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Human Capital in the Inner City

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This paper quantitatively characterizes the "code of the street" from the sociology literature, using the nationally-representative National Longitudinal Survey of Youth 1997 data set to investigate how black young males alter their behavior when living in violent neighborhoods. An astounding 26 percent of black males in the United States report seeing someone shot before turning 12. Conditional on reported exposure to violence, black and white young males are equally likely to engage in violent behavior. Black males' education and labor market outcomes are much worse when reporting exposure to violence; these gaps persist in estimated models controlling for many patterns of selection.

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 1).

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. 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 2, NCHS (2009), Leventhal et al. (2014)).

This paper investigates how exposure to violence and social isolation affect the outcomes of black young males in the US, using Elijah Anderson's urban ethnography to guide the analysis. 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 such as the formal labor market and the education system.

The central contribution of this paper is a quantitative characterization of the "code of the street." Descriptive and causal analyses using the nationally-representative NLSY97 data set serve as complements to Anderson's qualitative work, as well as related theoretical work (Silverman (2004), O'Flaherty and Sethi (2010a)) and previous quantitative studies that were constrained by data to be geographically focused on Chicago (Sharkey (2006), Sharkey (2010)). 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.[1] 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 tremendous amounts of violence at young ages: 26 percent of black

[1]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.

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 than available administrative variables.

I find that exposure to violence is related to the street behaviors of young males in ways that are consistent with Anderson's theory of personal security. Young males who report being exposed to violence are more likely to engage in both violent and non-violent street behaviors. Furthermore, although black males engage in more street behaviors than white males (Figure 3), the rate at which young males engage in such behaviors is nearly identical for blacks and whites once it is conditioned on exposure to violence (Figure 4). Exposure to violence is also related to the education and labor market outcomes of black young males in ways that are consistent with Anderson's theory of personal security. 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 under a variety of causal modeling strategies. 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.[2]

Since the estimated causal models can control for increasingly complex patterns of selection into treatment, they lend an increasingly credible causal interpretation to differences by exposure to violence.[3] 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 all of 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, adolescent exposure

[2]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)).

[3]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)).

decreases the high school graduation between 3.2 and 8.2 percentage points (9 and 24 percent of the high school dropout rate) and age 23 average weekly hours worked between 3.0 and 4.2 hours (0.15 and 0.21 σ). I also interpret the counterfactuals from the estimated models to indicate that mechanisms related to the code of the street could be useful for understanding how 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.[4] Another closely related line of research studies the role of segregation and institutional 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 (2012)), 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 (2013)) or HOPE VI (Aliprantis and Hartley (2013)).

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

[4]There is also 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), Hemenway (2006)), and maltreatment (Currie and Tekin (2012)) in the psychology, public health, and economics literatures.

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)). Unlike most of those papers, this study does not take the canonical model from Becker (1968) as its starting point. 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.[5] 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)). Social-cognitive skills might be a part of these 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. A descriptive analysis of human capital accumulation and exposure to violence from the data set are presented in Section 4. Section 5 specifies a model of human capital accumulation, and then estimates that model under two identifying assumptions that render the model either static or dynamic. After presenting the estimation results, I simulate data from the estimated models under counterfactual manipulations. Section 5 finishes with a discussion relating real-world counterfactuals to these model counterfactuals. 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

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

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).[6] 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 American neighborhoods.[7] 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

[6] "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).

[7] 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)).

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). 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).

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.[8]

3 Data: 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

[8]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).

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 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.[9] 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.[10] This variable is divided by 52 to obtain the average hours worked per week.

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

[10]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.

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.[11] 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.[12]

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, 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.[13]

3.3 Exposure to Violence

We also use data from the NLSY97 to measure respondents' exposure to violence. The NLSY97 asks respondents whether they had seen someone shot or shot at both before the age of 12 as well as between the ages of 12 and 18. We define a variable indicating exposure to violence during the

[11] 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."

[12] 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.

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

most recent completed time period as

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

where

$$\underline{D} = \begin{cases} 1 & \text{if exposed to violence before age 12;} \\ 0 & \text{otherwise} \end{cases}$$

and $\overline{D}$ is the analogous indicator for whether an individual was exposed to violence between the ages of 12 and 18.

Another measure of exposure to violence in the NLSY97 is a variable recording respondents' answer when asked how many days in a typical week they hear gunshots in their neighborhood. This variable will not be used in the causal analysis since it was only asked of a subsample during the first round, but these data will be used in the descriptive analysis to compare various measures of exposure to violence.

4 Descriptive Statistics

4.1 Human Capital

Focusing first on standard human capital choices, 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 1 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.

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 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.

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.

Figure 3 shows 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.

4.2 Exposure to Violence

Table 1b shows remarkable differences in exposure to violence experienced by black and white males in the NLSY97 when measured by witnessing acts of violence. Eight percent of white males had seen someone shot or shot at before the age of 12, and this might be considered a very high percentage. However, the exposure of white males is dwarfed by the exposure of black males, a full 26 percent of whom had seen someone shot or shot at before the age of 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 18 this grows to 43 and 15 percent, respectively.

These data suggest that exposure to violence influences street behavior. Figures 4c and 4d show the percentage of youth 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. The patterns of street behavior look remarkably similar for both black and white males when conditioning on having seen someone shot.

5 Causal Effects of Exposure to Violence

There are at least two ways to interpret correlations between exposure to violence and outcomes, and both have to do with counterfactual outcomes under manipulations of exposure to violence that leave other causal variables unchanged. 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.

The analysis in this Section estimates how much correlations between outcomes and exposure to violence can be attributed to causal effects of exposure, rather than sorting. We attempt to distinguish between these two mechanisms by jointly modeling selection into treatment (exposure to violence) together with potential outcomes. The appropriate estimation technique for causal effects of exposure to violence will depend on the assumptions made in this model. This Section estimates effects in models allowing for selection on observables, as well as models allowing for dynamic selection control, and interprets estimates and identifying assumptions.

5.1 A Model of Human Capital Accumulation

Assume that by age twelve 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 12, being exposed to violence before age 12 ($\underline{D}_i$), 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 12 to be zero ($K_v(12) \equiv 0$), and for $a \geq 13$, it is assumed individuals accumulate violent street capital $K_v(a)$ according to the rule

$$K_v(a) = \sum_{t=12}^{a-1} S_v(t), \tag{1}$$

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 "$\stackrel{\leftarrow}{=}$" to denote structural equations.[14] 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:

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

$$\begin{aligned} S_{nv,i}(a) \stackrel{\leftarrow}{=} \mathbf{1}\Big\{ & \beta^{nv} X_i + \gamma_{v,1}^{nv} K_v(a) + \gamma_{v,2}^{nv} K_v^2(a) + \gamma_{nv,1}^{nv} K_{nv}(a) + \gamma_{nv,2}^{nv} K_{nv}^2(a) \\ & + \overline{\gamma}^{nv}\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^{S_{nv}} + \lambda^{nv}(a) + u_i^{nv}(a) \geq 0 \Big\}, \end{aligned} \tag{3}$$

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

$$u_i^v(a) \sim \mathrm{iid}\, \mathcal{N}(0,1),$$
$$u_i^{nv}(a) \sim \mathrm{iid}\, \mathcal{N}(0,1).$$

[14] 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 (2014).

Figure 4 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:

$$\overline{D}_i \equiv \mathbf{1}\Big\{\beta^{\overline{D}} X_i + \xi_i^{\overline{D}} + \overline{\epsilon}_i \geq 0\Big\}, \qquad \overline{\epsilon}_i \sim \text{iid}\,\mathcal{N}(0,1). \tag{4}$$

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

$$\begin{aligned} G_i(a) \equiv \mathbf{1}\Big\{ & \beta^G X_i + \gamma_{v,1}^G K_v(a) + \gamma_{v,2}^G K_v^2(a) + \gamma_{nv,1}^G K_{nv}(a) + \gamma_{nv,2}^G K_{nv}^2(a) \\ & + \overline{\gamma}^G\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^G + \lambda^G(a) + u_i^G(a) \geq 0\Big\}, \end{aligned} \tag{5}$$

with $u_i^G(a) \sim \text{iid}\,\mathcal{N}(0,1)$ and $\lambda^G(a') \geq \lambda^G(a)$ for all $a' \geq a$.

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

$$W_i(a) \equiv \begin{cases} W_i^*(a) & \text{if } W_i^*(a) > 0; \\ 0 & \text{if } W_i^*(a) \leq 0, \text{ where} \end{cases} \tag{6}$$

$$\begin{aligned} W_i^*(a) \equiv\ & \beta^W X_i + \gamma_{v,1}^W K_v(a) + \gamma_{v,2}^W K_v^2(a) + \gamma_{nv,1}^W K_{nv}(a) + \gamma_{nv,2}^W K_{nv}^2(a) \\ & + \overline{\gamma}^W\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \gamma^W G_i(a) + \xi_i^W + \lambda^W(a) + u_i^W(a), \end{aligned} \tag{7}$$

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

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 is not a dynamic programming model in that it does not include next period's discounted value function in choice equations.[15] 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 γ 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 other choices modeled, these factors in the model could also represent the unobserved components

[15] Alternatively, one could interpret the model as a dynamic programming model in which agents are assumed to entirely discount next period's value function. The key point is that agents' choices are in no way determined by their beliefs about the future evolution of their state vector (Kydland and Prescott (1977)).

of the mechanisms about which we are trying to learn.

To illustrate these points, Figure 5 represents the specified model of human capital accumulation as a Directed Acyclic Graph (DAG). Focusing on the dynamic version of the model in Figure 5 (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 important for conducting and interpreting counterfactual simulations with the estimated model.

