The Influence of Prisons on Inmate Misconduct: A Multilevel Investigation

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ABSTRACT

This paper presents results of multilevel analyses of prisoner misconduct for the population of over 120,000 federal prisoners incarcerated during June 2001. Prior research has focused upon individual-level explanations of inmate misconduct, but this study explicitly examined whether prisons vary in their influence upon inmate misconduct. This paper demonstrated that model specification makes a difference in our understanding of which variables are related to misconduct. Second, the paper demonstrated that type of misconduct is important for understanding the effects of covariates of misconduct. Finally, the paper demonstrated the ease by which results of multilevel models can be used to compare the performance of prisons.

INTRODUCTION

This article focuses upon the effectiveness of prison operations, sometimes referred to as the prison environment, and inmate misconduct. Little quantitative research has been conducted in this area with the exception of the attention given to prison crowding. Prison crowding has been the justification for state and federal court intervention into prison operations, and this probably fueled the academic interest in prison crowding. Determining whether prisons differ in their impact upon inmate misconduct is important because it potentially allows for designing safer and more humane prisons and because the information can be used to address the relative effectiveness of public and private prisons, as discussed later. This is not to say that there has been no recognition given to the importance of prison management and prison operations. Researchers have long pointed to the link between correctional philosophy, management implementation, and prison operations (DiIulio, 1987, 1991; Jacobs, 1977; Wright, 1994). Researchers have also pointed to the consequences of prison operations and management and how this sets social conditions that can lead to either catastrophic outcomes, especially riots, or prison reform (Colvin, 1992; Goldstone & Useem, 1999; Useem & Goldstone, 2002). These studies, though, were based upon case studies to provide empirical content for systemic investigations. While useful, case studies are limited in the sense that they are time consuming to complete and not ideally suited to dealing with the individual details needed to compare the more mundane daily operations of a large number of prisons. What is needed are proactive criteria that flow from daily prison operations (and data collection) which can be used to produce detailed evaluations of those prison operations. This research begins to address that need.

Many criminologists have theorized about the effect of prison conditions on behavior within prison and after release. Some institutional characteristics are thought to affect the frequency of misconduct by increasing or decreasing opportunity (e.g., security level and effective operations) while others are thought to increase the skills and motivation for a crime-free lifestyle (e.g., prevalence of rehabilitation programs) or, conversely, to have a criminogenic effect (e.g., exposure to delinquent peers). Other researchers have examined the effectiveness of prison programs on reducing in-prison misconduct, criminal activity upon release, and return to drug use (see volume 3 of The Prison Journal in 1999 and Rhodes et al., 2001).

Bottoms (1999) has summarized a great deal of prior research on prison order and has argued that the prison environment exerts an influence upon inmate misconduct, especially interpersonal violence, above and beyond the influence of the characteristics of inmates. He particularly focuses on the social organization of prisons characterized by six factors. He notes that prisons are "total institutions" (Goffman, 1961, factor 1), organized around the administration of punishment (factor 2). Prisons have an internal organization composed of routine activities such as eating, work, and "locking up" that organize the time and space of an institution. These patterns can vary tremendously and can produce different social climates (factor 3). The daily routine of prison life of both prisoner and officer (factor 4) is instrumental in understanding prison life. Understanding how these routines "...structure and sustain social institutions over time..." and "... how individuals assimilate new routines..." (Bottoms, 1999: 209) is, according to Bottoms, a somewhat overlooked facet of prison social organization. There is a complex interrelationship between the captors and captives (factor 5, Sykes, 1958). Because the prison is a relatively self-contained environment and separated from many external influences, the management approach within a particular establishment can have a dramatic effect on institution culture (factor 6). In Great Britain, this latter point is often characterized as a difference in the prison regimes. Some managers emphasize regimented and restrictive environments. Others endorse a more relaxed and “democratic” approach. As Bottoms notes, “...prison scholars have failed adequately to develop socially contextualized accounts of prison violence that make real connections to the lived daily experience of prison administrators (Bottoms, 1999: 212).

In this paper, we make an attempt to analyze environmental influences on inmate misconduct. We agree with Bottoms that the organizational influences are relational and dynamic and not easily captured with static structural variables. As a first step, we begin with structural variables that proxy some of the dynamics of the social organization of prisons. The empirical question is whether prison management, through the means at its disposal, creates an environment within a prison that then exerts an influence upon inmate misconduct that is independent of the individual or collective characteristics of the inmates and staff who live and work at the prison. This is the primary question driving the present study. Whether we can explain the dynamics of the different environments that have this impact upon misconduct may be beyond the ability of the current data except as we incorporate this dynamic with the proxy measures at our disposal.

Despite speculation about the effects of prison, most often expressed as the debate between importation and deprivation (Paterline & Petersen, 1999), most empirical research on inmate misconduct has focused upon individual-level factors (Harer & Langan, 2001; Harer & Steffensmeier, 1996). To date, there has been only one empirical study that analyzed inmate misconduct with statistical techniques that allowed for adequate and simultaneous accounting of both individual- and prison-level effects upon misconduct (Wooldredge, Griffin, & Pratt, 2001). Wooldredge and his colleagues used the multilevel methods developed by Raudenbush and Bryk in the U.S. (2002) and Goldstein in the U.K (1995). These models allow for the correlation of observations within groups. For example, it would be naive to assume that inmate behavior is independent of other behavior occurring in the same institution, although this assumption is nearly universal. At the very least, the effective sample size is decreased as a function of the degree of correlation of behaviors within the different institutions (Snijders & Bosker, 1999: 16-35). Wooldredge and his colleagues demonstrated the potential of hierarchical linear models, but they recognized limitations to the data they analyzed and that significant conceptual and methodological problems remained.[1] These include (1) model specification, (2) identification of the appropriate type of misconduct to analyze, and (3) the use of HLM models to produce performance measures of the prisons themselves. Using misconduct data to assess the relative performance of individual prisons is particularly relevant in the current climate of privatizing government functions.

THINKING ABOUT MISCONDUCT

Misconduct, defined as the failure to follow explicit rules, is a slippery concept as anyone with children can testify. The concept becomes even more muddled when we examine it within prison. Criminologists have long been skeptical of prison misconduct as an indicator of criminal proclivity for at least two reasons. First, criminologists have been concerned with the amount of

[1] It is worth noting that we follow convention and call the models analyzed here hierarchical linear models. Technically, the models are nonlinear. The outcome measures analyzed are binary, but the measures are analyzed with a logistic transformation and that permits linear relationships to exist on the right-hand side of the equation.

discretion exercised by correctional staff in enforcing prison rules [Poole, 1980 #10; Light, 1990 #11], although an early examination of the disciplinary process in the prison system that is the subject of this study suggested that it was not racially biased in an obvious way (Hewitt, Poole, & Ragoli, 1984). Additionally, some forms of misconduct in prison, such as violence, are probably less susceptible to manipulation, and they are examined separately here. Second, the theoretical importance of prison misconduct is unclear because prison rule infraction and law violation may not share the same etiology. Prison rules have been questioned as overly restrictive and encompassing behaviors that are legal in other contexts. However, Langan and Camp (2002) recently demonstrated similarities in the types of inmates who commit serious and nuisance types of misconduct. As for the increased surveillance of inmates in prison that troubles some criminologists, we view it as an advantage. While not every act of misconduct in prison is captured, we expect prison misconduct data to more accurately reflect the universe of prison behavior than arrest or conviction data do for street crimes. In other words, official prison records contain less observational measurement error than official police records. Additionally, prison populations are "relatively homogenous on many crime-causal variables" (Hirschi & Gottfredson, 1983: 561).

In the Wooldredge et al. (2001) study, all forms of misconduct were collapsed into the dependent variable. We think that it makes sense to both examine misconduct overall as well as parsed into categories defined by substantive interest. Treating all misconduct as being equal implies a theory of criminality whereby crime is but one representation of an underlying propensity toward reckless and impulsive behavior (Gottfredson & Hirschi, 1990). We are not necessarily opposed to such a position, but it is not yet known whether a single latent trait underlies all crime and misconduct. Accordingly, we classified misconduct into the substantive areas related to violence, drug use, prison accountability (escapes), property offenses, security-related offenses (interfering with daily operations), and a residual category. This categorization is consistent with traditional categories of inmate misconduct and was used recently by Gaes and his colleagues in examining gang activity within the federal prison system (Gaes, Wallace, Gilman, Klein-Saffran, & Suppa, 2002).[2]

Thinking About Aggregate Influences Upon Misconduct

This study examines whether prisons differ in ways that influence misconduct by prisoners. Ideally, we would examine in complete detail the causes of these institutional differences, but we do not have available indicators of the quality of staff-prisoner relationships that Bottoms (1999) argues are crucial to understanding prison operations. Nonetheless, we do incorporate analysis at the level of the prison and we do consider a variety of theoretically meaningful factors at the institutional level. With the exception of crowding, institutional properties of prisons have not often been employed in explaining inmate misconduct. We wanted to address this oversight in greater detail than provided by Wooldredge et al. (2001). Institutional characteristics are interesting both theoretically and practically. Practically, prison administrators are interested in knowing, for example, what mixture of inmate demographic characteristics produce the lowest levels of violence. In this research, we are interested in two

[2]In a longer report, we examined misconduct categorized in two additional ways. In one classification, we grouped misconduct in terms of whether it represented illegal activity in the free world or whether the behavior was specifically prohibited in prison. In a different scheme, we used offense severity inherent to the Bureau of Prison's system of classifying misconduct. Those results are available from the authors. Essentially, the results mirror those reported later in this paper where context does matter. We dropped sexual misconduct from the current analysis as there was no significant variance for this type of misconduct at the institutional level.

types of influences upon inmate misconduct: the aggregate characteristics of the inmates and the aggregate characteristics of staff. The residual variance at the aggregate level will be assumed to be related to differences in prison performance across the different institutions. Hopefully, future research will be able to identify those sources of prison performance, and that is where we believe Bottom's theoretical work on prisoner-staff relationships can be most useful. In the present study we evaluated an ecological variable, composites of inmate demographics, indicators of staff-inmate relations, and contextual variables representing the collective criminal propensity of an institution.

