Abstract

Racial profiling—the use of race, ethnicity, or national origin by law enforcement officials to make judgments of criminal suspicion—is assessed in terms of its effect on targeted populations and on law enforcement efficiency. A mathematical simulation, comparing multiple profiling and non-profiling scenarios, is employed. This analysis indicates that racial profiling exacerbates incarceration disparities between groups whether or not the groups differ in criminality rates, and that the long-term effects of profiling in terms of criminal captures depend on the calibration of profiling rates to criminality rates. The highest long-term criminal capture rates appear to occur when stop rate ratios match, or are slightly below, criminality rate ratios between groups. When the possibility of a deterrent effect is modeled, profiling appears to yield fewer criminal captures and have little or no crime reduction effect, and may even increase overall crime rates. © 2006 by the Association for Public Policy Analysis and Management

INTRODUCTION

Racial disparities in the U.S. criminal justice system are pronounced (Council of Economic Advisors, 1999). The U.S. Department of Justice has projected that 28.5 percent of Black men will be incarcerated in their lifetimes, compared to 4.4 percent of White men (Bureau of Justice Statistics, 1997). These disparities, in and of themselves, do not necessarily indicate that racial prejudice is operating. It is possible that racial disparities in criminal justice represent real behavioral differences across groups, differences that may also interact with laws, regulations, and sentencing guidelines (e.g., for crack versus powder cocaine) which could introduce institutional bias. However, a large corpus of experimental research indicates that judicial decision makers are more likely to find guilty and give harsher sentences to minority defendants, all else being equal (e.g., see Sommers & Ellsworth, 2001; Sweeney & Haney, 1992).

Nevertheless, the extent to which racial bias is responsible for disparities in criminal justice remains an empirical question. The aim of the present analysis is to focus on a single but potentially influential stage of the criminal justice process, police stops, and a specific strategy, racial profiling, to investigate its implications for racial disparities.
The Efficacy and Effect of Racial Profiling

The rationale behind racial profiling involves the intuitively appealing presumption that targeting groups who have a higher criminality rate improves police efficiency and thereby increases public safety. An empirical evaluation of racial profiling, therefore, should also consider the extent to which it increases rates of criminal incapacitation. The purpose of the present analysis is to look at both the efficacy of racial profiling in terms of criminal incapacitation, as well as the effect it has on racial disparities in criminal justice, in order to inform the ongoing debate over this practice, which entails a tradeoff between public safety and civil liberties.

Racial Profiling

Racial profiling is the police practice of focusing on members of particular race (or ethnic or national origin) groups for extra surveillance. The most common example of racial profiling is traffic stops of young, Black men, and it appears to be most commonly employed as a drug-trafficking interdiction strategy. It is most often an implicit policy, but in some agencies, until recently, it has been prescribed protocol (see Harris, 2002, for a thorough historical review).

The inclination by police to use race as a factor in determining probable cause may explain why fully 42 percent of African Americans (compared to 6 percent of European Americans), in a national Gallup poll reported having been stopped by police on the basis of skin color (Newport, 1999). The list of prominent minority men, including celebrities, politicians, and academics, who report having been profiled is long (e.g., see Harris, 1999; Russell, 1998).

More systematic evidence is available in studies of police data. For example, a San Diego Police Department internal survey indicated that Black and Latino drivers were more likely to be stopped and searched than were White drivers (SDPD, 2001). A particularly compelling revelation comes from internal documents of the California Highway Patrol. In the period studied, Latino and Black drivers in California’s Central Coast and Central Valley were three and two times, respectively, more likely to be stopped by the CHP than were White motorists (Zamora, 2001). In neither case is it self-evident that such disparities are due to bias on the part of police. However, in the CHP case, racial disparities were most pronounced with regard to “consent searches.” These are searches wherein, because there is no evident probable cause (e.g., no visible evidence of wrongdoing), police must ask the driver to submit to a search voluntarily. Because by definition consent searches preclude probable cause, racial disparities are very likely to reflect racial bias. This analysis was sufficiently convincing to compel the CHP to end all searches during minor traffic stops (Broder, 2003).

The body of evidence from across the United States (see Harris, 2002, for a thorough review) appears to indicate that, despite official condemnations and disavowals, racial profiling is a real and perhaps pervasive phenomenon. Because there are a large number of drug-related arrests (approximately 1.6 million annually in the United States), a substantial proportion (about 12 percent) of which lead to prison sentences, with an average of two years (Western, in press, Table 2.3), racial profiling may have a substantial effect on society.

OVERVIEW

This paper considers the barriers to assessing the impacts of racial profiling on targeted populations and crime mitigation, primarily the absence of accurate data on drug crime rates and profiling rates. It then proceeds to describe a mathematical
The Efficacy and Effect of Racial Profiling

A simulation approach intended to circumvent those problems by projecting the outcomes of multiple scenarios under which profiling could be implemented to varying degrees, considering varying disproportions of criminality between race groups. The analysis involves projecting the effect on criminal capture rates over time, then compares long-term capture rates across multiple scenarios. Finally, the possibility of profiling having a deterrent effect is integrated into the model. Limitations of the model are considered, including the exclusion of the possibility of police continually adjusting profiles to optimize results. Implications are discussed with regard to the efficacy and effects of racial profiling.

Barriers to Studying Racial Profiling

Testing the effects of racial profiling is a challenging task because valid relevant data are difficult to obtain. In fact, the General Accounting Office attempted to study the prevalence and impact of racial profiling, only to conclude that the data to make such judgments are not available (United States General Accounting Office, 2000) and the Legislative Analyst Office (LAO) of the State of California more recently drew a similar conclusion (LAO, 2002).

Data that would be useful in studying racial profiling would include, first and foremost, the races of people who are stopped, but not cited or arrested by the police. Such data, however, is generally unavailable because law enforcement agencies resist collecting it, usually arguing that it would impose a crippling administrative burden. Furthermore, when law enforcement agencies do collect race-stop data, the reporting by agents may be inconsistent. For example, a study of the San Francisco Police Department found that police were giving citations to a greater number of motorists than the number of stops they were reporting (Schlosberg, 2002). When agencies analyze data internally, it has been observed that they often go to lengths, without adequate statistical basis, to explain away racial disparities in stops (LAO, 2002).

