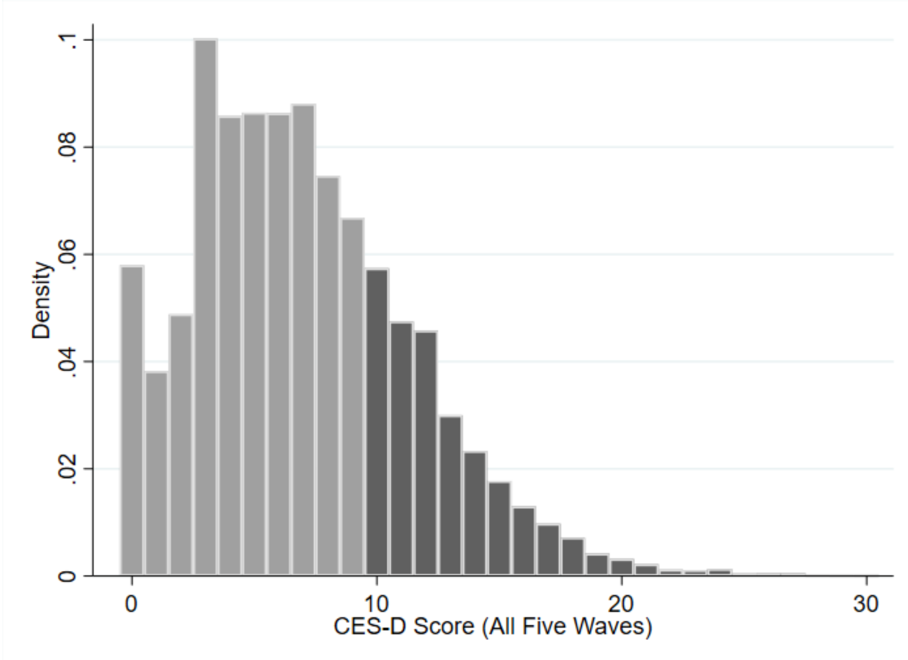
South Africa is a low- or middle-income country with the highest level of income and wealth inequality in the world (World Bank, 2018). The mean monthly household income per capita (standard deviation in parenthesis) in the study sample in 2017 is 3,262 ZAR (10,197).[8] This hides significant inequality 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).[9] In the balanced panel sample of NIDS, 87% of individuals report food expenditure levels

[6] 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.

[7] We use only violent crime records and discard non-violent crime records for this analysis.

[8] 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.

[9] 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).



Histogram of CES-D Scores

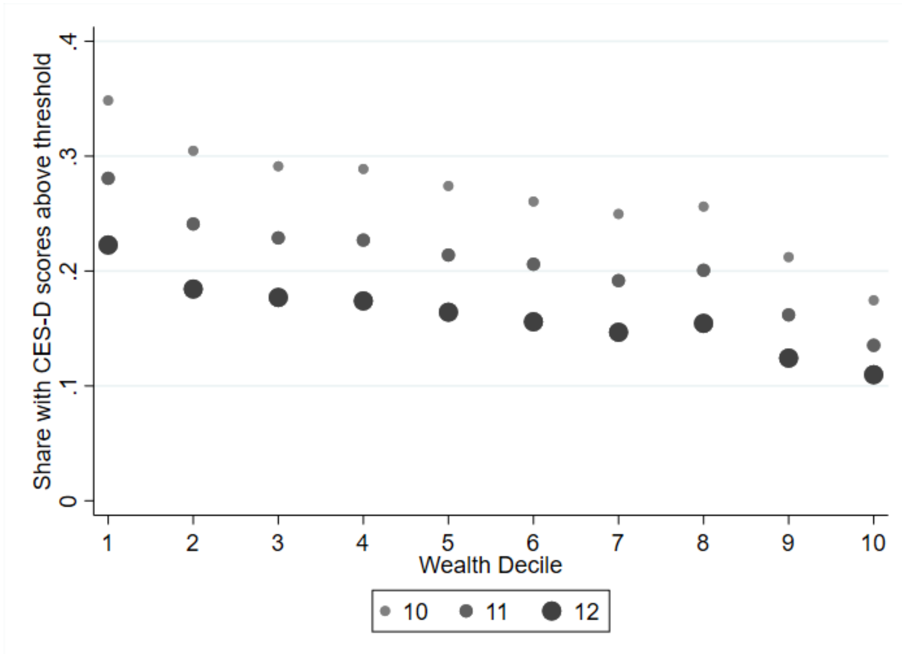
FIGURE I: Distribution of CES-D Scores and Changes between waves: Histogram of the CES-D scores shows that a significant portion of the population have scores above the threshold of 10 used by psychologists to screen for depression.

that are considered poor in at least one of the five waves. Additionally, 48% are poor in at least three out of the five waves and 11% are poor in all five waves of the panel.

