SELF-REPORTED VERSUS ADMINISTRATIVE IDENTIFICATION OF AMERICAN INDIAN AND ALASKA NATIVE ARRESTEES: EFFECTS ON RELATIVE ESTIMATES OF ILLICIT DRUG USE AND ALCOHOL ABUSE

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Abstract: Arrestee Drug Abuse Monitoring program data were used to consider the effects of two methods of racial classification upon estimates of illicit drug use and alcohol abuse among American Indian/Alaska Native (AI/AN) arrestees. Overall, compared to arrestees who self-identified as Black, White, Asian/Pacific Islander, or Hispanic, arrestees self-identifying as AI/AN were most likely to be identified administratively as something other than AI/AN. Results of 'difference of difference' analyses indicate that differences in estimates of AI/AN versus non-AI/AN arrestees' illicit drug use and alcohol abuse were much more extreme when identification was based on administrative records than when based upon arrestees' self-reports.

The complexity of American Indian and Alaska Native (AI/AN) identity contributes to the difficulties of studying behaviors such as illicit drug use and alcohol abuse within those populations. A panoply of factors underlie the identification of oneself or others as AI/AN, including biological, legal, cultural, geographic, and historic considerations (Gone, 2006; Mihesuah, 1998; Peroff & Wildcat, 2002). The lack of a commonly utilized demarcation of the AI/AN population makes for uncertain specification of study populations, which can limit the external validity of research results. Clearly, empirical conclusions regarding AI/AN substance use are, in part, a function of the parameters used to establish the study population. In this article, the patterns of substance use among two alternatively delineated groups of AI/AN arrestees were considered in order to understand how variation in identification methods affects estimates of AI/ANs' illicit drug use and alcohol abuse. Specifically, the illicit drug use and alcohol abuse of participants in the Arrestee Drug Abuse Monitoring (ADAM) program who were identified administratively as AI/AN were compared with the same behaviors of participants who self-identified as AI/AN.

PREVIOUS RESEARCH INVOLVING CATEGORIZATION OF AI/ANS

Numerous methods have been used to identify individuals as AI/AN for inclusion in social science and public health research. These methods typically fall into one of three categories. In some studies, AI/ANs are identified on the basis of *tribal enrollments*. Alternatively, respondents' *self-identification* as AI/AN is common in most surveys. Finally, *administrative identification* of individuals as AI/AN by health, social service, or criminal justice agency personnel also is used commonly.

Tribal Enrollment

A few different techniques are used to select research participants who are acknowledged as AI/AN through tribal enrollment. Some researchers have used membership lists as sampling frames, including tribal enrollment lists (May & Gossage, 2001) and AN regional corporation shareholder rosters (Wood & Magen, 2009). Similarly, samples of AI/ANs have been chosen from the records of institutions devoted to a tribally enrolled AI/AN clientele, including rosters of students attending reservation schools (Cockerham, 1975) and patients treated at Indian Health Service (IHS) clinics (Kunitz, Levy, McCloskey, & Gabriel, 1998). In urban areas, this method has also involved the use of samples of clients of AI/AN health and human service agencies (Buchwald et al., 2000; Chester, Mahalish, & Davis, 1999). In a similar fashion, individual study participants have been identified using eligibility rosters of a variety of federally funded programs that require sworn statements of tribal membership. A notable example of this approach is the survey of AI/AN youth in Seattle in which the sample was drawn from public school students whose parents had completed a *Title VII Student Eligibility Certification Form* (Walker et al., 1996) that attested to the youths' membership in a federally recognized tribe.

Although these sources are useful because of their governmental imprimatur and the discrete delineation they provide, there are problems with using tribal enrollment to identify AI/ANs for research. Because enrollment requirements vary from tribe to tribe, the characteristics that qualify individuals for tribal citizenship are anything but standardized. Combined permutations of requirements regarding AI/AN blood quantum, tribal blood quantum, residency, parental enrollment, adoption, and multiple membership, as well as rules for resignation, relinquishment, and disenrollment (Berger, 2013; Goldberg, 2002; Gover, 2010) make for tremendous differences in regulations used to decide tribal citizenship. Variations in eligibility for holding shares of AN regional corporations—some corporations' shareholders may include only those born before December 18, 1971, while others have extended ownership to children of those original shareholders (Case & Voluck, 2012)—create a similar lack of uniformity. Additionally, citizenship provisions written in response to federal regulations regarding tribal recognition that require members' participation in cultural and political activities (Goldberg, 2002) exclude those who would otherwise be enrolled if not for geographic separation. For instance, in an analysis of responses to the *California Health Interview Survey*, Satter, Seals, Chia, Gatchell, and Burhansstipanov (2005) estimated that only 16% of AI/ANs reporting heritage in a non-Californian tribe were enrolled in that tribe. Tribal enrollment requirements are also subject to change. Faced with dwindling numbers, a few tribes have reduced the required blood quantum, thereby easing enrollment requirements (Foster, 1997). Others, however, struggling with gaming windfalls, have made the rules much more stringent (Neath, 1995), increasing the number of citizens being disenrolled (Dao, 2011; Weeber, 2013). The use of tribal enrollment records may, therefore, not be as valid as could be expected.

Self-Identification

Subsamples of AI/ANs derived from general population surveys usually rely on self-identification of race (e.g., Akins, Mosher, Rotolo, & Griffin, 2003). For example, in the Behavioral Risk Factor Surveillance Survey, AI/ANs are identified by a response to the question "What is your race?" (Denny, Holtzman, & Cobb, 2003). Although self-identification is the U.S. government standard and is generally the preferred method for gathering data on race/ethnicity (Mays, Ponce, Washington, & Cochran, 2003), the reliability of self-reported ancestry for AI/ANs has been questioned. The results of a pair of re-interview studies indicate a lack of consistency in respondents' self-reports of AI/AN ancestry. According to a U.S. Census Bureau (1979) report cited by Ericksen (1997), roughly 10% of residents of Gallup, New Mexico, who identified themselves as AI on the 1970 U.S. Census failed to do so when re-interviewed in 1974. There was even less test/retest agreement over the two waves of the National Health and Nutrition Examination Survey (NHNES). In that survey, 85.6% of respondents who initially self-identified as AI reported another ancestry in a reinterview a decade later (Hahn, Truman, & Barker, 1996). Subsequently, while self-identification may be considered the standard in much research on AI/ANs, it carries validity problems of its own.

