# Human Capital in the Inner City

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**Abstract:** Twenty-six percent of black males in the United States report seeing someone shot at before turning 12. This paper investigates how black young males alter their behavior when living in violent neighborhoods, using the nationally-representative National Longitudinal Survey of Youth 1997 to quantitatively characterize the "code of the street" from the sociology literature. Black and white young males are equally likely to engage in violent behavior, conditional on reported exposure to violence. Education and labor market outcomes are worse when reporting exposure, unconditionally and controlling for observables. Mediators matching those documented in the ethnography are quantitatively important in the estimated structural model.

**Keywords:** Code of the Street; Interpersonal Violence; Human Capital; Race; Propensity Score Matching; Dynamic Selection Control

**JEL Classification Numbers:** I21, J15, J24, O15, O18, Z13

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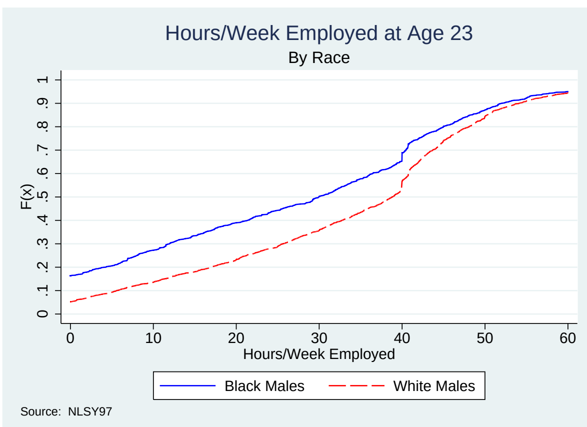
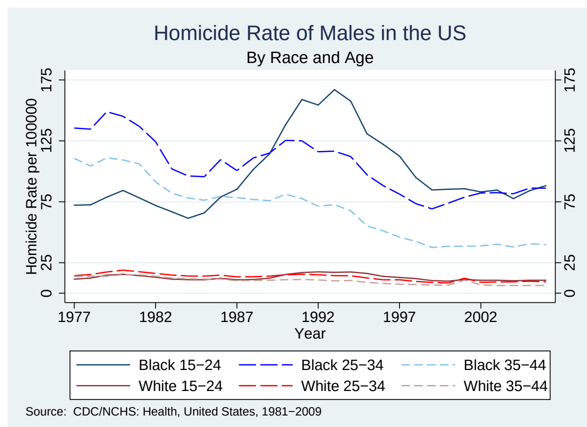
# 1 Introduction

Education and labor market outcomes are strongly correlated with race in the United States. For example, 37 percent of black males in the National Longitudinal Survey of Youth 1997 (NLSY97) had not earned a high school diploma by age 21, compared with 21 percent of white males. The median 23 year old black male in the NLSY97 worked nine hours less per week than his white counterpart (Figure 1a).

Exposure to violence is also strongly correlated with race in the US. While eight percent of white males in the NLSY97 report having seen someone shot at before the age of 12, this is true of an astonishing 26 percent of black males.[1] In recent years both the homicide death rate and the hospitalization rate for firearm injuries were approximately an order of magnitude higher for black young males than for their white counterparts (Figure 1b, NCHS (2009), Leventhal et al. (2014)).




(a) Employment of 23 Year-Old Males in the US




(b) Homicide Rate of Males in the US

Figure 1: Labor Market and Health Outcomes of Males in the US

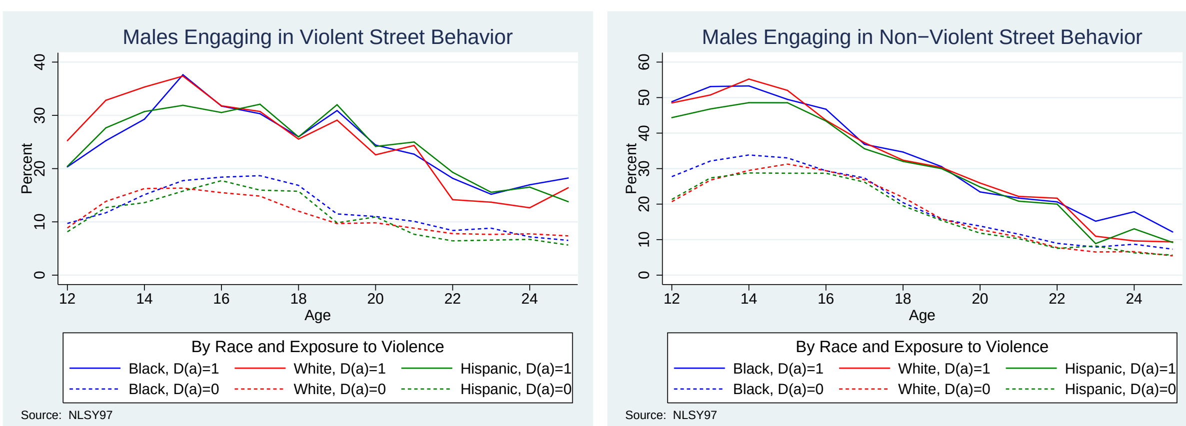
The sociology literature has developed a prominent theory linking these outcomes, based on years of urban ethnography. Anderson (1999) posits that weak institutions and labor market conditions have left a void in setting and maintaining the social order within many poor African American neighborhoods, allowing a "street" element to fill this void with its own code of conduct. Anderson has observed that individuals are likely to adopt this "code of the street," which encourages individuals to use violence to further their interests, when state institutions cannot ensure their personal security and when they feel isolated from mainstream institutions. Anderson has also observed that becoming invested in this code of conduct leads to disinterest in mainstream institutions like the formal labor market, the education system, and the church. While Anderson's qualitative work has motivated theory (Silverman (2004), O'Flaherty and Sethi (2010a)), and there is quantitative evidence of effects of violence in studies from Chicago (Sharkey (2006), Sharkey (2010)) and other countries (Damm and Dustmann (2014), León (2012)), the empirical magnitude of the code of the street phenomenon has yet to be established.

[1] The analogous percentages for white and black females are, respectively, five and 15 percent.

This paper quantitatively characterizes the "code of the street" using the nationally-representative NLSY97 data set. The NLSY97 has unique strengths for such an analysis, including extensive data on exposure to violence, with variables measuring exposure at both the county and the individual level.[2] The NLSY97 also has detailed measures of street capital, the distinct type of human capital useful for providing personal security in neighborhoods influenced by the code of the street. Young males are assumed in this analysis to acquire street capital by engaging in street behaviors recorded in the NLYS97, such as carrying a gun, attacking someone, belonging to a gang, selling drugs, stealing, committing a property crime, or being suspended from school.

I present a descriptive analysis of the NLSY97 data on exposure to violence, street behavior, high school graduation, and employment, with a focus on the outcomes of black young males. Black males report being exposed to substantial amounts of violence at young ages: 26 percent of black males saw someone shot by age 12, 29 percent between 12 and 18, and cumulatively 43 percent by age 18. This compares with 8, 10, and 15 percent, respectively, for white males. On average, black males report hearing 1.0 gunshots per week in their neighborhood, more than twice the average for white males, 0.4. Appendix B documents the broad ways these self-reported data in the NLSY97 are consistent with related administrative data, and the "ecometric" reasons these variables are likely to be an improved measure of exposure to violence relative to available administrative variables.

I find a highly invariant relationship between exposure to violence and the street behaviors of young males that is consistent with Anderson's theory of personal security. Although black males engage in more street behaviors than white or Hispanic males, the rate at which black, white, and Hispanic young males engage in violent behaviors is equal conditional *only* on exposure to violence (Figure 2). The increase in street behaviors associated with exposure to violence is also stable across mother's educational attainment and household type (Figure 9).




(a) Violent, By Race and Exposure

(b) Non-Violent, By Race and Exposure

Figure 2: Street Behavior by Exposure to Violence and Race/Ethnicity

[2]The county-level variables are homicide and assault rates, and the individual-level variables are having seen someone shot and the frequency of hearing gunshots in one's neighborhood. The county-level variables are created by combining the NLSY97 geocode file with the FBI's UCR data. Details are provided in Section 3.

I also find that exposure to violence is related to the education and labor market outcomes of black young males in ways that are consistent with exposure causing undesirable outcomes. Black young males who report being exposed to violence are much less likely to graduate from high school and work fewer hours than their counterparts who do not report being exposed to violence.

I conclude with a causal analysis in which I investigate whether differences in outcomes by exposure to violence persist after conditioning on observed characteristics, as well as permanent unobserved heterogeneity. I first estimate static models that match on the permanent observed characteristics of black young males. I then estimate effects of exposure to violence in a dynamic model of human capital accumulation that additionally allows for correlation between the unobserved permanent factors determining exposure to violence and outcomes.[3]

The estimated models are specified to control for complementary patterns of selection into treatment, in an attempt to give as much credibility as possible to a causal interpretation of differences by exposure to violence.[4] The matching models can accommodate selection into treatment based on the observed characteristics. The dynamic finite mixture model allows for more general patterns of selection, including a non-parametric correlation structure of permanent unobserved heterogeneity. To understand what this means, consider an example in which individuals choosing employment in the informal sector (as drug dealers) were systematically more likely to be exposed to violence and less likely to be employed in the formal labor market. This should be controlled for in the estimated model as a correlation in the permanent unobserved factors driving decisions.

I find that gaps in outcomes by exposure to violence persist in the estimated models, which I interpret as evidence that such gaps represent causal effects. Based on counterfactuals from the estimated models, I conclude that for the subpopulation exposed to violence, childhood exposure decreases the high school graduation rate between 8.0 and 16.5 percentage points (24 and 50 percent of the high school dropout rate) and adolescent exposure decreases age 23 average weekly hours worked between 3.5 and 4.9 hours (0.17 and 0.24 $\sigma$). Placebo tests on outcomes before exposure, like mother's age at birth and time spent in childcare, all return statistical zeros. Counterfactuals from the estimated structural model indicate that the accumulation of street capital is likely an important mechanism through which exposure to violence affects outcomes.

This quantitative evidence on the code of the street relates to several branches of literature. Most closely related is a set of studies looking at exposure to violence that does not formally model the residential sorting or institutional arrangements generating that exposure. This literature finds evidence of both acute (Sharkey (2010)) and durable (León (2012)) effects of exposure to violence.[5] Another closely related line of research studies the role of segregation and institu-

[3]This dynamic selection control model (Hotz et al. (2002)) employs panel data methods, and does have an updating, endogenous state variable, but is not dynamic in the broader case where agents' choices also depend on their beliefs about the future evolution of their state variable (Kydland and Prescott (1977)).

[4]Here credibility is defined as in Manski (2007) as the strength of assumptions necessary for inference. Although no researcher would subjectively rank the estimated models as having the same credibility one would achieve by randomly exposing individuals to violence, many researchers will find the weaknesses of their identification strategies to be preferable to avoiding the question at hand (Imbens (2010)).

[5]Related studies also find evidence of effects from trauma (Gerson and Rappaport (2012), Becker and Kerig (2011), Kilpatrick et al. (2003), Breslau et al. (1991), Abram et al. (2004)), gun violence (Cook and Ludwig (2002),

tional arrangements in generating outcomes like violence and crime (O'Flaherty and Sethi (2010a), O'Flaherty and Sethi (2010b), O'Flaherty and Sethi (2007), Bjerk (2010), Sampson et al. (1997), Verdier and Zenou (2004)). Included in this literature are studies that have also been directly inspired by Anderson (1999)'s description of the code of the street. For example, Silverman (2004) provides a theoretical model of how violent behavior can be interpreted as a signal in an environment where reputation impacts the likelihood of facing violent confrontations. In addition, Sharkey (2006) presents empirical evidence that adolescents' violent behavior is related to beliefs about their ability to limit the neighborhood violence to which they are exposed, which is itself affected by the collective efficacy in the neighborhood.

In addition to the literature directly studying the code of the street and its components, the evidence in this paper also contributes to the broader literature on neighborhood effects. The geographic distribution of violence, and the related geographic provision of safety, is likely to be an important component of the neighborhood effects studied in the literature beginning with Wilson (1987). Not only could neighborhood violence help to explain residential sorting patterns (Baum-Snow and Lutz (2011), Clampet-Lundquist and Massey (2008), Sampson (2008)), but it also provides a key mechanism through which racial segregation can have effects on crime (Weiner et al. (2009), Billings et al. (2012), Ludwig and Kling (2007)), education (Guryan (2004), Card and Rothstein (2007), Jacob (2004)), and other important outcomes (Collins and Margo (2000), Cutler and Glaeser (1997), Aliprantis and Carroll (2013)). Given both the importance of specifying the mechanisms through which neighborhood effects operate (Aliprantis (2015a)), and the qualitative evidence on the subject (Kling et al. (2005)), studying neighborhood violence might prove insightful for understanding the results of housing mobility programs like Moving to Opportunity (Kling et al. (2007), Aliprantis and Richter (2014)) or HOPE VI (Aliprantis and Hartley (2015)).