5.2 Identifying Assumptions

5.2.1 Selection on Permanent Observed Characteristics

The convention for classifying assumptions is adopted from Hotz et al. (2002), and is used to characterize two assumptions made in the analysis about the structure of unobservables in the model described in Equations 1-7. The standard Strong Ignorability (SI) assumption is that conditional on observed characteristics, the unobserved components of selection and outcomes are independent. In the context of our model, we label this as Assumption 1:

A1 $\boldsymbol{\xi}_i = \mathbf{0} \quad \forall \;\; i.$

The DAG representing this model is displayed in Figure 5 (b). Relative to the model shown in Figure 5 (a) that would be necessary to interpret raw differences in outcomes causally, we can see that this model additionally allows for observed confounders, or observed common causes, X_i. Since this weakens the assumptions under which differences in outcomes by exposure to violence can be interpreted as causal effects, I follow Manski (2007) and refer to estimates from this model as representing more "credible" causal effects than the raw differences reported in Section 4.

Assumption 1 will be implemented using Propensity Score Matching (PSM) on selection into $\overline{D}$ or an analogue to Equation 4 for $\underline{D}$. The vector of outcomes $\mathcal{O}_i$ jointly modeled to allow for matching on observables will be

$$(\underline{D}_i, S_{v,i}), \;\; (\underline{D}_i, S_{nv,i}), \quad (\overline{D}_i, S_{v,i}), \;\; (\overline{D}_i, S_{nv,i}), \quad (\underline{D}_i, G_i(23)), \;\; (\overline{D}_i, G_i(23)), \quad \text{and} \;\; (\overline{D}_i, W_i(23)).$$

The vector $\boldsymbol{\xi}_i$ in A1 for each of these models will be:

$$(\xi_\tau^{\underline{D}}, \xi_\tau^{S_v}), \;\; (\xi_\tau^{\underline{D}}, \xi_\tau^{S_{nv}}), \quad (\xi_\tau^{\overline{D}}, \xi_\tau^{S_v}), \;\; (\xi_\tau^{\overline{D}}, \xi_\tau^{S_{nv}}), \quad (\xi_\tau^{\underline{D}}, \xi_\tau^{G}), \;\; (\xi_\tau^{\overline{D}}, \xi_\tau^{G}), \quad \text{and} \;\; (\xi_\tau^{\overline{D}}, \xi_\tau^{W}).$$

Furthermore, we will adapt the model for the implementation of PSM techniques by assuming

$$(\gamma_{v,1} \;,\; \gamma_{v,2} \;,\; \gamma_{nv,1} \;,\; \gamma_{nv,2}) = (\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}).$$

If there were an instrument for selection into exposure to violence, this assumption could be tested in a cross-sectional setting (Heckman et al. (2010)). Since there is not such an instrument at present, these cross-sectional tests are not implemented.

5.2.2 Dynamic Selection Control

The panel nature of the NLSY97 data allows us to make other assumptions about the permanent components of unobserved heterogeneity in our model. One approach to estimating the model is to assume a finite mixture of perfectly correlated types (Heckman and Singer (1984)). This 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 2:[16]

A2 Individuals can be one of T types $\tau_i \in \{1, \ldots, T\}$, with

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

Returning to the DAGs in Figure 5, we can see that Assumption A2 allows for a more credible identification of causal effects than the model estimated under Assumption A1. Relative to the model displayed in the DAG in Figure 5 (b), we can see that the model in 5 (d) additionally allows for unobserved confounders $\boldsymbol{\xi}$. Consider that we can rule out a broad range of permanent unobserved confounders by estimating this dynamic finite mixture model. As just one example, this modeling strategy should control for the correlation in unobserved factors if individuals choosing employment in the informal sector as drug dealers were as a result more likely to be exposed to violence as well as less likely to be employed in the formal labor market. Since Assumption A2 is weaker than A1, I again follow Manski (2007)'s definition and give additional "credibility" to the interpretation of estimates from the model under A2 as causal effects relative to the estimates obtained from the model under Assumption A1.

Although it does allow for unobserved confounders, Assumption A2 nevertheless still imposes a specific structure on the distribution of these $\boldsymbol{\xi}_i$. Namely, A2 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 A2 using maximum likelihood. The likelihood function is derived in Appendix A, and before presenting estimation results some thoughts on identification are in

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

order. First, a finite mixture of $T = 5$ types is assumed.[17] 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 $\boldsymbol{\xi}^G$.

5.3 Estimation Results

The estimated dynamic model has 94 parameters, is estimated on a sample of approximately 1,000 individuals, and the value of the log-likelihood function at the estimated parameter values is $-13,893$. Table 2 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, street behavior, and high school graduation the model fits the data very well. The life-cycle patterns of street behavior are captured well, both in 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.

We can also see that the model over-predicts the mean average hours worked at age 23. Figure 6c shows model fit for this outcome in greater detail, helping to illustrate why the model fit is worst in terms of hours worked at age 23.[18] The finite mixture in the dynamic model has a difficult time fitting the hours worked data. Individuals working more than 65 hours per week are not well-explained by the model, and the presence of these individuals appear to be drawing one type far to the right of where it would be otherwise. At the same time, the mass of individuals anchored at 40 hours per week is also hard for such a finite mixture model to capture.

Table 3 shows estimated parameters in both the static and dynamic models. Parameters tend to have values in expected ranges. For example, estimated parameters indicate that family structure, mother's education, and highest grade completed at age 12 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 γ 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 0.40, but the effect of non-violent street capital on this index is much smaller at 0.11. In contrast, the effect of non-violent street capital on the non-violent street behavior latent index is 0.25, but the effect of violent street capital is not much lower at 0.18. Violent street capital also has larger effects on graduating from

[17] A2 could be relaxed by allowing ξ_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 the same as A1.

[18] Note: Simulated employment data from the model are generated for Figure 6c as follows: (1) 100 observations simulated for each individual in the data assuming type τ. (2) Individuals sampled as type τ using the estimated distribution. (3) Each individual contributes their 100 type τ simulated observations to the data.

high school than does non-violent street capital, although non-violent capital has the larger effect on employment.

Another notable feature of the estimated model parameters is its unobserved heterogeneity. The importance of the estimated unobserved heterogeneity can be observed in Table 4, 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.[19]

First and foremost, we can see that the heterogeneity in outcomes by type are much greater for education and labor market outcomes than for selection into violence or street behaviors. It is true that some types are more likely to engage in street behaviors or to be exposed to violence during adolescence. However, these differences between types are much smaller than differences in high school graduation and hours worked.

Type 3s and 4s do worse than average in terms of high school graduation and employment; all other types do better. Type 3s and 4s are also the types most likely to engage in street behavior, and comprise approximately 41 percent of the population. Comparing type 1s and 2s, we can see that the permanent factors increasing non-violent street behavior are actually correlated with permanent factors leading to increased hours worked.

5.4 Simulated Counterfactuals Using the Estimated Models

We are interested in answering the following question: "How much does exposure to violence influence the education and labor market outcomes of black young males in the US?" I conduct three counterfactuals after interventions to the DGP, as represented by the estimated models, to shed light on this question:[20]

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

Counterfactual II ($do(\overline{D} = 0)$): 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 III ($do(K_v(a) = 0)$ 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.

All of the models used to conduct these counterfactuals are estimated using data on childhood exposure to violence (exposure before age 12, $\underline{D}$), adolescent exposure to violence (exposure between

[19] As reported in Table 3, standard errors are huge for some type-specific effects. This is due to some of these parameters being estimated as large in magnitude negative numbers in bootstrapped replications, and have limited implications for the uncertainty of the remaining estimated model parameters.

[20] See Pearl (2009) for a definition and discussion of the *do* operator.

ages 12 and 18, $\overline{D}$), street behaviors (S) from ages 12 until 23, and on high school graduation (G) and average hours worked (W) for $a = 23$.

Table 5 presents results from Counterfactuals I and II using the estimated static model. The first two columns of Table 5 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 5 show Counterfactuals I and II from the static model estimated under A1, which is implemented by estimating the Average Effect of Treatment on the Treated (ATT) with propensity score matching techniques.[21] The third column of Table 5 reports results under nearest neighbor matching, and the fourth column under stratification matching. 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 education and labor market outcomes are quite muted once controlling for observables, but effects of the closer-in-time adolescent exposure are still very large for these outcomes.

In exchange for a highly stylized model with strong assumptions (Refer to Figure 5 (b)), one can unambiguously construct Counterfactuals I and II using the estimated static version of the model. On the other hand, the dynamic specification of the model allows us to specify weaker assumptions on selection and to investigate mechanisms through which exposure to violence is believed to impact outcomes (Counterfactual III), but does so at the expense of introducing ambiguity in the implementation and interpretation of model counterfactuals. For example, Counterfactual I cannot be constructed using the dynamic model.

To illustrate the differences between the static and dynamic models, consider how exposure to violence affects whether agents graduate from high school. In the static model, potential outcomes will only change due to either D_i or $u_i^G(23)$. The $u_i^G(23)$ represent the sequence of shocks each individual received in the static model, and under identifying assumption A1 these are distributed identically conditional on observed characteristics.

In the dynamic model there are three channels through which exposure to violence might impact an agent's choice to graduate from high school: $\boldsymbol{\xi}_i$, $\overline{D}_i$, or the sequence of $u_i^v(a)$ and $u_i^{nv}(a)$. The sequence of shocks to street behavior are now iid conditional on both observed and unobserved confounders (X_i and $\boldsymbol{\xi}_i$), and the sequence of shocks representing exposure to violence are no

[21] Estimated propensity scores are shown in Figures 6a and 6b, and estimated probit parameters are presented in Table 3.

longer contained in $u_i^G(23)$, so the assumption of its independent and identical distribution appears weaker.

