Childhood Exposure to Violence and Nurturing Relationships: The Long-Run Effects on Black Men

Dionissi Aliprantis[+] Kristen Tauber[*]

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Abstract: Black males who witnessed a shooting before turning 12 have 31 percent lower household earnings as adults and are 18 percentage points more likely to engage in violence at age 15. These gaps change little after adjusting for observables, and we present extensive evidence that violent behavior is not driven by selection on unobservables. Since effects are not mediated by incarceration or proxies for gang activity or broader neighborhood effects, we focus on toxic stress as the primary causal mechanism. Providing adolescents with nurturing relationships is almost as beneficial as preventing their exposure to violence and there are complementarities when improving both treatments simultaneously.

Keywords: Interpersonal Violence, Code of the Street, Toxic Stress, Nurturing Relationship, Race, Neighborhood Effect
JEL Classification Codes: H40, I38, J15, J24, R23

[+]: École Normale Supérieure de Lyon, *dionissi.aliprantis@ens-lyon.fr*

[*]: New York University, *knt2029@nyu.edu*

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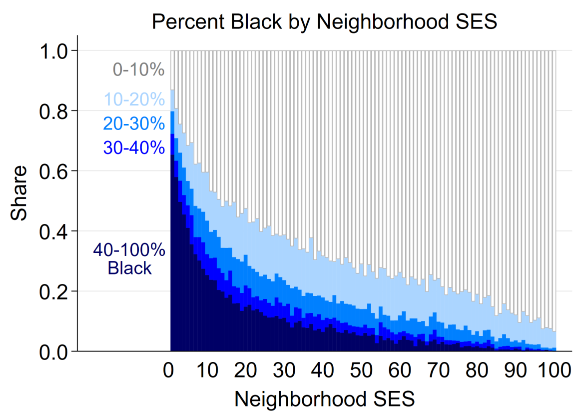
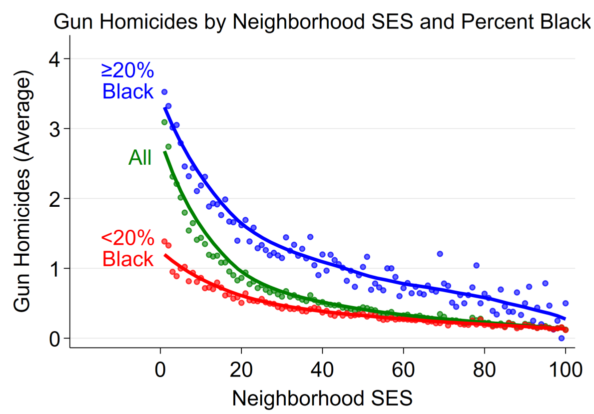
1 Introduction

The United States is residentially segregated by race. Figure 1a shows that as the socioeconomic status (SES) of neighborhoods decreases, there is an increase in the share of their residents who are Black, with the increase being especially steep in the lowest quintile of neighborhoods. One neighborhood effect associated with this segregation, shown in Figure 1b, is exposure to violence. The sociologist Elijah Anderson advocates for the importance of this neighborhood effect in his classic ethnography *Code of the Street*, arguing that "Of all the problems besetting the poor inner-city black community, none is more pressing than that of interpersonal violence and aggression" (Anderson (1999), p 32).



(a) Residential Segregation, 2014-2018



(b) Exposure to Violence, 2013-2018

Figure 1: Neighborhood Socioeconomic Status, Racial Composition, and Gun Homicides
Note: The left panel shows the percent of tract residents who are Black by percentiles of neighborhood SES, which is constructed by performing principal components analysis on tract-level poverty rate, educational attainment, and labor market outcomes as measured in the 2014-2018 American Community Survey (ACS); see the main text for details. The right panel displays local linear regressions showing the mean number of gun homicides as a function of a Census tract's neighborhood SES in the 2014-2018 ACS. Tract-level gun homicides are measured for 2013 to 2018 using data from the Gun Violence Archive, which is described in greater detail in the main text. The green line shows this relationship for all tracts, while the blue and red lines show this relationship separately for tracts in which, respectively, more and less than 20 percent of residents are Black.

The previous literature has documented the costs of Black males' disproportionately high rate of exposure to violence in terms of short-run effects.[1] Black males who witnessed a shooting in their childhoods are twice as likely to engage in violence themselves at age 15 and 13 percentage points more likely to drop out of high school (Aliprantis (2017b); Bingenheimer et al. (2005)). And Black students' academic performance declines after violent crime near their schools (Torrats-Espinosa (2020); Casey et al. (2018)) and in their neighborhoods (Sharkey et al. (2014), Burdick-Will (2018)), with the latter effect mediated by school safety (Laurito et al. (2019)). Residential segregation is an important cause of this exposure to violence (Cox et al. (2024), Light and Thomas (2019), Bjerk

[1]Young Black males are killed at eight times the rate of their white peers; see the data from NCHS (2021) in Appendix Figure 1 indicating that between 1977 and 2019, the average annual ratios of Black to white homicide rates for 15-24 and 25-34 year-old males were 8.1 and 8.4. As well, more than a quarter of Black men witnessed a shooting as a child, four times the rate of their white peers (Graham (2018)) and nearly double the rate for Black females.

(2010)).

This paper studies the long-run effects of early exposure to violence on the outcomes of Black men using the National Longitudinal Survey of Youth 1997 (NLSY97). The first contribution of this paper is a treatment effect analysis of exposure to violence during childhood (before age 12). We document large gaps in adult outcomes between Black men who witnessed a shooting during their childhoods and those who did not. We give these gaps a causal interpretation using treatment effect models that allow for selection on observed characteristics and find that the majority of the gaps remain after conducting propensity score matching. For example, when we focus on the area of common support, those exposed to violence during childhood have household earnings that are 27 percent lower in their late 30s. This gap is reduced to 26 percent when adjusting for the observed characteristics mother's educational attainment, household structure, and parental income.

As an aside, we provide evidence on how to interpret the fact that Black males in the NLSY97 are more likely to engage in violent behavior than their white or Hispanic counterparts. Murray (2021) appeals to racial essentialism, or inherent differences between racial groups, for explaining this difference. We present evidence in favor of an alternative, environmental explanation. We show that regardless of their race or ethnicity, adolescent males are equally likely to engage in violent behavior at age 15 after conditioning on childhood exposure to violence, and we show that this remains true even after adjusting for the observed characteristics of the adolescents.

More substantively, we investigate the extent to which our treatment effect estimates reflect selection on unobservables, a concern that has plagued previous evidence on the effects of exposure to violence (Bingenheimer et al. (2005); Holden (2005)). Using three strategies, we (i) examine patterns over the lifecycle and use repeated observations to estimate finite mixture models in which we impose the assumption that exposure to violence has no effect on violent behavior; (ii) estimate regressions that adjust for direct measures of personality traits; and (iii) implement recent advances in Masten et al. (2023) that compare the uncertainty under assumed levels of selection on unobservables to the selection implied by treating observed characteristics as if they were unobserved. All three strategies provide strong evidence that the correlation between childhood exposure to violence and age 15 violent behavior is better interpreted as the causal effect of exposure than as selection on unobservables.

We finish our study of childhood exposure to violence by investigating the mechanisms generating long-run effects on Black men. We show that the vast majority of the gap in household earnings between those exposed and not exposed in childhood remains after conditioning on ever being incarcerated, neighborhood socioeconomic status, or exposure to gang activity. These results may be surprising given the importance of incarceration for labor market outcomes and the strong correlation between exposure to violence and neighborhood SES (recall Figure 1b).

The second contribution of this paper is an analysis that engages with the literature on toxic stress to investigate whether nurturing relationships mitigate the effects of exposure to violence. If long-run effects are not explained by incarceration, gang activity, broader neighborhood externalities, selection on observables, or selection on unobservables, then what mechanisms might explain our estimates? By the process of elimination, we conclude that stress and trauma resulting from the exposure itself are likely to play an important role in generating long-run effects. This conclusion aligns with the large literature on toxic stress that has developed in response to the findings in the Adverse Childhood Experiences (ACEs) study (Felitti et al. (1998)). A broad literature documents the long-lasting biological impacts of stress (McLaughlin et al. (2019), Soares et al. (2021), Boyce et al. (2021)). While economics has produced considerable research on the long-run effects of early childhood environments and *in utero* nutrition, the field has engaged less directly with the literature on toxic stress.[2]

Garner and Yogman (2021) define toxic stress as the "wide array of biological changes that occur at the molecular, cellular, and behavioral levels when there is prolonged or significant adversity in the absence of mitigating social-emotional buffers."[3] Social-emotional buffers are a key part of this definition. Garner and Saul (2018) summarize a broad conclusion from the literature as follows: "From a neuroscience perspective, then, what is the antidote to early childhood adversity and toxic stress? It is safe, stable, and nurturing relationships" (p 46). The reason, as noted in Garner and Yogman (2021), is that nurturing relationships "turn off the body's stress machinery in a timely manner" (p 2), before this machinery can generate biological changes that are maladaptive and health harming over the long run.[4] We study the interaction between exposure to violence and nurturing relationships during adolescence (ages 12-18) because the NLSY97 has a wide variety of related variables during this time period, but extremely few during childhood (ages 0-11).

An important part of the analysis on nurturing relationships and exposure to violence is confronting the measurement issue of how to synthesize the NLSY97's 11 variables on exposure to violence and 31 variables related to nurturing relationships. We compare a sum of positive responses (analogous to the original ACE score in Felitti et al. (1998)), indexes created with Item Response Theory (IRT) and Principal Components (PC), and an item-anchored scale which weights variables according to how well they predict a later outcome (Cunha et al. (2010); Bond and Lang (2018); Nielsen (2022)). We find that the item-anchored index outperforms the other indexes in our application and that the other indexes are quite comparable. The similar performance of IRT, PC, and summing positive responses may be surprising in light of the sensitivity of results in education to the scale with which tests are measured (Bond and Lang (2013); Nielsen (2023); Agostinelli and Wiswall (2016); Cunha et al. (2021)), but similar results have been found for measuring overall health status (Hosseini et al. (2022)). This finding suggests a robustness of the results in the literature using ACE scores to measure adversity.

[2]Examples of work on early childhood enrichment programs include García et al. (2023) and Bailey et al. (2021), with related studies of social and emotional skills (ie, personality traits) including Vergunst et al. (2019), Heckman et al. (2013), and Almlund et al. (2011). Almond and Currie (2011) present a survey of economics' general support for the hypothesis that *in utero* nutrition can have long-run effects as originally posed in Barker et al. (1989). Some recent papers in economics corroborate mechanisms in the toxic stress literature, including Carneiro et al. (2023), Resnjanskij et al. (2024), and Villa-Llera (2024).

[3]These biological changes are referred to as "toxic" because they are often maladaptive and health harming, and contrast with "positive" and "tolerable" stress responses (Garner and Yogman (2021)).

[4]Recent evidence indicates that nurturing relationships are still important for youth development whether or not adversity is present (Bethell et al. (2019a), Bethell et al. (2019b)).

We estimate potential outcomes under a selection on observables assumption in which treatment-group-specific regressions are estimated (Imbens (2015)).[5] We find that providing nurturing relationships to adolescents is almost as beneficial as shielding them from violence. Consider an adolescent Black male in the worst treatment state, exposed to high levels of violence and low levels of nurturing relationships. Household earnings when aged 34-38 would increase by \$17,000 if such an adolescent were exposed to low levels of violence ($p = 0.01$). If such an adolescent were provided with high levels of nurturing relationships, his household earnings would increase by \$11,000 ($p = 0.04$). Protection from violence and providing nurturing relationships are not substitutes: the household earnings of our example adolescent would increase by \$32,000 ($p = 0.00$) on average if both of these treatments were improved.

2 Effects of Childhood Exposure to Violence

2.1 Model and Identification

Let $D_i \in \{0, 1\}$ be an indicator for individual i's exposure to violence. For the outcome Y_i, we are interested in characterizing the potential outcomes $Y_i(D)$ in terms of treatment effects such as the average treatment effect and the average effect of treatment on the treated,

$$\triangle^{ATE} \equiv \mathbb{E}[Y(1) - Y(0)] \quad \text{and} \quad \triangle^{ATT} \equiv \mathbb{E}[Y(1) - Y(0)|D_i = 1]$$

We denote a vector of observed characteristics of individual i as $W_i \in \mathbb{R}^{d_w}$ with support $\mathcal{W} = \text{supp}(W)$. We follow Masten et al. (2023) and consider three approaches to identification based on adopting various assumptions about selection into treatment.

$$Y(0), Y(1) \perp\!\!\!\perp D \qquad \text{(Random Selection)}$$

$$Y(0), Y(1) \perp\!\!\!\perp D \,|\, W \qquad \text{(Selection on Observables)}$$

$$\sup_{y_d \in \text{supp}(Y(D)|W=w)} \Big| \mathbb{P}(D = 1|Y(D) = y(d), W = w) - \mathbb{P}(D = 1|W = w) \Big| \leq c \qquad \forall\, w \in \mathcal{W}. \qquad \text{(Selection on } c\text{-Dependent Unobservables)}$$

To aid in assessing assumptions of c-dependence, we will examine the distribution of estimated leave-one-out changes in propensity scores. Denote dimension k of W as W_k and define the propensity score and leave-out-variable-k propensity score, respectively, as

$$\begin{aligned} \pi(w) = \pi((w_{-k}, w_k)) &= \mathbb{P}(D = 1|W = (w_{-k}, w_k)) \\ \pi(w_{-k}) &= \mathbb{P}(D = 1|W_{-k} = w_{-k}). \end{aligned}$$

[5] To assess the importance of selection for these estimates, we also conduct a robustness exercise in which we estimate potential outcomes of nurturing relationships and a more credibly exogenous treatment, non-violent adversity. We find similar results as our estimates of potential outcomes of nurturing relationships and exposure to violence.

These variables allow us to define the leave-one-out change in propensity score as

$$\triangle_k \equiv \left| \pi(w) - \pi(w_{-k}) \right|.$$

We will also sometimes adopt and examine the assumption

$$\pi(w) \in (0,1) \ \forall \ w \in \mathcal{W}. \qquad \text{(Common Support)}$$

2.2 Data for Treatment Effect Analysis

The primary sample used in our analysis is from the National Longitudinal Survey of Youth 1997 (NLSY97). Here we provide an overview of our data work, with a greater level of detail provided in Appendix B.

We focus our analysis on the subsample of non-Hispanic Black males, and sometimes also consider the subsample comprising non-Hispanic white males. We measure our treatment variable, exposure to violence, based on whether a respondent reports having seen someone shot or shot at. One survey question asks about this exposure prior to age 12 and another question asks about exposure between the ages of 12 and 18. We refer to these variables as childhood exposure (ages 0-11) and adolescent exposure (ages 12-18).

Some W variables we use from the NLSY97 are mother's educational attainment at the time of the first survey, household structure at the time of the first survey (two parents (both biological); two parents (one biological); single parent; grandparent(s); or other), and parental income at the time of the first survey. Parental income includes income from labor (earnings) and business, but also interest income, income from Aid to Families with Dependent Children (AFDC) benefits, or income from pensions, Social Security, or insurance.

We consider a few short-run outcomes. We follow Aliprantis (2017b) and define an indicator for engaging in violent behavior at a given age as having carried a gun in the past year, attacked or assaulted someone, or belonged to a gang. We also study the percentile score for the Armed Services Vocational Aptitude Battery (ASVAB) created by NLS staff based on the results of a computer-adaptive test taken by respondents in survey wave 1. The percentile score summarizes results on the four domains of Mathematical Knowledge, Arithmetic Reasoning, Word Knowledge, and Paragraph Comprehension.

We measure long-run outcomes using results from the 2017 and 2019 waves of the survey. Sometimes we will report results in terms of the year of the survey wave, the year to which the survey variable pertains, or in terms of the average age of respondents for a given survey wave. For example, respondents are aged 35-39 at the 2019 survey wave, so results might be reported for the average age of 37. Since respondents are asked about labor market outcomes in the year before the survey, these outcomes might be reported for ages 34-38. All earnings and income variables are inflated to 2018 dollars using the US Bureau of Economic Analysis' Gross Domestic Product Implicit Price Deflator, downloaded from the St. Louis Fed's FRED website. Weekly hours worked is equal to the total annual hours worked at all civilian jobs during the year divided by

52. We measure depression using the self-reported variable that asks how often the respondent has experienced depression in the last month. An indicator for a respondent ever being incarcerated by the time of the 2019 survey wave is measured using the created variables indicating whether the respondent was incarcerated at any point in the past. We follow Aliprantis and Chen (2016) and define deceased (or missing) using the variable recording the reason for non-interviews.

2.3 Descriptive Statistics

Tables 1 and 2 present summary statistics of the variables used in the treatment effect analysis. The first notable result in Table 1 is the massive gap in Black and white boys' exposure to violence. Over a quarter of Black boys reported seeing someone shot or shot at before age 12, with 7 percent of white boys reporting the same. By age 18, cumulatively 47 (16) percent of Black (white) adolescents have been exposed to this violence. These results are consistent with the exposure to shooting reported in the National Survey of Children's Exposure to Violence conducted in 2011 (Finkelhor et al. (2015)).[6]

Table 1: Summary Statistics of the NLSY97, Percentages (Unless Otherwise Noted)

Variable	Means for Males Black	Means for Males White
Treatment D: Seen Shot		
Childhood	26	7
Adolescence	31	11
Child. or Adolescence	47	16
Observable Characteristics W		
Mother's Ed		
Not Determined	9	11
Dropout	20	8
GED	6	4
HS Grad	48	48
AA	8	11
BA	9	17
Parent(s)' Income in 1996		
Mean (Thousands of 2018 $s)	39	71
HH Structure		
Two Parent (Both Bio)	26	60
Two Parent (One Bio)	14	17
Single Parent	50	21
Grandparent(s)	6	1
Other	4	1

Note: See text for variable descriptions.

Table 2: Summary Statistics of the NLSY97, Percentages (Unless Otherwise Noted)

Variable	Means for Males Black	Means for Males White
Outcomes Y		
Violent Behavior Age 15	22	18
Violent Behavior Age 21	14	10
ASVAB Percentile	26	56
HS Grad by 26	61	78
BA by 26	9	24
HH Earnings in 2018 (Thousands of 2018 $s)	51	95
Earnings in 2018 (Thousands of 2018 $s)	37	68
0 Earnings in 2018	22	9
Hours in 2018 (Weekly Avg)	33	39
Ever Incarcerated by 2019	26	12
Depressed in 2017	14	11
Obese in 2019	39	33
Smoked in 2015	37	36
Deceased by 2019	5	3
Deceased or Missing by 2019	9	5

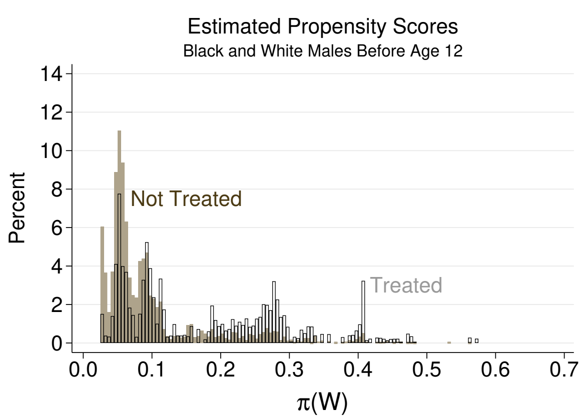
Note: See text for variable descriptions.

[6] For example, when the NLSY97 data are weighted to be representative of the national population, they broadly match the statistics for ages 14-17 reported in Table 5 in Finkelhor et al. (2015).

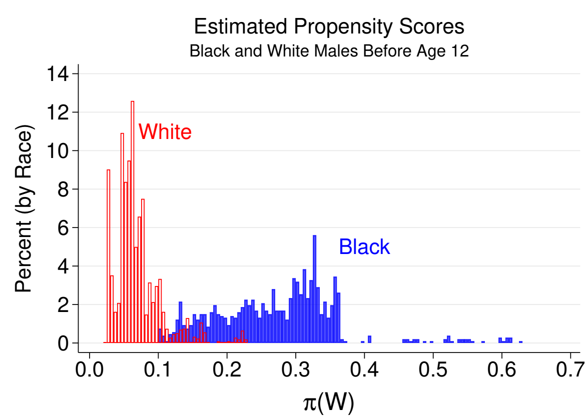
The second notable result in Table 1 is that Black males have less advantageous family backgrounds. Their mothers have lower educational attainment, their parents' income is lower, and they are much less likely to reside in a two-parent household than their white peers. We use a fine partition of household structure because exposure to violence is different in meaningful ways within coarser classifications, such as classifying together all two-parent households (Appendix Table 2).

The teenage outcomes in Table 2 show that Black adolescents are more likely to engage in violent behavior and have much lower test scores than their white peers. For the adult outcomes in Table 2, Black men have lower earnings at ages 34-38 than their white peers (in 2018), and are more likely to be depressed or deceased. The cumulative risk of ever being incarcerated in Table 2 is in line with the estimates for Black males in Table 1 of Western and Wildeman (2009), noting that our sample was born in 1980-1984 and at the time of the 2019 survey they were aged 35-39. The cumulative risk for white males in our sample is considerably higher than the estimates in Western and Wildeman (2009).

There are several additional variables available in the NLSY97 that we do not include in **W** because they look to us like "bad controls" (Angrist and Pischke (2009)), or variables that due to their time of measurement might have been affected by the treatment. This includes a range of questions on personality traits that are asked in the NLSY97 survey waves of 2002 and later, and variables like neighborhood characteristics, which are first observed in the NLSY97 after childhood exposure.



(a) Estimated Together



(b) Estimated Separately

Figure 2: Propensity Scores of Childhood Exposure by Sample
Note: The left panel shows estimated propensity scores for childhood exposure to violence, shown separately for those treated (exposed to violence) and those not treated (not exposed to violence). The propensity scores in the left panel are estimated on the full sample of Black and white males. The right panel shows propensity scores estimated separately on the Black and white subsamples, and shows estimates separately by both treatment status and race.

Results from propensity score matching explain why we focus our analysis on Black males. If we were to estimate propensity scores for childhood exposure to violence on the sample of non-Hispanic Black and white males, where we included the **W** variables and an indicator for race, we would find a result similar to that in Bingenheimer et al. (2005). Figure 2a shows that in the combined Black and white sample, those exposed to violence appear to be different on observed characteristics than those not exposed. This suggests problems for matching on observed characteristics (Heckman et al. (1998)). However, when we estimate propensity scores for childhood exposure to violence by race, Figure 2b shows that race is the variable separating those with a high likelihood of exposure and those unlikely to be exposed. Expected exposure to violence is completely different by race, even taking into account parental income, mother's educational attainment, and household structure. Appendix B.1.2 shows these results in greater detail.

2.4 Treatment Effect Estimation Results

We estimate propensity scores using a logit specification for $\pi(\mathbf{W})$, with results reported in Appendix B.1.2. We impose common support on our sample by dropping respondents with estimated propensity scores either below the 5th percentile of the untreated distribution or above the 95th percentile of the treated distribution. Figure 3 shows that in the left tail of the distribution of propensity scores, this drops a group of respondents who are not treated for which there are few observationally similar treated respondents. In the right tail, this drops a group of respondents who are treated for which there are few observationally similar untreated respondents.