Finally, the results in this paper contribute to the literature on the process by which individuals accumulate human capital. One related literature studies the accumulation of human capital used in the formal labor market when there is a tradeoff between labor market outcomes and criminal behavior (Lochner (2004), Imai and Krishna (2004), Gould et al. (2002), Sampson (1987)), and another literature studies the accumulation of criminal capital (Bayer et al. (2009), Mocan et al. (2005), Ward et al. (2015)). Unlike most of those papers, this study does not take the canonical model from Becker (1968) as its starting point. In particular, since the model in this paper focuses on human capital valuable for ensuring safety, not human capital valuable for committing crimes, the analysis is concerned with both pecuniary and non-pecuniary returns to behavior.[6] Returning to the types of human capital useful in the formal labor market, the estimated effects indicate that exposure to violence could be an important source of heterogeneity in the widely-documented pre-market factors contributing to racial gaps in labor market and education outcomes (Neal and Johnson (1996), Urzúa (2008), Keane and Wolpin (2000), Cameron and Heckman (2001)), and might play

Hemenway (2006)), and maltreatment (Currie and Tekin (2012)) in the psychology, public health, and economics literatures.

[6]Silverman (2004) discusses stylized facts motivating a focus on non-pecuniary returns.

a role in statistical discrimination (Fang and Moro (2011)). Social-cognitive skills might be a part of pre-market factors (Heller et al. (2012), Borghans et al. (2008)), and exposure to violence might affect these skills through a variety of mechanisms, such as non-pecuniary rewards like identity (Fang and Loury (2005), Akerlof and Kranton (2002), Austen-Smith and Fryer (2005)), or expectations about the future (Au (2008)).

The remainder of the paper is organized as follows: The code of the street is described in Section 2, which also includes a definition of street capital and a discussion of the two key mechanisms thought to drive the empirical results. The sample used from the National Longitudinal Survey of Youth 1997 (NLSY97) data set is described in Section 3, including the variables used to measure street capital and exposure to violence. Section 4 estimates causal effects of exposure to violence within static models using various matching techniques. Section 5 specifies and estimates a structural model of human capital accumulation that allows for dynamic selection control. Section 6 concludes.

## 2 The Code of the Street and Street Capital

This paper uses the "code of the street," an influential theory from the sociology literature, as a lens through which to quantitatively study how exposure to violence affects the outcomes of black young males in the US. The analysis first investigates how exposure to violence affects outcomes without attempting to understand the mechanisms through which these effects operate. After this initial analysis, the paper also studies exposure to violence using an estimated model that includes key mechanisms from the code of the street. The two key mechanisms, which I label personal security and social isolation, are described here to motivate the model specification presented later in the paper.

According to the qualitative evidence presented in Anderson (1994) and later more fully developed in Anderson (1999), weak institutions and labor market conditions have left a void in setting and maintaining the social order within poor African American neighborhoods, empowering a "street" element to fill this void with its own code of conduct. This code of conduct, known as the code of the street, encourages individuals to use violence in order to further their own interests. Although most people living in poor inner city neighborhoods adhere to a "decent" set of social norms which abhors violence (Anderson (1999), p 36), they must adjust their behavior to deal with the "street" social types who have a proclivity towards violence and "few moral compunctions against engaging in 'wrongdoing' and 'mistreating' others" (Anderson (1990), p 68).[7] This creates neighborhoods in which, as characterized by equilibria in the overlapping generations stage game in Silverman (2004), small proportions of street types are able to sustain high levels of violence.

Just as Austen-Smith and Fryer (2005) point out for the phenomenon of "acting white," it is important to note that this type of security arrangement is not unique to poor African Amer-

[7] "Street" and "decent" are the labels used by inner city residents themselves; for discussions of these label see page 35 of Anderson (1999) and Anderson (2002).

ican neighborhoods.[8] Nevertheless, the manifestation of this security arrangement in inner city neighborhoods has been heavily influenced by the alienation many blacks feel from mainstream institutions. Anderson (1999) argues that the code of the street is actually a cultural adaptation to a profound lack of faith in mainstream institutions, especially "in the police and the judicial system - and in others who would champion one's personal security" (p 34). The racial discrimination generating this lack of faith has also helped to create a narrative of black racial identity that venerates alienation from mainstream institutions and values. The role of this narrative within the code of the street is captured in Anderson's description of competing social norms: "The culture of decency is characterized by ... the value of treating people right, and a strong disapproval of drug use, violence, and teenage pregnancy. The street represents hipness, status based on one's appearance, and contempt for conventional values and behavior, which are easily discredited because of their association with whites. These behaviors can include doing well in school, being civil to others, and speaking Standard English" (p 287).

While historical distrust has helped to create and shape street culture, social isolation and the concentration of poverty have helped to sustain it (Wilson (1987), Aliprantis and Carroll (2013)). The weakness of social and state institutions in inner city neighborhoods allows the street group to dominate the public life of all children by violently punishing any children who do not join it (See Canada (1996).). This means that for any boy, "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" (Anderson (1999), p 114).

As described above, the first mechanism through which young males may be encouraged to engage in street behavior is as a means to provide personal security. The second mechanism, social isolation, is a bit more subtle, and can ultimately be traced back to the unique levels of segregation experienced by African Americans (Massey and Denton (1993)). Due to this high and persistent level of segregation it is possible for some to believe all African Americans follow "street" social norms. Anderson (2012) discusses how African Americans can encounter this belief regardless of their conduct, and regardless of whether they even come from a neighborhood influenced by the code of the street. These effects of segregation can be compounded through sensational representations of African Americans in the media (Rose (2008), Asante (2008), Perry (2004)).

Children experience the social isolation mechanism when adults' "efforts to combat the street may cause them to lump the good students with the bad, generally viewing all who display street emblems as adversaries" (Anderson (1999), p 96). This mechanism operates through "The knowledge that the wider system in the person of cops, teachers, and store managers downtown is instantly ready to lump them with the street element," which "takes a psychological toll on boys" (p 104).

[8] This security arrangement may in fact be viewed as a personalized version of *realpolitik* as defined in Kissinger (1995). To be clear, "street" is not a synonym for "black," as similar security arrangements can be found around the world and throughout history. For example, two contemporary groups operating under versions of the code of the street are the Taliban in Afghanistan (Gaviria and Smith (2009)) and Golden Dawn in Greece (Konstandaras (2013), Stangos (2013)).

This creates “a powerful incentive for young people. . . , especially for those sitting on the cultural fence, to invest themselves in the so-called oppositional culture, which may be confused with their ‘black identity.’ Such a resolution allows these alienated students to campaign for respect on their own terms, in a world they control” (pp 96–97).[9]

Youth may initially be motivated to engage in street behaviors through either mechanism, personal security or social isolation. Regardless of this initial motivation, however, engaging in street behaviors can be self-sustaining through the social isolation mechanism. This is especially important for marginal individuals, for whom participating in street behavior can be seen as an investment “in their own alienation” (Anderson (2008), p 17). These investments can influence such individuals so that “In time, . . . any fruits associated with the mainstream culture pale against the psychic rewards of the oppositional culture” (Anderson (2008), p 18).

If human capital is the set of skills and knowledge that is useful for people to acquire (Schultz (1961)), then we can define a specific type of human capital, street capital, to be the skills and knowledge useful for operating under the code of the street. This definition of street capital is slightly different from Sharkey (2006)’s notion of street efficacy, in that possessing street capital may provide safety through its enhancement of individuals’ ability to violently confront others, not only through the ability to avoid violent confrontations. Street capital is also distinct from social capital because it is something possessed by an individual rather than a group of individuals (Durlauf and Fafchamps (2004)). It is additionally worth noting that street capital is context-specific, as are all types of human capital.[10]

## 3 Data and Descriptive Statistics: The NLSY97

In order to study the personal security and social isolation mechanisms just described, I analyze relevant data on young males in the United States. The analysis uses variables on demographic characteristics, standard human capital, and street capital from the National Longitudinal Survey of Youth 1997 (NLSY97). Appendix B compares these data on exposure to violence with data from the Federal Bureau of Investigation’s Uniform Crime Reporting (UCR) Program.

Several of the variables used from the NLSY97 are self-reported, and require that respondents accurately report sensitive information about their criminal behavior and exposure to violence. Such variables pose serious measurement problems (Thornberrry and Krohn (2002), Elliott and Ageton (1980)), which should be remembered throughout the analysis. Nevertheless, the NLSY97 represents the state of the art in self-administered questionnaires designed to accurately elicit such information. For sensitive, self-reported questions, NLSY97 respondents recorded their answers on

[9]This mechanism is not only a result of statistical discrimination. A black person could face worse outcomes than a similar white person even in the absence of statistical discrimination, due to lower-quality schools, less resources for other things like public safety, inferior labor market networks or opportunities within commuting range, or even the types of social interactions they tend to have. All of these mechanisms affect the relative returns to choices made in response to statistical discrimination.

[10]Consider that although street capital “is not always useful or valued in the wider society, . . . it is capital nonetheless. It is recognized and valued on the streets, and to lack it is to be vulnerable there” (Anderson (1999), p 105).

a laptop in response to audio questions. This survey offered increased privacy and confidentiality relative to previous surveys requiring respondents to record their responses on paper or else by directly stating them to an interviewer.[11] Bjerk (2007) discusses why the NLSY97 self-administered questionnaire is likely to elicit substantially more truthful responses than other self-reported data sources, and Turner et al. (1998) provides related evidence.

### 3.1 Demographic Characteristics and Standard Human Capital

Data on demographic characteristics are taken from the NLSY97, which was designed to be representative of people living in the US in 1997 who were born between 1980 and 1984. This analysis uses the sample of 1,198 black and 2,702 white males in the NLSY97. Years are defined as the period from October 1$^{\text{st}}$ of one calendar year until September 30$^{\text{th}}$ of the next calendar year, and the age assigned to respondents for each year is their age on October 1$^{\text{st}}$. Other initial demographic characteristics of the respondents used in the analysis include the household structure (one parent, two parent, or other), the number of household members under 6, the resident mother's highest degree received (high school diploma, bachelor's degree, neither, or no resident mother), and the highest grade the child had completed by age 12.

The education and labor market outcomes analyzed are attainment and hours worked. Attainment is measured using a created variable reporting the highest degree completed by a respondent prior to the start of each academic school year. Hours worked are constructed using the event history of the NLSY97, which includes weekly variables on total hours worked in employee-type, self-employed, or freelance jobs. In order to align these data with the time periods defined above, we define the total hours worked in any period to be the total hours worked between the 40$^{\text{th}}$ week of the calendar year and the 39$^{\text{th}}$ week of the next calendar year.[12] This variable is divided by 52 to obtain the average hours worked per week.

Focusing first on educational attainment, 35.2 percent of black males had not earned a high school diploma by age 23, compared with 19.8 percent of white males. The median black male worked 30.0 hours at age 23, compared with 38.8 hours for his white counterpart. Sixteen percent of black males work 0 hours per week, compared with five percent of white males. Figure 3 shows the cumulative density function of the hours per week worked by males at age 23 by race and educational attainment. Black graduates work similar hours as white dropouts, and black dropouts work significantly less than all others.

[11] Appendix C reports the Introduction to the self-administered section of the NLSY97 questionnaire.

[12] For example, total hours worked in 1997 is the total hours worked between the 40$^{\text{th}}$ week of 1997 and the 39$^{\text{th}}$ week of 1998.

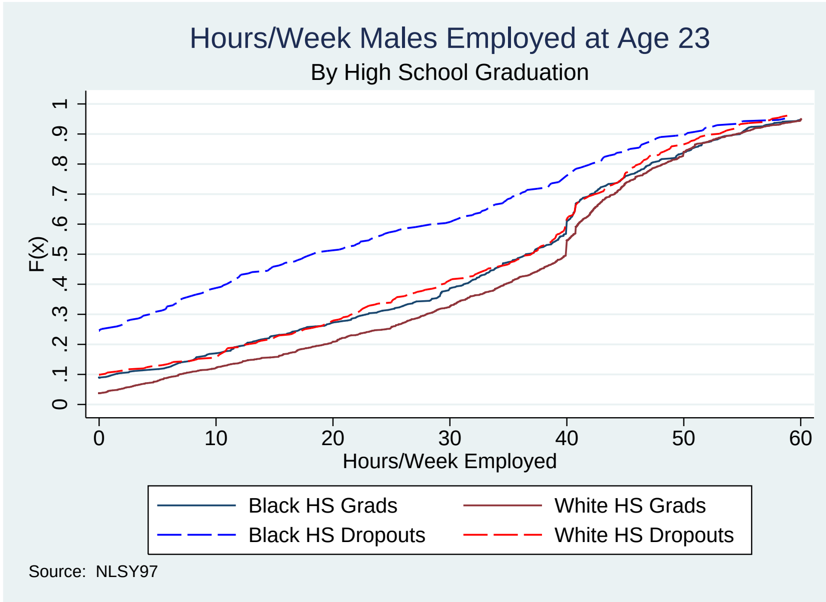



Figure 3: Employment of 23 Year-Old Males in the US

## 3.2 Street Capital

The NLSY97 contains unique self-reported variables on street behavior, which are used to create measures of violent and non-violent street behaviors. A respondent is defined to participate in violent street activities by attacking someone, carrying a gun, or belonging to a gang. Each of these questions is self-reported in the NLSY97.[13] A respondent participates in non-violent street behavior by breaking the rules of their school, selling drugs, stealing, committing a property crime, or engaging in non-violent, illegal behavior. 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.