The results from Counterfactual II implemented with the estimated dynamic model are presented in Tables 6, and are qualitatively similar to those when implemented with the estimated static model: being exposed to violence during adolescence has large, negative effects on the rate at which individuals graduate from high school graduation and the hours they work. In the dynamic model counterfactual, these effects are 3.2 percentage points and 4.2 hours, respectively. Although these effects are large, they are also very imprecisely estimated, so that they are not statistically distinguishable from zero when constructed with the dynamic model.[22]

The results from Counterfactual III 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 impacts outcomes. Table 7 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 11.2 percentage points. While the increase in hours worked is relatively smaller at 2 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 III is particularly illustrative of the importance of the second mechanism through which the code of the street operates, the social isolation mechanism. As discussed in Section 5.1, 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, Counterfactual III indicates that mechanisms related to the code of the street could be useful for understanding how exposure to violence impacts the outcomes of black young males in the US.

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.

[22] 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.). This is an advantage of specifying the dynamic selection control model relative to a full dynamic programming model.

The paper then used the qualitative evidence from Anderson's urban ethnography to guide the specification of a model of human capital accumulation that incorporated two 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. This model was estimated under assumptions rendering the model either static (selection on permanent observed characteristics) or dynamic (dynamic selection control with permanent unobserved heterogeneity). While these modeling assumptions do not identify the causal effects as credibly as randomly exposing individuals to violence, each of these assumptions renders the causal interpretation of exposure to violence to be increasingly credible.

Based on counterfactuals from the estimated models, I concluded that exposure to violence during adolescence has large effects on outcomes, decreasing the high school graduation between 3.2 and 8.2 percentage points (9 and 24 percent of the high school dropout rate) and age 23 average weekly hours worked between 3.0 and 4.2 hours (0.15 and 0.21 σ). I also interpreted the counterfactuals from the estimated models to indicate that mechanisms related to the code of the street could be useful for understanding how exposure to violence affects outcomes.

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7 Appendix A: Derivation of the Likelihood Function

To construct the likelihood function of the model under A2, begin by considering the conditional likelihood. Conditional on type, we can express

$$Pr(\overline{D}_i = 1|\tau_i = \tau) = \Phi(\beta X_i + \xi_\tau^D).$$

Similarly, if $S_i(a) = (S_{v,i}(a), S_{nv,i}(a))$, we can use the probabilities

$$\begin{aligned} Pr(S_{v,i}(a) = 1|\tau_i = \tau) = \Phi\Big(&\beta^v X_i + \gamma_v^v K_v(a) + \gamma_{v,2}^v K_v^2(a) + \gamma_{nv,1}^v K_{nv}(a) + \gamma_{nv,2}^v K_{nv}^2(a) \\ &+ \overline{\gamma}^v\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^{S_v} + \lambda^v(a) + u_i^v(a)\Big) \\ Pr(S_{nv,i}(a) = 1|\tau_i = \tau) = \Phi\Big(&\beta^{nv} X_i + \gamma_v^{nv} K_v(a) + \gamma_{v,2}^{nv} K_v^2(a) + \gamma_{nv,1}^{nv} K_{nv}(a) + \gamma_{nv,2}^{nv} K_{nv}^2(a) \\ &+ \overline{\gamma}^{nv}\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^{S_{nv}} + \lambda^{nv}(a) + u_i^{nv}(a)\Big) \end{aligned}$$

to express $Pr(S_i(a)|\tau_i = \tau) = Pr(S_{v,i}(a)|\tau_i = \tau)Pr(S_{nv,i}(a) = 1|\tau_i = \tau)$. The estimated model constrains time trends in street behavior to cross at a particular age, so that:

$$\begin{aligned} \lambda_4^v &= \frac{\lambda_1^v - \lambda_3^v}{16} + \lambda_2^v \\ \lambda_4^{nv} &= \frac{\lambda_1^{nv} - \lambda_3^{nv}}{14} + \lambda_2^{nv}. \end{aligned}$$

We can also write $Pr(G_i(a)|\tau_i = \tau)$ in terms of

$$\begin{aligned} Pr(G_i(a) = 1|\tau_i = \tau) = \Phi\Big(&\beta^G X_i + \gamma_{v,1}^G K_v(a) + \gamma_{v,2}^G K_v^2(a) + \gamma_{nv,1}^G K_{nv}(a) + \gamma_{nv,2}^G K_{nv}^2(a) \\ &+ \overline{\gamma}^G\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^G + \lambda^G(a) + u_i^G(a)\Big). \end{aligned}$$

Finally, where Φ and ϕ are the standard normal CDF and pdf, respectively, we will use the expressions

$$\begin{aligned} Pr(W_i(a) = 0|\tau_i = \tau) &= 1 - \Phi\Big(\big[\beta^W X_i + \gamma_{v,1}^W K_v(a) + \gamma_{v,2}^W K_v^2(a) + \gamma_{nv,1}^W K_{nv}(a) + \gamma_{nv,2}^W K_{nv}^2(a) \\ &\qquad + \overline{\gamma}^W\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \gamma^W G_i(a) + \xi_i^W + \lambda^W(a)\big]/\sigma_W\Big) \\ Pr(W_i(a) = w|\tau_i = \tau) &= \frac{1}{\sigma_W}\phi\Big(\big\{w - \big[\beta^W X_i + \gamma_{v,1}^W K_v(a) + \gamma_{v,2}^W K_v^2(a) + \gamma_{nv,1}^W K_{nv}(a) + \gamma_{nv,2}^W K_{nv}^2(a) \\ &\qquad + \overline{\gamma}^W\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \gamma^W G_i(a) + \xi_i^W + \lambda^W(a)\big]\big\}/\sigma_W\Big) \end{aligned}$$

to construct

$$Pr(W_i(a)|\tau_i = \tau) \;=\; \mathbf{1}\{W_i(a) = 0\}\; Pr(W_i(a) = 0|\tau_i = \tau) \;+\; \mathbf{1}\{W_i(a) > 0\}\; Pr(W_i(a) = w|\tau_i = \tau).$$

Writing an individual's outcome as $\mathcal{O}_i = (D_i, \mathbf{S}_i, \mathbf{G}_i, \mathbf{W}_i)$ and defining $\pi_\tau \equiv Pr(\tau_i = \tau)$, we can write

$$Pr(\mathcal{O}_i|\tau_i = \tau) = Pr(D_i|\tau_i = \tau)Pr(\mathbf{S}_i|\tau_i = \tau)Pr(\mathbf{G}_i|\tau_i = \tau)Pr(\mathbf{W}_i|\tau_i = \tau),$$

and

$$Pr(\mathcal{O}_i) = Pr(\mathcal{O}_i|\tau_i = 1)\pi_1 + \cdots + Pr(\mathcal{O}_i|\tau_i = T)\pi_T.$$

The estimated model conditions type probabilities on initial exposure to violence ($Pr(\tau|\underline{D} = 0)$ and $Pr(\tau|\underline{D} = 1)$). The log-likelihood function is

$$\mathcal{LL} = \sum_i ln\left(Pr(\mathcal{O}_i)\right).$$

8 Appendix B: Measuring Exposure to Violence and Ecometrics

The self-reported data on exposure to violence used in the analysis are consistent with related administrative data, such as the Centers for Disease Control and Prevention (CDC)/National Center for Health Statistics (NCHS) individual-level measures of homicide death rates (Figure 2). County-level administrative crime data from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) Program also relate large racial gaps in exposure to violence. At age 16 the average homicide rate per 100,000 residents in NLSY97 black males' county of residence was 11.2, again more than twice the average for NLSY97 white males, 5.2. On average, black males lived in counties at age 16 with 193 additional assaults per 100,000 residents compared to their white counterparts (517 versus 324).

Prominent researchers in the neighborhood effects literature have proposed directing attention to "ecometrics," or using tools from the psychometric literature to improve the quality of neighborhood-level measures (Sampson (2012), p 60). Relatedly, an important topic that has received little analysis in the empirical neighborhood effects literature is the appropriate definition of neighborhood (Durlauf (2004)). In this Appendix I provide preliminary ecometric evidence on the importance of the definition of "neighborhood" in measuring exposure to violence.

We might define neighborhoods as counties: This is the finest geographic partition available for the NLSY97, and there is ample variation in homicide or violent assault rates across counties even in the same metro area. If we were to define neighborhoods in this way, we would interpret the empirical evidence as falsifying Anderson's theory applying to an empirically large share of black young males, as there is no correlation between this measure of exposure to violence and street behavior. In contrast, if we measure exposure to violence using the self-reported variable in the NLSY97 asking whether respondents have seen someone shot, we find the strong correlations displayed in Figure 4.

8.1 UCR County-Level Measures of Exposure to Violence

An alternative measure of exposure to violence to the one used in the analysis in the paper would be constructed using homicide and assault rates in combination with data on county of residence from the NLSY97 Geocode File. I construct such a variable using crime data come from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) Program by way of the National Archive of Criminal Justice Data (NACJD), a project of the Inter-university Consortium for Political and Social Research (ICPSR).[23]

I use the county-level detailed arrest and offense files for the years 1997 until 2007, such as US DoJ (1997), to create county-level homicide and assault rates. These variables are considered missing if they have been imputed based on less than 6 months of data for the year. The homicide (assault) rate is calculated as the number of homicides (assaults) reported in a county divided by the

[23] It should be noted that the NACJD data are not official FBI UCR data, as the NACJD has made imputations.

county population of agencies reporting crimes. Following convention, this rate is then multiplied by 100,000 to be expressed as the annual homicide (assault) rate per 100,000 individuals. Using the Federal Information Processing Standards (FIPS) state and county codes in which NLSY97 respondents report residing, these county-level homicide and assault rates are then assigned to individuals for the period beginning in the previous year.

