Human Capital in the Inner City

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Abstract: Black males in the United States are exposed to tremendous violence at young ages: In the NLSY97 26 percent report seeing someone shot by age 12, and 43 percent by age 18. This paper studies how this exposure to violence and its associated social isolation affect education and labor market outcomes. I use Elijah Anderson's ethnographic research on the "code of the street" to guide the specification of a model of human capital accumulation that includes street capital, the skills and knowledge useful for providing personal security in neighborhoods where it is not provided by state institutions. The model is estimated assuming either selection on observables or dynamic selection with permanent unobserved heterogeneity. Counterfactuals from these estimated models indicate that exposure to violence has large effects, decreasing the high school graduation rate between 6.1 and 10.5 percentage points (20 and 35 percent of the high school dropout rate) and hours worked between 3.0 and 4.0 hours per week (0.15 and 0.19 σ).

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. By age 21, 37 percent of black males in the National Longitudinal Survey of Youth 1997 (NLSY97) had not earned a high school diploma, compared with 21 percent of white males. The median 23 year old black male in the NLSY97 worked 9 hours less per week than his white counterpart.

Exposure to violence is also strongly correlated with race in the US. Between 1986 and 2006, the homicide death rate of black males between 15-34 was typically eight times that of white males (Figure 1, NCHS (2009)). And 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.

This paper is concerned with understanding how exposure to violence and social isolation affect the outcomes of black young males in the US. The analysis is guided by the qualitative evidence in Elijah Anderson's urban ethnography. Anderson (1999) posits that weak institutions and labor market conditions have left a void in setting and maintaining the social order within many poor African American neighborhoods, allowing a "street" element to fill this void with its own code of conduct. Anderson has observed that individuals are likely to adopt this "code of the street," which encourages individuals to use violence to further their interests, when state institutions cannot ensure their personal security and when they feel isolated from mainstream institutions. Anderson has also observed that becoming invested in this code of conduct leads to disinterest in mainstream institutions such as the formal labor market and the education system.

The analysis in this paper is conducted using the NLSY97, which contains unique data for quantitatively studying the code of the street. Extensive data on exposure to violence are contained in the NLSY97, including variables measuring exposure at both the county and the individual level.[1] The NLSY97 also contains 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 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.

The analysis begins by documenting that black males are exposed to tremendous amounts of violence at young ages, with huge racial gaps in young males' exposure to violence. In the NLSY97, 26 percent of black males saw someone shot by age 12, 29 percent between 12 and 18, and cumulatively 43 percent by age 18. This compares with 8, 10, and 15 percent, respectively, for white males. On average, black males report hearing 1.0 gunshots per week in their neighborhood, more than twice the average for white males, 0.4. At age 16 the average homicide rate per 100,000 residents in black males' county of residence was 11.2, again more than twice the average for white males, 5.2. On average, black males lived in counties at age 16 with 192 additional assaults per 100,000 residents compared to their white counterparts.

[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.

The paper also presents evidence on the importance of the geographic level of measurement for neighborhood effects research. County-level measures of exposure to violence vary considerably, yet street behaviors are not correlated with county-level measures of exposure to violence. In contrast, individual-level measures of exposure are strongly correlated with street behaviors. Especially noteworthy is that although black young males engage in more street behaviors than their white counterparts, when conditioned on exposure to violence at the individual level, black and white young males are equally likely to engage in street behaviors. I interpret this as evidence that exposure to violence occurs locally at geographic levels finer than counties.

The paper next specifies and estimates a model of human capital accumulation. The specification of the model is guided by the qualitative evidence in Anderson's urban ethnography to incorporate two related mechanisms through street capital. This model is then estimated under assumptions rendering the model either static (selection on observables) or dynamic (dynamic selection control with permanent unobserved heterogeneity).

The remainder of the paper consists of using the estimated model to conduct counterfactual simulations, which are used to interpret the data on the outcomes of black young males in the US. Based on counterfactuals from the estimated models, I conclude that exposure to violence has large effects on outcomes, decreasing the high school graduation between 6.1 and 10.5 percentage points for various subpopulations (20 and 35 percent of the high school dropout rate) and hours worked for those exposed between 3.0 and 4.0 hours per week (0.15 and 0.19 σ) at age 23. 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.[2] 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,

[2] 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.

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 the Moving to Opportunity housing mobility program (Kling et al. (2007), Aliprantis and Richter (2012)).

Finally, the results in this paper contribute to the literature on the process by which individuals accumulate human capital. One related literature studies the accumulation of human capital used in the formal labor market when there is a tradeoff between labor market outcomes and criminal behavior (Lochner (2004), Imai and Krishna (2004), Gould et al. (2002), Sampson (1987)), and another literature studies the accumulation of criminal capital (Bayer et al. (2009), Mocan et al. (2005)). 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.[3] 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 considered in the empirical analysis. The samples used from the National Longitudinal Survey of Youth 1997 (NLSY97) and Uniform Crime Reporting (UCR) data sets are described in Section 3. A descriptive analysis and a comparison of the measures of exposure to violence from both data sets 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

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

counterfactual manipulations of the models. 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 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).[4] 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.[5] 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 ap-

[4] "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).

[5] This security arrangement may in fact be viewed as a personalized version of *realpolitik* as defined in Kissinger (1995), and similar versions can be found in locations all around the world.

pearance, and contempt for conventional values and behavior, which are easily discredited because of their association with whites. These behaviors can include doing well in school, being civil to others, and speaking Standard English" (p 287).

While historical distrust has helped to create and shape street culture, social isolation and the concentration of poverty have helped to sustain it (Wilson (1987), Aliprantis and Carroll (2013)). The weakness of social and state institutions in inner city neighborhoods allows the street group to dominate the public life of all children by violently punishing any children who do not join it (See Canada (1996).). This means that for any boy, "growing up in the 'hood means learning to some degree the code of the streets, the prescriptions and proscriptions of public behavior. He must be able to handle himself in public, and his parents, no matter how decent they are, may strongly encourage him to learn the rules" (Anderson (1999), p 114).

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

Children experience the social isolation mechanism when adults' "efforts to combat the street may cause them to lump the good students with the bad, generally viewing all who display street emblems as adversaries" (Anderson (1999), p 96). This mechanism operates through "The knowledge that the wider system in the person of cops, teachers, and store managers downtown is instantly ready to lump them with the street element," which "takes a psychological toll on boys" (p 104). 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 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.[6]

3 Data

In order to study the personal security and social isolation mechanisms just described, we analyze relevant data on young males in the United States. Data on demographic characteristics and human capital all come from the National Longitudinal Survey of Youth 1997 (NLSY97). Data on exposure to violence come from both the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) Program and the NLSY97.

3.1 Demographic Characteristics and Standard Human Capital: NLSY97

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

[6] 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).

[7] 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: NLSY97

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.[8] 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.[9]

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 the following 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.[10]

3.3 Exposure to Violence: UCR

As a first measure of exposure to violence we use data on homicide and assault rates in combination with data on county of residence from the NLSY97 Geocode File. The 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

[8] 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."

[9] 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.

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

for Political and Social Research (ICPSR).[11]

The county-level detailed arrest and offense files for the years 1997 until 2007, such as US DoJ (1997), are used 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 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.

