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Restrictive Housing Placement and Length of Stay: A Latent Class Analysis with Mixed Distributions

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Abstract

On average, one in five incarcerated persons will spend some time in restrictive housing (RH) during their incarceration. Despite a growing body of research on the topic of RH, few have taken into account the heterogeneity of the incarcerated individuals' pre-RH risk profiles. In the present study, we fill this gap by estimating a latent class analysis (LCA) model to explore the heterogeneity among a sample of incarcerated individuals in New Jersey. Our LCA has both dichotomous and count variables, and we specified a model with logit and Poisson functional forms. We then examine how the latent group membership predicted RH placement and length of stay, using a hurdle model. We identified a four-group LCA model, and found that groups featuring misconduct records were more likely to experience RH and stay longer in RH. Prior criminal records were less predictive of these RH outcomes.

Keywords: restrictive housing, segregation, typology, latent class analysis

Data Availability Statement

The dataset we used in the present study contains information on incarcerated people and is not publicly available. The dataset is maintained by the New Jersey Department of Corrections, and is available upon request from its Departmental Research Review Board. Interested parties may contact Laura Salerno via email at laura.salerno@doc.nj.gov.

Introduction

The placement of incarcerated individuals in restrictive housing (RH) has sparked a great deal of debate among scholars, practitioners, and activists. Some argue it is a form of cruel and unusual punishment that causes harm (Fellner & Mariner, 1997). Others posit that it is an effective management strategy that keeps the prison population safe by deterring and incapacitating problematic individuals (Mears et al., 2020). This debate has resulted in an increase in scholarly interest in the effect of RH placement on correctional institutions, the psychological well-being of individuals serving time in RH, and their post-release behaviors. In the fields of criminology and criminal justice, the bulk of the research has focused on the effects of RH on recidivism after release from correctional institutions, with mixed results being reported (Zgoba et al., 2020).

The mixed results may be due to potential variations in the incarcerated population, the types of individuals placed in RH, and the multidimensionality of risk. Differences in the measurement of *key constructs*, *facility conditions*, and *restrictive housing admission policy* may have all contributed to the variation in findings. The majority of published studies on RH used either a regression model to predict RH placement (Labrecque, 2018; Tasca & Turanovic, 2018) or a propensity score matching (PSM) approach that compares post-release outcomes between RH and non-RH individuals (Butler et al., 2017; Wildeman & Andersen, 2020; Zgoba et al., 2020). While both methods have greatly contributed to the RH literature, a common shortcoming is that neither directly examines the heterogeneity within the population. These studies investigate how each individual risk factor is associated with RH placement or recidivism, but they offer little insight into how these factors bundle together to form any typology from incarcerated people. The current study addresses this issue by employing a latent class analysis (LCA) with mixed underlying distributions to depict the types of incarcerated individuals. In doing this, we examine who is more likely to serve time in RH and the effect of “type” on RH placement and length of stay.

Restrictive Housing: What We Know

Restrictive housing (RH) placement generally means that individuals are segregated from the general prison population in various ways[1]. RH can take the form of administrative segregation (AS), disciplinary segregation (DS), and protective custody (PC, Frost & Monteiro, 2016). Generally, AS segregates individuals for longer indeterminate terms (i.e., 30 days or more) due to the persistent engagement of infractions and crime while incarcerated. DS segregates individuals for a shorter period as a form of punishment for prison rule infractions. PC segregates individuals to provide them with safety due to their identity or the crimes they have committed. Placement in restrictive housing is fairly common in correctional institutions, with 1 in 5 incarcerated individuals serving some time in this type of housing (Beck, 2015). Recent estimates suggest that approximately 66,000 incarcerated individuals are housed in some type of RH within American correctional institutions at any point in time (Baumgartel et al., 2015). Moreover, RH placement can be due to a variety of reasons. According to Tasca and Turanovic (2018), over half of RH placements were recorded as “routine operations” (such as reclassification and lateral transfer).

[1] RH does not necessarily mean individuals are placed in solitary confinement quarters, in some jurisdictions incarcerated individuals are double-bunked when in RH.

Theoretical Foundation of Restrictive Housing

From a theoretical perspective, the purpose behind restrictive housing is to remove the opportunity to commit additional infractions or prison-based violence. Other than protective custody, a form of primary prevention, most individuals are not preemptively placed in restrictive housing. The placement for AS and DS comes after an individual has committed an infraction or violence. Placement in RH removes the opportunity for subsequent disciplinary behavior. This type of opportunity reduction is a key component of situational crime prevention (SCP), a theoretical concept that looks beyond societal transformation and historic catalysts of crime and examines the basic opportunistic structure of how a crime was committed (Clarke, 1980; Freilich & Newman, 2017). Critically reviewing the specific context in which crimes occur allows for patterns, structures and opportunities to be determined. According to Freilich and Newman, this approach is commonly referred to as analyzing the opportunity structure of crimes (Clarke, 1995). Within this particular scenario, correctional administrators have determined that the best method to manage and reduce subsequent infractions and violence is to remove the physical opportunity to commit them by placing problematic individuals with high risk for infractions in solitary confinement, hence removing the opportunity to misbehave.

Other scholars posit that restrictive housing serves as a form of individual and general deterrence (Beccaria, 1963; Bentham, 1996; Nagin, 2013a). Deterrence theory argues that punishment that is certain, severe (and commensurate), and given swiftly would prevent individuals from engaging in crime via the mechanisms of specific (targeting individuals who have already committed a crime) and general deterrence (targeting the general public). In the prison context, it is based on the notion of scaring individuals away from misbehaving while incarcerated. Placement in RH for violating institutional rules and infractions would deter individuals from future misbehavior because they fear placement in this type of housing (i.e., specific deterrence). At the same time, other incarcerated individuals would witness the consequences of misbehavior and will not commit infractions due to the fear of being placed in RH themselves (i.e., general deterrence).

