IDENTIFYING PREDICTORS OF MENTAL ILLNESS IN COUNTY JAIL DATA

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We thank each of the nine county jails and the Sheriffs from those counties for their generosity of time and data. This project would not have been possible without their willingness to speak with us candidly about their booking process, send us data (sometimes in multiple, and iterative batches), and helping us connect to new and different staff when our contacts moved on from their positions. We are very grateful for their willingness to participate in the research process.

Finally, thank you to Mr. Joe Hood, former Deputy Commissioner of the Department of Community Health, for asking the question in the first place. His need to know an estimate of the prevalence of mental illness within our county jails is the foundational research question for this study.

Estimating Prevalence of Mental Illness Among Persons Booked into Georgia Jails (2013-2018 Study Period)

Data from Nine Georgia County Jails, Computerized Criminal History, Department of Corrections, and Department of Community Supervision
3 Urban, 3 Suburban, 3 Rural Jails Participating

Jail Counties Covering 30% of Georgia's Population	**Urban Pop (1,959,763)**	**Suburban Pop (1,074,019)**	**Rural Pop (131,169)**
Number of People Booked (369,748)	**Urban (203,998)**	**Suburban (142,416)**	**Rural (23,334)**
Number of Booking Episodes (611,432)	**Urban (384,115)**	**Suburban (217,504)**	**Rural (45,813)**
Arrest ID Matches (71%)	**Urban (124,439) (61%)**	**Suburban (187,053) (86%)**	**Rural (31,153) (68%)**

Conservative Estimate of Prevalence of Mental Illness Among Persons booked in County Jails

Bookings Involving Mental Illness
(59,998)

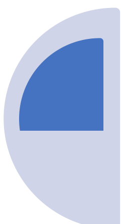
 # People with Mental Illness Booked
(17,538)

14% Booking Episodes Involve Mental Illness

9% of Persons Booked Have Mental Illness

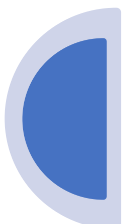
Risk Factors Associated with Mental Illness and Impact on Jails

Mental Illness	No Mental Illness
Average Length of Stay: **54 Days**	Average Length of Stay: **26 Days**
Average Days Between Bookings: **299**	Average Days Between Bookings: **328**
Average Number of Cell Movements Per Booking : **10**	Average Number of Cell Movements Per Booking : **5**
Average Number of Days from First Arrest to Most Recent: **5,777**	Average Number of Days from First Arrest to Most Recent: **3,769**



<u>2x More Likely to Have Mental IIllness</u>

- Homeless Persons
- Persons with at least 1 quality of life arrest



<u>1.5x More Likely to Have Mental IIllness</u>

- Men
- Persons booked within the same year
- Persons with more than one booking episode in the study period

Background and Literature

In 2018 legislative session, the Senate passed bill 407 which struck the previous prohibitions in Georgia code that precluded inmates in prison or jails from being assessed for eligibility for Medicaid. Additionally, the bill allowed use of Medicaid funds to pay for services rendered at eligible medical institutions for prison or jail inmates. While the removal of this restriction represents a boon and potential cost savings for county jails and the state prison system, the Georgia Department of Community Health, which administers the Medicaid program, needed to ascertain how many county jail inmates may qualify for Medicaid under current eligibility criteria. The federal Social Security Administration (SSA) has established data exchanges with the county jail management system vendors to identify persons arrested and booked so that benefits could be suspended until the person is released. SSA shares these data with the Department of Community Health so that Medicaid benefits may also be suspended, and not cancelled, as they had historically been.

A recent BJS published issue brief using jail and prison inmate self-report found that more than a quarter of jail inmates had experienced symptoms of serious psychological distress in the 30 days prior to the survey. More alarming, 44% of BJS jail survey respondents asserted that a health professional had diagnosed them with a mental disorder [i]. A recent Government Accountability Office study [ii] of states that did and did not expand Medicaid under the Affordable Care Act found that in non-expansion states, approximately 2% of the prison population would qualify for Medicaid. Jail inmates were not considered in the study. Criteria in non-expansion states for Medicaid eligibility includes income thresholds and medical diagnosis that indicates disability for those younger than 65.