Administrative Classification

Alternatively, some research on AI/ANs has used administrative records from institutions serving the general population in which the classification of individuals as AI/AN is generally made by a public official without reference to self-identification or tribal enrollment. In other words, AI/AN identification is often determined by public officials' own subjective assessments of other individuals' racial/ethnic background, which may be biased or inaccurate for a host of reasons. An obvious example is the measurement of racial/ethnic variations in criminal behavior or public drunkenness using arrest records generated by the police (Perry, 2004), in which classifications are left to the best guess of an arresting officer or overburdened jail clerk. In a similar fashion, state-level interracial comparisons of student suspension or expulsion rates may be based upon public school administrators' classification of student race/ethnicity (e.g., DeVoe & Darling-Churchill, 2008). In addition to errors of personal observation by data collectors, administrative misclassification of AI/ANs often results from use of Hispanic surnames to determine race or from a lack of an AI/AN response category on intake forms (Burhansstipanov & Satter, 2000).

Tribal Enrollment Compared With Self-Identification

Numerous studies have observed that measures based upon both self-reports and administrative records differ substantially from those based upon tribal enrollments only. The considerable disagreement between measures relying on self-reported AI/AN heritage and measures based on tribal enrollments becomes apparent, for example, when one considers the results of the U.S. Census relative to indicators of tribal enrollments. Typically considered to be a tally of self-reported AI/ANs, the U.S. Census allows respondents to report being all or part AI/AN and allows, but does not require, respondents to specify a tribal affiliation (Snipp, 2002). According to the 2000 U.S. Census, one quarter of the respondents who reported being AI/AN did not report tribal affiliation (Ogunwole, 2002). As a result, the number of individuals who self-reported being AI/AN was much greater than the number of individuals who were enrolled in an AI/AN tribe. Based on comparisons of tribal enrollment figures with U.S. Census results, Thornton (1997) estimated that one third of those who reported being AI/AN in the 1980 U.S. Census, and two fifths of those who reported likewise in the 1990 U.S. Census, were not members of a federally recognized tribe. Of these, many reported Mexican, Central American, or Canadian indigenous heritage, while others reported membership in a tribe without federal recognition. In an analysis of restricted-use micro-data, Liebler and Zacher (2013) found that tribal nonresponse in the 2000 U.S. Census was especially prevalent among those reporting less education or a lack of English proficiency, those who probably misunderstood the question about race (e.g., single-race AIs who reported West Indian or South Asian Indian ancestry), and those with other racial and/or ethnic heritages (e.g., multiracial individuals, Hispanics, or the foreign born) for whom a tribal identity is secondary.

Tribal Enrollment Compared With Administrative Classification

While estimates of the AI/AN population are greater when based on self-identification rather than on tribal enrollments, they are both considerably lower than estimates based upon administrative identification by government or medical record keepers. For instance, a number of validation studies using IHS records as indicators of tribal enrollments have shown that state surveillance systems understate the incidence and/or prevalence of numerous maladies among AI/ANs, including HIV/

AIDS (Bertolli, Lee, & Sullivan, 2007; Lieb, Conway, Hedderman, Yao, & Kerndt, 1992), cancer (Espey et al., 2008; Foote, Matloub, Strickland, Stephenson, & Vaughan-Batten, 2007; Gomez & Glaser, 2006; Johnson et al., 2009), sexually transmitted diseases (Thoroughman, Frederickson, Cameron, Shelby, & Cheek, 2002), cardiovascular disease (Rhoades, 2005), and traumatic injury (Sugarman, Soderberg, Gordon, & Rivara, 1993). Studies comparing death certificates against tribal enrollments (Graber, Corkum, Sonnenfeld, & Kuehnert, 2005; Stehr-Green, Bettles, & Robertson, 2002) provide further indication of the degree to which AI/ANs are differentially classified and of the effects such incongruence has upon estimates of mortality. In some cases, there is even incongruence between different forms of administrative records, as evidenced in research examining the differential identification of AI/ANs by comparing race recorded on death certificates with race recorded on birth certificates (Epstein, Moreno, & Bacchetti, 1997; Harwell et al., 2002; Watson, Bennett, Reed, McBroom, & Helgerson, 1993).

Self-Identification Compared With Administrative Classification

Finally, and most important for the purposes of this article, there are the considerable inconsistencies between the categorization of individuals as AI/AN by self-identification and in administrative records. Survey responses that have been cross-referenced with a number of administrative record sources, including the Department of Veterans Affairs (VA; Kressin, Chang, Hendricks, & Kazis, 2003), Medicare (McAlpine, Beebe, Davern, & Call, 2007; Waldo, 2004), and health maintenance organizations (Gomez, Kelsey, Glaser, Lee, & Sidney, 2005), have shown that, relative to African American, White, and Asian American patients, AI/AN patients are the most likely to have disparate classifications. For instance, a comparison of survey data with VA records found that self-identified AI dental outpatients were much more likely to be classified as another race by the VA (70.5%) than were dental outpatients who self-identified as White, Black, or Asian (1.5%, 5.0%, and 13.8% were classified as another race by the VA, respectively; Boehmer et al., 2002). There was a similar pattern of inconsistences between self-reports in the National Longitudinal Mortality Study survey and the records of the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) population-based cancer registry; more than three fourths (78%) of patients who self-identified as AI/AN were categorized as belonging to another race by SEER—much greater than what was found for Hispanic (21%), Asian/Pacific Islander (7%), Black (6%), or White (1%) patients (Clegg et al., 2007). West et al. (2005) reported an even greater level of inconsistency between self-reports and medical records, finding that 94.4% of mastectomy patients who self-identified as AI/AN were categorized as another race in the records of six integrated health care delivery systems (the next largest inconsistency was for self-identified Latina patients, who were categorized differently 36% of the time).

Validation studies of death certificate records have shown a similar pattern. For instance, a national survey used to validate death certificate data found that approximately one quarter (23.8%) of decedents classified as AI/AN by their relatives were not classified as such on their death certificates (Poe et al., 1993). Comparisons of data in the U.S. Census Bureau's Current Population Survey with information reported on death certificates also showed a similar rate of disagreement (26.4%) for AI/ANs (Sorlie, Rogot, & Johnson, 1992). Finally, the NHNES actually found that *none* of the respondents who self-reported AI ancestry in the initial survey wave and subsequently passed away were classified as such on their death certificates, but were instead categorized as African American or White (Hahn et al., 1996).