Ecological Variables. We looked at one "ecological factor" thought to influence inmate behavior, prison crowding. As already noted, prison crowding has generated the most interest from researchers.[3] Based in part upon findings from rat experiments, researchers hypothesized that crowding would lead to increased violence among inmates. Of course, the theory is more sophisticated than that of a simple stimulus producing a response, and researchers note that crowding produces intermediate psychological states, such as depression, that then lead to misconduct. The most recent empirical study in this tradition is provided by Wooldredge et al (2001). Using multilevel methods, Wooldredge and his colleagues entered crowding as a covariate describing prisons and found a positive effect that was contrary to findings in previous crowding research (Gaes, 1985, 1994). Of course, having only one measure to describe the

[3]In preliminary analyses, we looked at other institutional-level variables. For example, we looked at admission rates, percentage of inmates who were Hispanic, staff to inmate ratios, custody staff to inmate ratios, percentage of custody staff who were female, median sentence length, and percentage of inmates incarcerated on a drug charge. None of these variables were included in final models as they proved not to be significant, and the models analyzed here could not support additional variables at the institutional level.

complexity of prisons placed the study in grave peril of model misspecification, a fact recognized by Wooldredge et al.

Inmate Demographics. Inmate demographic composition included a racial composition index and average inmate age. We used the normalized integration index, most recently described by Reardon (2000; 2002), as a measure of racial composition. The integration index measures the concentration of any one racial group at a given prison. A score of zero means that one racial group dominated the composition where a value of one means that the racial groups were evenly represented. The three racial groups used to compute the normalized integration index in this study were white, black, and other. Because of the small numbers of inmates who were Asian and American Indian, the only two racial categorizations used by the Bureau of Prisons (BOP) to supplement black and white, Asian and American Indian were combined together into the other category.

Staff-Inmate Relations. Variables that reflect staff-inmate relationships included percentage of female staff, percentage of white staff, and the proportion of staff who had one year or less of tenure. Staff experience is probably an important aggregate indicator. Camp and Gaes (2002), for example, noted an apparent relationship between staff stability and inmate misconduct in a survey of private prisons. In this study, we controlled for the percentage of staff who were in their first year on the job with the expectation that institutions with greater numbers of inexperienced staff would be at greatest risk of misconduct. Given the mismatch that often exists between race and sex of staff and inmates, these factors remain of concern to correctional administrators. Concerns about normalizing the prison experience and complying with equal opportunity legislation led current prison administrators to make greater use of minority and female staff than was true historically. As such, it is useful to examine whether having different mixes of staff produce differences in prison environments from a policy standpoint. We also used an indicator variable to assess whether an institution was in its activation phase. This latter variable is particularly important to prison administrators. New prisons hiring large numbers of new staff have greater potential to change their racial or sex composition than prisons with staff already in place. While this variable obviously captures more than just staff-inmate relations, it does represent in a static way, the process of relationships and "institution culture" that evolve over time. The dynamics of prison culture seem to depend, in large part, in the way a prison is activated, creating a kind of socio-cultural momentum (Fleisher, 2000).

Collective Criminal Propensity. We introduced a variable that captured the collective propensity to criminality of the inmate population by adding the average custody score for a particular institution. In prior studies, the effect of propensity has been proxied by entering dummy variables for the institutional security level of the prisons. We preferred the average custody score because it discriminates among institutions that are assigned the traditional classifications of minimum, medium, etc. Instead of treating all medium-security prisons, for example, as having the exact same mix of inmates, the average custody score provides an indication of which prisons are "softer" or "harder" places to do time. Currently, prison administrators house inmates together based on their propensity for violence, misconduct, and escape. The idea behind this is that grouping dangerous inmates together allows prison administrators to concentrate surveillance resources on those most in need, and it reduces opportunities for predation on weaker inmates. But there may be unintended and undesirable consequences associated with "prisonization" that outweigh these benefits (Clemmer, 1940), and others have used a discontinuity approach to examine the effect of individual-level custody scores across security levels (Chen & Shapiro, 2002),.

All of the institutional variables used here are to some extent under the control of prison administrators. Heeding Bottom's admonishment, that it is time to move in the direction of informing our understanding of prison administration and consider institutional variables that compose the "social organization" and context of inmate-to-inmate and inmate-to-staff interactions, we built models to investigate those relationships

Thinking about Individual-Level Influences Upon Misconduct

Most of the individual-level predictors of misconduct that we used are well-established in the literature, although we add an important predictor variable seldom used in prior research. Primarily, we used actuarial measures. We used the initial custody classification score computed by the BOP upon the inmate's entry into the system as a sentenced felon.[4] Others have found that this was a positive predictor of violent misconduct (Harer & Langan, 2001), and we included the squared term to allow for the effect to dampen at higher scores. Higher custody scores indicate a more serious history of criminality most of which occurs prior to prison admission. We also incorporated the prior history of the misconduct under question, a measure of past propensity toward crime that occurs within the prison setting. This measure has rarely been used to study prison misconduct, although Gaes et al., (2002) used this measure of criminal propensity to study gang-related behavior.

[4]The custody classification score ranges from 0-27 points, where the larger the score the greater the risk of violent and other misconduct. The score is the sum of six items including: type and number of prior incarcerations (0-3), seriousness of current offense (0-7), recency and seriousness of history of violence (0-7), recency and seriousness of history of escape (0-3), having a pending charges or a subsequent sentence in another jurisdiction and the seriousness of the charge (0-7), whether inmate was released without bond prior to conviction (up to 3 points subtracted).

In addition to the actuarial measures of past propensity toward misconduct, we included inmate demographic variables. Variables that controlled for race, sex, age, and citizenship were employed. Race was categorized as black, white and other. White was the excluded category when dummy variables were created for analysis. The BOP actually uses four categories for race, but the two categories of Asian and American Indian contain small counts at any one given institution. We did not have specific hypotheses in mind for the effect of race given our extensive attempt to capture demonstrated propensity toward crime. If, for example, blacks are more likely to engage in violence because of their greater exposure to a subculture of violence, then race should be unrelated to future violence after controlling for individual differences in past violent behavior as this is a more direct control for subculture of violence. Indicators for race are nevertheless included because they may capture residual variance in individual criminal propensity not fully captured by history of prior violence. Age was expected to show the almost universally reported negative association with misconduct (Gendreau, Goggin, & Law, 1997). Since the effect of age cannot extend indefinitely, the square of age was also included in models to allow the linear effect of age to taper off at some point. For sex, we expected males to be more involved in misconduct even after controlling for prior history of propensity. Citizenship was classified into four groups: U.S. citizens, Mexican citizens, Cuban citizens, and other foreign nationals. U.S. citizens comprised the comparison group when dummy variables were created for citizenship. No real expectations existed for the effects of citizenship, except to note that non-U.S. citizens tend to have less known about their previous criminal history than U.S. citizens. This knowledge is critical to the ability to properly classify inmates during the initial custody classification.

There was also a control for the amount of time that an inmate was at risk for the type of misconduct being examined. The at risk variable captured either how long it had been since the inmate had a prior instance of the misconduct under question or how much time had elapsed from the current prison admission up to the month used to record misconduct. The latter definition was used if the inmate had no prior history of misconduct. Regardless, the at risk variable does not include time that the inmate spent outside of a main prison, either during transport, time spent in jails awaiting trial, etc.

DATA AND METHODS

The data collected covered inmates who were incarcerated during June 2001 in the Federal Bureau of Prisons.[5] The BOP electronically records inmate information in areas such as educational and psychological programming, medical care, disciplinary infractions, and inmate movement. We were able to use archival information generated from the normal backup process used for these databases, collectively known as SENTRY, to create the data sets for our analysis. The individual-level demographic, criminal history, and misconduct data taken from SENTRY were supplemented with data taken from a management information system used by BOP managers that is known as Key Indicators/Strategic Support System (KI/SSS). The KI/SSS system summarizes data from SENTRY and other data sources for managerial consumption. Most of the information we captured from KI/SSS pertained to aggregate staff characteristics.