Recent studies have found certain indicators common to persons with serious mental illness (SMI) which serve as proxy indicators to estimate the number of inmates in county jail with mental illness, who might qualify for social security and thus Medicaid. These factors include [iii] :

- Length of Jail stay
- Likely to be detained pre-trial
- Likelihood to make bail
- Number of Booking Episodes

Background and Literature Cont

Recidivism among persons with serious and persistent mental illness is also a concern for Georgia's current Governor, Brian Kemp. During the 2019-2020 legislative session, the General Assembly passed HB 514, which created the Georgia Behavioral Health Reform and Innovation Commission. Among the issues the Commission will examine over four years is "the impact behavioral health issues have on the court system and correctional system, ... the need for aftercare for persons exiting the criminal justice system." Given the concerns surrounding recidivism, and that roughly more than a quarter of jail inmates experience symptoms of serious psychological distress,[iv] understanding the scope of issues underlying mental health service utilization is of growing interest to policy makers. Studies in both urban and rural settings have consistently found that substance abuse disorders[v] and co-occurring disorders are drivers of jail readmission[vi] . Other studies have found that individuals with serious mental illness return to prison in about half the time as those without.[vii]

Although service provision affects both mental health outcomes[viii] and recidivism rates[ix] , inmates appear to experience more difficulty in obtaining health insurance that could assist in accessing these services upon release. Moreover, a recent study suggests that jail inmates are denied Medicaid coverage at higher rates than both prison inmates and psychiatric patients[x].

Barriers to Medicaid coverage for inmates are a critical concern for service utilization considering more than 70 percent of inmates use health care services within the first 10 months of release[xi] . To circumvent low coverage approval rates, the Substance Abuse and Mental Health Services Administration (SAMHSA) funds a national technical assistance program dedicated to increasing Medicaid approval across the U.S. The SSI/SSDI Outreach, Access, and Recovery (SOAR) method uses in-depth medical and personal summaries of disability to facilitate in the SSI application process. Based on data from SAMSHA's SOAR technical assistance website, criminal justice best practice sites had completed 407 SSI/SSDI applications for persons in either prisons or jails. Of those, 73% were approved in an average of 85 days. This is compared to the average approval rate of 29% for eligible applications. Further, the increases in acceptance for Medicaid coverage have led to upward of five million dollars in reimbursements in some cases[xii].

Identifying the prevalence of mental illness among county jail inmates is a challenge because of the heterogeneity of jail management systems, and the way data are collected. Jails tend not to focus on data collection for research or reporting, further compounding the difficulty of using jail management system data for systematic analysis[xiii]. The present analysis creates a standardized dataset using data from nine county jails in Georgia so those records can be matched to computerized criminal history and other state criminal justice administrative data. Once matched, we assessed the predictive value of proxy indicators within the county jail datasets on inmate mental illness. We also use the administrative data to estimate the prevalence of persons with mental illness in county jails.

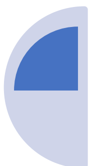
Methodology

The present study consisted of secondary data analysis of county jail, Georgia Bureau of Investigations' computerized criminal history (CCH), Department of Corrections (GDC), and Department of Community Supervision (DCS) data. Work was divided between the Georgia Statistical Analysis Center (GASAC), a division of the Criminal Justice Coordinating Council; and Applied Research Services (ARS). Where one agency or the other was primarily responsible for a portion of the work, we use that entity's acronym. Otherwise, the first-person plural "we" is used.

Prior to obtaining data from the jails, we conducted semi-structured interviews with jail intake staff, medical staff, and jail commanders.

Jail Selection

ARS stratified county jails in Georgia using jail census, demographic, and county urban/rural designations from the Census and the Health Resources and Services Administration. Any counties that were part of Metropolitan Statistical Areas, but not the locus of the city around which the MSA is built, were designated suburban. We initially identified 11 counties of interest.



Rural/Partial Rural
Four Counties
1 Northwest
1 Northeast
2 Southeast

Suburban
Three Counties
2 Metro Atlanta
1 Macon Area

Urban
Four Counties
1 East
1 Southeast
2 North Central

GASAC received data from nine counties. Below is a breakdown of the final county participation count.