Overall, it is clear that there are substantial inconsistencies among the various methods of classifying AI/ANs, especially when comparing self-identification with administrative records. Research also indicates that these inconsistencies often result in widely varied estimates of the prevalence of disease in AI/AN populations. Subsequently, it appears that estimates of disease among AI/ANs are much more likely to be influenced by the definition of the population at risk than is the case for other races.

For the most part, consideration of inconsistencies in classification of AI/ANs has been limited to vital statistics or research on chronic disease. To expand the scope of this line of research, this article considers the effects of two different methods for identifying individuals as AI/AN when estimating rates of illicit drug use and alcohol abuse among those in contact with the criminal justice system. Specifically, records from the Arrestee Drug Abuse Monitoring (ADAM) program were used to consider the similarity between arrestees' self-reported race and their race as recorded by third parties in administrative (jail) records in order to determine what effect the method of racial identification had upon relative estimates of arrestees' patterns of illicit drug use and alcohol abuse. Based upon the literature reviewed above, we expected that (1) AI/ANs would be the racial group with the greatest discrepancy between self-reported and administratively ascribed race and (2) estimates of differences between the illicit drug use and alcohol abuse of AI/AN arrestees and that of non-AI/AN arrestees would vary according to the method used to classify arrestees as AI/AN.

METHODS

The data utilized in this research were originally gathered in 43 cities between 2000 and 2003 for the ADAM program, which was designed to provide quarterly estimates for surveillance of local patterns and trends in illicit drug use and alcohol abuse by those accused of criminal behavior (Hunt & Rhodes, 2001). As a tool to estimate the prevalence of illicit drug use and alcohol abuse among the criminally accused, the ADAM program was unique because it combined urine tests to detect recent drug use with interviews of a sample of recent adult arrestees about their illicit drug use and alcohol abuse. In addition to their intended use as part of a local-level arrestee drug use surveillance system, data from the ADAM program have been considered in aggregate across all of the study sites in analyses of the offense and drug use patterns of foreign-born arrestees (Kposowa, Adams, & Tsunokai, 2010), the effects of concentrated disadvantage and race upon arrestees' methamphetamine use (Fox & Rodriguez, 2010), the number of crimes that could be averted given the national prevalence of arrestees requiring drug and alcohol treatment (Bhati & Roman, 2010), and the overall prevalence of illicit drug use and alcohol abuse by American arrestees (Brecht, Anglin, & Lu, 2003). The results presented below are based on all interviews and urine tests of male arrestees gathered between 2000 and 2003. Overall, interviews were completed with 90,717 male arrestees; 82,305 of those interviewed also provided urine samples.

The sample of male ADAM program participants was chosen using probabilistic methods intended to allow for generalizability to all male arrestees at the county level for each ADAM site. To enhance representativeness, arrestees were selected proportionally on the basis of time of day and day of week of arrest as well as by jurisdiction within a county. The response rate of arrestees who were asked to participate ranged from 81% to 83% over the period 2000-2003 (National Institute of Justice [NIJ], 2001, 2002, 2004a, 2004c). Arrestee participation in ADAM—both the interview component and the urine testing—was completely voluntary. To maintain confidentiality of individual arrestee responses, interviewers hired specifically for the ADAM program gathered all interview data and urine samples.

The ADAM data are ideal for this research because they provide information on arrestee race that comes from two different sources: administrative records and self-identification. First, information transcribed from booking files in which arrestee race is classified by police or jailors serves as the administrative record of whether an arrestee was identified as AI/AN. (Given that police records of arrest in *some* ADAM sites combined race and ethnicity into a single indicator, information on administrative identification of race gathered from booking files from *all* ADAM sites used this least common denominator [NIJ, 2004b]. Effectively, the ethnic category Hispanic/Latino(a) in the booking records is treated as if it is equivalent to a race even though those who are Hispanic could belong to any race.[1]) Second, responses to ADAM interviewers' questions regarding race were used to differentially measure self-identification of AI/AN ancestry (NIJ, 2004b). This approach to measuring race and ethnicity follows the accepted practice of first asking about ethnicity and then asking about race so that the two concepts are distinct. Unfortunately, given the lack of information about arrestees' tribal membership in the ADAM data, we were unable to compare the effects of that form of identification upon estimates of illicit drug use and alcohol abuse.

For the purposes of comparing illicit drug use and alcohol abuse estimates, the two methods of identification were collapsed into dichotomous measures. Each arrestee was categorized as either self-identified AI/AN or non-AI/AN and as either administratively identified AI/AN or non-AI/AN. Furthermore, because arrestees could be identified as multiracial, dichotomous measures for single-race or multiracial AI/AN versus non-AI/AN arrestees for both methods of identification were used.

Different sets of outcome measures were used to consider the relative effects of the two different methods of identifying arrestees as AI/AN. The first set of outcome measures are based on urine tests that were completed within 48 hours of booking for a fairly reliable estimate[2] of arrestees' consumption of commonly used illicit drugs prior to the time of arrest. All other outcome measures come from arrestees' self-reported illicit drug use and alcohol abuse, and risk for drug and alcohol dependence. The majority of these measures came from questions in the National Household Survey on Drug Abuse[3] (Hunt & Rhodes, 2001) that focused on heavy and binge drinking, and the use of marijuana, crack cocaine, powder cocaine, heroin, or methamphetamine (over one's lifetime, the past year, and the past month). Questions measuring the risk for drug and alcohol dependence originated in a subset of questions from the Substance Use Disorder Diagnostic Schedule clinical assessment tool, which were based on criteria for dependence as defined in the *Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition* of the American Psychiatric Association (APA, 2000).