Who is placed in RH

Despite the multitude of justifications on record (Tasca & Turanovic, 2018), RH is often reserved for incarcerated individuals who are considered problematic or a threat to the safe operation of a prison. Butler et al. (2013) reviewed RH admission criteria in 42 states and found that correctional policies allow prison authorities to place individuals in RH for such violations as posing a threat to institutional safety, repeating violent behavior, presenting an escape risk, engaging in riotous behavior, and belonging to a security threat group (e.g., gang). Research that has examined who is placed in RH with state and national samples support these findings (for a recent meta-analysis, see Labrecque, 2018). Compared to general prison populations, those housed in RH are more likely to have a history of disciplinary infractions and serve longer sentences (Butler & Steiner, 2017; Lovell et al., 2000; Mears & Bales, 2010). Relatedly, placement is also a tool used to manage gangs. Pyrooz and Mitchell (2020) found that gang members are “three times more likely” to be housed in RH than non-gang-affiliated persons. Individuals placed in RH are also more likely to suffer from a mental illness, which could contribute to their disruptive behavior while incarcerated (Lovell et al., 2000;

O'Keefe, 2007). A history of prison escapes and prior escape convictions also increases the odds of placement (Mears & Bales, 2010). Additionally, researchers have found that male, younger, as well as Black and Hispanic incarcerated individuals were all more likely to receive RH placement (Butler & Steiner, 2017; Cochran et al., 2018; Logan et al., 2017) than female, older, and White incarcerated individuals.

Understanding Dimensions of Risk through Typology

The criminal justice system operates with the assumption that not every individual has the same level of risk. Factors such as prior criminal justice contacts, age, socioeconomic status, and physical and mental health all predict an individual's risk of committing crimes or recidivism (Blumstein et al., 1986; Hawkins, 1999). The decision around RH placement is no exception. For example, in Florida, Mears et al. (2020) found that the length of stay in RH varied based on gender, race, and history of mental illness. Prior studies have identified a host of "common" characteristics of individuals placed in RH, such as the history of disciplinary infractions while incarcerated, history of mental illness, history of escapes and prior escape convictions, and gang membership (Butler & Steiner, 2017; Lovell et al., 2000; Mears & Bales, 2010; Pyrooz & Mitchell, 2020).

The exploration of risk factors has extended into studies examining post-release outcomes. To date, only one study by Pizarro et al. (2014) has examined how the characteristics of incarcerated individuals who served time in RH may impact post-release outcomes. They found that relative to RH individuals who do not recidivate, those who did recidivate were younger, more likely to have a drug conviction, have a prior correctional history, and have disciplinary charges while incarcerated. They also found that there are important differences among RH-placed individuals, and these differences can result in varying post-release outcomes. As a result, Pizarro and colleagues' findings elucidate the importance of employing "type" (i.e., typologies) in the study of criminality and deviance to better understand the dynamics that increase risk. Theoretically, the importance of this is elucidated in situational crime prevention and theories of crime. These perspectives posit that specific risks create specific opportunities, and that prevention interventions should be tailored accordingly (Clarke, 1997).

It is noteworthy that studies on the notion of risk—in both realms of crime and delinquency research (Piquero et al., 2003; Wu et al., 2020; Yan & Augustine, 2023) and the society's criminal justice responses (Hausam et al., 2020; Yan, 2019)—can and often entail multiple dimensions. Although, at times, criminal justice system actors refer to certain individuals as "risky" or even "bad" colloquially (Liebling, 1999; Nardulli et al., 1988), that term can be based on a variety of different grounds. Examples include prior criminal and incarceration records (Roberts, 1997), being charged/incarcerated due to a violent crime (Roberts et al., 2007), aggressive behavior or continued disciplinary issues (Labrecque, 2018), and even physical appearance (King & Johnson, 2016)—all these factors, despite some being more indicative than others of the amenity to rehabilitation and reintegration, can potentially lead to a harsher response from the society and the criminal justice system.

Although extant studies have revealed much on the *pairwise* relationship between the outcome of interest and individual risk factors (e.g., between prior history and RH placement or between aggression and RH placement), there has been relatively scant attention on how these risk factors bundle with each other, and how they *jointly* shape the need for specifically focused interventions. It is common for actors in the criminal justice system to separate criminal-justice-involved individuals into different types and treat each perceived type accordingly (Clements, 1996; Pardue et al., 2011). Compared with the more common and conventional analyses relying on regression coefficients for individual risk factors, the type-based approach is gaining popularity in domains such as criminal careers (Nieuwbeerta et al., 2011) and courts and sentencing (Kimchi, 2019).

The current study builds on the work of existing studies by employing latent class analysis (LCA)—a common mixture modeling technique—to examine the grouping of individuals based on their pre-RH placement risk profiles, and to identify the various types of incarcerated individuals who may be placed in RH, and whether incarcerated individual type affects the length of stay in RH. Moreover, we expand the application of LCA by incorporating both count and dichotomous risk factor variables into our models, an approach that improves model fit. We have not located similar methodologies in studies published in major criminology journals. Our analyses further discern the different risk levels and patterns between incarcerated individuals, and contribute to the ongoing theoretical and policy debates around the use of RH.

Methods

Study Overview and Site

In the present study, we adopt a refined approach from the current literature to first explore the types of incarcerated individuals through their behaviors and prior criminal justice contacts, using LCA (detailed below). We then examine whether these types predict RH placement and length of stay. Our analyses include a sample of 18,917 men and women who were incarcerated in the New Jersey Department of Corrections (NJDOC) and released during calendar years 2012 and 2013.

Currently, the NJDOC oversees eleven facilities throughout the state. For the past four decades, it has maintained separate units that segregate incarcerated individuals who are considered disruptive to the function and safety of the general prison population. These units are not standalone facilities, but separate units within the secure perimeter of the facilities. The bed capacity of each unit is approximately 350, yielding a total of 1,400 bed spaces at any given point. In New Jersey, "restrictive housing" and "administrative segregation" had often been used interchangeably.[2] Administrative segregation had been the umbrella term used for all types of restrictive housing in New Jersey. For this sample, the majority of RH cases involved AS and DS.

Extensive demographic and institutional information was collected for each individual from NJDOC files. Data collection included comprehensive information on each individual's demographics, offense history, index offense, incarceration and release details, interventions during incarceration, and disciplinary record. Criminal history data were attached to each incarcerated individual using New Jersey Computerized Criminal History (CCH) reports, which are maintained by the

[2] It is important to note that NJ has amended the name of RH at the NJDOC and it is now referred to as "restorative housing." While still functioning as a form of restrictive housing, this name change has also amended the policy surrounding the amount of time an individual spends in RH. Specifically, the goal was to minimize the number of days an individual spends in RH for an infraction. This study utilizes a sample from when AS/RH was still in use (2012-2013) and therefore the temporal terminology is used.