3.4 Exposure to Violence: NLSY97

As an alternative to using county-level measures of the violence to which youth are exposed, we also use data from the NLSY97 regarding respondents' experiences. 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 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

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

percent of black males work 0 hours per week, compared with five percent of white males. Figure 2 shows the cumulative density function of the hours per week worked by males at age 23 by race and educational attainment. The Figure shows that 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 8a that six percent of black males engage in violent street behaviors at age 11, and that this climbs to a maximum of 23 percent at age 15, before declining gradually to 10 percent at age 25. Figure 8a 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 8b). 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. 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 UCR County-Level Measures of Exposure to Violence

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 4a and 4c show rates of street behavior after dividing black males in the NLSY97 into county homicide rate quartiles, and Figures 4b and 4d 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 5 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 reside. Figure 6a 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 6b shows similar patterns when we look by age of respondents in the NLSY97.

One explanation for the surprising results in Figure 4 is that county-level homicide or assault rates do not accurately measure the violence to which youth are exposed. Consider the following evidence from Cleveland, Ohio on the variation in homicide rates between census tracts within the same county. Figure 7 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.

4.3 NLSY97 Individual-Level Measures of 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.

Contrary to the county-level data examined earlier, using these data to measure exposure to violence suggests that being exposed to violence does indeed influence street behavior. Figures 8c and 8d 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). We now see the expected pattern that those 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.

4.4 Comparing Measures of Exposure to Violence

The ensuing analysis 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 9a and 9b 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 9c).

We do not use gunshots heard as a measure of exposure 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, gunshots heard in one's neighborhood is strongly correlated with race (Figure 9d). Surprisingly, Figure 9e 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.

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 vector of these factors is 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

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

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.[12] Given a time-invariant set of observable characteristics X_i, agents choose to engage in violent and non-violent street behaviors according to the following latent index models:

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

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

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

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

Figure 8 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

[12] See Chen and Pearl (2012) for a discussion on the importance of this distinction.

model as follows:

$$\overline{D}_i \equiv \mathbf{1}\Big\{\beta^{\overline{D}} X_i + \xi_i^{\overline{D}} + \overline{\epsilon}_i \geq 0\Big\}, \qquad \overline{\epsilon}_i \sim \text{iid}\,\mathcal{N}(0,1). \tag{3}$$

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

$$\begin{aligned} G_i(a) \equiv \mathbf{1}\Big\{&\beta^G X_i + \gamma_{v,1}^G K_v(a) + \gamma_{v,2}^G K_v^2(a) + \gamma_{nv,1}^G K_{nv}(a) + \gamma_{nv,2}^G K_{nv}^2(a) \\ &+ \overline{\gamma}^G\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^G + \lambda^G(a) + u_i^G(a) \geq 0\Big\}, \end{aligned} \tag{4}$$

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:

$$W_i(a) \equiv \begin{cases} W_i^*(a) & \text{if } W_i^*(a) > 0; \\ 0 & \text{if } W_i^*(a) \leq 0, \text{ where} \end{cases} \tag{5}$$

$$\begin{aligned} W_i^*(a) \equiv\, &\beta^W X_i + \gamma_{v,1}^W K_v(a) + \gamma_{v,2}^W K_v^2(a) + \gamma_{nv,1}^W K_{nv}(a) + \gamma_{nv,2}^W K_{nv}^2(a) \\ &+ \overline{\gamma}^W\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi_i^W + \lambda^W(a) + u_i^W(a), \end{aligned} \tag{6}$$

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.[13] 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 of the mechanisms about which we are trying to learn.

To illustrate these points, Figures 10 and 11 represent the specified model of human capital accumulation as a Directed Acyclic Graph (DAG). Focusing on the dynamic version of the model in Figure 10, 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

[13] 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 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 Observables

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 3-6. The standard Strong Ignorability (SI) assumption is that conditional on observables, the unobservable components of selection and outcomes are independent. In the context of our model, we label this as Assumption 1:

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

Assumption 1 will be implemented using Propensity Score Matching (PSM) on selection into $\overline{D}$ or an analogue to Equation 3 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

$$(\boldsymbol{\gamma}_{v,1} \ , \ \boldsymbol{\gamma}_{v,2} \ , \ \boldsymbol{\gamma}_{nv,1} \ , \ \boldsymbol{\gamma}_{nv,2}) = (\mathbf{0}, \mathbf{0}, \mathbf{0}, \mathbf{0}).$$

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:[14]

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

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

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

The model is estimated under A2 using maximum likelihood. The likelihood function is derived in the Appendix, and before presenting estimation results some thoughts on identification are in order. First, a finite mixture of $T = 5$ types is assumed.[15] 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 $\boldsymbol{\xi}^G$.

Assumption A2 imposes a specific structure on the distribution of the $\boldsymbol{\xi}_i$. 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.

5.3 Estimation Results

The estimated dynamic model has 93 parameters, and the value of the log-likelihood function at the estimated parameter values is $-15,910$. Table 2 shows some moments from the data along with those predicted by the estimated dynamic model. We can see that overall, the model fits the data well. The model performs worst at predicting street behavior, under-predicting behavior at older ages. However, the model accurately predicts the average levels of street capital at age 19. The model also slightly over-predicts the high school graduation rate, but predicts the mean average hours worked at age 23 extremely well.

Figure 12 also shows model fit for the estimated static and dynamic models. We can see that the observed characteristics X are more highly predictive of childhood exposure to violence than of adolescent exposure. We can also see that the finite mixture in the dynamic model has a difficult time fitting the hours worked data. Individuals working more than 75 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.

Table 3 shows estimated parameters in both the static and dynamic models. Parameters tend to

[15] 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.

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 little 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 much smaller. The magnitude of these parameters is quite similar in both the violent and non-violent equations. For example, the effect of violent street capital on the violent street behavior latent index is 0.35, and the effect of non-violent street capital on the non-violent street behavior latent index is 0.32. Non-violent street capital has larger effects on graduating from high school than does violent street capital.

Another notable feature of the estimated model parameters is the extent of 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.[16]

Type 4s and 5s together make up roughly one quarter of the population. These two types are both highly likely to be exposed to violence and to engage in street behavior. Type 4s in particular represent the 12 percent of the population who engage in by far the most street behavior. Type 1s and 2s, who together make up just over half of all black males in the US, are much less likely to engage in street behavior, and are also relatively unlikely to be exposed to violence. And type 3s, who make up the last quarter of the population, are somewhere between the type 1s and 2s and type 4s and 5s. Type 3s are less likely to engage in violent street behavior than the population on average, but they engage in about the same amount of non-violent street behavior. It is worth noting that type 3s are also relatively unlikely to be exposed to violence.

Undesirable outcomes appear to be driven by type 3s and type 4s. Type 1s and 2s, which again are estimated to represent about half of African American males in the US, graduate from high school at higher rates than the population on average and also work more hours at age 23. The 14 percent of type 5s are likely to be exposed to violence and engage in street behavior, but also appear to do well in terms of high school graduation and the formal labor market. The roughly one third of youth who are type 3s or 4s are responsible for a large share of high school dropouts, and these are also the types who work much less than the other types in the finite mixture.

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 two counterfactuals with the estimated models to shed light on this question:[17]

[16] 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.

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

Counterfactual I ($do(\underline{D} = 0)$): For individuals with $\underline{D}_i = 1$, simulate outcomes after manipulating $\underline{D}_i$ to equal 0. 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. 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 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.[18] 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, 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 investigate mechanisms through which exposure to violence is believed to impact outcomes, but does so at the expense of introducing ambiguity in the implementation and interpretation of model counterfactuals. Consider, for example, 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 observable characteristics. Thus counterfactually manipulating D_i in the static model represents the only way of changing exposure to violence in that model.

[18]Estimated propensity scores are shown in Figures 12a and 12b, and estimated probit parameters are presented in Table 3.