With the exception of suspensions, data on street behavior in the NLSY97 is collected on a different time frame than the work and schooling data in the event history. In the first round respondents are asked if they have ever taken part in a particular behavior, the first and most recent times they did so, and the number of times they have done so in the past 12 months. The number of incidents in the past 12 months are assumed to be uniformly distributed between the first and last occasions respondents report being involved in a behavior.[14]

In each subsequent round respondents are asked if they have taken part in specified behavior since the date of the last interview. Since the interviews do not take place on a regular interval,

[13] Respondent's have attacked someone if they report they have "attacked someone with the idea of seriously hurting them or have a situation end up in a serious fight or assault of some kind," or police have charged them with "an attack ... such as battery, rape, aggravated assault, or manslaughter."

[14] Variables collected related to carrying a gun and having been in a gang are exceptions. The last time a respondent carried a gun is not recorded in the first round, so the incidents in which one has carried a gun in the past 30 days are assumed to be uniformly distributed between the age when a respondent first carried a gun and their current age. A respondent is assumed to have been in a gang at all times between the first and last times they report belonging to a gang.

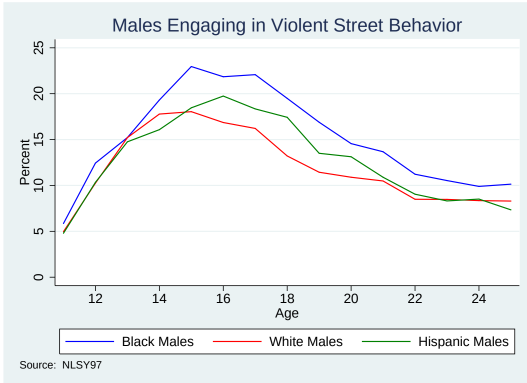
these data will not be consistent with respect to the defined time periods. Thus we make several assumptions with respect to the timing of street behavior. If a respondent reports participating in some type of street behavior since the date of the last interview, it is assumed that the respondent has participated in this behavior in each month since the month following the last interview, including the month of this year's interview. If a respondent was not interviewed in the last round, then their response is assumed for the previous 12 months as well. For each year in which we observe an agent's street choices we construct the ratio of months in which an agent participates in street behavior to the months during that year in which the agent's choice is observed. An individual participates in street behavior if this ratio is at least 0.5 for the period in question.[15]

Looking at the unconditional percentage of youth engaging in street behaviors, we can see in Figure 4a that six percent of black males engage in violent street behaviors at age 11, climbing to a maximum of 23 percent at age 15 before declining gradually to 10 percent at age 25. Figure 4a also shows the street behavior of white and Hispanic males for the purpose of comparison. White males' violent street behavior also peaks at age 15, but it does so at a lower rate, 18 percent. Black and white rates of violent street behavior are comparable between 11 and 14, but black males engage in noticeably more violent street behavior beginning at age 15. Hispanic males tend to engage in violent street behaviors at rates between those of whites and blacks.

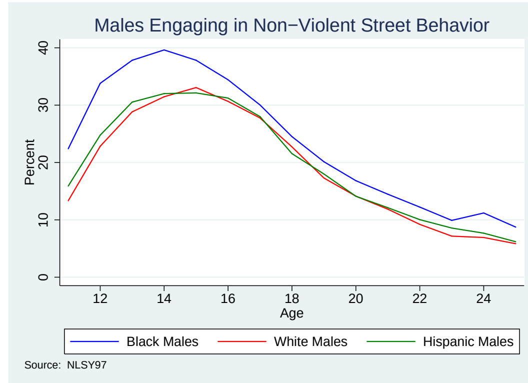
A much higher percentage of youth engage in non-violent street behavior, and the overall age profile is similar to that of violent street behavior (Figure 4b). Twenty two percent of black males engage in non-violent street behavior at age 11, which then peeks at 40 percent at age 14 before declining to nine percent at age 25. In contrast to violent street behavior, the largest difference by race occurs between 11 and 14 and then subsides from age 15 onwards.

Figures 4c and 4d show the frequency of each component of street behavior by age for black young males. Attacking someone is the most frequent source of violent street behavior, especially at younger ages. However, the rate of attacks decreases over age. In contrast, the rate of carrying a gun stays relatively constant over age, so that by the early twenties this is the greatest source of violent street behavior. At early ages suspensions and property crimes are by far the greatest sources of non-violent street behavior. These behaviors decline with age, so that by the early twenties arrests and drug dealing are the greatest sources of non-violent street behavior.

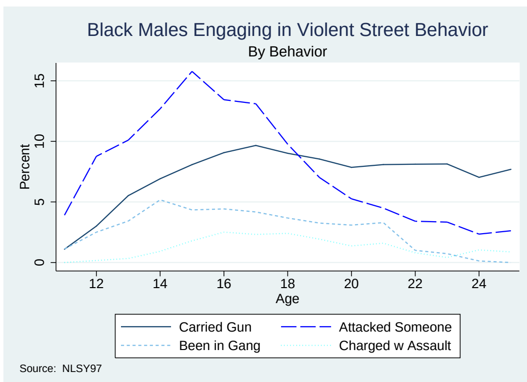
[15] An individual's choice is considered missing if there are observations for 5 or less months during any year.



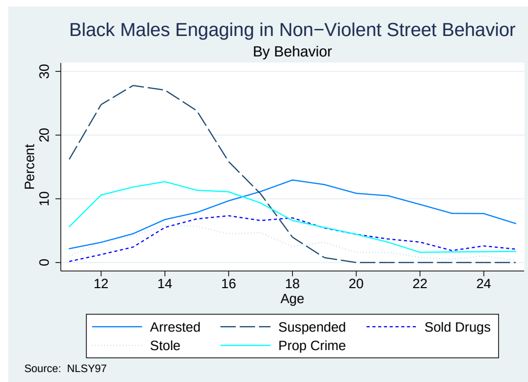

(a) Violent




(b) Non-Violent




(c) Violent




(d) Non-Violent

Figure 4: Street Behavior of Males in the NLSY97

### 3.3 Exposure to Violence

Respondents' exposure to violence is also measured using data from the NLSY97. Two variables record whether respondents self-report having seen someone shot or shot at before the age of 12 as well as between the ages of 12 and 18. We denote these variables as:

$$\underline{D} = \begin{cases} 1 & \text{if exposed to violence when age} \in \{0, 1, \ldots, 11\}; \\ 0 & \text{otherwise} \end{cases}$$

and

$$\overline{D} = \begin{cases} 1 & \text{if exposed to violence when age} \in \{12, 13, \ldots, 18\}; \\ 0 & \text{otherwise} \end{cases}$$

We also define a variable indicating exposure to violence during the most recent completed time period as

$$D(a) = \underline{D}\ \mathbf{1}\{12 \leq a \leq 18\} + \overline{D}\ \mathbf{1}\{19 \leq a \leq 25\}.$$

Table 1 reports the empirical frequencies of these variables, revealing large differences in the exposure to violence experienced by black and white males. Eight percent of white males had seen someone shot or shot at before the age of 12, and this might be considered a high percentage. However, the exposure of white males is dwarfed by that of black males, a full 26 percent of whom had seen someone shot or shot at before they reached age 12. These differences persist in older ages; 29 (10) percent of black (white) males had seen someone shot or shot at between the ages of 12 and 18, and cumulatively by 19 this grows to 43 and 15 percent, respectively.

| | Before Age 12 | | Between 12 and 18 | | Cumulative by 18 | |
|---|---|---|---|---|---|---|
| Race | Yes | n | Yes | n | Yes | n |
| Black | 26.1** | 1,170 | 29.2** | 1,032 | 43.2** | 1,004 |
| Hispanic | 14.9** | 953 | 18.0** | 832 | 27.3** | 813 |
| White | 7.6 | 2,662 | 10.4 | 2,351 | 15.5 | 2,318 |

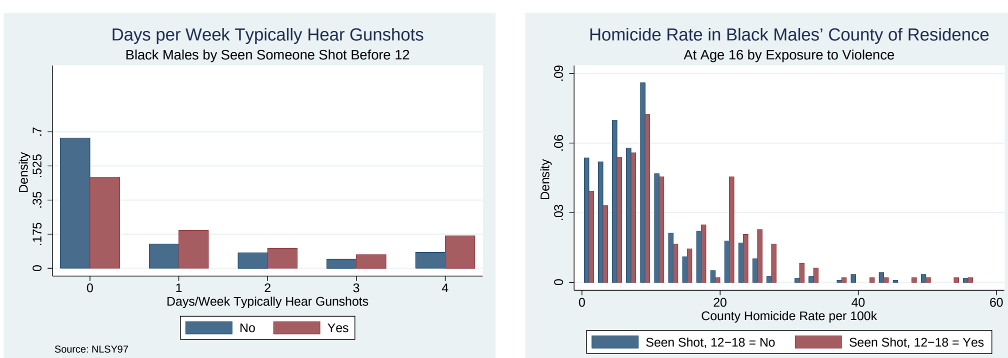
** indicates statistically significant difference from white percentage.

(a) Percent Seen Someone Shot or Shot at

Table 1: The Environment of Young Males in the US, NLSY97 by Race/Ethnicity (%)

### 3.3.1 Other Measures of Personal Security

Figure 5 shows $\underline{D}$ and $\overline{D}$ together with other measures of personal security.[16] In the first wave of the survey, a subset of NLSY97 respondents were asked how many days they hear gunshots in their neighborhood in a typical week. Figure 5a shows that black males who had seen someone shot at before age 12 are more likely to report hearing gunshots in their neighborhood. The homicide rates in counties where black males had seen someone shot at were typically higher than in counties where such youth were not exposed to violence.



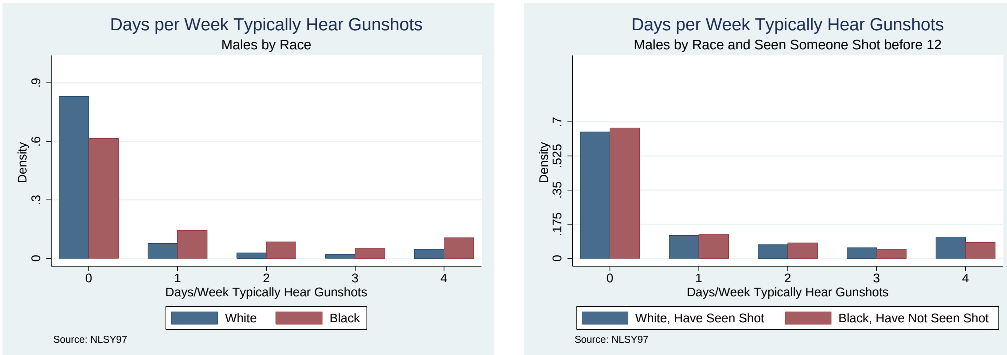

(a) Seen Shot and Days Hear Gunshots

(b) County Homicide Rate and Seen Shot

Figure 5: Measures of Exposure to Violence

[16] Appendix B compares $\underline{D}$ and $\overline{D}$ with county-level measures of violent crime as measures of exposure to violence.

Looking at differences across race, Figure 6a shows that black young males report hearing more gunshots in their neighborhoods than their white counterparts. White males who are exposed to violence report hearing similar numbers of gunshots in their neighborhood as black males who are not exposed to violence (Figure 6b).




(a) Days Typically Hear Gunshots in Nbd, by Race

(b) Seen Shot and Days Hear Gunshots, by Race

Figure 6: Measures of Exposure to Violence

Table 2a shows that the homes of black young males' are more likely to be broken into than those of their white counterparts. The evidence presented in Table 2 is also consistent with institutional differences generating different environments for black and white males. Although blacks and whites report relatively similar rates of being threatened at school or bullied, black young males do not feel as safe at school, are more likely to have had something stolen at school, and are more likely to have been in a fight at school than their white counterparts.