New Jersey State Police. These reports track all official criminal justice-related events, including arrests, convictions, and incarcerations that occur within the state of New Jersey. Arrests, convictions, and incarcerations that occurred outside of the state of New Jersey, including all 50 states and U.S. territories, were also incorporated through a review of Interstate Identification Index (III) reports.

The LCA Model with Multiple Indicator Types

Latent class analysis typically starts with a set of observed risk factor variables, and assumes that an unobserved categorical variable (types/groups) explains the variation in those observed variables. It is noteworthy that the observed variables used in LCA can take many formats. The most common coding scheme is dichotomous—whether or not each given individual has experienced certain events or exhibited certain traits. However, as we discuss below, the presence/absence dichotomy neglects the variation among those who fall in the "presence" category, which may be problematic in certain research settings.

The classic LCA model starts with a group of observed dichotomous risk factor variables. In the corrections setting, each variable may be one type of problematic behavior, such as substance use or prior records, coded as present (1) or absent (0). In LCA, the researcher would input the number of groups, and an expectation-maximization (EM) algorithm calculates the group sizes and characteristics given the designated number of groups (Collins & Lanza, 2010; Dempster et al., 1977). Then, the researcher would compare across the models with various numbers of groups and identify the one that best represents the data (e.g., Azimi et al., 2021; Cochran & Mears, 2017).

We do acknowledge that dichotomous coding helps the interpretation of the findings.[3] However, many variables of interest for criminal justice research are count or continuous variables. Examples include the total number of crimes one commits in lifetime or a given time period, the amount of monetary sanction or restitution, and many others. Despite the ubiquitous use of dichotomizing count and continuous variables in social science research, both statistical and applied literature have long cautioned against this practice (e.g., Fedorov et al., 2009; MacCallum et al., 2002; Walters, 2007). The common concerns include loss of information and statistical power, reduction of model fit, and introduction of artificial measurement error and bias. While most studies focused on the regression context, Macia and Wickham (2019) brought up the issue of dichotomization specifically for LCA. They conducted a Monte Carlo simulation and found that misspecification of indicator variables—including but not limited to dichotomization of count variables—led to increased bias in parameter estimates and recovery of class membership. All of the evidence called the dichotomization practice into question.

The present study includes both observed dichotomous and count variables (see below for details). Therefore, we fit a set of LCA models with a joint logit and Poisson underlying distribution. The Poisson distribution is a widely-used tool in criminological research to model the count of events within a given time period (for application examples, see Canela-Cacho et al., 1997; Eggleston et al., 2004;

[3] Dichotomizing the observed variables may be less problematic in two scenarios. Either the theory emphasizes the presence/absence distinction more than the variation or involvement levels within the presence subgroup, or there is little actual variation in the levels themselves. However, as we present in detail below, neither appears to be the case in the context of the present study.

Nagin & Land, 1993; Walters, 2007). This distribution has one parameter, λ, serving as both the mean and the variance. It is interpreted as the frequency or rate of an event (e.g., crime or misconduct). Both theories and empirical findings have supported the heterogeneity in λ within the population on a host of crime and criminal justice outcomes (Canela-Cacho et al., 1997; Nagin, 2013b; Piquero et al., 2003).

Similar to the group sizes and conditional probabilities in more conventional, dichotomous LCA settings, researchers can now also estimate λs using the EM algorithm. Most early textbooks (e.g., Collins & Lanza, 2010; McCutcheon, 1987; Vermunt & Magidson, 2007) and software packages (e.g., Lanza et al., 2015) did limit LCA to categorical observed variables. Nevertheless, recent work in both statistics (Lanza et al., 2013; Muthén, 2008) and package development (Bartus, 2017) enabled the accommodation of Poisson components into LCA. To demonstrate the significance of our approach, we also estimated the same LCA model using the more conventional, dichotomy-based observations, and compared and contrasted the findings between the two models. We estimated all LCA models in this paper with the -gsem- command in Stata 17.0 (StataCorp, 2021).

Hurdle Model on LCA Placement and Length

After estimating the LCA model, we further examined the correlation between the types of incarcerated people and two RH-related outcomes: placement into RH (dichotomous), and length of stay in RH (continuous in days). Since spending any time in RH depends on RH placement, there is a selection issue here. One of the most frequently used analytic tools for this scenario is the double-hurdle model or Cragg hurdle model (for application examples in crime and criminal justice contexts, see Gibbs, 2017; Sattler et al., 2022). The model simultaneously estimates the relationship between the regressors and both outcomes—selection into RH, as well as the length of stay in RH of those who did receive RH placement. Because the length of RH placement is overdispersed (see Figure 1), the linear hurdle model failed to converge. To solve the problem, we estimated an exponential hurdle model rather than a linear (and more typical) one. The exponential hurdle model uses the log-transformed length of RH stay rather than the raw length as the dependent variable of the length analysis.[4]

Variables

LCA Variables

We used seven variables, four dichotomous and three counts, for the LCA used in this study. We coded education dichotomously to reflect whether those in the sample had *a high school diploma or above*. *Substance use* was coded dichotomously as having one or more affirmative responses within three variables: attendance in Alcohol Anonymous, attendance in Narcotics Anonymous, and/or attendance in a prison-run drug treatment program. Individuals entering the institution are asked to self-disclose the amount they drink and participate in drug activity through the Addiction Severity Index (ASI). This tool is then used to make referrals to any of the aforementioned programs. In addition, we examined whether individuals participated in *a vocational education program while*

[4] To test the robustness of our findings, we also estimated a two-part model--a logistic regression model explaining RH placement, and then for those who did get RH placement, a zero-truncated negative binomial regression explaining its length (for application examples in criminal justice studies, see Hester & Hartman, 2017; Jordan & Bowman, 2022), which led to similar findings to the main analysis. We are unable to present the two-part model in the manuscript due to length limits, but the results are available upon request from the corresponding author.

incarcerated and whether they were *admitted to prison for a violent crime*. For the count variables, we included *the total number of convictions prior to the current admission crime* (*prior convictions*), *the total number of prison admissions prior to the current admission* (*prior prison admissions*), and *the total number of prison disciplinary charges* on the record (*disciplinary records*).