Even where policies have been adopted mandating data collection and external analysis, one powerful irony of racial profiling can render such data of limited value. The act of profiling itself serves to skew resulting statistics. Specifically, if profiling is employed, wherein Blacks, for example, are disproportionately stopped by police at least in part because of their skin color, the threshold for suspicious behavior will necessarily be lower for police to stop Blacks than to stop Whites. Consequently, Whites who are stopped will have typically behaved most suspiciously. They may, in turn, be more likely to have committed a crime (e.g., possess narcotics or a concealed weapon) and, therefore, be arrested. As a result, the relative ratios of stops to arrests for Blacks and Whites will be skewed to favor (i.e., make appear less criminal) Blacks, in contradiction to the prevailing stereotype. This scenario is likely what explains the findings of the Office of the Attorney General (OAG) of the State of New York (1999) in its investigation of New York City's Stop and Frisk program, and the ACLU's analysis of San Francisco Police Department data (Schlosberg, 2002).

We are left with an empirical catch-22. To determine the impact of racial profiling, we must first identify when and where it is occurring. But to find out if racial profiling is being carried out, we must determine not only whether or not a greater proportion of one group is being stopped by the police than are others, but also whether...

1 There are encouraging exceptions, including Minnesota, Missouri, Florida, and Boston.
2 See Ayres (2002) for a similar discussion with regard to “outcome tests” of discrimination.
or not this is the case because of group membership and not greater criminality. However, as the New York City and San Francisco data suggest, if profiling is occurring, it will confound our determination of the real relative criminality rates.

With considerable effort, some analysts have obtained valid estimates of profiling. Specifically, Lamberth (1994), in his capacity as an expert witness in legal actions relating to racial profiling, has surveyed the racial/ethnic makeup of the drivers and passengers in specific areas and transit corridors (e.g., the New Jersey Turnpike), and the rates at which members of different race and ethnic groups are stopped, searched, detained, and arrested; but importantly, also the rates of traffic violations as a function of race and ethnicity in those studied areas. This approach is essential to determining the extent to which racial profiling is occurring because traffic violations are the pretexts under which race-based vehicle stops are made. Without this latter data, known as “benchmarks” (Lamberth, 2000), one cannot make a determination about the extent to which racial profiling is occurring. Lamberth has used benchmark data to demonstrate that police stop-rates for minorities were disproportionate to their rates of traffic violations, to the satisfaction of a New Jersey State Superior Court [State v. Pedro Soto, 734 A. 2d 350 (N.J. Super. Ct. Law. Div. 1996), as cited in Harris, 2002]. Such procedures, however, are exceedingly labor intensive. Further, they have been critiqued for failing to distinguish between types of violations, and even if they could, it is unclear which types of violations are most likely to provoke traffic stops (Ahmed & Rezmovic, 2001).

Another potential source of data on race and criminality is the National Crime Victimization Survey (NCVS), a large, national survey of approximately 100,000 people that includes the race of criminal offenders for violent crimes, as reported by victims in the sample. It indicates that Blacks are over-represented as reported offenders—for example, 22.5 percent for violent crimes in 1998 (Bureau of Justice Statistics, 1999). However, the NCVS is not helpful with regard to racial profiling because profiling is most commonly employed in the prosecution of “victimless” crimes, especially drug crimes.

Recently, economists have attempted to, in the absence of data about criminal prevalence, determine whether or not profiling has occurred in specific jurisdictions (see Antonovics & Knight, 2004; Anwar & Fang, 2004; Bjerk, 2004; Borooah, 2001; Dharmapala & Ross, 2004; Dominitz, 2003; Hernández-Murillo & Knowles, 2004; Knowles, Persico, & Todd, 2001; Persico, 2002; see Harcourt, 2004, for a critical review). Specifically, most of these studies, starting with Knowles et al. (2001), have applied economic general equilibrium models to differentiate between racial/ethnic disparities in police searches arising from prejudice (bias or animus) as opposed to “statistical discrimination” (real base-rate differences in criminality) (Becker, 1957). According to these models, assuming that criminals and police are aware of, and sensitive to, each other's aggregate behavior (specifically, crime rates and targeting rates), to the extent that search rates of different groups yield comparable hit rates (findings of contraband and/or arrest), there is no evidence of bigotry. If minorities are stopped and searched at higher rates than Whites, as long as their hit rates are not discrepant, this reflects only “statistical discrimination” and it is rational from a police efficiency maximizing perspective, many of these models hold. Such approaches promise to have substantial value in developing methods for evaluating law enforcement units with regard to racial bias, but at this stage, there is still considerable disagreement about which equilibrium assumptions are appropriate, resulting in conflicting results and interpretations (see Dharmapala & Ross, 2004; Knowles et al., 2001).
The general equilibrium models are also unable to distinguish between prejudice (bigotry, racial animus) motivating disparate stop and search rates and inaccurate stereotypes having that effect. Specifically, if police are searching higher proportions of minorities with lower hit rates, it could be due to holding a stereotype that minorities are more likely to carry contraband that is correct in terms of direction but not magnitude—such a stereotype need not be motivated by racial animus. Furthermore, citing evidence that police reports of traffic stops can be incomplete and inaccurate (Cordner, Williams, & Velasco, 2002), Lundman (2004) has argued that the use of police report data may be inadequate for a clear assessment of racial profiling.

**SIMULATING RACIAL PROFILING**

In the absence of unconfounded information about race and drug crime rates or race and police stops, we can adopt another approach to study the effects of racial profiling on criminal captures—a mathematical simulation.

The present model is designed to project the effects of racial profiling, assuming it is (or, in some scenarios, is not) happening. The economic equilibrium models described above bear similarities to this, but the present study differs from these approaches in its goals and methods. First, it does not aim to determine whether or not racial profiling has occurred in a given place or time, or whether it resulted from statistical discrimination versus bigotry, but rather what the effect of profiling of varying degrees might be. Second, recognizing the limitations of available data with regard to criminality rates and profiling rates, this study circumvents such limitations by engaging in hypothetical modeling or simulation, explicitly acknowledging that the results are not intended to describe any real locale or population. Finally, the present model does not attempt to project the effect of profiling on crime rates, at least not directly. Rather, it focuses on incarceration rates, recognizing that incarceration rates have indirect effects on crime rates through incapacitation and deterrence.