The need to include staff information in our analyses did generate problems. The staff data summarized in KI/SSS were taken from the personnel data maintained for the BOP. Staff

[5] We plan to expand the current study to include inmates incarcerated between January 2000 and December 2001. In addition to the one month types of analyses conducted here, we will analyze the trends represented in the monthly prison performance measures generated from the misconduct data over the entire time period.

are identified as working at a specific institution based on the budget codes for the respective prisons. One problem is that workers at private prisons under contract with the BOP are not paid by the BOP directly, so there is no corresponding information for private prison workers in the personnel database or any other centralized database maintained by the BOP. In addition, there is a problem with the availability of staff data for minimum security satellite camps. Many institutions incarcerating more secure inmates, such as heavily staffed medium- and high-security prisons, have lightly staffed camp facilities located in close proximity. The relationship between the camp and main institution is reciprocal. The camp benefits by not having to run full kitchen operations, medical operations, and other functions since these services are available from the main facility. The main institution benefits by having a work cadre of minimum-security inmates to perform tasks outside of the secure perimeter of the main prison. The problem for our analysis is that workers split their time at both facilities, and it is impossible to determine from the automated systems which staff are assigned to the camps. As such, in analyses where we include staff data, we were also forced to drop inmates at satellite camps from the analyses.

To deal with the problem of missing staff data, and because we were very interested in examining the performance of the private prisons under contract to the BOP, we ran two sets of models, with and without staff data. In the models without staff data, we were able to include all facilities including the satellite camps and private prisons. In the results and discussion sections, we discuss the ramifications of not including the staff data in the models of inmate misconduct. In essence, we examine whether the other covariates in the models are sensitive to the exclusion of the staff data, and we correlate the prison performance measures generated from the respective models to assess whether it is possible to trust the performance measures from models that exclude staff information.

Since the data are operational data, the problem of other types of missing data were greatly minimized. The only variable (other than the variables generated with staff data) for which there was significant amounts of missing data was for the variable measuring custody classification at intake. For the analysis of all inmates, there were 127,894 inmates available for analysis. However, 6,843 (or 5.3 percent) inmates were excluded from the analyses because they were missing custody classification information. Primarily, the only individuals in the BOP without an initial custody classification are pre-trial inmates or inmates in other special statuses (such as individuals brought in by prosecutors for psychological evaluations). Because of the small amount of missing data, cases with missing data for any of the models were deleted from the model under consideration. Thus, the inferences we draw from these analyses pertain to sentenced prisoners.

The general methodological plan was as follows. We compared the current BOP technique for evaluating institution performance with respect to inmate misconduct (which are monthly rates for the various types of misconduct) with a method that adjusts for the types of individuals housed in the facilities (including their prior institution misconduct) and aggregate characteristics of the prisons (e.g., crowding and the aggregate composition of inmates and staff). To do this, we invoked a multilevel approach that accounts for the nesting of inmates within different prisons.[6] Such techniques are now common in the social sciences, and several

[6]Ideally, the method would also account for the movement of inmates between institutions during the time period being examined. Multiple membership models allow for this structure in the data (Browne & Goldstein, 2001; Hill & Goldstein, 1998). Unfortunately, the software we used (HLM) does not allow for multiple membership models. This is not critical in our analysis as 94.7 percent of inmates are in only one institution during June 2001. In

applications in criminology and penology have been published in addition to the study by Wooldredge et al. previously discussed (Camp, Saylor, & Harer, 1997; Horney, Osgood, & Haen, 1995; Sampson & Raudenbush, 1999).

Since the counts of misconduct in any one month period are relatively low for inmates engaged in misconduct, we dichotomized our outcome variables. The models were "intercepts as outcomes" in HLM jargon, meaning that the intercepts were the only level-1 coefficients treated as random and modeled at level-2. Schematically, the logistic models were as follow:

Level 1:

$$\log\left[\frac{prob(Y_{ij} = 1)}{1 - prob(Y_{ij} = 1)}\right] = \beta_{0j} + \sum \beta X_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \sum \gamma W + u_{0j}$$

The βX represent the effects of the fixed, level-1 coefficients. Level-1 coefficients were entered to control for age, race, Hispanic ethnicity, sex, time at risk of misconduct, citizenship, count of prior instances of misconduct, and initial custody classification score. Continuous variables–age, time at risk, count of prior misconduct, and the custody classification score–were centered around the respective grand means. Centering produces meaningful values of the intercept (the expected value when all independent variables take on a value of 0) and provides numerical stability during estimation. Dummy variables were not centered as 0 is already a meaningful

preliminary analyses not reported here, we compared models with inmates who were only at one institution to models with all inmates and found no substantive differences. We assigned those inmates who were at more than one prison to the prison where they spent the most time. Only 0.6 percent of the inmates spent less than 50 percent of their time at their institution as determined by this method.

value for these variables. An error term at level-1 was not included in the equation as the value for the error term is fixed in logistic models to allow model identification.

The intercepts in the level-1 equations, the $\beta_{0j,}$ were modeled with the level-2 aggregate measures, the γW, and the unique contribution of each facility, the u_{0j}. The u_{0j} form the performance measures, or how much the level of misconduct is pushed up or down for the typical inmate by serving time at the prison in question. The γW terms included crowding (ecological), average inmate age (demographic), the normalized integration index for race (demographic), the average custody classification score (collective criminality), and whether the institution was in activation (aggregate staff-inmate relations). In some of the models without staff characteristics, an aggregate dummy variable for the facility type of satellite low was included.[7] For some types of misconduct, this variable was dropped when the models failed to converge. For the models using inmates who were not in private prisons or satellite camps, the level-2 models of the intercepts also included additional staff-inmate relationship variables including variables for the percentage of staff in their first year of employment, the percentage of female staff, and the percentage of white staff.

To assess both the correspondence between models with staff variables and models without, as well as the correspondence between measures of prison performance as traditionally defined by the BOP (unadjusted rates) and as calculated here, correlations were computed between the respective ratings. Spearman rho correlations were used in favor of the traditional

[7]Satellite low facilities are a recent innovation in the BOP. Because foreign citizens who may be deported at the completion of their sentence are prohibited by policy from serving time in prison camps, inmates who are otherwise of the lowest risk have traditionally served time in the more secure (and costly) low-security prisons. Satellite low facilities are a compromise. They are staffed more like prison camps and are associated with main facilities, but they have more perimeter security than the typical prison camp. There are other inmates who qualify for satellite lows than foreign citizens, but this is the largest group in the new type of facility.

Pearson correlation coefficients. The rho statistic allows for comparing the rankings produced by different models, which is our main interest. For one selected type of misconduct, graphs are presented to further highlight the findings of the correlation analysis that demonstrates certain models of misconduct are more appropriate for constructing comparisons than others. Finally, a different type of graph is presented, called a "caterpillar" plot, to demonstrate how prisons can be compared with the performance measures derived from the HLM models.

RESULTS

Descriptive statistics for the two data sets that were analyzed are presented in Table 1. Panel A of Table 1 presents the results for all inmates under the supervision of the BOP whether in a BOP-operated prison or a prison operated for the BOP by a private vendor. While the models based on the data presented in Panel A are all-inclusive of the sentenced inmates at the BOP, the database does not include information on the staff variables as this information was not available for BOP satellite camp facilities and private prisons. Panel B of Table 1 presents the information for the data analyzed on only BOP prisons, excluding private prisons and satellite camps. For the remainder of this paper, for parsimony, we will sometimes refer to the data set containing all of the sentenced inmates as the "inclusive" data set and the data set limited to inmates in institutions excluding private prisons and satellite camps as the "limited" data set.

All of the outcome variables listed in Table 1 are dichotomies, where "1" indicates that there was an instance of misconduct. As such, the means reported in Table 1 for the outcomes represent the proportion of inmates with the misconduct in question. For example, the value of 0.03 for all misconduct means that in June of 2001 about 3 percent of BOP inmates were involved in some type of misconduct. The other variables that received a dummy coding of 0 and

1 are interpretable in the same manner. For example, the value of 0.07 for female means that 7 percent of the BOP inmates held in June 2001 were women. The other statistics presented in Table 1 are self-evident.

Since we examined all misconduct considered together as well as categorized, plus we ran the models against all prisons where the level-2 staff variables were excluded (inclusive data set) and a subset of prisons where the level-2 staff data were included (limited data set), we generated fourteen separate models. This was a daunting amount of information to present and discuss. We simplified the presentation by organizing the discussion around the impact of the covariates at the different levels instead of stepping through the models one by one. At the end of the results section, we also discuss the performance measures obtained from the empirical Bayes residuals of the models.[8]

Effects of Individual-Level Characteristics upon Misconduct

At the individual level, there were two consistent findings across all models, regardless of how misconduct was categorized. First, the count of previous instances of the type of misconduct being modeled as an outcome was positive and significant, and the effect was the strongest predictor during the month in question.[9] The t-values for this variable are the largest in

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[8]Because of the large amount of information that could have been presented for the fourteen models examined here, we had to make some decisions about condensing the information. To make the information most compact, we decided to simply present the odds ratios for the coefficients in the models with an indication of whether the variable attained significance at the p=.05 level for aggregate effects and p=.01 for individual-level effects.With over 100,000 observations at the individual level, a reviewer felt that we needed to increase the level of certainty for these coefficients. We do not show it in the tables, but the variance for the performance measures, the empirical Bayes estimates, taken from the HLM models are significant in all fourteen models.