Table 2: NLSY97 Males' Environment, by Race (%)

(a) Victim of Bullying or Home Break-In

| | Percent Victim of Bullying By Age | | | Percent Had Home Broken Into By Age | | |
|---|---|---|---|---|---|---|
| Race | $< 12$ | $12 - 18$ | By 19 | $< 12$ | $12 - 18$ | By 19 |
| Black | 22 | 9** | 25 | 22** | 14** | 29** |
| Hispanic | 18** | 9** | 23** | 17** | 11** | 22** |
| White | 23 | 12 | 28 | 13 | 9 | 18 |

(b) Percent At School

| | Have Ever: | | | Feel Safe: | |
|---|---|---|---|---|---|
| Race | Had Something Stolen | Been Threatened | Been in a Fight | Strongly Agree | Disagree or Strongly Disagree |
| Black | 32.3** | 22.2 | 33.1** | 22.4** | 20.7** |
| Hispanic | 24.7 | 20.4 | 24.8** | 29.9 | 12.8 |
| White | 24.5 | 23.6 | 19.7** | 35.2 | 10.5 |

# 4 Causal Effects of Exposure to Violence in Static Models

## 4.1 Potential Outcomes and Selection into Treatment

Adopting some notation from Heckman and Vytlacil (2005), consider a model of potential outcomes

$$Y_i(1) = \mu_1(X_i, U_{1i}), \tag{1}$$

$$Y_i(0) = \mu_0(X_i, U_{0i}), \tag{2}$$

where potential outcomes $\big(Y_i(1), Y_i(0)\big)$ represent the values of individual $i$'s outcome $Y$ under the minimal intervention setting treatment $D_i$ to 1 and 0, respectively. Observed outcomes $Y_i$ are then

$$Y_i = (1 - D_i)Y_i(0) + D_iY_i(1). \tag{3}$$

A Rubin Causal Model is completed by jointly specifying a selection model

$$D_i = \mathbf{1}\{D^*(X_i, Z_i) - V_i \geq 0\}, \tag{4}$$

where the latent index $D^*$ is a function of some permanent observed characteristics $X_i$, an instrument $Z_i$, and unobserved factors $V_i$. We sometimes refer to the propensity score,

$$P(x) = \mathbb{E}[D_i|X_i = x] = Pr(D_i = 1|X_i = x).$$

In the absence of an instrument, for this analysis I focus on estimating the Average Treatment Effect (ATE) and Average Effect of Treatment on the Treated (ATT) parameters:

$$\begin{aligned} \triangle^{ATE} &= \mathbb{E}[Y(1) - Y(0)], \text{ and} \\ \triangle^{ATT} &= \mathbb{E}[Y(1) - Y(0) \,|\, D = 1]. \end{aligned}$$

## 4.2 Identifying Assumptions

The $\triangle^{ATE}$ and $\triangle^{ATT}$ parameters can be identified by adjusting for permanent observed characteristics $X_i$ under the joint assumptions of Ignorability,

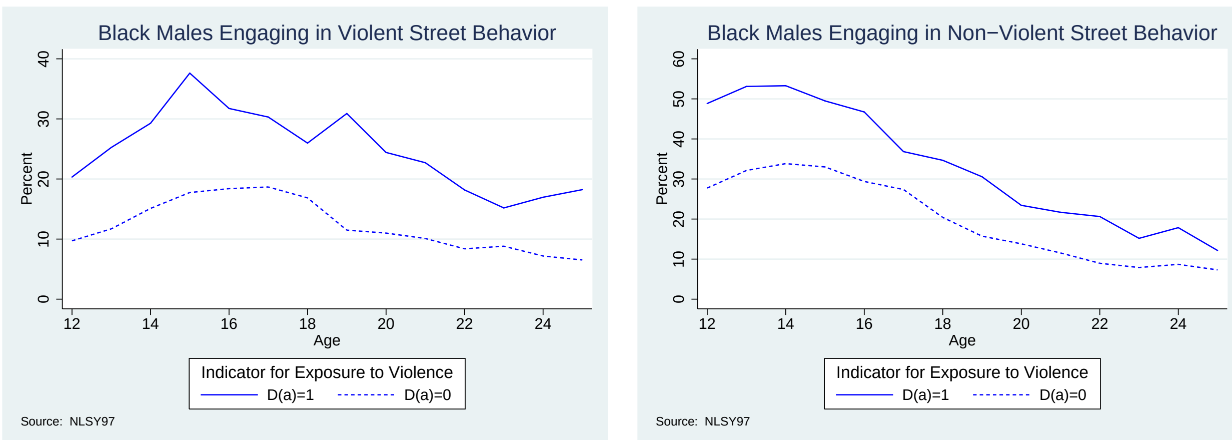
$$\big(Y_i(1), Y_i(0)\big) \perp\!\!\!\perp D_i \;\big|\; X_i\,, \tag{A-1}$$

and Overlap,

$$0 < P(X) < 1 \text{ for all } X, \tag{A-2}$$

which together are often referred to as Strong Ignorability (Heckman et al. (2006), Imbens (2004), Imbens and Wooldridge (2009)).[17]

For the moment, define the outcome of interest $Y$ to be engagement in street behavior. Figures 7a and 7b show the percentage of black young males engaging in street behaviors conditional on whether the young males had seen someone shot or shot at (ie, conditional on $D$). Consistent with Anderson's theory of personal security, youth exposed to violence are more likely to engage in violence. At age 15 black males are 20 percentage points more likely engage in violent street behavior if they had seen someone shot at before the age of 12. Non-violent street behavior is also closely related to exposure to violence; at age 14 black males are 16 percentage points more likely to engage in non-violent street behavior if they had seen someone shot before the age of 12.




(a) Violent, By Exposure to Violence

(b) Non-Violent, By Exposure to Violence

Figure 7: Street Behavior of Black Males, By Exposure to Violence

In the specified model of potential outcomes, there are at least two ways to interpret the differences in outcomes shown in Figures 7a and 7b. A first interpretation is that potential outcomes for the same individual are different when exposed to violence than when not exposed to violence. That is, exposure to violence causes differences in outcomes, and this is the source of the correlations we observe in the data. A second interpretation is that potential outcomes are not different for the same individual when exposed to violence as compared to those when not exposed to violence. This interpretation attributes the observed correlations in the data to individuals with similar potential outcomes sorting into similar neighborhoods, at least with respect to violence.

We know that since $Y$ and $D$ are correlated, either $D$ causes $Y$, $Y$ causes $D$, or they share a common cause (Chalak and White (2012)). Some DGPs consistent with these causal structures are displayed in 8. $D$ causes $Y$ in Figures 8a-8e, while the correlation between $D$ and $Y$ is entirely due to a common cause in Figures 8f and 8g. While these do not represent all of the DGPs compatible

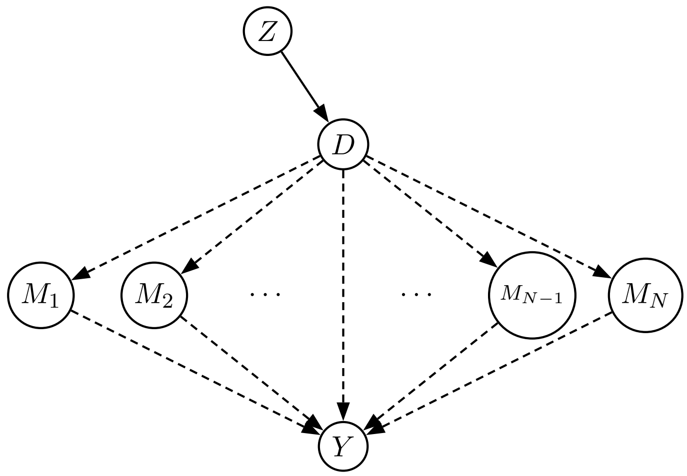
[17] Additional assumptions are imposed in the potential outcome framework. For example, there cannot be general equilibrium effects such as a feedback mechanism in which individuals adopting the code of the street weakens institutions (Heckman and Vytlacil (2007)). Similarly, there cannot be social interaction effects, so that another individual $j$'s exposure to violence cannot influence individual $i$'s treatment response (Manski (2010)). These assumptions are also imposed in the dynamic models specified in Section 5.

with the model of potential outcomes (Aliprantis (2015b)), they do represent some of the key DGPs hypothesized to generate the potential outcomes (Pearl et al. (2014)).

We proceed by testing an implication of the DGP displayed in 8g in which $D$ and $Y$ share a common cause. The implication of the confounding model is that $Y \perp\!\!\!\perp D|X$, which itself implies that $\mathbb{E}[Y|D, X = x] = \mathbb{E}[Y|X = x]$. Figure 9 shows $\mathbb{E}[Y|D, X = x]$ for several observed factors $X$, such as race, mother's educational attainment, and household structure. We see that the implication of the DGP in Figure 8g is clearly rejected.

In fact, not only is $Y \not\perp\!\!\!\perp D|X$, but the correlation between $Y$ and $D$ is remarkably stable. For race and mother's educational attainment, $\mathbb{E}[Y|D, X = x] = \mathbb{E}[Y|D]$. If $D$ were randomly assigned, this evidence would be consistent with these $X$'s satisfying an exclusion restriction (ie, $Y(x, D) = Y(x', D)$ for all $x \neq x'$ for all $D$).

While I cannot directly test condition A-1, I do interpret the invariance of $\mathbb{E}[Y|D, X = x]$ in Figure 9 as evidence in favor of a causal relationship between exposure to violence and engaging in street behaviors. While this evidence does not obviate the need for careful consideration of study design, the stability of a correlation between two variables across groups and circumstances can be interpreted as evidence in favor of a causal relationship. Two prominent examples of this type of inductive inference include smoking and lung cancer (Woodward (2003)) and water supply and cholera infection (Freedman (1999)).




(a) Potential Outcomes $Y(D)$

$Z \equiv$ Intervention Setting Treatment

$D \equiv \mathbf{1}\{\text{Exposed to Violence}\}$

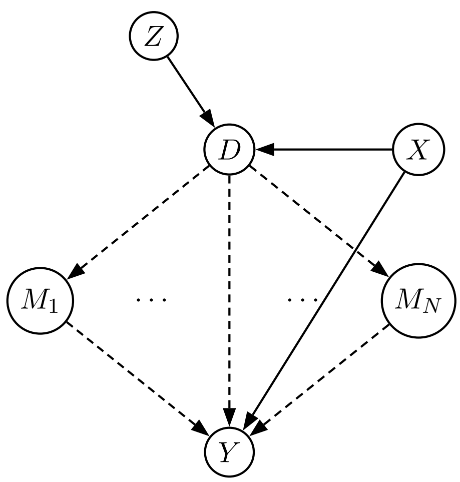
$X \equiv$ Observed Factors (Permanent)

$U \equiv$ Unobserved Factors (Permanent) $\equiv (U_0, U_1, V)$

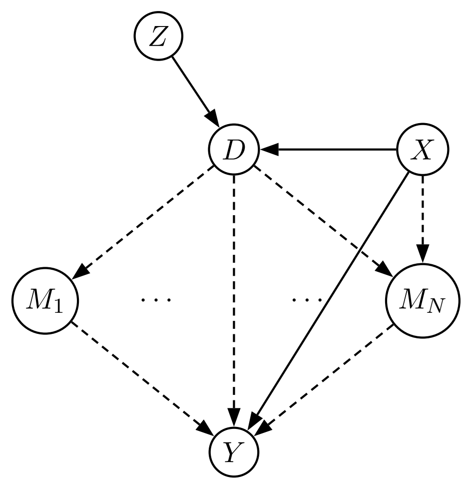
$\{M_1, \ldots, M_N\} \equiv$ Mediators

$Y \equiv$ Outcome

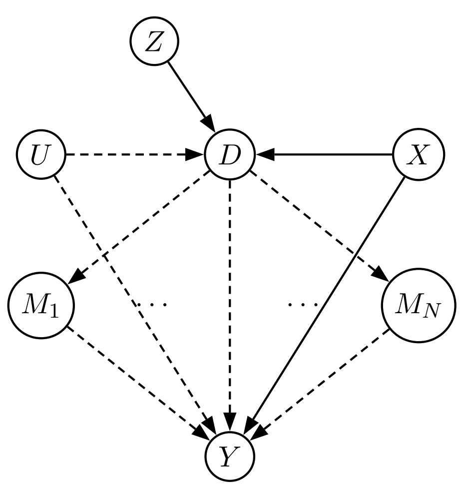
(b) Variables



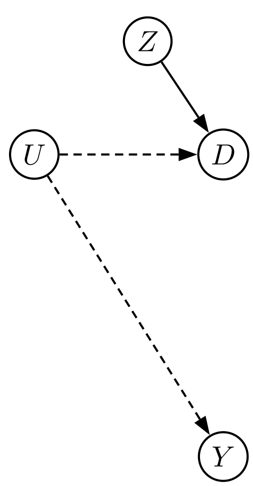

(c) $\big(Y(1), Y(0)\big) \perp\!\!\!\perp D \mid X$



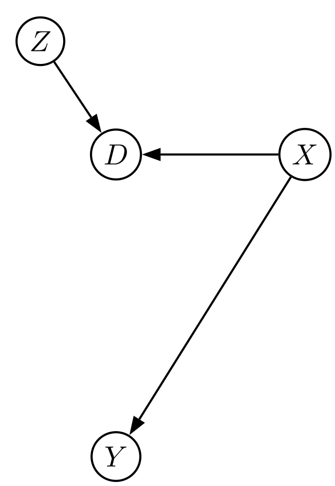

(d) $\big(Y(1), Y(0)\big) \perp\!\!\!\perp D \mid X$




(e) $\big(Y(1), Y(0)\big) \not\perp\!\!\!\perp D \mid X$

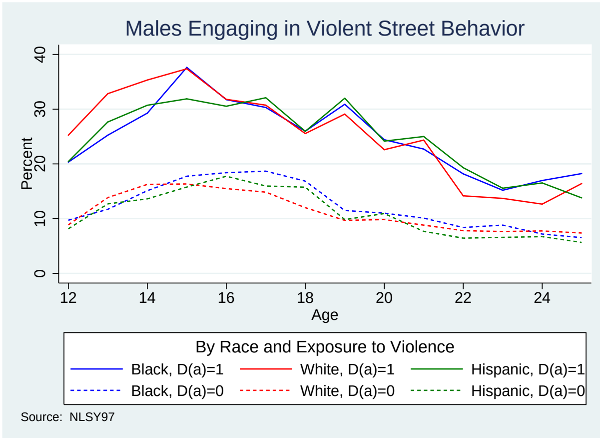



(f) $Y_i(1) = Y_i(0)$, $Y \not\perp\!\!\!\perp D \mid X$, $\big(Y(1), Y(0)\big) \not\perp\!\!\!\perp D \mid X$