In the dynamic model, however, 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 $u_i^{nv}(a)$. Thus neither Counterfactual I nor II represents a manipulation to all of the avenues through which exposure to violence influences outcomes. Since $\underline{D}_i$ only enters the dynamic model through $\boldsymbol{\xi}_i$, I implement Counterfactual I by simulating outcomes after changing the type distribution to be $Pr(\xi_i = \xi_\tau | \underline{D} = 0)$ for all individuals, including those for whom $\underline{D}_i = 1$ in the data. Counterfactually manipulating the distribution of the $\boldsymbol{\xi}_i$ in this way represents a counterfactual change in childhood exposure if exposure to violence is the only reason for differences in the conditional type distributions. I also implement Counterfactual II using the dynamic model by directly manipulating $\overline{D}_i$ to be 0 for all i.

The results from Counterfactuals I and II using the estimated dynamic model are presented in Tables 6 and 7. The results from Counterfactual I implemented with the estimated dynamic model are qualitatively similar to those when implemented with the estimated static model: being exposed to violence during childhood has large, negative effects on the rate at which individuals graduate from high school graduation. In the dynamic model counterfactual, this effect is 10.5 percentage points. However, childhood exposure to violence has effects on hours worked that are statistically indistinguishable from zero in both models.

The effects from adolescent exposure to violence determined in Counterfactual II are qualitatively different when implemented with the estimated dynamic model than those when implemented with the estimated static model. The dynamic model counterfactual results in 7 are not entirely surprising: Since estimation in the graduation equation (Equation 4) used age 18 street capital, adolescent exposure could only have affected the graduation decision directly. The effects of adolescent exposure on hours worked at age 23 are remarkably similar in magnitude in both the dynamic model counterfactual and the static model counterfactual, although the subpopulations to which they pertain differs. The effects in the dynamic model, though, are very imprecisely estimated, making them statistically indistinguishable from 0. One reason may be the difficulty of the finite mixture model in fitting the hours worked data of those working over 75 hours per week, as discussed in Section 5.3 and shown in Figure 12c.

To summarize the dynamic model counterfactuals then, Counterfactual I results in large effects on educational attainment, but no effects on employment, while Counterfactual II results in no effects on attainment but large effects on employment. What might explain the large differences between these dynamic model counterfactuals? It is possible that childhood exposure to violence is the most important for educational attainment, while adolescent exposure has the largest impact on employment. In this case it is possible that the maximum likelihood estimation technique attributed the effects of early childhood exposure in the estimated model to the $\boldsymbol{\xi}_i$, and the effects of adolescent exposure are found in the $\overline{\gamma}$ parameter estimates. Unlike the static version of the model, exposure to violence can express itself in multiple ways in the dynamic model. Thus neither counterfactual manipulation to the dynamic model represents "the" effect of exposure to violence.

How much does the dynamic model allow us to differentiate between sorting of individuals with similar abilities and preferences versus externalities as the driving force of correlations between exposure to violence and outcomes? If childhood exposure to violence enters the model only through the conditional distributions of $\boldsymbol{\xi}_i$, and these parameters only differ for the subpopulations with different exposure to violence due to that exposure, then Counterfactual I captures effects on outcomes from childhood exposure to violence. If the conditional distributions of $\boldsymbol{\xi}_i$ differ as well for the subpopulations with different exposure to violence due to sorting of individuals by abilities and preferences, then Counterfactual I will represent a combination of effects from childhood exposure to violence and effects from changing the ability and preference distribution in the population. Counterfactual I could also represent changing neighborhood or school attributes other than violence that impact outcomes.

These considerations help us to interpret what we can learn from Counterfactuals I and II conducted with the estimated models. We might interpret the results from these counterfactuals implemented with the estimated static and dynamic models to represent upper and lower bounds on effects from exposure to violence. In this case, we would conclude that depending on the subpopulation, childhood exposure to violence would increase the high school graduation rate of black males in the US between 6.1 and 10.5 percent. These effects represent, respectively, 20 and 35 percent of the high school dropout rate of black males. Furthermore, we might also conclude that for those exposed to violence, adolescent exposure decreases the average hours per week that 23 year-old black young males work between 3.0 and 4.0, or between 0.15 and 0.19 standard deviations.

To conclude, I also conduct a counterfactual simulation with the dynamic model aimed at answering the following question: "Is street capital an important mechanism for understanding how exposure to violence influences the education and labor market outcomes of black young males?" This counterfactual is as follows:

Counterfactual III ($do(K = 0)$): Simulate outcomes after setting $K_v(a) = 0$ and $K_{nv}(a) = 0$ for all a. Find the associated changes in average outcomes.

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 8 shows that about eight percent more of the population would graduate from high school if street capital would not accumulate from engaging in street behaviors. However, Counterfactual III indicates that if this were the case then there would not be large changes in age 23 average hours worked.

Counterfactual III is particularly important for showing 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 compliment 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 three 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. Finally, the paper presented an empirical result generally useful for neighborhood effects research, that the level of measurement matters when studying externalities. Street behaviors in the NLSY97 are not correlated with county-level measures of exposure to violence, despite the strong correlation with individual-level measures.

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 observables) or dynamic (dynamic selection control with permanent unobserved heterogeneity). The estimated model was used to conduct counterfactuals, which were then used to interpret data on the outcomes of black young males in the US.

Based on counterfactuals from the estimated models, I concluded that exposure to violence has large effects on outcomes, decreasing the high school graduation between 6.1 and 10.5 percentage points (20 and 35 percent of the high school dropout rate) and age 23 average weekly hours worked between 0 and 4.0 hours (0 and 0.19 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

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

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

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

$$\begin{aligned}
Pr(S_{v,i}(a) = 1|\tau_i = \tau) = \Phi\Big(&\beta^v X_i + \gamma^v_v K_v(a) + \gamma^v_{v,2} K^2_v(a) + \gamma^v_{nv,1} K_{nv}(a) + \gamma^v_{nv,2} K^2_{nv}(a) \\
&+ \overline{\gamma}^v\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi^{S_v}_i + \lambda^v(a) + u^v_i(a)\Big) \\
Pr(S_{nv,i}(a) = 1|\tau_i = \tau) = \Phi\Big(&\beta^{nv} X_i + \gamma^{nv}_v K_v(a) + \gamma^{nv}_{v,2} K^2_v(a) + \gamma^{nv}_{nv,1} K_{nv}(a) + \gamma^{nv}_{nv,2} K^2_{nv}(a) \\
&+ \overline{\gamma}^{nv}\, \overline{D_i}\, \mathbf{1}\{a > 18\} + \xi^{S_{nv}}_i + \lambda^{nv}(a) + u^{nv}_i(a)\Big)
\end{aligned}$$

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:

$$\begin{aligned}
\lambda^v_4 &= \frac{\lambda^v_1 - \lambda^v_3}{16} + \lambda^v_2 \\
\lambda^{nv}_4 &= \frac{\lambda^{nv}_1 - \lambda^{nv}_3}{14} + \lambda^{nv}_2.
\end{aligned}$$

