Addressing the Race Gap in Incarceration Rates: An Agent Based Model

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Abstract

Using an agent-based model (ABM) of incarceration, we conduct a series of simulation experiments that speak to the efficacy of policy interventions designed to address racial disparities in incarceration rates. The first experiment eliminates race-based sentencing disparities. We then conduct additional experiments that eliminate race-based disparities in sentencing and disrupt the observed clustering in the social networks of incarcerated individuals. Our findings suggest that simply eliminating race-based sentencing disparities will not result in a substantial closing of the incarceration gap. Instead, our models support previous studies that find the geographic clustering of ex-offenders to be a contributing factor to offender recidivism and racial disparities in incarceration rates. Our model also shows that addressing sentencing biases combined with interventions designed to break the clustering of incarcerated individuals in tight social networks would reduce race-based incarceration gaps. Appropriate policy implications based on these findings are discussed.

KEY WORDS: Agent Based Modeling; Mass Incarceration; Racial Disparities in Incarceration; Recidivism; Sentencing Disparities; Social networks
Addressing the Race Gap in Incarceration Rates: An Agent Based Model

The United States has the highest per capita incarceration rate in the world with more than 2.2 million adults incarcerated (Glaze & Kaeble, 2014). The United States’ reliance on mass incarceration has disproportionately affected minority communities: of the roughly 2.2 million incarcerated adults, a disproportionately large number are people of color (Alexander, 2010; Tonry, 2011; Wacquant, 2011). In 2010, the imprisonment rate for Black Americans was 4.6 times higher than that of Whites (National Research Council, 2014), and as of 2012, approximately 60% of those in American prisons are minorities (Carson & Sabol, 2012).

Although racial disparities in incarceration have long been part of the American criminal justice system and the disparity has declined from its peak in the early 1990s (Carson & Sabol, 2012), academics, policy analysts, and government officials agree that there remains an urgent need to reduce racial inequalities in incarceration (Alexander, 2010; Cloud, Parsons, & Delany-Brumsey, 2014; Raphael & Stoll, 2014; Tonry, 2011). However, addressing the issue effectively requires understanding its causes and developing strategies for testing and comparing policies, the effects of which may not be fully realized for decades to come.

Simulation models offer one promising solution. As Eck and Lieu (2008, p. 101) note “Simulations allow the testing of innovative interventions prior to their being taken into the field.” In the context of criminology and criminal justice research, simulation models have been used to understand burglary (Birks, Townsley, & Stewart, 2012; Johnson, 2008), robbery (Groff, 2007; Groff, 2008; Wang, Liu, & Eck, 2008), victimization risk (Park et al., 2011), cybercrime (Gunderson & Brown, 2000), crime patterns overall (Brantingham & Tita, 2008, Wang et al., 2008), and the efficacy of law enforcement strategies (Groff & Birks, 2008; Dray, Mazerolle, Perez, & Ritter, 2008; Zhang & Brown, 2013). Recently, researchers have used simulation-based
mathematical models common to epidemiology to model mass incarceration as an epidemic (Akers & Lanier, 2009; Drucker, 2011; Lum, Swarup, Eubank, & Hawdon, 2014). These models offer possible explanations for the existence of racial disparities in incarceration rates and provide tools to evaluate the potential outcomes of policy changes.

Using an extension of an epidemiological agent-based model (ABM) of incarceration that has previously been shown to effectively reproduce many important aspects of the incarceration “epidemic” in the United States (Lum et al., 2014), we conduct a series of simulation experiments designed to investigate the likely effects of simple policy interventions that address racial disparities in incarceration rates. The first experiment eliminates differences in sentencing by race to explore whether this policy is sufficient to eliminate racial disparities in incarceration rates. We conduct several more simulation experiments to explore the extent to which clustering in the simulated population’s social network causes the persistence of the racial disparities in rates of incarceration. More broadly, this paper extends the use of simulation modeling in criminology and criminal justice by focusing on incarceration. While much of the work utilizing simulation models in criminology and criminal justice has focused on crime and policing, to our knowledge, only one study has simulated sentencing policies, and this study did not use ABM (see Auerhahn, 2008). Thus, the current study adds to the minimally extant work bridging simulation and criminal justice policy. In the following sections, we begin by briefly discussing the dramatic increase in incarceration witnessed in the U.S. since the late 1970s, specifically focusing on policies that significantly contributed to existing racial disparities in incarceration rates. Next, we summarize recent work that uses ABM to model incarceration (Lum et al., 2014) that serves as the basis of our analysis. We then present results from our simulation experiments,
which show that simply making Black prison sentences equal to White prison sentences will not eliminate racial disparities in incarceration. Next, we present results from additional experiments that suggest an explanation for the persistence of racial disparities despite equalized sentencing. Finally, we conclude with the policy implications of our research.