The following model enables one to vary the presumed criminality rates of hypothetical populations and then determine their incarceration rates as a function of the differential rates at which they are stopped by police. In this manner, we can simulate the short- and long-term effects of racial profiling.

Racial profiling adds a probabilistic component to policing; based on presumed prior probabilities of criminality as a function of group membership, police target different groups differentially. Accordingly, this model aims to assess the contribution of that probabilistic component, but does not address the other variables (e.g., suspect behavior) that also influence police decisions. One of the strengths of this approach is its parsimony, a first-order criterion for mathematical modeling. The model employs as few assumptions and variables as necessary. Because of its hypothetical nature, it allows for a comparative analysis, specifically a sensitivity analysis, comparing the impact of racial profiling under multiple scenarios holding basic parameters constant.

3 Decades of psychological research has shown that there are many mechanisms by which perceptions of groups can become distorted, regardless of the quality of information (see Hamilton & Gifford, 1976; Mackie, Hamilton, Susskind, & Rosselli, 1996). Furthermore, stereotypes have been shown to be resistant to change, even in the presence of contradictory evidence (see Kunda & Oleson, 1995; Rothbart & John, 1985; Weber & Crocker, 1983), and indeed to bolster themselves through confirmatory biases (Nickerson, 1998) and self-fulfilling prophecies (Jussim & Fleming, 1996).
Assumptions of the Model

In order to run a computational simulation of the effects of racial profiling, several assumptions have to be made about the hypothetical populations. First, we must assume that the actual percentage of each group that is inclined to commit crimes is stable across time—that as old criminals die off or are reformed, new ones are born and develop to replace them. It is likely that in the real world such things fluctuate over time, but it is beyond the scope of, and not necessary for, this analysis to include such trends. A related assumption holds that at any given point in time, there will be a finite number of criminals, so that for every criminal taken off the street, there will not be an unlimited supply ready to take his or her place. Again, this is not necessarily the case in real demographics; for example, drug dealing may operate in a zero-sum market and so as one drug dealer or courier is removed from the streets, someone who might otherwise not have gotten involved in crime may be swayed by the opportunity. However, there must be limits to the extent to which this would occur, and we will assume that such a phenomenon would not differ as a function of group membership (e.g., race).

This model is designed to determine the effects of racial profiling, so the incarceration rates it predicts will be due only to profiling, where race is used as a basis for suspicion. Convictions and incarcerations that may result from crime reports, where the perpetrator is recognized and identified, for instance, are a separate matter. The model is based on probabilities, as is the practice of racial profiling. Therefore, the model assumes that, given the proportion of members of a group that are actually criminals, and are not already incarcerated, that same proportion of the number of people of that group who are stopped by the police will, by virtue of their culpability and having now been apprehended, be convicted and incarcerated. Needless to say, this is an oversimplification of the real process, where criminals are not stopped at random, and real criminals are often let go by the police, not prosecuted, given probation, or acquitted by courts. However, as noted above, the model is intended to make probabilistic estimates about the contribution racial profiling makes to criminal justice, and this assumption allows that. As a consequence of this assumption, the current model can test the degree to which racial profiling discriminates and is effective even if we assume (however tenuously) that members of all groups are getting a fair shake in the criminal justice system at every stage, except being stopped by the police.

Finally, the model does not assume that groups differ or are the same in their actual rates of criminality. In fact, criminality is an important variable in the model. We want to know what happens as a result of profiling when members of different groups are and are not equally likely to commit crimes, and with this model, we can test multiple scenarios to make this determination. This capacity reflects one of the major advantages of a simulation analysis of this sort. “Criminality rate” is a latent variable that is essentially unknowable at any given time, particularly given the likelihood of biases in criminal justice statistics, as well as limitations of crime report and victimization survey data. Nevertheless, it is a crucial factor in understanding the efficacy and impact of racial profiling.

4 For example, if 10 percent of the non-incarcerated members of a group are criminals (e.g., engage regularly in drug trafficking or possession), and 100 members of that group are randomly stopped by the police, the model will hold that 10 of those 100 will be arrested, convicted, and incarcerated.
Executing the Model

The effect of racial profiling on incarceration rates can be expressed mathematically with the following formula:

\[ I_t = I_{t-1} + \sigma(C - I_{t-1}) - \rho I_{t-1} \]

where, for a given group, \( I \) represents the proportion of people in a given group (e.g., race) who are incarcerated, \( C \) is the proportion of that group who are criminals (and, the model assumes, will be discovered as such if stopped), \( \sigma \) is the rate at which that group is stopped by the police (this determines the profiling rate), \( \rho \) is the re-entry rate of incarcerated criminals (i.e., the percent of incarcerated criminals that leave prison and are replaced in the general population in each cycle, either by returning to the population or by dying and being replaced\(^5\)), and \( t \) is a period of time during which a full cycle of stopping (\( \sigma \)) occurs. The re-entry rate (\( \rho \)) is set somewhat arbitrarily. If it is below the overall incarceration rate, incarcerated populations will tend to grow, as has been the case in the United States in recent decades. This variable enables the incarcerated population to change independent of the overall population,\(^7\) thereby allowing for a test of the effectiveness of profiling with regard to criminal incapacitation. The re-entry rate (\( \rho \)) is set at 5 percent for the scenarios reported below and the other variables in the model are manipulated around it to allow for comparisons.

In the equation, \( I_{t-1} \) (the percent of the group who are incarcerated in the previous epoch) is subtracted from \( C \) (the percent of the total group who are criminals) and the result is multiplied by \( \sigma \) (the stopping, or profiling, rate). This is done to take into account that the percent of the at-large (non-incarcerated) population that is criminal is smaller than the percent of the total (at-large plus incarcerated) population of that group that is criminal.\(^8\)

In order to test the effect of profiling over time, we run multiple iterations of the equation, building on the updated parameters from each previous iteration. We, therefore, test for the effects of profiling at time \( t+1, t+2, \text{ etc.} \)

It should be noted that the results presented below reflect simulations wherein the absolute number of each group stopped in each iteration is fixed—a percentage of the total group population (e.g., if there are 20,000 people in group A and the stop rate for that group is 5 percent, then 4,000 are stopped in each epoch). This enables the total number stopped per epoch to remain constant, again accommodating a test of police efficiency. However, it may seem problematic because this means that a larger proportion of the group will be stopped with each iteration (if the group is

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\(^5\) \( C \), the proportion of the total group that is criminal, is a constant (as noted previously in the assumptions), but the proportion of the group at-large that is criminal \( (C-I_{t-1}) \) varies, as a function of \( I_{t-1} \).