Rural (3)
- 1 Declined
- 1 Dropped for Non-Cooperation
- 1 Non-Selected County Volunteered

Suburban (3)
- 1 Total Participation - No Counties Declined or Dropped Out

Urban (3)
- 1 Declined
- 3 Accepted Participation

Interviews and Standardized Dataset

The interviews probed on the data collected throughout the intake process and the purpose for which data are collected. In total, we interviewed 21 jail intake, command, or medical staff.

Rural

8 Jail Staff Interviewed

Suburban

Nine Interviewees

7 Jail Staff

2 Medical Staff

Urban

5 interviewees

2 Jail Staff

2 Medical Staff

1 Competency Restoration Staff

All but one agency used a commercially available jail management systems. The one agency on a legacy, mainframe system was transitioning to a commercial system shortly after delivering the data to GASAC. All but one agency had data available from January 1, 2013 to December 31, 2018. The common data elements we identified from the interviews included:

Person Data

- System identifier
- State Identification
- Number
- Frist name
- Last name
- Race
- Sex
- Gender
- DOB
- Address

Booking Episode Data

- Booking Date
- Release Date
- Booking Episode ID
- Charges Booked
- Bond Information

Additional Data

- Cell Movement Data
- Charge Disposition
- Arresting Officer and Agency
- Alerts/Notes about an Inmate

No jails maintained any information about a booked person's medical history. All jails had contract medical providers with their own electronic medical record systems. None of the jails maintained any information in their jail management systems about discharge planning. Indeed, discharge planning was not part of standard jail operations. Often people cycled through the jail too quickly to adequately plan for discharge.

Prior to requesting data, we scheduled virtual meetings with each jail to walk through the data entry screens in their jail management systems. We completed these walk-throughs with four of the jails. We received screenshots of data entry screens from the JMS vendor for 2 other jails. We were not able to schedule walk throughs with the remaining three jails.

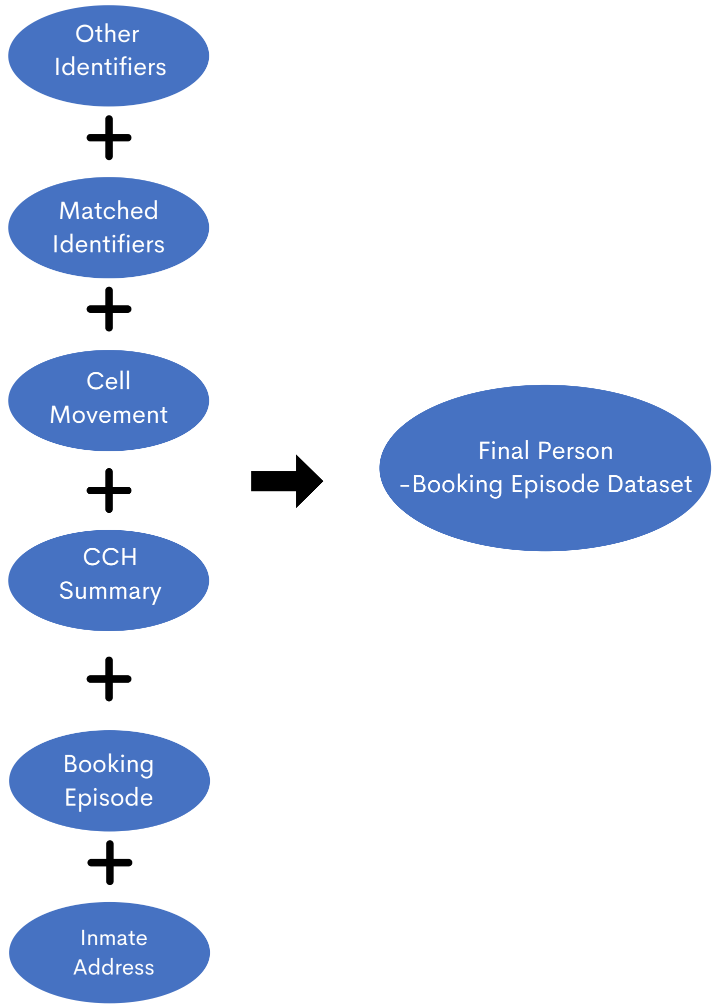
Data Harmonization and Transformation

Upon receipt of each jail dataset, GASAC isolated the person identifiers to create a unique hashkey for each inmate. These included:

Identifier	Number of Jails Providing
First Name	8
Last Name	8
Address	7
Race	9
Sex	9
Date of Birth	9
Native JMS Person Identifier	9
State Identification Number	3

Once GASAC assigned the hashkey, data were sent to ARS to match with computerized criminal history, Department of Community Supervision, and Georgia Department of Corrections data. The latter two datasets contributed information about whether a person had a mental illness – based on a mental health level of 2 or greater in GDC data, or an elevated score on DCS' 11-point mental health screener.