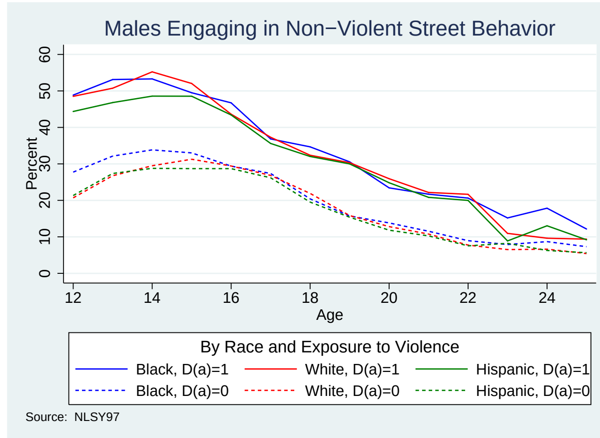



(g) $Y_i(1) = Y_i(0)$, $Y \perp\!\!\!\perp D \mid X$

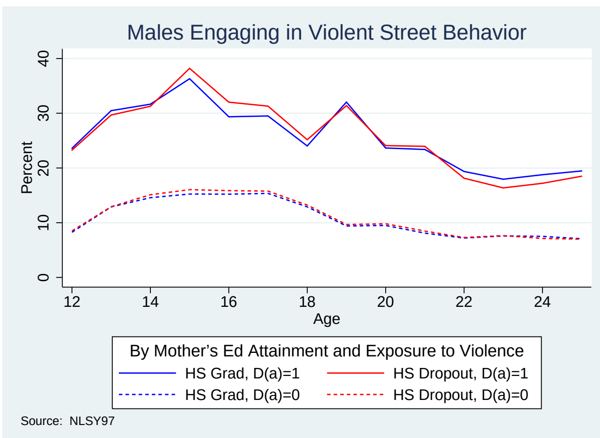
Figure 8: DAG Representation of DGPs Generating Potential Outcomes



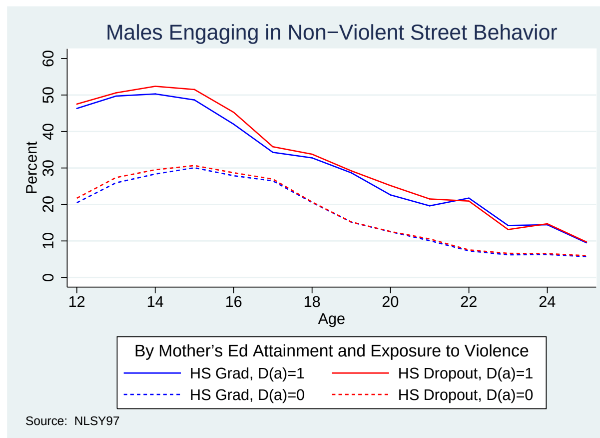

(a) Violent, By Race and Exposure



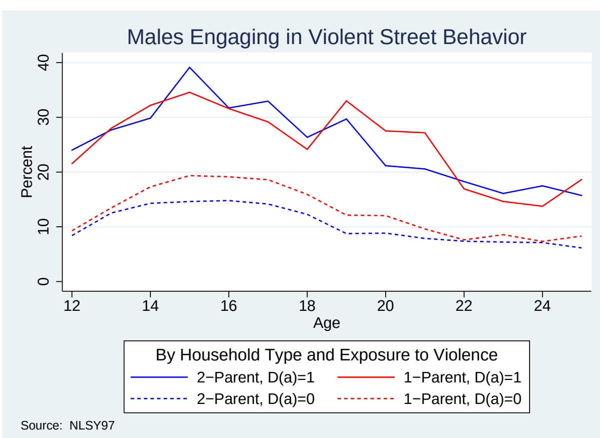

(b) Non-Violent, By Race and Exposure



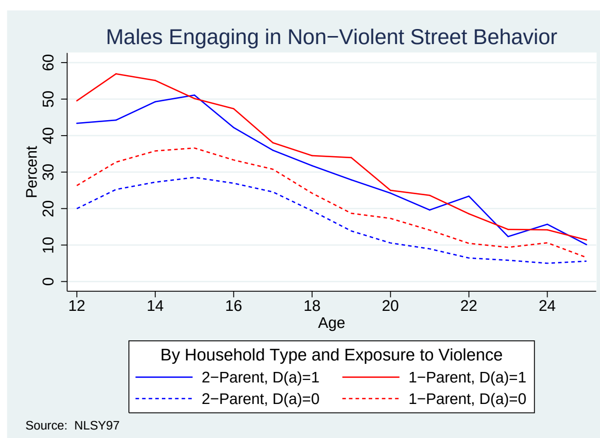

(c) Violent, By Mother's Ed and Exposure




(d) Non-Violent, By Mother's Ed and Exposure




(e) Violent, By HH Type and Exposure




(f) Non-Violent, By HH Type and Exposure

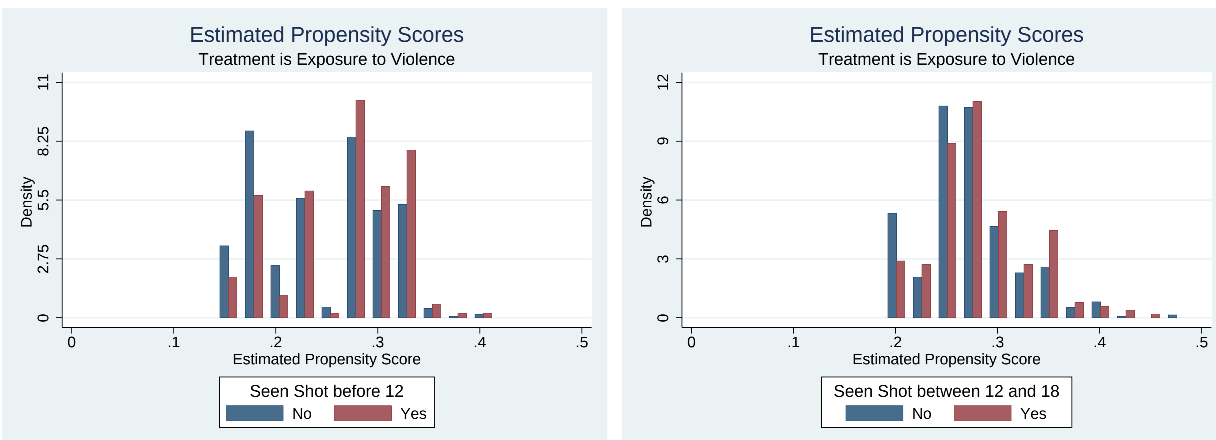
Figure 9: Street Behavior by Exposure to Violence and Demographic Characteristics

If condition A-2 does not hold for all observed characteristics $X$, then typically one restricts the analysis to the support of $X$ for which condition A-2 is true. Figure 10 provides evidence pertinent for determining this area of common support

$$\mathcal{S}(D) = Supp(P(X)|D = 1) \cap Supp(P(X)|D = 0)$$

over which matching is justified (Heckman et al. (1998)). Neither plot shows mass near 0 or 1, and the two estimated densities overlap. Since these figures give no reason for concern about violations of the overlap assumption, the region of common support is the full support of the estimated propensity score conditional on being treated, or:

$$\widehat{\mathcal{S}}(\underline{D}) = Supp(\widehat{P}(X)|\underline{D} = 1) = [0.12, 0.44),$$
$$\widehat{\mathcal{S}}(\overline{D}) = Supp(\widehat{P}(X)|\overline{D} = 1) = [0.22, 0.51).$$




(a) Estimated Propensity Scores, Childhood Exposure (b) Estimated Propensity Scores, Adolescent Exposure

Figure 10: Common Support

Table 3 shows the strata generating by the *pscore* command in Stata with the goal of achieving balanced covariates within blocks. All of the covariates pass two-sample $t$-tests (with equal variances) for balance in all blocks, with the exception of two-parent households in Block 3 of Adolescent Exposure.[18]

Table 3: Stratification Matching: Blocks

| | Block 1 | Block 2 | Block 3 |
|---|---|---|---|
| Childhood Exposure (<12) | $[0.12, 0.20)$ | $[0.20, 0.40)$ | $[0.40, 0.44)$ |
| Adolescent Exposure (12-18) | $[0.22, 0.30)$ | $[0.30, 0.40)$ | $[0.40, 0.51)$ |

[18]A two-parent indicator (relative to the reference group other household type) is not balanced in this block, although a one-parent indicator is balanced.

Estimated probit coefficients are reported in the first two columns of Table 8.

### 4.3 Estimation Results

Table 4 presents estimates of treatment effects on black young males when treatment is either childhood (before age 12, $\underline{D}$) or adolescent (between ages 12 and 18, $\overline{D}$) exposure to violence, and outcomes $Y(D)$ are street behaviors ($S$) from ages 12 until 23, high school graduation ($G$) by age 23, and average weekly hours worked ($W$) at age 23. The first two columns of Table 4 present the sample data showing the mean outcomes of black males not exposed to violence and the difference in the mean outcomes for those who were exposed to violence. We can see that there are large differences in outcomes by exposure to violence. At age 15, those who saw someone shot before the age of 12 were 112 percent more likely to engage in violent street behavior and 43 percent more likely to engage in non-violent street behavior. Differences in age 21 street behaviors exhibit similar, large differences by adolescent exposure to violence. Although education and labor market outcomes display largely similar patterns, one difference is that adolescent exposure to violence is more strongly correlated with age 23 hours worked than is childhood exposure.

The third and fourth columns of Table 4 show parameters from the static model estimated under Assumptions A-1 and A-2, which is implemented by estimating the Average Effect of Treatment on the Treated (ATT) with propensity score matching techniques. The third column of Table 4 reports results under nearest neighbor matching, with Abadie-Imbens standard errors (Abadie and Imbens (2006)). The fourth column reports results under stratification matching, with standard errors obtained by 1,000 bootstrapped replications.[19] The causal effects of exposure to violence for those exposed, the ATTs, are very similar to the unconditional differences in means. In terms of street behavior, estimates under the assumption of selection on observables are of very large effects. Effects of childhood exposure to violence on age 23 labor market outcomes are quite muted, but this is true regardless of whether one controls for observables, and the effect of the closer-in-time adolescent exposure is still very large for this outcome.

Finally, the fifth column of Table 4 shows ATTs constructed using linear OLS regressions. Assuming that

$$\mathbb{E}[Y(1)|X, D = 1] = m_1(X) = \beta_1 X,$$
$$\mathbb{E}[Y(0)|X, D = 0] = m_0(X) = \beta_0 X,$$

after estimating $\widehat{\beta}_1^{OLS}$ and $\widehat{\beta}_0^{OLS}$, we can construct counterfactuals $\widehat{m}_1^{OLS}(X)$ and $\widehat{m}_0^{OLS}(X)$ for each individual. The ATT estimate is then obtained as

$$\begin{aligned}\widehat{\triangle}^{ATT} &= \mathbb{E}[\widehat{Y}(1) - \widehat{Y}(0) \mid D = 1] \\ &= \mathbb{E}[\widehat{m}_1^{OLS}(X) - \widehat{m}_0^{OLS}(X) \mid D = 1],\end{aligned}$$

[19]The correct standard errors for this estimator have yet to be established (Imbens (2004), p 14), with the asymptotic behavior of this and related estimators being an active area of research (Abadie and Imbens (2012)).

with standard errors again obtained by 1,000 bootstrapped replications. We see that the additional linear functional form assumption imposed by the OLS model results in only very modest differences from the nonparametric Propensity Score Matching estimates.