8.2 Descriptive Statistics

Surprisingly, street behaviors appear independent of the violence in a respondent's county of residence, regardless of whether it is measured by the homicide or assault rate. Figures 7a and 7c show rates of street behavior after dividing black males in the NLSY97 into county homicide rate quartiles, and Figures 7b and 7d do the same by assault rate quartiles. We can see that respondents are no more likely to engage in street behaviors when residing in more violent counties than when living in less violent counties. Street behaviors of white males follow similar patterns that are also uncorrelated with violence in a respondent's county of residence.

One fact making these data especially surprising is that there is substantial variation in homicide rates between counties, even within the same Metropolitan Statistical Areas (MSAs). Figure 8 shows such variation between 1997 and 2007 between counties in the same MSA. For example, the homicide rate in St. Charles, Missouri was 1.15 per 100,000 in 2007, compared with 39.92 in St. Louis City. The homicide rate in Montgomery County, Maryland was 2.80 per 100,000 in 1997, compared with 56.90 in the District of Columbia. Even among less extreme examples there is considerable variation in homicide rates between counties.

There is also significant variation in the homicide rate between the counties of residence of African American males in the NLSY97. Figure 9a shows that while the homicide rate of counties in which NLSY97 males lived decreased between 1997 and 2007, it is clear that African American males still lived in much more violent counties in 2007 than white males did in 1997. The 75th percentile county-level homicide rate for white males was 8.5 in 1997 and 7.5 in 2007. For black males in the NLSY97 the 75th percentiles for 1997 and 2007 were, respectively, 15.5 and 14.3. Figure 9b shows similar patterns when we look by age of respondents in the NLSY97.

8.3 Comparing Measures of Exposure to Violence

The analysis in the paper uses seeing someone shot as the variable measuring exposure to violence. Despite the obvious caveat that it is self-reported, this variable is assumed to be a better measure of the local experience of exposure to violence than county-level homicide or assault rates due to its correlation with outcomes. If the gunshots heard in one's neighborhood are also a better local measure of exposure to violence than county-level measures, then this assumption is consistent with the empirical evidence. Figures 11a and 11b shows that seeing someone shot is not only more strongly correlated than county homicide rates with outcomes, but also with hearing gunshots in one's neighborhood. This is especially important because seeing someone shot does not appear to be strongly correlated with the homicide rate in one's county of residence (Figure 11c).

I do not use the gunshots heard variable as a measure of exposure to violence since it was only collected for a subsample of NLSY97 respondents. It can, however, give insight into whether seeing someone shot measures different experiences by race. This might be a concern due to residential sorting patterns by race. Clearly, the number of gunshots heard in one's neighborhood is strongly correlated with race (Figure 11d). Perhaps surprisingly, Figure 11e shows that black males who have not seen someone shot report hearing similar numbers of gunshots in their neighborhoods as do white males who have seen someone shot.

8.4 Interpretation and Ecometrics

If we believed that county-level crime variables accurately measure the neighborhood violence to which individuals were exposed, these data would be interpreted as empirical evidence falsifying Anderson's theory applying to an empirically large share of black young males. This highlights the importance of ecometrics, because another explanation for the surprising results in Figure 7 is that county-level homicide or assault rates do not accurately measure the violence to which youth are exposed. This analysis adopts the second interpretation, using two key justifications.

First, consider the following evidence from Cleveland, Ohio on the variation in homicide rates between census tracts within the same county. Figure 10 shows data from the Northeast Ohio Community and Neighborhood Data for Organizing (NEO CANDO) illustrating that homicide rates exhibit tremendous variation between census tracts in Cleveland City, only one municipality of the 58 located within Cuyahoga County, Ohio. In 1990 the 90th percentile homicide rate per 100,000 residents for census tracts in Cleveland City was 116, and in 2000 it was 43. Since county of residence is the finest geographic partition available for the NLSY97 data, this evidence from the NEO CANDO data set suggests this partition could be too coarse to accurately measure the violence to which youth are exposed in their neighborhoods.

Second, the individual-level measures of exposure to violence self-reported in the NSLY97 exhibit patterns consistent with Anderson's theory. These variables are then used to measure exposure to violence in the analysis, since it is plausible that these variables are more accurate measures, and since they are consistent with the qualitative evidence documented by urban ethnographers.

9 Appendix C: The Self-Administered Section of the NLSY97 Questionnaire

The Introduction to the self-administered section of the NLSY97 questionnaire is as follows (Taken from page 210 of NLSY97 (2000)):

"(INTERVIEWER: IT IS NOW TIME TO ADMINISTER THE AUDIO CASI SECTION OF THE INTERVIEW. PLEASE INSERT THE HEADPHONES INTO THE LAPTOP AND THEN READ THIS INTRODUCTION TO THE RESPONDENT:)

This part of the interview is different from the previous parts. In the previous parts I read you the questions and recorded your answers. For this section you will hear the question through the headphones while you read the question on the computer screen. Let me show you how this works. We have several practice questions. The first practice question asks you if you like chocolate ice cream.

(INTERVIEWER: TURN LAPTOP AROUND AND HAND RESPONDENT THE HEADPHONES.)"

Figures

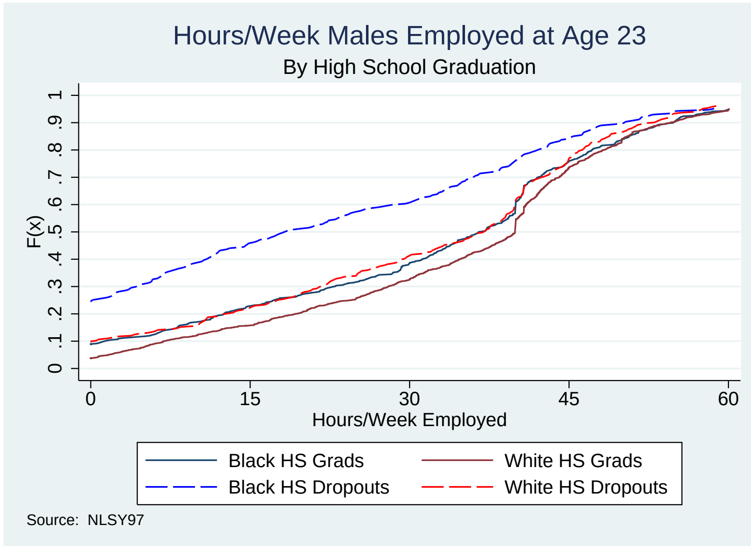


Figure 1: Employment of 23 Year-Old Males in the US

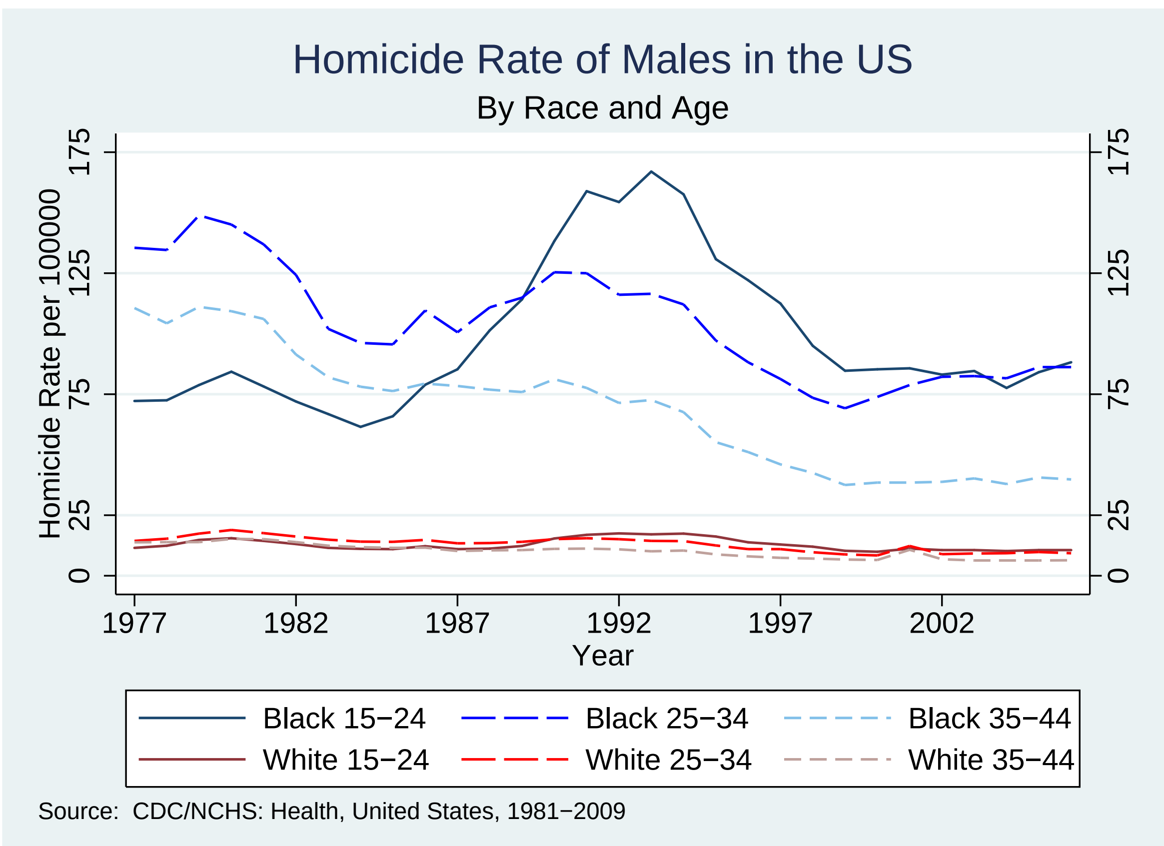
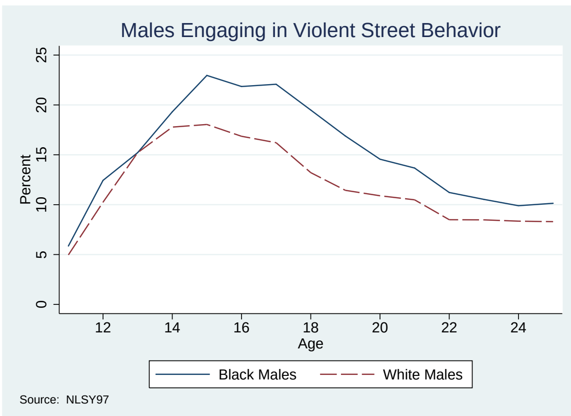
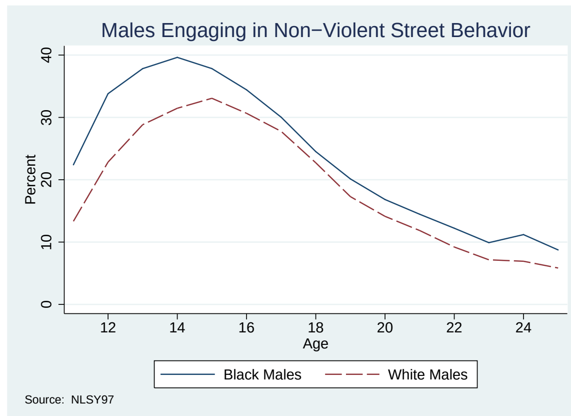