[9]Because of space limitations, the t-values for the coefficients are not presented, but complete results are available from the authors upon request. Since the coefficients presented in the table are all odds ratios, a positive coefficient is denoted by an odds ratio in excess of 1, and a negative coefficient for a variable produced an odds ratio less than one. For example, for a dummy variable, an odds ratio of .75 would mean that the variable produced a 25 percent *drop* in the likelihood of the outcome. Conversely, an odds ratio for a dummy variable of 1.22 would mean

any of the models examined here, both for the inclusive and limited data sets. Individuals with higher counts of prior misconduct were more likely to be involved in a current instance of misconduct. Another consistent finding was the effect of age. All other things being equal, older inmates were less likely to be engaged in misconduct than younger inmates. Age was significant across all categories of misconduct, and the finding held for both the inclusive and limited data sets, with one exception. Age was not significant for property offenses when all prisons were included in the model. The findings for age and count of prior misconduct were expected given prior research.

The effect of age was curvilinear in many of the models, as noted by the positive and significant coefficient for the squared term for age. However, the squared term for age when entered into some models caused both the main effect of age as well as the squared term to become nonsignificant. In these models, the squared term for age was removed, and the negative and significant main effect for age was restored. The squared term for age was not entered into models of either the inclusive or limited data sets for analyses of violent misconduct and drug misconduct. In addition, the squared term for age was not entered into the model of property misconduct for the analysis of the limited data set that included the additional staff variables.

In addition to the count of prior instances of misconduct, another actuarial type of variable was significant in most of the models, the base custody score that the inmates had upon admission to incarceration. Inmates with more serious histories of criminal behavior were at greater likelihood of a current instance of misconduct. This result held in all models except for the models of drug and security-related misconduct. Inmates with more serious histories of

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that the dummy variable produced a 22 percent increase in the likelihood of the event.

criminal behavior were no more likely to be found guilty of a drug violation or a breach of security than other inmates. A nonsignificant finding was also noted for property offenses, but only when the data were restricted to the prisons for which staff data were available. As can be seen in the results of the models, the effect of custody score was not always linear as the squared custody score attained significance and was negative in many of the models. This simply means that the rate at which misconduct increases was lower at higher levels of the custody score than it was at the lower levels.

Other demographic variables examined presented some interesting results. For the sex variable, females only differed significantly from males in the model of drug misconduct, and that finding only held in the model run against the limited data set that excluded minimum security prisons. In these prisons, females were less likely than males to be involved in drug misconduct. But after controlling for the other variables in the model, both at the individual and aggregate levels, females did not differ from males in their likelihood to be involved in the other forms of misconduct. The race variables were also not usually significant in the models examined. The coefficients for the other race variable never attained significance in the models, indicating that other race individuals did not differ from whites in their likelihood of misconduct. Being African American was only significant in raising the likelihood of misconduct for a few categories. It is also notable that being African American did not raise the likelihood of being involved in violent misconduct as reported by Harer and Steffensmeier (1996).[10] Another interesting finding for African Americans is that they were less likely to be found guilty for a

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[10]In models not reported here, being African American did increase the likelihood of having a *history* of violent misconduct. So, in our population of inmates, blacks were more likely than whites to have been convicted in the past for a violent act, but they were at no greater risk in a given month once previous history was known.

drug misconduct. This finding replicates the finding reported by Harer and Steffensmeier and holds in models with and without the staff variables.

Being African American consistently raise the likelihood of only one category of misconduct, the other types of misconduct.[11] Interestingly, Hispanics did not differ from non-Hispanics in their likelihood of misconduct in any of the categorizations of misconduct.

Citizenship variables did make a difference in many of the models, but only Mexican citizenship. We attribute this finding to the fact that prior record is often unknown or otherwise underestimated for Mexican citizens – with the result that citizenship becomes an indicator of criminal propensity. Of course, it would seem that the same logic should have been true for Cubans and citizens in the other citizenship category, but it was not.

Finally, at the individual level, the effect of time at risk was consistently significant for only one category of misconduct, although not for all misconduct considered together. Time at risk was significant, lowering the odds of misconduct in both the inclusive and limited data sets for accountability types of misconduct. Inmates who had longer periods without an instance of misconduct were less likely to have any instance of that misconduct. This same effect was noted for violence but only when the data covered all prisons and the models did not include staff variables.

Effects of Aggregate-Level Characteristics upon Misconduct

The aggregate inmate variable that showed up consistently whether the models included staff variables or not was the average security level of inmates at the prison, but it was not a

[11] In analyses not reported here, a model of security-related was run that did not include the staff variables and only included the institutions for which staff data were available. The coefficients for African American were not significant in these models suggesting that the nonsignificant results reported in Table 3 were a product of the restricted data and not the model specification.

significant predictor in all models. The average security level of inmates was not important in predicting all types of misconduct considered together, but it was significant in predicting some types of misconduct that are of special concern to prison administrators, namely violent misconduct and drug misconduct (refer to Tables 2 and 3). For both of these measures, the effects of being in a prison with more inmates having a higher collective propensity to crime was to increase the level of these forms of misconduct. Interestingly, the effect of the collective propensity was reversed for property types of misconduct. The effect of being in a prison with inmates having a higher collective criminal propensity was to reduce the odds of a property offense, although the effect was only significant in the model using all prisons and no staff variables.

For the other aggregate inmate variables, e.g., average age of inmates, the integration index for race, and crowding, the effects were nonsignificant in most of the models, and where the effects were significant, they attained significance in the models of the limited data set for which staff data were available. The effect of crowding was significant in only two of the fourteen models. Crowding increased the odds of other misconduct in both the inclusive and limited data sets by a half percent in the month under study.

The integration index for race did not have a significant effect upon any of the categorizations of misconduct when the data came from all of the prisons. It did have a significant effect upon one model when the staff variables were included and the prisons were limited to those with staff data. In the models of security-related misconduct, the effect of more racially integrated prisons was to lower the likelihood that the typical inmate would be involved in these types of misconduct. Generally speaking, the average age of inmates at the prisons did not have a significant effect upon misconduct categorized in the different ways examined here.

The findings for the aggregate staff variables depended upon the category of misconduct. For the model of all misconduct, both the percentage of staff who were female and the percentage of staff who were white were linked with misconduct. At institutions with higher percentages of white and female staff, the typical inmate was more likely to be involved in all forms of misconduct considered together. The percentage of white staff was also positively associated with misconduct in the models for accountability types of misconduct and property misconduct. In short, the finding that prisons with greater numbers of white staff had more misconduct of all types was “pushed” by more innocuous forms of misbehavior. Percentage of white staff was not significant in models of violence and drug use.

A similar pattern is noted for the finding for percentage of female staff for all types of misconduct considered together. The percentage of female staff is positively associated with misconduct in models of drug use and accountability. Drug use is a particular concern to prison administrators, but there was no significant finding for violent misconduct.

The finding for the last staff aggregate variable, the percentage of staff working in their first year, was not significant for the majority of the models. Only the models for security-related misconduct showed a significant effect for inexperienced staff. For these models, having higher numbers of staff in their first year on the job increased the likelihood that the typical inmate would be convicted of this type of misconduct.

Measures of Institution Impact Upon Misconduct

The consequences of the different choices for measures of institutional performance can be understood from Table 4. In the column labeled, "Correlation with Models Containing Staff Information," the ranks of institutions based upon the HLM models of the inclusive data sets were compared to the ranks of institutions based upon HLM analyses of the limited data sets. The latter contained level-2 aggregate staffing data. The correlations indicate that for most categories of misconduct, the rankings of institutions based upon results from models with level-2 staffing covariates produce different results than models without these variables. For some categories of misconduct (notably for violent misconduct), the correlations between the results produced by the different models were quite high, in excess of 0.95. However, for the model of drug misconduct (see Table 3 above), the correlation between the respective models was only 0.872. While this may seem to be a large correlation by the usual standards of the social sciences, the correlation masks the fact that the rankings produced by the different measures can be quite discrepant.

For example, Graph 1 presents the results for the different HLM measures of all misconduct for the 96 prisons for which there was staff information available. The two HLM-produced measures of performance correlated at 0.917 as shown in Table 4. In the top panel of the graph, the institutions are presented in the order in which they ranked on the outcome measure as defined by the model for all prisons where level-2 staff variables were <u>not</u> included. In the bottom panel of the graph, the same ordering of institutions is used, but now the performance measure is based upon the model that included level-2 information representing contextual information about staff. As can be seen in the graph, there are some institutions for which the inclusion of the aggregate staff characteristics produced large differences. There are three institutions, in particular, that ranked fairly high on estimated inmate misconduct when the measure was determined by the model excluding level-2 staff variables. Ranking high on these graphs is not good because that means the institution is above the BOP average. When level-2 staff covariates were added, these institutions were still above their respective expected values, but they were only marginally higher.