As we show in Figure 2, considerable variation existed in both prior records and disciplinary records within the sample. Over 80% had prior convictions before the index crime, and among those, slightly over a half had between one and four priors. The overall dispersion is less profound for disciplinary records, as less than 40% had them. Nevertheless, among those who had any disciplinary records, less than 40% had one, and around a quarter had four or more disciplinary records. While all individuals had between zero and three prior prison admissions, there was a visible variation among those who did have prior admissions as well. Coding all three of these variables dichotomously treats individuals with one or two counts the same as those with tens of counts, which, according to the figures and numbers presented, can potentially distort the nature of the underlying distribution, and sometimes severely so.

A primary assumption of LCA is conditional independence—that class membership explains all correlations among the observed variables (Collins & Lanza, 2010). Out of the three count variables, two pairs of variables (disciplinary records and prior convictions, disciplinary records, and prior prison admissions) had very low zero-order correlation (*r*s = -0.10 and -0.08 respectively). The numbers of prior convictions and prior prison admissions had the highest pairwise correlation (r = 0.52), but it was still moderate and did not appear to lead to dependence issues. Although convictions were generally prerequisites for prison admissions, both variables were counts as opposed to presence/absence. This coding scheme made it less concerning in light of the conditional independence assumption, as it is harder for one to predict the number of either variable from the other. As is the case in most studies, all three count variables had a distribution skewed to the right (i.e., a small number of individuals having a large value). We top-coded all both prior convictions and prior ad at the 90th percentile of the entire sample (at ten prior convictions and three prior admissions respectively), and disciplinary records at the 95th percentile of the entire sample (six) to prevent the model instability caused by overdispersion in the LCA variables.

Variables

Dependent variables. For the LCA, the dependent variable is the incarcerated individual typology created from the observed characteristics (which also serves as the primary independent variable for the regression part). For the regression analysis, the present study has two dependent variables of interest. The first is *assignment into RH* while incarcerated, coded dichotomously as having served time in RH during the present stay or not. The second is the *length of time spent in restrictive housing*, coded continuously in days.

Control variables. We controlled for a set of variables on the incarcerated individuals' demographics and crime involvement since prior research has found them to be significant covariates of RH placement and recidivism (e.g., Cochran et al., 2018; Lovell et al., 2000; Mears & Bales, 2010; O'Keefe, 2007; Zgoba & Salerno, 2017). We coded the incarcerated individuals' *race* as White, Black, Hispanic, and other, and *sex* as male and female. There were no incarcerated individuals who identified as transgender within this particular sample. Incarcerated individuals' *age at admission* was recorded in whole numbers. There were five categories for *marital status* including: single, married, divorced, widowed, and separated. We also included the incarcerated individuals' *DOC admission type* (new commitment, supervision violation, or other). For all control variables with missing information, we also created an additional category to indicate missingness.

Missing Data

Overall, there did not appear to be major missing data problems. For the variables used in the latent class analysis, no missing values were reported for substance use, vocational training, disciplinary actions, prior convictions, and prior prison admissions. About 6.9% of individuals (*n* = 1,302) had their education level missing, and less than 0.5% (*n* = 72) had the intake crime type information missing. For the variables used in the LCA (high school diploma and violent admission crime), we used listwise deletion. While we could have also created a separate category for both variables indicating missingness, this will inevitably lead to additional complexity in the interpretation of the LCA findings (Collins & Lanza, 2010). To check the sensitivity of our decision, we also imputed the missing values in both variables in both manners (i.e., assuming everyone with missing information had/did not have a high school degree and were/were not admitted for a violent crime respectively), and found no meaningful differences in our substantive findings. The final analytic sample consisted of all individuals with no missing information in all LCA variables (*n* = 17,615, 93.1% of *N*).

Among the variables used in regression models, no missing data were reported for restrictive housing status, gender, and age at admission. Race and DOC admission type each had less than 0.5% (*n*s = 123 and 75 respectively) missing. Marital status was missing for around 21.0% of individuals (*n* = 3,976). For these variables, we created a separate category for missing cases in parallel with other categories in each of the variables.

Results

Descriptive Statistics

We present the descriptive statistics of our sample in Table 1. Among our sample, 22.4% had been placed in restrictive housing while incarcerated. Among those who served in RH, the average time served was averaged 214.7 days (*SD* = 288.2), with a median of 113 days. Over half were Black (56.8%), and slightly over a quarter were White (27.7%). The sample was predominantly male (93.1%), and the average age at admission was 32.5 years. Two-thirds of the sample were single (66.3%), and only 6.3% were married. A total of 6.9% were divorced, widowed, or separated. The vast majority—83.0%—were admitted into a correctional facility for a new crime, and 16.3% were admitted for a supervision violation. Drug crimes (26.8%), violent crimes (23.6%), community supervision violations (17.8%), and property crimes (16.3%) were the most common admission crime types.

Regarding the variables used in the LCA, 71.4% of the sample had a high school diploma or a higher education level. A total of 22.1% of the sample had reported substance use issues, and 13.5% participated in a vocational training program while incarcerated. On average, they had 3.86 prior convictions (*SD* =

3.30), 0.98 prior prison admissions (*SD* = 1.12), and 0.99 disciplinary record (*SD* = 1.68). The standard deviation values suggest considerable variation in prior criminal justice contacts and in-prison behaviors among the individuals in the sample. A mixture modeling technique like LCA would be necessary to classify them into meaningful groups.

The Four-Group LCA Model

Model Selection Overview

The first step of the present study was to determine the best-fitting LCA model for the analytic sample. We started with a one-group model, then gradually increased the number of groups up to eight. We examined the fitting statistics (the Bayesian Information Criterion or Schwarz Bayesian Information Criterion, BIC, Schwarz, 1978), diagnostic statistics (average posterior probabilities, avePPs, Nagin, 2005), and substantive implications of the models. As presented in Table 2, the BIC continued to improve throughout the process, but the magnitude of improvement declined as the number of groups increased. Both the seven-group and eight-group models had at least one group with an avePP lower than .7, a rule-of-thumb threshold suggested by Nagin (2005). We compared the four-group model and five-group model closely and made the decision to utilize the four-group model, since the fifth group added little to the substantive implications of the study.[5]

Model Specifics

[5] Details on the model selection process are omitted for manuscript length reasons and available upon request from the corresponding author.