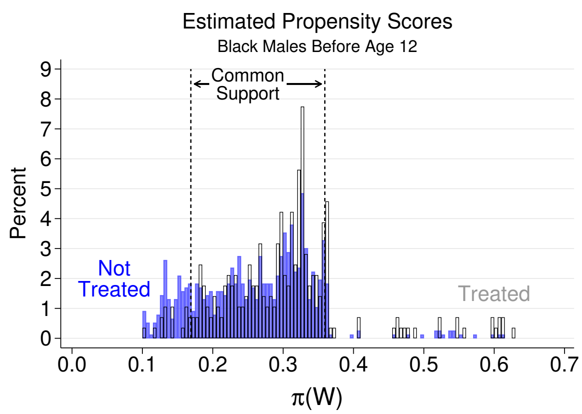


Figure 3: Imposing Common Support Using Propensity Scores of Childhood Exposure
Note: This figure shows the distributions of propensity score estimates for childhood exposure to violence by exposure. The vertical lines show the boundaries of common support, set as the 95th percentile of the exposed (ie, treated) sample and the 5th percentile of the sample not exposed to violence.

We begin our analysis by estimating the treatment effects of exposure to violence in childhood and adolescence on later life outcomes. The results are reported in Table 3. The first and second columns show control means and effects under the assumption of random selection. The third column shows effects assuming selection on observables where matching is achieved through entropy balancing (Hainmueller (2012); Zhao and Percival (2016)).

Table 3: Treatment Effects of Exposure to Violence on Black Males

	Effects by Assumption about Selection into Treatment					
	Childhood Exposure			Adolescent Exposure		
	Random		on Obs.	Random		on Obs.
Outcome	C. Mean	Effect	Entr. Bal.	C. Mean	Effect	Entr. Bal.
Violent Behavior at Age 15 (%)	17	20 [0.00]	20 [0.00]			
ASVAB Pctl	25	–5 [0.00]	–5 [0.01]			
Violent Behavior at Age 21 (%)				9	15 [0.00]	14 [0.00]
HS Grad by 26 (%)	63	–16 [0.00]	–15 [0.00]	64	–13 [0.00]	–13 [0.00]
BA by 26 (%)	7	–2 [0.25]	–2 [0.26]	8	–4 [0.06]	–4 [0.02]
HH Earnings in 2018 ($1,000s)	48	–13 [0.00]	–12 [0.00]	49	–12 [0.00]	–12 [0.00]
Ind. Earnings in 2018 ($1,000s)	34	–7 [0.02]	–7 [0.02]	34	–7 [0.03]	–7 [0.01]
0 Earnings in 2018 (%)	20	9 [0.02]	9 [0.03]	21	5 [0.17]	6 [0.10]
Weekly Hours in 2018	33	–5 [0.03]	–5 [0.04]	33	–4 [0.10]	–4 [0.10]
Ever Incarcerated by 2019 (%)	26	8 [0.02]	8 [0.03]	21	21 [0.00]	22 [0.00]
Smoked in 2015 (%)	35	5 [0.22]	5 [0.25]	35	7 [0.07]	6 [0.13]
Deceased by 2019 (%)	5	3 [0.13]	3 [0.17]	4	3 [0.05]	3 [0.06]
Deceased or missing by 2019 (%)	8	5 [0.02]	5 [0.04]	7	3 [0.10]	4 [0.11]

Note: Childhood (adolescent) exposure to violence is seeing someone shot or shot at when aged 11 or younger (aged 12 to 18). "On Obs." is "On Observables," "C. Mean" is "Control Mean," and "Entr. Bal." is "Entropy Balancing." "GAD" is Generalized Anxiety Disorder Scale and "CESD" is Center for Epidemiologic Studies Depression Scale. The sample is Black males in the NLSY97. Values in brackets are the p-values associated with each coefficient being different from zero.

We find that exposure to violence has large and significant impacts on behavior, educational attainment, labor market outcomes, and health. Additionally, the treatment effects from childhood exposure are often greater than those from adolescent exposure.

First, we examine violent behavior at ages 15 and 21. Respondents who saw someone shot or shot at before the age of 12 are 20 percentage points more likely to engage in violent behavior at age 15. Similarly, respondents who saw someone shot or shot at between the ages of 12 and 18 are 14 percentage points more likely to engage in violent behavior at age 21.

The estimated treatment effect of childhood exposure on obtaining a high school diploma by age 26 is −15 percentage points. Respondents who were exposed to violence in adolescence are 13 percentage points less likely to obtain a high school diploma. The impact on earning at least a bachelor's degree is smaller for both measures of exposure. Respondents who were exposed in childhood were a statistically-insignificant 2 percentage points less likely to obtain a degree, and those who were exposed in adolescence were 4 percentage points less likely to obtain a degree.

Next, we examine labor market outcomes in 2018. The effects of exposure in childhood are similar to the effects of exposure in adolescence. Respondents who were exposed in childhood earned \$7,000 less in 2018. Those who were exposed in adolescence also earned \$7,000 less. Childhood exposure made respondents 9 percentage points more likely to have zero earnings in 2018, whereas adolescent exposure did not result in statistically significant differences. Respondents who saw someone shot or shot at before the age of 12 also worked 5 hours less per week in 2018. These results are consistent with recent evidence on effects of crime victimization on adults' labor market outcomes, such as Bindler and Ketel (2022) and Ornstein (2017), who find large negative effects that persist for years.

We find that exposure to violence has a large and significant impact on incarceration. In 2019, those who had been exposed to violence in childhood were 8 percentage points more likely to have been incarcerated at least once. Adolescent exposure increased the likelihood of having been incarcerated by 22 percentage points.

2.5 Heterogeneity across Race

While the analysis in this paper is focused on understanding effects on Black males, here we consider a small analysis of heterogeneity across race. One argument present in the current public discourse is that Black and white Americans face equal opportunities, but Black people are inherently less capable of taking advantage of those opportunities, either because they have less mental capacity (Herrnstein and Murray (1996)) or are inherently more prone to violence (Murray (2021)).[7]

The NLSY97 provides evidence on violent behavior by race. Figure 4 shows that there are indeed significant group differences in outcomes, consistent with the empirical fact pointed out by Murray (2021). Murray (2021) proceeds to interpret these differences in outcomes as the result of racial essentialism, or fundamental differences across racial groups.

Figure 5 presents evidence that differences in violent behavior need not be attributed to racial essentialism, but can instead be explained by similar human beings facing different environments.

[7]See Manski (2011), Goldberger and Manski (1995), O'Flaherty (2015), and O'Flaherty (2016) for critical discussion of the ideas in Herrnstein and Murray (1996).

The left panel shows that adolescent males of different racial and ethnic groups are equally likely to engage in violent behavior conditional on whether they are exposed to violence as children. The light blue column on the left shows that conditional on not experiencing childhood exposure to violence, 17 percent of adolescent males who are Black engage in violence at age 15. The dark blue column shows that conditional on exposure to violence during childhood, there is a doubling to 35 percent of Black adolescent males engaging in violence at age 15. The red bars and green bars show that a nearly identical pattern holds, respectively, for the white and Hispanic groups. Figure 5b presents evidence that these differences are not driven by respondents' household structure, parental income, or mother's educational attainment. Using OLS regressions that condition on these variables for each exposure and race/ethnicity group, predicted violent behavior does not change.

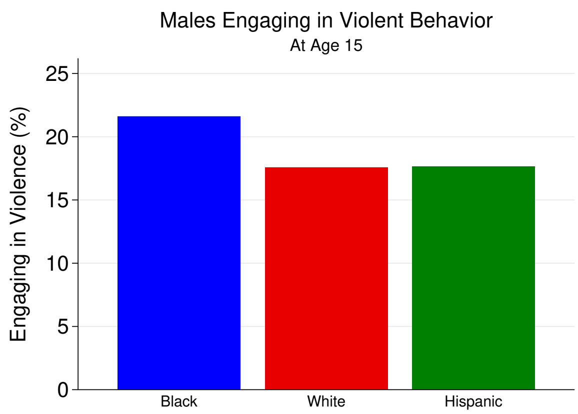
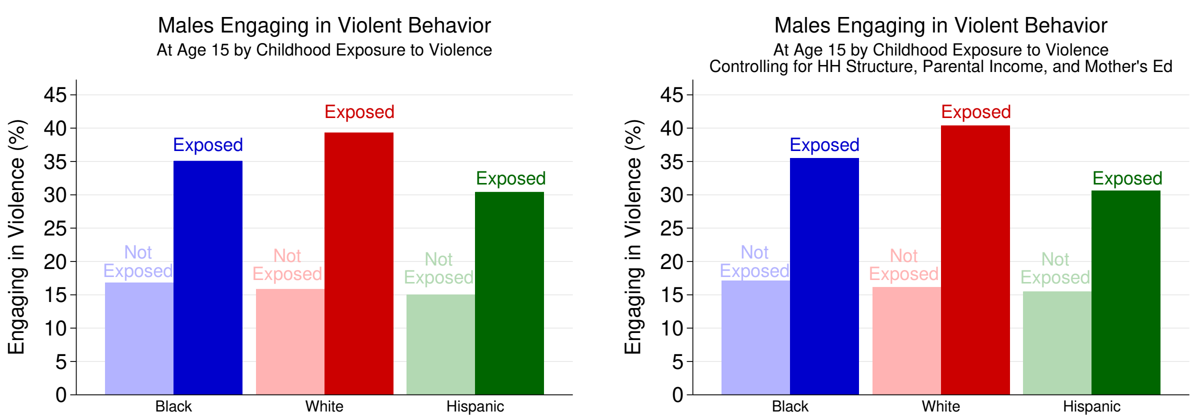


Figure 4: Violent Behavior by Race and Ethnicity
Note: This figure shows the percent of 15-year-old males who engaged in violent behavior. A respondent engages in violent behavior by attacking someone with the intention of seriously hurting them, being charged with an assault, carrying a handgun, or belonging to a gang. Black and white groups both exclude Hispanic respondents, and the Hispanic group includes all races.



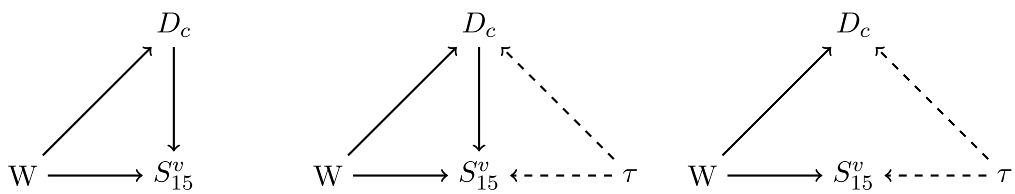
(a) By Race

(b) By Race, Controlling for Observables

Figure 5: Violent Behavior by Race and Exposure to Violence
Note: Childhood exposure to violence is an indicator for whether the respondent reported seeing someone shot or shot at before age 12. See the note to Figure 4 for more details.

3 Robustness to Selection on Unobservables

Figures 6a shows the causal model through which we have interpreted the differences in means of violent behavior at age 15 (S_{15}^v) conditional on childhood exposure to violence (D_c) and observed characteristics (W). It is possible, though, that this interpretation is incorrect because the observed characteristics we use in our analysis do not fully capture the correlation between selection into treatment and potential outcomes. There could be some unobserved characteristic τ that is not captured by our observables (household structure, parental income, and mother's educational attainment), but that is driving both selection into treatment and violent behavior. This scenario, shown in Figures and 6b and 6c, could result if something unmeasured, like permanent personality traits like prosociality (Vergunst et al. (2019)), impulsiveness, or recklessness (Holden (2005)) were jointly causing both selection into treatment and later outcomes rather than treatment affecting outcomes.



(a) Model 1 (b) Model 2 (c) Model 3

Figure 6: Directed Acyclic Graphs of Selection Assumptions

We now consider three approaches to assessing the likelihood that Models 2 or 3 more accurately represent the Data Generating Process (DGP) than Model 1. We first consider a model of permanent unobserved heterogeneity driving behaviors, using repeated observations of exposure to violence during childhood and adolescence together with adolescent behaviors. We compare descriptive statistics with the predictions of such a model, and then go on to estimate finite mixture models that assume there is no effect of childhood exposure on later outcomes and that τ has a finite support. Second, we examine how the coefficient changes in a regression of S_{15}^v on D_c when we condition on some variables that might proxy for τ. If Model 3 most accurately describes the DGP, then this coefficient should fall to 0 once conditioning on τ. Finally, we use the recently-developed notion of c-dependence (Masten and Poirier (2018), Masten and Poirier (2020)) to assess how the selection on an unobserved characteristic like τ would need to compare to selection on the observed characteristics in our analysis for inference to break down that there is indeed causal effect of D_c on S_{15}^v.

We interpret our results as strong evidence that our estimates of a large causal effect of childhood exposure to violence on adolescent violent behavior are robust. The basic patterns in the data are inconsistent with permanent unobserved heterogeneity being the primary driver of correlations between exposure to violence and violent behavior. The estimated finite mixture models confirm this interpretation. Coefficients on childhood exposure to violence are generally uniform across self-reported personality traits measured several years post-treatment. And in the c-dependence analysis, the breakdown frontier for violent behavior at age 15 is either far in the tail or entirely outside the support of leave-one-out propensity score changes, a strong signal that the differences in this outcome conditional on treatment are driven by the causal effect of treatment and not by selection on unobservables. Much of our subsequent analysis is focused on the outcome of violent behavior at age 15 because this outcome has been the focus of previous controversial results (Bingenheimer et al. (2005), Holden (2005)) and because this outcome is judged to be the most robust in the analysis using c-dependence.

3.1 Using Repeated Observations to Test for Permanent Unobserved Heterogeneity

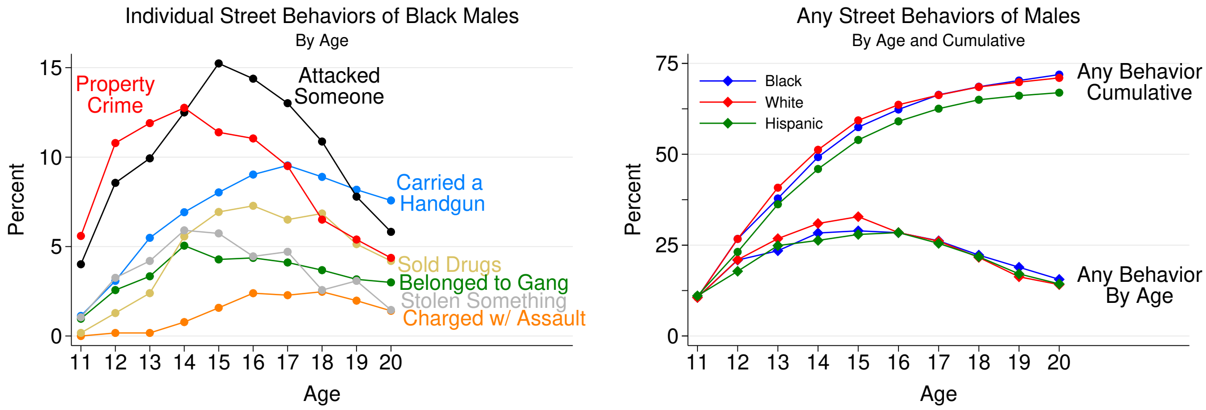
We begin by leveraging the repeated observations in the NLSY97 as evidence regarding selection on unobservables. We observe exposure to violence during respondents' childhood (ages 0-11) and adolescence (ages 12-18) together with observations on respondents' violent behavior. If the respondents who are exposed to violence in childhood are the same respondents exposed to violence in adolescence, and this same group of respondents is the group most likely to engage in violent behavior, this would be evidence in favor of the selection on unobservables hypothesis. In this case, we would conclude that the correlation between exposure and behavior is driven by an unobserved type of respondent predisposed for both exposure to violence and violent behavior.

In the subsequent analysis we use S^v_{15} to denote an indicator for violent street behavior at age 15, measured by either having carried a gun, attacked or assaulted someone, or belonged to a gang. And S^n_{15} is an indicator for non-violent street behavior at age 15, which includes any behavior such as breaking the rules of one's school, selling drugs, stealing, committing a property crime, or engaging in non-violent, illegal behavior.[8]

The descriptive evidence is inconsistent with the selection on unobservables hypothesis. Violent and non-violent street behaviors increase considerably over adolescence (Figure 7). Recall from Table 1, however, that exposure to violence increases only slightly in adolescence relative to childhood.[9] An unobserved "violent" type of respondent should either have uniformly high exposure and violent behavior, or else their exposure to violence should increase as they age along with their violent behavior. Perhaps most importantly, referring again back to Table 1, the respondents exposed to violence during adolescence are typically different than the respondents who are exposed to violence during childhood.

[8] The violent and non-violent "street" labels come from Anderson (1999) and the classifications are from Aliprantis (2017b). Respondents self-report if they have helped to sell illegal drugs, if they have stolen more than \$50, if they have committed any property crimes, as well as if they have been suspended from school or arrested for a non-violent offense.

[9] Appendix C displays each specific street behavior by age and race/ethnicity, where we find that Black males are more likely to have attacked someone or belonged to a gang, but white males are more likely to have committed a property crime or sold drugs.



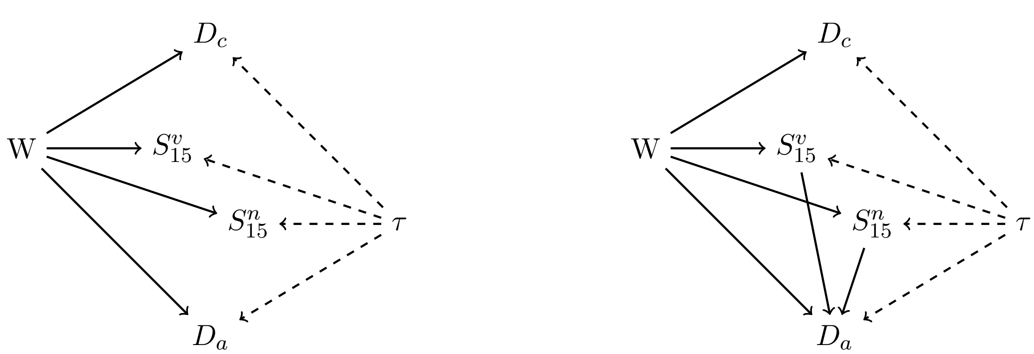
(a) Street Behaviors by Age

(b) Street Behaviors by Age and Race/Ethnicity

Figure 7: Street Behaviors by Age

Note: The left panel shows the percent of Black males engaged in specific behaviors at a given age. The right panel shows the percent of males who engaged in any of these behaviors at a given age by race and ethnicity, where the Black and white groups are both non-Hispanic. The right panel also shows by age the cumulative percent of males within each racial or ethnic group who engaged in at least one of these behaviors.

Turning to the formal estimation of finite mixture models, Figures 8a and 8b show Directed Acyclic Graphs (DAGs) of the models we estimate. Recall that D_c is an indicator for childhood exposure to violence, measured by respondents' self-reporting of seeing someone shot or shot at while aged 11 or younger. D_a is an indicator for adolescent exposure to violence, measured by respondents' self-reporting of seeing someone shot or shot at while aged 12-18. As described just above, S^v_{15} is an indicator for violent street behavior at age 15 and S^n_{15} is an indicator for non-violent street behavior at age 15. Observed characteristics W remain mother's educational attainment at the time of the first survey, household structure at the time of the first survey (two parents (both biological); two parents (one biological); single parent; grandparent(s); or other), and parental income at the time of the first survey.



(a) Model 4

(b) Model 5

Figure 8: Permanent Unobserved Heterogeneity and Repeated Observations

Model 4 assumes that all of the correlation between exposure to violence and violent behavior is driven by selection on unobservables. In this model exposure to violence reflects the fact that one has a personality trait making one more likely to engage in violent or non-violent street behavior at age 15. Model 5 assumes that all of the correlation between *childhood* exposure to violence and violent behavior is driven by selection on unobservables. In this model exposure to violence still does not cause violent behavior. However, while childhood exposure to violence remains a reflection of the fact that one has the personality trait making one more likely to engage in violent or non-violent street behavior at age 15, *adolescent* exposure to violence could reflect this selection either directly or through the mediator of age 15 street behaviors, whether violent or non-violent.

In both models we assume unobserved heterogeneity takes finite support, so that the unobserved types are $\tau \in \{1, 2, 3\}$, and then estimate latent indexes where each type has its own intercept terms in the latent indexes. This approach has successfully captured permanent unobserved heterogeneity in a range of applications (Heckman and Singer (1984), Keane and Wolpin (1997), Cameron and Heckman (1998), Hotz et al. (2002)).

Table 4 reports the results of estimating these models. The estimation results do not support a theory that permanent unobserved heterogeneity drives selection into exposure to violence and violent behavior.

Table 4: Models 4 and 5 Estimation Results

	Type-Specific Predictions					
	Model 4			Model 5		
	$\tau = 1$	$\tau = 2$	$\tau = 3$	$\tau = 1$	$\tau = 2$	$\tau = 3$
$Pr(\tau)$	74	26	1	80	9	11
100 $\times$						
$\mathbb{E}[D_c \vert \tau]$	31	15	100	30	8	20
$\mathbb{E}[S^v_{15} \vert \tau]$	0	75	69	10	91	79
$\mathbb{E}[S^n_{15} \vert \tau]$	42	2	16	33	57	38
$\mathbb{E}[D_a \vert \tau]$	2	96	0	21	93	45
N	987			987		
$\mathcal{LL}$	–2,269.1			–2,291.1		

Note: For both Model 4 and Model 5, all predictions $\mathbb{E}[\cdot \mid \tau]$ are evaluated using parameter estimates and modal mother's educational attainment (HS Diploma), modal household type (single parent), and mean parental income. For Model 5, predictions for adolescent exposure to violence, $\mathbb{E}[D_a|\tau]$, are evaluated at the type-specific predicted mode of age 15 violent and non-violent street behaviors.

In neither Model 4 nor in Model 5 is the type for which childhood exposure to violence the highest also the type for which adolescent exposure to violence the highest. In Model 4 the types for which childhood exposure is highest, Type 1s, engage in no violent behavior at age 15. Moreover, the estimates produce the bizarre result that types are almost perfectly inclined to either violent or non-violent street behavior at age 15.[10] In Model 5 we again see that the type least exposed to

[10]We do not focus attention on Type 3 individuals in Model 4 because they are estimated to make up only 0.6 percent of the overall population of Black males.

violence in childhood, Type 2s, are those most likely to engage in violent behavior. And again in Model 5, the type least exposed to violence in childhood, Type 2s, are those most likely to be exposed in adolescence.

3.2 Using Personality Traits to Proxy for Permanent Unobserved Heterogeneity

Another way of testing for the presence of unobserved confounders is to adjust for measures proxying potential confounders, such as personality traits. The NLSY97 contains a range of variables measuring personality traits, with the survey questions of the form "How much do you feel that *trait x* describes you as a person?" where *trait x* includes *conscientious*, *agreeable*, *disorganized*, *thorough*, *difficult*, *stubborn*, *trustful*, or *undependable*. Respondents are asked to give an answer on a scale from 1 to 5; for example, they are instructed to answer "Where 1 means not conscientious and 5 means conscientious." To increase the power of this analysis, we also create an index that is the sum of all of these questions (where each is coded so that 1 represents a negative personality trait and 5 is a positive trait).