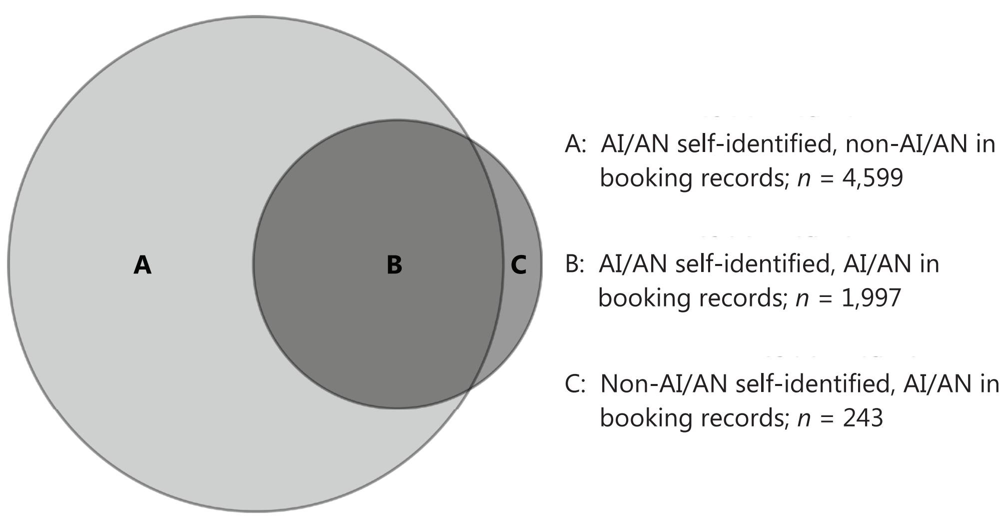
Two sets of analyses were conducted. First, we considered the correspondence between self-reported race and administratively identified race. For these analyses, we calculated the proportion of arrestees who self-identified as a specific race and who were similarly identified in administrative records. Second, we calculated cross-tabulations to measure the effect of the two methods of classifying AI/ANs upon estimates of their illicit drug use and alcohol abuse. Unadjusted binary odds ratios (OR) were calculated as measures of association (Morris & Gardner, 1988) to estimate the magnitude of difference between AI/AN arrestees' drug use or alcohol abuse rates and those of non-AI/AN arrestees for each method of classification. Confidence intervals (CI) of the odds ratios from each set of comparisons of illicit drug use or alcohol abuse were then examined for overlaps, the lack of which indicated the statistical significance of the differences of differences (Schenker & Gentleman, 2001). Although this technique is overly conservative because it increases the chances of a Type II error, where the null hypothesis is incorrectly accepted as true when it really is false (Payton, Greenstone, & Schenker, 2003), its use was necessary given a lack of accepted methods for testing the statistical significance of the difference in odds ratios taken from non-independent samples.

RESULTS

Sample

The analyses were conducted without use of the case weights typically employed when dealing with ADAM data because the primary concern was the consideration of the effects of two methods of racial identification upon illicit drug use and alcohol abuse estimates, rather than the generalization of outcomes to the population of all arrestees in a given ADAM site. While ADAM case weights are intended to ensure that the arrestees who were interviewed and urine-tested were reflective of all individuals who were arrested and booked during the data-gathering period, those weights were calculated to insure local representativeness across the days and times of arrest (Heliotis, Kuck, & Hunt, 2001) rather than across the sociodemographic characteristics that are usually of importance when assigning post-sampling stratification weights. A means comparison indicates that the use of ADAM case weights would bias illicit drug use and alcohol abuse estimates toward arrestees identified as AI/AN in jail booking records. Those classified administratively as AI/AN represented nearly three times as many arrestees (mean weight = 179.6 arrestees) as those who self-identified as AI/AN, but who were classified administratively as some other race (mean weight = 64.0 arrestees); this difference was statistically significant, $t(3041) = 3.81$, $p < .001$. Given that the set of arrestees who self-identified as AI/AN includes nearly all of the arrestees who were classified administratively (see Figure 1[4]), estimates of the substance use patterns of the former would actually be more indicative of substance use patterns of the latter if the ADAM case weights had been used.

Figure 1
Proportional Distribution of ADAM Arrestees by AI/AN Identity and Source of Identification



Of the 90,717 arrestees who were interviewed, 2,219 were identified administratively as only AI/AN and another 21 were identified administratively as being a combination of AI/AN and some other race. As shown in Figure 1, and as the literature reviewed above might lead us to expect, a larger proportion of arrestees self-identified as AI/AN than were identified administratively as AI/AN, such that 4,720 arrestees declared AI/AN as their only race and 1,876 declared partial AI/AN ancestry. On the other hand, nearly all arrestees who were identified administratively as AI/AN also self-identified as AI/AN. Nonetheless, the majority of arrestees who self-identified as AI/AN (either single race or multiracial) were identified as some other race during booking.

The two methods of racial classification were each operationalized as dichotomous variables to indicate whether an arrestee was or was not AI/AN. The first method, administrative identification, categorized 2.5% of the arrestees as single race or multiracial AI/AN, while the remainder were categorized as non-AI/AN. When using interview responses for classification, however, 7.3% of arrestees self-identified as single-race or multiracial AI/AN. Excluding those categorized as multiracial, roughly 1 in 40 arrestees (2.4%) was classified as AI/AN during booking while more than 1 in 20 (5.2%) self-identified as AI/AN during interviews.

Correspondence Between Self-Reports and Administrative Records of Race/Ethnicity

Relative to other races, the disagreement between self-reports and administrative records was greatest for AI/AN arrestees. Considering only those arrestees who self-reported a single race (see Table 1), there was very strong correspondence between self-reports and administrative records of race for White and Black arrestees, with somewhat weaker agreement for Hispanic and Asian/Pacific Islander arrestees. Among AI/AN arrestees, however, administrative classification was more likely to ascribe a category of race other than what they self-reported; only two in five (40.7%) arrestees who self-reported AI/AN heritage were also classified administratively as such.