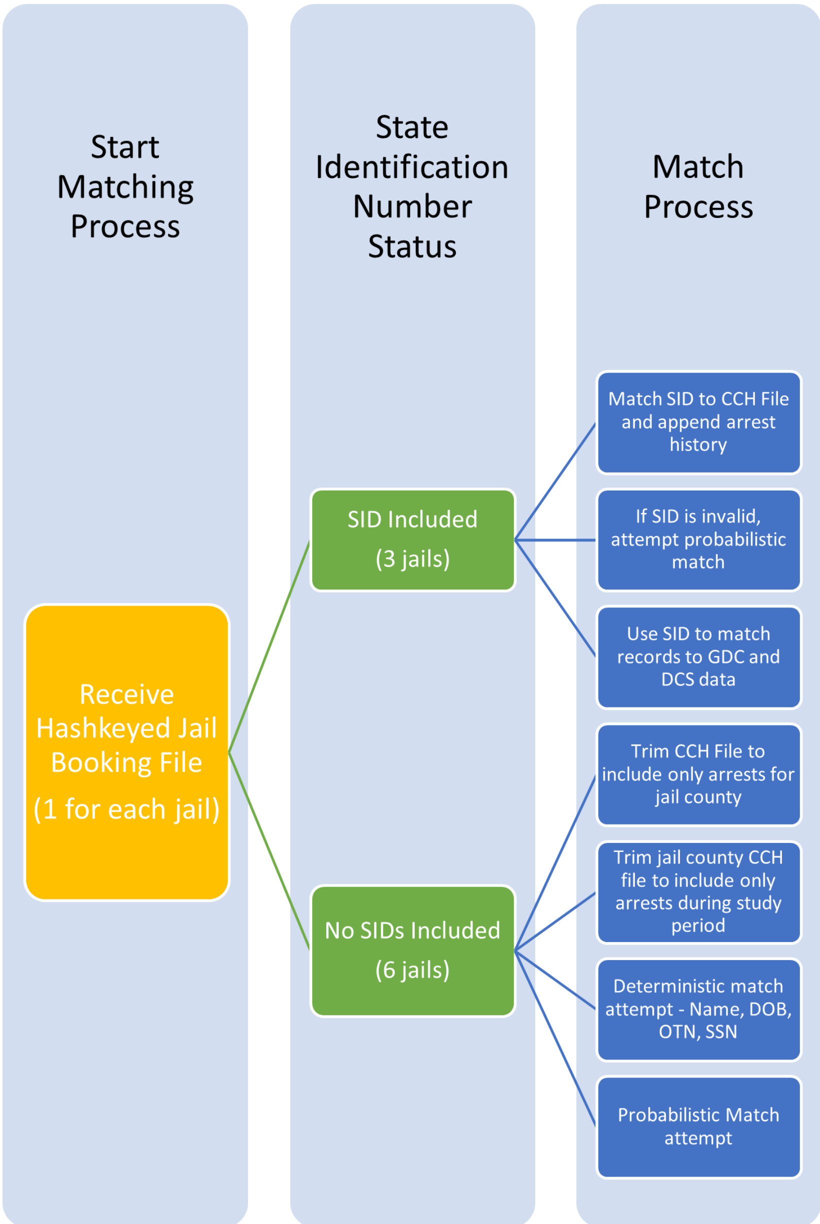
The remaining variables were divided into tables to create the final datasets. The final dataset contained 58 variables and was structured at the person-booking episode level – meaning that each person may be listed multiple times for different booking episodes. The dataset was derived from individual databases created for each jail. The databases consisted of 6 tables.