**Research Background**

The growth in the U.S. incarceration rate over the past four decades is well documented (Alexander, 2010; Beckett & Sasson, 2003; National Research Council, 2014; Tonry, 1999; Tonry, 2011; Wacquant, 2009a). After remaining relatively stable from 1920 until the 1970s, the incarceration rate increased at an alarming rate. With nearly 2.2 million people in American prisons and jails, the U.S. now has the world’s highest incarceration rate that is “5 to 10 times higher than rates in Western Europe and other democracies” (National Research Council, 2014, p. 2). As America’s incarceration rates peaked in 2010 with approximately 2,279,100 adults serving time in jails and prisons or in jail awaiting trial (Glaze & Kaeble, 2014), some began to question the efficacy of using mass incarceration as the dominant criminal justice strategy. A number of politicians and scholars, including former U.S. Attorney General Holder, proposed reducing sentences for non-violent offenders as a means to curb the growing incarceration epidemic (also see Raphael & Stoll, 2014). While fiscal concerns, court orders, and a general change in attitudes toward mass incarceration resulted in decreases in the overall prison population (Glaze & Kaeble, 2014), the sentencing practices that helped fuel the growth in the prison population exacerbated racial disparities in incarceration.

Although there are a number of explanations for the heightened incarceration rates, it is well established theoretically and empirically that these were not a result of increasing crime
rates (Alexander, 2010; Beckett & Sasson, 2003; Hawdon & Woods, 2014; National Research Council, 2014). Instead, the elevated incarceration rate is likely due to a combination of factors, but the rich debate concerning these factors and their relative contribution to the growth in incarceration is beyond the scope and intent of the current paper. We instead discuss two specific sentencing policies that scholars identify as contributing to the rapid increase in the incarceration rate and the rise of racial disparities in incarceration. These policies include mandatory minimum sentencing and Three Strikes laws (National Research Council, 2014).

Mandatory minimum sentences impose a minimum penalty for a particular offense that must be served before the possibility of release. While the eligible offenses and imposed sentences of Three Strikes laws vary by state, most require stiff sentences for repeat offenses. For example, California’s Three Strikes laws double sentences for a person’s second felony conviction and call for a 25-years-to-life sentence for a person’s third felony conviction (Ricciardulli, 2002).

**Sentencing Policies and Racial Disparities**

Racial disparities in incarceration, which peaked in the early 1990s (Carson & Sabol, 2012) are due to a number of factors. Legally relevant factors, such as the gravity of the offense and the perpetrator’s criminal record, have the greatest effect on sentencing decisions; however, the offender’s race also influences sentencing (Brennan & Spohn, 2008; Mitchell, 2005). For example, while race-neutral in theory, substantial evidence suggests the adoption of mandatory minimum sentencing exacerbated racial disparities in sentencing, largely due to differential mandatory sentences for offenses involving crack—for which Black people were more likely to be arrested—versus offenses involving powder cocaine (McDonald & Carlson, 1994). Originally, most mandatory minimum sentencing policies called for each gram of crack to be
equivalent to 100 grams of powder cocaine (100:1) in calculating sentences which was eventually reduced to 18 grams of powder cocaine (18:1) in 2010 (Fair Sentencing Act, 2010). Despite inconsequential differences in rates of use between Whites and Blacks (Hawdon, 2005) or in selling drugs (Tonry, 2011), drug-related arrest rates for Blacks were six times higher than those of Whites during the 1980s (Blumstein & Wallman, 2006). Even more recently, drug-related arrest rates for Blacks remain four times higher than those of Whites (Mitchell & Caudy, 2013; National Research Council, 2014). In addition, Blacks received 10% longer prison sentences than Whites after sentencing guidelines were imposed (Mustard, 2001; Maxfield & Kramer, 1998), and the U.S. Sentencing Commission (1991) found that 46% of White defendants were sentenced below the mandatory minimum, compared to only 32% of Black defendants (also see Meierhoefer, 1992).

Three Strikes laws also contributed to racial disparities in incarceration. Studies in California and Florida indicate that African-Americans receive third-strike sentences more often than do Whites, even when the nature of the offense, the defendant’s prior record, and parole status are controlled (Chen, 2008; Rodriguez, 2003; Sutton, 2013). In addition, prosecutorial bias likely contributes to differing incarceration rates since sentencing disparities between Blacks and Whites are wider in offenses where prosecutors decide whether to charge the crime as a felony or a misdemeanor than in crimes where prosecutors have less discretion (Chen, 2008).

The effect of these policies was most pronounced among minorities living in the nation’s most disadvantaged communities (Alexander, 2010; Western and Petit, 2010; Western & McClanahan, 2000). In many of these communities, incarceration is now a “part of life” and its effect on African Americans has been called “the new Jim Crow” (Alexander, 2010). Realizing
how these sentencing practices contributed to racial disparities in incarceration rates has led a number of states to rethink them. For example, in 2011, the NAACP’s Legal Defense and Education Fund (LDF) launched a ballot campaign for California’s *Three Strikes Reform Act* (Proposition 36). Their motives for doing so were because California’s Three Strikes law “was applied disproportionately against African-Americans” (Stanford Law School & LDF, 2013, p. 4). Other states, including New Jersey and New York, also eliminated mandatory minimum sentencing to help address burgeoning correction costs and racial disparities in incarceration rates (McLeod, 2011).