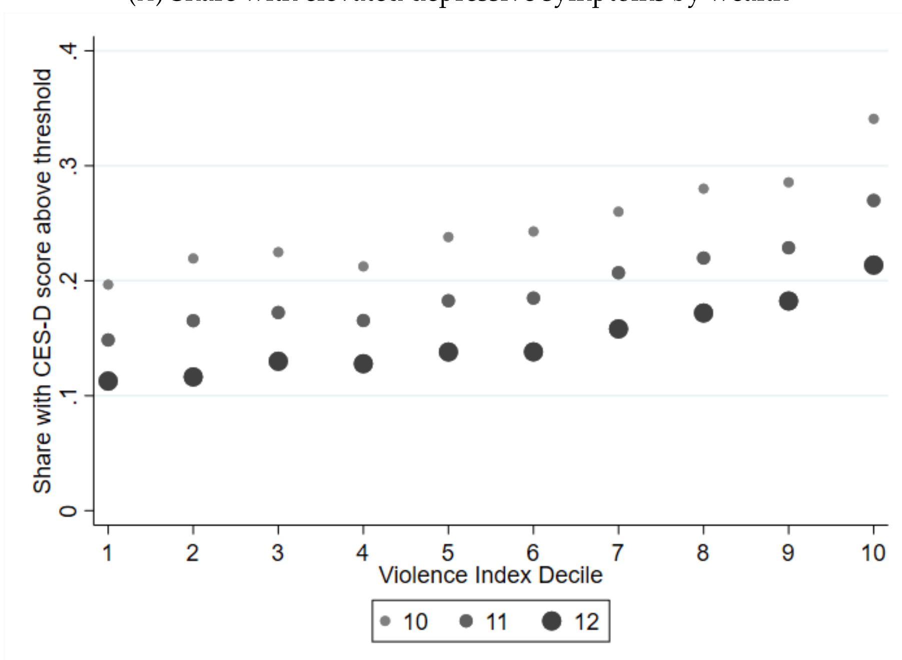
In the study sample, the mean CES-D score (standard deviation) for all five waves is 6.8 (4.4) and shows a decreasing trend where the average score is 8.2 (4.9) in 2008 and 6.62 (4.3) in 2017. The within person standard deviation in the CES-D score is 3.6. Figure I illustrates the distribution of CES-D 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% in 2008 to 17.7% in 2017. Nearly 54% of the panel sample record a CES-D score of 11 or above at least once in all five waves.[10]

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 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 shows

[10] 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 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.

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 increases, the share of individuals who have elevated depressive symptoms also increases.[11] Moreover, Figure A.2 in the Appendix combines the above two 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 30.7 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 10.6 percent.

2.2 Violence 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 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 datasets allows us to show that crime is overall higher in districts with higher levels of inequality.[12] 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 III(A) breaks this down further and

[11] This pattern is very similar when excluding the household-level questionnaire respondent (see Figure A.1 in the Appendix). As discussed in Section 3.1, 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.

[12] 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.

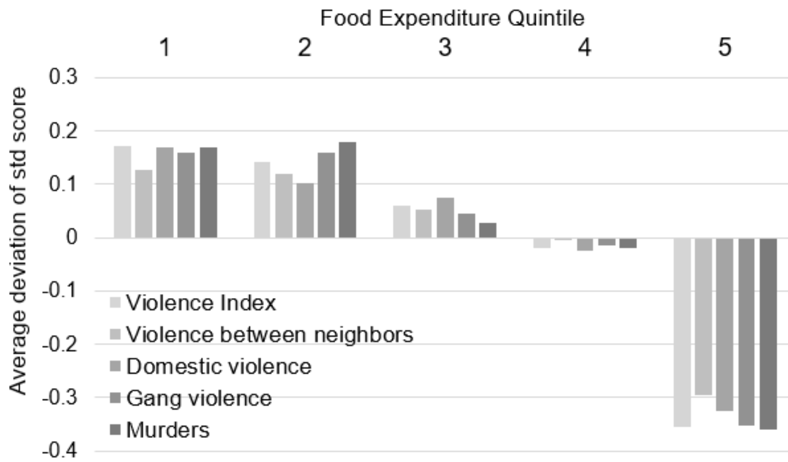
Year	2010	2012	2014	2017
South Africa				
Homicide rate	30.0	26.7	27.9	30.3
Sexual assault rate	120.1	109.5	101.9	78.3
Assault rate	357.0	324.2	295.7	267.7
Armed robbery rate	203.1	174.7	196.9	226.6
Property crime rate	233.1	209.1	196.0	185.3
Cape Town				
Homicide rate	37.7	39.5	52.5	57.9
Sexual assault 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	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).

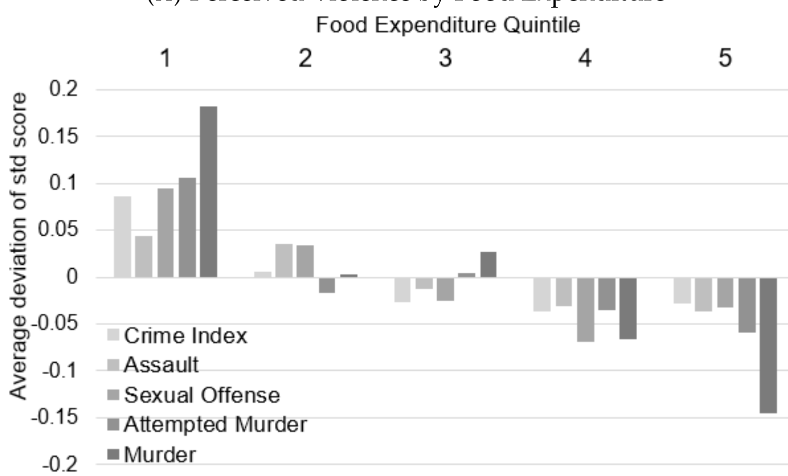
shows that greater household material well-being is associated with lower violence overall. Estimates in the figure show that in urban areas respondents from the highest food expenditure household quintile live in neighborhoods that they perceive to have over 0.5 standard deviations lower violence than those living in the poorest quintile.[13] This pattern looks similar for all 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.

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



(A) Perceived Violence by Food Expenditure



(B) Matched SAPS Data on Crime by Food Expenditure

FIGURE III: 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.

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 III(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.[14]

[14]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.

2.3 Data Validation

Violence is a multi-dimensional concept and can be difficult to define. Therefore, the self-reported nature of our measure of the frequency of violence may be problematic. With that said, 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 (Kruger, Reischl and Gee, 2007; Curry, Latkin and Davey-Rothwell, 2008). Despite this, it is important to see if objective measures of violence predict self-reported measures of the frequency of violence (perceived violence) in the NIDS sample.

The main data we use to validate the perceived violence measures 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 and property 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. It is likely that these data under-report the actual amount of crime committed in each district, with higher rates of under-reporting in relatively poor districts.