Generally speaking, there was greater agreement between AI/ANs' self-reports and administrative identification in those locations with higher proportions of AI/AN arrestees. Across the 43 ADAM sites, there was a fairly strong association, $r(41) = .73$, $p < .001$, between the proportion of interviewed arrestees who were AI/AN at a site and the likelihood of agreement between self-reports and administrative identification for AI/ANs. There was considerable agreement between self-reports and administrative identification at sites with sizable proportions of AI/AN arrestees (e.g., 77% agreement in Anchorage, and 51% agreement in Albuquerque). Among the 43 ADAM sites, there was a moderately strong positive association between (1) the level of correspondence between self-identification and administrative identification for AI/AN arrestees and (2) the proportion of the county population that reported being AI/AN in the 2000 Census, $r(41) = .50$, $p < .001$. In eight of the sites, zero self-identified AI/ANs were identified administratively, which resulted in a total lack of correspondence between the two classifications (See Appendix A). While it is possible that some of the sites with no AI/ANs identified administratively used record-keeping systems that did not include AI/AN as an option for identifying arrestees, in five of these eight sites (Atlanta, Houston, Los Angeles, Kansas City, and Washington, DC) arrests of AI/ANs were reported by the police to the Federal Bureau of Investigation (FBI) during 2000-2003 (FBI, 2009a, 2009b, 2009c, 2010).

Table 1
Agreement between Self-reported Race and Administrative Records on Race among Single-race Arrestees (N = 83,188)

	Self-reported Race				
Administrative Record of Race/Ethnicity	AI/AN	Asian/Pacific Islander	Black	Hispanic[a]	White
AI/AN	**40.7%**[b]	4.8%	0.1%	0.4%	0.1%
Asian/Pacific Islander	0.3%	**73.1%**	0.0%	0.6%	0.1%
Black	6.2%	4.9%	**97.4%**	2.0%	2.4%
Hispanic	25.9%	3.4%	1.2%	**70.9%**	0.6%
White	26.9%	13.8%	1.3%	26.1%	**96.7%**

[a] Even though those who are Hispanic can belong to any race, the ethnic category Hispanic/ Latino(a) in some police agencies' booking records is treated as if it is equivalent to a race. As a result, information on administrative identification of race gathered from booking files from all ADAM sites used this least common denominator (National Institute of Justice, 2004b). [b] Agreement between the two data sources is shown in **bold type**.

Differences in Differences of Estimated Illicit Drug Use and Alcohol Abuse

Results of analyses considering the effects of the two different identification methods upon illicit drug use and alcohol abuse estimates of AI/ANs relative to non-AI/ANs are presented in Tables 2 and 3. These results indicate that identification method did have an impact upon the estimates. The differences between AI/AN and non-AI/AN arrestees were larger when using administrative identification than when arrestees self-identified.

Comparisons Based on Urine Testing

As shown in Table 2, the results indicate that, for some illicit drugs, but not others, the method of identification did have an impact on the relative proportions of arrestees with positive urine test results. With the exception of marijuana, AI/AN arrestees were generally less likely to test positive for common street drugs when compared to non-AI/AN arrestees. When considering those arrestees identified as single-race AI/AN, there were statistically significant differences between the odds ratios for the comparisons based on administrative identification versus the comparisons based on self-identification for arrestees' use of cocaine, methamphetamine, or for at least one NIDA-5 drug[5], such that AI/AN arrestees were significantly less likely than non-AI/ANs to test positive when identification was based on administrative records rather than self-report. For instance, the odds of AI/AN arrestees testing positive for methamphetamine use were 58% less than the odds for non-AI/AN arrestees when the comparison was based on administrative identification, but only 6% less when the comparison was based on self-identification; given that the confidence intervals of the two odds ratios did not overlap, this difference can be considered statistically significant.

Table 2
Positive Urine Test Results for Commonly Used Illicit Drugs for AI/AN versus Non-AI/AN Arrestees by Method of Racial Identification

	Administrative Identification of Race				Self-identification of Race			
	% Testing Positive				% Testing Positive			
Commonly Used Illicit Drugs by Level of Racial Identification	AI/AN	non-AI/AN	Odds Ratio	95% CI	AI/AN	non-AI/AN	Odds Ratio	95% CI
Single-race	*n* = 2,061	*n* = 80,244			*n* = 4,374	*n* = 77,931		
Marijuana	42.2	42.3	1.00	(0.91-1.09)	42.2	42.3	1.00	(0.94-1.06)
Cocaine	14.5	29.2	**0.41**[a]	**(0.36-0.46)**	19.4	29.4	**0.58**	**(0.53-0.62)**
Methamphetamine	5.6	12.3	**0.42**	**(0.35-0.51)**	11.5	12.2	**0.94**	**(0.86-1.03)**
Opiates	4.7	7.8	0.59	(0.48-0.72)	6.1	7.8	0.76	(0.67-0.87)
Phencyclidine (PCP)	0.4	1.9	**0.21**	**(0.10-0.41)**	1.0	1.9	**0.51**	**(0.37-0.69)**
Any NIDA-5 Drug	51.9	66.6	**0.54**	**(0.50-0.59)**	58.6	66.6	**0.71**	**(0.67-0.75)**
Single-race or Multiracial	*n* = 2,079	*n* = 80,226			*n* = 6,083	*n* = 76,222		
Marijuana	42.2	42.3	1.00	(0.91-1.09)	44.1	42.2	1.08	(1.03-1.14)
Cocaine	14.5	29.2	**0.41**	**(0.36-0.46)**	20.8	29.5	**0.63**	**(0.59-0.67)**
Methamphetamine	5.6	12.3	**0.43**	**(0.35-0.52)**	12.7	12.1	**1.06**	**(0.98-1.15)**
Opiates	4.7	7.8	0.59	(0.48-0.72)	6.1	7.8	0.76	(0.68-0.85)
Phencyclidine (PCP)	0.4	1.9	**0.20**	**(0.10-0.41)**	1.3	1.9	**0.66**	**(0.52-0.83)**
Any NIDA-5 Drug	52.0	66.6	**0.54**	**(0.50-0.59)**	61.7	66.6	**0.81**	**(0.77-0.86)**

[a] Values in **bold type** are for non-overlapping 95% confidence intervals, indicating that the difference between odds ratio for administrative identification and odds ratio for self-identification is statistically significant.

As presented in the bottom half of Table 2, similar results were seen when the illicit drug use of non-AI/AN arrestees was compared to that of single-race or multiracial AI/AN arrestees. There were statistically significant differences between the odds ratios for comparisons using administrative identification and the odds ratios for comparisons using self-identification for arrestees testing positive for cocaine, methamphetamine, phencyclidine (PCP), and at least one NIDA-5 drug. Once again, the differences between AI/AN arrestees and non-AI/AN arrestees were greatest when comparisons were based on administrative identification rather than on self-identification. Regarding methamphetamine use, there was no difference between AI/AN and non-AI/AN arrestees when the comparison was based upon self-identification (OR = 1.06, 95% CI [0.98, 1.15]), whereas the odds ratio for the comparison based on administrative identification indicates that the odds of testing positive were 57% less for AI/AN arrestees relative to non-AI/AN arrestees (OR = 0.43, 95% CI [0.35, 0.52]).