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

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

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

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

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

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

Figures

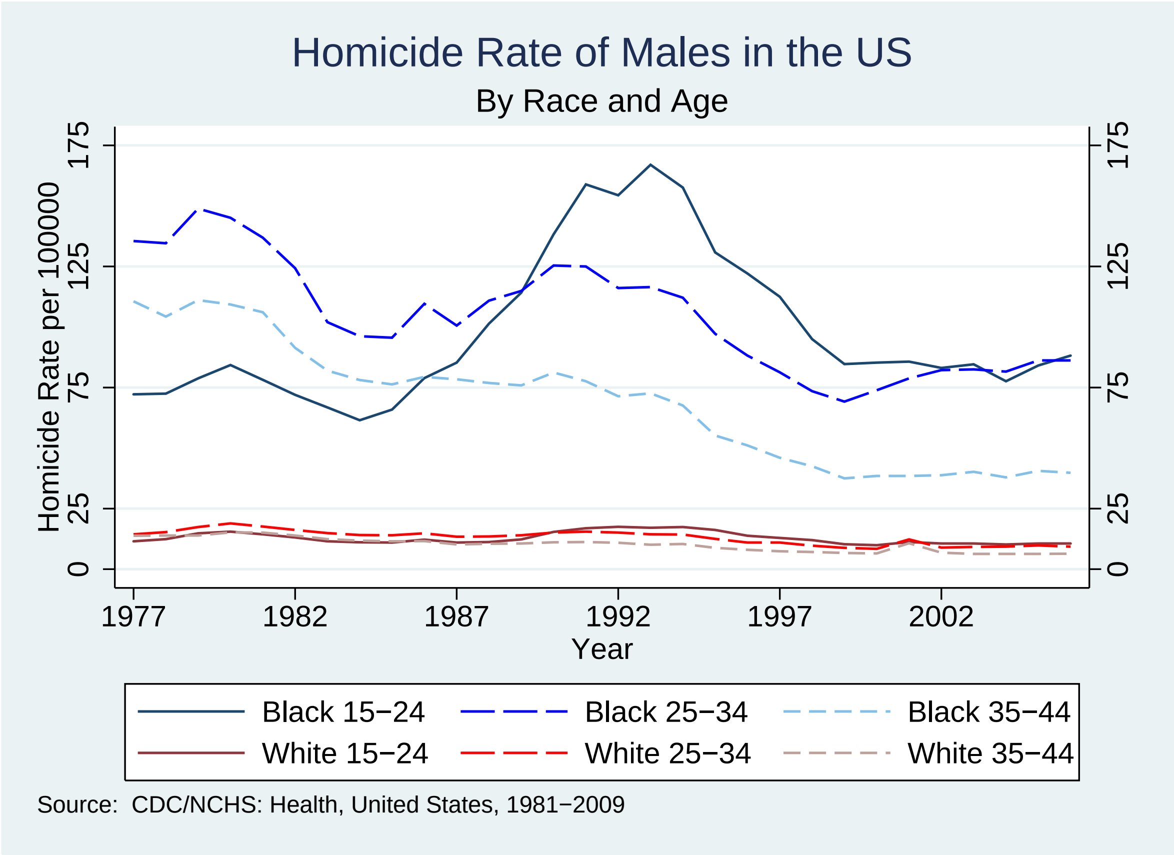


Figure 1: Homicide Rate of Males in the US

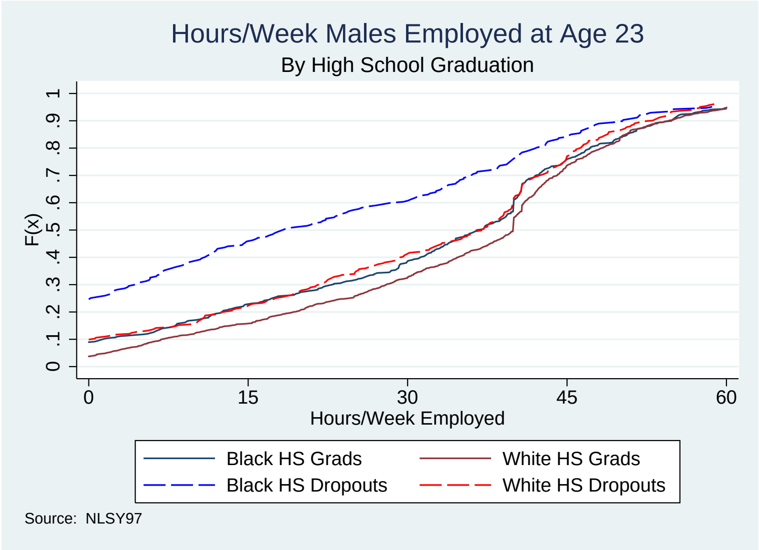
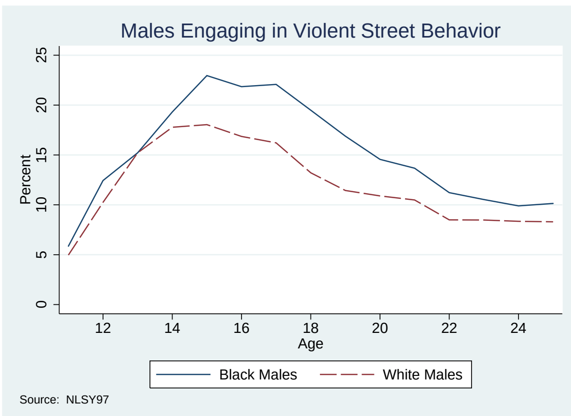
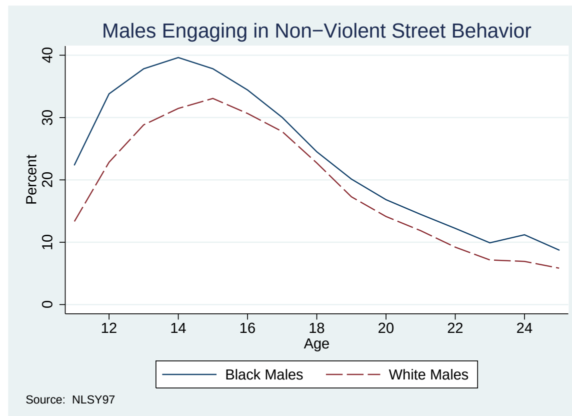


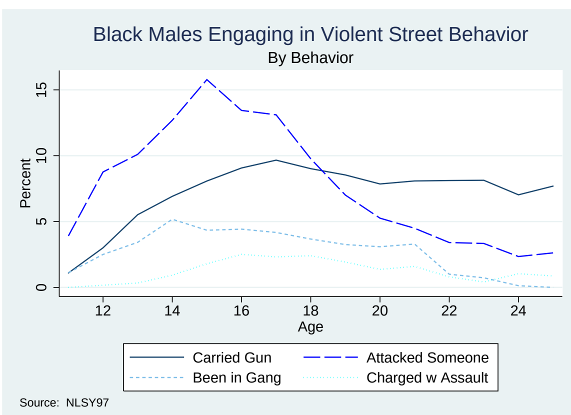
Figure 2: Employment of 23 Year-Old Males in the US