We assess the importance of personality traits by estimating the short and long regressions:

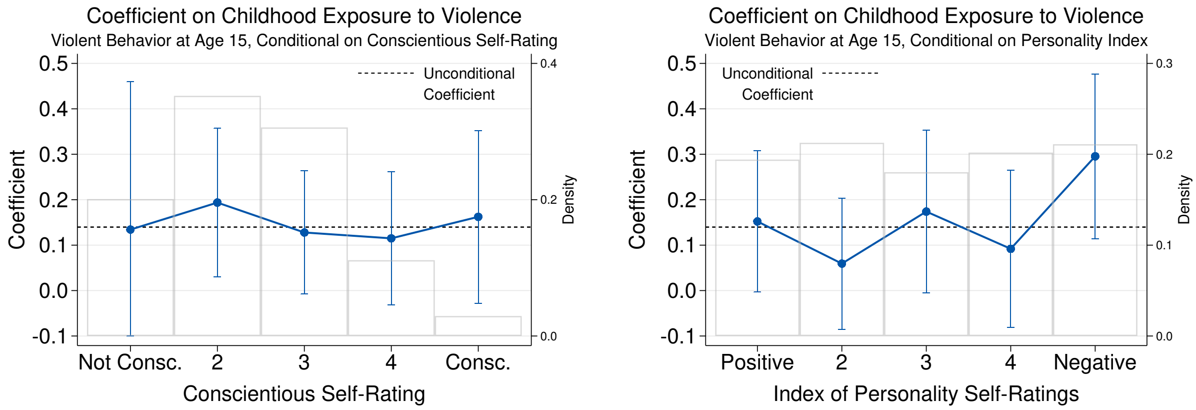
$$S^v_{15,i} = \beta_0 + \beta_1 D_{c,i} + \varepsilon_i \tag{Short}$$

$$S^v_{15,i} = \beta^p_0 + \beta^p_1 D_{c,i} + \varepsilon^p_i \tag{Short-Conditional}$$

$$S^v_{15,i} = \beta_0 + \beta_1 D_{c,i} + \beta_2 P_i + \varepsilon_i \tag{Long}$$

where S^v_{15} is an indicator for engaging in violence at age 15, D_c is an indicator for childhood exposure to violence, and P is a measure of personality traits. The Short-Conditional regressions are estimated conditional on P taking value p, and we estimate all regressions via Ordinary Least Squares (OLS) as linear probability models. If post-treatment personality traits are not affected by treatment and Model 3 most accurately describes the DGP, then the coefficient on D_c will fall to 0 in the Short-Conditional and Long regressions.

Figure 9 presents evidence against selection on personality traits. The gap in violent behavior at age 15 is not highly correlated with either conscientiousness or the full index of personality traits. Figures 9a and 9b both show that the estimated coefficients on childhood exposure to violence in the Short-Conditional regressions are close to the coefficient of 0.140 from the Short regression.



(a) Conscientiousness

(b) Personality Index

Figure 9: Violent Behavior at Age 15, Conditional on Conscientiousness and Personality Index
Note: The blue dots in this figure show the coefficients of a regression of an indicator for violent behavior at age 15 on childhood exposure to violence, conditional on each respondent's self-reported personality trait. The blue vertical lines show 90 percent confidence intervals for those coefficients. The dashed black horizontal line shows the coefficient on childhood exposure to violence unconditional on each respondent's self-report. The rectangles outlined in grey report the probability mass function of respondents in the sample, which is Black males in the NLSY97 who were administered the personality trait questions. In the left panel the self-reported variable is conscientiousness, which is self-reported in the 2003 survey, when respondents were aged 18-22. In the right panel the variable is the index of all personality trait questions, including all 8 variables described in the text focused on whether respondents are *conscientious*, *agreeable*, *disorganized*, *thorough*, *difficult*, *stubborn*, *trustful*, or *undependable*.

There are large standard errors around the Short-Conditional regression coefficients, in part due to the small sample sizes conditional on specific levels of personality traits, in part due to the fact that personality trait questions in the NLSY97 were only asked of a subsample of respondents. Given these noisy point estimates from the Short-Conditional regression specifications, an alternative approach to assessing the importance of personality traits is to compare the stability of the coefficient on childhood exposure to violence across the Short and Long regressions. This approach also finds little evidence that the correlation between violent behavior and exposure to violence is driven by personality traits behaving as an unobserved confounder. Table 5 reports the coefficients on childhood exposure to violence D_c for the Short and Long regressions specified above. In the Long regressions, the personality traits P are either a quadratic of the index constructed by adding all variables together (second column), or else a quadratic in each component of the index (column 3). What we can see is that the coefficient on D_c changes extremely little across the specifications. While the coefficient in the Short regression is 0.140, this only declines to 0.138 in the Long regression with the full index and only changes to 0.134 in the Long regression with each personality trait that is a component of the index.

Table 5: Stability of Coefficient on Childhood Exposure to Violence after Adjusting for Personality Traits

	Regression Specification		
	Short	Long	
		Index	Components
Coeff. on D_c	0.140	0.138	0.134
	(0.038)	(0.038)	(0.038)
N	622	622	622

Note: This table reports the coefficients when violent behavior at age 15 is regressed on childhood exposure to violence, with standard errors reported in parentheses. The first column is the short regression with exposure alone. The second column is the long regression that includes a quadratic of the index of personality traits. The third column is the long regression that includes a quadratic of each component personality trait of the index. The last row reports the sample size of Black males in the NLSY97 who were asked the personality trait questions.

We make two notes before concluding the analysis using personality traits. First, it is important to point out that the interpretation of the just-presented analysis is complicated by the fact that these variables are measured post-treatment: Personality traits are self-reported in the 2003 wave of the NLSY97, when respondents are aged 18-22. Thus, while personality traits like conscientiousness are predictive of criminal activity (O'Riordan and O'Connell (2014)) and appear relatively stable over adolescence and young adulthood (Elkins et al. (2017)), it is possible these variables could themselves be affected by the treatment of childhood exposure to violence. Second, we point interested readers to Appendix E for the full set of results based on all of the personality trait questions in the NLSY97. Appendix E also reports results based on related questions, such as whether a respondent believes they will be arrested at least once in the next year (whether rightly or wrongly); respondents' age at first sex; and whether respondents' fathers were imprisoned before the respondent turned 16.

3.3 Using c-Dependence to Test for Sensitivity to Selection on Unobservables

As a final approach to studying the robustness of our results, we follow Masten et al. (2023) to use assumptions about selection on unobservables in the form of c-dependence.[11] We use Masten et al. (2023)'s *tesensitivity* package in Stata to estimate breakdown frontiers for each outcome we investigate. Each breakdown frontier we consider is the maximum value of c for which c-dependence

[11]Masten et al. (2023) themselves build on a body of work in Masten and Poirier (2020), Masten and Poirier (2018), and Horowitz and Manski (1995); Appendix A of Masten and Poirier (2020) provides a discussion of this literature.

implies that the sign of the treatment effect's Manski (1990) bounds are of the same sign as the estimated treatment effect. Thus, the breakdown points for each outcome, $c^*(Y)$, allow us to judge the robustness of our estimates by quantifying the weakest assumption about selection on unobservables under which the estimated treatment effect keeps its sign.

While the breakdown points for each outcome, $c^*(Y)$, give us a means of judging the robustness of our estimates, this judgment remains subjective. Masten et al. (2023) suggest an approach, broadly following the approaches in Altonji et al. (2005) and Oster (2019), of comparing breakdown points representing a scalar summary of selection on unobservables with measures of the degree of selection on observables. For this purpose Masten et al. (2023) focus on the distribution of selection on observables when one variable is omitted from the estimation of the propensity score, defining Δ_{ki} as the change in individual i's propensity scores when the single observable variable w_k is left out of the specification of the propensity score.

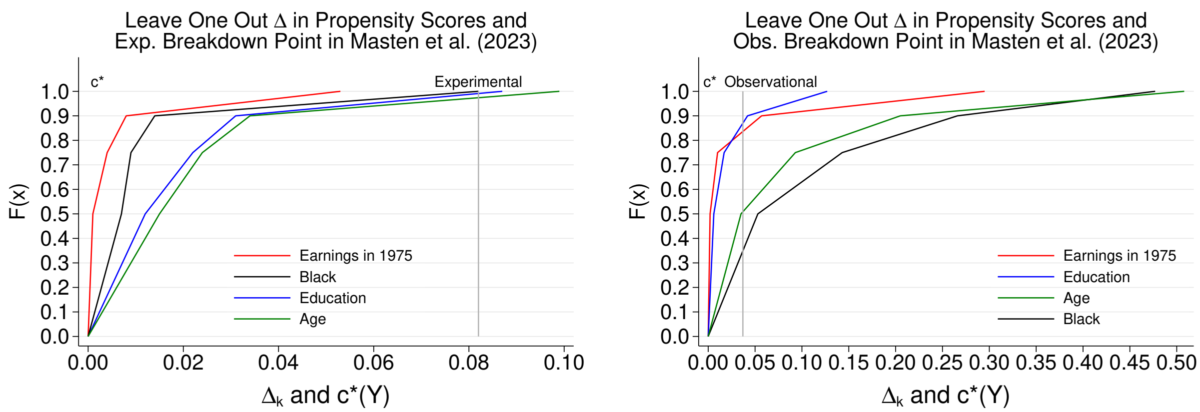
Figures 10a and 10b provide a concrete example of comparing breakdown points to the distribution of leave-one-out propensity scores. Masten et al. (2023) consider The National Supported Work (NSW) demonstration as an example in which an estimate on an experimental sample is broadly robust and an estimate on an observational sample is generally not robust. Comparing the gray vertical line in Figure 10a with the Cumulative Distribution Functions (CDFs) of changes in propensity scores from leaving out an observable shows that the breakdown point for the experimental sample is far in the right tail of leave one out changes. Making the same comparison in Figure 10b shows that the breakdown point for the observational sample is either in the middle or even in the left tail of leave one out changes for two observables. Figures 10a and 10b therefore provide a sense for what evidence suggests robust estimates.

Figures 10c and 10d then show our estimates for a few key outcomes. Recall from the discussion of Figures 10a and 10b that the further right a breakdown point is in the CDFs in these figures, the more robust a treatment effect estimate is. Respondents are included in the short-run sample if their BA attainment is observed, and they are included in the long-run sample if their earnings in 2018 are observed.[12]

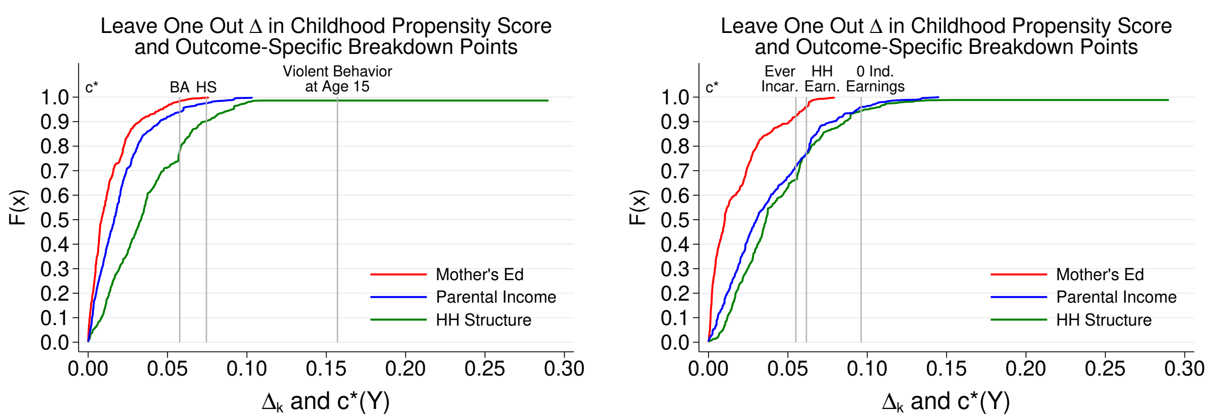
Looking at short-run outcomes in Figure 10c, we find that the effects of childhood exposure to violence are robust for educational attainment and extremely robust for engaging in violent behavior at age 15. This robustness is evidence that the correlation between childhood exposure and violent behavior is more likely the result of pre-emptive violence driven by fear (O'Flaherty and Sethi (2019)) than youth who are inherently more violent selecting into both exposure and behavior. The least robust educational outcome, attaining a BA, is robust at a cutoff of the 90th percentile for mother's educational attainment and parental income and at the 75th percentile for

[12]This is a slight variation from the approach in the *tesensitivity* package. The package computes outcome-specific breakdown points using the subsample of units observed for each outcome, which are the breakdown points we use here. However, the package also computes the distribution of Δ_{ki} for each outcome separately using the outcome-specific subsample. We compare the distribution of Δ_{ki} estimated on one sample to the breakdown points estimated for several specific outcomes to facilitate the comparison of breakdown points across multiple outcomes. Also note that all of these calculations are made on the sample with common support discussed earlier.

household structure.



(a) Experimental Breakdown Point in Masten et al. (2023) (b) Observational Breakdown Point in Masten et al. (2023)



(c) Breakdown Points of Short-Run Outcomes (d) Breakdown Points of Long-Run Outcomes

Figure 10: Breakdown Points and Changes in Childhood Exposure Propensity Scores
Note: In these figures vertical lines represent outcome-specific breakdown points, which are described in the main text. The CDFs represent the individual-level distribution of changes in the propensity score when one variable or set of indicator variables is removed from the estimation of the propensity score. In the top left panel, the knots are taken from Table 5 of Masten et al. (2023) and in the top right panel the knots are taken from Table 3. In the bottom left panel, holding a high school diploma ("HS") or attaining a BA ("BA") are measured when the respondent is aged 26. In the bottom right panel, individual earnings ("Ind. Earnings") and household earnings ("HH Earnings") are measured in the 2019 wave of the survey regarding their values in 2018, when respondents were aged 34-38. "Ever Incar." is an indicator for whether a respondent was ever incarcerated by the time of the 2019 survey. See the text for more details on each variable.

Looking at long-run outcomes in Figure 10d, we find that the effects are slightly less robust than are the short-run outcomes. Household earnings are reasonably robust; the breakdown point is around either the 75th or 90th percentile for all variables. The most robust result is for 0 individual earnings, which is beyond the 90th percentile for all variables, and which is notable given the importance of non-work (Thompson (2021); Aguiar et al. (2021)).

4 Mechanisms Related to Childhood Exposure to Violence

4.1 Are Our Estimates of Effects of Exposure to Violence Really Effects of Overall Neighborhood Conditions?

Our analysis has interpreted the treatment effects of exposure to violence as being caused by the exposure itself. But an alternative possibility is that witnessing a shooting during childhood indicates that a respondent grew up in a neighborhood that negatively affected their outcomes through other mechanisms. In this case, the effects we observe could ultimately be caused by the respondent's exposure to the broader neighborhood context rather than his exposure to violence (Aizer (2009); Perry et al. (2015)).

Here we investigate the possibility that the effects of exposure to violence reflect the effects of more general neighborhood conditions, motivated by the strong correlation between exposure to violence and neighborhood socioeconomic characteristics. To measure the key neighborhood characteristics thought to affect residents, we first calculate a tract-level ranking of neighborhood socioeconomic status (SES) following Aliprantis (2017a) and Aliprantis and Richter (2020). The neighborhood SES measure is the percentile ranking of the first principal component of a tract's national rankings on six socioeconomic characteristics. The six characteristics used to calculate neighborhood SES are the poverty rate, the share of adults 25+ with a high school diploma, the share of adults 25+ with a BA, the Employment to Population Ratio for adults 16+, the labor force participation rate for adults 16+, and the share of families with children under 18 with only a mother or father present.

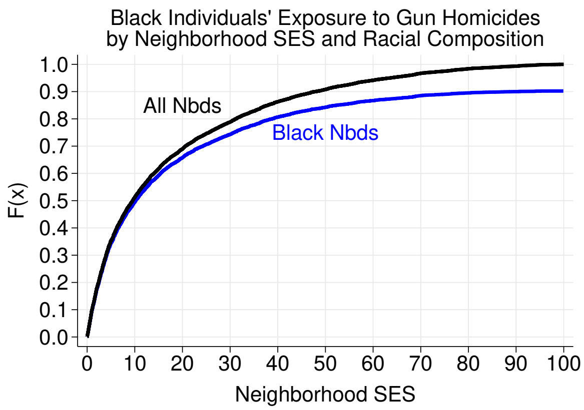
To understand the relationship between neighborhood SES and exposure to violence, we first use neighborhood SES estimated on the 2014-2018 ACS together with geolocated data on gun homicides from 2013 to 2018 from the Gun Violence Archive (GVA). The GVA is an independent organization that does research and collects data on gun violence in the United States with the goal of providing detailed and accessible data on all gun-related injuries, deaths, and crimes. The GVA collects and verifies daily data from over 7,500 sources that include local and state police, media, data aggregates, government, and other sources. Geolocations allow us to match incidents to Census tracts. We provide additional analysis of GVA data in Appendix G.

Black Americans' exposure to violence is highly concentrated in the lowest SES neighborhoods. We first show this fact using the GVA data on gun homicides before showing this fact with the NLSY97 data on witnessing a shooting. We use the GVA to create a tract-level measure of Black Americans' exposure to gun homicides,

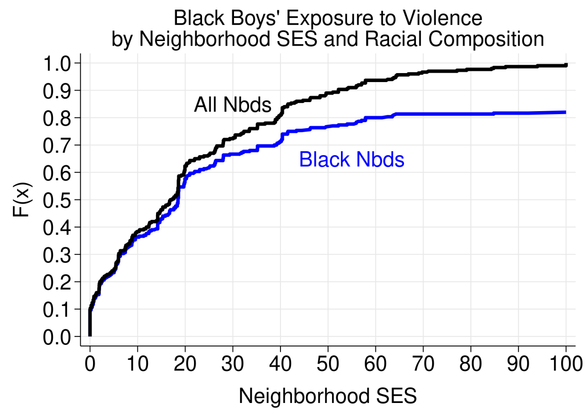
$$\text{exposure to gun homicides in tract } j \;=\; \#\text{ of Black residents in tract } j \;\times\; \#\text{ of gun homicides in tract } j.$$

Figure 11a shows CDFs of Black Americans' exposure to gun homicides by their tract's SES ranking. Half of Black individuals' exposure to gun homicides is experienced in the bottom decile of neighborhood SES. An additional 20 and 10 percent of exposures are added, respectively, in the second and third deciles.

There is an important interaction between gun homicides, neighborhood SES, and racial composition. This is evident from the red and blue lines in Figure 1b, which shows that there is a level effect with Black neighborhoods experiencing higher homicide rates even conditional on neighborhood SES (Cheon et al. (2020)). Figure 11a shows that about 90 percent of Black individuals' exposure to violence occurs in neighborhoods where at least 20 percent of the residents are Black. This implies that there are important aspects of neighborhood-level public safety that are race specific, both in terms of neighborhood sorting (Aliprantis et al. (2022), O'Flaherty and Sethi (2007)) and public policy (Sylvera (2023), O'Flaherty and Sethi (2010)).



(a) GVA and ACS Data



(b) NLSY97 and ACS Data

Figure 11: Black Americans' Exposure to Violence by Neighborhood SES
Note: The left panel shows the cumulative exposure of Black residents to gun homicides in their Census tract by their tract's neighborhood SES ranking. The right panel shows the cumulative exposure of Black males in the NLSY97 to witnessing a shooting during their childhood by their initial tract's neighborhood SES ranking.

Similar patterns hold when using shootings witnessed in the NLSY97 or gun homicides in the GVA as our measure of exposure to violence. This consistency is important because there are many ways of measuring exposure to violence (Bancalari et al. (2022)). Figure 11b plots CDFs of Black respondents' reporting witnessing a shooting by their tract's SES ranking in the first wave of the NLSY97 (See Appendix B.1 for data on the calculation of neighborhood SES in 1997.). The CDFs show that 40 percent of the Black male respondents in the NLSY97 who witnessed a shooting lived in the first decile of neighborhood SES. About 20 percent more of the shootings were witnessed by someone living in the second decile of neighborhood SES, and by the 30th percentile of neighborhood SES about three-quarters of shootings had been witnessed.

We note three key differences between the measures of exposure to violence in Figures 11a and 11b. First, the GVA is for all Black individuals, while the NLSY97 measure is only for Black males aged 11 or younger. Second, the GVA measures both the intensive and extensive margins of exposure, while the NLSY97 variable only measures the extensive margin. Third, the GVA measures exposure at the same time residents are recorded in tracts in the ACS, while the exposure measured in the NLSY97 occurred when respondents were aged 0-11 and their tract of residence in 1997 was measured at the time of their first interview, when the respondents were primarily aged 12-16 (Six percent were either 17 or 18 when first interviewed.).

Given the high concentration of Black men's childhood exposure to violence in neighborhoods with the lowest SES, it would seem plausible that the treatment effects estimated earlier in the paper are driven by neighborhood conditions other than violence. Figure 12 shows, however, that the effects of Black men's childhood exposure to violence are independent of neighborhood SES. Regardless of their childhood neighborhood's SES ranking, the household earnings of Black men in their late 30s who were exposed to violence as children are considerably lower than those of the men who were not exposed to violence during their childhood.

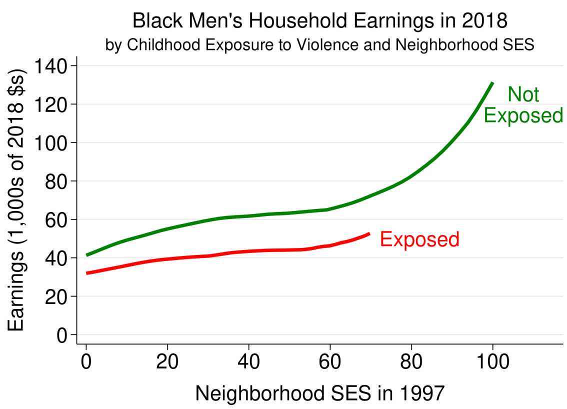


Figure 12: Black Men's Household Earnings by Exposure to Violence

Note: This figure shows local linear regressions of household earnings in 2018 on neighborhood SES in 1997 for Black men who did, and did not, witness a shooting during their childhood.

Table 6: Regression Coefficients with and without Decile of Childhood Neighborhood SES

Dependent Variable	With	Without
HH Earnings	–17.4	–16.8
(Thousands of 2018 $s)	(4.6)	(4.5)
HS	–17.6	–16.5
	(3.2)	(3.2)
BA	–5.6	–4.9
	(1.9)	(1.9)
Incar.	10.5	10.3
	(2.9)	(2.9)

Note: Regression coefficients represent percentages unless otherwise noted.

Table 6 expands on this analysis to present regression results and to include additional outcomes. We see that the coefficients on childhood exposure change very little when the regressions include indicators for deciles of neighborhood SES. This is true for household earnings, attainment of a high school diploma or BA, and ever being incarcerated by 2019.