Table 4: Treatment Effects

| | | | ATT | | |
|---|---|---|---|---|---|
| | Unconditional | | PS Matching | | Regressions |
| Outcome and Time of Exposure | Control Mean | Effect | NN | Strat | OLS |
| **Street Behavior** | | | | | |
| Childhood Exposure (<12) | | | | | |
| Violent (Age 15, %) | 17.3 | 19.4 | 19.8 | 19.4 | 19.2 |
| | (1.5) | (2.9) | (3.4) | (3.4) | (3.2) |
| Non-Violent (Age 15, %) | 32.8 | 14.2 | 12.5 | 13.6 | 12.5 |
| | (1.8) | (3.5) | (3.8) | (3.7) | (3.4) |
| Adolescent Exposure (12-18) | | | | | |
| Violent (Age 21, %) | 10.3 | 11.6 | 11.7 | 11.6 | 11.5 |
| | (1.3) | (2.5) | (2.9) | (2.8) | (2.8) |
| Non-Violent (Age 21, %) | 10.9 | 9.8 | 8.4 | 9.1 | 9.1 |
| | (1.4) | (2.5) | (3.0) | (2.9) | (2.6) |
| **Education** | | | | | |
| Childhood Exposure (<12) | | | | | |
| HS Diploma (Age 23, %) | 70.0 | –12.9 | –8.0 | –10.5 | –8.9 |
| | (1.9) | (3.7) | (4.1) | (3.8) | (3.8) |
| Adolescent Exposure (12-18) | | | | | |
| HS Diploma (Age 23, %) | 69.2 | –8.7 | –6.2 | –8.0 | –6.9 |
| | (1.9) | (3.6) | (3.7) | (3.5) | (3.4) |
| **Labor Market** | | | | | |
| Childhood Exposure (<12) | | | | | |
| Employed (Age 23, Hrs/Wk) | 28.9 | –1.2 | 0.5 | –0.8 | –0.6 |
| | (0.8) | (1.2) | (1.8) | (1.7) | (1.7) |
| Adolescent Exposure (12-18) | | | | | |
| Employed (Age 23, Hrs/Wk) | 29.9 | –4.4 | –3.5 | –4.2 | –4.3 |
| | (0.8) | (1.6) | (1.6) | (1.5) | (1.8) |

Note: Treatment is seeing someone shot or shot at (or additionally being shot at between 12 and 18). NN is Nearest Neighbor and Strat is Stratification, both methods of Propensity Score Matching. OLS is Ordinary Least Squares.

### 4.4 Robustness: Placebo Tests and Fixed Effects Models

Table 5 shows placebo tests on outcomes that should not be affected by exposure to violence, primarily because they occurred before the exposure might have taken place. These outcomes are the respondent's mother's age at first birth, her age at the birth of the respondent, and an indicator for whether the respondent spent more than 20 hours per week in childcare during the first year of their life. While the null treatment effects displayed in the table are not a direct test of A-1, they lend it credibility in this application (Imbens (2014)).

Table 5: Placebo Tests

| | | | ATT |
|---|---|---|---|
| Outcome and Time of Exposure | Unconditional Control Mean | Unconditional Effect | PS Matching NN |
| **Mother's Age** | | | |
| Childhood Exposure (<12) | | | |
| At First Birth (Years) | 21.4 | –0.7 | –0.2 |
| | (0.2) | (0.4) | (0.4) |
| At Respondent's Birth (Years) | 24.4 | –0.5 | –0.1 |
| | (0.2) | (0.4) | (0.5) |
| Adolescent Exposure (12-18) | | | |
| At First Birth (Years) | 21.1 | 0.3 | 0.5 |
| | (0.2) | (0.3) | (0.4) |
| At Respondent's Birth (Years) | 24.4 | –0.4 | –0.3 |
| | (0.2) | (0.4) | (0.4) |
| **Childcare in First Year of Life** | | | |
| Childhood Exposure (<12) | | | |
| $\geq$ 20 Hours/Week (%) | 33.9 | –1.0 | 1.5 |
| | (1.8) | (3.6) | (3.8) |
| Adolescent Exposure (12-18) | | | |
| $\geq$ 20 Hours/Week (%) | 32.8 | –0.6 | 0.6 |
| | (1.9) | (3.5) | (3.5) |
| **Educational Attainment at Age 12** | | | |
| Adolescent Exposure (12-18) | | | |
| Highest Grade Completed | 5.4 | 0.0 | 0.0 |
| | (0.0) | (0.1) | (0.1) |

Note: Treatment is seeing someone shot or shot at (or additionally being shot at between 12 and 18). NN is Nearest Neighbor Propensity Score Matching.

As an additional robustness check, we can estimate fixed effects models.[20] Assume that street behavior follows a linear model with age effect $\tau(a)$:

$$S_i(14) = \alpha_i + \beta X_i + \delta D_i(14) + \tau(14) + \epsilon_i(14)$$
$$S_i(19) = \alpha_i + \beta X_i + \delta D_i(19) + \tau(19) + \epsilon_i(19)$$

Then

$$\triangle_i^S = S_i(19) - S_i(14) = \delta[D_i(19) - D_i(14)] + [\tau(19) - \tau(14)] + [\epsilon_i(19) - \epsilon_i(14)]. \tag{5}$$

We might also try related specifications generating estimating equations:

$$\begin{aligned} \triangle_i^S &= \left[\frac{S_i(19) + S_i(20)}{2} - \frac{S_i(14) + S_i(15)}{2}\right] \\ &= \delta[D_i(19) - D_i(14)] + [\tau(19,20) - \tau(14,15)] + [\epsilon_i(19,20) - \epsilon_i(14,15)] \qquad (6) \\ \triangle_i^S &= \left[\frac{S_i(19) + S_i(20) + S_i(21)}{3} - \frac{S_i(14) + S_i(15) + S_i(16)}{3}\right] \\ &= \delta[D_i(19) - D_i(14)] + [\tau(19,21) - \tau(14,16)] + [\epsilon_i(19,21) - \epsilon_i(14,16)] \qquad (7) \end{aligned}$$

Table 6 presents OLS estimates of $\delta$ from specifications 5-7, which are consistent with the treatment effects estimated in Table 4.

| | Specification | | |
|---|---|---|---|
| | (7) | (6) | (5) |
| $\delta_v$ | 0.07** | 0.08** | 0.08** |
| | (0.02) | (0.02) | (0.03) |
| $\delta_{nv}$ | 0.03 | 0.04 | 0.06 |
| | (0.02) | (0.03) | (0.03) |

** indicates $p < 0.01$.

Table 6: FE Regression Coefficients

[20] These models do not play a more prominent role in the analysis for three reasons. First, the measures of exposure to violence are each over several years. As a result, we do not know precisely when the exposure to violence occurred. Second, since we only have measures of exposure over two time periods, $T = 2$ if we are thinking about changes in exposure. Third, the most appropriate outcome variable given the data is street behavior, which is binary.

## 5 Causal Effects of Exposure to Violence in a Structural Model

### 5.1 A Model of Human Capital Accumulation

Assume that by age eleven each individual has accumulated some factors influencing their choices in a permanent way from that point into the future. The permanent observed characteristics are denoted $X_i$, and the permanent unobserved factors are written as a vector with choice-specific elements, with the full vector denoted by $\boldsymbol{\xi}_i$. Included in $\boldsymbol{\xi}_i$ are household- and school-level investments in the individual by age 11, being exposed to violence by age 11 ($\underline{D}_i$), as well as unobserved personal attributes like preferences and abilities.

The model includes street capital as defined in Section 2 to help capture incentives to learn how to interact with violent individuals due to the code of the street. Violent street capital is initialized at age 11 to be zero ($K_v(11) \equiv 0$), and for $a \geq 12$, it is assumed individuals accumulate violent street capital $K_v(a)$ according to the rule

$$K_v(a) = \sum_{t=11}^{a-1} S_v(t), \tag{8}$$

where $S_v(t)$ is an indicator for whether individual $i$ engaged in violent street behavior at age $t$. Non-violent street choices and the accumulation of non-violent street capital are defined analogously.

In the remainder of the analysis I use "=" to denote statistical equations and identities and "$\stackrel{\leftarrow}{=}$" to denote structural equations.[21] Given a time-invariant set of characteristics $X_i$ and $\boldsymbol{\xi}_i$, agents choose to engage in violent and non-violent street behaviors according to the following latent index models:

$$\begin{aligned} S_{v,i}(a) \stackrel{\leftarrow}{=} \mathbf{1}\Big\{ & \beta^v X_i + \gamma_v^v K_v(a) + \gamma_{v,2}^v K_v^2(a) + \gamma_{nv,1}^v K_{nv}(a) + \gamma_{nv,2}^v K_{nv}^2(a) \\ & + \overline{\gamma}^v\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^{S_v} + \lambda^v(a) - u_i^v(a) \geq 0 \Big\} \end{aligned} \tag{9}$$

$$\begin{aligned} S_{nv,i}(a) \stackrel{\leftarrow}{=} \mathbf{1}\Big\{ & \beta^{nv} X_i + \gamma_{v,1}^{nv} K_v(a) + \gamma_{v,2}^{nv} K_v^2(a) + \gamma_{nv,1}^{nv} K_{nv}(a) + \gamma_{nv,2}^{nv} K_{nv}^2(a) \\ & + \overline{\gamma}^{nv}\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^{S_{nv}} + \lambda^{nv}(a) - u_i^{nv}(a) \geq 0 \Big\}, \end{aligned} \tag{10}$$

where $\lambda(a)$ represents time fixed effects and the transitory components of street behavior are identically distributed at each age:

$$(u_i^v(a), u_i^{nv}(a)) \sim \mathcal{N}\left( \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho^S \\ \rho^S & 1 \end{bmatrix} \right)$$

[21] I adopt Definition 5.4.1 of structural equation from Pearl (2009), so that a structural equation communicates all exclusion restrictions at a given level of measurement. Further discussion can be found in Aliprantis (2015b).

Figure 7 is used to guide the parameterization of $\lambda(a)$, which is specified as:

$$\lambda^{v}(a) = (\lambda_1^{v} + \lambda_2^{v} a)\,\mathbf{1}\{a \leq 15\} + (\lambda_3^{v} + \lambda_4^{v} a)\,\mathbf{1}\{a \geq 16\},$$
$$\lambda^{nv}(a) = (\lambda_1^{nv} + \lambda_2^{nv} a)\,\mathbf{1}\{a \leq 13\} + (\lambda_3^{nv} + \lambda_4^{nv} a)\,\mathbf{1}\{a \geq 14\}.$$

Agents select into exposure to violence between ages 12 and 18 according to a latent index model as follows:

$$\overline{D}_i \equiv \mathbf{1}\Big\{\beta^{\overline{D}} X_i + \xi_i^{\overline{D}} - \bar{\epsilon}_i \geq 0\Big\}, \qquad \bar{\epsilon}_i \sim \text{iid}\,\mathcal{N}(0,1). \tag{11}$$

Agents choose to graduate from high school by age 23 according to the following model:

$$\begin{aligned} G_i \equiv \mathbf{1}\Big\{&\beta^{G} X_i + \gamma_{v,1}^{G} K_v(18) + \gamma_{v,2}^{G} K_v^2(18) + \gamma_{nv,1}^{G} K_{nv}(18) + \gamma_{nv,2}^{G} K_{nv}^2(18) \\ &+ \overline{\gamma}^{G}\,\overline{D_i}\,\mathbf{1}\{a > 18\} + \xi_i^{G} - u_i^{G}(a) \geq 0\Big\}, \end{aligned} \tag{12}$$

with $u_i^{G}(a) \sim \text{iid}\,\mathcal{N}(0,1)$.

Finally, agents in the model choose hours worked at age 23 according to a standard Tobit Model:

$$W_i \equiv \begin{cases} W_i^* & \text{if } W_i^* > 0; \\ 0 & \text{if } W_i^* \leq 0, \text{ where} \end{cases} \tag{13}$$

$$\begin{aligned} W_i^* \equiv\, &\beta^{W} X_i + \gamma_{v,1}^{W} K_v(18) + \gamma_{v,2}^{W} K_v^2(18) + \gamma_{nv,1}^{W} K_{nv}(18) + \gamma_{nv,2}^{W} K_{nv}^2(18) \\ &+ \overline{\gamma}^{W}\,\overline{D_i}\,\mathbf{1}\{a > 18\} + \gamma^{W} G_i + \xi_i^{W} - u_i^{W}, \end{aligned} \tag{14}$$

where $u_i^{W}(a) \sim \text{iid}\,\mathcal{N}(0, \sigma_W^2)$.