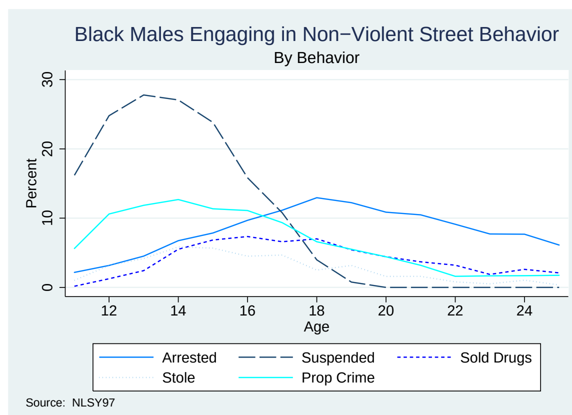
(a) Violent



(b) Non-Violent

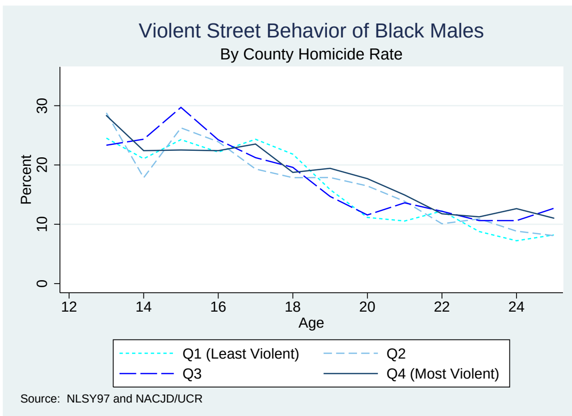


(c) Violent

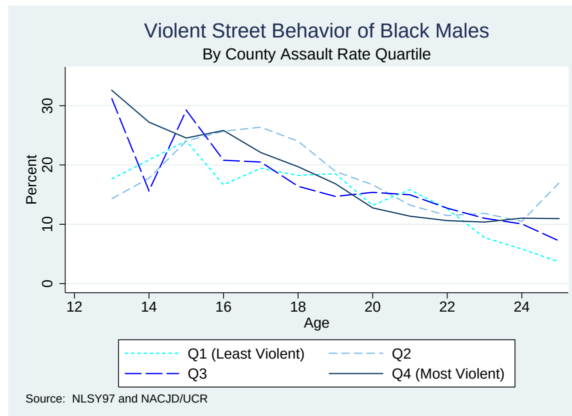


(d) Non-Violent

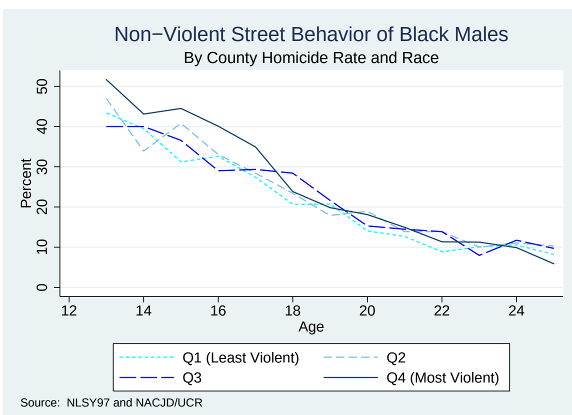
Figure 3: Street Behavior of Males in the NLSY97



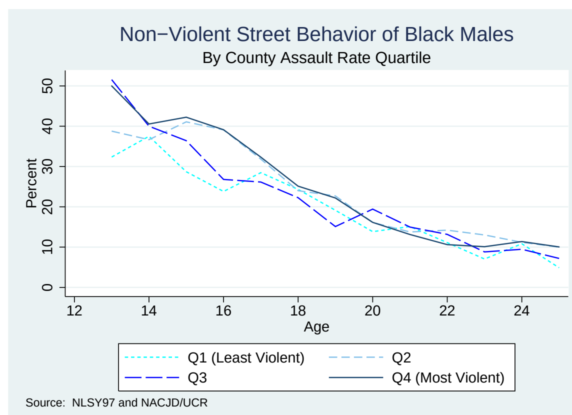
(a) By County Homicide Rate Quartile



(b) By County Assault Rate Quartile

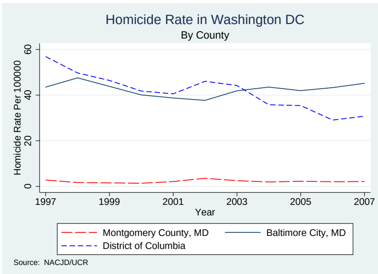


(c) By County Homicide Rate Quartile

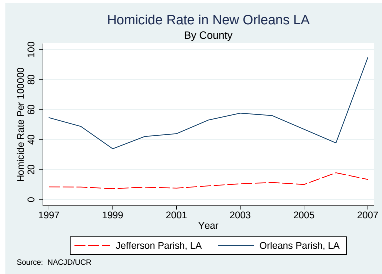


(d) By County Assault Rate Quartile

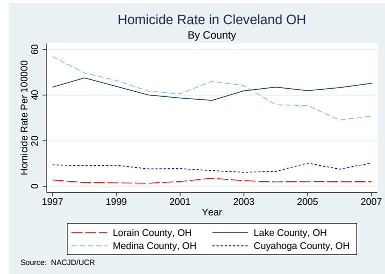
Figure 4: Street Behavior of Black Males by Violence in County of Residence