Table 4 also shows that the unadjusted measures of prison performance (the raw rate of prison misconduct without any modeling) were simply not adequate. This can be seen in the last four columns of the table. In the column labeled "Correlation with Unadjusted Rates," the correlations of the HLM models for all institutions were compared to unadjusted rates. As can be seen there, the correlations were more modest than the correlations between the performance measures generated from the two HLM models. The lowest value was for violent misconduct where the correlation was only .497. The highest correlation between the HLM results and the unadjusted results was for security-related misconduct, where the correlation was 0.828. Even for this measure, the correlation is less than one presented above for the two HLM-produced measures of performance for all misconduct. And in that example, we saw significant differences in the rankings of institutions. In the last three columns of Table 4, an alternative measure is presented to represent the relationship between the unadjusted and the HLM-produced measures.

The displacement of rankings was calculated as the difference between the ranking score (from 1 to 156) produced by using unadjusted rates and the HLM-produced performance scores. The absolute value of the difference was then taken to compute the median difference. As can be seen in Table 4, the median differences were quite striking. Take all misconduct, for example. For all misconduct, the typical institution moved 28 places (either up or down) as the result of basing the measure of performance on HLM-produced results instead of unadjusted measures. The range is also presented in Table 4. For all misconduct, the range of change varied between 0 and 138. At least one institution moved 138 places depending upon which model of prison performance was used. The results are similar for the other measures. Another way to make this comparison is with a graph similar to that used to compare the two HLM-produced measures of prison performance. In Graph 2, all 156 institutions are ranked on the unadjusted measure of all misconduct in the top panel of the graph. In the bottom panel, the same ranking of institutions is used, but the measure of prison performance is based upon the results of the HLM analyses. As can be seen in Graph 2, the differences were quite noticeable. In particular, two institutions who were on the far right side of the graph, indicating poor performance were actually doing quite well when the factors known to influence misconduct were entered into the HLM model, and thus controlled. These institutions actually had lower levels of misconduct than expected.

Although it is not the intention of this paper to compare the performance of all of the BOP and private prisons for all of the measures of misconduct presented here, it is our intention to demonstrate how readily the information from HLM models can be presented graphically to illustrate the relative performance of different prisons. While the actual values of the measures are not readily understood, the comparative performance of different prisons as well as whether a specific prison is significantly above or below the BOP average performance is easily determined. Caterpillar graphs for all types of misconduct and violent misconduct are presented, respectively, in Graphs 3 and 4. The models were based upon all prisons, even though we recognize that the models that included staff variables were superior. The two measures were deliberately chosen because of their methodological properties, and we wanted to use all prisons for a substantive reason. Any type of misconduct has a relatively high reliability (.638) where violent misconduct has a lower reliability (.389).

The graphs were limited to low-security prisons to make the plots less dense and also because we wanted to make a point about four prisons in particular. The four prisons identified in Graphs 3 and 4 have been closely monitored as part of an evaluation of prison privatization in the BOP (McDonald et al., 2002). Taft Correctional Institution (TAF in the graphs), is operated by Wackenhut Corrections Corporation for the BOP. The other three prisons have been formally designated as the most appropriate comparisons for Taft because they are the same size as the Taft prison, they were built upon the same architectural design, and they activated at about the same time as Taft (Camp, Gaes, & Saylor, 2002).

Graphs 3 and 4 contain plots of the empirical Bayes residuals that result from the HLM analyses of the performance measures for the different prisons. Each residual has a 95 percent confidence interval placed around the estimate, and the plots are ordered from best performance to worst. Best performance is obviously an institution where an inmate's propensity to commit misconduct was reduced. As is readily apparent when Graphs 3 and 4 are compared, the indicators of institution effect upon all misconduct have tighter confidence intervals than was noted for violent misconduct. This is a corollary to the respective values for the reliability of the measures. Several other points are worth making about the plots. For " all misconduct," it is apparent that Taft was not doing well in comparison to the BOP average. The confidence interval for the Taft measure was well above the value of 0, meaning that the typical inmate at Taft was more likely to be involved in misconduct than at the average BOP prison. In contrast, the three BOP comparison prisons, FCI Forrest City (FOR), FCI Yazoo City (YAZ), and FCI Elkton

(ELK) were doing well on this measure. All of these institutions were clearly below the BOP average. The respective performance of the institutions can also be inferred from the graph. The confidence interval for Taft is much higher than the respective confidence intervals for Forrest City, Yazoo City, and Elkton. Formally, a Bonferonni or similar adjustment would be necessary when making multiple comparisons, but with such a large difference, the general finding would hold.

The results for institution effects upon "violent misconduct," represented in Graph 4, demonstrate the price that is paid by using measures that have lower reliability. In this plot, many more of the confidence intervals for the different prisons include 0, meaning that differential performance is harder to uncover. Nonetheless, there are some institutions on both ends of the scale where performance is considerably above or below the average level for the BOP. One of the BOP comparison institutions falls into the "better" end of the outlier institutions. At Forrest City, the typical inmate is less likely to be involved in violent misconduct. For the other prisons of interest, their confidence intervals include 0. When comparing the four prisons of interest, it is obvious that the confidence intervals overlap for all of them. This means that even though Forrest City is doing better than the BOP average, they are not necessarily doing better than Taft.[12]

DISCUSSION

It is clear that Bottom's (1999) argument that the social organization of prisons is important in understanding inmate violence was supported by our findings. Indeed, almost all

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[12]Of course, these interpretations are predicated on whether or not we trust the models without staff variables as they provided the data points for Graphs 3 and 4. As stated above, the models including staff variables do produce slightly different results. We think these models are to be preferred, but they are not available at this point for making comparisons between BOP and private prisons.

inmate misconduct is affected by institution context. While we were not able to explicitly operationalize all of Bottom's theoretical components, we feel that we clearly demonstrated that compositional and contextual effects of staff, inmate, and ecological variables impact the probability of many forms of misconduct in addition to, and separate from, individual-level characteristics of inmates. Future research must uncover the most relevant aspects of the prison organization following theoretical proposals by Bottoms and others.

At the outset of the paper, we noted that Wooldredge et al. had provided a promising start in demonstrating the effectiveness of using hierarchical linear models to examine prison misconduct. We also noted that significant methodological work remained, to tease out the consequences of model specification, to specify the appropriate types of misconduct to analyze, and to demonstrate how HLM models can be used to generate performance measures for prisons. The results from the various models we have presented shows the importance of model specification. For example, where Woodredge et al. found a significant and positive effect for inmate crowding, we rarely found such an impact when we entered other variables at level-2 of the models. In analyses not reported here, we did reproduce the positive and significant effect for crowding when it was the only level-2 variable, similar to the specification used by Woodredge et al. That specification was not adequate on theoretical or methodological grounds. Also, we saw that proper model specification made a difference for individual-level variables. For most forms of misconduct, we did not replicate the positive association between misconduct and being African American that others have reported. As we noted, this was due to our level-1 specification. Adding the relevant history of misconduct to the level-1 specification vitiated the effect. Because race is such an important and politically sensitive variable, we also tested whether a level-2 specification alone could affect the substantive interpretation of this variable. Using the data set that contained violence as the dependent variable and included all of the institutions, we found that we could exclude the history of violence at level 1 but still eliminate the significance of race at level 1 by adding the level-2 specification. This would imply that there are institutionally relevant factors that researchers must explore when drawing inferences about individual behaviors. Since the racial effects were not the primary purpose of this study, we did not try to discover which variable(s) in either level 1 or level 2 were important in limiting the influence of the level-1 racial effect.

The findings for models with staff variables suggested that such variables should be included in models of inmate misconduct. While developing performance measures from models without these variables is clearly superior to the current BOP practice of presenting unadjusted rates, better models can be obtained if the data are collected in the future.

It is also clear that some breakout of misconduct into meaningful categories is necessary to interpret the meaning of level-1 and level-2 structural variables. For example, in the all-misconduct model, two of the level-2 staff variables were significant. Prisons with higher percentages of whites and females placed inmates at a higher likelihood of all misconduct. But when we looked at the three different categorizations of misconduct, the results implied a more revealing interpretation of the data. The effect of having a higher percentages of white and female staff was most pronounced on the less severe forms of misconduct. Admittedly, we are making a value judgement about which types of misconduct are more serious, but the judgement is probably shared by many. Prisons with higher percentages of white and female staff were no more likely to have inmates engaged in violent misconduct.

Finally, we noted that Wooldredge et al. (2001) did not extend the HLM results to their full capabilities by which performance measures could be constructed for different prisons. We think that the simple caterpillar plots that we presented provide an easy method of summarizing institutional performance, and the plots are readily interpretable by both research professionals and practitioners.

CONCLUSIONS

We demonstrated a number of points in this paper. First and foremost, we established that prisons do differ in their effect upon individual inmates' propensity to become involved in misconduct. In other words, prison management and operations do make a difference in a smaller context than generating riots or reforms as demonstrated by other researchers. This means that as researchers, we have the capability to use operational data to identify problematic prisons before more catastrophic outcomes become manifest. On a more technical note, we showed that model specification makes a difference in understanding which variables are related to misconduct. In particular, we found at the individual level that controlling for previous history of misconduct made a substantive difference in the interpretation of the effect of race on misconduct. Properly specified hierarchical linear models can greatly expand our substantive knowledge about the correlates of misconduct and criminal behavior. At the aggregate level, we found that crowding was not significant in more adequately specified models. We also demonstrated that the type of misconduct is important to our understanding of the effects of structural variables, especially some of the staff covariates. We established that relying exclusively upon the categorization of "all misconduct" has the potential to mislead scholars in their investigation of the effects of structural variables. There does not appear to be a one-sizefits-all answer. Finally, we demonstrated how easily the results of HLM models can be used to generate meaningful comparisons of prison performance, whether our interest in performance is relevant to the debate about prison privatization or simply motivated by our interest in well-managed prisons This is consistent with Bottom's conclusion that the management and social organization of prisons are equally important as individual-level variables in understanding prison order.