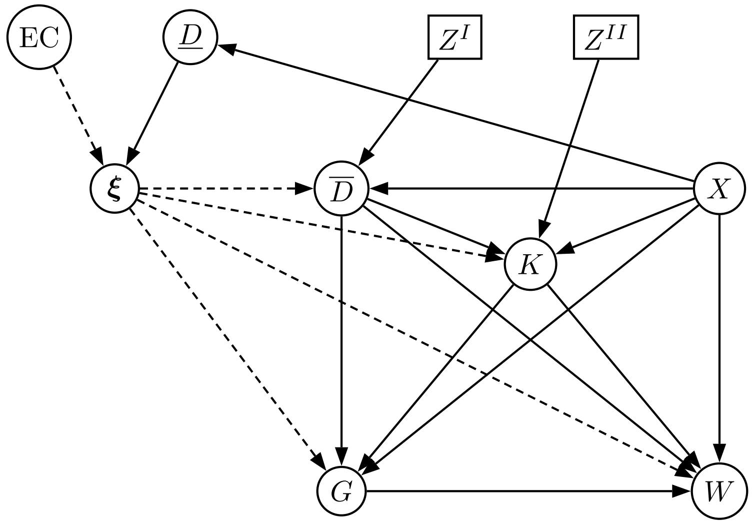
The specified model is dynamic in the sense that previous shocks enter into contemporaneous choice equations through the history of previous choices. However, the model does not include next period's discounted value function in choice equations. Such a model is typically not considered a dynamic programming model, as agents' choices are not determined by their beliefs about the future evolution of their state vector (Kydland and Prescott (1977)).[22] These assumptions on the dynamics in the model can be justified by the fact that the empirical analysis focuses on choices between ages 12 and 23, and static models have performed well in related contexts at these ages early in the life cycle (Keane and Wolpin (1997)).

In terms of the mechanisms discussed in Section 2, both the $\overline{\gamma}$ and the $\gamma$ parameters are best interpreted as representing a combination of the personal security and social isolation mechanisms as they operate through variables observable to us. It is important to recognize, however, that both of these mechanisms could also be expressed in the model through the shocks or through the permanent unobserved heterogeneity. Thus while the unobserved heterogeneity in the model could represent individuals' "innate" preferences for selecting into exposure to violence and making the

[22]Alternatively, one could interpret the model as a dynamic programming model in which agents are assumed to entirely discount next period's value function, or as a dynamic programming model without $\beta = 0$ under stochastic concavity (Cunha et al. (2007)).

other choices modeled, these factors in the model could also represent the unobserved components of the mechanisms about which we are trying to learn.

To illustrate these points, Figure 11 represents the specified model of human capital accumulation as a Directed Acyclic Graph (DAG). Focusing on the dynamic version of the model in Figure 11 (d), we can see that childhood exposure to violence impacts individuals' $\boldsymbol{\xi}$ vector, which in turn impacts outcomes directly as well as through the mechanisms of adolescent exposure to violence and the accumulation of street capital. Furthermore, adolescent exposure to violence impacts outcomes not only directly, but also through the accumulation of street capital. Understanding the multiple channels through which exposure to violence impacts outcomes in our model will be a central goal




(a) DAG Representation of Dynamic Selection Control Model

$EC \equiv$ Early Childhood Factors

$\boldsymbol{\xi} \equiv$ Unobserved Factors (Permanent)

$Z^I - Z^{II} \equiv$ Interventions I-II

$\overline{D} \equiv \mathbf{1}\{$Adolescent Exposure to Violence$\}$

$K \equiv$ Street Capital

$G \equiv \mathbf{1}\{$Graduate from High School$\}$

$W \equiv$ Work (Hours)

(b) Variables

Figure 11: DAG Representation of Dynamic Selection Control Model

Figure 11 demonstrates three important assumptions of the model. First, the model assumes that exposure to violence affects the likelihood of engaging in street behavior, but that engaging in street behavior does not influence one's exposure to violence. While this seems like a reasonable assumption for childhood exposure (before age 12), relaxing this assumption for adolescent exposure (between 12 and 18) is an area of future research. Second, imprisonment is not explicitly incorporated into the model.[23] This mechanism is likely to operate mainly through the impediment to employment created by a criminal record, and contributes to the coefficients on street capital. Third, as discussed earlier, the model rules out the possibility of a feedback mechanism in which individuals adopting the code of the street weakens institutions. Such a mechanism might be especially important in a model with overlapping generations.

[23] I did not include imprisonment explicitly in the analysis for two reasons: 1) The event history data on imprisonment spells are entirely missing for the 2003 ($7^{\text{th}}$) round of the NLSY97 due to a survey error (McClaskie (2009)). And 2) Imprisonment is relatively rare – at least in a direct/incapacitation sense. At age 16, less than two percent of black males spent more than 6 months imprisoned. See Holzer et al. (2006) and Western et al. (2001) for related evidence.

### 5.1.1 Dynamic Selection Control

The panel nature of the NLSY97 data allows us estimate the model with permanent components of unobserved heterogeneity. One approach to estimating the model is to assume a finite mixture of perfectly correlated types (Heckman and Singer (1984)), similar to the dynamic selection control model in Hotz et al. (2002). The assumption is that the permanent components of unobserved heterogeneity have discrete support, $\boldsymbol{\xi}_i \in \{\boldsymbol{\xi}_1, \ldots, \boldsymbol{\xi}_T\}$, and it is labeled Assumption D-1:[24]

**D-1** Individuals can be one of $T$ types $\tau_i \in \{1, \ldots, T\}$, with

$$\begin{aligned} \tau_i = 1 \quad &\Rightarrow \quad \boldsymbol{\xi}_i = (\xi_1^{\overline{D}}, \xi_1^{S_v}, \xi_1^{S_{nv}}, \xi_1^{G}, \xi_1^{W}) \\ &\vdots \\ \tau_i = T \quad &\Rightarrow \quad \boldsymbol{\xi}_i = (\xi_T^{\overline{D}}, \xi_T^{S_v}, \xi_T^{S_{nv}}, \xi_T^{G}, \xi_T^{W}). \end{aligned}$$

Although it does allow for unobserved confounders, Assumption D-1 nevertheless still imposes a specific structure on the distribution of these $\boldsymbol{\xi}_i$. Namely, D-1 imposes that the grouping of people who exhibit unobservable heterogeneity with respect to selection into exposure to violence is also the same grouping of people who exhibit unobservable heterogeneity with respect to street behaviors, graduating from high school, and hours worked. The joint model of selection and outcomes is identified under the assumption that identical groups of individuals exhibit common unobserved heterogeneity along each of the dimensions of choice in the model.

The model is estimated under D-1 using maximum likelihood. The likelihood function is derived in Appendix A, and before presenting estimation results some thoughts on identification are in order. First, a finite mixture of $T = 5$ types is assumed.[25] We must normalize $\boldsymbol{\xi}_1$ to $(0, 0, 0, 0, 0)$ for identification, so that $\{\xi_1, \xi_2, \xi_3, \xi_4, \xi_5\} \in 0 \times \mathbb{R}^4$ for each outcome equation. After making this normalization, identification of $\xi_2^{S_v}, \ldots, \xi_5^{S_v}$ and $\xi_2^{S_{nv}}, \ldots, \xi_5^{S_{nv}}$ comes from the variation in street behaviors in the panel data. The cross-sectional variation in hours worked identifies $\xi_2^{W}, \ldots, \xi_5^{W}$. Estimating these choices jointly identifies the grouping of the heterogeneity in the data, which in turn identifies the remaining unobserved heterogeneity parameters, $\boldsymbol{\xi}^D$ and $\boldsymbol{\xi}^G$.

### 5.1.2 Estimation Results

The estimated dynamic model has 90 parameters, is estimated on a sample of 748 individuals, and the value of the log-likelihood function at the estimated parameter values is $-12,180$. Table 7 shows some moments from the data along with those predicted by the estimated dynamic model. We can see that in terms of exposure to violence, high school graduation, and employment the model fits the data very well. The life-cycle patterns of street behavior are captured well, both in

[24] See Cameron and Heckman (1998) and Keane and Wolpin (1997) for discussions about unobserved heterogeneity modeled in this way.

[25] D-1 could be relaxed by allowing $\xi_i$ to be a random variable with some covariance structure across individuals. Such an assumption could also allow for the special case in which each component is independent, which is analogous to A-1.

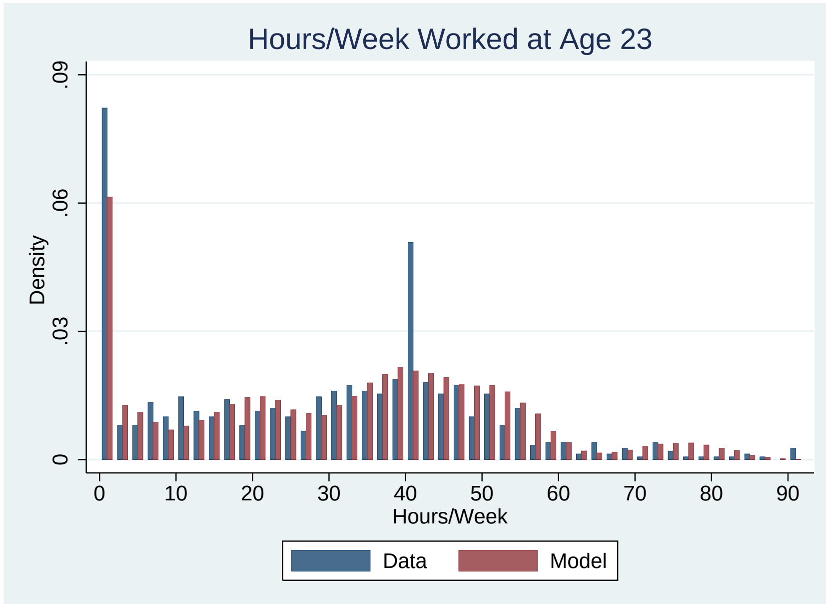
terms of cross-sectional probabilities at a given age, and in terms of individual-level persistence of behavior across ages as measured by the accumulation of street capital by age 19. The estimated model has the most difficulty in capturing the persistence of non-violent street behavior.

Table 7: Dynamic Model Fit

| Outcome | Sample Data | Model Prediction |
|---|---|---|
| **Selection into Treatment** | | |
| Prob of Selection into $\overline{D}$ (%) | 28 | 28 |
| **Street Behavior** | | |
| Violent | | |
| Age 15 (%) | 24 | 21 |
| Age 18 (%) | 21 | 21 |
| Age 21 (%) | 12 | 14 |
| Non-Violent | | |
| Age 15 (%) | 35 | 38 |
| Age 18 (%) | 25 | 28 |
| Age 21 (%) | 14 | 15 |
| **Street Capital** | | |
| Violent | | |
| Age 18 ($\mu$) | 1.2 | 1.1 |
| Non-Violent | | |
| Age 18 ($\mu$) | 2.2 | 1.7 |
| **Education** | | |
| HS Diploma at Age 23 (%) | 67 | 67 |
| **Labor Market** | | |
| Employed at Age 23 ($\mu$, Hrs/Wk) | 29 | 30 |

Figure 12a shows model fit for mean average hours worked at age 23.[26] The finite mixture in the dynamic model generates a smoother distribution than the empirical distribution of hours worked, which is especially evident for individuals working 90 hours per week and for the mass of individuals anchored at 40 hours per week.

[26]Note: Simulated employment data from the model are generated for Figure 12a as follows: (1) 100 observations simulated for each individual in the data assuming type $\tau$. (2) Individuals sampled as type $\tau$ using the estimated distribution. (3) Each individual contributes their 100 type $\tau$ simulated observations to the data.




(a) Estimated Hours Worked at Age 23 (Dynamic Model)

Figure 12: Model Fit

Table 8 shows estimated parameters in both the static and dynamic models, with the standard errors for parameters of the dynamic model calculated using the outer product of numerical first derivatives. Parameters tend to have values in expected ranges. For example, estimated parameters indicate that family structure and mother's education impact outcomes in the ways one would expect, with the notable exception that family structure has a relatively muted impact on street behaviors. Another notable feature of the estimated model parameters is the magnitude and pattern of the various $\overline{\gamma}$ and $\gamma$ parameters. The effect of street capital on the same type of street behavior is of a large magnitude, with the cross effect being smaller. The magnitude of these parameters points to violent street capital as being more influential than non-violent street capital. For example, the effect of violent street capital on the violent street behavior latent index is 0.43, but the effect of non-violent street capital on this index is much smaller at 0.15. Similarly, the effect of non-violent street capital on the non-violent street behavior latent index is 0.29, and the effect of violent street capital is lower at 0.22. Non-violent street capital has a large effect on employment.