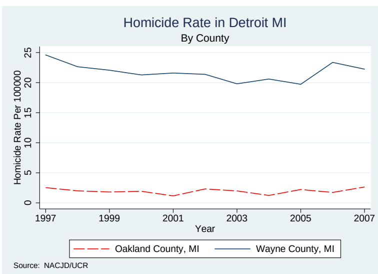
(a) Washington, DC



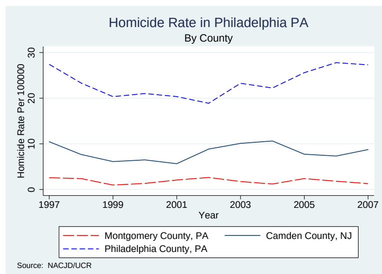
(b) New Orleans, LA



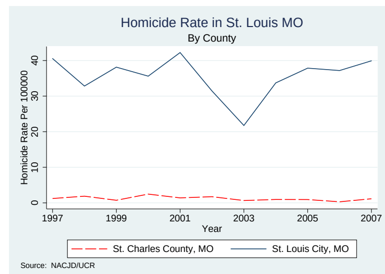
(c) Cleveland, OH



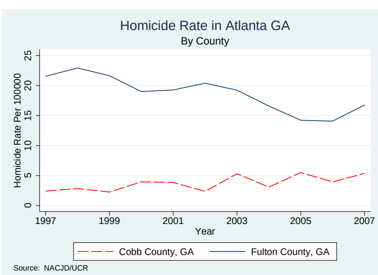
(d) Detroit, MI



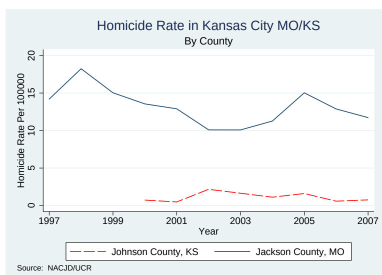
(e) Philadelphia, PA



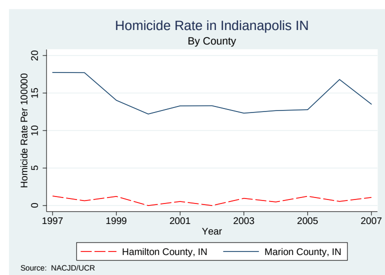
(f) St. Louis, MO



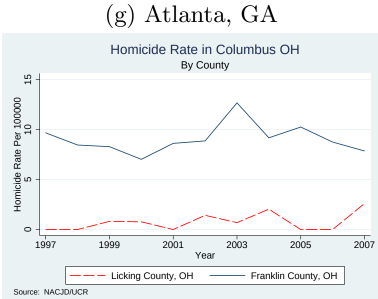
(g) Atlanta, GA



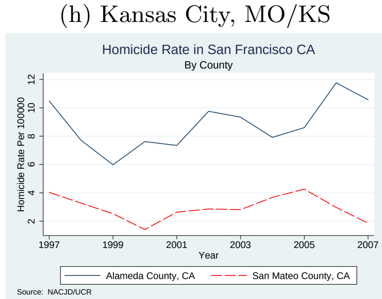
(h) Kansas City, MO/KS



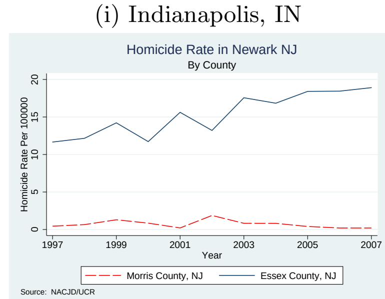
(i) Indianapolis, IN



(j) Columbus, OH

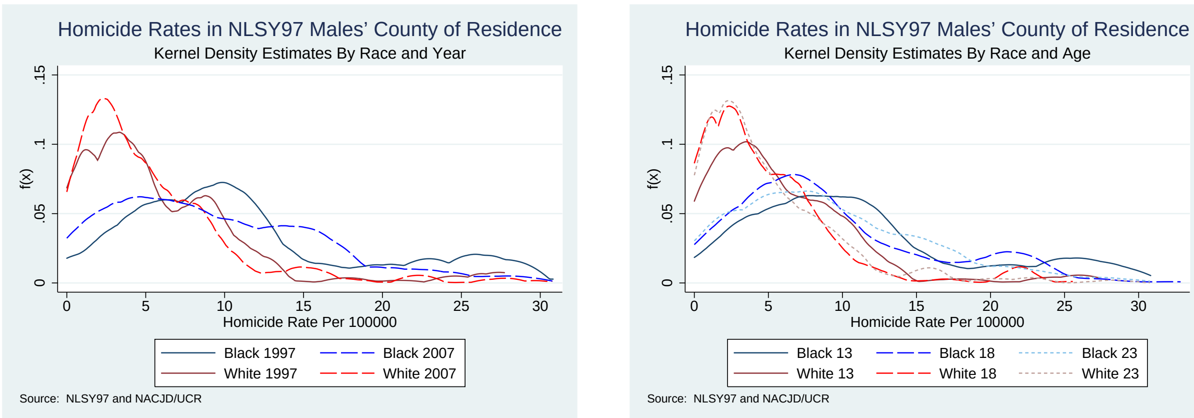


(k) San Francisco, CA



(l) Newark, NJ

Figure 5: Homicide Rates in Select MSAs (by County)



(a) Males in the NLSY97 by Year

(b) Males in the NLSY97 by Age

Figure 6: Homicide Rates in NLSY97 Males' County of Residence

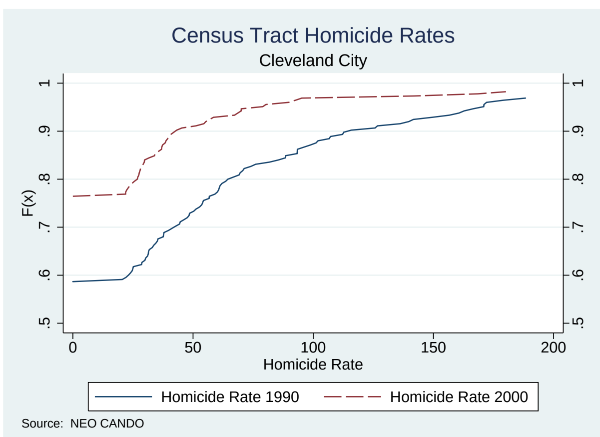
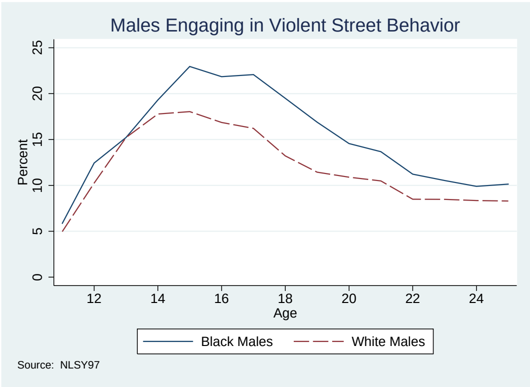
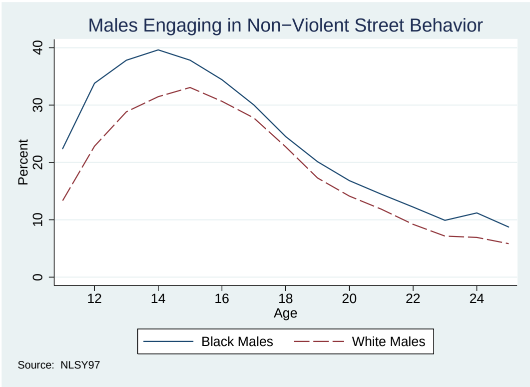


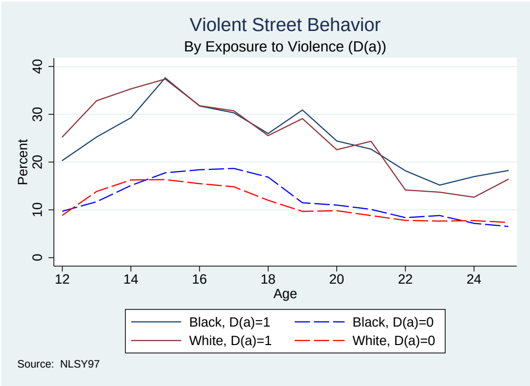
Figure 7: Distribution of Homicide Rate by Census Tract in Cleveland City, Ohio



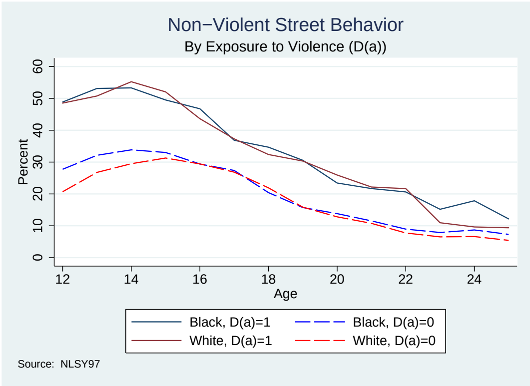
(a) Violent



(b) Non-Violent

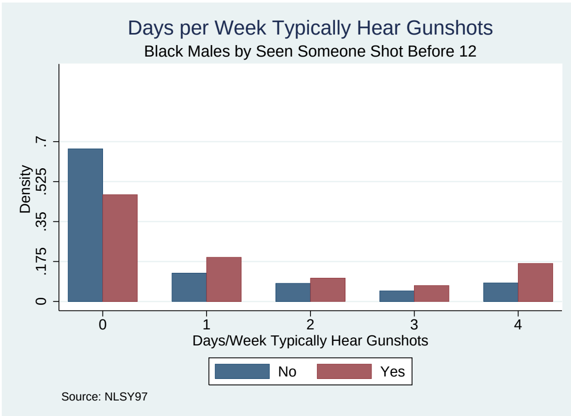


(c) Violent, By Exposure to Violence

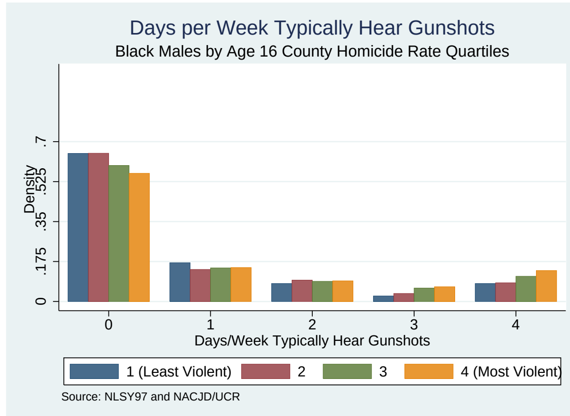


(d) Non-Violent, By Exposure to Violence

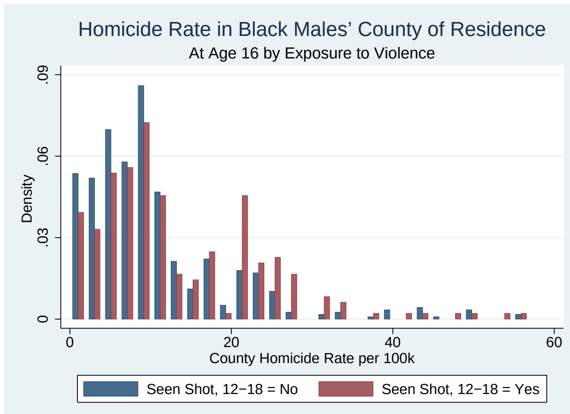
Figure 8: Street Behavior by Race and Exposure to Violence