A secondary data source we use to validate perceived violence measures are the ACLED data, which 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 some of the most detailed quantitative information on the prevalence of conflict and violence available.

We use these two supplementary data sources to demonstrate the validity of 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 SAPS and ACLED) to the main self-reported index measure of perceived violence (as recorded in the NIDS). Table II reports these validation results. 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. The reported standard errors are clustered at the PSU level.[15]

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) that control for district-fixed effects and wealth of the respondent suggest that a one SD change in the objective crime index increases the perceived violence index by 0.2 standard

[15]PSUs are defined geographic areas based on the 2011 census in South Africa on which the sampling for NIDS took place. All standard errors reported in this paper are clustered at the PSU level.

TABLE II: 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.

deviations. These estimated associations are quite meaningful. Moreover, we find that the association between district-level objective crime and perceived neighborhood violence is driven mainly by poor households—the estimated coefficient is approximately 0.35 for the bottom three quintiles of wealth and statistically insignificant for the top two quintiles. This suggests that when district-level crime increases, it is likely mainly increasing in poor neighborhoods. It is important to note again that if the objective crime variables were aggregated instead at a smaller geographical unit, we expect the predictive value to be even larger.

3 Empirical Approach and Results

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

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

In equation (1) pw_{ihdt} represents measures of psychological well-being: 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.[16] 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, number of children, and neighborhood services such as electricity, trash collection, and streetlights. $\boldsymbol{Y_{hdt}}$ are household-level controls that proxy

[16]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).

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. 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.[17] 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.

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

We estimate equation (2) to take advantage of the panel nature of these data and better control for income which is likely an important confounder. Taking into account both current and prior income is an important robustness test for the credibility of our results.[18] 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).

The core identification assumption is $Cov(V_{hdt}, \epsilon_{ihdt}) = 0$. Although this assumption is ultimately not directly testable, throughout Section 3.1 and explicitly in Section 4 we demonstrate the robustness of our results to several alternative estimation approaches. In Section 4.1 we show results using matching methods (Imbens, 2015; Rosenbaum and Rubin, 1983; LaLonde, 1986; Heckman, Ichimura and Todd, 1998; Dehejia and Wahba, 2002). In Section 4.2 we exploit spikes in drug-related violence within various neighborhoods starting in 2016 as an instrumental variable. Finally, in Section 4.3 following the insights of Altonji, Elder and Taber (2005) and the methods of Oster (2019), we test the validity of our identifying assumption by considering selection on observables as an indication of selection on unobservables. Each of these robustness tests, which crucially rely on different assumptions, support our identification strategy in the present context.

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

[18] Estimating a fixed effects regression with lagged dependent variables leads to Nickell bias, so as a robustness check for 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. 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 differenced endogenous variables.

3.1 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). The results in column (5) suggest that a 1 standard deviation (SD) increase in the perceived violence index is associated with a 0.42-point increase in an individual's CES-D score. This corresponds to approximately a 0.13 SD increase in depressive symptoms.[19] The estimated coefficient is also positive and statistically significant for the probability of having a high CES-D score (greater than or equal to 11). A 1 standard deviation increase in the perceived violence index is associated with a 3.1 percentage point increase in the likelihood of being at high risk of depression—with baseline probabilities near 20%, this is a 15% increase.[20] Finally, it is worth noting that the lagged violence index variable is also a significant—albeit weaker—predictor of depressive symptoms even when controlling for current and lagged socioeconomic variables.

Given the sensitivity of violence and the effects of depression on perceptions, we may encounter issues related to reverse causality and recall bias (i.e., that those prompted to to recall violence in a survey questionnaire can have an effect on psychological well-being measures). We address this potential issue 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.[21] In Table A.2 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.[22] 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 addition 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.

[19]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.

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

[21]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.

[22]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 III: Perceived Violence and Psychological Well-being

	Panel A: CES-D Score				
	(1)	(2)	(3)	(4)	(5)
Violence Index$_t$	0.58***	0.54***	0.53***	0.48***	0.42***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)
Violence Index$_{t-1}$			0.13***	0.09***	0.23***
			(0.05)	(0.04)	(0.05)
	Panel B: Dummy variable: CES-D≥11				
	(6)	(7)	(8)	(9)	(10)
Violence Index$_t$	0.039***	0.037***	0.034***	0.033***	0.031***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)
Violence Index$_{t-1}$			0.006	0.003	0.015***
			(0.004)	(0.003)	(0.005)
Indiv & HH Characteristics		✓	✓	✓	✓
Neighborhood Services		✓	✓	✓	✓
Income Controls		✓	✓	✓	✓
Lagged Income Controls			✓	✓	✓
Lagged CES-D Score			✓	✓	✓
Urban Dummy				✓	✓
District Wave Fixed Effect				✓	✓
Individual Fixed Effect					✓
N	64,784	64,784	31,829	31,829	31,829

Note: Standard errors clustered at the PSU level are in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Our main results show a robust link between the perceived violence index and depressive symptoms.

This leads to our second approach. In Table A.3 in the Appendix, we calculate a leave-one-out in-group means for the violence index at the PSU (Primary Sampling Unit) level.[23] Using the mean of the violence index of other households within the PSU of individual $i's$ household allows us to proxy for neighborhood violence that is exogenous to intra-household correlations in psychological well-being. These results show that the estimated coefficients of the within-PSU leave-one-out average of perceived violence on psychological well-being are qualitatively similar to, and if anything slightly larger than, the main estimates shown in Table III.