We maintain that penologists and criminologists must begin to investigate individual- and aggregate-level influences simultaneously in their models. We are certainly not the first researchers to sing that tune (see Wooldredge et al., 2001). However, we think that the research presented here throws down the challenge to researchers who approach prison misconduct in other ways. Future research must provide a more thorough test of inmate-staff relationships at the institutional level. Likewise, it would be desirable to have dynamic risk factors at the individual level in the models, factors that capture such things as motivation to change or assessments of cognitive deficiencies. Much work remains to be done, but the possibilities are exciting.

Table 1. Univariate Statistics for Variables Considered in HLM Models

	Panel A. All Prisons, No Staff Variables			Panel B. Prison Subset, Staff Variables		
	N	Mean	SD	N	Mean	SD
Outcome Variables						
All Misconduct	120,855	0.03	0.18	101,890	0.04	0.19
Violent Misconduct	120,855	0.01	0.08	101,890	0.01	0.08
Drug Misconduct	120,855	0.00	0.07	101,890	0.00	0.07
Security Misconduct	120,855	0.01	0.08	101,890	0.01	0.09
Accountability Mis.	120,855	0.01	0.11	101,890	0.01	0.11
Property Misconduct	120,855	0.01	0.08	101,890	0.01	0.08
Other Misconduct	120,855	0.00	0.07	101,890	0.00	0.07
Level-1 Variables						
Prior Any Misconduct	120,855	2.23	5.57	101,890	2.51	5.98
Prior Violent Miscon.	120,855	0.35	1.47	101,890	0.41	1.59
Prior Drug Misconduct	120,855	0.29	1.26	101,890	0.34	1.36
Prior Security Miscon.	120,855	0.26	0.74	101,890	0.28	0.78
Prior Accountability Mis.	120,855	0.74	2.19	101,890	0.83	2.35
Prior Property Miscon.	120,855	0.30	0.91	101,890	0.33	0.97
Prior Other Misconduct	120,855	0.25	0.96	101,890	0.28	1.03
At Risk: Any[†]	120,855	6.85	7.88	101,890	6.77	7.84
At Risk: Violent[†]	120,855	9.76	10.14	101,890	9.85	10.22
At Risk: Drug[†]	120,855	10.03	10.19	101,890	10.16	10.26

Table 1. Continued

	Panel A. All Prisons, No Staff Variables			Panel B. Prison Subset, Staff Variables		
	N	Mean	SD	N	Mean	SD
At Risk: Security†	120,855	9.86	10.31	101,890	10.05	10.46
At Risk: Accountability†	120,855	9.02	9.55	101,890	9.12	9.63
At Risk: Property†	120,855	9.61	10.04	101,890	9.79	10.17
At Risk: Other†	120,855	10.12	10.32	101,890	10.32	10.44
Custody Score (0-27)	120,855	8.30	5.31	101,890	9.00	5.33
Custody Score Squared	120,855	97.18	112.56	101,890	109.35	117.29
Age (Years)	120,855	36.03	10.44	101,890	35.82	10.33
Age Squared	120,855	1407.05	844.69	101,890	1390.04	832.29
Mexican Citizen (1=Yes)	120,855	0.14	0.35	101,890	0.13	0.33
Other Citizen (1=yes)	120,855	0.11	0.31	101,890	0.12	0.33
Cuban Citizen (1=yes)	120,855	0.02	0.14	101,890	0.02	0.15
Female (1=yes)	120,855	0.07	0.26	101,890	0.06	0.24
African Amer. (1=yes)	120,855	0.41	0.49	101,890	0.43	0.49
Other Race (1=yes)	120,855	0.03	0.17	101,890	0.03	0.17
Hispanic (1=yes)	120,855	0.30	0.46	101,890	0.30	0.46
Level-2 Variables						
Crowding	156	113.52	36.31	96	128.26	33.51
Average Inmate Age	156	36.73	2.33	96	35.87	1.86
Integration Index–Race	156	0.45	0.10	96	0.47	0.08
Prison Activating (1=yes)	156	0.10	0.30	96	0.04	0.20
Average Custody Score	156	7.09	3.66	96	8.91	3.53
% Female Staff	N/A	N/A	N/A	96	26.66	8.23
% White Staff	N/A	N/A	N/A	96	76.35	17.75
% Staff in First Year	N/A	N/A	N/A	96	8.36	6.04
Satellite Low	156	0.02	0.14	N/A	N/A	N/A

† The "at risk" variables are expressed as the time at risk in 100 day intervals.

Table 2. Odds Ratio Coefficients for Models with Camps and Private Prisons, No Staff Variables Included

	All	Violent	Drug	Security	Account	Property	Other
Average Age	0.97	1.01	1.01	0.95	0.98	1.02	0.95
Integration–Race	0.66	0.99	0.83	0.39	0.94	0.34	0.27
Activation (1=yes)	1.04	0.98	0.76	0.70	1.01	0.95	1.61
Crowding	1.00	1.00	0.99	0.99	1.00	1.00	1.01*
% White Staff	NA	NA	NA	NA	NA	NA	NA
% Female Staff	NA	NA	NA	NA	NA	NA	NA
% Less than 1 Year	NA	NA	NA	NA	NA	NA	NA
Average Custody Score	1.01	1.13*	1.20*	0.99	1.01	0.95*	1.00
Satellite Low Prison	0.2 7*	NA	NA	0.62	0.35	0.48	0.27
Count Prior Misconduct	1.05*	1.12*	1.18*	1.302*	1.10*	1.27*	1.20*
Initial Custody Score	1.07*	1.13*	1.06	1.02	1.07*	1.03*	1.09*
Custody Score Squared	0.99*	0.99*	0.99	NA	0.99*	NA	0.99
Time at Risk	0.99	0.99*	0.99	1.01	0.99*	1.00	0.99
Age	0.91*	0.96*	0.97*	0.91*	0.88*	0.95	0.88*
Age Squared	1.00*	NA	NA	1.00	1.00*	1.00	1.00*
Mexican Citizen(1=yes)	1.38*	2.57*	1.01	0.84	1.38*	1.49*	1.06
Cuban Citizen (1=yes)	1.23	1.59	0.83	0.87	1.08	1.50	2.06
Other Citizen (1=yes)	0.96	1.40	0.61	0.80	1.11	0.85	0.95
Female (1=yes)	1.03	1.10	0.27	1.17	0.97	1.01	1.07
Af. American (1=yes)	1.03	1.14	0.53*	1.21	1.13	0.96	1.36*
Other Race (1=yes)	0.97	1.02	1.06	0.86	1.10	0.85	0.79
Hispanic	0.96	1.11	1.06	0.94	0.95	0.93	0.97
Reliability of u_j	0.66	0.58	0.52	0.66	0.63	0.59	0.43

* Significant at $p \leq 0.05$ for level-2 variables (top panel), $p \leq .01$ for level-1 variables (bottom panel)
Number of Prisons=156
Number of Individuals=120,855
NA=Not Applicable or Not Applied

Table 3. Odds Ratio Coefficients for Models without Camps and Private Prisons, Staff Variables Included

	All	Violent	Drug	Security	Account	Property	Other
Average Age	.96	0.99	0.95	0.96	0.95	1.01	0.95
Integration–Race	.38	1.30	0.10	0.11*	0.49	0.39	0.34
Activation (1=yes)	1.02	0.92	0.9 6	0.91	0.80	1.36	1.48
Crowding	1.00	1.00	1.00	1.00	1.00	1.00	1.01*
% White Staff	1.01 *	0.99	0.99	1.00	1.01*	1.01*	1.01
% Female Staff	1.02*	1.02	1.05*	1.00	1.04*	1.01	0.99
% Less than 1 Year	1.01	1.02	1.02	1.03*	1.00	0.99	1.01
Average Custody Score	1.03	1.14*	1.30*	0.98	1.03	0.94	1.01
Satellite Low Prison	NA	NA	NA	NA	NA	NA	NA
Count Prior Misconduct	1.05*	1.12*	1.18*	1.31*	1.10*	1.26*	1.20*
Initial Custody Score	1.08*	1.13*	1.03	1.06	1.07*	1.07	1.09*
Custody Score Squared	0.99 *	0.99*	0.99	1.00	0.99*	0.99	0.99
At Risk (per 100 Days)	0.99	0.99	0.99	1.00	0.98*	1.00	0.99
Age	0.91 *	0.96*	0.97*	0.91*	0.88*	0.96*	0.89*
Age Squared	1.00*	NA	NA	0.98	1.03*	0.94	1.00*
Mexican Cit. (1=yes)	1.41 *	2.65*	0.99	0.89	1.38*	1.52*	1.1 7
Cuban Citizen (1=yes)	1.26	1.59	0.81	0.90	1.12	1.61	2.17
Other Citizen (1=yes)	0.96	1.41	0.63	0.83	1.11	0.91	0.93
Female (1=yes)	0.92	0.74	0.10*	1.32	0.69	1.07	0.99
Af. American (1=yes)	0.92	1.13	0.54*	1.11	1.14	0.93	1.36*
Other Race (1=yes)	0.93	1.01	1.05	0.88	1.04	0.84	0.78
Hispanic	0.95	1.12	1.10	0.89	0.93	0.89	0.97
Reliability of u_j	0.74	0.58	0.52	0.66	0.63	0.59	0.43