We present the specifics of the model in Table 3. The relative size of the four groups varied visibly between 11.4% and 39.5% of the full sample. Nevertheless, none of the groups appeared too rare or predominant. The conditional probabilities and averages of the observed variables for each group depict the characteristics of its members. For ease of presentation, we gave each group a name, as shown in Table 3. However, we caution our readers that this naming practice does not necessarily mean that the groups were deterministic and completely apart from each other. Rather, they only reflect finite points of support in a continuous probabilistic distribution (Nagin, 2005; Tahamont et al., 2015).

The first group, *Low Risk*, is the second-largest group (34.1% of the sample). Over 70% of the Low Risk individuals had a high school diploma (highest among the groups), and 12.2% participated in vocational training while incarcerated. Around 16.2% reported substance issues, the lowest among the groups. Slightly over a quarter were admitted for a violent crime. On average, those identified as Low Risk had 1.23 prior convictions, 0.27 prior prison admissions, and 0.21 disciplinary records (all second-lowest among the groups).

The next two groups, which we name as *High Disciplinary* (11.4% of the sample, smallest among the four) and *High Priors* (39.5% of the sample, largest among the four) respectively, had patterns that directly contrasted each other. Both groups were similar in the conditional probabilities for a high school diploma (72.0% vs. 70.3%) and substance use (26.5% vs. 21.8%), but major differences were present among the rest. Individuals identified as High Disciplinary had the highest conditional probability for participation in vocational training (31.5%), whereas those identified as High Priors had the lowest (9.2%). More importantly, High Disciplinary had the highest conditional probability among the groups of admission for a violent crime (63.8%) and the highest average number of disciplinary records (3.55), but the lowest numbers of both prior convictions (0.87) and prison admissions (0.07). On the contrary, individuals in the High Prior group had the highest averages for both prior record numbers (6.50 prior convictions and 1.71 prior prison admissions), but the lowest conditional probability for admission due to violent crime (0.09%) and average disciplinary records (0.20). Both groups exhibited a higher level of risk than *Low Risk*. However, given that the two groups exhibited risk along two different dimensions, we would, for now, refrain from ranking between them.

The last group, which we named *Multidimensional Risk*, was also relatively small (15.0% of the sample). Among the four groups, these individuals had the highest conditional probability for substance use (33.0%) and the second-highest conditional probability for violent admission crime (26.8%). More notably, these individuals had high conditional averages in *all* three count variables (5.15 prior convictions, 1.36 prior prison admissions, and 2.93 disciplinary records). While none of the three averages was the highest, the values were all much closer to the leading group (i.e., High Disciplinary for disciplinary records and High Priors for prior convictions and prison admissions) than to the rest of the sample. Therefore, we assert that Multidimensional Risk had the overall highest risk among the groups due to the relatively high value in both prison misconduct and prior records.

The LCA Model with Dichotomized Variables

To demonstate the necessity of having count variables in our main LCA model, we also estimated an LCA model using the same seven variables as the main analysis, but all in dichotomous form (all three count variables were recoded as one or more = 1, none = 0). The results are in Table 4. Because we limited the value range of all variables to be between zero and one, the groups now appear much closer than they are. For example, two of the groups in the all-dichotomous LCA model had conditional probabilities of 0.19 and 0.24 for having disciplinary records, which are similar to the average counts found in the main model (0.20 and 0.21 respectively). However, the other two groups in the all-dichotomous LCA model had conditional probabilities of 0.62 and 0.67 for having any disciplinary records, but average counts of 2.93 and 3.55 when the model allows for count variables. Similarly, the probability of having prior convictions ranged between 0.42 and 0.99 when the prior conviction variable was dichotomous, but the range of prior conviction numbers was between 0.87 and 6.50 when the LCA model had count variables. The dichotomization of count variables made the differences among the groups artificially (and incorrectly) smaller than the count specification.

Regression Analysis Findings

Results for Group Membership

Our regression analysis, presented in Table 5, examined the relationship between class membership, the control variables, and the length of RH placement. We specified a hurdle model that estimated the process as two parts at the same time: the selection into RH, and the length of RH stay once selected. Regarding RH placement, individuals classified as High Priors had virtually the same probability of spending time in restrictive housing as those classified Low Risk, as the coefficient was small and non-significant ($b = 0.02$, $p = .49$). Meanwhile, individuals assigned to High Disciplinary and Multidimensional Risk groups were both more likely to be admitted to restrictive housing, respectively (*b*s = 1.80 and 1.72, $p < .001$ for both). By switching the reference group, we further found that the difference in the probability of restrictive housing placement between the latter two groups (i.e., High Disciplinary and Multidimensional Risk) was non-significant ($b = 0.002$, $p = .49$). The same pattern emerged for the length of RH stay too. Individuals classified as both High Disciplinary and Multidimensional Risk were both receiving longer RH stay times (*b*s = 1.668 and 1.671, $p < .001$ for both), and individuals classified as High Priors did not receive statistically significantly longer RH stay compared with the Low Risk group ($b = -0.05$, $p = .59$).

Results for Demographic Variables

After considering the role of group membership, we still found statistically significant gender and racial disparities in RH placement and length. Women were statistically significantly less likely to receive RH placement than men ($b = -1.26$, $p < .001$), but did receive longer stay than men once placed in RH ($b = 0.59$, $p = .006$). Black and Hispanic individuals were both more likely to be admitted to restrictive housing than White individuals (*b*s = 0.16 and 0.15, $p < .001$ for both), but individuals of other and unknown races did not see a significant disparity in RH placement (*p*s = .46 and .45 respectively). Nevertheless, there were no statistically significant disparities in RH length across the board among those who did receive RH (*p*s between .30 and .91). There appeared to be a curvilinear relationship between restrictive housing placement and incarcerated individuals' age. The probability of restrictive housing placement increased with age for those younger than 33.9 years old, and decreased with age for those older than 33.9 years. For the RH length, we also found a curvilinear pattern but in a different shape. For individuals younger than 47.0 years old, the length of RH decreased with age; for those older than 47.0 years, the length of RH increased with age. We found no statistically significant disparities in either stage regarding the marital status of individuals.

Sensitivity Checks

To check the sensitivity of our findings, we conducted a set of sensitivity checks. We kept the main LCA model (i.e., the ones with count variables), but estimated the models explaining RH placement and length analysis using a different and separate set of specifications—a logistic regression model for RH placement, and then for those who received RH, a zero-truncated negative binomial regression model for RH length. We found similar main findings—relative to the Low Risk group, individuals assigned to both High Disciplinary and Multidimensional Risk groups were more likely to face RH placement, and stayed in RH longer once placed there. However, we saw no statistically significant disparities between Low Risk and High Incarceration groups. Details of these additional analyses are available upon request from the corresponding author.