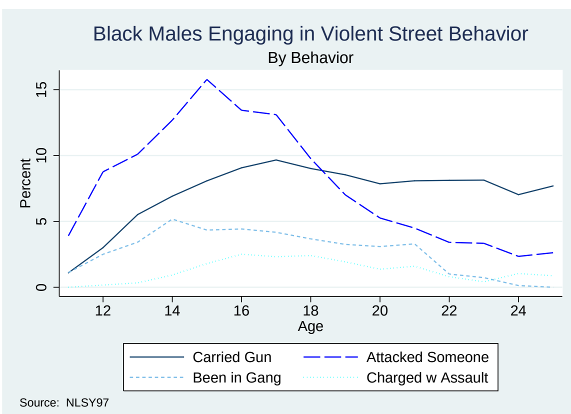
Figure 2: Homicide Rate of Males in the US



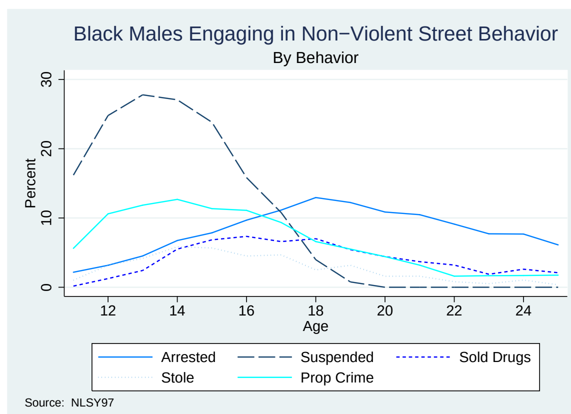
(a) Violent



(b) Non-Violent

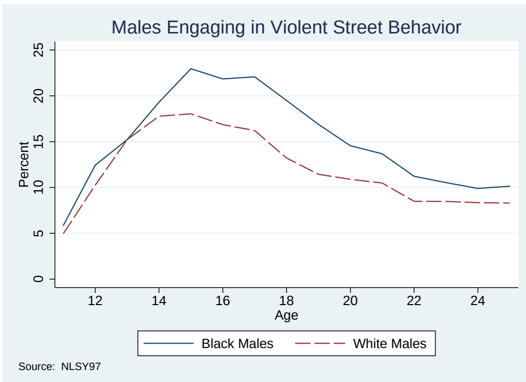


(c) Violent

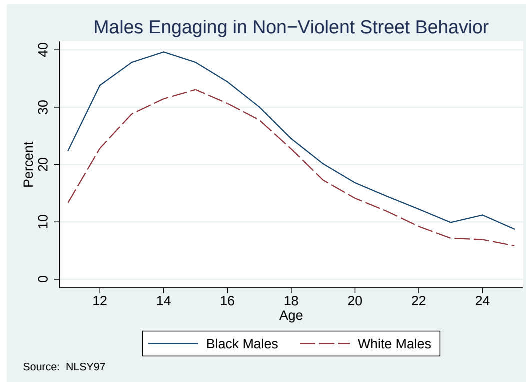


(d) Non-Violent

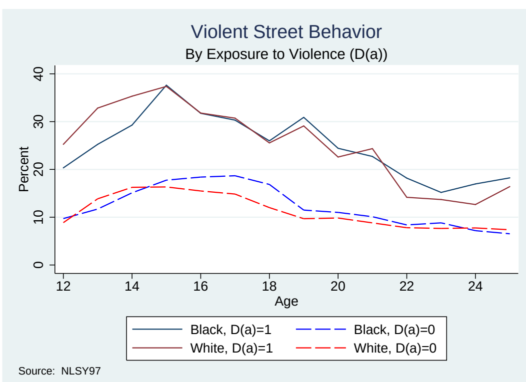
Figure 3: Street Behavior of Males in the NLSY97



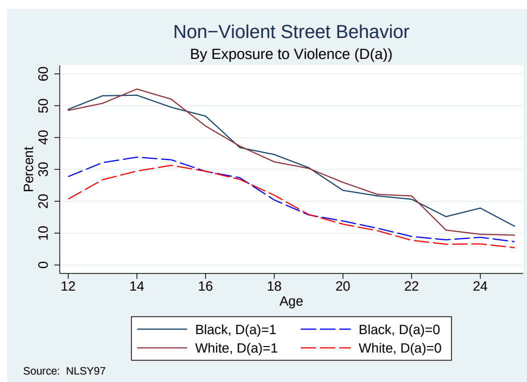
(a) Violent



(b) Non-Violent

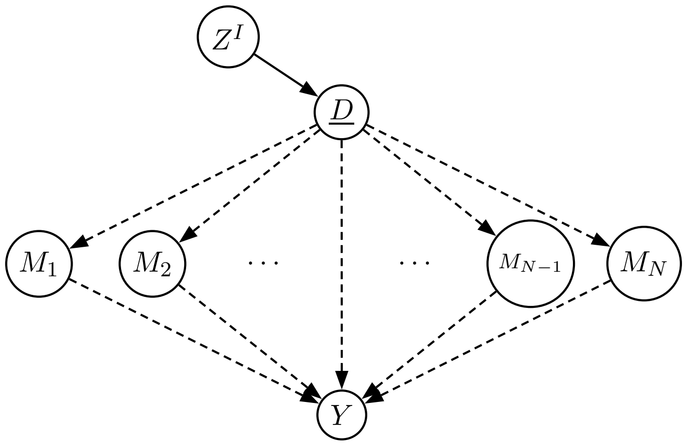


(c) Violent, By Exposure to Violence

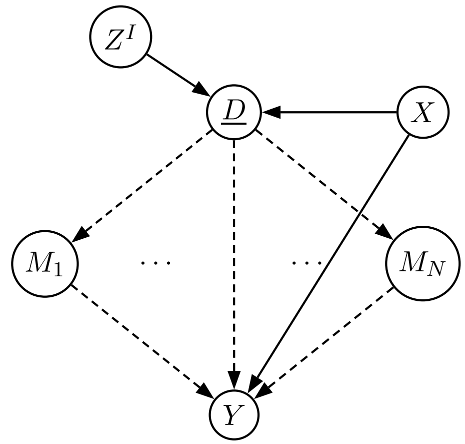


(d) Non-Violent, By Exposure to Violence

Figure 4: Street Behavior by Race and Exposure to Violence



(a) Raw Differences



(b) Under Assumption A1 (Static Matching)

$Z \equiv$ Intervention Setting Treatment

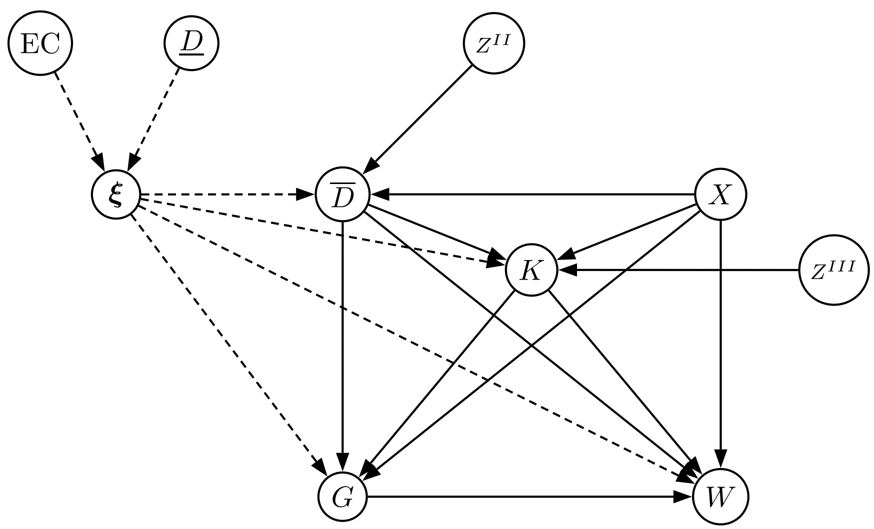
$\underline{D} \equiv \mathbf{1}\{$Childhood Exposure to Violence$\}$