* Significant at $p \leq 0.05$ for level-2 variables (top panel), $p \leq .01$ for level-1 variables (bottom panel)
Number of Prisons =96
Number of Individuals=101,890
NA=Not Applicable or Not Applied

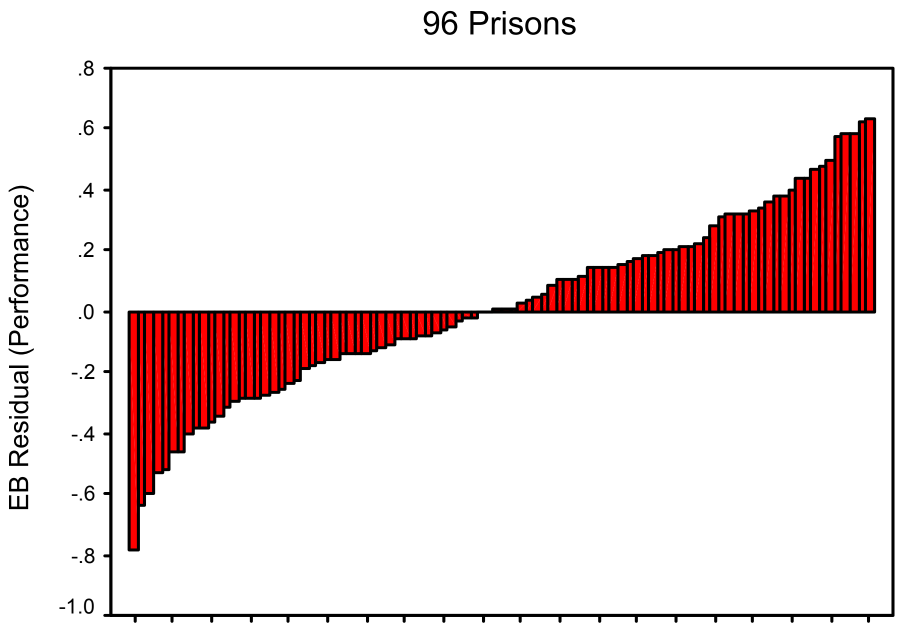
Table 4. Comparability of Performance Measures Derived From HLM Models with All Institutions (No Staff Variables) with Alternative Definitions

Outcome Variable	Correlation with Models Containing Staff Information	Correlation with Unadjusted Rates	Median Displace-ment*	Min. Dis-placement	Max. Dis-placement
All Misconduct	0.92	0.65	28.0	0	138
Classification 1					
Violent Misconduct	0.97	0.50	34.0	1	133
Drug Misconduct	0.87	0.58	25.0	0	129
Security Misconduct	0.9 5	0.83	16.0	0	92
Accountability Miscon.	0.90	0.78	22.0	0	93
Property Misconduct	0.94	0.86	11.8	0	97
Other Misconduct	0.94	0.57	29.5	0	134

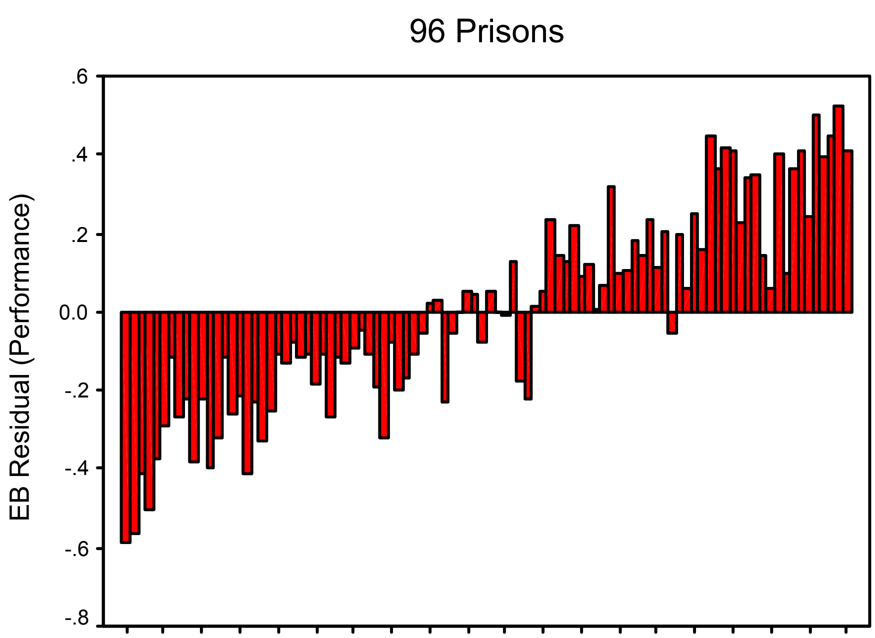
* Median Displacement as defined here is the median of the absolute values of the differences in the rankings produced with unadjusted rates and the rankings produced with the HLM models for all institutions (without staff variables). The measure is dependent upon the number of items being ranked. In all cases, 156 separate prisons were ranked with the respective measures, so the magnitude of the displacement values for the different types of misconduct can be compared.

Graph 1
Comparing Adjusted Measures of Prison Performance for ALL MISCONDUCT
from HLM Models With Staff Variables and Without

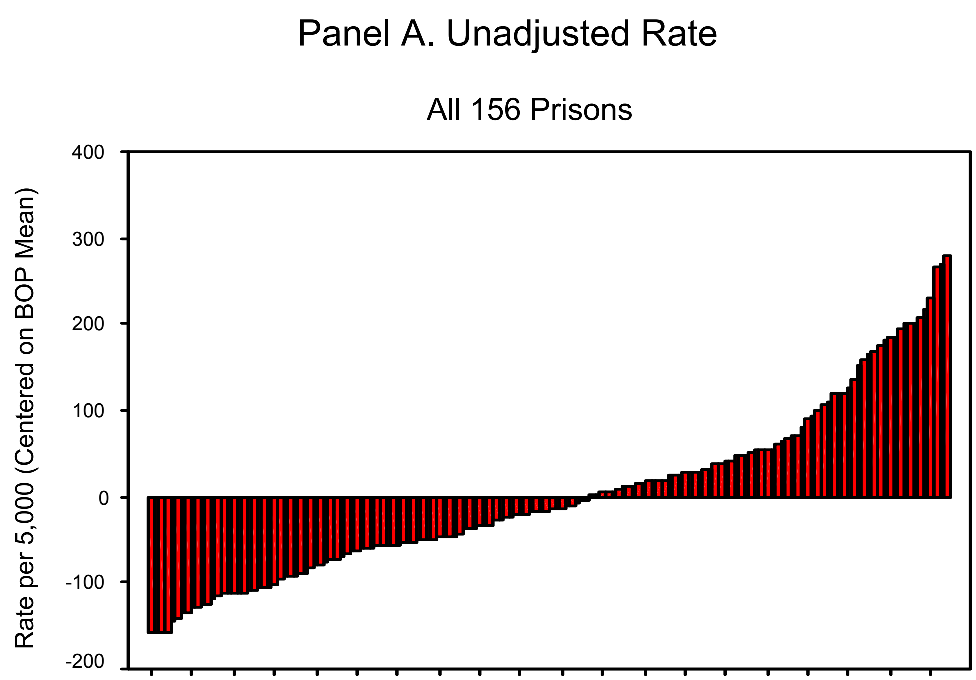
Panel A. HLM Model Without Staff Variables