While it logically follows that revoking the policies that led to high incarceration rates and racial disparities would help address these issues, it is possible that we have passed a tipping point. It is well documented that incarceration produces serious problems for individuals, their families, and their communities (Alexander, 2010; National Research Council, 2014; Western & McClanahan, 2000; Western & Petit, 2010). If incarceration behaves like an infectious disease by creating a criminogenic environment or official bias (Lum et al., 2014), it is possible that existing incarceration patterns would persist even if sentencing disparities were eliminated. That is, existing rates of incarceration can conceivably generate conditions that spread incarceration through society in a manner aptly described by the language and models of epidemiology (Akers & Lanier, 2009; Drucker, 2011; Lum et al., 2014). And, like with a disease, high prevalence rates can persist even if the average disease duration decreases, provided the incidence rate increases proportionately. Given that a person’s incarceration significantly increases the likelihood of his or her associates being incarcerated (Thornberry, 2009; Wakefield & Wildeman, 2011; Wildeman, 2009; Wildeman, 2010), it is possible that the recent incarceration of mass numbers
will create enough new inmates (i.e., a high incidence rate) to offset the effect that reducing the average duration of incarceration (i.e., disease duration) would have on the incarceration rate (i.e., prevalence).

**The Contagion of Incarceration**

Recently, Lum et al. (2014) demonstrated that incarceration could be modeled as contagion. Noting that incarceration behaves much like an epidemic in that the members of an incarcerated person’s social network have a much higher probability of being incarcerated than do those not associated with an incarcerated person, Lum and her colleagues used a susceptible-infected-susceptible (SIS) model to test the hypothesis that observed racial disparities in incarceration rates could be accounted for by differential sentencing between the two groups. Under their model, incarceration was “transmitted” through family and community networks (see Lum et al., 2014 for details). This transmission can happen because, first, the incarceration of a family member causes changes in other family members’ structural location and life chances that increase the probability of the family members becoming incarcerated (Dallaire, 2007a, b; Murray & Farrington, 2005; Western, 2010). Second, the incarceration of a close contact can expose family members to criminal norms and involve them in a criminal subculture, thereby increasing the probability they would themselves commit crimes and be incarcerated (Dallaire, 2007b; Reed & Reed, 1997). Indeed, Sutherland’s (1947) differential association theory is, at its heart, a contagion model since criminal behavior is learned through interaction in intimate social groups. Finally, once a person is incarcerated, *official bias* leads police and courts to focus more on the inmate’s family and friends, thereby increasing the probability they will be arrested,
prosecuted and imprisoned (Besemer, Farrington, & Bijleveld, 2013; Farrington, Jolliffe, Loeber, Stouthamer-Loeber, & Kalb, 2001).

As the authors argue, regardless of the precise mechanisms involved, even controlling for demographic risk factors, the incarceration of one family member undoubtedly increases the likelihood of other family members being incarcerated, which suggests a model of contagion can appropriately represent the spread of incarceration (Lum et al., 2014). Using transmission probabilities based on Dallaire’s (2007b) findings regarding the proportion of inmates whose family members are incarcerated, the model demonstrates that the contagion-like effects of incarceration could produce significant disparities even with the relatively small differences in sentencing (three months, on average, for drug offenses) that are observed empirically. Moreover, the model accurately reproduced other aspects of incarceration, including historical patterns of the growth or incarceration rates by race in the United States as well as well as patterns of recidivism (Lum et al., 2014).

While it seems logical to assert that racial disparities in incarceration would decrease if sentencing disparities were eliminated, this may not be the case. Given existing differences in incarceration rates and the contagion-like behavior of incarceration, the disparities in incarceration rates can potentially persist even if sentencing differences are closed. Determining which of these scenarios is accurate is important if we are to address the incarceration issue effectively, but observing which of these scenarios is most accurate will take decades. Moreover, there are practical concerns about shortening prison sentences, and it has proven extremely difficult to eliminate racial biases from the system. We are therefore unable to test these hypotheses in the real world; however, using Lum’s (2014) model of incarceration contagion, we
can test the probability of these scenarios occurring in a virtual world. In a computational simulation, we can manipulate the sentences of mass numbers of inmates without concern about crime rates, and we can make virtual people truly “color blind.”

The Simulation

We begin by briefly describing the simulation model developed by Lum et al. (2014) that serves as the foundation for this study. This simulation develops an evolving social network model where individuals are born, go through various life stages, acquiring family and friend social network connections, and eventually die. This stylized social network model is necessary to be able to connect three empirical sources of information: (a) administrative (state government) data on incarceration levels in the population, and (b) survey data on the rates at which an incarcerated person’s family members and friends are also incarcerated in state or federal prisons (Dallaire, 2007b), and (c) Bureau of Justice Statistics on racial disparities in sentence lengths.

The simulated social network is initialized with a certain proportion of individuals in the “incarcerated” state. Then, using the probabilities of transmission, the spread of incarceration is simulated. At each step of the simulation, the number of individuals incarcerated can be aggregated to generate a curve of incarceration rates over time, which can be compared with historical incarceration rates. Below, we present the details of the simulation model. Validation of the model can be found in Lum et. al (2014).