Table 3
Self-reported Illicit Drug Use and Alcohol Abuse and Risk for Substance Dependence for AI/AN versus Non-AI/AN Arrestees by Method of Racial Identification

Form of Illicit Drug Use or Alcohol Abuse by Level of Racial Identification	Administrative Identification of Race: % Reporting AI/AN	Administrative: % Reporting non-AI/AN	Administrative: Odds Ratio	Administrative: 95% CI	Self-identification of Race: % Reporting AI/AN	Self-identification: % Reporting non-AI/AN	Self-identification: Odds Ratio	Self-identification: 95% CI
Single-race Identity	*n* = 2,219	*n* = 88,498			*n* = 4,270	*n* = 85,997		
Binge Drinking Past Month[a]	76.2	47.8	**3.50**[c]	**(3.16-3.87)**	64.3	47.6	**1.98**	**(1.87-2.11)**
Heavy Drinking Past Month[b]	46.5	27.0	**2.35**	**(2.15-2.56)**	38.6	26.9	**1.71**	**(1.61-1.82)**
Past Year Marijuana Use	52.9	52.1	1.03	(0.95-1.12)	52.8	52.1	1.03	(0.97-1.09)
Past Year Cocaine Use	22.1	25.9	0.82	(0.74-0.90)	23.4	25.9	0.88	(0.82-0.94)
Past Year Heroin Use	4.7	7.2	**0.63**	**(0.52-0.77)**	6.6	7.2	**0.90**	**(0.80-1.02)**
Past Year Methamphetamine Use	10.2	15.1	**0.64**	**(0.56-0.74)**	15.6	15.0	**1.05**	**(0.97-1.14)**
Past Year Use of At Least 1 of the Above Illicit Drugs	58.9	63.8	0.81	(0.75-0.88)	61.7	63.8	0.91	(0.86-0.97)
At Risk for Alcohol Dependence	56.8	28.4	**3.31**	**(3.04-3.62)**	45.1	28.2	**2.09**	**(1.97-2.22)**
At Risk for Other Drug Dependence	31.7	38.9	0.73	(0.67-0.80)	35.1	38.9	0.85	(0.80-0.91)
Single-race or Multiracial Identity	*n* = 2,240	*n* = 88,477			*n* = 6,596	*n* = 84,121		
Binge Drinking Past Month	75.9	47.8	**3.44**	**(3.11-3.79)**	61.3	47.5	**1.75**	**(1.67-1.85)**
Heavy Drinking Past Month	46.3	27.0	**2.33**	**(2.14-2.54)**	36.7	26.8	**1.59**	**(1.50-1.67)**
Past Year Marijuana Use	53.0	52.1	1.03	(0.95-1.12)	55.2	51.9	1.14	(1.09-1.20)
Past Year Cocaine Use	22.1	25.9	0.81	(0.74-0.90)	24.3	25.9	0.92	(0.87-0.98)
Past Year Heroin Use	4.7	7.2	**0.62**	**(0.51-0.76)**	6.4	7.2	**0.87**	**(0.79-0.96)**
Past Year Methamphetamine Use	10.2	15.1	**0.64**	**(0.56-0.74)**	17.4	14.8	**1.21**	**(1.13-1.29)**
Past Year Use of At Least 1 of the Above Illicit Drugs	58.9	63.8	**0.81**	**(0.75-0.89)**	64.4	63.6	**1.03**	**(0.98-1.09)**
At Risk for Alcohol Dependence	56.6	28.4	**3.28**	**(3.01-3.58)**	41.4	28.1	**1.81**	**(1.72-1.90)**
At Risk for Other Drug Dependence	31.7	38.9	**0.73**	**(0.67-0.80)**	36.9	38.8	**0.92**	**(0.87-0.97)**

[a] $\geq$ 5 drinks/setting. [b] $\geq$ 5 drinks/setting on $\geq$ 5 out of 30 days. [c] Values in **bold type** are for non-overlapping 95% confidence intervals, indicating that the difference between odds ratio for administrative identification and odds ratio for self-identification is statistically significant.

Comparisons Based on Self-reported Illicit Drug Use and Alcohol Abuse

With the exception of alcohol abuse patterns, the results based upon arrestee interviews (i.e., self-reports) correspond with data from arrestee urine tests. For some illicit drugs, as seen in the top half of Table 3, differences in single-race AI/AN and non-AI/AN arrestees' self-reported illicit drug use were greater when based upon administrative identification rather than self-identification. Although there was no statistically significant difference between self-identified AI/AN and non-AI/AN arrestees for heroin use, the odds of self-reported past year use of heroin were 37% less for AI/AN arrestees compared to non-AI/AN arrestees when based on administrative identification. A similar pattern was found for methamphetamine, with no statistically significant difference for comparisons based on self-identification and a 36% difference when comparisons were based upon administrative identification. With an overlap of the confidence intervals for the odds ratios, a comparison of differences for a composite measure of past year illicit drug use (including self-reported use of marijuana, cocaine, heroin, and/or methamphetamine) indicated no statistically significant difference in reported use based on method of classification. Thus, it initially appears that there are fewer and smaller significant differences in illicit drug use between self-identified AI/ANs and non-AI/ANs.

As with illicit drugs, the differences in self-reported alcohol abuse between single-race AI/AN arrestees and non-AI/AN arrestees were greater when based upon administrative identification rather than self-identification. These differences, however, are in the direction opposite that for illicit drugs, with AI/ANs (either self-identified or administratively identified) *more* likely than non-AI/ANs to report alcohol abuse. For binge drinking over the past month (i.e., having 5 or more drinks at 1 sitting), the odds were 3.5 times higher for AI/AN arrestees relative to non-AI/AN arrestees when identified administratively, but were twice as high when self-identification was used. While not as dramatic, the differences in estimates of heavy drinking (defined at the time ADAM was conducted as having 5 or more drinks in a day 5 or more times in the past month) and the risk for alcohol dependence were also greater in analyses using administrative identification rather than self-identification.