\(^6\) With regard to re-entered criminals, the model makes the somewhat cynical assumption that these re-entered criminals are still ‘criminals’ and will be apprehended if stopped. This enables us to keep the criminality rate constant for each group.

\(^7\) An alternative would be to allow the prison population to grow unchecked, which would yield a very misleading representation, one in which the rate of incarceration could exceed 100 percent. Alternatively, we could set the re-entry rate equal to the total new conviction rate for each period, thereby holding prison population constant, but allowing disparities between groups to emerge. This, too, would be misleading, especially because one purpose of this investigation is to determine the efficacy of racial profiling for criminal incapacitation/crime reduction.

\(^8\) For example, if 10 percent of the total population of some group are criminals, but 4 percent of the group (all of whom are criminals) are incarcerated, then only 6.25 percent of the remaining, non-incarcerated group are criminals. Consequently, when members of that group are stopped during the next epoch, only 6.25 percent of those stopped will be sent to prison, according to the present model.
profiled—a smaller proportion would be stopped for a group that is undersampled) and police would have to look longer and harder for members of that group to stop as their absolute non-incarcerated numbers declined but the number they stopped remained constant. This poses a reasonable point of concern. Accordingly, we can run corresponding scenarios wherein the absolute number stopped per group per iteration is a fixed percentage of the number of non-incarcerated members of that group.\(^9\) Results using this adaptation of the model are virtually identical to those reported below.

Each simulated scenario described below compares the incarceration rates of two groups (A and B) over time. Group A is the minority group, comprising 20 percent of the total population, and Group B comprises the remaining 80 percent. Their proportions of the total population are important because, as will become clear, the overall incarceration rate tends to follow that of the majority group more closely, for the simple reason that the larger group contributes more weight to the total percentage.

**Scenario 1: Equal Criminality, Equal Stopping.** In the first scenario, included to establish a baseline for comparisons, the two groups have equal “true criminality” rates (10 percent). This means that 10 percent of group A and 10 percent of group B (and, therefore, 10 percent of the total population) are inclined to commit crimes and will be caught doing so if stopped by the police. This scenario also presumes that both groups start with the same incarceration rate, 5%, reflecting an assumption that there has been no prior group-based disparate treatment.

Profiling involves the differential treatment of members of the two groups, based on their group membership. Consequently, the variable of greatest interest is the stop rate. If the police were profiling, \(\sigma\) would differ for the two groups. For this first, baseline scenario, \(\sigma\) is 5 percent and does not differ for the two groups, because profiling is not happening. Consequently, the long-term incarceration rate is the same, 5 percent, and, in fact, constant, for both groups and the total (combined) population.\(^10\) There is no change in incarceration rate over time in this scenario because the overall re-entry rate (\(\rho\)) is set equal to the overall stop rate (\(\sigma\)). This provides a useful baseline for making comparisons between this (as well as the next) profiling-free scenario, and scenarios in which profiling is utilized to increase efficiency by diverting, but not increasing, resources. In this scenario, there should be no expectation of an increase in criminal incarcerations—it represents the theoretical status quo.

**Scenario 1’: Unequal Criminality, Equal Stopping.** In Scenario 1, the criminality and stop rates were equal for both groups and so there were no differences in incarceration rates. Another possibility is that there is no profiling, but there are real differences between the groups in terms of criminality rates. In this scenario, therefore, all parameters are the same as those in Scenario 1, except that the criminality rates for the two groups are changed such that group A, the minority group, has a rate (25 percent) four times that of group B (6.25 percent), the majority group, thus maintaining the overall criminality rate of 10 percent in order to facilitate comparison. Additionally, maintaining the assumption that there has been no criminal justice bias to date, the percent incarcerated at the start differs for the two groups (12.5

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\(^9\) For example, if there are 20,000 As, the stop rate is 20 percent (4,000), and 1,000 are already incarcerated, then 3,800 would be stopped in the next iteration.

\(^10\) In the interest of conserving space, no graphical depiction of the first two scenarios is provided. These two scenarios serve to establish a no-profiling baseline where, because police resources are fixed, there is no change over time in incarcerations. They also serve to establish that the equation and program written to execute the model function properly, yielding no incarceration disparities or changes where none are expected.
percent vs. 3.125 percent), reflecting their differential criminality rates. Accordingly, as in Scenario 1, half of the criminals from each group and the total population have been incarcerated at the start of the projection. Similar to Scenario 1, the net effect, given no additional resources allocated and no profiling, is the status quo for both groups and the total population—5 percent of the population is incarcerated at all times. Like Scenario 1, this serves as a good comparison standard, or baseline, for determining the effects of racial profiling, assuming that no additional resource allocations accompany the initiation of profiling.

Scenario 2: Equal Criminality, Unequal Stopping. Figure 1 illustrates what might happen to incarceration rates over time if there are no true differences between groups but racial profiling is instituted nevertheless. In this scenario, at Time 1 and thereafter, 20 percent of A’s and only 1.25 percent of B’s (and still 5 percent of the overall population, reflecting an attempt at increased efficiency with no increased expenditures) are stopped by the police. Prior to this, it is assumed, there was no profiling. Because there are no criminality differences and there has been no profiling to date, prior incarceration rates for the two groups are identical (5 percent). Regardless of the fact that members of group A are no more likely to be criminals, targeting them leads to a climb in the number of their incarcerations that ultimately asymptotes. In contrast, by virtue of having resources diverted away from group B, the incarceration rate for that group declines from the status quo, even though they are committing crimes in equal proportions. In fact, the number of criminals at-large for group B grows over time as fewer of them are captured, and the converse is true for group A. It is also worth noting from this scenario that while the percent of B’s who are incarcerated drops, the overall number of incarcerations (for the total population) parallels that development because group B comprises the majority of the total population. In this case profiling leads not only to an overrepresentation of one group in prison, but also to an under-representation of the other group. Because this latter group is in the majority, this leads to a drop in overall incarcerations of criminals. This is not the necessary effect of racial profiling, but it does represent a range of possibilities wherein profiling could be counterproductive with regard to criminal incapacitation.