Finally, in Section 4.3, we follow the insights of Altonji, Elder and Taber (2005) and

[23]The PSUs in NIDS are formed by dividing up districts into geographically proximate areas. We assume here that the psychological well-being of individual i does not directly affect the psychological well-being of another individual in the same PSU, however the mean PSU violence index describes the violence in the geographical area. We run the same specification as equation (1) but instead of the household-level violence index, we use the mean of the violence index for other households who are in the same PSU as individual i. Using the average perception of violence of other similar households rules out the effect of intra-household correlation in psychological well-being while still capturing neighborhood violence—the correlation between leave-one-out in-group means and the violence index of individual i is approximately 0.5.

the methods of Oster (2019) to test the sensitivity of the results in Table III to potential unobserved heterogeneity. This method considers selection on observables as indicative of the selection on unobservables. We find that any omitted unobserables would need to be eight to 12 times more important than included control variables to explain away these results as spurious artifacts.

3.2 Falsification

A key threat to identification in the present context 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 $j = 0, 1, 2, 3$:

$$
\begin{aligned}
pw_{ihd(t-j)} = \alpha_1 V_{hdt} + \alpha_2 V_{hd(t-j)} + \alpha_2 V_{hd(t-j-1)} + pw_{ihd(t-j)}\sigma + \boldsymbol{Y'_{hd(t-j)}}\boldsymbol{\gamma_1} \\
+\boldsymbol{X'_{hd(t-j)}}\boldsymbol{\beta} + \boldsymbol{Z'_{ihd(t-j)}}\delta + \theta_{t-j} + \tau_d + \epsilon_{ihd(t-j)}
\end{aligned}
\tag{3}
$$

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.

Figure IV presents these results. When $j = 0$ we simply replicate the result from Column 4 in Table III. When $j > 0$ we estimate the effect of present day violence on lagged psychological well-being and, conditional on contemporaneous levels of violence, expect to see estimates that are statistically indistinguishable from zero. Indeed, the effect of V_{hdt} on $pw_{ihd(t-j)}$ for $j = 1, 2, 3$ is statistically indistinguishable from zero. Therefore, we find no evidence of pre-trend effects that potentially bias our main results.

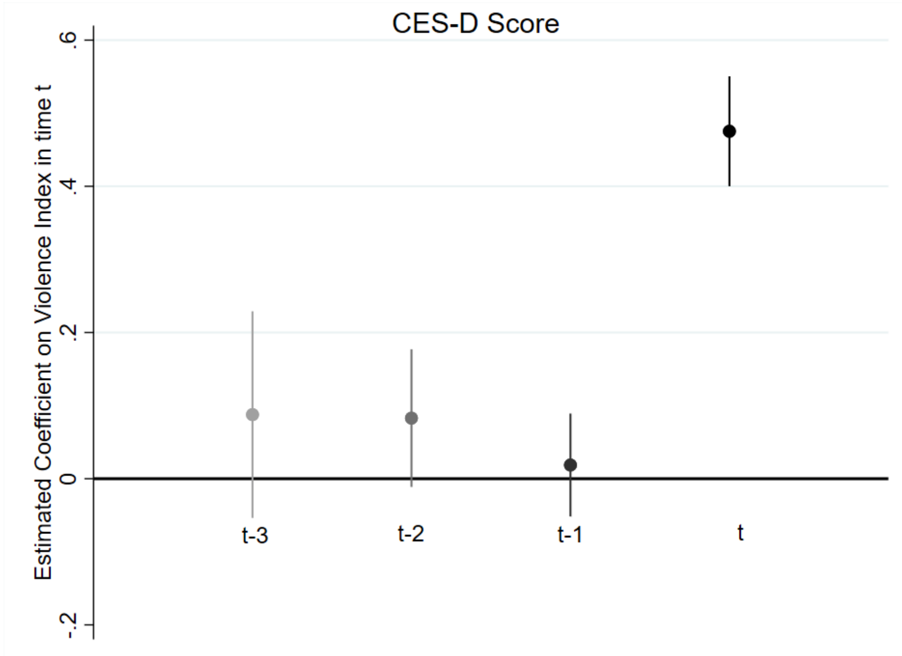


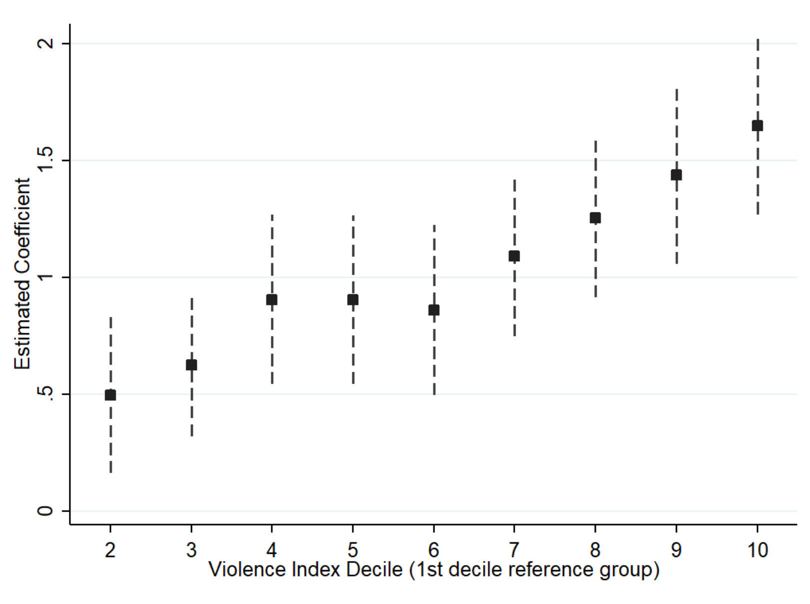
FIGURE IV: Coefficients on Violence Index in time t on CES-D scores in time periods t, t-1, t-2, and t-3. This falsification tests shows no evidence of pre-trend effects of present violence on the CES-D score in previous periods.