4.2 Are Effects of Exposure to Violence Mediated by Incarceration?

Incarceration is critical for understanding the labor market outcomes of Black men in recent decades (Bayer and Charles (2018); Neal and Rick (2014)). A single spell of incarceration has a permanent lifetime effect that flattens the earnings of young men, Black or white (Neelakantan et al. (2022)). Given this evidence, together with the evidence in Table 3 that childhood exposure increases incarceration rates, we might expect that the effects of childhood exposure to violence on labor market outcomes are mediated through incarceration.

Perhaps surprisingly, then, Table 7 and Figure 13 show that incarceration does not mediate the effects of exposure to violence on adult household earnings. Table 7 displays regression results that those exposed to violence during their childhood (ie, before age 12) had household earnings in 2018 that were $17,000 lower than those who were not exposed to violence. This gap only shrinks by 13 percent, to $15,000, when conditioning on ever experiencing a spell of incarceration. Figure 13 shows that for the never incarcerated group, shown in green, the gap in earnings between exposure groups grows steadily as the cohort ages. The gap is smaller for those who have experienced incarceration, shown in red, and later years might be interpreted as statistical noise. However, the dip and rebound in respondents' late 20s reflects the state of the labor market during the Great Recession, and the mid-20s pre-Great Recession gap between exposure groups indicates that earnings truly are higher for those not exposed.

Table 7: Household Earnings

Independent Variable	Coefficient in Earnings Regression		
Childhood Exposure	–17.4 [0.00]		–15.2 [0.00]
Ever Incarcerated		–33.8 [0.00]	–33.3 [0.00]
R^2	0.02	0.06	0.07

Note: This table reports coefficients from regressions where the dependent variable is Black men's household earnings in 2018 and the independent variables are dummies for childhood exposure to violence alone (first column), ever being incarcerated alone (second column), or both (third column). Values in brackets are the p-values associated with each coefficient being different from zero.

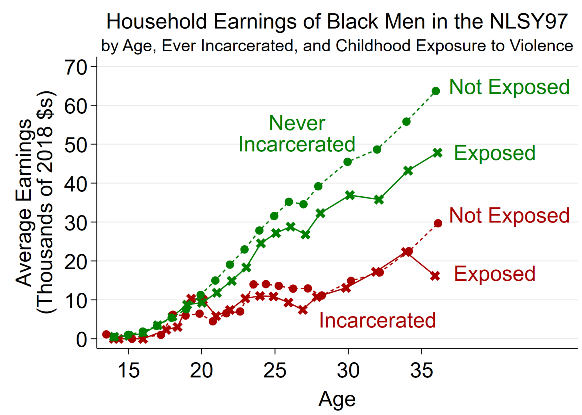


Figure 13: Household Earnings by Age, Childhood Exposure to Violence, and Incarceration
Note: This figure shows the means of Black men's household earnings by the average age in the wave of the NLSY97 for each of four groups. Those groups are the four combinations of the binary indicators for childhood exposure to violence and ever being incarcerated.

Appendix H shows similar results for both individual earnings and for the probability of earning zero dollars in a given year, with the gap between exposure groups again clearer for the never incarcerated group.

4.3 Are Effects of Exposure to Violence Capturing Gang Activity?

We know that children could be exposed to violence through the crime created by gangs (Bruhn (2021); Monteiro and Rocha (2017)), as well as the police response in trying to reduce gang behavior (Wagner (2021)). A natural question, then, is whether our estimated effects of exposure to violence capture the effects of exposure to gang activity. In addition to exposure to violence, the NLSY97 also asks questions about exposure to gang activity. We have data on how many respondents reported living in a neighborhood with gangs by the age of 18, the percent of the respondent's peers who they report were in gangs in 1997, and whether the respondent had siblings or close friends who were in gangs from 1997 to 2005.

Exposure to violence and exposure to gang activity are not perfectly correlated for Black males in the NLSY97. Figure 14 shows that while there is a correlation between seeing someone shot and peers in a gang, among those who saw someone shot, the majority still report that few peers belong to a gang.

Exposure to violence and exposure to gang activity also appear to have distinct effects for Black males in the NLSY97. Table 8 shows the results of multivariate regressions of outcomes on an indicator for childhood exposure to violence and indicators for the percentage of peers reported to belong to a gang. The reference group in these regressions is the group of Black men who did not see someone shot and who reported that less than 10 percent of their peers belonged to a gang. If seeing someone shot during childhood was purely capturing gang activity, we would expect its coefficient to go to zero when conditioning on the percent of peers in a gang. However, for all outcomes, the coefficient remains both statistically and economically significant. For most outcomes, seeing someone shot during childhood is correlated at a similar magnitude as reporting that between 75 and >90 percent of peers belong to a gang. The transition from <10 to approximately 25 percent of peers belonging to a gang does very little to most outcomes, while the transition to 50 percent of peers belonging to a gang tends to result in a large negative change in outcomes. Outcomes tend to be monotonically improving as the percentage of peers in a gang decreases.

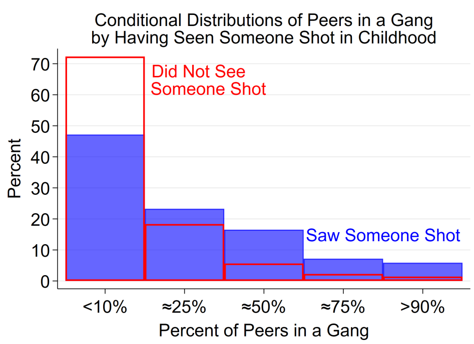


Figure 14: Exposure to Gang Activity by Exposure to Violence
Note: This figure shows the percent of peers that respondents reported belonging to a gang conditional on whether the respondent reported childhood exposure to violence.

Table 8: Gangs and Childhood Exposure to Violence

Outcome	Ref. Mean	Seen Shot	Peers in Gangs ≈ 25%	≈ 50%	≈ 75%	> 90%
Violent at 15 (%)	16	17	−1	−0	4	21
		[0.00]	[0.99]	[0.99]	[0.42]	[0.00]
HS Diploma (%)	67	−16	6	−3	−11	−19
		[0.00]	[0.54]	[0.54]	[0.06]	[0.00]
BA (%)	12	−5	0	−5	−6	−10
		[0.02]	[0.08]	[0.08]	[0.09]	[0.01]
Incarcerated (%)	21	9	1	5	5	16
		[0.00]	[0.20]	[0.20]	[0.32]	[0.01]
Earnings ($1,000s)	43	−10	−2	−12	−11	−20
		[0.01]	[0.01]	[0.01]	[0.11]	[0.01]
HH Earnings ($1,000s)	61	−15	−4	−18	−18	−29
		[0.00]	[0.01]	[0.01]	[0.05]	[0.00]

Note: This table reports coefficients from regressions of outcomes on indicators for childhood exposure to violence and reported percent of peers in a gang. The reference group is Black men who were not exposed to violence during childhood and who reported that less than 10 percent of their peers were in a gang in the 1997 wave of the NLSY97. Values in brackets are the p-values associated with each coefficient being different from zero.

5 Mechanisms Related to Adolescent Exposure to Violence

5.1 Toxic Stress and Nurturing Relationships

By the process of elimination, the results of Section 2 point to the psychological costs and trauma of childhood exposure to violence as being the primary mechanism generating long-run effects on the outcomes of Black men. The effects of witnessing a shooting before age 12 do not appear to be driven by selection on observables (Section 2.4) or selection on unobservables (Section 3). Nor do the effects of this childhood exposure to violence appear to represent broader neighborhood effects (Section 4.1), to be mediated by incarceration (Section 4.2), or to proxy for gang activity (Section 4.3).

We consider psychological costs to be a plausible mechanism for generating the effects we estimate. The psychological costs of navigating violent environments have been described as large by those who have experienced them (Coates (2015)).[13] And many Black males have described the inability of escaping the violence in their neighborhoods (Canada (1995)).[14]

The importance of psychological costs from exposure to violence is also consistent with the large literature on toxic stress responses. Garner and Yogman (2021) define toxic stress as the "wide array of biological changes that occur at the molecular, cellular, and behavioral levels when there is prolonged or significant adversity in the absence of mitigating social-emotional buffers." The literature on toxic stress originated in the study of Adverse Childhood Experiences (ACEs, Felitti et al. (1998)), which found that childhood exposures to abuse, neglect, and household dysfunction were correlated with long-run outcomes experienced many years later in adulthood.[15,16] Focusing on stress responses, which can be measured in objective, biological terms, a range of studies has found that stress affects developing brains' neural function and structure (McLaughlin et al. (2019)); biologically embeds childhood adversity for life by activating neuro-immuno-endocrine systems (Soares et al. (2021)); and alters developmental trajectories as a key component of the epigenetic

[13]Coates recalls that during his childhood "each day, fully one-third of my brain was concerned with… securing the body. … I think I was always, somehow, aware of the price. I think I somehow knew that that third of my brain should have been concerned with more beautiful things" (p 24).

[14]Canada describes this pervasiveness in terms of a friend: "In many ways he was a reluctant warrior. Bigger than everybody else but gentle, Melvin seemed to reflect the basic conflict that most of the young men struggled with – how to be decent and yet get respect from those who weren't." (Canada (1995), p 51) In a similar vein, Anderson (1999) writes that "Whatever a boy's home life is like, growing up in the 'hood means learning to some degree the code of the streets, the prescriptions and proscriptions of public behavior. He must be able to handle himself in public, and his parents, no matter how decent they are, may strongly encourage him to learn the rules." (p 114) The pervasiveness of violence in certain public spaces creates the need to "become proficient on the streets and accumulate a certain amount of capital. This kind and form of capital is not always useful or valued in the wider society, but it is capital nonetheless. It is recognized and valued on the streets, and to lack it is to be vulnerable there." (p 105)

[15]Findings on ACEs parallel those from the literatures on *in utero* nutrition (Barker et al. (1989); Almond and Currie (2011)), early childhood deprivation (Mackes et al. (2020); Tottenham et al. (2010)), and early childhood education (García et al. (2023); Bailey et al. (2021)). In addition to the literature reviews cited in the text, see Tough (2018) for discussions of several strands of related literature.

[16]Many researchers, such as Rajan et al. (2019) and Finkelhor et al. (2013), advocate for exposure to violence to be classified as a type of ACE. Similar to other ACEs, exposure to violence is associated with symptoms of trauma, post-traumatic stress, and diminished long-run health outcomes (Turner et al. (2021); Thompson and Massat (2005); Ford and Browning (2014)).

dance between the environment and the expression of one's genes (Boyce et al. (2021)).

Stressors need not lead to a toxic stress response, though, and this is why we turn our attention to nurturing relationships. Shonkoff and Garner (2012) and Scientific Council (2014) identify three broad categories of stress responses that are a function of stressors in combination with the social and emotional buffers to which individuals have access. Brief and mild stressors tend to lead to *positive* stress responses when youth are guided by a caring and responsive adult. Even longer and more severe stressors can lead to *tolerable* stress responses where stress response systems return to their baseline, as long as youth are guided by a caring and responsive adult. What is typically needed to generate *toxic* stress responses is frequent or prolonged exposure to severe stressors in the absence of social or emotional buffers. Looking across the literature on stress responses, Garner and Saul (2018) thus conclude that "From a neuroscience perspective, ... the antidote to early childhood adversity and toxic stress... is safe, stable, and nurturing relationships" (p 46). Garner and Yogman (2021) reason that this is because nurturing relationships "turn off the body's stress machinery in a timely manner" (p 2), before this machinery can generate biological changes that are maladaptive and health harming over the long run.[17]

5.2 Measuring Exposure to Violence and Nurturing Relationships

The following analysis quantifies how combinations of violent stressors and social/emotional buffers during adolescence lead to long-run outcomes for Black men. The reason for our focus on adolescence is that the NLSY97 does not have a great deal of information on exposure to violence and Nurturing Relationships (NRs) during respondents' early childhood years beyond the variables studied in Section 2. However, the NLSY97 does contain a rich set of variables on exposure to violence and Nurturing Relationships (NRs) during respondents' adolescence. These variables are displayed in Table 9.

How should we go about synthesizing the information from these variables? For the sake of exposition the following discussion is focused on exposure to violence. Many related studies create an index or score that is simply the sum of having each type of specific experience. For example, if a measure of exposure to violence V^j is experienced by individual i, then $V_i^j = 1$, otherwise $V_i^j = 0$. An index using the sum of measured variables, analogous to the ACE score, would be

$$\theta_i^{Sum} = \sum_{j=1}^{J} V_i^j.$$

Alternatively, one might consider using Item Response Theory (IRT) to estimate the value of a latent index θ_i^V most likely to produce an individual's response pattern to the variables $V_1, \ldots, V_J$. In this case, we would assume that each item V_i^j is associated with parameters (α_j, β_j) and an

[17] Recent evidence indicates that nurturing relationships are important for youth development even in the absence of adversity (Bethell et al. (2019a), Bethell et al. (2019b)).

Table 9: Measures of Adolescent Exposure to Violence and Nurturing Relationships in the NLSY97

Exposure to Violence	**Nurturing Relationships**
saw someone shot or shot at^1	about both the resident mother and father, whether^2
had home broken into^1	each is residing with the respondent
victim of repeated bullying^1	respondent thinks highly of them
victim of a violent crime^1	respondent thinks they want to be like them
siblings or friends were in a gang^1	respondent really enjoys spending time with them
percent of peers belong to gang^2	they often criticize the respondent or their ideas
got into a physical fight at school^2	respondent thinks they are supportive
something of value stolen at school^2	they often help the respondent
threatened to be hurt at school^2	they blame the respondent for their problems
felt unsafe at school^2	they often cancel plans with the respondent
days/week typically hear gunshots^2	they know a lot about the respondent's friends
	they know the parents of the respondent's friends
	they know details when respondent not at home
	they often praise the respondent
	whether school's teachers are^2
	interested in the students
	good
	whether other students get in the way of learning^2
	percent of peers who^2
	cut class or skip school
	plan to go to college

Note: 1 indicates variable is measured between ages 12 and 18 (over multiple waves of the NLSY97 survey).
2 indicates variable is measured in wave 1 of the NLSY97 survey, asked only of those respondents aged 14 and younger at the time of the interview.
Violent crime includes physical or sexual assault, robbery, or arson.
Questions about percentages of peers allow for responses in five discrete bins (less than 10 percent; approximately 25, 50, or 75 percent; or more than 90 percent).

error distribution ϵ_i^j governing positive responses as

$$V_i^j = \begin{cases} 1 & \text{if } \alpha_j(\theta_i^{IRT} - \beta_j) - \epsilon_i^j \geq 0 \\ 0 & \text{if } \alpha_j(\theta_i^{IRT} - \beta_j) - \epsilon_i^j < 0. \end{cases}$$

Likewise, we might also consider using Principal Components (PC) Analysis to estimate the location θ_i^{PC} on the line explaining the most variation in the responses to the J questions about exposure to violence. Finally, we might follow Nielsen (2022) and anchor items to a later outcome like high school graduation $Y_i \in \{0, 1\}$, estimating a regression of the form

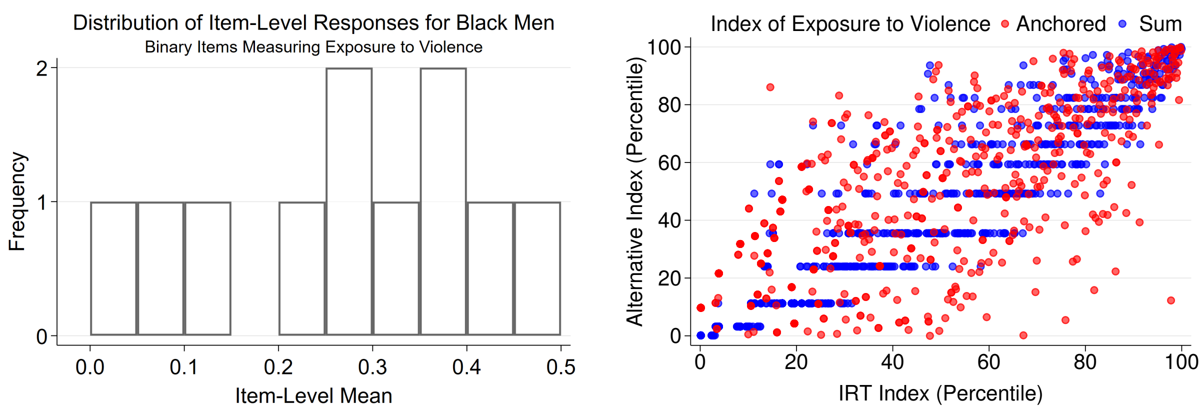
$$Y_i = \beta^1 V_i^1 + \cdots + \beta^J V_i^J + \epsilon_i$$

via Ordinary Least Squares (OLS) to obtain

$$\theta_i^{Anchored} = \mathbb{E}[Y | V_i^1, \ldots, V_i^J] = \beta^{1,OLS} V_i^1 + \cdots + \beta^{J,OLS} V_i^J.$$

We could think of the Sum index as giving all questions the same weight, and the IRT, PC, and Anchored approaches as ways of weighting some questions more than others in the creation of the index. These latter approaches are appealing if we think that specific items are more informative about exposure to violence than others. The unequal weighting approaches should be particularly appealing in cases when there is variation in the positive response rates to questions. Figure 15a shows that this is indeed the case after converting the positive responses for all specific items to binary variables.[18] The items measuring exposure to violence have positive response rates that are nearly uniformly distributed between 0 and 50 percent.

Figure 15b shows the disagreement between how the various indexes rank the exposure of individuals. The percentile of the IRT index is represented on the x-axis.[19] On the y-axis in red is the anchored index and in blue is the index that is simply the sum of positive responses.[20] The index anchored to attaining a high school diploma by age 26 has somewhat greater disagreement with the IRT index than does the sum index, and we can also see the discrete nature of the sum index.



(a) The Raw Data

(b) Indexes Created from the Data

Figure 15: Indexes of Exposure to Violence
Note: The left panel shows the positive response rates to the specific variables used in the construction of the exposure to violence indexes. The right panel shows the joint distributions of several of these indexes.

Given the range of positive response rates across items, together with their disagreement, we might expect these indexes to predict outcomes differently. Figure 16 compares the indexes' predictiveness of outcomes like household earnings and ever incarcerated, showing a binned scatterplot together with a line fit by OLS. A completely unpredictive index would be a horizontal line, while the steeper the slope of the line, the more predictive it is of a given outcome.

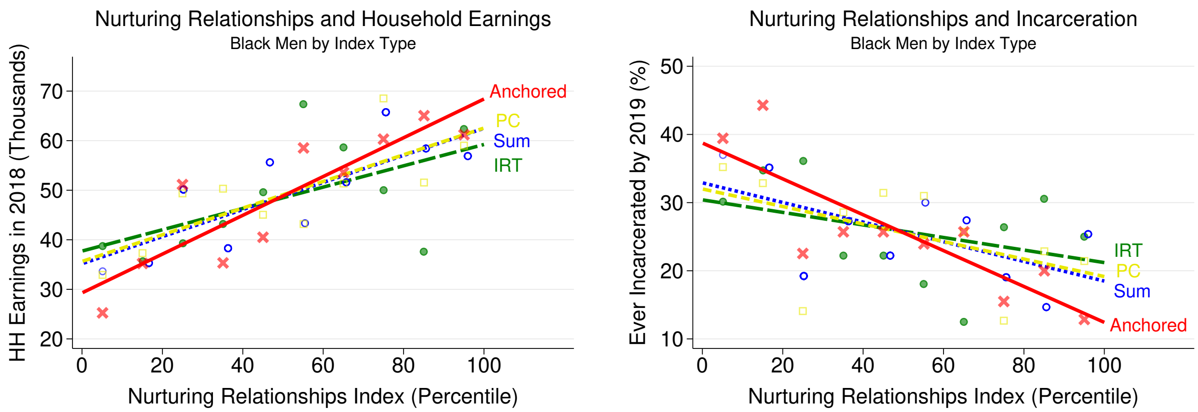
We see that the index Anchored to high school graduation outperforms the other indexes for the Nurturing Relationships index, having a steeper relationship with outcomes than do any of the other indexes. Further, the indexes using equal weights (Sum) and weights chosen to explain variation in all responses (IRT, PC) perform almost identically. The key distinction between the weights chosen by the Anchored index and those chosen by the IRT or PC indexes is that the Anchored index weights items by their ability to predict future outcomes rather than their ability to predict

[18]For example, the item "How many days per week do you typically hear gunshots in your neighborhood" is converted into an indicator for typically hearing gunshots at least 1 day per week.

[19]Details of the IRT estimation, including robustness to alternative distributional assumptions, are available in Appendix J.

[20]Multi-valued responses are handled in the anchored index using quadratic terms and in the sum index simply using all possible values.

other items. Figure 16a shows that for predicting household earnings in adulthood, the Sum and PC indexes perform very similarly, with a slightly more moderate slope for the IRT index. Figure 16b shows the same pattern for ever being incarcerated; the Sum, IRT, and PC indexes perform similarly, with the IRT index the least predictive. Appendix K shows that these patterns hold for additional outcomes, with the Anchored and PC indexes performing more similarly for exposure to violence.



(a) Household Earnings

(b) Ever Incarcerated

Figure 16: Nurturing Relationships Indexes and Adult Outcomes
Note: These figures show binned scatterplots and best fit lines of household earnings (left panel) and ever being incarcerated (right panel) as a function of the percentile of each index of nurturing relationships, with the Anchored index anchored to high school graduation.

Two comparisons are natural for these findings. Most notably, several results in education have been shown to be sensitive to the scale with which tests are measured (Bond and Lang (2013); Nielsen (2023); Agostinelli and Wiswall (2016); Cunha et al. (2021)). This would seem to suggest that the IRT or PC indexes would outperform the sum index. However, consistent with our findings, Hosseini et al. (2022) show that an equally weighted frailty index of health performs similarly to a PC-weighted index in predicting health outcomes. Understanding when the relative strengths of each index apply to specific empirical contexts is an important direction for future research.

We define our treatment using the Anchored index as a result of its outperformance of the other indexes. Denoting percentile p of the distribution of random variable X as $\pi_p(X)$, we define discrete treatment variables as:

$$D^V = \begin{cases} \text{Low} & \text{if} \quad \theta^V \geq \pi_{50}(\theta^V) \\ \text{High} & \text{if} \quad \theta^V < \pi_{50}(\theta^V), \end{cases} \qquad \text{and} \qquad D^{NR} = \begin{cases} \text{Low} & \text{if} \quad \theta^{NR} < \pi_{50}(\theta^{NR}) \\ \text{High} & \text{if} \quad \theta^{NR} \geq \pi_{50}(\theta^{NR}). \end{cases}$$

Our discretized treatment variables order respondents by their exposure to violence and nurturing relationships. Table 10 shows that as we move from the low to high levels of our exposure to violence treatment, the percent of respondents who reported seeing someone shot at between 12 and 18 increases from 11 to 40 percent. All of the specific variables measuring exposure to violence used in the estimation follow this pattern, to such an extent that our discrete treatment appears to capture the key variation in the data.