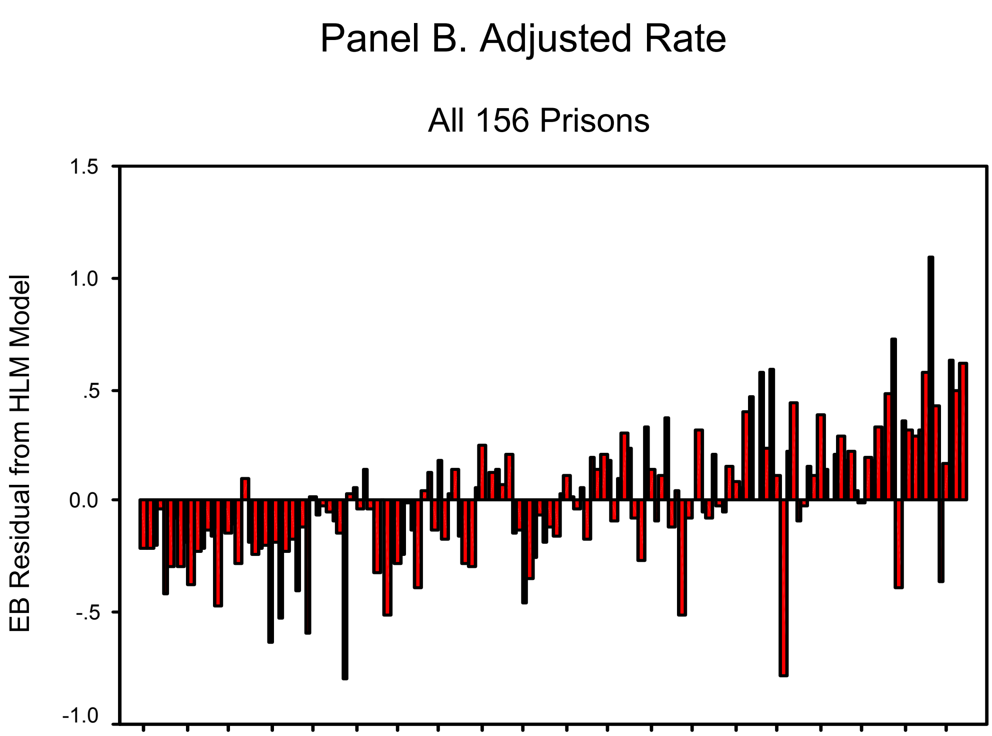


Panel B. HLM Model with Staff Variables



Graph 2
Comparing Unadjusted and Adjusted Rankings of Prison Performance
ALL MISCONDUCT

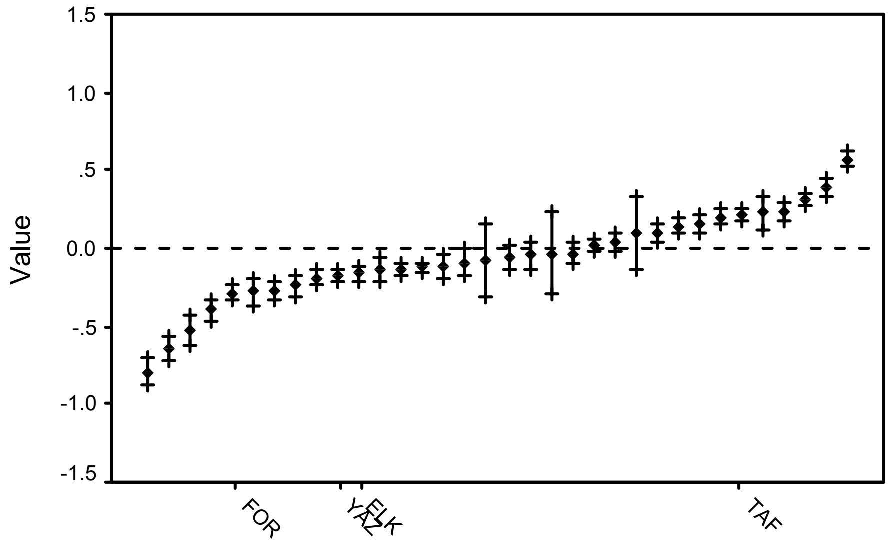




Graph 3.

Prison Effect on Likelihood of ALL MISCONDUCT

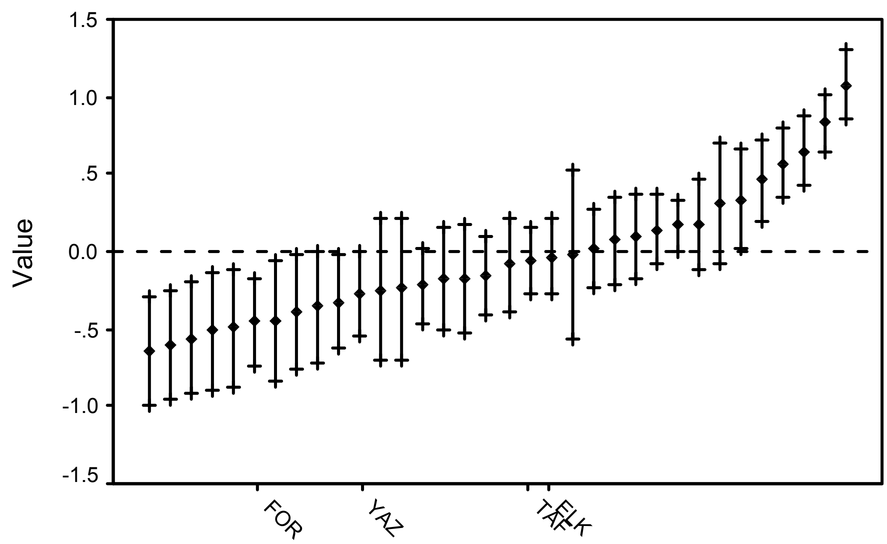
Low-Security Prisons Only



Graph 4.

Prison Effect on Likelihood of VIOLENT MISCONDUCT

Low-Security Prisons Only



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Appendix. Misconduct Codes and Categories

Code	Short Description	Category
100	Killing	Violence
101	Assaulting with Serious Injury	Violence
102	Escaping–Secure Custody or with Violence	Security
103	Setting a Fire	Violence
104	Possessing A Dangerous Weapon	Violence
105	Rioting	Violence
106	Encouraging Others to Riot	Violence
107	Taking a Hostage	Violence
108	Possessing a Hazardous Tool	Violence
109	Possessing Drugs/Drug Items (Replaced with 113)	Drug
110	Refusing to Take a Drug Test	Drug
111	Introduction of Drugs/Drug Items	Drug
112	Use of Drugs/Drug Items	Drug
113	Possessing Drugs/Drug Items	Drug
197	Phone Abuse, Criminal	Security
198	Interfering with Staff–Greatest Severity	Security
199	Disrupting Conduct–Greatest Severity	Security
200	Escaping	Accountability
201	Fighting with Another Person	Violence
203	Threatening Bodily Harm	Violence
204	Extorting/Blackmail/Protecting	Violence
205	Engaging in Sexual Acts	Sexual*
206	Making Sexual Proposal/Threat	Sexual*
207	Wearing a Disguise or Mask	Security
208	Interfering with Security Devices	Security
209	Adultering Food or Drink	Property
211	Possessing Staff Clothing	Security
212	Engaging in Group Demonstration	Security
213	Encouraging Refusal of Work	Security
215	Introducing Alcohol into Facility	Drug
216	Bribing Official, Staff Member	Security

Appendix. Continued

Code	Short Description	Cat. 1
217	Exchanging Money for Contraband	Security
218	Destroying Property over $100	Property
219	Stealing	Property
220	Using Martial Arts/Boxing	Violence
221	Being in Unauthorized Area with Opposite Sex	Accountability
222	Possessing Intoxicants	Drug
223	Refusing to Take Alcohol Test	Drug
224	Assaulting without Serious Injury	Violence
297	Phone Abuse, Non-Criminal	Security
298	Interfering with Staff–High Severity	Security
299	Disruptive Conduct–High Severity	Security
300	Indecent Exposure	Sexual*
302	Misusing Medication	Drug
303	Possessing Unauthorized Money	Property
304	Lending for Profit	Property
305	Possessing Unauthorized Item	Property
306	Refusing Work/Program Assignment	Accountability
307	Refusing to Obey an Order	Accountability
308	Violating a Condition of Furlough	Other
309	Violating a Condition of a Community Program	Other
310	Being Absent from Assignment	Accountability
311	Failing to Work as Instructed	Accountability
312	Being Insolent to Staff Member	Other
313	Lying or Falsifying Statement	Other
314	Counterfeiting or Forging Document	Property
315	Participating in Unauthorized Meeing	Security
316	Being in Unauthorized Area	Accountability
317	Failing to Follow Safety Regulations	Accountability
318	Using Unauthorized Equipment/Machinery	Security
319	Using Equipment Contrary to Instructions	Security
320	Failing to Stand Count	Accountability

Appendix. Continued

Code	Short Description	Cat. 1
321	Interfering with Taking Count	Security
324	Gambling	Property
325	Conducting a Gambling Pool	Property
326	Possessing Gambling Paraphernalia	Property
327	Contacting Public without Authorization	Security
328	Giving/Accepting Money without Authorization	Property
329	Destroy Property $100 or Less	Property
330	Being Unsanitary or Untidy	Other
331	Possessing a Non-Hazardous Tool	Property
332	Smoking in Unauthorized Area	Accountability
397	Phone Abuse, Non-Criminal	Security
398	Interfering with Staff–Moderate Severity	Security
399	Disruptive Conduct–Moderate Severity	Security
400	Possessing Unauthorized Property	Property
401	Possessing Unauthorized Amount of Clothing	Property
402	Malingering, Feigning Illness	Accountability
403	Smoking in Unauthorized Area	Accountability
404	Using Abusive/Obscene Language	Accountability
405	Tattooing or Self-Mutilation	Other
406	Using Phone or Mail without Authorization	Security
407	Violating Visiting Regulations	Security
408	Conducting a Business without Authorization	Security
409	Unauthorized Physical Contact	Sexual*
497	Phone Abuse, Non-Criminal	Security
498	Interfering with Staff–Low to Moderate Severity	Security
499	Disruptive Conduct–Low to Moderate Severity	Security

* Sexual misconduct was not analyzed in the current report. Sexual misconduct simply did not have a multilevel structure.