Model Details
Our model is based on the susceptible-infected-susceptible (SIS) model—a model that is commonly used in epidemiology to model the transmission of diseases. In this model, agents transition between susceptible (S) states and infected (I) states and back. Suppose that agent $i$ is infected. Under the SIS model, the infected individual is contagious for $s$ consecutive periods. During this period of infectivity, agent $i$ transmits the disease to agent $j$ with probability $p(i,j)$, where the probability of transmission may depend on the individuals, their characteristics, or their relationship. In the agent-based modeling context in which we have a graph of agent interactions and relationships, $p(i,j) = 0$ if agents $i$ and $j$ are not connected in the graph. In disease modeling, an edge often represents physical contact or close spatial proximity. In models of social influence such as the current model, edges represent social relationships between agents. If agent $j$ is infected (by agent $i$ or otherwise), it then enters the infected state as well, potentially infecting its neighbors in the network for $s$ periods. Unlike the models commonly employed in disease modeling, our model also allows for the possibility of spontaneous-infectious. This twist on the SIS model has also been used in Hill et. al. (2010) to model the contagion of emotions through a network. After $s$ periods, agent $i$ returns to a susceptible state, from which it may become re-infected, either from other infected nodes with which it shares an edge or spontaneously.

In order to generate realizations of this epidemic, three main components are required: a synthetic population of individual agents and their social influence network through which the “disease” will be spread; transmission probabilities, $p(i,j)$; and a period of infectivity, $s$.

**Influence Network.** To initialize the population, we begin with 1500 seed agents that will be the predecessors of all of the agents in our simulation. Each seed agent is randomly
assigned a location on the unit square, $[0,1]$. These locations may be thought of as geographic (e.g. home address locations) or a preference space. Regardless, these locations will be used to determine affinity for relationships with other agents--agents prefer nearby individuals for friends and spouses. Finally, at birth agents are assigned a life duration conditional on sex. The distribution of lifespan conditional on sex is taken directly from the Social Security Administration’s 2009 life tables (http://www.ssa.gov/oact/STATS/table4c6.html). Our reliance on modern life tables produces a population with great longevity.

In our simulated population, female agents drive childbirth and the spouse selection processes. As such, female agents are also assigned the age at which they will first give birth. The distribution of age at first birth is based on data from the Center for Disease Control which gives 25.6 years as the mean age at first birth for women in 2011 (http://www.cdc.gov/nchs/data/nvsr/nvsr62/nvsr62_01.pdf). To simulate from a distribution that is consistent with this figure, we draw the age at first birth as 15 plus a Poisson random variable with parameter 10.6. We selected this distribution because its minimum is 15, the lower end of what is reported in the CDC’s data and tends not produce values greater than the low 40’s. Although we acknowledge that childbirth may be possible both before age 15 and after the early 40’s, we believe this distribution reasonably represents the typical range of ages of first childbirth in the United States.

Female agents are also assigned the number of children they will have throughout their lifetime. In order to simulate from an appropriate distribution for the number of children for each woman, we use information on the distribution of number of children per woman and the national fertility rate as obtained from the US Census.
To make our influence network, we need to track all close family and friendship relationships for all the agents in our simulation since incarceration will be transmitted to close friends and family members. When the agent reaches 10 simulated years of age, the agent creates friendship ties. We use data on the number of people with whom respondents share personal conversations from the General Social Survey (http://www3.norc.org/gss+website/). To select the specific friends with whom a friendship edge will be formed, we consider only non-siblings between ages 9 and 11, whose locations are spatially proximate to the agent selecting friends. The age range of potential friends is informed by data from the National Longitudinal Study of Adolescent Health (http://www.cpc.unc.edu/projects/addhealth; data not publicly available).

When female agents reach the age at which their first child is born, they select a male partner. Here, the pool of potential partners is all non-family and non-friend male agents with ages between the female agent’s and nine years older. This figure is loosely based on data from the US Census which indicates that in 80% of marriages, the husband is between one year younger and nine years older than the wife. From the pool of potential mates, she selects the agent that is closest in Euclidean distance to her. Unlike friendship ties, spousal ties are necessarily reciprocated.

At a female agent’s iteration of first childbirth, her first child is initialized. Its sex and lifespan are assigned using the same probability distributions as used to initialize the seed agents. The child agent’s location is set to be half way between the two parents’ locations plus random jitter. Subsequent children are also initialized at this point with gaps between their births drawn from a Poisson distribution with mean parameter 4.5. The value 4.5 was chosen based on a
manual calibration to CDC data that gives the distribution of age at childbirth (any childbirth, not first childbirth).

**Period of Infectivity (Sentence Lengths).** We consider sentences for drug possession in this simulation. According to data from the Bureau of Justice Statistics (2011), the mean sentence for Whites is 14 months with a median of 10 months. For Blacks, the mean sentence was 18 months with a median of 12 months for the same crime. The mean and median do not uniquely specify the distribution—we assume a negative binomial form for the distribution. Through manual tuning, we found that a negative binomial(r,p) distribution with parameters r = 1.2 and b = r/14 or b = r/17 for the White and Black sentence lengths respectively fits the prescribed mean and median remarkably well.