Discussion

In order to fill an existing gap in the literature, the present study employed a novel approach to examine restrictive housing. Instead of exploring the role of individual risk factors, we focused on first exploring the correlation among the risk factors, and how they jointly portray the typology of risk profiles. This study utilized a robust sample collected over two calendar years, containing over 17,000 incarcerated individuals; of this, over 20% of the sample spent time in restrictive housing. We use LCA to identify groups among the sample, then examine whether these groups or types predict their placement and length of stay in RH.

The LCA identified four groups of incarcerated individuals that we named – Low Risk, High Disciplinary, High Priors, and Multidimensional Risk. These groups demonstrate clear heterogeneity among them, as the risk was not equally distributed. The four groups had varying levels in all variables used to create the typology, but the most visible differences were among the probability of being admitted to prison for a violent crime, the counts of prior criminal records, and disciplinary records. It is noteworthy that none of the groups appeared too rare or predominant, which further reflects the complexity among incarcerated persons. Following a semi-hierarchical pattern, the Low Risk group demonstrated as the most highly educated, with the lowest substance use issues, priors and disciplines. The two middle groups, the High Disciplinary and High Priors groups, had patterns that directly contrasted each other; however, they both presented as higher risk than the Low Risk group. While both of these risk profiles reside in the middle of the hierarchy, they each present a separate construct of risk—one focusing on in-prison disciplinary problems and the other on a high number of prior criminal engagements. While these two groups present varying types of risk, neither outranks the other. The last group, the Multidimensional Risk, had the highest substance use, the second-highest amount of violent admission crimes, as well as high priors and in-prison disciplinary infractions. Given these high rankings, we determined that the Multidimensional Risk group had the overall highest risk among the groups.

It is worth noting that while there appeared to be some hierarchy in the apparent risk among the groups, for the effect on RH placement and time served in RH, the four groups were basically condensed into two. The Low Risk and High Priors groups were near-identical, while the High Disciplinary and Multidimensional Risk groups were near-identical in both RH admissions and time served. Individuals assigned to High Disciplinary and Multidimensional Risk Groups were more likely to be admitted to restrictive housing and they served over double the amount of time in placement.

These findings stand in contrast to the more conventional and unidimensional perception of risk—that all indicators of risk bear equal weight and point to the same direction. In other words, the typology of incarcerated individuals is more complicated than “good” versus “bad,” or “less risky” versus “risky.” This is especially important considering the current sample consists of only individuals already admitted to prison. Compared with other frequently-studied samples in the criminal justice context, such as individuals who commit crimes or arrestees, everyone in the current sample arguably lies on the higher end of the overall spectrum of risk (Cochran & Mears, 2017). The mere existence of RH in today’s correctional institutions suggests that there is a need for a higher level of attention and restriction for some incarcerated individuals than others. The present study further dives into the sample and tries to identify the specific factors explaining the need. The most notable pattern we found in the regression models is that prior records—a classic indicator of risk in many criminological studies (Kurlychek et al., 2006)—are much less predictive of both RH placement and RH placement length than misconduct. Without the simultaneous demonstration of misconduct, those with a higher number of prior records did not appear to be more likely to face RH than those who had the lowest visible risk. The findings echo with recent calls to move beyond the mere counts of prior records and examine more closely additional factors associated with risk (Cihan et al., 2017; Yan & Walker, 2022). While we have no intention to negate the significance of prior records in the criminal justice context, we also caution against the "one-variable-fits-all" thinking pattern when evaluating the risk factors in different settings.

These findings elucidate the need to study incarcerated individuals with the use of typologies disaggregated manner to better understand the dynamics that lead to specific behaviors and outcomes in correctional settings. Although this finding seems obvious, this conclusion was rarely confirmed with robust analytic methods or specific risk typologies. Theoretically, our findings corroborate one of the main propositions of situational crime prevention, which indicate that certain circumstances influence the occurrence of "specific" types of events (Clarke, 1997). Hence, scholars who study restrictive housing and their effects on correctional settings and society would benefit from employing a more focused inclusion of varying levels of risks.

In addition to the substantive findings, our study also contributes to the field methodologically. Although the use of LCA is gaining attention in criminological studies (e.g., Cochran & Mears, 2017; Kimchi, 2019), we have not seen application examples in the area that expand LCA to accommodate both dichotomous and count variables, even when the statistical literature has considered the latter as both beneficial and feasible (Macia & Wickham, 2019). For our regression analysis, we also heed the call from recent literature to model the length of RH as a hurdle model. Both approaches provide better overall model fit than the more conventional analytic strategies.

Although the risk groups we identified may not be perfectly consistent with the classification process inside all correctional facilities, it provides a blueprint for policy progress. In a time of limited resources faced by correctional agencies, our findings shed light on programmatic and therapeutic need allocation. Prison administrators may be able to direct additional services to those determined at the outset to be the most in need, as well as the highest risk. The highest risk groups demonstrated elevated amounts of substance use, prior criminal charges, violent index offenses and in-prison disciplines. Age also played a significant factor, as younger individuals were more likely to be placed in restrictive housing. Given that the pathway to RH is more likely than not through the commission of a prison violation, prison officials may be able to preemptively identify individuals who demonstrate these factors and enable individuals to avoid RH placement. As an intervention, or matter of prison policy, focused services and therapeutic programming can potentially be made available to individuals displaying these factors, thereby reducing their likelihood of incidents that may result in RH placement. An example of similar efforts exists in the Arizona Department of Corrections, Rehabilitation & Reentry, whereby those placed in RH participate in a cognitive behavioral therapy program that involves counseling, self-study, educational modules, practice to adherence to prison rules and regulations, and frequent interactions with staff (Zgoba et al., 2020). Meyers et al. (2018) recently evaluated this program and found that those who participated committed fewer assaults on incarcerated individuals and staff. If possible, correctional facilities that utilize restrictive housing strategies should adopt similar programming and potentially incentivize participation.