$X \equiv$ Observed Factors (Permanent)

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

$Y \equiv$ Outcome

(c) Variables



(d) Under Assumption A2 (Dynamic Selection Control)

$EC \equiv$ Early Childhood Factors

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

$Z^I - Z^{III} \equiv$ Interventions/Counterfactuals I-III

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

$K \equiv$ Street Capital

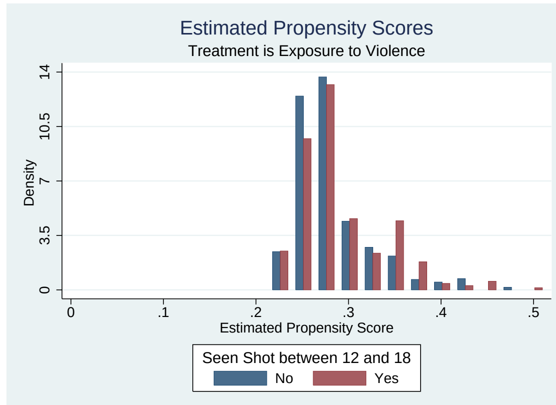
$G \equiv \mathbf{1}\{$Graduate from High School$\}$

$W \equiv$ Work (Hours)

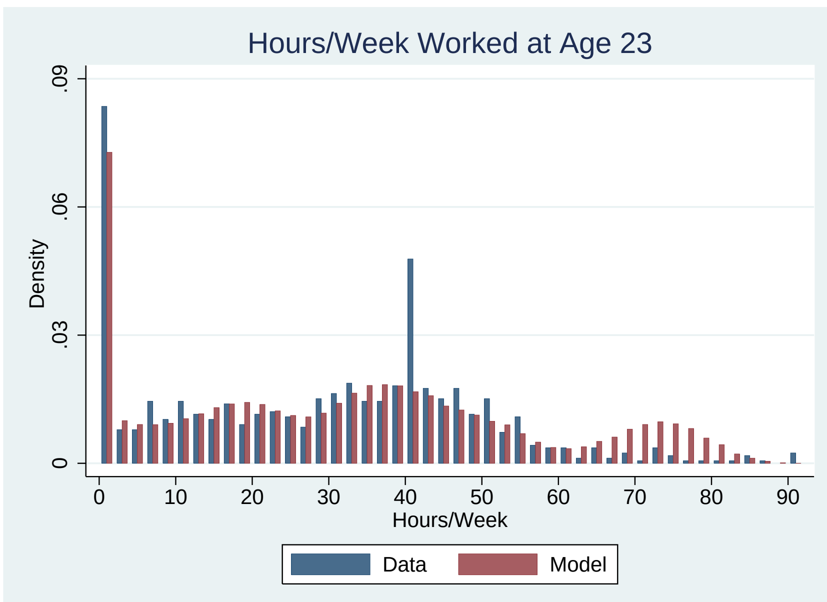
(e) Variables

Figure 5: DAG Representation of Causal Effects

(a) Estimated Propensity Scores, Childhood Exposure (Static Model)

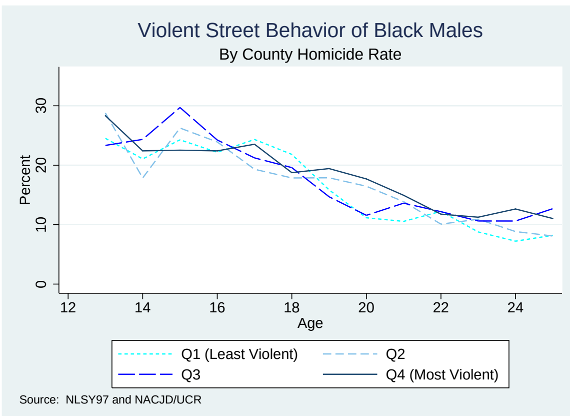


(b) Estimated Propensity Scores, Adolescent Exposure (Static Model)

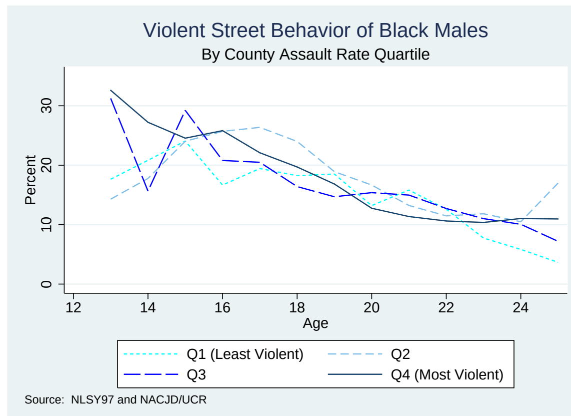


(c) Estimated Hours Worked at Age 23 (Dynamic Model)

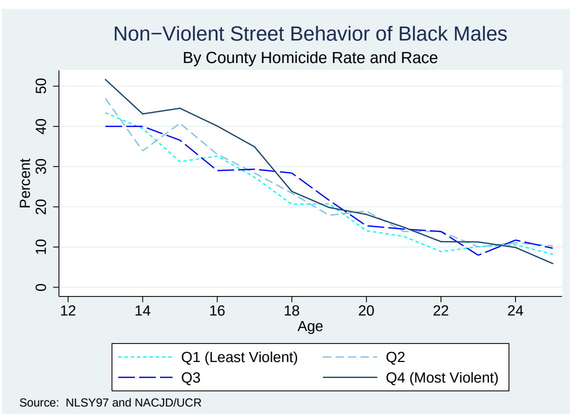
Figure 6: Model Fit



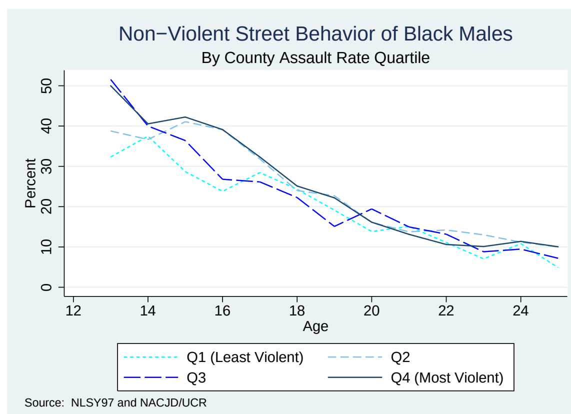
(a) By County Homicide Rate Quartile



(b) By County Assault Rate Quartile

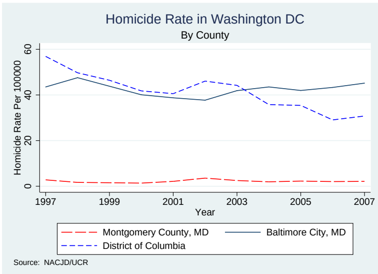


(c) By County Homicide Rate Quartile

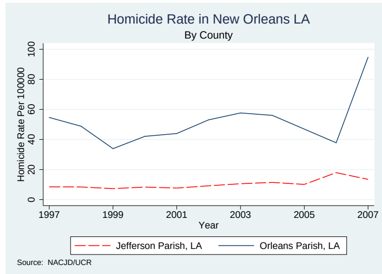


(d) By County Assault Rate Quartile

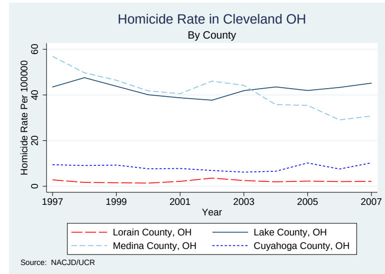
Figure 7: Street Behavior of Black Males by Violence in County of Residence