Table 8: Probit and Dynamic Model Parameter Estimates

| | Selection | | | Outcomes | | | | Type Distribution | |
|---|---|---|---|---|---|---|---|---|---|
| | PS Matching | | | Dynamic Model | | | | | |
| Effect on Latent Index | $\underline{D}$ | $\overline{D}$ | $\overline{D}$ | $S_v$ | $S_{nv}$ | $G(23)$ | $W(23)$ | $Pr(\tau \mid \underline{D}=0)$ | $Pr(\tau \mid \underline{D}=1)$ |
| **Observed Factors** | | | | | | | | | |
| Other Family | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| One-Parent Family | -0.25 | -0.05 | -0.39 | -0.07 | 0.01 | -0.35 | -0.59 | | |
| | (0.14) | (0.14) | (0.16) | (0.28) | (0.23) | (6.03) | (0.72) | | |
| Two-Parent Family | -0.56 | -0.14 | -0.48 | -0.13 | -0.08 | -0.01 | 2.85 | | |
| | (0.19) | (0.19) | (0.15) | (0.07) | (0.08) | (1.81) | (1.51) | | |
| HH Members under 6 | 0.05 | 0.17 | 0.15 | 0.02 | 0.03 | -0.11 | 3.09 | | |
| | (0.07) | (0.07) | (0.06) | (0.07) | (0.12) | (0.24) | (3.48) | | |
| No Resident Mother | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | |
| Mom HS Dropout | 0.27 | 0.15 | 0.36 | 0.03 | 0.00 | -0.17 | 4.35 | | |
| | (0.18) | (0.18) | (0.18) | (0.05) | (0.06) | (1.14) | (2.40) | | |
| Mom HS Grad | -0.15 | -0.04 | 0.10 | 0.01 | -0.05 | 0.68 | 2.48 | | |
| | (0.11) | (0.11) | (0.49) | (0.04) | (0.05) | (0.19) | (5.42) | | |
| Mom BA Holder | -0.26 | -0.08 | -0.27 | -0.01 | -0.02 | 0.59 | 0.56 | | |
| | (0.16) | (0.14) | (0.19) | (0.09) | (28.2) | (0.26) | (0.58) | | |
| HS Grad at 23 | | | | | | | 0.00 | | |
| | | | | | | | (0.19) | | |
| **Unobserved Factors** | | | | | | | | | |
| $\beta_0$ | -0.44 | -0.62 | -0.54 | ··· | ··· | 0.94 | 13.69 | 22.31 | 19.17 |
| | (0.14) | (0.14) | (0.49) | ··· | ··· | (4.00) | (14.90) | (12.59) | (36.90) |
| $\xi_2$ | | | -0.51 | -0.26 | -0.22 | -0.07 | 18.17 | 30.56 | 23.89 |
| | | | (0.17) | (2.10) | (1.13) | (0.07) | (3.97) | (557.33) | (44.33) |
| $\xi_3$ | | | -0.04 | -0.01 | -0.10 | 0.34 | 31.82 | 22.22 | 30.18 |
| | | | (0.07) | (0.24) | (0.35) | (0.09) | (4.18) | (17.78) | (40.77) |
| $\xi_4$ | | | 0.08 | -0.02 | 0.02 | -0.39 | -19.16 | 19.32 | 19.69 |
| | | | (0.04) | (0.23) | (0.59) | (0.23) | (39.30) | (9.08) | (22.61) |
| $\xi_5$ | | | 0.35 | 0.07 | -0.06 | 0.31 | 56.49 | 5.59 | 7.08 |
| | | | (0.37) | (0.08) | (0.24) | (1.31) | (18.47) | – | – |
| $\rho_S$ | | | | 0.44 | | | | | |
| | | | | (0.68) | | | | | |
| **Safety/Social Exclusion** | | | | | | | | | |
| $\overline{\gamma}$ | | | | 0.15 | 0.00 | 0.00 | -5.88 | | |
| | | | | (0.21) | (0.51) | (0.17) | (1.60) | | |
| $\gamma_{v,1}$ | | | | 0.43 | 0.22 | -0.09 | -0.33 | | |
| | | | | (0.08) | (0.03) | (0.96) | (4.89) | | |
| $\gamma_{v,2}$ | | | | -0.04 | -0.02 | -0.01 | 0.01 | | |
| | | | | (0.02) | (0.01) | (0.30) | (0.06) | | |
| $\gamma_{nv,1}$ | | | | 0.15 | 0.29 | -0.22 | -1.56 | | |
| | | | | (0.12) | (0.41) | (0.05) | (1.03) | | |
| $\gamma_{nv,2}$ | | | | -0.01 | -0.02 | 0.00 | 0.03 | | |
| | | | | (0.00) | (0.00) | (0.00) | (0.59) | | |
| **Wage/Age Trends** | | | | | | | | | |
| $\sigma_W$ | | | | | | | 3.67 | | |
| | | | | | | | (0.67) | | |
| $\kappa_1$ | | | | -1.42 | -0.55 | | | | |
| | | | | (0.29) | (0.38) | | | | |
| $\kappa_2$ | | | | 0.02 | 0.01 | | | | |
| | | | | (0.01) | (0.13) | | | | |
| $\kappa_3$ | | | | 1.60 | 2.50 | | | | |
| | | | | (0.35) | (0.89) | | | | |
| $\kappa_4$ | | | | -0.17 | -0.21 | | | | |
| | | | | – | – | | | | |

Table 9: Simulated Outcomes from the Estimated Dynamic Model for all Individuals in the Sample

| Outcome | Data $\mu$ | Type 1 $\mu$ | Type 2 $\mu$ | Type 3 $\mu$ | Type 4 $\mu$ | Type 5 $\mu$ |
|---|---|---|---|---|---|---|
| **Type Distribution** | | | | | | |
| Share $\mid \underline{D} = 0$ (%) | $\cdots$ | 22 | 31 | 22 | 19 | 6 |
| Share $\mid \underline{D} = 1$ (%) | $\cdots$ | 19 | 24 | 30 | 20 | 7 |
| Share of Population (%) | $\cdots$ | 22 | 29 | 24 | 19 | 6 |
| **Selection** | | | | | | |
| $Pr(\overline{D} = 1)$ (%) | 28 | 31 | 16 | 30 | 34 | 44 |
| **Street Behavior** | | | | | | |
| Violent | | | | | | |
| Age 15 (%) | 24 | 23 | 16 | 22 | 22 | 25 |
| Age 21 (%) | 12 | 15 | 10 | 15 | 15 | 16 |
| Non-Violent | | | | | | |
| Age 15 (%) | 35 | 41 | 33 | 37 | 42 | 39 |
| Age 21 (%) | 14 | 17 | 13 | 15 | 17 | 16 |
| **Education** | | | | | | |
| HS Diploma at Age 23 (%) | 67 | 67 | 65 | 76 | 54 | 76 |
| **Labor Market** | | | | | | |
| Employed at Age 23 (Hrs/Wk) | 29 | 16 | 34 | 47 | 1 | 73 |

Another notable feature of the estimated model parameters is its unobserved heterogeneity. The importance of the estimated unobserved heterogeneity can be observed in Table 9, which shows outcomes from the sample data and from simulated data for each type generated by the estimated model. This Table allows us to characterize how outcomes would be different if we were to sample from particular types relative to sampling from the population in the data.

We can see that type 2s are exceptional with respect to exposure to violence and street behavior: They are exposed to much less violence and engage in the least street behavior. Nevertheless, their education and labor market outcomes are average. With respect to education and labor market outcomes, type 4s are the exceptional type. In addition to engaging in the most non-violent street behavior, these types are the most likely to drop out of high school and work the fewest hours. Type 5s comprise a small share of the population that engages in much street behavior, but also has good education and labor market outcomes.

## 5.2 Simulated Counterfactuals Using the Estimated Model

We are now interested in using the model for two purposes. The first is quantifying how much exposure to violence influences the education and labor market outcomes of black young males in the US, and to see if these estimates from the dynamic model are consistent with the static estimates from earlier in the analysis. Second, we are interested in understanding whether the code of the street is an important mechanism through which exposure to violence influences outcomes.

To investigate these issues, I conduct two counterfactuals with the structural model:

**Counterfactual I ($do(\overline{D} = 0)$):** For individuals with $\overline{D}_i = 1$, simulate outcomes after manipulating $\overline{D}_i$ to equal 0 but intervening on no other features of the DGP. Find the associated changes in average outcomes.

**Counterfactual II ($do(K_v(a) = 0)$ and $do(K_{nv}(a) = 0)\ \forall\ a$):** For all individuals, simulate outcomes after manipulating $K_{v,i}(a)$ and $K_{nv,i}(a)$ to equal 0 for all ages $a$, intervening on no other features of the DGP. Find the associated changes in average outcomes.

The results of these counterfactuals are reported in Tables 10 and 11.[27]

Table 10: Counterfactual I (Adolescent Exposure)

| Outcome | Model Prediction for Subpopulation | Counterfactual Prediction (after Intervention to DGP) | Difference |
|---|---|---|---|
| **Education** | | | |
| HS Diploma at Age 23 (%) | 59.5 | 59.6 | 0.1 |
| **Labor Market** | | | |
| Employed at Age 23 ($\mu$, Hrs/Wk) | 24.9 | 29.8 | 4.9 |

Table 11: Counterfactual II (No Street Capital Accumulation)

| Outcome | Model Prediction for Population | Counterfactual Prediction (after Intervention to DGP) | Difference |
|---|---|---|---|
| **Education** | | | |
| HS Diploma at Age 23 (%) | 66.9 | 83.6 | 16.8 |
| **Labor Market** | | | |
| Employed at Age 23 ($\mu$, Hrs/Wk) | 29.1 | 32.2 | 3.1 |

In the dynamic model there are three channels through which exposure to violence might impact an agent's choice to graduate from high school: $\overline{D}_i$, $\boldsymbol{\xi}_i$, or the sequence of $u_i^v(a)$ and $u_i^{nv}(a)$. The sequence of shocks to street behavior is allowed to be correlated conditional on both observed and unobserved confounders ($X_i$ and $\boldsymbol{\xi}_i$), and the sequence of shocks representing exposure to violence are no longer contained in $u_i^G(23)$, so the assumption of its independent and identical distribution is not as strict as it would otherwise be.

[27] Because counterfactuals are complicated functions of both parameters and data, standard errors of counterfactual changes are typically not reported when based on dynamic programming models due to the computational intensity of estimation (See Keane and Wolpin (2009) for some examples.).

The results from Counterfactual I indicate that if exposure to violence does affect high school graduation, then it is not through the first channel, $\overline{D}_i$, adolescent exposure. This is consistent with the static results of larger effects from childhood exposure, which would be captured in the second channel, $\boldsymbol{\xi}_i$. In contrast, adolescent exposure has a large direct effect on employment.

The results from Counterfactual II indicate that there would also be large effects on educational attainment if we were to shut down the single mechanism through which both ($u_i^v(a)$, $u_i^{nv}(a)$) and ($\xi_i^{S_v}$, $\xi_i^{S_{nv}}$) impact education and labor market outcomes, as well as one of the mechanisms though which adolescent exposure ($\overline{D}_i$) impacts outcomes. Table 11 shows that if we shut off the street capital mechanism so that engaging in street behavior does not result in the accumulation of street capital, the estimated model indicates that high school graduation would increase by 16.8 percentage points. This is 50 percent of the high school dropout rate for black males. While the increase in hours worked is relatively smaller at 3.1 hours per week, this is again a non-trivial change in outcomes. It is worth noting that this total effect on employment operates both through the direct effects of street capital and the direct effect of increased high school graduation.

Counterfactual II is particularly illustrative of the importance of the second mechanism through which the code of the street operates, the social isolation mechanism. As discussed earlier, the parameters in the model reflect effects from exposure to violence occurring within a particular social setting. It is conceivable that these parameters could change under various changes to the social setting, whether those changes were to occur through features as broad as institutions or social norms, or through features as narrow as policy interventions. Nevertheless, the key lesson from Counterfactual II is that mechanisms related to the code of the street can account for a large share of the total effect of exposure to violence on outcomes.[28]

# 6 Conclusion

This paper presented quantitative evidence to complement Elijah Anderson's ethnographic research on the "code of the street," in an attempt to quantify the effects of exposure to violence and social isolation on the outcomes of black young males in the US. The paper began by documenting two key facts in the NLSY97. First, black males are highly exposed to violence at young ages: 26 (8) percent of black (white) males saw someone shot by age 12, and 43 (15) percent by age 18. Second, black young males engage in more street behaviors than their white counterparts, but not when conditioned on exposure to violence.

The paper then estimated static models capable of matching on the permanent observed characteristics of black young males. Qualitative evidence from Anderson's urban ethnography was also used to guide the specification of a model of human capital accumulation that incorporated two

[28]Using the mediation formula stated as Equation 16 in Pearl (2014), the Natural Direct Effect (NDE) of violent street capital on violent street behavior at ages 15 and 21 is 72 and 82 percent of the nearest-neighbor total effect of exposure to violence (the ATTs in Table 4), and the NDE of non-violent street capital on non-violent street behavior is 43 and 54 percent of the total effect of exposure. As well, the NDE of non-violent street capital on graduation is 72 percent of the total effect of exposure, and the NDE of violent street capital on age-23 hours worked is 95 percent of the total effect of exposure.

related mechanisms through street capital, a distinct type of human capital defined as the skills and knowledge useful for providing personal security in neighborhoods where it is not provided by state institutions. The human capital accumulation model was specified as a dynamic finite mixture model allowing for more general patterns of selection than the static model, including a non-parametric correlation structure of permanent unobserved heterogeneity.

Gaps in outcomes by exposure to violence persisted in the estimated models, which I interpreted as evidence that such gaps represent causal effects. Based on counterfactuals from the estimated models, I conclude that for the subpopulation of black young males exposed to violence, childhood exposure decreases the high school graduation rate between 8.0 and 16.5 percentage points (24 and 50 percent of the high school dropout rate) and adolescent exposure decreases age 23 average weekly hours worked between 3.5 and 4.9 hours (0.17 and 0.24 $\sigma$). Estimation results also indicated that mechanisms related to the code of the street could be useful for understanding how exposure to violence affects outcomes.

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