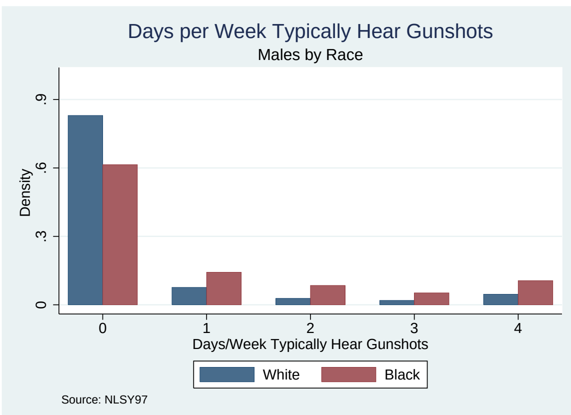
(a) Seen Shot and Days Hear Gunshots



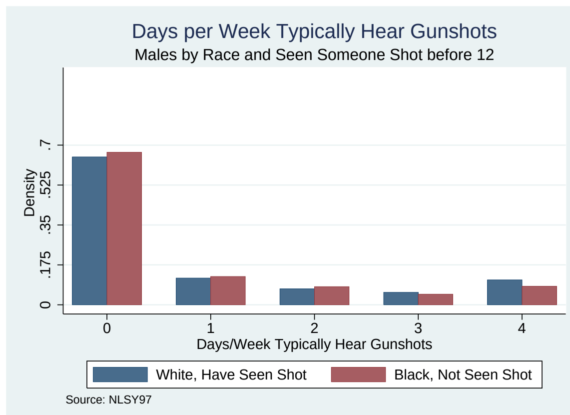
(b) County Homicide Rate and Days Hear Gunshots



(c) County Homicide Rate and Seen Shot

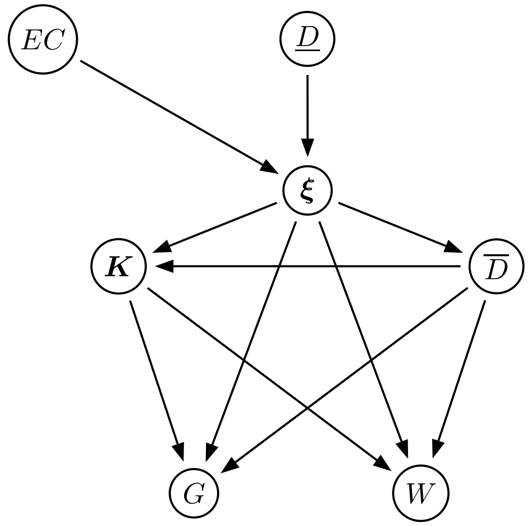


(d) Days Typically Hear Gunshots in Nbd, by Race



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

Figure 9: Measures of Exposure to Violence



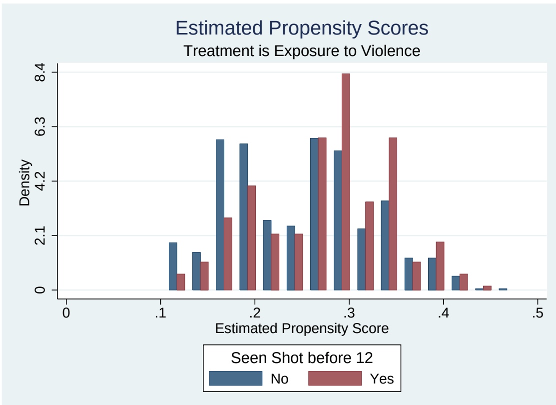
EC = Early childhood factors $\underline{D}$ = Exposure to violence before age 12

K = Street capital ξ = Permanent unobserved factors $\overline{D}$ = Exposure to violence between 12 and 18

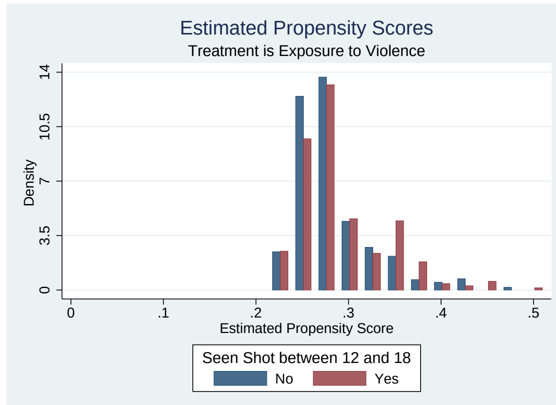
G = Graduating from high school by age 23 W = Hours worked at age 23

Figure 10: DAG Representation of Dynamic Model (Conditional on Observed Characteristics X)

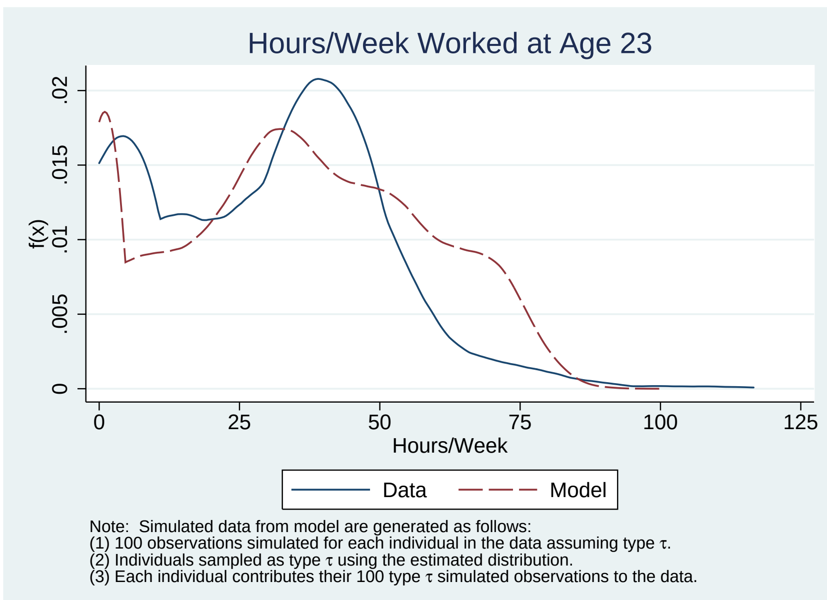
Figure 11: DAG Representation of Static Models (Conditional on Observed Characteristics X)



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



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



(c) Estimated Wages (Dynamic Model)

Figure 12: Model Fit

Tables

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

(a) Percent Seen Someone Shot or Shot at

Race	Before Age 12 Yes	Before Age 12 n	Between 12 and 18 Yes	Between 12 and 18 n	Cumulative by 18 Yes	Cumulative by 18 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