Table 10: Means of Specific Violent Experiences
for Adolescent Black Males by Level of Treatment D^V

	D^V	
Specific Measure of Exposure	Low	High
saw someone shot or shot at (%)	11	40
had home broken into (%)	12	14
victim of repeated bullying (%)	4	10
victim of a violent crime (%)	0	9
siblings or friends were in a gang (%)	32	65
% of peers belong to gang	14	32
Hear gunshots in nbd (days/week)	0.5	1.6
at school:		
got into a physical fight (frequency)	0.1	1.5
something of value stolen (frequency)	0.5	0.9
threatened to be hurt (frequency)	0.5	1.0
felt unsafe (%)	4	9

Note: D^V is our created binary treatment measuring exposure to violence.

Table 11 shows that as we move from the low to high levels of our nurturing relationships treatment, the percent of respondents who report thinking highly of their father increases from 61 to 86 percent. Only 52 percent of respondents in the low NR treatment report that their father often praises them, compared with 69 percent of respondents in the high NR treatment. Just as we saw with the exposure to violence treatment, nearly all of the specific variables measuring NRs used in the estimation follow the desired pattern, with the discrete treatment capturing important variation in the data.

Table 11: Means of Specific Nurturing Relationships Questions
for Adolescent Black Males by Level of Treatment D^{NR}

	Mother D^{NR}		Father D^{NR}	
Specific Measure of Parental NRs	Low	High	Low	High
Residing with respondent (%)	90	98	45	66
respondent thinks highly of them (%)	70	92	61	86
respondent thinks they want to be like them (%)	52	63	40	64
respondent really enjoys spending time with them (%)	79	85	63	80
they often praise the respondent (%)	70	80	52	69
they often help the respondent (%)	81	80	61	65
they know a lot about the respondent's friends (%)	51	40	25	29
they know the parents of the respondent's friends (%)	31	33	16	31
they know details when respondent not at home (%)	54	74	35	51
they know the respondent's teachers (%)	61	72	39	47
they often criticize the respondent or their ideas (%)	25	8	16	16
they blame the respondent for their problems (%)	9	3	3	6
they often cancel plans with the respondent (%)	9	3	13	7

	D^{NR}	
Specific Measure of Non-Parental NRs	Low	High
teachers care about the students (%)	74	89
teachers are interested in the students (%)	75	93
% of peers who plan to go to college	59	63
% of peers who cut class	33	27
peers disrupt learning (%)	38	32

Note: D^{NR} is our created binary treatment measuring Nurturing Relationships.

5.3 Potential Outcomes and Causal Effects

We estimate potential outcomes as functions of exposure to violence and nurturing relationships as $\mathbb{E}[Y(D^V, D^{NR})]$ where each treatment is the binary variable defined in the previous section. We estimate these potential outcomes under an assumption of selection on observables

$$D^V, D^{NR} \perp\!\!\!\perp Y(D^V, D^{NR}) \,|\, W. \tag{1}$$

We follow Imbens (2015) in implementing the selection on observables assumption in Equation 1 by estimating

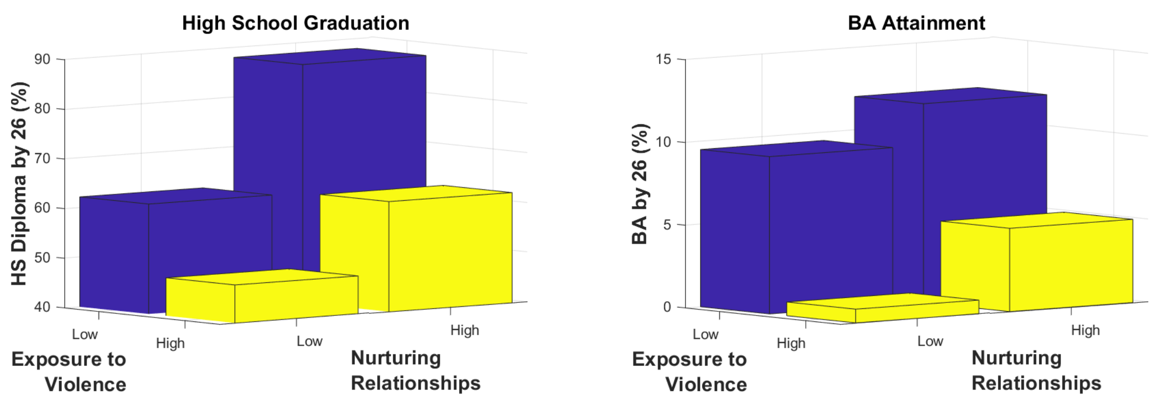
$$\mathbb{E}[Y|W, D^V, D^{NR}]$$

via OLS with separate coefficients for each subgroup of D^V and D^{NR}. We then estimate potential outcomes $\mathbb{E}[Y^{D^V=L,D^{NR}=L}]$ as

$$\mathbb{E}[Y^{LL}] = \mathbb{E}[\widehat{\beta}^{LL}_{OLS}W],$$

with the potential outcomes in the other treatment combinations $\mathbb{E}[Y^{LH}]$, $\mathbb{E}[Y^{HL}]$, and $\mathbb{E}[Y^{HH}]$ estimated analogously.

Figure 17 shows the estimated potential outcomes for educational attainment by age 26. In Figure 17a we can see a large drop-off in high school graduation rates as exposure to violence increases. Likewise, at all levels of exposure to violence, increasing NRs has large positive effects on graduation rates. Similar patterns obtain for BA attainment as shown in Figure 17b.

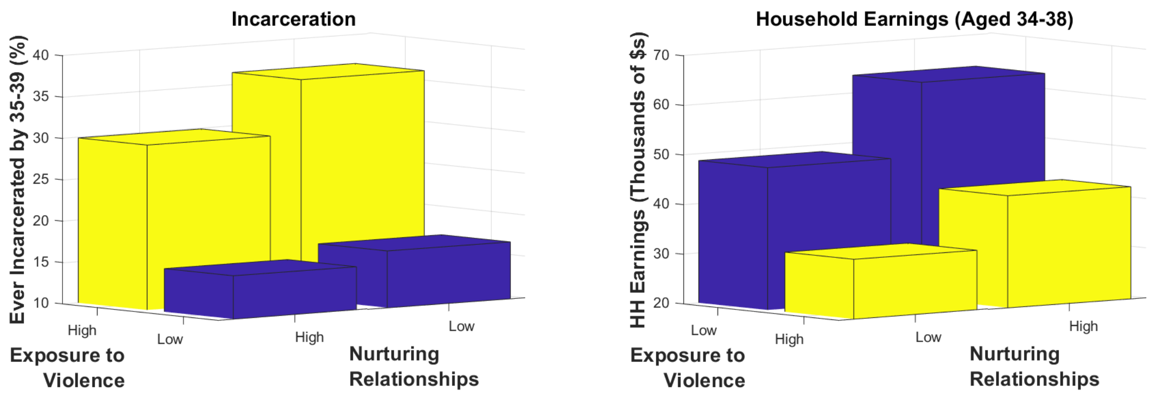


(a) High School

(b) BA

Figure 17: Potential Outcomes for Educational Attainment

Figure 18 shows that there are large effects of adolescent exposure to violence and nurturing relationships on the adult outcomes of Black men. Figure 18a shows a massive difference in the incarceration rates of those exposed to high versus low levels of violence in their adolescence. In terms of incarceration, the benefits from nurturing relationships accrue to those who were exposed to high levels of violence. Figure 18b shows that Black men's household earnings in their late 30s is highest when they were exposed to low levels of violence and high levels of nurturing relationships during their adolescence. In terms of household earnings, the benefits of nurturing relationships are experienced by those exposed to both high and low levels of violence, although the greatest benefits are to those exposed to low levels of violence.



(a) Incarceration

(b) Household Earnings

Figure 18: Potential Outcomes for Incarceration and Household Earnings

Table 12 provides the numerical values of the treatment effects implied by these potential outcomes along with one-sided p-values of these effects being different from zero obtained from 1,000 bootstrap replications of the estimation of both the item-anchored index and the potential outcomes. These effects are economically large and statistically significant.

Table 12: Effects of Changing Treatments

	Given High Exposure to Violence and Low Nurturing Relationships		
	$\downarrow D^V$	$\uparrow D^{NR}$	Both
HS Diploma	14.5	14.5	40.3
(% by 26)	[0.00]	[0.00]	[0.00]
BA Attainment	8.7	4.2	11.2
(% by 26)	[0.03]	[0.12]	[0.00]
Household Earnings	16.6	10.5	31.6
(1,000s of 2018 $s)	[0.01]	[0.04]	[0.00]
Ever Incarcerated	–19.6	–6.5	–21.3
(% by 2019)	[0.00]	[0.00]	[0.00]

Note: The p-values of one-sided tests for each coefficient being different from 0 are reported in brackets [ ] and are obtained from 1,000 bootstrap replications. See text for variable descriptions.

The results highlight the importance of nurturing relationships in several ways. One feature of nurturing relationships is that they improve outcomes at all levels of exposure to violence. For example, providing an adolescent Black male with high levels of nurturing relationships would increase their adult household earnings by $11,000 when exposed to high levels of violence and $15,000 when exposed to low levels of violence. Another feature is that nurturing relationships are not only substitutes for shielding adolescents from violence, but complementary. For example, providing adolescent Black males with high levels of nurturing relationships or shielding them from high levels of exposure to violence would increase their high school graduation rates by 15 percentage points, from a base of 48 percent. Improving both of these treatments at the same time would increase high school graduation rates by 40 percentage points. We note that these large improvements in outcomes are broadly in line with the magnitudes of changes in flourishing found in Bethell et al. (2019b).

When interpreting these results, we emphasize that they are exploratory in many ways, pointing to the need for more work on the precise mechanisms by which nurturing relationships improve outcomes. In our study, the effects of nurturing relationships are mainly driven by parents because the NLSY97 has richer variables on these relationships than others. Since similar results have been found in data sets containing richer information on other relationships (Bethell et al. (2019); Pierre et al. (2020); Kraft et al. (2023)) or in contexts focused on other relationships (Resnjanskij et al. (2024); Villa-Llera (2024); Falk et al. (2020); Kosse et al. (2020); Oreopoulos et al. (2017)), we therefore expect that providing nurturing relationships beyond parents will also have beneficial effects on Black men's outcomes.

It is also possible that an important share of our estimated effects could be mediated by parental stress, as there is evidence that parents' stress is itself affected by neighborhood violence (Mendenhall et al. (2023); Lee et al. (2021)) and job loss (Carneiro et al. (2023)). Likewise, we cannot tell if positive relationships inspire positive behavior (Villa-Llera (2024), Lavecchia et al. (2020), Guryan et al. (2023)), or if they simply incapacitate youth from spending time engaging in negative behaviors (Jacob and Lefgren (2003)). Finally, we are interested in better understand how our effects relate to those from exposure to a range of violent events such as school shootings (Beland and Kim (2016), Cabral et al. (2021)), mass shootings (Lowe and Galea (2017)), bullying (Sarzosa and Urzúa (2021), Eriksen et al. (2014)), domestic violence (Carrell and Hoekstra (2010)), police homicides (Ang (2020)), civil war (León (2012)), and gang turf battles (Monteiro and Rocha (2017); Wagner (2021)).

5.4 Robustness of Effects during Adolescence: Non-Violent Adversity

The key identification assumption for the estimates above is selection on observables. Here we present some robustness analysis using non-violent adversity and nurturing relationships, noting that non-violent adversity from an unemployed parent or the death of a parent or sibling is more plausibly random than exposure to violence.

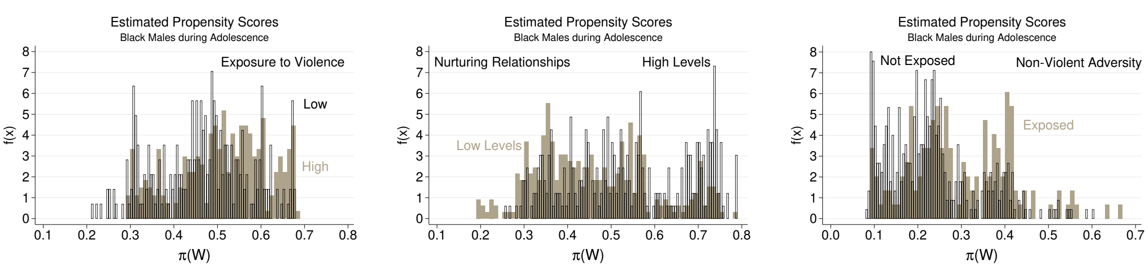
We measure exposure to non-violent adversity using an indicator for whether a respondent experienced an incarcerated parent, homelessness, an unemployed parent, or the death of a parent or sibling. The variables chosen for inclusion in our measure of non-violent adversity are distinct from those used to define Adverse Childhood Experiences (ACEs), with Appendix I discussing our variable selection. Table 13 shows that there is very little overlap in exposure to each variable capturing a form of non-violent adversity. This lack of overlap suggests that an IRT or PC model would not do a good job of summarizing the variation in these variables, as these responses do not look as though they are the noisy responses determined by the same latent index. For this reason we define non-violent adversity as an indicator for having responded affirmatively to one of these experiences. The death of a close family member or an unemployed parent are the main forms of non-violent adversity experienced by adolescent Black males.

Table 13: Black Adolescents' Non-Violent Adversity, Ages 12-18

Specific Adversity	Percent	Cumul.
Incarcerated Parent	1.2	1.2
Homeless	1.6	2.8
Unemployed Parent	6.4	9.0
Death of parent or sibling	15.0	23.6
Any Non-Violent Adversity	23.6	23.6

Note: See text for variable descriptions.

We first use non-violent adversity to gauge the strength of selection on observables for the treatment variables in our main analysis. Figure 19 shows the propensity score estimates of Black males during adolescence for exposure to violence, nurturing relationships, and non-violent adversity when using the observed characteristics W that are parental income, mother's educational attainment, and household structure. The strongest selection on observables appears to be into nurturing relationships and the weakest selection on observables appears to be into non-violent adversity. While there is, as expected, less selection on observables into non-violent adversity, the selection for the treatments in our main analysis is broadly comparable and does not appear overwhelming. There is plenty of overlap in the distributions of propensity scores for high and low treatments.



(a) Exposure to Violence (b) Nurturing Relationships (c) Non-Violent Adversity

Figure 19: Propensity Scores of Black Males during Adolescence for Various Treatments

We next compare effects of non-violent adversity to those of exposure to violence. We do this not to formally test any hypothesis, but as a potentially useful benchmark. We find that estimated effects are generally of a similar magnitude across models, with effects that tend to be larger in the model with exposure to violence.

The first three columns of Table 14 reproduce the earlier results of a model in which there are four treatment states that depend on exposure to violence and nurturing relationships. The last three columns of Table 14 show the estimates from a similar model in which there are four treatment states that depend on non-violent adversity and nurturing relationships. Comparing columns 1 and 4, we see that exposure to violence has larger effects than non-violent adversity, with the exception of household earnings when aged 34-38. Comparing columns 2 and 5, we see that improving the level of nurturing relationships has similarly positive effects when either exposure to violence or non-violent adversity remains high. The one exception, again, is household earnings, where improving nurturing relationships is more effective when non-violent adversity remains high than when exposure to violence remains high. Finally, when comparing columns 3 and 6, we see that the effect of simultaneously improving treatments is quite similar across models, with slightly larger effects in the model with exposure to violence.

Table 14: Effects of Changing Treatments

	Given High Exposure to Violence and Low Nurturing Relationships			Given High Non-Violent Adversity and Low Nurturing Relationships		
	$\downarrow D^V$	$\uparrow D^{NR}$	Both	$\downarrow D^{NV}$	$\uparrow D^{NR}$	Both
HS Diploma	14.5	14.5	40.3	4.4	12.3	32.3
(% by 26)	[0.00]	[0.00]	[0.00]	[0.06]	[0.00]	[0.00]
BA Attainment	8.7	4.2	11.2	4.8	4.3	9.2
(% by 26)	[0.03]	[0.12]	[0.00]	[0.03]	[0.20]	[0.00]
Household Earnings	16.6	10.5	31.6	16.7	18.1	28.0
(1,000s of 2018 $s)	[0.01]	[0.04]	[0.00]	[0.03]	[0.11]	[0.00]
Ever Incarcerated	–19.6	–6.5	–21.3	–5.6	–6.6	–14.0
(% by 2019)	[0.00]	[0.00]	[0.00]	[0.07]	[0.11]	[0.00]

Note: The p-values of one-sided tests for each coefficient being different from 0 are reported in brackets [ ] and are obtained from 1,000 bootstrap replications. See text for variable descriptions.

5.5 Potential Outcomes and a Policymaker's Decision Problem

We take three main policy implications from our findings. First, because their adult outcomes are so negatively affected by childhood exposure to violence, Black males' long-run outcomes are likely to be improved by reducing overall violence and/or providing youth with safe places. Second, the magnitude of our effects indicate that adolescence as a time period can matter in profound ways for adult outcomes (Chang et al. (2023), Carneiro et al. (2023), Carneiro et al. (2021), Wodtke et al. (2016)). And third, providing students with nurturing relationships appears to be a highly effective mechanism for improving adult outcomes. Our results contribute to the evidence on the potential for leveraging nurturing relationships as the driving mechanism in interventions supporting parents (Olds (2002), Gertler et al. (2014), Cunha et al. (2022)) and in effective tutoring, mentoring, and community-building programs targeting both children and adolescents (Kraft and Falken (2021), Oreopoulos et al. (2017), Lavecchia et al. (2020), Guryan et al. (2023), Carneiro et al. (2023)).

We now use the potential outcomes estimated earlier as inputs into a policymaker's decision problem by supposing that a program Z would lead some share of compliers to change the treatment they receive from low to high nurturing relationships or to change from high to low exposure to violence. Assuming that potential outcomes are uniform across compliers, always-takers, never-takers, and defiers, we can use the potential outcomes estimated in the previous section to calculate the benefit an intervention would have assuming a specific share of compliers.

Table 15 presents estimates of the benefits of programs accruing from long-run effects on Black men. For this exercise we assume that programs benefit 10 or 25 percent of those eligible. These compliance rates are in line with survey evidence in Villa-Llera (2024) that among 10-15 year olds living in London in 2010, 10 percent of respondents reported attending youth centers nearly every day and 41 percent reported attending monthly. Table 16 presents the estimated costs of programs that might provide adolescent Black males with nurturing relationships, safety, or both. Even focusing only on benefits directly accruing from the effects on Black men, the costs are outweighed by the benefits of scaling programs like either Boys and Girls Clubs for all 12-18 Black males (Seitz et al. (2022)) or else wrap-around services provided via a dedicated family support specialist serving each K-12 Title I school (modeled after the Say Yes Cleveland).

Table 15: Annual Program Benefits Accruing from Black Males' Participation

		Benefit of Providing:		
	Compliers	NRs	Safety	Both
Ind. Earnings				
	10%	\$3.7B	\$5.2B	\$12.0B
	25%	\$9.1B	\$13.1B	\$29.9B
Incarceration				
	10%	\$1.4B	\$5.4B	\$9.4B
	25%	\$3.4B	\$13.6B	\$23.5B

Note: Providing NRs means an intervention alters D^{NR} from 0 to 1. Providing safety means an intervention alters D^V from 1 to 0. Increased individual earnings are calculated for the population of prime age Black men, or those aged 25-54, in five year windows using an age-earnings profile estimated on the Black males in the National Longitudinal Survey of Youth 1979 (1979) following the assumptions adopted in Aliprantis et al. (2023). Decreased costs of incarceration are calculated assuming one spell of 6 months randomly timed before age 40 for Black men at the Federal Register's estimate of an average of \$108 per day using data from fiscal year 2019.

Table 16: Annual Program Costs

Program	Program/Study	Cost
Boys and Girls Clubs*	Boys & Girls Clubs (2023)	\$2.2B
Big Brothers/Big Sisters*	Alfonso et al. (2019)	\$3.0B
Wrap-Around Services*	Say Yes Cleveland	\$5.2B
School-Wide Tutoring*	Kraft and Falken (2021)	\$5-\$16B
Summer/After-School	American Rescue Plan	\$6B
High-Dosage Tutoring*	Guryan et al. (2023)	\$9.5-11.7B
Student Supports*	Oreopoulos et al. (2017)	\$19.0B

Note: * indicates all students in Title I K-12 Schools. * indicates Black males aged 12-18 in the 2020 Census. Cost estimates in Oreopoulos et al. (2017) are in 2018 dollars.

When considering nurturing relationships and safety as a place-based policy, it is worth noting that related programs could have increasing marginal returns to investment (Billings et al. (2019);

Carrell et al. (2018)). This contrasts with dispersing participants through housing mobility programs that would, at some point, seem to have decreasing marginal returns to spending (Agostinelli et al. (2020); Aliprantis et al. (2023)). We also note that due to the nature of the interventions, programs that focus on providing either a safe place or nurturing relationships for youth typically end up providing both. This detail makes the final column in Table 15 relevant for the comparison of costs and benefits.

6 Conclusion

In an unsafe environment, ensuring one's physical security can dominate one's life. This is true for Black males growing up in unsafe areas in the US, a phenomenon that has been described in academic studies (Anderson (1999); Tack and Small (2017)) and personal memoirs (Coates (2015); Canada (1995)).

This paper made contributions to the literature on exposure to violence by showing the magnitude of long-run effects on Black men in the US. We found that seeing someone shot or shot at when aged 11 or younger was associated with 31 percent lower household earnings in the late 30s. We found that when viewed as a causal effect, this gap is not driven by sorting on observables. We also presented a range of evidence indicating that this gap is not driven by sorting on unobservables. When we investigated mechanisms, we found that the effects of childhood exposure are distinct from those of growing up in a low SES neighborhood, as the gap in household earnings from childhood exposure to violence is constant across neighborhood socioeconomic status (SES). This result is somewhat surprising given the concentration of exposure to violence in the neighborhoods with the lowest SES. We also found that incarceration is not a major mediator of exposure to violence, and that the reported exposure to violence is distinct from exposure to gang behavior. Collectively, these results indirectly implicate the trauma and toxic stress response from childhood exposure to violence as the main mechanism through which exposure to violence affects long-run outcomes.

Guided by the literature on Adverse Childhood Experiences (ACEs) and toxic stress responses, we went on to study how nurturing relationships moderate the effects of exposure to violence in adolescence. The NLSY97 has a wide range of variables measuring these treatments, so we first investigate how to best synthesize these variables. We found that simply summing the positive responses to all variables predicts later outcomes just as well as indexes created by Item Response Theory (IRT) or the first Principal Component (PC) of the variables. In contrast, indexes based on item-anchored scales predict outcomes better than indexes based on summing, IRT, or PC. A strength of our analysis is that with the rich set of variables available in the NLSY97, we were able to estimate potential outcomes under a selection on observables assumption.

Our findings on exposure to violence and nurturing relationships during adolescence have a clear implication: nurturing relationships are a lever capable of supporting positive long-run outcomes, even for adolescents. Our results are located at the intersection of the literature on neighborhood effects and the role of family and peers in child development. Neighborhoods matter because of the people with whom children and adolescents interact in them. Relationships matter because of the way they help children and adolescents navigate those interactions. Our results point to the strength of these mechanisms, operating both independently and together.