Lastly, many states are moving toward a progressive, more humane utilization of restrictive housing and turning toward ‘restorative housing’ units. While still a form of restrictive or segregated housing, this modification offers an advancement in both punitive thinking and correctional practice. New Jersey partnered with the Vera Institute on the Safe Alternatives to Segregation Initiative to reimagine restrictive housing in one correctional facility. The state also passed the Isolated Confinement Restriction Act in 2019. The new law states that individuals should not be placed in isolated confinement for more than 20 consecutive days, or more than 30 days during a 60-day period. Those determined to be ‘vulnerable populations’ (this includes 65-and-older, 21-and-younger, mental illness or developmental disability, pregnancy or who identify as LGBT) should be placed in RH as a matter of exception only. Additionally, New Jersey’s partnership with the Vera Institute resulted in reforms that focus on the reduction of utilization of restrictive housing, while still maintaining correctional safety (Wilcox, 2017). These reforms include the following: creating less restrictive confinement, restructuring disciplinary hearings, and creating more frequent restrictive housing meetings and specialized units. To date, the modifications have led to reductions in both RH placement and time spent in placement.

Although this study contributes to the understanding of RH effects, and provides an innovative approach to the study of this incarceration practice, these findings presented here must be viewed within the context of the study’s limitations. First, although LCA identified the four groups based on the pattern of our observed variables, the types may or may not be consistent with the classification standards inside correctional facilities. Moreover, these groups are probabilistic and are discrete points of support within a continuous distribution. They should not be perceived as definitive or hard-cut for theoretical and policy purposes. In addition, recent research has demonstrated that a number of variables have shown importance in the discussion surrounding restrictive housing. However, due to data limitations, we could not examine a variety of variables included in prior research such as escape history,[6] gang membership, and mental health status. Individuals with escape histories or mental health challenges and gang membership may prove to be different from those examined here. It is possible that the inclusion of these variables would demonstrate variations among the four risk groups that were developed and their effect on placement and length of stay in restrictive housing. The inability to examine these variables makes it incumbent that we stress these risk categories are a preliminary effort toward understanding who is placed in RH and how long they stay. Future research should build on these findings and include all empirically relevant variables.

Conclusion

In conclusion, this study provides evidence for heterogeneity among incarcerated individuals, as well as the multidimensionality of risk. Researchers should build on the findings and methodology of this and prior studies, and explore whether these risk categories are replicated. Future studies should also adopt LCA

[6] It should be noted that there were almost no escape attempts or completed escapes within the sample of individuals. Therefore, adding this variable may contribute little significance.

analytic techniques in order to account for the heterogeneity in the population. Related, adopting the LCA framework should continue to include multiple types of variables, and try to adopt distributional assumptions that are consistent with the nature of the data. Finally, criminologists should also examine the various facets of RH that are currently underexamined, such as procedural justice related to these units, other behavioral effects that placement may have on individuals (e.g, physical and mental health), as well as the effect that the use of these units by departments of corrections have on their general prison population (e.g., does RH serve as a general deterrent).

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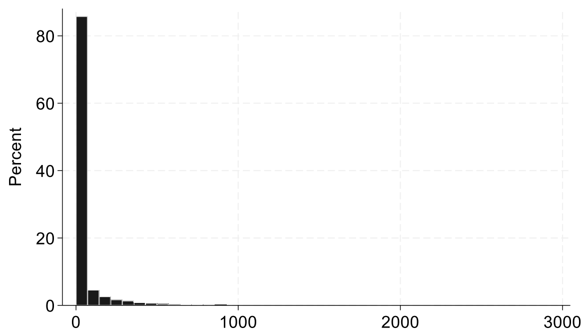
Figure 1. Histograms of RH Stay Length, in Days

(a) Full sample (b) Individuals who spent any time in RH



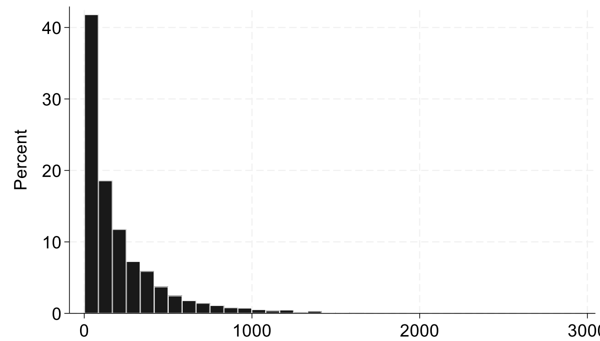
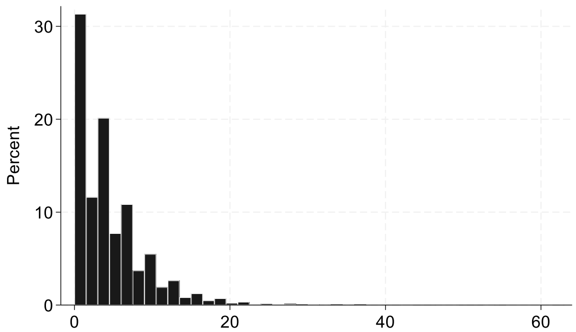
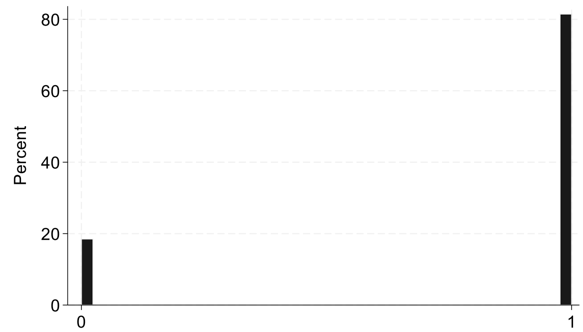


Figure 2. Histograms of Count Variables Used in LCA, in Raw and Dichotomous Forms