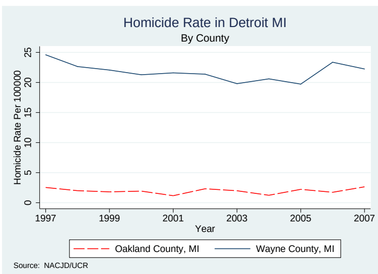
(a) Washington, DC



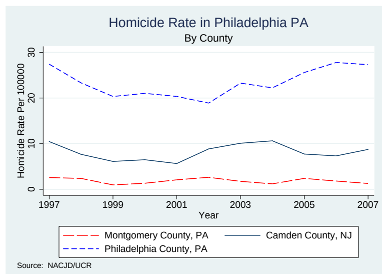
(b) New Orleans, LA



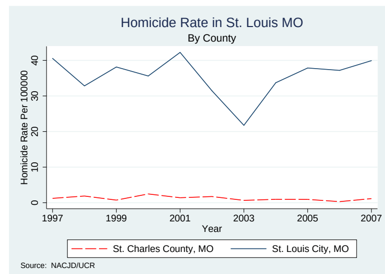
(c) Cleveland, OH



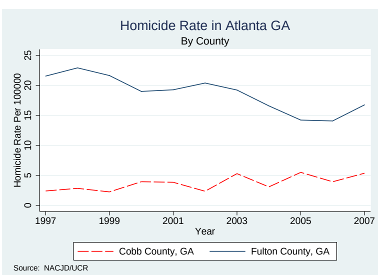
(d) Detroit, MI



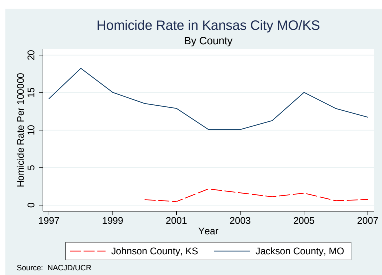
(e) Philadelphia, PA



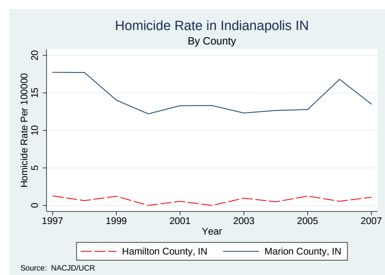
(f) St. Louis, MO



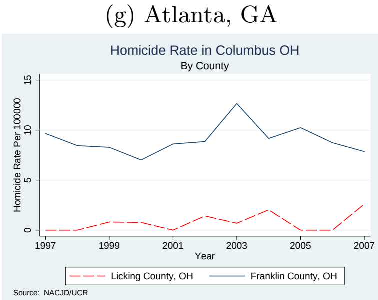
(g) Atlanta, GA



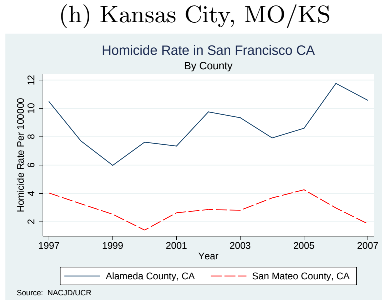
(h) Kansas City, MO/KS



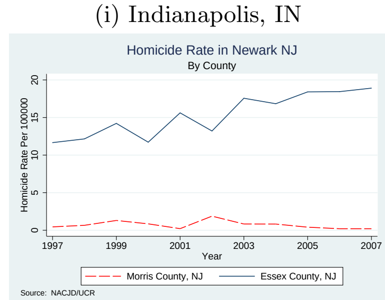
(i) Indianapolis, IN



(j) Columbus, OH

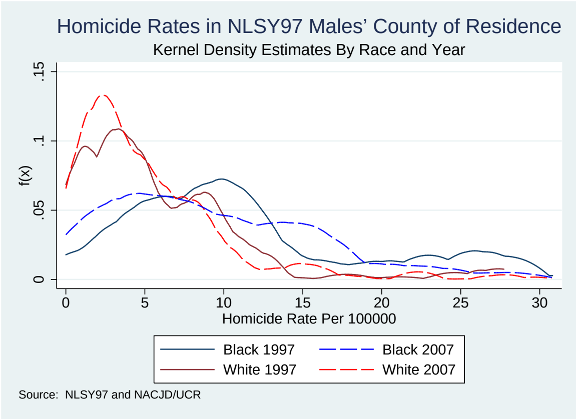


(k) San Francisco, CA

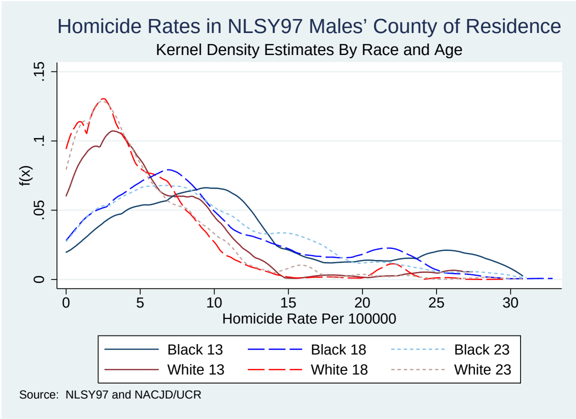


(l) Newark, NJ

Figure 8: Homicide Rates in Select MSAs (by County)



(a) Males in the NLSY97 by Year



(b) Males in the NLSY97 by Age

Figure 9: Homicide Rates in NLSY97 Males' County of Residence

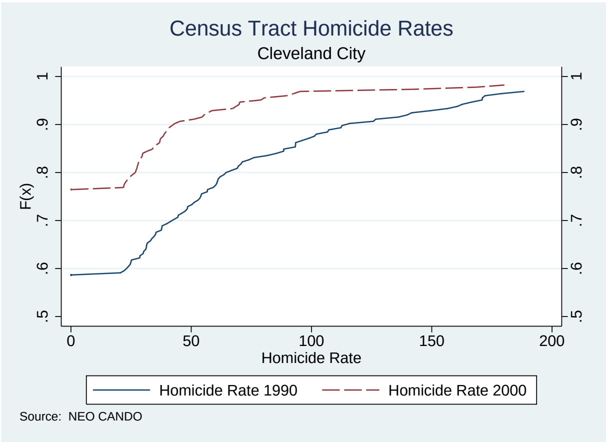
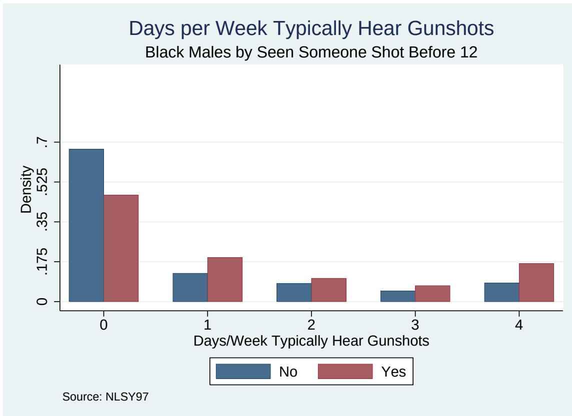
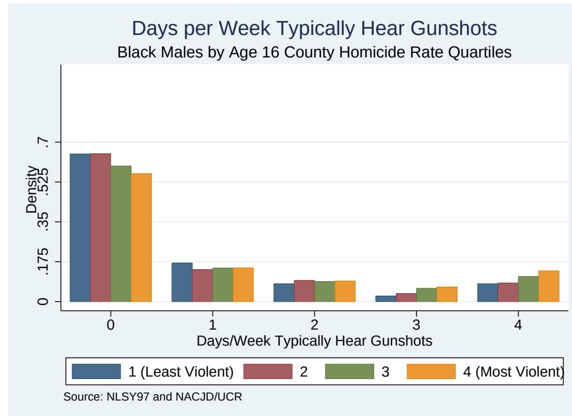


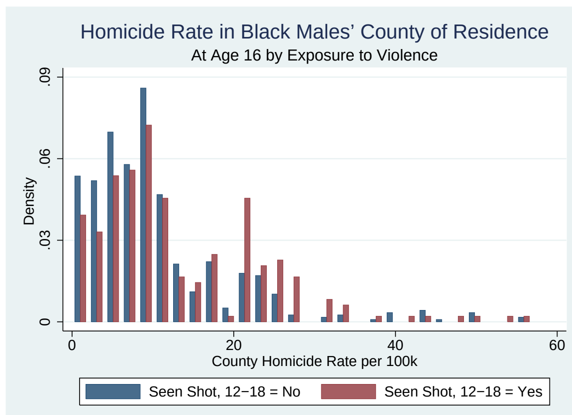
Figure 10: Distribution of Homicide Rate by Census Tract in Cleveland City, Ohio



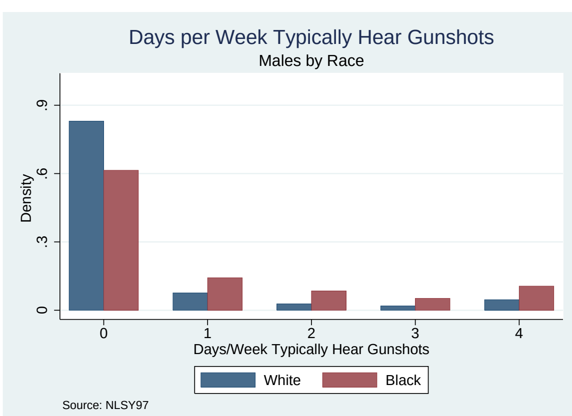
(a) Seen Shot and Days Hear Gunshots



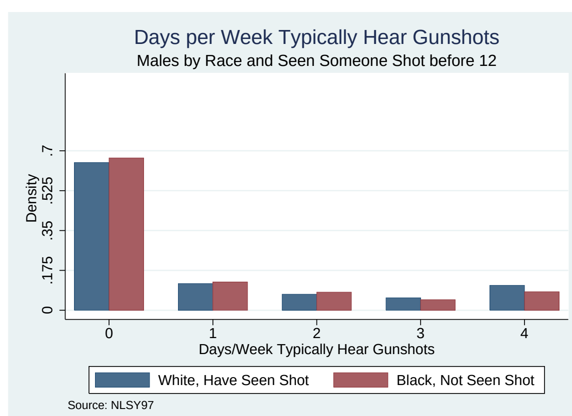
(b) County Homicide Rate and Days Hear Gunshots



(c) County Homicide Rate and Seen Shot



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



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

Figure 11: Measures of Exposure to Violence

Tables

Table 1: NLSY97 Males' Neighborhood and School Characteristics, by Race (%)

(a) Percent Seen Someone Shot or Shot at

	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
White	7.6**	2,662	10.4**	2,351	15.5**	2,318

(b) Percent Victim of Bullying

	Before Age 12		Between 12 and 18	
Race	Yes	n	Yes	n
Black	21.5	1,171	8.5**	1,032
White	23.1	2,662	11.7**	2,350