When comparisons of single-race or multiracial AI/AN identity (as seen in the bottom portion of Table 3) were considered, patterns of self-reported illicit drug use and alcohol abuse were similar to those for comparisons using single-race AI/AN identity in some regards, and were more pronounced in others. For alcohol abuse, AI/ANs were much more likely than non-AI/ANs to report problem drinking patterns or being at risk for alcohol dependence when the comparison was based upon administrative identification, rather than upon self-identification. On the other hand, AI/AN arrestees were less likely than non-AI/AN arrestees to report having used heroin, methamphetamine, or any other illicit drug when comparisons were based on administrative identification rather than self-identification. For example, when questioned about ever using heroin, the odds of AI/AN arrestees reporting its use were 38% less and 13% less than the odds for non-AI/AN arrestees when comparisons were based on administrative identification and self-report, respectively. Estimates of lifetime methamphetamine use among AI/AN arrestees were contradictory depending upon the method of classification, as the odds of it being reported by AI/AN arrestees were less than the odds for non-AI/AN arrestees when administrative records were the basis for classification (OR = 0.64, 95% CI [0.56, 0.74]), while the odds of it being reported by AI/AN arrestees were greater than the odds of it being reported by non-AI/AN arrestees when the comparisons were based upon self-identification (OR = 1.21, 95% CI [1.13, 1.29]).

DISCUSSION AND CONCLUSION

As expected given earlier research on the incongruence between multiple methods of identifying AI/AN populations for research purposes, the mismatch between self-identified and administratively identified race was greatest for AI/ANs. More often than not, arrestees who participated in the ADAM program and who self-identified as AI/AN were classified administratively as something other than AI/AN. At the same time, however, when arrestees were classified administratively as AI/AN during the booking process, they almost always identified themselves as AI/AN as well.

The lack of congruence between self-reports and administrative reports of AI/AN identity was not randomly distributed, but instead varied across locations participating in ADAM. Generally, correspondence was closest where the number of AI/ANs was large relative to the general population. In those locations it is possible that jail staff would be more aware of subtle differences in physical and behavioral characteristics that distinguish some AI/ANs from other groups and would have been more likely to recognize certain surnames as markers of AI/AN heritage (e.g., "Yazzie" or "Begay" among the Navajo or names consisting of a noun modified by an adjective or adverb among the Lakota). Jail staff at ADAM sites with large AI/AN populations might also have been more likely to be AI/AN themselves, which could be expected to increase the chances of corresponding identification. Finally, it is possible that sites with stronger correspondence between administrative identification and self-identification of AI/ANs have policies that require booking officers to ask arrestees their race instead of making an assumption.

Two different pictures of AI/AN arrestees' illicit drug use and alcohol abuse emerge depending upon the method of classification. For the most part, the differences between AI/AN and non-AI/AN arrestees' illicit drug use and alcohol abuse were greatest when administrative identification was used to determine who was AI/AN, compared to when self-identification was used. With the general exception of marijuana use, urine test results and interview responses indicated that AI/AN arrestees' illicit drug use was substantially less than that of the general population of arrestees when identification was based on administrative records rather than self-report. For interview measures of alcohol abuse, the same types of differences by method of classification were found, only in the opposite direction than those found for illicit drugs. Relative to comparisons based on self-identification, AI/AN arrestees were much more likely than non-AI/AN arrestees to report alcohol abuse when identification was based on administrative records. All of these patterns—for both illicit drug use and alcohol abuse—held true regardless of whether the comparisons involved only single-race AI/ANs or multiracial AI/ANs as well.

Overall, it is clear that the method of identification did affect estimates of AI/AN arrestees' illicit drug use and alcohol abuse patterns compared to the patterns of non-AI/AN arrestees. The divergence was greatest when administrative identification served as the basis for comparisons. AI/AN arrestees who were identified administratively as such had much lower odds relative to non-AI/AN arrestees for testing positive for common illicit drug use and for reporting illicit drug use in the past year. At the same time, however, the odds that AI/AN arrestees would report problematic alcohol use (i.e., binge drinking, heavy drinking, alcohol dependence) were much higher. The magnitude of differences in estimates of AI/AN and non-AI/AN arrestees' patterns of illicit drug use and alcohol abuse was reduced when those comparisons were based upon ADAM participants' self-identification. Although self-identified AI/ANs were more likely than non-AI/ANs to report alcohol abuse, the difference was much less substantial than when the comparison was based upon administrative identification. For a few of the illicit drugs analyzed, the self-identified AI/AN arrestees actually reported higher rates of past year use than did non-AI/AN arrestees.

While our results provide clear indication that the method of identification can influence the outcomes of research involving AI/ANs, these results should be considered in light of a few limitations. A primary issue with our analyses is that we have used the ADAM data in a way that goes beyond the program's original intent of providing quarterly estimates of local drug use trends. Despite claims to the contrary (e.g., Cooper, Fox, & Rodriguez, 2012, p. 25), ADAM data are not a *nationally* representative sample of recent arrestees in metropolitan counties and, therefore, cannot be seen as a source of reliable national estimates of arrestee substance use (Heliotis et al., 2001). Our multisite pooled analyses essentially treat the participating ADAM arrestees as a convenience sample which, ultimately, precludes generalization of our results beyond the sample considered.

A second limitation of this study is that the AI/AN arrestees who were part of the ADAM sample are not likely to be representative of AI/AN arrestees in general. The ADAM sample is comprised mostly of arrestees who resided in metropolitan areas: Roughly 94% of all arrestees were residents within an urban ZIP code, and those with residence in a rural ZIP code were outnumbered by homeless or transient arrestees (i.e., those without a residential ZIP code). The proportion of AI/AN arrestees from urban ZIP codes was greater than the 70% of the general AI/AN population residing in urban areas according to the 2000 U.S. Census (Urban Indian Health Institute, 2004); the odds of an AI/AN ADAM study participant having an urban residence were more than six times greater (OR = 6.71) than the odds for AI/ANs in general. An additional limitation of our study is that the results could be affected by nonresponse bias, i.e., the one in five arrestees who refused participation in ADAM could have had different illicit drug use and alcohol abuse patterns relative to those arrestees who did participate. Furthermore, given that the only measures of race in ADAM were based upon self-reports or upon administrative identification, we were unable to consider the effect of identification by tribal membership on estimates of illicit drug use and alcohol abuse. Finally, it is necessary to reiterate that even if the sample were nationally representative and there was little nonresponse bias, it would only be an accurate reflection of the population of male arrestees. As such, the estimates of illicit drug use and alcohol abuse would apply only to those males who have been accused of a criminal act that has brought them to the attention of the police, and would not apply to the general population.