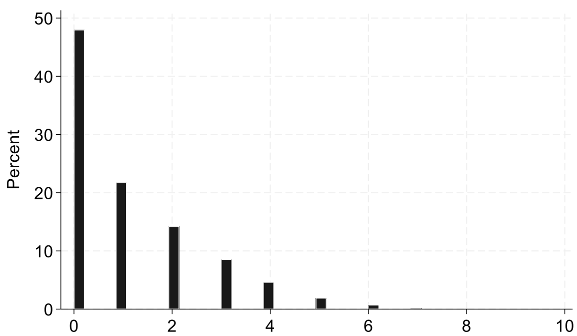
(a) Prior convictions, raw counts



(b) Prior convictions, dichotomized

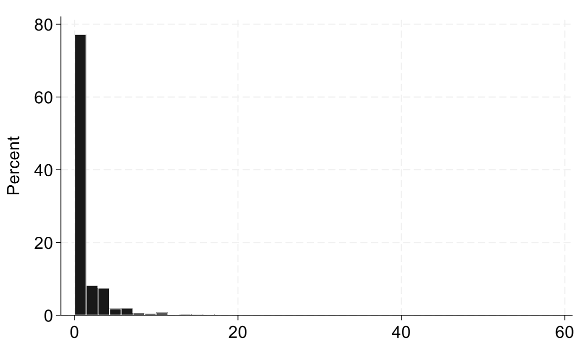


(c) Prior prison admissions, raw counts



(d) Prior prison admissions, dichotomized

(e) Disciplinary records, raw counts



(f) Disciplinary records, dichotomized

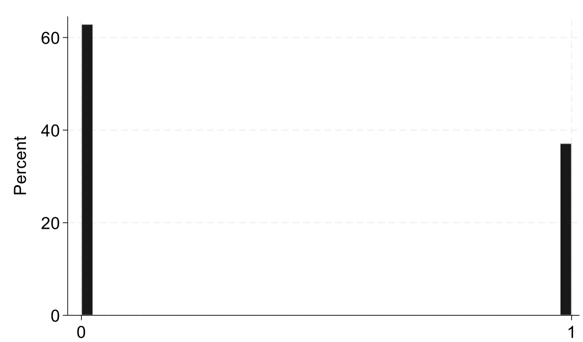


Table 1. Descriptive Statistics

	M	*SD*	Min	Max
Dependent Variables				
RH placement	0.224	0.417	0	1
RH length	48.047	161.011	0	2995
RH length for those place in RH (*n* = 4,126)	214.741	288.193	1	2995
LCA Variables				
High school diploma	0.714	0.452	0	1
Substance use	0.221	0.415	0	1
Vocational training	0.135	0.342	0	1
Violent admission crime	0.236	0.425	0	1
# of prior convictions, top coded	3.860	3.301	0	10
# of prior prison admissions, top coded	0.978	1.121	0	3
# of disciplinary records, top coded	0.992	1.677	0	6
# of prior convictions, raw	4.335	4.627	0	55
# of prior prison admissions, raw	1.093	1.394	0	9
# of disciplinary records, raw	1.247	2.966	0	60
Marital Status				
Single	0.663	0.473	0	1
Married	0.063	0.243	0	1
Divorced	0.041	0.198	0	1
Widowed	0.005	0.070	0	1
Separated	0.024	0.153	0	1
Unknown	0.205	0.404	0	1

Female	0.069	0.254	0	1
Race/Ethnicity				
White	0.277	0.447	0	1
Black	0.568	0.495	0	1
Hispanic	0.144	0.352	0	1
Other	0.006	0.076	0	1
Unknown	0.004	0.066	0	1
Age	32.507	10.229	13	88
DOC Admission Type				
New commitment	0.830	0.376	0	1
Supervision violation	0.163	0.369	0	1
Other	0.003	0.057	0	1
Unknown	0.004	0.063	0	1
N	17,615			

Table 2. LCA Model Selection

Total Groups	Log Likelihood	*df*	*BIC*
1	-141561.6	7	283191.7
2	-128115.6	15	256377.9
3	-123196.7	23	246618.2
4	-121410.1	31	243123.4
5	-120621.8	39	241624.9
6	-120359.4	47	241178.4
7*	-120239.9	55	241017.5
8*	-120160.0	63	240936.0

Note: Models with * have avePP < .7 for at least one group

Table 3. The Four-Group LCA Model with Mixed Logit and Poisson Specification

	(1) Low Risk	(2) High Disciplinary	(3) High Incarceration	(4) Multidimensional Risk
High School	0.725	0.720	0.703	0.715
Substance use	0.162	0.265	0.218	0.330
Vocational training	0.122	0.315	0.092	0.141
Admission for violent crime	0.253	0.638	0.094	0.268
# of prior convictions	1.231	0.867	6.501	5.147
# of prior prison admissions	0.266	0.068	1.709	1.360
# of disciplinary records	0.207	3.546	0.198	2.929
Group size	34.10%	11.40%	39.50%	15.00%

Table 4. The Four-Group LCA Model with All Variables Dichotimized

	(1)	(2)	(3)	(4)
High School	0.696	0.754	0.692	0.750
Substance use	0.132	0.266	0.151	0.405
Vocational training	0.045	0.355	0.062	0.213
Admission for violent crime	0.247	0.776	0.057	0.280
# of prior convictions	0.417	0.475	0.950	0.991
# of prior prison admissions	<0.001	<0.001	0.730	0.710
# of disciplinary records	0.185	0.674	0.241	0.622
Group size	13.97%	14.41%	49.65%	21.98%

Table 5. Cragg Hurdle Model Explaining RH Placement and Length

	(1)	(2)
	RH Placement	Length of RH
LCA Group (Ref: Low Risk)		
High Disciplinary	1.80***	1.67***
	(0.04)	(0.09)
High Priors	0.02	-0.05
	(0.03)	(0.10)
Multidimensional Risk	1.72***	1.67***
	(0.04)	(0.08)
Marital Status (Ref: Single)		
Married	0.02	0.02
	(0.05)	(0.12)
Divorced	0.02	0.13
	(0.07)	(0.16)
Widowed	-0.11	-0.14
	(0.22)	(0.54)
Separated	-0.06	0.15
	(0.09)	(0.19)
Unknown	-0.25***	0.00
	(0.03)	(0.08)
Female	-1.26***	0.59**
	(0.08)	(0.22)
Race (Ref: White)		
Black	0.16***	0.07
	(0.03)	(0.07)

Hispanic	0.15***	0.03
	(0.04)	(0.09)
Other	-0.15	-0.14
	(0.20)	(0.47)
Unknown	0.15	0.05
	(0.20)	(0.47)
Age	0.02*	-0.12***
	(0.01)	(0.02)
Age Squared	-0.0003**	0.001***
	(0.0001)	(0.0003)
DOC Admission Type (Ref: New Admission)		
Parole Violation	-0.002	0.15
	(0.03)	(0.08)
Other	-0.11	0.48
	(0.22)	(0.46)
Unknown	0.37*	0.66*
	(0.18)	(0.29)
Observations	17,615	17,615

Standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05