**Transmission Probabilities.** We use the survey presented in Dallaire (2007b) to derive transmission probabilities. In the Survey of Inmates in State Correctional Facilities and the Survey of Inmates in Federal Correctional Facilities, which provide nationally representative data on persons held in State and Federal prisons, inmates were asked to note which of their family members (brothers, sisters, mothers, fathers, and children) were also incarcerated. This data is reported by sex of the inmate. Using this data, we back calculate the corresponding transmission rate by noting that if there is a probability ps of transmission of the entirety of a sentence of length s, the ps(i,j) = 1-(1-p(i,j))s, where p(i,j) is the monthly transmission rate from agent i to agent j. We can then plug in the values given in the survey for p(i,j)s to calculate the monthly transmission rate, p(i,j). We set s=14 for this calculation, the mean sentence length under the White distribution. The data we used from the Dallaire (2007b) survey and the derived
monthly transmission rates are reported in Table 1. In our simulation, friends are treated as siblings in terms of transmission rate.

***Insert Table 1 here***

The main finding of Lum et al. (2014) is that the small disparity in average sentence lengths for Blacks and Whites (for the same offence) can explain the large disparity in overall incarceration rates. This is because the difference in sentence lengths puts the transmission rates for the two populations on opposite sides of a tipping point. This tipping point, known as the epidemic threshold, is the value of the transmission rate at which an epidemic “takes off” and becomes endemic in a population.

Since one of ABM’s strengths is as a policy-evaluation tool (Auerhan, 2008; Eck & Lieu, 2008), we now turn to our simulation experiments to assess how various policies may affect racial disparities in incarceration rates. Using the methodology described above, we simulate 50 different synthetic influence networks. On each synthetic network, we allow the incarceration epidemic to spread and record the number of incarcerated agents at each iteration of the simulation. For each of the experimental conditions, we run this analysis and display the iteration-wise incarcerated population, averaged across all 50 synthetic influence networks.

**Experiment 1: Equalizing Black and White Sentence Lengths**

We do a simulation to investigate the effect of reducing future Black sentences to the same distribution as current (and future) White sentences. In this experiment, the simulation is first run with the Black sentencing regime for thirty simulated years, so that the incarceration level builds up in the population as has been shown by Lum et al. (2014). At the thirty-year
mark, the sentencing regime is switched so that all individuals being sentenced from this point or after receive sentences drawn from the White distribution to model the policy change. Results are shown in Figure 1.

As we see in Figure 1, the Black incarceration levels drop rapidly at first, but, in less than ten years, begin decreasing at a much slower rate. At the time of the change, the peak of the ratio of the simulated Black incarceration rate to the simulated White incarceration rate is 4.5:1. After 10 years, this ratio drops abruptly to roughly 2.9:1. However, after 30 years, this ratio has only decreased to 2.5:1. After 40 simulated years, the ratio finally decreases to 2.4:1. This result demonstrates that even if raced-based sentencing disparities were the only factor behind racial disparities in incarceration, simply eliminating these will not reduce the racial gap in incarceration rates. To explore why this happens, we do additional simulations.4

** Insert Figure 1 Here **

Experiment 2: “Scrambling” the Incarcerated Nodes and Equalizing Sentencing

One possible reason that eliminating race-based sentencing differences does not close the racial gap in incarceration is that incarcerated individuals tend to be highly clustered in the population. To quantify this, we calculate the “average incarceration clustering coefficient” (AICC), which we define as the average number of network neighbors of an incarcerated individual who are also incarcerated. Under the Black sentencing regime, at the time of intervention, the AICC is ~0.29 and under the White sentencing regime, it is ~0.21, as shown in Figure 2.
This difference might produce pockets where individuals keep “re-infecting” each other even after the sentence lengths are reduced. Since Blacks have a far higher rate of incarceration and close associates are likely to be of similar races, the rate of “re-infecting” would be higher among the Black population. Although it is likely impossible to implement this in the real world, we can disrupt this clustering of incarcerated individuals in the simulated world. Doing this provides a test of the hypothesis that the “transmission of incarceration” among dense clusters of incarcerated individuals perpetuates the racial gap in incarceration rates. This hypothesis is tested in the next experiment.

We run the simulation with the Black sentencing regime as before for thirty simulated years. At this point, in addition to switching the sentencing regime to the White distribution, we scramble the set of incarcerated nodes. This means that we make a copy of the remaining sentences of all the incarcerated nodes, mark all nodes “unincarcerated,” and then choose a random set of nodes from the entire network and assign them the sentences we copied in the first step. This process destroys the clustering structure of incarcerated nodes in the network. This is not an experiment that could ever be done in reality, but in a computational simulation, it serves as a test of the hypothesis that the clustering of incarcerated nodes causes the disparity in incarceration levels to persist.