Race	Before Age 12 Yes	Before Age 12 n	Between 12 and 18 Yes	Between 12 and 18 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	31
Street Behavior		
Violent		
Age 15 (%)	22	19
Age 18 (%)	20	15
Age 21 (%)	14	7
Non-Violent		
Age 15 (%)	37	35
Age 18 (%)	24	20
Age 21 (%)	14	7
Street Capital		
Violent		
Age 19 (μ)	1.3	1.2
Non-Violent		
Age 19 (μ)	2.3	2.2
Education		
HS Diploma at Age 23 (%)	67	72
Labor Market		
Employed at Age 23 (μ, Hrs/Wk)	29	29

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}	$G(23)$	$W(23)$	$Pr(\tau \mid \underline{D}=0)$	$Pr(\tau \mid \underline{D}=1)$
Observed, Predetermined Factors									
Other Family	0	0	0	0	0	0	0		
One-Parent Family	-0.23	-0.06	-0.28	-0.04	-0.06	0.02	-3.96		
	(0.18)	(0.18)	(0.23)	(0.08)	(0.07)	(0.30)	(2.98)		
Two-Parent Family	-0.54	-0.14	-0.50	-0.04	-0.13	0.50	-1.24		
	(0.19)	(0.19)	(0.24)	(0.08)	(0.08)	(0.30)	(2.75)		
HH Members under 6	0.04	0.17	0.16	-0.03	-0.01	0.02	0.56		
	(0.07)	0.07	(0.10)	(0.04)	(0.04)	(0.14)	(1.96)		
No Resident Mother	0	0	0	0	0	0	0		
Mom HS Dropout	0.25	0.15	0.47	0.06	0.12	-0.61	5.29		
	(0.18)	(0.18)	(0.27)	(0.05)	(0.05)	(0.30)	(4.13)		
Mom HS Grad	-0.11	-0.05	-0.24	-0.05	-0.14	0.41	5.25		
	(0.11)	(0.11)	(0.17)	(0.04)	(0.05)	(0.19)	(4.08)		
Mom BA Holder	-0.23	-0.09	-0.05	0.03	-0.13	0.81	0.64		
	(0.16)	(0.15)	(0.25)	(0.04)	(0.07)	(0.32)	(2.14)		
Grade at 12	-0.10	-0.03	0.01	-0.05	-0.16	0.69	1.33		
	(0.05)	(0.05)	(0.10)	(0.03)	(0.04)	(0.12)	(1.46)		
Unobserved Factors									
β_0	0.07	-0.76	-1.07	0	0	-2.81	18.96	33.9	21.1
	(0.31)	(0.31)	(0.62)	...	...	(0.72)	(10.62)	(7.7)	(6.6)
ξ_2			0.13	-0.24	-0.25	0.62	16.22	21.1	18.6
			(335.25)	(0.23)	(0.22)	(0.30)	(7.27)	(10.1)	(3.4)
ξ_3			-0.01	0.09	0.21	-0.28	-29.56	23.0	22.2
			(0.02)	(0.11)	(0.12)	(0.25)	(334.74)	(5.1)	(6.6)
ξ_4			1.40	0.03	1.04	-0.33	-4.14	9.0	19.9
			(0.31)	(0.17)	(0.18)	(0.41)	(12.94)	(2.8)	(3.6)
ξ_5			1.59	0.13	0.14	0.52	36.33	12.9	18.3
			(0.53)	(0.19)	(0.24)	(0.35)	(11.77)	(3.2)	(3.0)
Safety/Social Exclusion									
$\overline{\gamma}$				-0.09	0.05	0.00	-18.63		
				(0.11)	(0.09)	(0.21)	(8.02)		
$\gamma_{v,1}$				0.35	0.07	-0.13	-0.16		
				(0.06)	(0.05)	(0.13)	(1.06)		
$\gamma_{v,2}$				-0.03	0.00	0.01	-0.04		
				(0.01)	(0.01)	(0.03)	(0.03)		
$\gamma_{nv,1}$				0.09	0.32	-0.30	0.37		
				(0.05)	(0.05)	(0.11)	(1.24)		
$\gamma_{nv,2}$				-0.02	-0.04	0.03	-0.02		
				(0.01)	(0.01)	(0.02)	(0.03)		
Wage/Age Trends									
σ_W							6.28		
							(0.68)		
κ_1				-1.53	0.26				
				(0.42)	(0.22)				
κ_2				0.04	0.00				
				(0.03)	(0.00)				
κ_3				0.88	2.82				
				(0.34)	(0.30)				
κ_4				-0.12	-0.18				
				(0.02)	(0.01)				

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 100 bootstrap replications.

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

Outcome	Data μ	Type 1 $\mu\|\overline{D}=0$	Type 2 $\mu\|\overline{D}=0$	Type 3 $\mu\|\overline{D}=0$	Type 4 $\mu\|\overline{D}=0$	Type 5 $\mu\|\overline{D}=0$
Type Distribution						
Share $\| \underline{D}=0$ (%)	...	34	21	23	9	13
Share $\| \underline{D}=1$ (%)	...	21	19	22	20	18
Share of Population (%)	...	31	21	23	12	14
Selection						
$Pr(\overline{D}=1)$ (%)	29	15	18	14	61	70
Street Behavior						
Violent						
Age 15 (%)	22	13	10	14	49	29
Age 21 (%)	14	4	3	5	21	12
Non-Violent						
Age 15 (%)	37	28	19	37	77	35
Age 21 (%)	14	4	2	6	27	6
Education						
HS Diploma at Age 23 (%)	67	72	87	63	51	82
Labor Market						
Employed at Age 23 (Hrs/Wk)	29	31	48	4	26	67

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		
	Unconditional		PS Matching	
Outcome and Time of Exposure	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 I (Childhood Exposure) Using the Estimated Dynamic Model

Outcome	Model Prediction	Counterfactual Prediction	Difference
Education			
HS Diploma at Age 23 (%)	71.8	82.3	10.5
	(4.2)	(5.4)	(2.6)
Labor Market			
Employed at Age 23 (μ, Hrs/Wk)	28.6	28.3	–0.3
	(1.9)	(1.8)	(0.7)

Note: Counterfactual I is setting exposure $\underline{D}_i$ to 0 for all i, where exposure is seeing someone shot or shot at. This counterfactual is implemented in the dynamic model by setting the distribution $Pr(\xi_i = \xi_\tau)$ to the estimated distribution $Pr(\xi_i = \xi_\tau | \underline{D} = 0)$ for all i.

Table 7: Counterfactual II (Adolescent Exposure) Using the Estimated Dynamic Model

Outcome	Model Prediction	Counterfactual Prediction	Difference
Education			
HS Diploma at Age 23 (%)	71.8	71.7	0.0
	(4.2)	(5.7)	(6.4)
Labor Market			
Employed at Age 23 (μ, Hrs/Wk)	28.6	32.9	4.3
	(1.9)	(6.3)	(6.7)

Note: Counterfactual II is setting exposure $\overline{D}_i$ to 0 for all i.

Table 8: Counterfactual III (No Street Capital Accumulation) Using the Estimated Dynamic Model

Outcome	Model Prediction	Counterfactual Prediction	Difference
Education			
HS Diploma at Age 23 (%)	71.8	79.7	7.9
	(4.2)	(3.3)	(3.0)
Labor Market			
Employed at Age 23 (μ, Hrs/Wk)	28.6	29.3	0.7
	(1.9)	(2.3)	(1.6)

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