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A Homicide

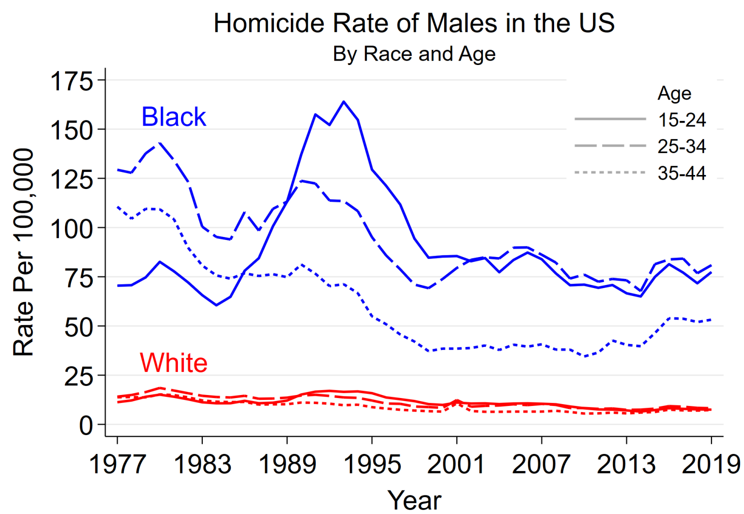


Figure 1: Homicide Rates by Race and Age
Note: This figure presents data from NCHS (2021).

B Additional Details on the Data

B.1 NLSY97

The primary sample used in our analysis is from the National Longitudinal Survey of Youth 1997 (NLSY97). We focus our analysis on non-Hispanic Black males, and in the main text we sometimes also consider a sample comprising non-Hispanic white males.

We measure long-run outcomes using results from the 2019 wave of the survey. Weekly hours worked is equal to the total annual hours worked at all civilian jobs during year Y-1 divided by 52. Earnings are equal to zero if the respondent says they did not receive income from a job, and equal to their estimate if they say they did. However, not all respondents are able to provide an estimate immediately, in which case they are subsequently prompted to select an income range. In these cases, earnings are equal to the midpoint of the range selected.

Educational attainment by age 26 is created using variables CV_HIGHEST_DEGREE_EVER for 1997 and CV_HIGHEST_DEGREE_EVER_EDT_Y for subsequent rounds. We split educational attainment into 4 groups, where a dropout is a respondent who does not have a high school diploma or GED; greater than or equal to a GED; greater than or equal to a high school diploma; and greater than or equal to a Bachelor's degree. Ever incarcerated is measured using the INCARC_STATUS_Y_M_XRND. The respondent is considered to have been incarcerated if at any point the status is positive. Marital status is measured using CV_MARSTAT_COLLAPSED_Y. The respondent is considered to have been married if at any point they report being married, separated, divorced, or widowed. We follow Aliprantis and Chen (2016) and define deceased (or missing) using the variable RNI_2019 (codes 80, 98, or 90). We follow Aliprantis (2017b) and define violent behavior at a given age as having carried a gun in the past year, attacked someone with the intent of seriously harming them, been charged with an assault, or belonged to a gang.

B.1.1 Earnings and Attrition

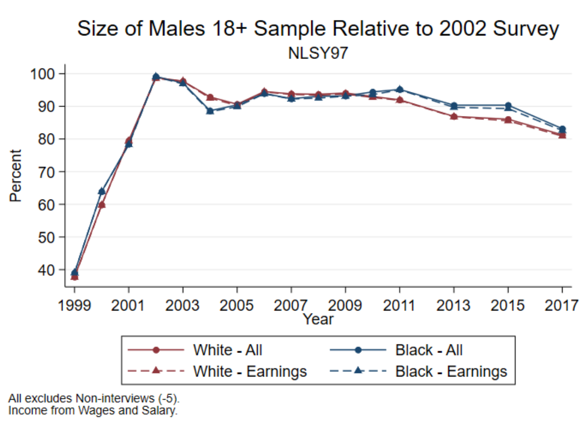
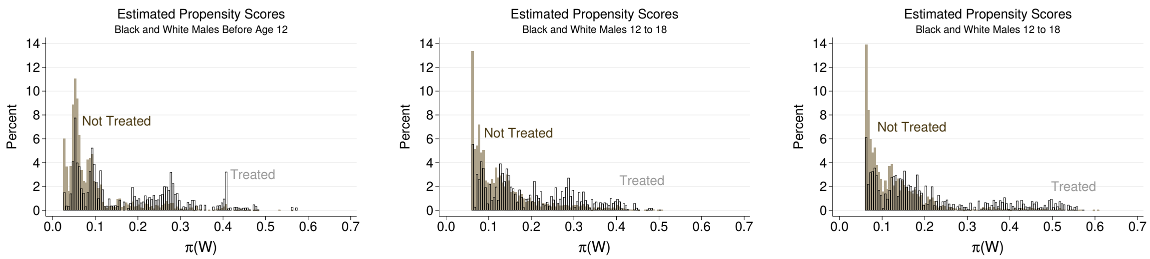


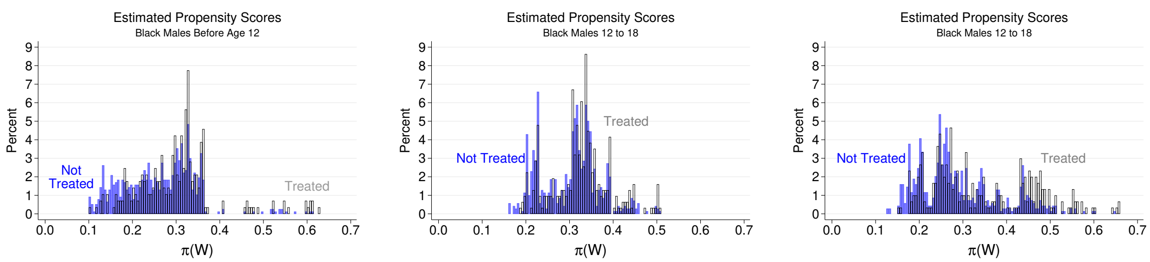
Figure 2: Attrition rate for Males 18+ relative to 2002 sample.
Note: We see that the attrition rate is similar for all races, and never falls below 80 percent. Years are one year before the survey year because we are analyzing earnings.

B.1.2 Exposure to Violence: Propensity Scores and Raw Probabilities



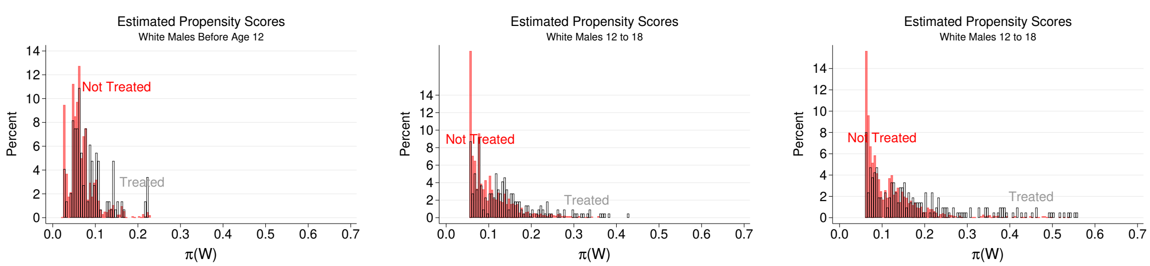
(a) **W** (b) **W** (c) **W** and Childhood Exposure

Figure 3: Propensity Scores of Black and White Males' Exposure to Violence by Covariates



(a) **W** (b) **W** (c) **W** and Childhood Exposure

Figure 4: Propensity Scores of Black Males' Exposure to Violence by Covariates



(a) **W** (b) **W** (c) **W** and Childhood Exposure

Figure 5: Propensity Scores of White Males' Exposure to Violence by Covariates

Table 1: Propensity Score Estimation Results
Childhood Exposure to Violence for Black Males

	Mother's Ed Attainment					Household Structure by Parents				Parental Income	
	Dropout	GED	HS	AA	BA	2 Bio	2 Other	Single	Grand	Linear	Quadratic
Coefficient	0.37	0.28	0.23	-0.03	0.20	–1.73	–1.11	–1.15	–1.28	–5.97e-6	6.29e-12
Standard Error	0.34	0.40	0.31	0.39	0.39	0.37	0.38	0.35	0.45	7.80e-6	6.85e-11

Note: This table reports coefficients estimated from a logit propensity score specification where treatment is childhood exposure to violence, measured as seeing someone shot or shot at when aged 11 or younger. The sample is 1,047 non-Hispanic Black males in the NLSY97 and log likelihood at the estimates is –591.74. The household structure categories here are formed from the NLSY97 categories as follows: The "Two Bio Parent" category includes "Both biological parents." The "Two Other Parent" category includes "Two parents, biological mother" and "Two parents, biological father." The "Single Parent" category includes "Biological mother only" and "Biological father only." The "Grandparent" category includes "No parents, grandparents." The reference group is the "Other" household structure, which includes "adoptive parent(s)," "foster parent(s)," "no parents, other relatives," and "anything else." The reference group for mother's educational attainment is not determined.

Table 2: Exposure to Violence
by Age, Race, and Household Structure

Household	Black by Age			White by Age		
Structure	0-11	12-18	0-18	0-11	12-18	0-18
Two Parent (Both Bio)	15	22	34	5	8	12
Two Parent (One Bio)	28	38	50	11	16	23
Single Parent	30	34	52	8	15	20
Grandparent	27	26	44	5	11	17
Other	45	33	63	5	16	20

Note: The categories here are formed from the NLSY97 categories as follows: The "Two Parent (Both Bio)" category includes "Both biological parents." The "Two Parent (One Bio)" category includes "Two parents, biological mother" and "Two parents, biological father." The "Single Parent" category includes "Biological mother only" and "Biological father only." The "Grandparent" category includes "No parents, grandparents." And the "Other" household structure includes "adoptive parent(s)," "foster parent(s)," "no parents, other relatives," and "anything else."

B.1.3 Calculating Neighborhood SES in 1997

Calculating neighborhood SES in 1997 requires imposing assumptions about the evolution of tracts over time, as this year is not the subject of a decennial Census or ACS. Therefore we calculate neighborhood SES for each tract in 1997 using Census data from a range of years downloaded from the National Historical Geographic Information system (NHGIS, Manson et al. (2017)). We first calculate neighborhood SES using the 2000 US Census and each 5-year American Community Surveys (ACS) from the years 2005-2009 until 2015-2019, interpolating data from 2010 to 2000 tract boundaries using the Longitudinal Tract Data Base (LTDB) when necessary.[21] We then

[21]See important details about the LTDB in Logan et al. (2014), Logan et al. (2016), and Logan et al. (2021).

estimate tract-level regressions of neighborhood SES on year and use the estimated regression to predict neighborhood SES in 1997.

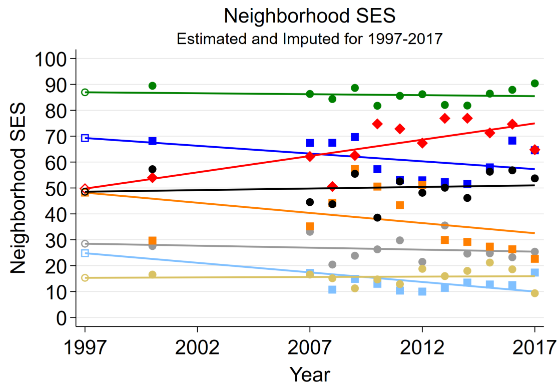
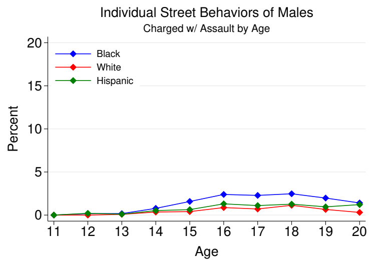


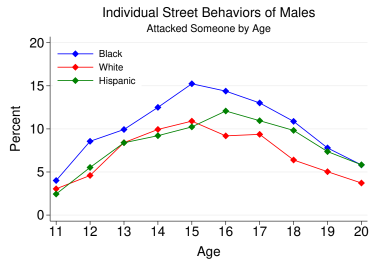
Figure 6: Calculating Neighborhood SES in 1997

Note: This figure shows estimated and imputed neighborhood SES by year for eight randomly chosen Census tracts. The solid markers denote estimates from the 2000 Census and the middle year of each 5-year American Community Survey. The hollow markers denote values imputed via tract-level regressions.

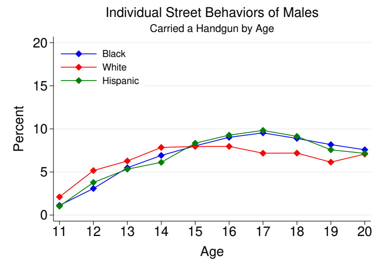
C Street Behavior of Males by Age and Race/Ethnicity



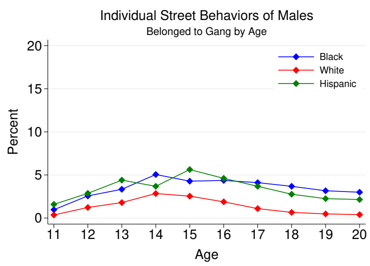
(a) Charged with Assault



(b) Attacked Someone

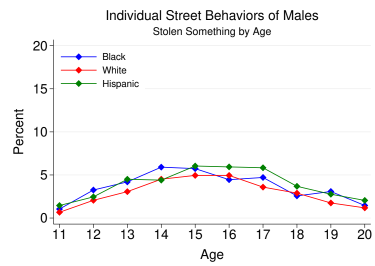


(c) Carried a Handgun

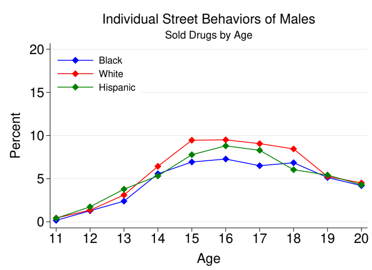


(d) Belonged to a Gang

(e) Committed a Property Crime



(f) Stolen Something Valuable



(g) Sold Drugs

Figure 7: Street Behaviors

D Full Specification of Finite Mixture Model

Recall that D_c is an indicator for childhood exposure to violence, measured by respondents' self-reporting of seeing someone shot or shot at while aged 11 or younger. D_a is an indicator for adolescent exposure to violence, measured by respondents' self-reporting of seeing someone shot or shot at while aged 12-18. S^v_{15} is an indicator for violent street behavior at age 15, measured by either having carried a gun, attacked or assaulted someone, or belonged to a gang. And S^n_{15} is an indicator for non-violent street behavior at age 15, which includes any behavior such as breaking the rules of one's school, selling drugs, stealing, committing a property crime, or engaging in non-violent, illegal behavior.[22] Observed characteristics W are mother's educational attainment at the time of the first survey, household structure at the time of the first survey (two parents (both biological); two parents (one biological); single parent; grandparent(s); or other), and parental income at the time of the first survey.

We model each latent index as

$$\begin{aligned}
D^*_{i,c} &= \beta_0^{c,\tau} + \beta_1^c W_{i,1} + \cdots + \beta_J^c W_{i,J} - \epsilon_i^c && \epsilon^c \sim \mathcal{N}(0,1)\\
S^{v*}_{i,15} &= \beta_0^{v,\tau} + \beta_1^v W_{i,1} + \cdots + \beta_J^v W_{i,J} + \delta^v D_{i,c} - \epsilon_i^v && \epsilon^v \sim \mathcal{N}(0,1)\\
S^{n*}_{i,15} &= \beta_0^{n,\tau} + \beta_1^n W_{i,1} + \cdots + \beta_J^n W_{i,J} + \delta^n D_{i,c} - \epsilon_i^n && \epsilon^n \sim \mathcal{N}(0,1)\\
D^*_{i,a} &= \beta_0^{a,\tau} + \beta_1^a W_{i,1} + \cdots + \beta_J^a W_{i,J} + \beta_v^a S^v_{i,15} + \beta_n^a S^n_{i,15} - \epsilon_i^a && \epsilon^a \sim \mathcal{N}(0,1).
\end{aligned}$$

In both of the specifications estimated in the main text we impose the constraint that $\delta^v = \delta^n = 0$, and in Model 4 we impose the constraint that $\beta^a_v = \beta^a_n = 0$.

Given the probit equations

$$D_{i,c} = \mathbf{1}\{D^*_{i,c} > 0\} \qquad S^v_{i,15} = \mathbf{1}\{S^{v*}_{i,15} > 0\} \qquad S^n_{i,15} = \mathbf{1}\{S^{n*}_{i,15} > 0\} \qquad D_{i,a} = \mathbf{1}\{D^*_{i,a} > 0\},$$

the type-specific probability of observing outcomes $\mathcal{O}_i = (D_{i,c}, S^v_{i,15}, S^n_{i,15}, D_{i,a})$ is

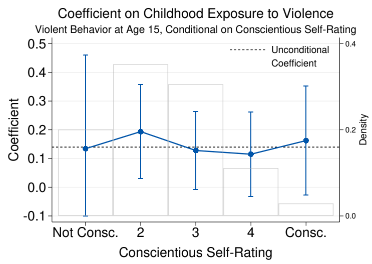
$$\begin{aligned}
Pr(\mathcal{O}_i|\beta,\tau) = &\Phi(\beta_0^{c,\tau} + \beta_1^c W_{i,1} + \cdots + \beta_J^c W_{i,J})^{D_{i,c}} \cdot [1 - \Phi(\beta_0^{c,\tau} + \beta_1^c W_{i,1} + \cdots + \beta_J^c W_{i,J})]^{1-D_{i,c}}\\
&\cdot \Phi(\beta_0^{v,\tau} + \beta_1^v W_{i,1} + \cdots + \beta_J^v W_{i,J} + \delta^v D_{i,c})^{S^v_{i,15}}\\
&\quad \cdot [1 - \Phi(\beta_0^{v,\tau} + \cdots + \beta_1^v W_{i,1} + \cdots + \beta_J^v W_{i,J} + \delta^v D_{i,c})]^{1-S^v_{i,15}}\\
&\cdot \Phi(\beta_0^{n,\tau} + \beta_1^n W_{i,1} + \cdots + \beta_J^n W_{i,J} + \delta^n D_{i,c})^{S^n_{i,15}}\\
&\quad \cdot [1 - \Phi(\beta_0^{n,\tau} +] \beta_1^n W_{i,1} + \cdots + \beta_J^n W_{i,J} + \delta^n D_{i,c})]^{1-S^n_{i,15}}\\
&\cdot \Phi(\beta_0^{a,\tau} + \beta_1^a W_{i,1} + \cdots + \beta_J^a W_{i,J} + \beta_v^a S^v_{i,15} + \beta_n^a S^n_{i,15})^{D_{i,a}}\\
&\quad \cdot [1 - \Phi(\beta_0^{a,\tau} + \beta_1^a W_{i,1} + \cdots + \beta_J^a W_{i,J} + \beta_v^a S^v_{i,15} + \beta_n^a S^n_{i,15})]^{1-D_{i,a}}.
\end{aligned}$$

[22]Respondents self-report if they have helped to sell illegal drugs, if they have stolen more than \$50, if they have committed any property crimes, as well as if they have been suspended from school or arrested for a non-violent offense.

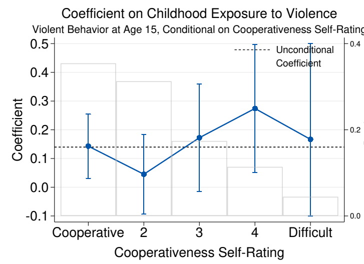
Given $Pr(O_i|\beta) = \sum_{\tau=1}^{T} Pr(O_i|\beta, \tau)Pr(\tau)$, the log-Likelihood function is

$$\mathcal{LL}(\mathcal{O}_i|\beta) = \sum_{i=1}^{N} ln(Pr(\mathcal{O}_i|\beta)).$$

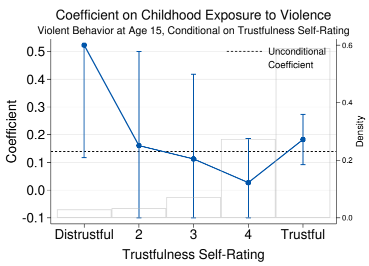
E Additional Measures of Personality Traits



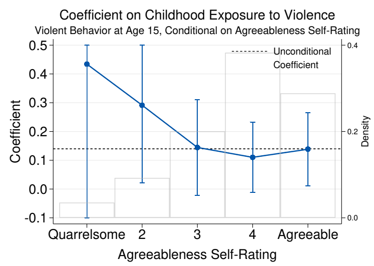
(a) Conscientiousness



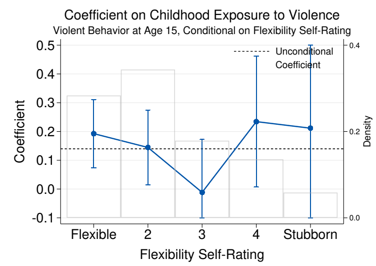
(b) Cooperativeness



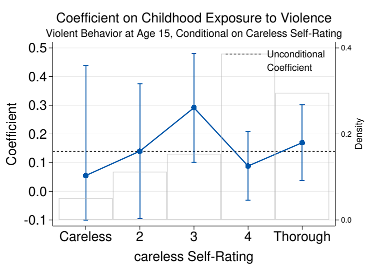
(c) Trustfulness



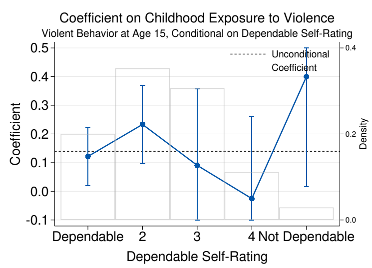
(d) Agreeableness



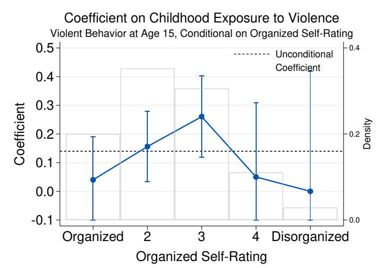
(e) Flexibility



(f) Carelessness



(g) Dependability



(h) Organized

Figure 8: Violent Behavior at Age 15, Conditional on Self-Rated Personality Traits
Note: The blue dots in this figure show the coefficients of a regression of an indicator for violent behavior at age 15 on childhood exposure to violence, conditional on each respondent's self-reported expectation or personality trait. The blue vertical lines show 90 percent confidence intervals for those coefficients. The dashed black horizontal line shows the coefficient on childhood exposure to violence unconditional on each respondent's self-report. The rectangles outlined in grey report the probability mass function of respondents in the sample, which is Black males in the NLSY97.

We now consider using the age at which each respondent first had sex as a proxy for risk aversion / recklessness. This variable records the response to the question "Thinking about the very first time in your life that you had sexual intercourse with a person of the opposite sex, how old were you?"

Table 3 and Figure 9 show that the gap in violent behavior at age 15 is not highly correlated with respondents' age at first sex. Table 3 presents the ordinary least squares estimates from a linear probability model where engaging in violent behavior is the dependent variable and childhood exposure to violence is always an independent variable. An age at first sex of 12 versus 17 is associated with, respectively, being 16 versus 13 percentage points more likely to engage in violence conditional on exposure to violence. Note the p-value of 0.651 associated with the exposure×age at first sex coefficient, indicating that this difference is not statistically significant. Figure 9 shows that estimating the coefficient on childhood exposure to violence conditional on age at first sex produces noisy estimates that are close to the unconditional coefficient of 0.18.