3.3 Effect Heterogeneity

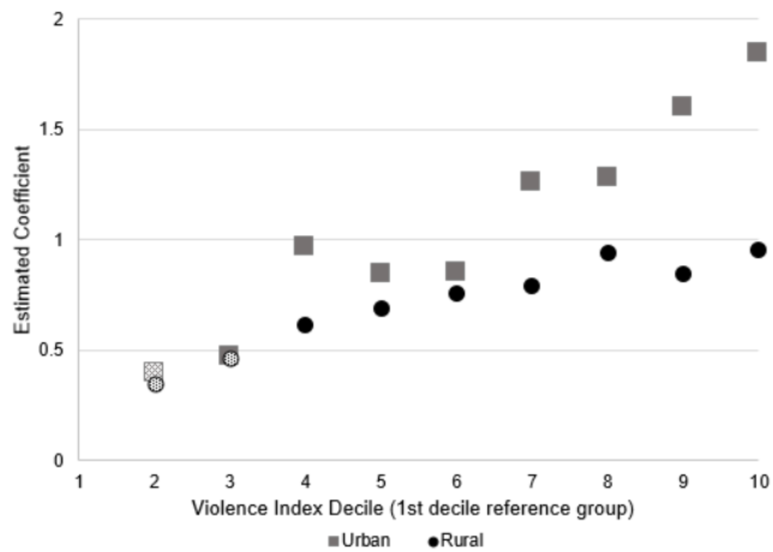
The results reported in Table III show average effects, and obscures any potential effect heterogeneity or effect non-linearity at different levels of violence or depression. In this sub-section, we explore effect heterogeneity in a variety of dimensions.

In Figure V(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 III 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 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 (0.4 SD) higher than do those in the lowest violence neighborhoods.

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 V(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.



(A) Flexible Specification for Violence Index



(B) Differentiating Urban and Rural settings

FIGURE V: Flexible estimation approach. Estimated coefficients are increasing by Violence Index Deciles and differences for higher deciles are larger in Urban areas. In Panel B, solid shapes indicates statistically significant estimates at the 95% level.

In Figure V(B) the squares represent coefficient estimates for urban households and circles represent coefficient estimates for rural households. Solid shapes indicates statistically significant estimates at the 95% level. These results show 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 at least two ways. First, 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). Second, these results may also be due to the fact that overall violence in rural areas is less frequent. Since a perception of high violence is, by definition, a relative measure and in rural areas there is objectively less violence, the frequency of violence may naturally have a smaller effect on psychological well-being in rural areas compared to urban areas.

The NIDS data provide perceptions of different types 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 IV we pull apart these various types of perceived violence and estimate their relationship with psychological well-being. Both violence between households and domestic violence are highly associated with depressive symptoms and the likelihood of being at risk of depression. Gang violence is also statistically significant but coefficient estimates are 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.

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 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 (4) in Table III.

TABLE IV: Types of Perceived Violence

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
Panel A: Frequency of Violence between Households	0.422***	0.379***	0.029***	0.027***
	(0.054)	(0.05)	(0.003)	(0.004)
Panel B: Frequency of Domestic Violence	0.459***	0.352***	0.031***	0.025***
	(0.044)	(0.055)	(0.004)	(0.005)
Panel C: Frequency of Gang Violence	0.296***	0.221***	0.019***	0.017**
	(0.038)	(0.057)	(0.003)	(0.005)
Panel D: Frequency of Murder	0.109***	0.058	0.009***	0.008*
	(0.036)	(0.056)	(0.003)	(0.005)
Indiv & HH Characteristics	✓	✓	✓	✓
Neighborhood Services	✓	✓	✓	✓
Income Controls	✓	✓	✓	✓
Lagged Income Controls	✓	✓	✓	✓
Lagged CES-D Score	✓	✓	✓	✓
Urban Dummy	✓	✓	✓	✓
District Fixed Effect	✓	✓	✓	✓
Individual Fixed Effect		✓		✓
N	32,516	32,516	32,516	32,516

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.

Figure VI 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 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 a multitude of factors—such as poverty—may experience larger increases in their CES-D score when neighborhood violence increases. This finding is also consistent with the importance of environmental mechanisms that can shield individuals from the psychological effects of neighborhood violence (Stockdale et al., 2007).

In the Appendix (Table A.4) 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.

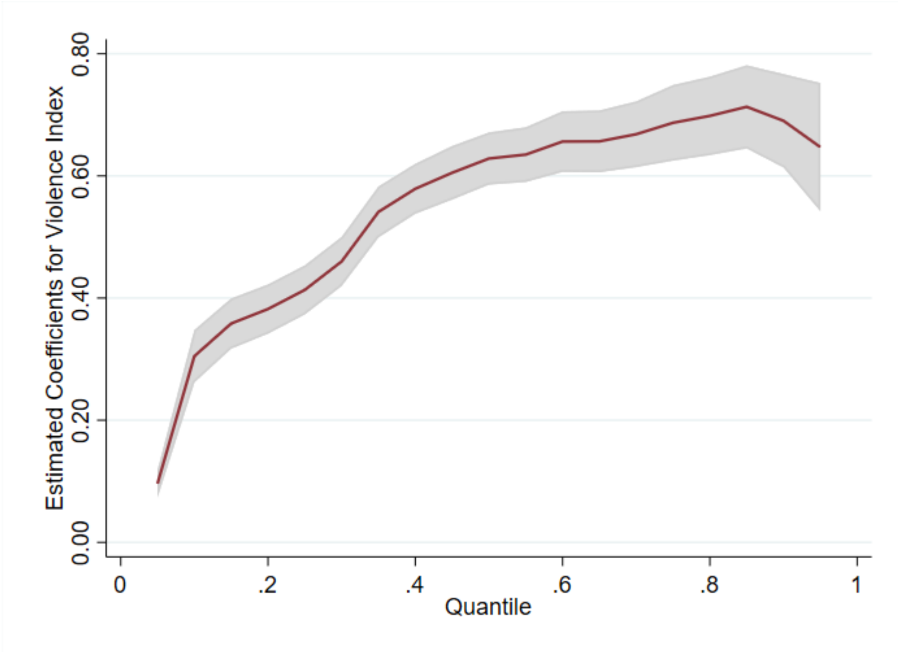


FIGURE VI: Quantile regression results show that the estimated link between violence and psychological well-being is higher for those with more depressive symptoms who are on the higher end of the CES-D score.