![Figure 1](image)

Notes to Figure 1: Group A is the minority group (20% of population). Both groups have the same criminality rate (C) of 10%. Total criminality is therefore 10%. Half of the criminals (5%) are incarcerated at the origin (I_{0}). The stop rate (σ) is higher for Group A (20%) than for Group B (1.25%), yielding 5% for the total population.

**Figure 1.** Effect of racial profiling over time, Scenario 2—No criminality differences, profiling occurring.
Scenario 2': Unequal Criminality, Unequal Stopping. Scenario 2 illustrates that profiling alone can lead to disparities in conviction rates for groups, even if those groups have identical levels of criminality, and that this tactic can even lead to a decline in overall convictions/incarcerations of criminals. However, proponents (and many opponents and dispassionate observers) of racial profiling believe that the typically targeted groups do indeed have higher criminality rates, and consequently see profiling as justifiable because it maximizes the likelihood of capturing criminals. To model the effects of profiling under these conditions, Scenario 2', like 1', places Group A’s criminality rate at 25 percent and Group B’s at 6.25 percent, a fourfold ratio. This keeps the overall rate (for both groups combined) at 10 percent, for the purpose of comparison with the preceding scenarios. Because the groups differ in actual criminality, it is likely that their prior incarceration rates would differ proportionately. Accordingly, their initial incarceration rates have been set to 12.5 percent and 3.125 percent (differing, as with criminality rate, by a factor of 4), thus maintaining a combined rate of 5 percent, as in the preceding scenarios. The effect of profiling with these group differences is illustrated in Figure 2.

As we can see from Figure 2, profiling with these parameters has only a modest and temporary positive effect on overall incarcerations (even with fairly generous assumptions about the differences in criminality between the groups) but has a lasting effect on the exaggeration of differences between the two groups.

Optimization Analysis

These effects can be more thoroughly investigated using a sensitivity analysis wherein we systematically vary the profiling rate across a continuum, testing its effect on criminal capture rates. Such an analysis, summarized in Table 1, allows for an assessment of the rates at which profiling would yield optimal results (i.e., the greatest net increase in criminal captures).

The analysis manipulates the ratios of stop rates for the two groups from extremes of 25:0 (the most extreme level of profiling possible, given our baseline of

![Figure 2: Effect of racial profiling over time, Scenario 2’—Criminality differences, profiling occurring.](image)
The Efficacy and Effect of Racial Profiling

an overall 10% criminality rate (for the total population) to 1:1 (no profiling). In this analysis, we consider only a situation in which the minority group really does have a higher criminality rate because, in the absence of that, there is no rationale for profiling and it is mathematically clear that profiling cannot yield greater efficiency (see, for example, Figure 1).

The ratio of criminality rates for Groups A and B is 25:6.25 or 4:1. As this analysis reveals, that same ratio (4:1) in terms of stop rates for the two groups yields the highest long-term criminal incapacitation rate: 54.9 percent of the criminal population. As the ratio moves away from 4:1 in both directions, with one exception, the overall incapacitation rate declines. At the extreme, it drops below the status quo (without profiling) of 5 percent when profiling is dramatic (greater than 16:1). The exception to the decay is for the 3:1 ratio, which yields the same overall, long-term incapacitation rate. It should be noted, however, that the 4:1 profiling ratio has a higher apex (5.6), which it reaches earlier (the 12th cycle) than the 3:1 ratio (5.53 at the 14th cycle). If profiling is planned to be temporary and starting from a point at which profiling had not been previously occurring, this would be a worthwhile consideration.

Another important consideration is the disparities in the percentages of the groups being incarcerated under different scenarios. Here, a linear trend is evident wherein the disproportion of Group A and Group B members being incarcerated increases as the profiling rate increases (that is, as the ratio goes from low to high). Consequently, whereas the same long-term incapacitation rate could be attained (54.9 percent of criminals) with the 3:1 and 4:1 ratios, the latter has a more disproportionate effect on the minority community, incarcerating 17.86 percent as

<table>
<thead>
<tr>
<th>Profiling Rate</th>
<th>Outcomes</th>
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<tr>
<td>% Stopped per Cycle</td>
<td>Ratio of %</td>
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<tr>
<td>Group A</td>
<td>Group B</td>
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<tr>
<td>5.00</td>
<td>5.00</td>
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<tr>
<td>6.82</td>
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<td>8.33</td>
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<td>12.50</td>
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<td>13.89</td>
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<td>15.00</td>
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<td>16.67</td>
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<td>0.00</td>
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</tbody>
</table>

Notes: aGroup A comprises 20 percent of the total population and has a criminality rate of 25 percent. bGroup B comprises 80 percent of the total population and has a criminality rate of 6.25 percent. cThe “percent of group incarcerated” statistics reflect the percent after repeated cycles and the trends have reached their steady states. Numbers in parentheses are the percent of the criminal population within each group that would ultimately be incarcerated.

In fact, the more extreme the profiling (given a higher criminality rate for the targeted group), the higher and more precipitous the climb in incarcerations. For example, the 25:0 profiling rate yields a peak incarceration rate of 5.82 at the 5th cycle, but it falls off rapidly thereafter.
opposed to 17.04 percent of them. Nevertheless, even under this “optimal” profiling condition, the ratio of percent incarcerated for the two groups is 6.55:1 while the criminality ratio between the two groups is only 4:1. Only when the profiling ratio is 1:1 are the incarceration rates proportionate to the criminality rates.