Table 3: Violent Behavior at Age 15

Independent Variable	Coefficient in Linear Probability Model	
Childhood Exposure	0.177 [0.000]	0.253 [0.276]
Age at First Sex		−0.031 [0.000]
Exposure × Age at First Sex		−0.007 [0.651]
Intercept	0.172 [0.000]	0.640 [0.000]
N	1,120	946

Note: This table reports coefficients from regressions where the dependent variable is an indicator for engaging in violence at age 15, which is itself an indicator for either having carried a gun in the past year, attacked or assaulted someone, or belonged to a gang. The independent variables in the linear probability model always include childhood exposure to violence (having seen someone shot or shot at aged 11 or younger). The sample in the first column of estimates is all Black males in the NLSY97, and the sample in the second column is restricted to those who reported an age at first sex of at least 10 and no more than 18. This sample restriction is imposed to deal with the long left tail and a lack of variation in treatment for those reporting ages 19 and older. Values in brackets [·] are the p-values associated with each coefficient being different from zero.

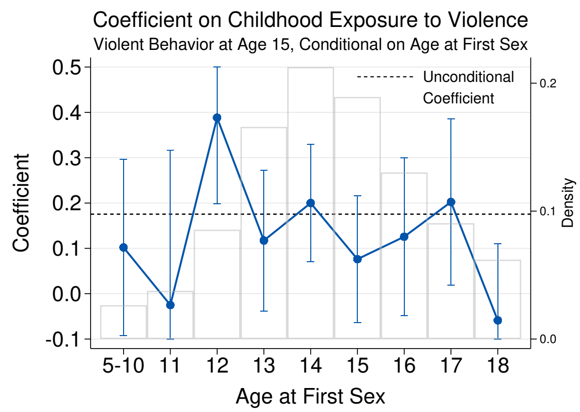


Figure 9: Violent Behavior at Age 15, Conditional on Age at First Sex
Note: The blue dots and lines in this figure show the coefficients of a regression of an indicator for violent behavior at age 15 on childhood exposure to violence conditional on the age at which the respondent first had sex. The sample is Black males in the NLSY97. The rectangles outlined in grey report the probability mass function of respondents in the sample.

Table 4: Violent Behavior at Age 15, Conditional on Expectation of Arrest

Independent Variable	Coefficient in Linear Probability Model	
Childhood Exposure	0.1775	0.1568
	[0.000]	[0.085]
Expectation of Arrest		0.0014
		[0.302]
Exposure × Expectation of Arrest		0.0007
		[0.747]
Intercept	0.1715	0.1398
	[0.000]	[0.005]
N	1,120	249

Note: This table reports coefficients from regressions where the dependent variable is an indicator for engaging in violence at age 15, which is itself an indicator for either having carried a gun in the past year, attacked or assaulted someone, or belonged to a gang. The independent variables in the linear probability model always include childhood exposure to violence (having seen someone shot or shot at aged 11 or younger). The sample in the first column of estimates is all Black males in the NLSY97, and the sample in the second column is restricted to those who reported a positive probability of arrest in the next year when asked in the first (1997) survey. Values in brackets [·] are the p-values associated with each coefficient being different from zero.

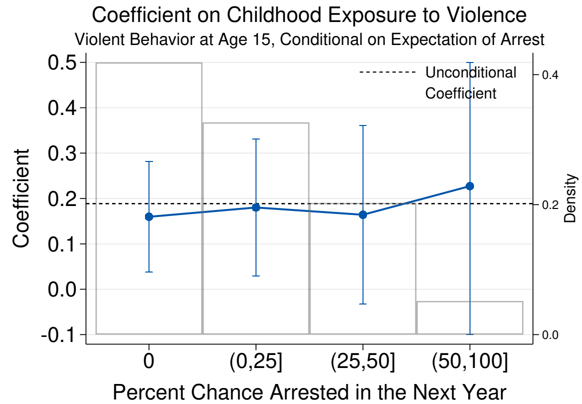


Figure 10: Violent Behavior at Age 15, Conditional on Expectation of Arrest
Note: The blue lines and dots in this figure show the coefficients of a regression of an indicator for violent behavior at age 15 on childhood exposure to violence, conditional on each respondent's expected chance of being arrested in the year following the first survey, 1997, when respondents are aged 15-18. The sample is Black males in the NLSY97. The rectangles outlined in grey report the probability mass function of respondents in the sample.

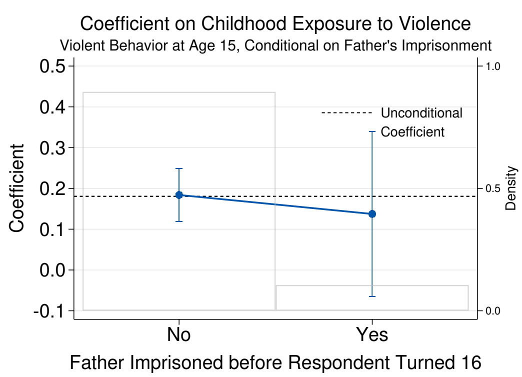
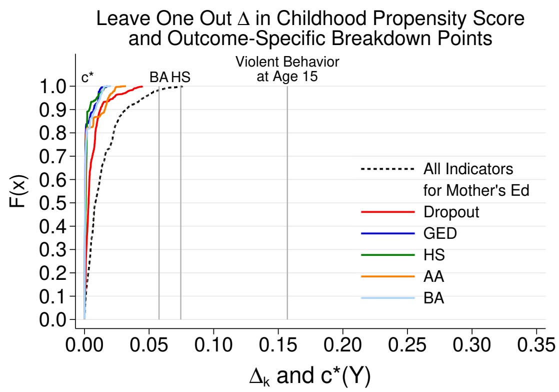
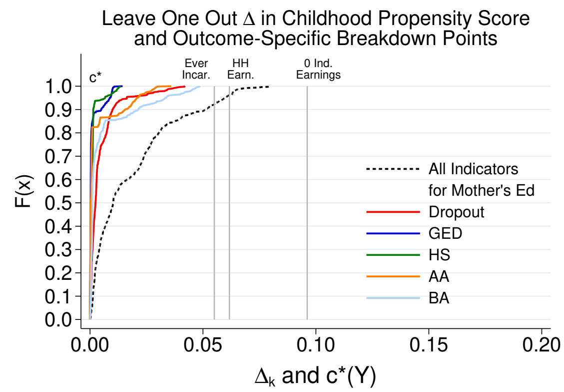


Figure 11: Violent Behavior at Age 15, Conditional on Father's Imprisonment
Note: The blue lines and dots in this figure show the coefficients of a regression of an indicator for violent behavior at age 15 on childhood exposure to violence, conditional on whether each respondent's father spent time imprisoned before the respondent turned 16. The sample is Black males in the NLSY97. The rectangles outlined in grey report the probability mass function of respondents in the sample.

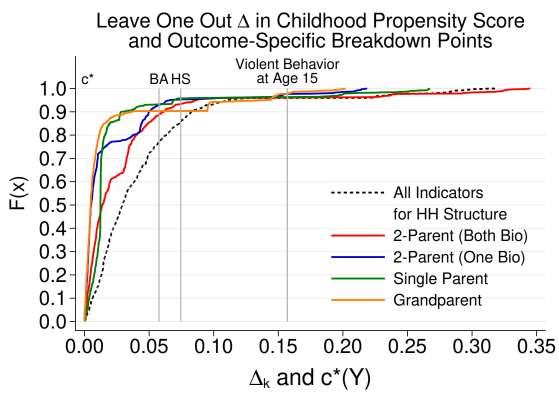
F Robustness to c-Dependence in Masten et al. (2023)



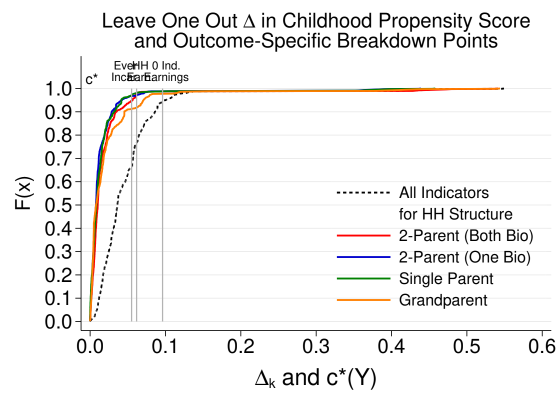
(a) Mother's Educational Attainment



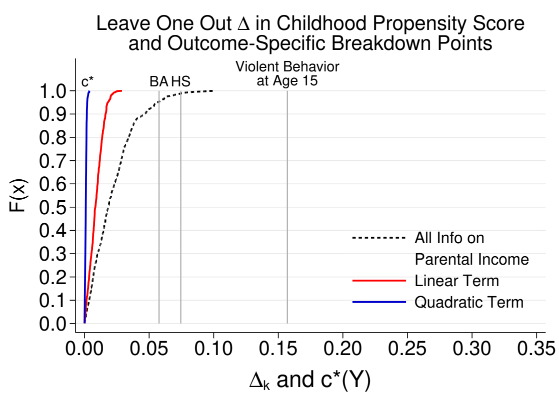
(b) Mother's Educational Attainment



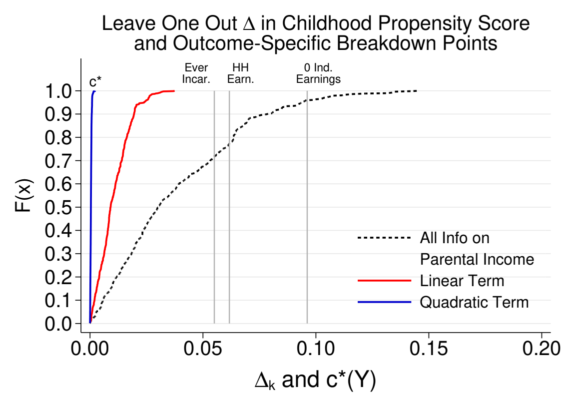
(c) Household Structure



(d) Household Structure



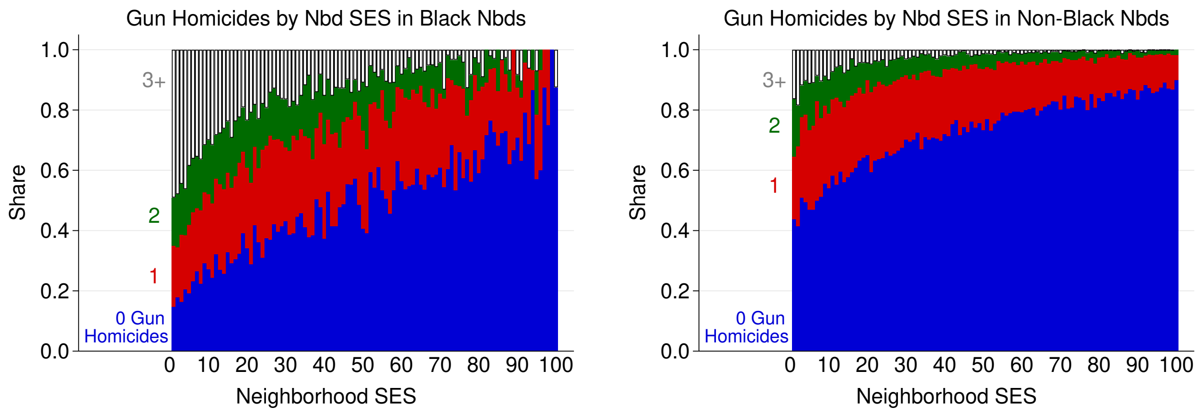
(e) Parental Income



(f) Parental Income

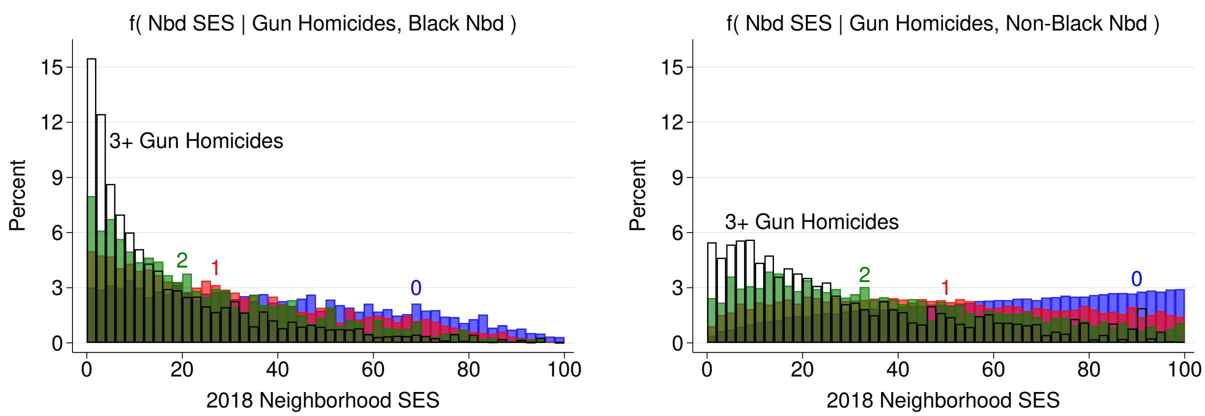
Figure 12: Breakdown Points and Changes in Childhood Exposure Propensity Scores
Note: In these figures vertical lines represent outcome-specific breakdown points, which are described in the main text. The CDFs represent the individual-level distribution of changes in the propensity score when one variable or set of indicator variables is removed from the estimation of the propensity score. In the left panel, holding a high school diploma ("HS") or attaining a BA ("BA") are measured when the respondent is aged 26. In the right panel, individual earnings ("Ind. Earnings") and household earnings ("HH Earnings") are measured in the 2019 wave of the survey regarding their values in 2018, when respondents were aged 34-38. "Ever Incar." is an indicator for whether a respondent was ever incarcerated by the time of the 2019 survey. See the text for more details on each variable.

G Neighborhood Violence and Neighborhood SES



(a) Tracts ≥20% Black (b) Tracts <20% Black

Figure 13: Gun Homicides by Neighborhood SES and Racial Composition
Note: These figures plot the tract-level distribution of number of gun homicides by percentile of neighborhood SES. The left panel displays tracts that are at least 20 percent Black and the right panel displays other tracts. The text describes the data on gun homicides from the Gun Violence Archive (GVA) and the data on tract-level characteristics from the American Community Survey (ACS).



(a) Tracts ≥20% Black (b) Tracts <20% Black

Figure 14: Neighborhood SES by Number of Gun Homicides and Racial Composition
Note: These figures plot the distribution of neighborhood SES by the number of gun homicides. The left panel displays tracts that are at least 20 percent Black and the right panel displays other tracts. The text describes the data on gun homicides from the Gun Violence Archive (GVA) and the data on tract-level characteristics from the American Community Survey (ACS).

H Incarceration Mediating Childhood Exposure for Earnings

Table 5: Individual Earnings in 2018

Variable	Independent		
Childhood	–11.7		–10.0
Exposure	[0.00]		[0.00]
Ever		–25.5	–25.1
Incarcerated		[0.00]	[0.00]
R^2	0.01	0.06	0.07

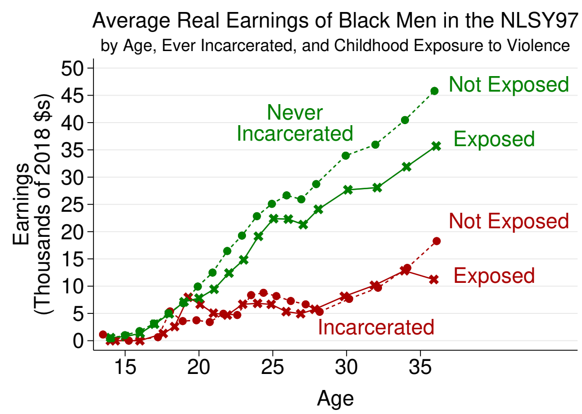


Figure 15: Individual Earnings

Table 6: Earning $0 in 2018

Variable	Independent		
Childhood	11.5		9.8
Exposure	(3.2)		(3.1)
Ever		25.2	24.8
Incarcerated		(3.1)	(3.1)
R^2	0.01	0.07	0.08

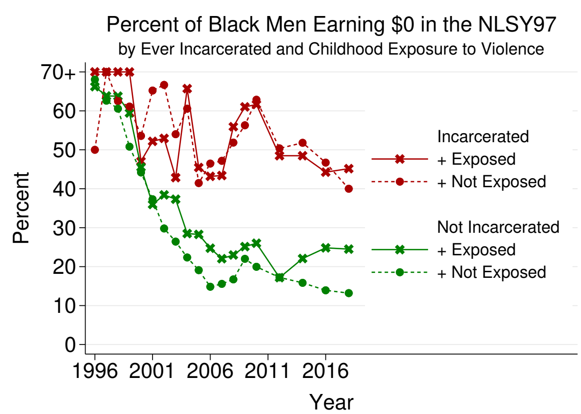


Figure 16: Earning $0

I Non-Violent Adversity

I.1 Measuring Non-Violent Adversity

The variables chosen for inclusion in our measure of non-violent adversity are distinct from those used to define Adverse Childhood Experiences (ACEs). These choices are partly driven by the NLSY97 data set. The NLSY97 includes few of the measures used in the original ACEs study (Felitti et al. (1998)). This may be partly due to the fact that unlike the retrospective design of the original ACEs study, the NLSY97 interviewed children while they were still living with their parents. Asking children about their parents' abuse (physical, sexual, or emotional); neglect (physical or emotional); or household dysfunction (intimate partner violence, mental illness, or substance abuse) would have likely resulted in uncooperative survey respondents.

The variables chosen for inclusion in our measure of non-violent adversity are also driven by the sample of Black males we are studying. Appendix Table 7 shows that the variables included in the non-violent adversity indicator tend to be highly predictive of long-run outcomes for both Black and white males.[23] In contrast, Appendix Table 8 shows that divorce and family hospitalizations have differential associations with outcomes for Black and white men.[24] These results add an important point to the discussion of what experiences should be included in a measure of adversity (Finkelhor et al. (2015)): The best measure is likely to be group specific.

The variables chosen for inclusion on our measure of non-violent adversity are also driven by the sample of Black males we are studying. While it is unsurprising, Table 7 shows that the variables included in the non-violent adversity indicator tend to be highly predictive of long-run outcomes for both Black and white males. The large effects of parental unemployment on adult earnings for white males coupled with a statistically insignificant effect on high school graduation rates is consistent with the results in Carneiro et al. (2023) on the effects of parental job displacement in Norway.

[23]The large effects of parental unemployment on adult earnings for white males coupled with a statistically insignificant effect on high school graduation rates is consistent with the results in Carneiro et al. (2023) on the effects of parental job displacement in Norway.

[24]The results for white men are almost always large and statistically significant, consistent with the results on family hospitalizations in Johnson and Reynolds (2013).

Table 7: Adult Outcomes and Included Measures of Non-Violent Adversity

	Parent Incarcerated		Homeless		Parent Unemp.		Parent/Sib. Death	
Variable	Black	White	Black	White	Black	White	Black	White
HS	-47.1	-20.6	-13.5	-45.4	-8.8	-2.0	-10.1	-9.7
	[0.00]	[0.03]	[0.27]	[0.00	[0.16]	[0.64]	[0.02]	[0.00]
BA	-9.8	-15.7	-10.0	-27.3	-3.6	-8.8	-5.5	-10.7
	[0.25]	[0.13]	[0.18]	[0.00]	[0.35]	[0.07]	[0.04]	[0.00]
incar	32.3	15.2	36.9	6.3	8.4	-2.7	3.3	12.0
	[0.01]	[0.05]	[0.00]	[0.32]	[0.14]	[0.46]	[0.39]	[0.00]
earnings	-16.5	-34.5	-18.4	-22.5	-10.7	-11.1	-12.8	-13.8
	[0.32]	[0.03]	[0.21]	[0.12]	[0.11]	[0.17]	[0.00]	[0.02]

Note: This table reports coefficients from regressions of the outcome variables on an indicator for each measure of non-violent adversity. The p-values of tests for each coefficient being different from 0 are reported in braces [ ].

A more surprising set of results relates to the exclusion of divorce and family hospitalizations and is shown in Table 8. The table shows that for long-run outcomes of Black men, differences between those exposed to each excluded measure of non-violent adversity and those not exposed are small and statistically insignificant. In contrast, for white men, differences are almost always large and statistically significant, in line with the results from Johnson and Reynolds (2013). These results add an important point to the discussion of what experiences should be included in a measure of adversity (Finkelhor et al. (2015)): The best measure is likely to be group specific.

Table 8: Adult Outcomes and Omitted Measures of Non-Violent Adversity

	Divorce		Parent or Sibling in Hospital	
Outcome	Black	White	Black	White
HS by 26	3.8	–12.6	–5.9	–5.1
	[0.38]	[0.00]	[0.19]	[0.05]
BA by 26	1.2	–15.2	–1.9	–8.1
	[0.66]	[0.00]	[0.50]	[0.01]
Incar. by 2019	1.7	3.5	2.2	0.8
	[0.68]	[0.07]	[0.60]	[0.72]
Earnings in 2018	–2.1	–0.4	–1.3	–7.8
(1,000s of 2018 $s)	[0.64]	[0.93]	[0.79]	[0.10]

Note: This table reports coefficients from regressions of the outcome variables on an indicator for each measure of non-violent adversity. The p-values of tests for each coefficient being different from 0 are reported in braces [ ].