4 Robustness Tests

Our results are, so far, robust to including a host of control variables, including lagged controls and outcome variables, and individual fixed effects. Our core results are also robust to excluding the household respondent (Table A.2) and estimating the effect on the leave-one-out mean of violence on psychological well-being (Table A.3). Robustness to this wide variety of specifications lends considerable credence to the credibility of our central finding that perceived violence increases depression symptoms and the risk of depression. Nevertheless, alternative estimation approaches allow for additional robustness tests. In this section we present results using matching methods, instrumental variables, and coefficient stability tests.

4.1 Matching Methods

An alternative method to estimate the effect of violence on 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).[24]

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

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 improve the credibility of the 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 (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.[25] 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*.[26] 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* (in the top quintile of perceived violence vs the other four quintiles).[27] 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 outcomes), lagged income variables (concurrent income variables are likely actual outcomes of violence).

The results in Table V show results using two approaches to matching: propensity score matching (in columns 1 and 3) and nearest neighbor matching (in columns 2 and 4).[28] We

[25]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.

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

[27]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.

[28]See King and Nielsen (2019) for a discussion of the substantive difference between propensity score matching and nearest neighbor matching.

TABLE V: Matching Results

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
High Violence$_t$	1.041***	1.338***	0.082***	0.076***
	(0.098)	(0.104)	(.010)	(0.007)
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

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.

find that both approaches estimate qualitatively similar results to the main results. Living in a high violence neighborhood on average increases CES-D scores by approximately 1 point (0.3 SD) and the likelihood of having a score above 11 by about 8 percentage points, this is nearly a 35% increase. These results, therefore, support the credibility of the core finding that exposure to violence increases symptoms 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.3 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 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.[29] 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 3.2. 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

[29] 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.

plausibility of the unconfoundedness assumption.

4.2 Instrumental Variables

Active debate within the psychology literature questions 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). It may be the case that the most important mechanism through which objective measures of violence affect an individual's psychological well-being is through their perception of violence. It is plausible, however, that high levels of violence objectively measured could affect psychological well-being through alternative channels—such as decreased income or access to public services. If we are able to control for a multitude of these alternative potential mechanisms including district-fixed effects, it is plausible to use objective measures of crime and violence as an instrument for the perception of violence in the neighborhood.

While levels of objective crime in the district are correlated with a number of aggregated district-level variables, a number of cities in South Africa experienced spikes in drug-related violence in poorer neighborhoods starting in 2016. Within urban areas, we do not find any observable aggregated district-level characteristics that predict which districts experienced these spikes in violence. We identify districts that experienced a surge in murder rates since between waves.[30] Restricting the analysis to urban areas, we use this indicator variable as an instrument for perceived violence while controlling for lagged district-level crime, in addition to other individual, household, and neighborhood characteristics. We also control for district and wave fixed effects in addition to individual fixed effects.[31]

The results in Table VI suggest that the effects of neighborhood violence on psychological well-being are larger than the estimates using OLS and fixed effect specifications reported in Table III.[32] These instrumental variable results are local average treatment effects (LATEs) and therefore it is challenging to directly compare these results to the previous OLS and fixed effects estimates. With that said, the results reported in Table VII report the effect of violence for those who comply to the instrument. Given that these surges in violence mainly affected poorer areas, the *compliers* are likely poorer overall and start

[30] We use a cutoff of 10% increase in murders as indicative of a surge in violence.

[31] The excludability of an instrumental variable is generally not directly testable. In this case, bias would need to be driven by some district-level time-variant factor that is independent of individual and household characteristics, neighborhood services, income, the lags of these controls, and included fixed effects as summarized in Table VI.

[32] We investigate our choice of instrument further by employing the method proposed by Lewbel (2012) using nonlinearities of heteroscedasticity as additional moment conditions which allow us to test the validity of our external instrument. We find no evidence against the validity of this instrument—we find that the Lewbel moment conditions on their own result in similar coefficient estimates on the perceived violence index.

TABLE VI: Instrumental Variable Results—Surges in Violence

	CES-D Score		Dummy CES-D≥11	
	(1)	(2)	(3)	(4)
Violence Index$_t$	1.393**	1.268*	0.085	0.092
	(0.740)	(0.768)	(0.061)	(0.069)
Indiv & HH Characteristics	✓	✓	✓	✓
Neighborhood Services	✓	✓	✓	✓
Income Controls	✓	✓	✓	✓
Lagged Controls	✓	✓	✓	✓
District & Wave Fixed Effects	✓	✓	✓	✓
Individual Fixed Effect		✓		✓
N	16,641	16,167	20,268	16,167
First-stage F	33.59	29.62	33.59	29.62

Note: Standard errors clustered at the PSU level are in the parentheses: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrumental variable results using an indicator variable for districts that experienced surges in violence show large effects of perceived violence of CES-D.

with lower levels of psychological well-being; they may be less able to protect themselves from exposure to violence.[33] This combination could explain the larger magnitude of these instrumental variable results. Finally, in terms of the qualitative result, these instrumental variable estimates broadly support the finding that neighborhood violence may reduce individual level psychological well-being.

4.3 Unobservable Selection and Coefficient Stability

A final approach to test the robustness of our results builds on the insights of Altonji, Elder and Taber (2005) and the methods of Oster (2019). This approach considers selection on observables as an indication of selection on unobservables. In doing so it 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 "long" 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).

[33]This can be observed in the data as the district-level surge in violence indicator variable predicts higher changes in the perceived violence index variable for poorer households.