**Steady State Analyses: A Broader Summary of Possibilities**

While the above-plotted curves and sensitivity analysis provide a relatively in-depth perspective on a limited set of scenarios, it is also possible to use the present model to test a broader spectrum of possibilities. Specifically, with less regard to dynamics, we can solve for the steady states that are achieved for each set of parameters and analyze comparative static changes in the equilibrium incarceration rate.\(^\text{12}\)

Specifically, from the original profiling equation:

\[
I_t = I_{t-1} + \sigma(C - I_{t-1}) - \rho I_{t-1}
\]

we can derive the percent of the group that will be incarcerated when \(I_t = I_{t-1} = I\) (i.e., the steady state, or asymptote) using the following equation\(^\text{13}\):

\[
I = \frac{\sigma C}{\sigma + \rho}
\]

The fundamental inferences from this relation are that incarceration rates (\(I\)) will increase with increases in stop rates (\(\sigma\)), (provided \(\rho > 0\)), or with increases in criminality rates (\(C\)), but decrease with increases in criminal re-entry (\(\rho\)); conclusions that are hardly remarkable in and of themselves. However, with this steady state equation, we can, as in the scenarios in Figures 1–4, average incarceration rates for two groups with varying relative criminality and stop rates. Retaining the assumption that police resources are constrained such that the total number of stops are fixed but numbers of each group who are stopped can vary provided they sum to that total number, we can chart the long-term, steady state total incarceration rates for numerous scenarios as a function of the profiling rate (i.e., the ratio of proportions of each group stopped by the police) and the criminality ratio (i.e., the relative proportions of each group who are criminals).

Figure 3 plots projections where the population ratio is 1 to 4 (i.e., the minority group comprises one fifth of the total population, as in the previous scenarios charted in Figures 1 and 2). This manner of generating projections allows for a more fine-grained and comprehensive scenario analysis. It reveals that when the profiling rate is close to, and typically slightly below, the criminality ratio, the returns are the greatest, in terms of incarcerating the greatest proportion of criminals (i.e., the curve reaches its apex). For example, when the criminality ratio is 6:1, the optimal effects (highest rate of incarcerations) are achieved with a profiling rate of 5. Similarly, when the criminality ratio is 12:1, the highest incarceration rate is achieved with a profiling rate of 11. Deviations from this proportionality reduce effectiveness.

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\(^\text{12}\) The term “steady state” is used here to refer to the mathematical equilibrium that is met after many iterations of a profiling regimen. It should not be confused with the use of the term to reflect a situation in which an equilibrium occurs because incentives are no longer present to change behavior.

\(^\text{13}\) I thank an astute, anonymous reviewer for this helpful suggestion. The appropriate equation can be derived by assuming that at a steady state (where incarceration rates have reached an equilibrium and will persist given a constant level of policing) the incarceration rate (\(I\)) is constant. Accordingly, we can simplify the equation to \(I = \sigma C/(\sigma + \rho)\).
At the higher criminality ratios, this pattern is subtly different, such that optimal effects are achieved with profiling rates that slightly exceed the criminality ratio. When the criminality ratio is 20:1, the highest incarceration rate is attained at a profiling rate of 24.\textsuperscript{14} At the extreme, when the criminality ratio is 25 to 1\textsuperscript{15} (top curve, Figure 3) the highest incarceration rates are achieved when the profiling rate is 41, although the smallness of the difference in overall proportion incarcerated for the 41 profiling rate (0.720690) and the 25 profiling rate (0.720015) is noteworthy. Nevertheless, it is clear that when the minority group has a higher criminality rate than the majority’s, it is generally efficient to stop members of the two groups at relative rates proportional to (or slightly below) their criminality, but not, for the most part, in excess of it.

When there is no difference in criminality (bottom curve, Figure 3), any amount of racial profiling (meaning, differential stop rates) leads to a deficit in criminal incarcerations relative to the status quo, a trend that worsens as the profiling rate increases. These general trends are consistent across scenarios (not depicted in Figure 3) varying the proportions of the populations (i.e., how small the minority

\textsuperscript{14} This fine distinction requires that the incarceration rates are carried out to four decimal places, with a total incarceration rate of 0.7009 at the 24 profiling rate and 0.7008 at a profiling rate of 20.

\textsuperscript{15} It should be noted that a 25-to-1 criminality ratio strains the limits of plausibility, requiring a near zero criminality rate among the majority, although it could be argued that such high ratios are possible among international terrorists.
The Efficacy and Effect of Racial Profiling

group is), except that the smaller the minority (e.g., one in ten vs. one in five), the less efficient profiling appears to be: curves peak earlier and trend downward more dramatically. This is for the simple reason that focusing on a small proportion of the population will have limited utility.

The distribution of steady state incarceration rates presented in Figure 3 indicates that when minority criminality rates are disproportionately high, higher rates of police stops for that group increase capture rates, but when minority criminality rates are not much higher than, or are equal, to the majority’s, disproportionate attention is counterproductive. Needless to say, if minority criminality rates are lower than the majority’s, focusing attention on them will only diminish overall capture rates. It should also be noted that, as discussed in regard to the scenario analysis depicted in Table 1, comparable overall capture rates can be achieved for group stop ratios (profiling rates) that are slightly below criminality disproportions, thus having a less disparate impact on innocent minority civilians and creating less disproportionate incarceration rates.

It is worth noting that while overall incarceration rates decline when profiling exceeds criminality ratios, the proportion of the minority population that is incarcerated continues to climb, as does the ratio of the minority over the majority population proportions incarcerated. In other words, after profiling has ceased to yield gains (assuming the targeted group has a higher criminality rate) in overall incarcerations, it continues to increase the minority-majority disparity in incarceration rates until both curves asymptote, at which point it maintains that disparity even though the at-large population has a higher rate of criminality among the majority group (see Bunzel & Marcoul, 2003; Harcourt, 2004; and Persico, 2002, for similar conclusions achieved through somewhat different approaches).

Deterrence. The preceding simulations could be criticized for focusing exclusively on criminal incapacitation, as opposed to another public safety enhancing objective of policing: deterrence (Levitt, 2002). Without considering deterrence, the impact of profiling on crime can be fully represented by incarceration rates, assuming criminal activity rates (what criminologists refer to as $\lambda$—crime frequency per active criminal; see Blumstein & Cohen, 1987) among criminals from both populations are equal on average. When including the possibility of a deterrent effect, differential changes in $\lambda$ and participation rate among the at-large populations, as a result of profiling, must also be considered. Theoretically, if racial profiling is sufficiently prevalent to be recognized by members of targeted groups, it could serve to reduce criminal behavior on the part of members of those groups. This could offer an additional crime reduction benefit, beyond incapacitation via incarceration.