The result of this simulation is shown in Figure 3 (labeled “ES + Scramble”). For comparison, the result of the previous simulation is also shown in this figure. We see from this comparison that the Black incarceration levels still stabilize at a higher level than the White
incarceration levels. There is a significant drop in the Black incarceration levels, but the disparity is not entirely eliminated. This shows that, in our model, it is not the clustering of incarcerated nodes alone that is causing the disparity in incarceration levels to persist after the Black sentencing regime is changed to match the White sentencing regime.

**Insert Figure 3 Here**

**Experiment 3: Reassigning Sentences with the White Sentencing Regime**

Since there would be a large number of individuals still incarcerated with long sentences (assigned under the Black sentencing regime) when the policy change of equalizing sentences occurs, the higher “infectivity” of these individuals could prevent the disparity from disappearing entirely. To test this, we again run the simulation for the first thirty years. At the thirty-year mark, when we change the sentencing regime to be the White sentencing regime, we also assign every incarcerated node a new sentence chosen from the White sentencing regime. If the node has already served more time than its newly assigned sentence, the individual is released. Otherwise, the simulated individual serves the remainder of its newly assigned sentence. We then run the simulation for fifty more simulated years. Again, this is not an experiment that could ever be carried out in reality, but in a computational simulation, it serves as a test of the hypothesis that the remaining extended sentences after the policy change cause the disparity in incarceration levels to persist at a reduced rate.

The result of this simulation is also shown in Figure 3 (labeled “ES + Early Release (ER)”). This time we see that the Black incarceration curve drops more than the ES + Scramble case, but still not to the level of the White incarceration curve. This suggests that the longer sentences of the currently incarcerated population at the time of the intervention contributes
more to the persistence of the disparity after sentencing is equalized than clustering does, but also does not entirely account for the disparity by itself.

**Experiment 4: “Scrambling” and Reassigning Sentences**

Finally, we combine the two tests so that when sentencing is equalized, we also scramble the set of incarcerated nodes and reassign sentences among the agents using the White sentencing regime. This time, we see that, within approximately ten simulated years, the incarceration levels for Blacks and Whites are indistinguishable (Fig. 3, “ES + ER + Scramble”). Note that when we reassign sentences to the incarcerated nodes according to the White sentencing regime, some nodes might have already served a longer sentence. For example, an individual who has served five months of a six-month sentence might receive a new sentence of only four months. This individual would be immediately released at the time of the intervention. With this combination of interventions, we see that the disparities in incarceration levels disappear over time.

*It is important to stress that we are not suggesting either scrambling of incarcerated nodes or reassignment of sentences as an actual policy to be implemented.* These are hypothetical computational experiments that serve to elucidate the causal mechanisms behind the persistence of racial disparities in incarceration (albeit at a reduced level) that show up in our simulation model after eliminating the disparity in future sentence lengths. We note that the model operated as expected during these experiments, and we are therefore confident that it has uncovered important mechanisms in the process that result in persistent racial disparities in incarceration. This highlights an additional advantage of ABM; while ABM is often used to test theory (Birks et al., 2012; Johnson & Groff, 2014; Liu, Wang, Leck, Liang, 2005), ABM results
can also suggest new investigations and theoretical explorations (Eck & Liu, 2008; Epstein, 2008). While we are not suggesting specific incarceration policies, our model does suggest strategies to be explored. We discuss these strategies below.

Discussion

The U.S. witnessed an unprecedented increase in incarceration rates between 1980 and 2010, and the country now has the highest incarceration rates in the world. Much of this growth in incarceration rates can be traced to policies that were enacted in the 1980s. Foremost among these were the widespread adoption of mandatory minimum sentencing and Three Strikes laws. While these policies led to mass incarceration in general, the effect of these policies was most pronounced among disadvantaged minorities.

Fiscal and constitutional concerns are forcing a number of states to address the mass incarceration issue, and the glaring discrepancies in incarceration rates between White and Black Americans have activists, scholars, and politicians calling for the repeal of the policies that significantly contributed to those discrepancies. However, it is difficult to predict the effect such policy changes will have on the overall prison population. Given that any changes in the criminal justice system are likely to take years to be implemented and produce noticeable changes, it would be beneficial if we had a model that could be used to forecast the effect of policy changes. We, like others (Auerhahn, 2008), argue that an agent-based model of incarceration can serve this purpose, and we use an existing agent-based model of incarceration to simulate the likely outcome of eliminating race-based sentencing disparities on incarceration rates.

The results of our simulation experiments are both discouraging and encouraging. While principles of social justice demand the elimination of race-based sentencing differences that exist
after legally relevant factors are considered, doing so would likely be insufficient to reduce racial disparities in incarceration rates. The ABM used here indicates that simply eliminating sentencing differences results in an initial decrease in the racial incarceration gap; however, the gap will persist for decades, leveling at a ratio of approximately 3-to-1. Thus, we directly test if equalizing Black and White sentences would reduce racial disparities in incarceration, and our results reveal that doing so would not eliminate those disparities.