TABLE VII: Unobservable Selection and Coefficient Stability

	Short (1)	Long (2)	Oster's δ (3)	Short (4)	Long (5)	Oster's δ (6)
			Panel A: CES-D Score			
Violence Index$_t$	0.58***	0.49***	8.11	0.54***	0.490***	9.12
	(0.046)	(0.041)		(0.053)	(0.052)	
Violence Index$_{t-1}$				0.148***	0.133***	
				(0.047)	(0.043)	
R^2	0.015	0.096		0.015	0.095	
N	65,536	64,723		39,756	31,859	
			Panel B: Dummy CES-D $\geq$ 11			
Violence Index$_t$	0.039***	0.035***	10.19	0.034***	0.032***	11.89
	(0.004)	(0.003)		(0.004)	(0.004)	
Violence Index$_{t-1}$				0.007*	0.007*	
				(0.004)	(0.004)	
R^2	0.008	0.052		0.007	0.049	
N	65,536	64,723		39,756	31,859	

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Therefore, assuming R_{Max} to have a value of one may be 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 VII presents the results of these unobservable selection and coefficient stability tests. Panel A shows the coefficient stability results when using the full CES-D scale as the dependent variable and Panel B shows results when using a dummy variable indicating if the CES-D score is greater than or equal to 11. Columns (1) and (4) report results from "short" regressions without additional controls and columns (2) and (5) report results from "long" regressions including additional controls. Columns (3) and (6) report the proportional selection coefficient or "Oster δ." The proportional selection coefficient estimates how much more important would selection on unobservables need to be, relative to selection on observables, to produce an estimated effect of zero. In each of the cases presented in Table VII, Oster's δ is between eight and 12. This suggests that any omitted unobservables would need to be eight to 12 times more important than the included control variables to explain away our result as spurious. Based on Oster (2019), which argues that δ values greater than 1 are robust to potential unobservable selection, these results support the credibility of our core results.

5 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 II(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.

To investigate how exposure to violence influences 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.

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 VIII 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 24 percentage points. Being poor and living in a neighborhood with high levels of violence two years ago adds another 7 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

TABLE VIII: Predicting Future Poverty

	Low Wealth$_t$		Growth	
	(1)	(2)	(3)	(4)
Low Wealth$_{t-1}$	0.263***	0.242***	0.069***	0.099***
	(0.016)	(0.017)	(0.0026)	(0.036)
High Violence$_{t-1}$	0.006	-0.004	0.0096	0.023
	(0.008)	(0.008)	(0.002)	(0.024)
Low Wealth$_{t-1}$*High Violence$_{t-1}$		0.068**		-0.132**
		(0.030)		(0.065)
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.

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

The poor in South Africa, especially in urban areas, live in neighborhoods where they perceive higher levels of violence than relative higher income households. In our sample we find that individuals in the poorest food expenditure decile perceive violence to be 0.5 standard deviations higher than those in the highest food expenditure decile. These perceptions of violence are based on objective reality. Using data from the South African Police Service and ACLED we find that objective data on violent crimes are strong predictors of the subjective perception of violence reported by individuals in the NIDS data.

We then show that perceived violence is 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 those who live in urban areas in South Africa and among those who already express more depressive symptoms.

We employ a number of empirical approaches to estimate the relationship between neighborhood violence and psychological well-being. Across each of our estimation approaches, we find evidence of strong effects of neighborhood violence on psychological well-being. Specifically, the highest quintile in the NIDS data have an average CES-D score that is 1.8 points lower than the poorest quintile. These same individuals in the highest quintile report an approximately 0.5 standard deviation lower perception of violence. Our results indicate that differences in neighborhood violence could explain anywhere between 15% (OLS with fixed effects) to 44% (matching) to 50-72% (instrumental variables) of the differences in psychological well-being as measured by CES-D scores.

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.

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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 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: 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.3: Perceived Violence and Psychological Well-being: Leave-one-out means

	Panel A: CES-D Score				
	(1)	(2)	(3)	(4)	(5)
Violence $\text{Index}_t{}^{(-i)}$	0.82***	0.93***	0.71***	0.54***	0.42***
	(0.11)	(0.12)	(0.14)	(0.12)	(0.22)
Violence $\text{Index}_{t-1}{}^{(-i)}$			0.16	0.05	0.09
			(0.14)	(0.12)	(0.18)
	Panel B: Dummy variable: CES-D≥11				
	(6)	(7)	(8)	(9)	(10)
Violence $\text{Index}_t{}^{(-i)}$	0.050***	0.055***	0.042***	0.043***	0.036***
	(0.008)	(0.009)	(0.011)	(0.010)	(0.020)
Violence $\text{Index}_{t-1}{}^{(-i)}$			0.009	-.001	-0.002
			(0.011)	(0.010)	(0.015)
Indiv & HH Characteristics		✓	✓	✓	✓
Neighborhood Services		✓	✓	✓	✓
Income Controls		✓	✓	✓	✓
Lagged Income Controls			✓	✓	✓
Lagged CES-D Score			✓	✓	
Urban Dummy				✓	✓
District Wave Fixed Effect				✓	✓
Individual Fixed Effect					✓
N	64,784	64,784	31,829	31,829	31,829

Note: Standard errors clustered at the PSU level are in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Leave-one-out means use the mean of violence index for households in the same geographic area which is likely a good measure of violence in the neighborhood without being subject to issues intra-household correlation in psychological well-being.

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	✓	✓	✓	✓
Lagged respondent 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.