I.2 Potential Outcomes and Causal Effects

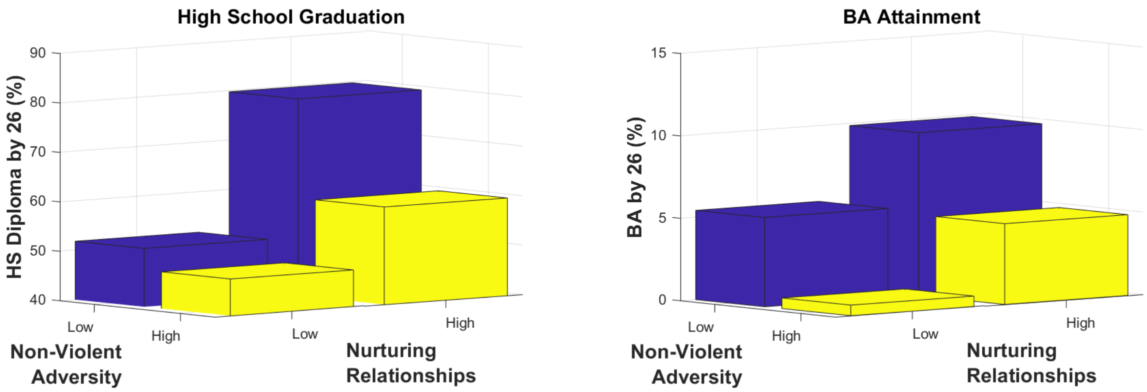


Figure 17: Potential Outcomes for Educational Attainment

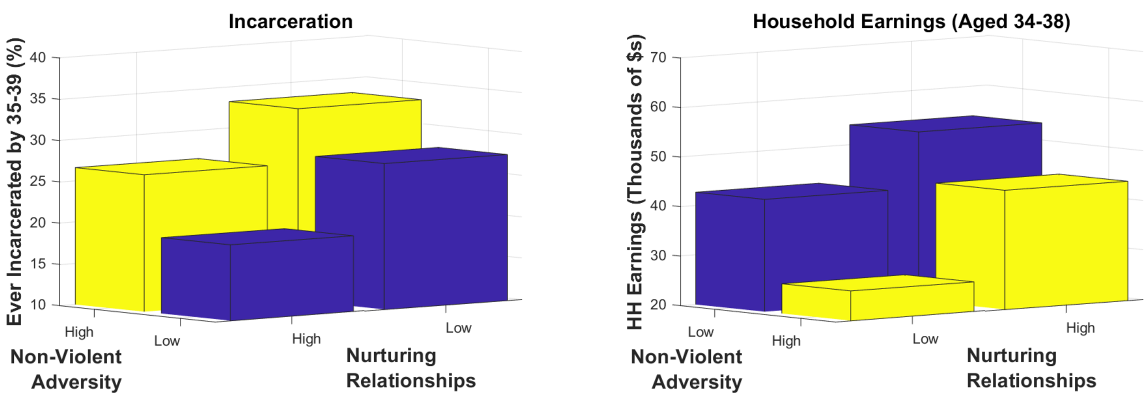


Figure 18: Potential Outcomes for Incarceration and Household Earnings

Table 9: Effects of Changing Treatments in Non-Violent and Nurturing Relation. Model

	Given High Non-Violent Adversity and Low Nurturing Relationships		
	$\downarrow D^{NV}$	$\uparrow D^{NR}$	Both
HS	4.4	12.3	32.3
	[0.06]	[0.00]	[0.00]
BA	4.8	4.3	9.2
	[0.03]	[0.20]	[0.00]
HH Earnings	16.7	18.1	28.0
	[0.03]	[0.11]	[0.00]
Incarceration	–5.6	–6.6	–14.0
	[0.07]	[0.11]	[0.00]

Note: The p-values of one-sided tests for each coefficient being different from 0 are reported in braces [ ] and are obtained from 1,000 bootstrap replications.

J Details on the Item Response Theory Estimation

J.1 The Likelihood Function

We estimate our Item Response Theory (IRT) model using the `irt` command in Stata. We study the robustness of distributional assumptions on the latent index by estimating the model in MATLAB. We infer the precise estimation routine in Stata using a combination of Stata (2021), de Ayala (2022), Raykov and Marcoulides (2018), and Harwell et al. (1988).

We observe $j \in \{1, 2, \ldots, J\}$ noisy measures V_i^j of a latent index θ_i^V representing each respondent's exposure to violence.[25] Our Item Response Theory (IRT) model assumes that each binary measure V_i^j for respondent i and measure $j = 1, \ldots, J$ is a function of the latent index as

$$V_i^j = \begin{cases} 1 & \text{if } \alpha_j(\theta_i^{PCE} - \beta_j) - \epsilon_i^j > 0 \\ 0 & \text{if } \alpha_j(\theta_i^{PCE} - \beta_j) - \epsilon_i^j \leq 0. \end{cases}$$

Assuming ϵ_i follows a type-1 extreme value distribution, then

$$Pr(V_i^j = 1|\alpha, \beta, \theta_i) = \text{logit}[\alpha_j(\theta_i^{PCE} - \beta_j)]$$

where the α_j term is often referred to as the discrimination of item j, the β_j term is typically referred to as the difficulty of item j, and the combined parameters α_j, β_j are often called the item parameters. If we further assume that the latent index follows a standard normal distribution, or $\theta_i \sim \Phi$, we can write each individual's contribution to the Likelihood as

$$\mathcal{L}_i(\alpha, \beta) = \int_{-\infty}^{\infty} Pr(V_i|\alpha, \beta, \theta_i) d\Phi(\theta_i) \tag{2}$$

where

$$Pr(V_i|\alpha, \beta, \theta_i) = \prod_{j=1}^{J} Pr(V_i^j = 1|\alpha, \beta, \theta_i)^{V_i^j} (1 - Pr(V_i^j = 1|\alpha, \beta, \theta_i))^{1-V_i^j},$$

Because θ_i is not observed, to calculate each individual's likelihood in Equation 3 one must use numerical integration, or numerical quadrature, as

$$\mathcal{L}_i(\alpha, \beta) = \sum_{q=1}^{Q} Pr(V_i|\alpha, \beta, \theta_q) \widehat{\varphi}(\theta_q) \tag{3}$$

where there are Q quadrature points and $\widehat{\varphi}(\theta_q)$ is the numerical probability mass function (pmf) approximating the standard normal distribution. This marginal likelihood is estimated in each iteration before parameters are found, which respectively represent the Expectation and Maximization steps of the EM algorithm. The resulting estimates of the item parameters $\widehat{\alpha}$ and $\widehat{\beta}$ are often referred to as the marginal maximum likelihood (MML) estimates (Raykov and Marcoulides

[25] The same procedure is used for nurturing relationships.

(2018)).

Once the MML item parameters are estimated, one can compute Empirical Bayes estimates of each individual's latent index as

$$\overline{\theta}_i = \int \frac{\theta Pr(V_i|\widehat{\alpha}, \widehat{\beta}, \theta)\varphi(\theta)}{Pr(V_i|\widehat{\alpha}, \widehat{\beta}, \theta)\varphi(\theta)} d\theta.$$

This binary IRT model can be generalized to ordered responses along the lines by which a logit model is extended to an ordered logit model. A given measure

$$V_i^j = \begin{cases} 1 & \text{if } \alpha_j \theta_i^V - \epsilon_i < C_1^j \\ 2 & \text{if } C_1^j \leq \alpha_j \theta_i^V - \epsilon_i < C_2^j \\ \vdots & \vdots \\ K & \text{if } \alpha_j \theta_i^V - \epsilon_i > C_{K-1}^j, \end{cases}$$

will have likelihood

$$\mathcal{L}_i(\alpha, \beta, C) = \int_{-\infty}^{\infty} Pr(V_i|\alpha, \beta, C, \theta_i) d\Phi(\theta_i)$$

where

$$Pr(V_i|\alpha, \beta, C, \theta_i) = \prod_{j=1}^{J} \left[\sum_{k=1}^{K} \mathbf{1}\{V_i^j = k\} Pr(V_i^j = k|\alpha, \beta, C, \theta_i) \right].$$

Thus the log-Likelihood is

$$\mathcal{LL}(\alpha, \beta, C) = ln[\prod_{i=1}^{N} \mathcal{L}_i(\alpha, \beta, C)] = \sum_{i=1}^{N} ln \left[\mathcal{L}_i(\alpha, \beta, C) \right].$$

J.2 Robustness to Distributional Assumptions

A key distributional assumption in the estimation of the IRT model is that the latent indexes follow standard normal distributions. Here we show that this distributional assumption has no implications for our discrete treatment; individuals will receive the same treatment label based on their percentile in the distribution of the estimated latent index.

We estimate the IRT model described above for exposure to violence under two distributional assumptions:

$$\theta^V \sim \begin{cases} \mathcal{N}(0,1); \text{ and} \\ \text{U}[-5,5]. \end{cases}$$

Figure 19 shows a scatter plot of the resulting estimates of the latent indexes, together with the terciles of the empirical distributions. What is evident from this plot is that the estimated θ_i^V is in the same tercile of the distribution nearly all of the time when it is estimated under the assumption of a normal or uniform distribution. This fact is quantified in Table 10. In our sample 97 percent of individuals are labeled with the same three-leveled treatment regardless of whether we assume

θ_i^V follows a normal or a uniform distribution. In our sample 1.4 percent of individuals are ranked higher under the assumption that θ_i^V follows a normal distribution and 1.5 percent of individuals are ranked higher under the assumption that θ_i^V follows a uniform distribution.

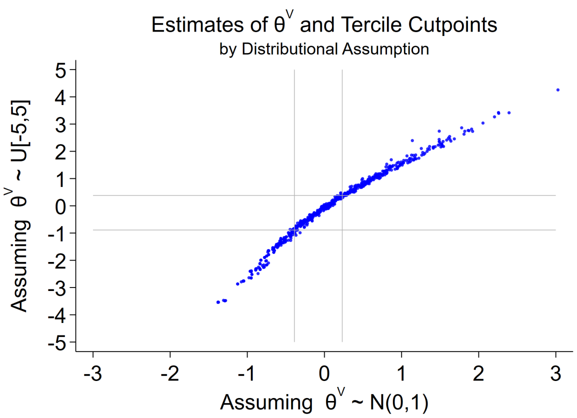


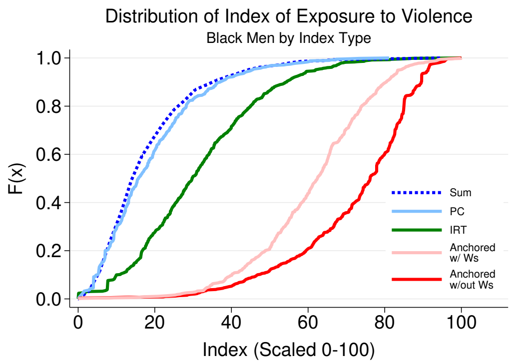
Figure 19: Estimated θ_i^V's by Dist. Assumption
Note: This figure shows the distribution of Empirical Bayes estimates of θ_i^V in the Item Response Theory model under the assumptions that $\theta_i^V \sim \mathcal{N}(0,1)$ and $\theta_i^V \sim \mathrm{U}(-5,5)$. The grey vertical and horizontal lines display the terciles of each distribution, which can be used to define 3-level treatment variables analogous to the binary treatment variable used in the analysis in the main text.

Table 10: Difference in 3-Level Treatments by Distributional Assumption

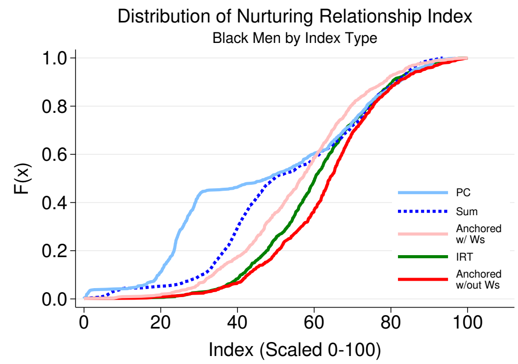
	Difference in 3-Level Treatments $D_U^V - D_N^V$		
	–1	0	1
Frequency	10	700	11
Percent	1.4	97.1	1.5

Note: This table reports the difference in a 3-level treatment estimated under the assumption that $\theta_i^V \sim \mathrm{U}[-5,5]$, denoted by D_U^V, and a 3-level treatment estimated under the assumption that $\theta_i^V \sim \mathcal{N}(0,1)$, denoted by D_N^V.

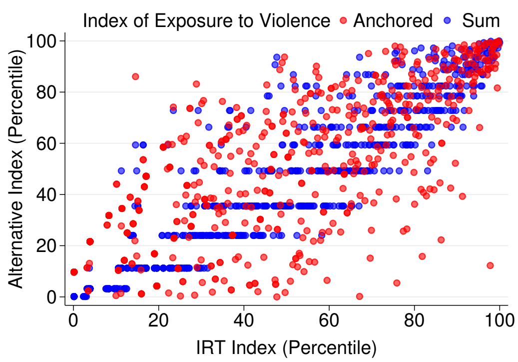
K Comparison of Approaches to Calculating Indexes: Item Response Theory, Additive, and Principal Components



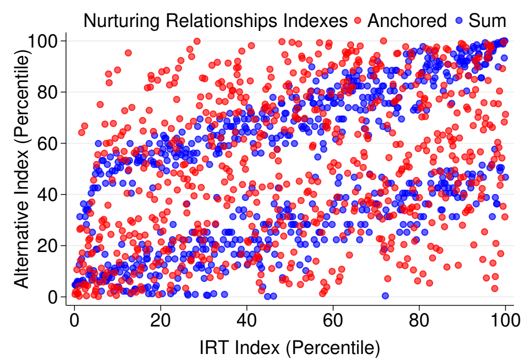
(a) Exposure to Violence



(b) Nurturing Relationships



(c) Exposure to Violence



(d) Nurturing Relationships

Figure 20: Indexes by Estimation Method

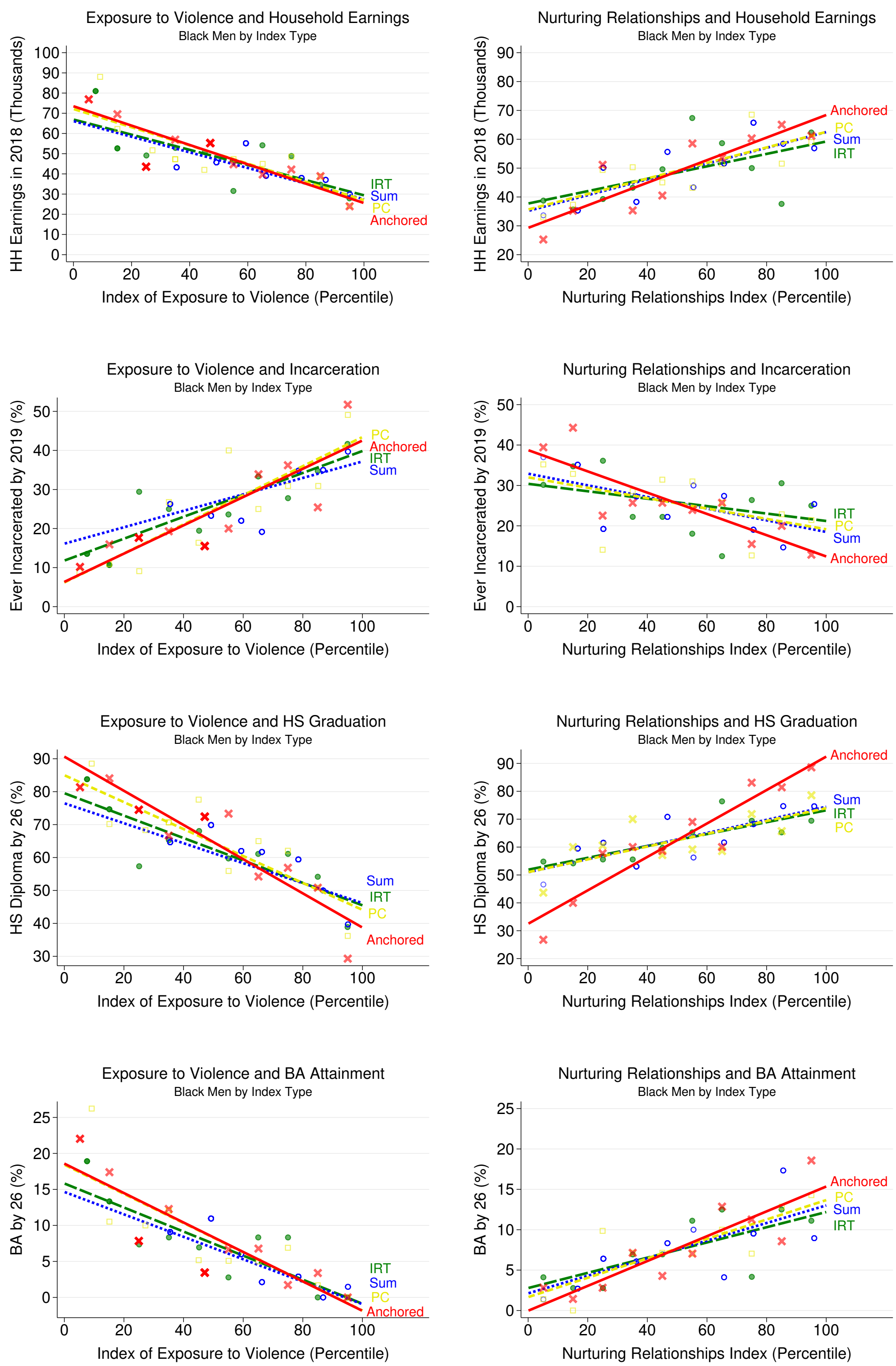


Figure 21: Binned Scatterplots of Black Men's Outcomes and Indexes

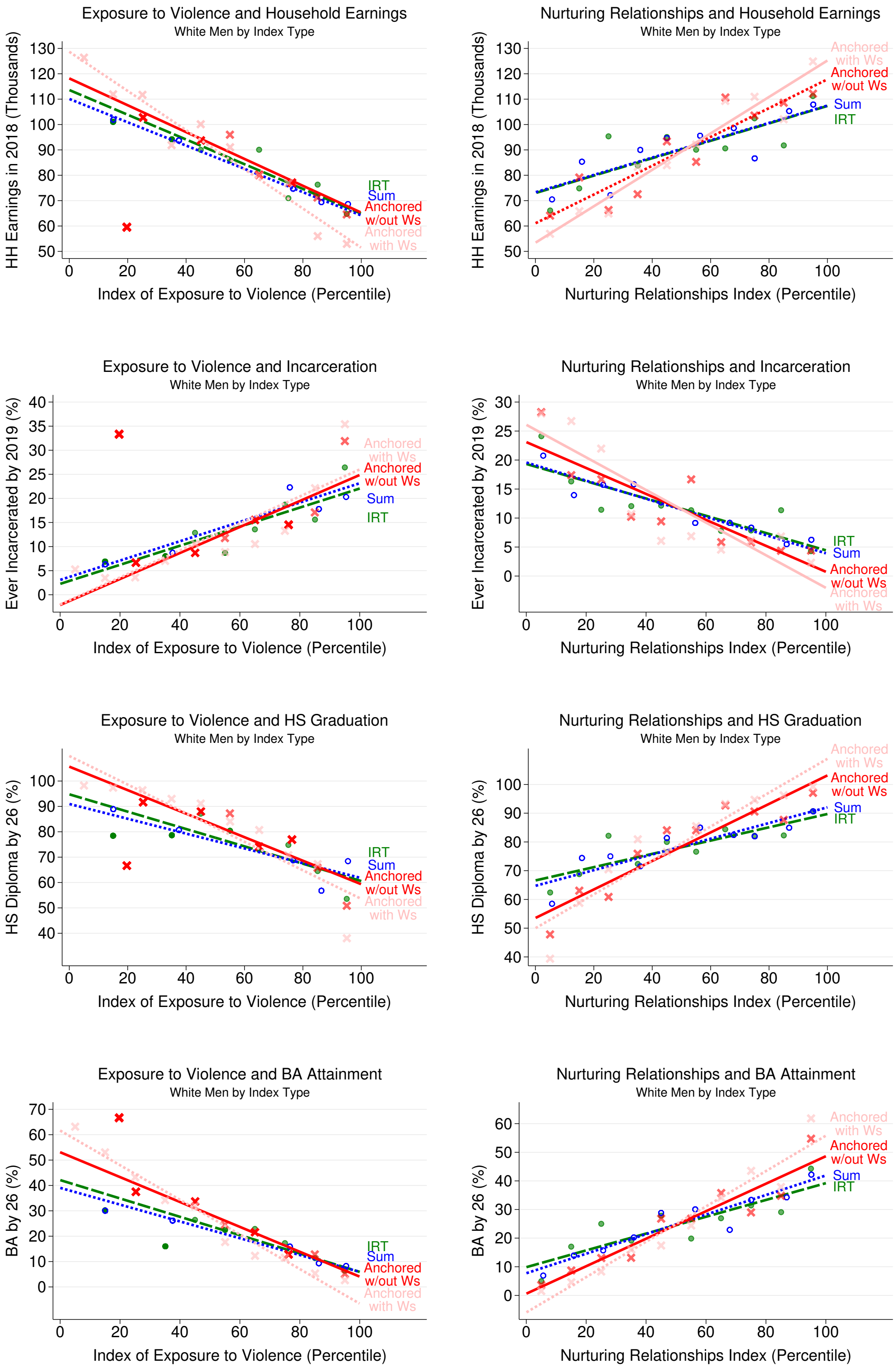


Figure 22: Binned Scatterplots of White Men's Outcomes and Indexes

Figures 23 and 24 show the weights assigned to each item via an estimated linear probability model for attaining a HS diploma by age 26. A few notable features are (1) the range of weights, with some items receiving large weights, both positive and negative, and others receiving weights near 0. (2) the respondent living with their father is highly positive while living with their mother is highly negative. The negative coefficient for the mother is not surprising, as this is net of all of the other questions about the mother. (3) not shown, but consistent with the results in Nielsen (2022), is that anchoring to different outcomes generates different weights.

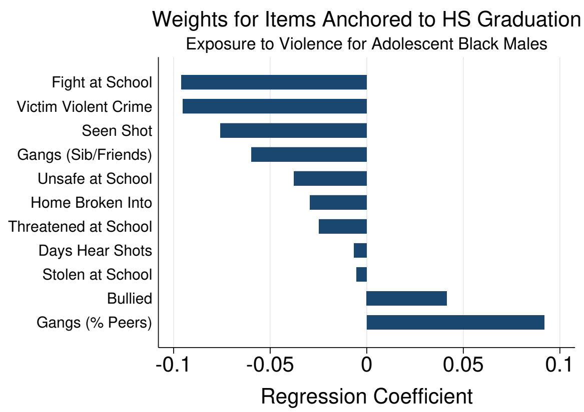
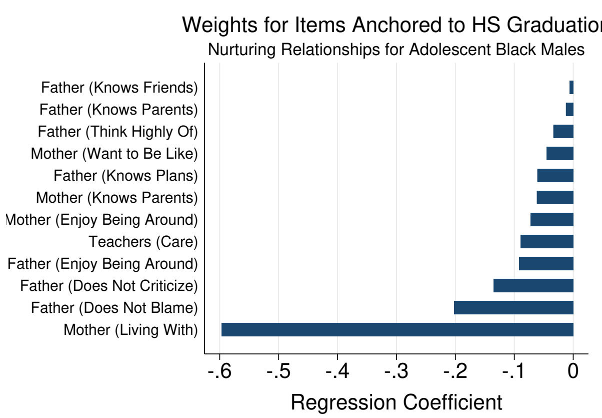
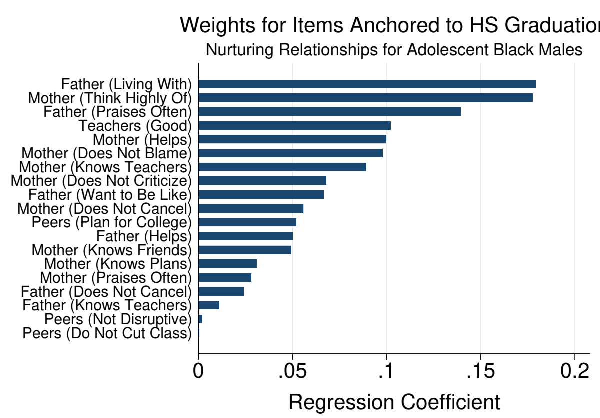


Figure 23: Item-Anchored Weights



(a) HS Graduation by Nurturing Relationships Indexes



(b) HS Graduation by Nurturing Relationships Indexes

Figure 24: Item-Anchored Weights

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