There are several reasons to be cautious about including deterrence in the present model. First, these simulations seek only to project incarceration rates, whereas deterrence has its primary effects on crime rates, which have only indirect effects on incarceration rates. Another reason for caution when including deterrence in the present model is that the rational choice models necessary for explaining risk avoidance on the part of potential criminals are problematic (Caulkins & MacCoun, 2003; MacCoun, 1993). Furthermore, Bjerk (2004) points out that police can observe only a fraction of any given population and, therefore, can never raise the probability of being apprehended to a very high rate. Consequently, it would be difficult to establish precise parameters for modeling a deterrent effect.

In the preceding model, C, the criminality rate, can be considered the product of $\lambda$ and $P$—participation rate (Blumstein & Cohen, 1987).
The Efficacy and Effect of Racial Profiling

The above-mentioned concerns notwithstanding, we can draw upon the literature on criminal deterrence to attempt to derive reasonable parameters to incorporate in the model, in the service of getting a more comprehensive picture of the efficacy of racial profiling. Studies investigating the effects of changes in arrest and incarceration rates have attempted to parse the effects of incapacitation and deterrence on future crime (e.g., Kuziemko & Levitt, 2004; Levitt, 1998; Spelman, 1994, 2005). Estimated deterrent effects vary across studies, populations, and crime categories, but there is reasonable agreement that incarceration rates have a combined deterrent and incapacitative effect of about –0.4, for all types of crime combined. The deterrent component of the elasticity of crime rates with respect to the risk of imprisonment, therefore, falls somewhere between 0 and –0.4. With regard to drug war profiling, an elasticity of –0.2 is consistent with MacCoun’s (1993) estimate that deterrence effects account for less than 5 percent of the variance in reported marijuana use. Accordingly, the following simulations are centered on a –0.2 deterrent effect, with those results graphed, and a range of alternative effect sizes for this elasticity also considered.

In order to incorporate deterrence in the model, a new parameter \( e \) is added, which represents the supply elasticity of crime with respect to the probability of punishment. The criminality rate \( C \) for each group is recalculated as follows:

\[
C_i = C_i + e(\sigma_i - \sigma_j),
\]

where \( C_i \) is the new (deterrence-affected) criminality rate given elasticity of \( e \) and police stop rate \( \sigma_i \). \( C_i \) is the criminality rate when the stop rate equals that of the other group (i.e., the undeterred criminality rate), and \( \sigma_j \) is the stop rate when it equals that of the other group (i.e., the stop rate proportion equals 1). The model now assumes that when police increase surveillance of a group, criminals among that group detect that change and modify their behavior (i.e., commit less crime). In all of the present simulations, we assume fixed police resources. Because profiling involves the reallocation of police resources, and not an overall increase in them, it follows that when surveillance of one group increases, surveillance of others decreases. Accordingly, when one group detects increased surveillance and reduces their crime rate, the remainder of the population of criminals would detect decreased surveillance and, with the expected cost of behaving criminally decreasing, would increase their criminal activity. The above equation allows for this as well.

Figure 4 depicts a steady state analysis similar to that presented in Figure 3, but with deterrence incorporated. The general effect of profiling-induced deterrence is that criminal incapacitations drop overall. For example, whereas without a deterrent effect (see Figure 3), when the criminality ratio is 4 to 1, the peak incarceration rate is 54.95 percent; with a deterrent effect of –0.2, that peak drops to 54.32 percent. When profiling is more extreme, incorporating deterrence yields greater decrements in criminal captures. This general pattern can be seen by comparing Figures 3 and 4, noting the lower and steeper downward slopes of the series in Figure 4.

The reduction in criminal incarcerations resulting from profiling-induced crime deterrence consists of two reinforcing effects: (1) criminal activity declines in response to an increase in law enforcement attention and there are consequently

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17 This coefficient refers in economics to the “elasticity” of criminal offending conditional upon incarceration rates, such that, with an effect size of –0.2, a 10 percent increase in incarcerations will yield a 2 percent decrease in crime.
fewer captures among the profiled group; and (2) law enforcement attention shifts away from the non-profiled group while criminal activity increases among them. Although Figure 4 depicts effects with only one set of scenarios, this pattern of results is not dependent on the chosen magnitude of the negative supply elasticity coefficient. As long as the rate of police surveillance is negatively associated with criminal activity, group-specific deterrence (i.e., due to profiling with fixed resources) causes a reduction in overall criminal captures.

Effect of Profiling-Induced Deterrence on Crime Rates. The results presented here with regard to deterrence must be considered very cautiously, primarily because the dependent variable in this analysis is criminal captures. The usual desired effect of deterrence is a direct reduction in crime. Because the present analysis does not seek to project crime rates, that point could, but should not, be overlooked here.

The manner in which deterrence is modeled here, wherein it is assumed that crime elasticity will be symmetrical for groups who receive more and less surveillance, results in an invariant overall criminality rate. As a consequence, the pres-

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18 If police resources are shifted to one group, that group’s criminal activity will decrease proportionally to the increase in surveillance (by a factor of the elasticity coefficient). Such a shift will have the complementary effect on the group or groups away from whom attention has gone. The size of the group affects the proportional change in surveillance and the probability of being stopped, so a majority group will have a smaller percentage change in criminality for a given reallocation of police resources.
ent model concludes that racial profiling would have no deterrent effect on overall crime rates. Because profiling involves diversion of limited police resources, and because crime reduction can involve both incapacitation and deterrence, even if there is a deterrent effect on those targeted there might be no overall, or even a net negative, crime reduction effect if non-profiled groups increase their criminal activity. In sum, deterrence in the context of racial profiling, where change in surveillance rates is group-dependent in a zero-sum manner, is a very special case that should not be readily confused with traditional models of deterrence.

Dynamic Profiling: Optimizing through Monitoring and Adjustment

One manner in which racial profiling could achieve optimal results would be for police to continually modify their stop rates based on changes in the groups’ criminality rates among the at-large population, thereby always targeting the group with the highest potential hit rate. This dynamic, moving target approach would most certainly yield the greatest efficiency in terms of high capture rates per police hour (not considering police hours devoted to calculating criminality rates). This approach would also, it should be noted, still exacerbate racial disparities in criminal justice.

For the reasons stated in the introduction with regard to the difficulty of obtaining true criminality rates among the at-large population (e.g., incarceration rates may be confounded by past profiling), the dynamic profiling approach would be challenging. However, the further development and standardization of economic equilibrium models (see Knowles et al., 2001) could provide law enforcement agencies with methods, albeit highly complex, for estimating crime rates among groups based solely on arrest rates.