(c) Percent Typically Hear Gunshots

	Days Per Week				
Race	0	1	2	3	4+
Black	61.4	14.3	8.5	5.2	10.6
White	83.0	7.6	2.8	1.9	4.6

(d) Percent At School

	Have Ever:		
Race	Had Something Stolen	Been Threatened	Been in a Fight
Black	32.3**	22.2	33.1**
White	24.5**	23.6	19.7**

(e) Percent At School

	Feel Safe:	
Race	Strongly Agree	Disagree or Strongly Disagree
Black	22.4**	20.7**
White	35.2**	10.5**

Table 2: Dynamic Model Fit

Outcome	Sample Data	Model Prediction
Selection into Treatment		
Prob of Selection into $\overline{D}$ (%)	29	29
Street Behavior		
Violent		
Age 15 (%)	22	20
Age 18 (%)	20	20
Age 21 (%)	14	14
Non-Violent		
Age 15 (%)	37	36
Age 18 (%)	24	25
Age 21 (%)	14	14
Street Capital		
Violent		
Age 19 (μ)	1.3	1.1
Non-Violent		
Age 19 (μ)	2.3	2.1
Education		
HS Diploma at Age 23 (%)	67	67
Labor Market		
Employed at Age 23 (μ, Hrs/Wk)	29	31

Table 3: 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}	$G(23)$	$W(23)$	$Pr(\tau\|\underline{D}=0)$	$Pr(\tau\|\underline{D}=1)$
Observed Factors									
Other Family	0	0	0	0	0	0	0		
One-Parent Family	-0.23	-0.06	-0.44	-0.08	-0.06	-0.33	-4.17		
	(0.18)	(0.18)	(0.20)	(0.07)	(0.09)	(0.33)	(2.60)		
Two-Parent Family	-0.54	-0.14	-0.54	-0.15	-0.15	0.06	-0.10		
	(0.19)	(0.19)	(0.23)	(0.09)	(0.10)	(0.31)	(2.68)		
HH Members under 6	0.04	0.17	0.19	0.06	0.05	-0.16	-1.39		
	(0.07)	0.07	(0.10)	(0.04)	(0.03)	(0.11)	(2.80)		
No Resident Mother	0	0	0	0	0	0	0		
Mom HS Dropout	0.25	0.15	0.69	0.01	0.02	-0.21	4.15		
	(0.18)	(0.18)	(0.31)	(0.05)	(0.06)	(0.31)	(4.12)		
Mom HS Grad	-0.11	-0.05	-0.27	-0.02	-0.05	0.32	1.10		
	(0.11)	(0.11)	(0.20)	(0.05)	(0.05)	(0.20)	(4.23)		
Mom BA Holder	-0.23	-0.09	-0.02	0.04	0.00	0.58	0.08		
	(0.16)	(0.15)	(0.24)	(0.05)	(0.08)	(0.29)	(2.90)		
Grade at 12	-0.10	-0.03	0.07	0.06	-0.13	0.63	0.88		
	(0.05)	(0.05)	(0.08)	(0.04)	(0.04)	(0.11)	(1.11)		
HS Grad at 23							1.09		
							(2.61)		
Unobserved Factors									
β_0	0.07	-0.76	-1.13	0	0	-2.14	29.49	28.56	18.78
	(0.31)	(0.31)	(0.62)	...	...	(0.62)	(14.88)	(8.08)	(9.29)
ξ_2			0.16	0.03	0.11	0.07	13.39	16.75	18.60
			(0.81)	(1.11)	(0.51)	(0.85)	(30.8)	(7.15)	(8.88)
ξ_3			0.05	0.10	0.27	-0.68	-37.08	14.92	25.69
			(1.64)	(1.27)	(0.43)	(0.87)	(28.99)	(8.73)	(9.97)
ξ_4			0.30	0.18	0.27	-0.30	-18.26	25.43	16.95
			(1.81)	(0.82)	(0.83)	(1.43)	(28.58)	(10.21)	(7.61)
ξ_5			0.00	0.11	0.03	0.34	37.81	14.34	19.98
			(1.61)	(0.83)	(0.46)	(0.86)	(30.55)	(6.14)	(6.04)
Safety/Social Exclusion									
$\overline{\gamma}$				0.20	0.17	-0.11	-5.17		
				(0.10)	(0.10)	(0.23)	(6.18)		
$\gamma_{v,1}$				0.40	0.18	-0.21	-0.10		
				(0.06)	(0.05)	(0.11)	(1.04)		
$\gamma_{v,2}$				-0.03	-0.01	0.02	-0.04		
				(0.01)	(0.01)	(0.02)	(0.04)		
$\gamma_{nv,1}$				0.11	0.25	-0.11	-0.55		
				(0.05)	(0.05)	(0.09)	(1.01)		
$\gamma_{nv,2}$				-0.01	-0.01	-0.00	0.00		
				(0.01)	(0.01)	(0.02)	(0.03)		
Wage/Age Trends									
σ_W							3.75		
							(1.12)		
κ_1				-1.93	0.16				
				(0.52)	(0.25)				
κ_2				0.03	0.00				
				(0.03)	(0.01)				
κ_3				1.10	3.06				
				(0.44)	(0.32)				
κ_4				-0.16	-0.20				
				(0.02)	(0.02)				

Note: Models are specified in Section 5, and the likelihood function for the dynamic model is fully specified in the Appendix. Standard errors for parameters in the dynamic model are obtained using 50 bootstrap replications.

Table 4: Simulated Outcomes from the Estimated Dynamic Model for all Individuals in the Sample

Outcome	Data μ	Type 1 μ	Type 2 μ	Type 3 μ	Type 4 μ	Type 5 μ
Type Distribution						
Share $\mid \underline{D} = 0$ (%)	$\cdots$	29	17	15	25	14
Share $\mid \underline{D} = 1$ (%)	$\cdots$	19	19	26	17	20
Share of Population (%)	$\cdots$	26	17	18	23	16
Selection						
$Pr(\overline{D} = 1)$ (%)	29	25	30	27	35	25
Street Behavior						
Violent						
Age 15 (%)	22	18	19	21	23	21
Age 21 (%)	14	12	13	14	16	14
Non-Violent						
Age 15 (%)	37	31	35	41	41	32
Age 21 (%)	14	12	14	17	17	12
Education						
HS Diploma at Age 23 (%)	67	71	73	52	63	79
Labor Market						
Employed at Age 23 (Hrs/Wk)	29	33	47	0	15	71

Table 5: The Average Effect of Treatment on the Treated (ATT) Constructed from Counterfactuals I and II (Changing Exposure) Using the Estimated Static Models

			ATT	
			PS Matching	
Outcome and Time of Exposure	Unconditional Control Mean	Effect	NN	Strat
Street Behavior				
Childhood Exposure (<12)				
Violent (Age 15, %)	17.3	19.4	19.7	19.0
	(1.5)	(2.9)	(3.5)	(3.4)
Non-Violent (Age 15, %)	32.8	14.2	13.3	11.5
	(1.8)	(3.5)	(3.9)	(3.7)
Adolescent Exposure (12-18)				
Violent (Age 21, %)	10.3	11.6	11.9	11.1
	(1.3)	(2.5)	(3.0)	(2.9)
Non-Violent (Age 21, %)	10.9	9.8	9.8	8.8
	(1.4)	(2.5)	(3.0)	(2.9)
Education				
Childhood Exposure (<12)				
HS Diploma (Age 23, %)	70.0	–12.9	–6.1	–6.4
	(1.9)	(3.7)	(4.2)	(3.8)
Adolescent Exposure (12-18)				
HS Diploma (Age 23, %)	69.2	–8.7	–6.7	–8.2
	(1.9)	(3.6)	(4.0)	(3.7)
Labor Market				
Childhood Exposure (<12)				
Employed (Age 23, Hrs/Wk)	28.9	–1.2	0.5	–0.4
	(0.8)	(1.2)	(1.9)	(1.7)
Adolescent Exposure (12-18)				
Employed (Age 23, Hrs/Wk)	29.9	–4.4	–3.0	–4.0
	(0.8)	(1.6)	(1.7)	(1.6)

Note: Counterfactual I is setting exposure $\underline{D}_i$ to 0 for all i, where exposure is seeing someone shot or shot at, and Counterfactual II is setting exposure $\overline{D}_i$ to 0 for all i. NN is Nearest Neighbor and Strat is Stratification, both methods of Propensity Score Matching.

Table 6: Counterfactual II (Adolescent Exposure) Using the Estimated Dynamic Model

Outcome	Model Prediction for Subpopulation	Counterfactual Prediction (after Intervention to DGP)	Difference
Education			
HS Diploma at Age 23 (%)	58.5	61.7	3.2
	(5.5)	(2.5)	(6.2)
Labor Market			
Employed at Age 23 (μ, Hrs/Wk)	27.9	32.2	4.2
	(4.4)	(2.5)	(5.2)

Note: Counterfactual II is an intervention setting exposure $\overline{D}_i = 0$ for the subpopulation i observed to have $\overline{D}_i = 1$.

Table 7: Counterfactual III (No Street Capital Accumulation) Using the Estimated Dynamic Model

Outcome	Model Prediction for Population	Counterfactual Prediction (after Intervention to DGP)	Difference
Education			
HS Diploma at Age 23 (%)	67.5	79.2	11.2
	(2.9)	(1.9)	(2.6)
Labor Market			
Employed at Age 23 (μ, Hrs/Wk)	31.5	33.4	1.9
	(2.3)	(2.1)	(2.3)

Note: Counterfactual III is an intervention setting $K_v(a) = 0$ and $K_{nv}(a) = 0$ for all a and for all i.