Despite these limitations, the findings presented above support the argument that the methods used to identify study participants as AI/AN ultimately can affect research outcomes. Had the comparisons been made only on the basis of administrative identification, the differences between AI/AN and non-AI/AN arrestees' illicit drug use and alcohol abuse would have appeared to be rather extreme. On the other hand, had those comparisons been made based solely upon self-identification, we would have observed mixed results, with the odds of AI/AN arrestee illicit drug use and alcohol abuse being lower than the odds of non-AI/AN arrestee illicit drug use and alcohol abuse for some substances and higher for others.

The substantial discrepancies between self-identification and administrative identification for AI/ANs during initial booking following arrest have ramifications for the study of decision making throughout the disposition of criminal cases because the identification of race made at the booking stage is duplicated for later criminal justice decisions in most paper (e.g., Illinois Bureau of Identification, 2010) and electronic (e.g., Draper, 2002) record-keeping systems in the U.S. As a result, the reliability of demographic information about AI/ANs in studies of disparities in criminal justice decision-making (e.g., when police refer cases for prosecution, when prosecutors decide to lay charges, or when judges impose sentences) is particularly precarious. Ultimately, just as it has consistently been demonstrated in the field of public health, the way that AI/ANs are identified for research purposes should also be of concern in the study of criminal justice.

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FOOTNOTES

[1] In the mid-1970s, for instance, in California the "Race" for a given arrestee would be (1) White, (2) Mexican-American, (3) Negro, (4) American-Indian, (5) Chinese, (6) Japanese, or (7) Other (California Bureau of Criminal Statistics, 1976). By the time that the ADAM program was being conducted a quarter century later the variable was referred to as "Race/Ethnicity" while continuing to treat Hispanics as a racial group (California Criminal Justice Statistics Center, 2004).

[2] Although urine testing is a direct measure of drug use, it is not a perfectly reliable measure of drug use. The enzyme multiplied immunoassay test used in ADAM has a false positive rate between 4 and 5% for cocaine and marijuana, as confirmed by gas chromatography/mass spectrometry tests (which are said to be totally accurate; Harrison, 1995).

[3] This is now called the National Survey on Drug Abuse and Health.

[4] The Venn Diagram Plotter software used to make Figure 1 was freely provided by the Proteomics Research Resource for Integrative Biology of the Pacific Northwest National Laboratory. It can be downloaded from http://omics.pnl.gov/software/VennDiagramPlotter.php.

[5] The NIDA-5 (National Institute of Drug Abuse) drugs include cocaine, marijuana, methamphetamine, opiates, and phencyclidine (PCP; Zhang, 2004). (When using ADAM data to report estimates of illicit drug use, it is common practice to report on individual drugs comprising the NIDA-5 as well as the NIDA-5 as a whole; therefore, in this study, analyses were also done separately on each drug.)

Appendix A
Correspondence between Methods of Identification of AI/AN Arrestees, by ADAM Site, 2000-2003

ADAM Site[a]	Total Number of Interviews	AI/AN Arrestees Interviewed		Percentage Self-identified also Administratively Identified[b]
		Self-identified	Administratively Identified	
Albany, NY	1,777	84	8	6.0
Albuquerque, NM	1,938	394	214	50.8
Anchorage, AK	1,929	662	537	76.6
Atlanta, GA	2,196	58	0	0.0
Birmingham, AL	1,880	25	7	24.0
Boston, MA	111	9	1	11.1
Charlotte, NC	1,739	61	4	6.6
Chicago, IL	2,875	23	5	4.3
Cleveland, OH	3,656	72	5	2.8
Dallas, TX	3,519	106	4	0.9
Denver, CO	2,895	223	82	35.0
Des Moines, IA	1,708	68	14	17.6
Detroit, MI	985	16	1	6.3
Fort Lauderdale, FL	352	12	0	0.0
Honolulu, HI	2,005	87	7	4.6
Houston, TX	852	47	0	0.0
Indianapolis, IN	2,774	66	3	3.0
Kansas City, MO	550	10	0	0.0
Laredo, TX	770	14	2	14.3
Las Vegas, NV	4,349	275	36	10.5
Los Angeles, CA	460	34	0	0.0
Miami, FL	950	26	0	0.0
Minneapolis, MN	2,986	238	135	50.0
New Orleans, LA	2,553	11	0	0.0
New York, NY	3,505	83	6	3.6
Oklahoma City, OK	2,793	341	127	33.4
Omaha, NE	2,030	111	37	29.7
Philadelphia, PA	2,256	70	1	0.0
Phoenix, AZ	6,399	585	331	49.7
Portland, OR	2,851	222	43	15.8
Rio Arriba County, NM	201	35	10	22.9
Sacramento, CA	2,593	224	20	5.8
Salt Lake City, UT	2,643	226	130	52.7
San Antonio, TX	2,677	352	1	0.0
San Diego, CA	2,959	233	27	11.2

continued on next page

Appendix A, Continued
Correspondence between Methods of Identification of AI/AN Arrestees, by ADAM Site, 2000-2003

ADAM Site	Total Number of Interviews	AI/AN Arrestees Interviewed		Percentage Self-identified also Administratively Identified
		Self-identified	Administratively Identified	
San Jose, CA	3,173	267	10	1.5
Seattle, WA	3,423	309	107	31.7
Spokane, WA	1,807	232	81	28.0
Tampa, FL	800	29	1	0.0
Tucson, AZ	2,514	315	120	31.4
Tulsa, OK	1,357	277	95	31.8
Washington, DC	665	24	0	0.0
Woodbury County, IA	262	40	28	67.5

[a] Not all sites participated in all 4 years considered. [b] Some arrestees administratively identified as AI/AN did not self-identify as AI/AN, so these percentages do not necessarily equal the number of administratively identified AI/ANs divided by the number of self-identified AI/ANs.

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