A.2 Figures

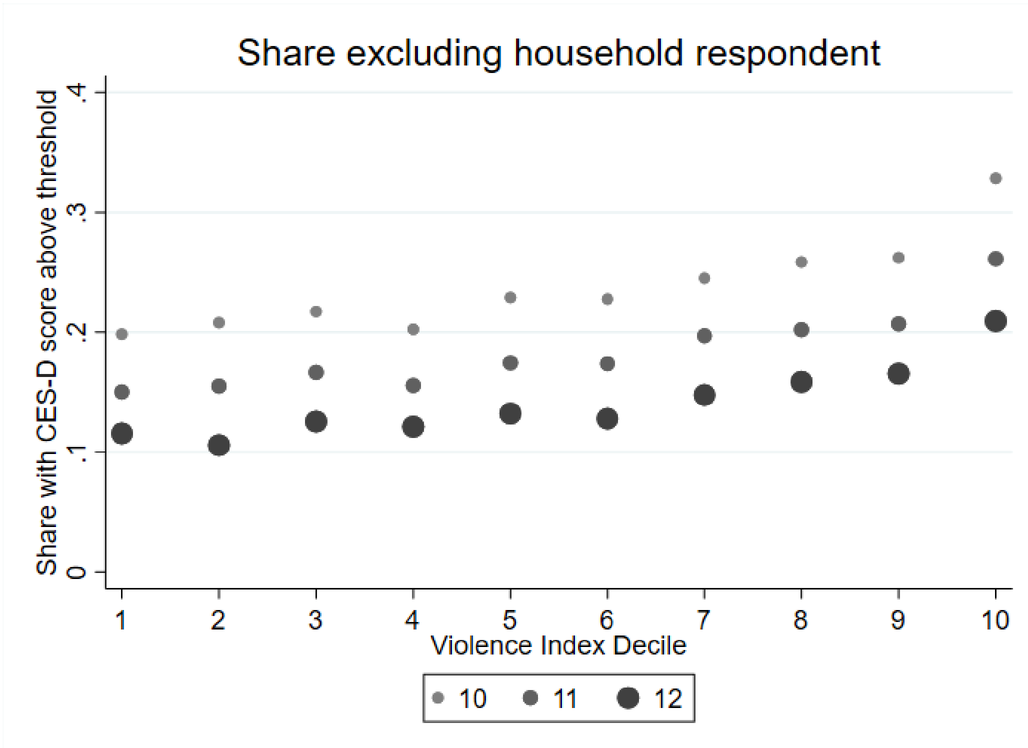

FIGURE A.1: Share above depression thresholds by Wealth Decile. This figure shows these shares when excluding the household respondent who completed the frequency of violence questions. The pattern is very similar to the full sample in Figure II(b).

Panel A: CES-D Score						
		Wealth Quintile				
		1=poorest	2	3	4	5=richest
	1=least violent	7.13	6.60	6.01	6.15	4.99
Violence	2	7.29	6.82	6.50	6.35	5.52
Index	3	7.24	6.95	6.66	6.68	6.10
Quintile	4	7.79	7.32	6.85	6.83	6.29
	5=most violent	8.32	7.67	7.42	7.41	7.13

Panel B: CES-D ≥ 11						
		Wealth Quintile				
		1=poorest	2	3	4	5=richest
	1=least violent	0.211	0.178	0.158	0.160	0.106
Violence	2	0.225	0.195	0.164	0.148	0.116
Index	3	0.217	0.199	0.175	0.182	0.146
Quintile	4	0.262	0.221	0.197	0.202	0.170
	5=most violent	0.307	0.260	0.240	0.234	0.213

FIGURE A.2: CES-D scores and shares above depression threshold by Wealth and Violence quintiles. Poor households in violent neighborhoods have much higher CES-D scores and shares above the depression thresholds than do wealthy households in neighborhoods with low levels of violence.

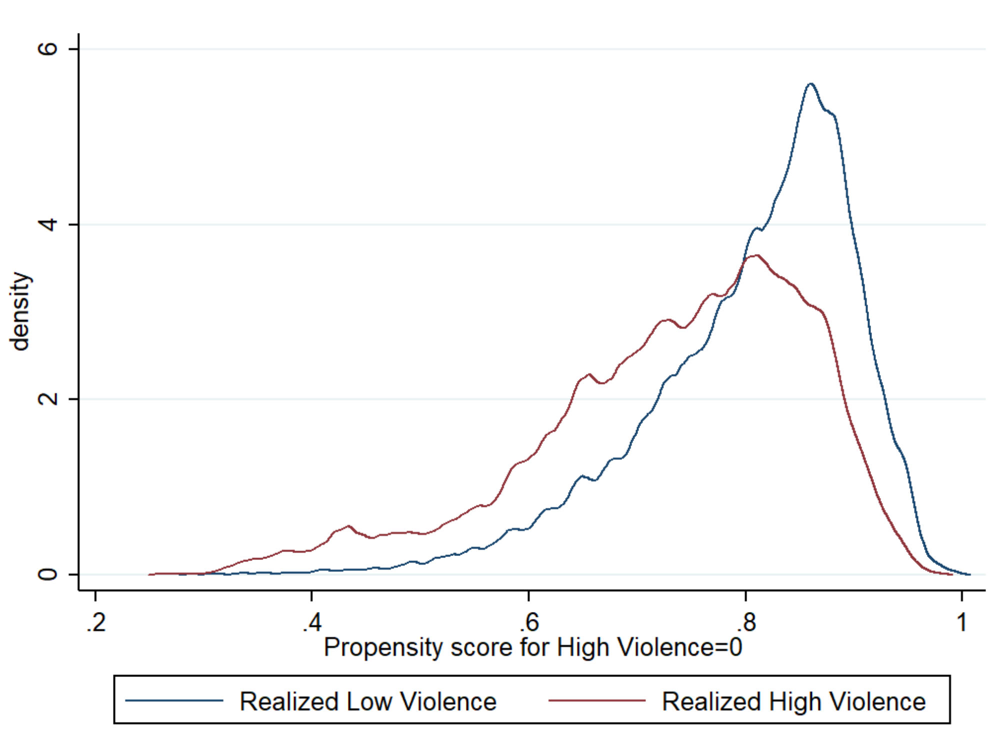

FIGURE A.3: The distributions of the propensity scores for living in neighborhoods that are not violent show significant overlap.