Expanding the ABM’s directly focus on the social network of offenders, we demonstrate that the persistence of racial disparities in incarceration is due to a combination of the clustering of incarcerated individuals and the presence of incarcerated individuals within the system who are still serving relatively long sentences. When we test this hypothesis by eliminating these two factors, the model indicates that racial disparities in incarceration would drop dramatically and virtually disappear. Therefore, addressing racial biases in sentencing is not enough; this is discouraging. However, our model also shows that addressing sentencing biases combined with interventions designed to break the clustering of incarcerated individuals in tight social networks would reduce race-based incarceration gaps.

As others have found and our simulation confirms, clustering of ex-offenders exacerbates existing patterns of incarceration. One possible way to weaken the influence of clustering would be to address the geographic concentration of incarceration. In a manner similar to how incarceration is clustered in our simulation, incarceration is geographically clustered in reality, and evidence suggests that where ex-offenders live influences their likelihood of recidivating (Kirk, 2015; La Vigne, Kachnowski, Travis, Naser, & Visher, 2003; Sampson, 2012; Sampson & Loeffler, 2010). For example, prisoners relocated from their former neighborhood after hurricane
Katrina had lower recidivism rates than parolees who returned to their former neighborhoods (Kirk, 2009; Kirk, 2015). Similarly, spatial contagion strongly influences the likelihood of recidivism among youth (Mennis & Harris, 2011) and adult (Stahler et al., 2013) ex-offenders. Thus, recidivism is also spatially clustered within regions of a city, and this clustering helps generate high re-incarceration rates (Kirk, 2015).

Since criminals embedded in networks with other criminals commit more crimes than do those in social networks comprised predominantly of non-criminals (Andrews, Bonta, & Wormith, 2011; Papachristos, Meares, & Fagan, 2012; Visher & Travis, 2003), it follows that ex-prisoners are more likely to recidivate and be re-incarcerated if they live near other recidivists. It also follows they are more likely to recidivate if they return to their old networks of criminal associates (Huebner & Berg, 2011; Yahner & Visher, 2008). In addition, the geographic clustering of previously incarcerated individuals can create “coercive mobility” that destabilizes neighborhoods, depletes social capital, and leads to more crime (Clear, 2007; Clear, Rose, & Ryder, 2001; Lynch & Sabol, 2001; Sampson & Loeffler, 2010). Given this body of research, prisoner reentry programs may want to relocate ex-offenders to neighborhoods far from the neighborhood in which they lived prior to their arrest. Of course, this is much harder to accomplish than it may sound.

First, authorities cannot control residency once ex-offenders complete their parole. Next, many ex-offenders cannot relocate as many are dependent on their friends’ and family’s tangible and emotional support, especially shortly after their release from prison (Huebner & Berg, 2011; Visher & Travis, 2003). Moreover, reintegration models are based on ex-offenders participating in civic life and reconstructing prosocial ties to their communities (Bazemore & Stinchcomb,
2004; Ward & Langlands, 2009); however, making these social connections (or re-connections) requires a willingness on the community to do so, and most residents are not overly supportive of prisoner reintegration programs (Hardecastle, Bartholomew, & Graffam, 2011).

Another problem with implementing a strategy that breaks the geographic clustering of ex-offenders would be the potential consequences this would have on probation and parole supervision. While evidence suggests that closely monitoring parolees can be effective at preventing crime (Kleiman, 2009), this positive effect on recidivism requires maintaining high levels of certainty of punishment. That is, programs that closely monitor parolees and provide certain detection and punishment for misbehavior prevent re-offending (see Durlauf & Nagin (2011) for review of evidence and a theoretical discussion of this issue). While such findings are encouraging, implementing policies that break geographic cluster would make implementing successful supervision difficult. Simply put, geographic clustering makes monitoring ex-offenders easier and breaking this clustering could potentially overburden the agencies that provide community supervision. In essence, a policy that calls for shortening prison sentences would transfer a supervisory role from prisons to probation and parole. While such a policy would have positive effects if imprisonment is indeed criminogenic, releasing large numbers of prisons and implementing a policy that simultaneously breaks the geographic cluster of these offenders could result in heightened levels of crime if such policies overwhelm the community’s ability to monitor the ex-offenders. Therefore, implanting such a policy will demand inter-agency cooperation because a successful monitoring system will require a coordinated effort by police, parole and probation officers, the courts, and the community at large.
Overcoming these obstacles would undoubtedly be challenging, but our model suggests efforts to do so would be effective. Breaking the geographic clustering of incarceration would not only reduce recidivism and overall crime rates, but it also could provide a necessary piece for addressing racial disparities in incarceration. While consideration of how to achieve this goal is beyond the scope of this work, it seems logical to suggest that authorities examine community willingness and readiness for offender reintegration and supervision programs prior to implementing them. Higher levels of community readiness would likely translate into greater access to resources and social networks, and access to these provide buffers to reincarceration and clearly improve re-entry outcomes (Kubrin & Stewart, 2006). It also seems logical to suggest that release programs concentrate efforts in geographic areas where spatial contagion of reincarceration is likely. Alternatively, programs could provide employment services and housing opportunities that open the opportunities of those returning from prison to relocate (Kirk, 2015). It would of course be necessary to test the efficacy of these alternative strategies, and we demonstrate here that agent based modeling can be used to test the likely outcomes of a broad range of programs dealing with incarceration.