One could posit that police will, with some degree of accuracy, estimate criminality rates based on their own individual hit rates (e.g., contraband finds per search, or arrests per stop) with suspects from different groups. However, as long as they are profiling in the first place, their hit rates will be confounded. In fact, they will tend to underestimate the criminality rates of groups they target because they will have deflated hit rates for them, having set lower standards of probable cause (see Ayres, 2002). Furthermore, psychological research has consistently demonstrated that stereotypes such as those on which racial profiling is based are highly resistant to change (e.g., see Kunda & Oleson, 1995; Rothbart & John, 1985; Weber & Crocker, 1983). Economists Bunzel and Marcoul (2003), in attempting to model the effects of profiling, have also noted the psychological distortions that are likely to compromise police criminality estimates, specifically the tendency to self-enhance or, in their terms, be “over-confident” in one’s own expertise. Because racial profiling is, with rare exceptions, an informal and unofficial process, it is likely that it will be driven more by informal stereotypes than by careful, actuarial analysis of criminality rates, even if such accountings were feasible. In order for dynamic profiling to be effective, it would require a high degree of formalization and standardization of data collection, analysis, and dissemination within each agency.

Limitations of the Simulation

The mathematical simulation of the effects of racial profiling presented here is not without its limitations, and it is worth considering them in order to assess the utility of the analysis and possibilities for future analyses. First, this model is hypo-
The Efficacy and Effect of Racial Profiling

Theoretical and, therefore, does not make projections of real trends. In order to do that, a complex, multivariate model, including best estimates of current and predicted parameters would be necessary. This is perhaps achievable, but such parameters would no doubt be controversial, or at least would be limited to specific places and times. The purpose of the present model is to illustrate simply the general patterns that are likely as a consequence of police diverting resources to surveillance of certain social groups. It is not meant to make specific predictions so much as depict the nature of the contribution of racial profiling as one of many factors in policing—that, as it turns out, it will inevitably exacerbate racial/ethnic disparities in incarceration rates and will achieve the highest incapacitation gains if proportional to criminality differences.

In attempting to achieve parsimony, the model has been designed with as few variables as possible: population proportion, criminality rate, stop rate, and, in the simulations, including deterrence, elasticity. As a consequence, certain potential variables were held constant and embedded in the assumptions of the model. For one, it was assumed that racial disparities do not exist elsewhere in the criminal justice system. This is likely untrue. Nevertheless, as stated above, the purpose of the model was to depict the unique contribution of profiling. Other biases in the system would only contribute to disparities above and beyond those illustrated here.

The present analysis does not consider another important effect of racial profiling: disproportions in the numbers of innocent group members who are stopped by the police. Clearly, profiling has the effect of increasing the proportion of innocent civilians from the targeted group who are stopped. Although beyond the scope of the present analysis, which is focused on incarceration rates, a direct demonstration of the effect of racial profiling on stop rates of innocent group members would be a valuable contribution to understanding the impact of racial profiling and should be considered for future study.

This analysis is based primarily on drug war profiling and, accordingly, employs parameters (e.g., minority-majority group relative population sizes) that are roughly applicable there. However, in the current social context, profiling is perhaps most seriously considered and debated as a policy option with regard to counter-terrorism. In this regard, the results of the simulation may be of limited value for several reasons. First, the base rates for terrorist activity are much lower than for drug crimes, while the negative societal impact of a single terrorist attack is much greater than that of a single drug crime. Consequently, the concern about disproportionate incarcerations is lower and the value of a single capture or deterrence is higher. But because terrorists are such a small fraction of any racial or ethnic group, the utility of race or ethnicity as a predictor may be very low. Second, terrorism typically reflects an ideological motivation that is often tied in some way to the race or ethnicity of the perpetrators. In this sense, the race or ethnicity in the profile has an instrumental connection to the behavior that may make it a better predictor. The concern about any deterrent effect of profiling on the targeted group having a facilitative effect on other groups who receive less attention is still relevant to national security in the United States, where terrorism has been most often perpetrated by Whites, assuming the current targeted group is Middle-Easterners.

19 Re-entry rate is a quasi-variable that was not varied in this analysis but serves to create an equilibrium for establishing baseline condition.

20 Even in the case of domestic terrorism by “patriots” or “separatists,” such as Timothy McVeigh and Eric Rudolph, White, Christian identity plays a role.
CONCLUSION

Aggressive police tactics and tough sentencing laws aimed at reducing drug use and related crimes have led to dramatic increases in the incarcerations of nonviolent criminals in recent decades (Levitt, 2004; MacCoun & Reuter, 1998). What is clear from all scenarios in the present simulations in which one group is profiled is that profiling invariably has the effect of increasing differences in incarceration rates between groups. Harcourt (2004) refers to this as a “ratchet effect.”21 If racial profiling is as prevalent as many suspect, it could explain a large portion of the disparity in the incarceration rates of Black and White Americans.

The Bureau of Justice Statistics (2003) estimates that 12 percent of Black men, 4 percent of Latino men, and 1.6 percent of White men in their twenties and early thirties were in prison or jail in the United States at mid-year 2002. With such a large proportion of Black men incarcerated, the likelihood that a Black child will have a close friend or family member in prison is very high. Furthermore, Pager (2003) has revealed that criminal records are especially stigmatizing for Black job-seekers, and Raphael (2004) has demonstrated that high incarceration rates for Black men have substantial indirect, negative effects on employment prospects of unincarcerated Black men. The racial disparities in incarcerations that necessarily result from racial profiling, therefore, have a substantial negative societal impact.

What also appears clear from the preceding analysis is that racial profiling is neither inherently efficient nor inefficient, but that popular presumptions about its efficiency are probably overconfident. There are conditions under which it will be effective and conditions under which it will be counterproductive. Under all conditions, racial profiling increases racial disparities in criminal justice. This presents policymakers and the public with difficult choices, but it also offers a more comprehensive and nuanced set of factors in weighing public safety gains against civil liberties sacrifices.

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JACK GLASER is Assistant Professor at the Goldman School of Public Policy, University of California, Berkeley.

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21 Harcourt (2004) defines a ratchet effect as occurring “when racial profiling produces a supervised population disproportionate to the distribution of offending by racial groups” (p. 1,279).