Limitations

While we believe our model provides important information that can inform policy, we recognize several limitations to our research. Primarily, our experiments are conducted on synthetic people. While the model of incarceration upon which our experiments are based have been validated, the model is, nevertheless, a model. As with any model, our results are dependent on its underlying assumptions. If these assumptions are incorrect, the results of our
experiments are dubious. Moreover, as with any model, we rely on over simplification. We cannot model everything that gives rise to incarceration and the racial disparities observed in the American penal system. We therefore have bracketed many potential complicating factors. The advantages and disadvantages of simulation models for criminology and criminal justice research are discussed in detail by others (Birks et al., 2012; Brantingham & Brantingham, 2004; Eck & Liu, 2008; Groff & Mazerolle, 2008; Groff, 2015; Johnson & Groff, 2014; Townsley & Birks, 2008), and we urge readers to consider the limitations such modeling has when interpreting our findings. Yet, while we recognize the limitations of our research, we do believe it provides a valuable piece of evidence that can help guide policy because it is based on sound theory and empirical observations. Nevertheless, we agree with Durlauf and Nagin (2011, p. 45) when they state, “policy recommendations should be based on cumulative evidence from statistically and scientifically sound research.”

Conclusion

Mass incarceration has recently attracted considerable attention and numerous calls for system-wide reform. Doing so, however, can potentially affect the low crime rates Americans have enjoyed for nearly two-decades. We propose that using agent based models of incarceration can guide these efforts without creating potentially dangerous situations or depleting state’s already strained fiscal reserves. Our models demonstrate that simply eliminating existing racial disparities in sentencing will not close the racial gap in incarceration rates without also disrupting the clustering of offenders that fuels the transmission and re-transmission of incarceration. From these models and a wealth of more traditional forms of criminological
research, we argue that the geographical clustering of ex-offenders is a contributing factor to both offender recidivism and racial disparities in incarceration.

We base this argument on using experiments conducted on a synthetic population that we could not practically conduct in the real world because doing so would require behaviors to be observed for decades or longer. It would be impractical (if not impossible) to implement our experiment in the real world for other reasons too. First, it would be impossible to totally break the effect of offender clustering like we did in our experiment. While programs could be designed to address the geographic clustering of offenders, these would only weaken its effects at best. Offenders and ex-offenders are socially connected to their families and peers, regardless of where they live. While relocating them could reduce their influence, it would probably not eliminate it (and it would undoubtedly create its own problems). In addition, it is highly unlikely that we will ever eliminate racial differences in sentencing because not all of these differences are due to racial bias. Thus, while our experiment can generate valuable insights for the real world, it can only be conducted in a synthetic one.

Our hope is that we further demonstrated the utility of ABM for criminology and social science in general. As noted, ABM not only provides a means for critical tests of theory, it also provides a mechanism for testing the likely outcomes of social policies. Our research suggests that policies designed to reduce the social and geographic clustering of offenders could reduce both initial offending and re-offending. Such policies will have to be designed, implemented, and tested. ABM can provide initial tests cheaply and effectively.
**Endnotes**

1. Some of the explanations for the increase in incarceration rates include the rise of the garrison state (Fitch, 1985), the use of crime as a wedge issue (Beckett, 1999; Beckett & Sasson, 2003), the rise of the independent public prosecutor system and bureaucratic actors interested in expanding the criminal justice system (Gottschalk, 2006), neo-liberal policies (Beckett & Sasson, 2000; Wacquant 2009a, b, 2010, 2011), cyclical trends in criminality and responses to these trends (Musto, 1987), fractionated politics and the broad public appeal of penal crime policies (Caplow & Simon, 1999), and the use of the criminal justice system as a system of racial control (Alexander, 2010). Readers interested in various perspectives should see Michael Tonry’s (1999) discussion of five (empirical, psephological, journalistic, political, and historical) reasons why U.S. incarceration rates are so high.

2. Scholars recognize that truth-in-sentencing practices and life without parole sentencing significantly increased sentence lengths; however, these are not widely considered as the primary causes of racial disparities in incarceration. Truth-in-sentencing increased incarceration by minimizing or eliminating the possibility of prisoners being released before serving their entire sentence (Ditton & Wilson, 1999; Sabol, Rosich, Mallik-Kane, Kirk, & Dubin, 2002; Turner, Fain, Greenwood, Chen, & Chiesa, 2001). Life without parole denies prisoners serving life sentences the possibility of early release (National Research Council, 2014).
References


Eck, J. E., & Liu, L. (2008). Contrasting simulated and empirical experiments in crime


Table 1 Derived transmission rates and original survey data from Dallaire (2007b)

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<th>Relationship to inmate</th>
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Figures

Figure 1 Epidemic curves under equal sentencing
Figure 2 Incarceration clustering coefficients over time by intervention
Figure 3 Epidemic curves under all interventions