Administrative Dataset Matching

ARS maintains the CCH research database for the Georgia Bureau of Investigations. Because the firm designed and validated the actuarial risk assessment for the Georgia Department of Corrections, and the Department of Community Supervision, ARS also has ready access to research datasets for those two state agencies. Without these three datasets, we would be unable to estimate mental illness within the county jail population using solely administrative data. The graphic below provides an overview of the matching process ARS uses with computerized criminal history. ARS uses CDC's LinkPlus registry program to combine CCH data to other administrative datasets using both deterministic and probabilistic matching.

Once ARS matches the person to a valid SID, they can pair the person's entire arrest history within the state of Georgia. The offenses in that history are scored and translated into categories and flagged. Where a jail had some missing data on race or sex information about someone, ARS could use the CCH race and sex to populate those fields.



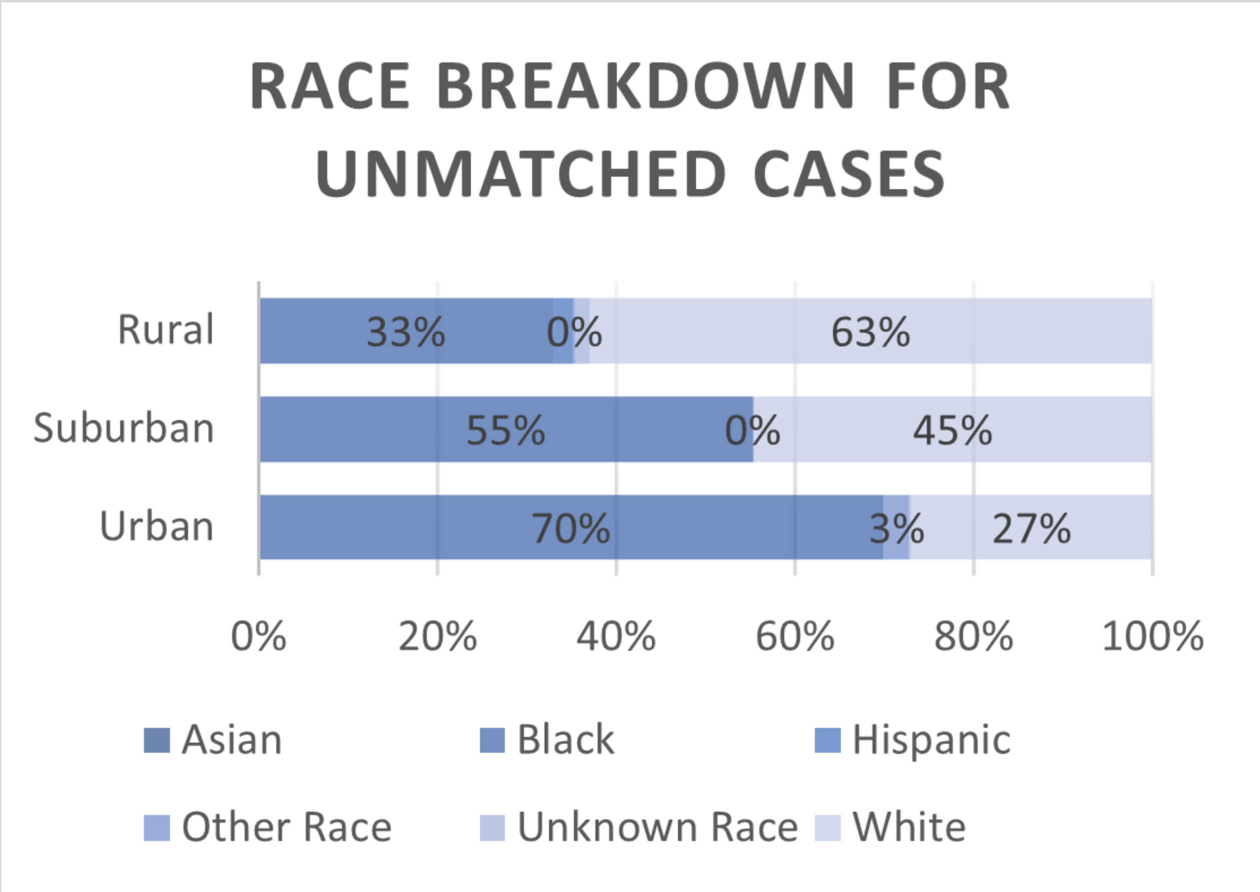
The SID from CCH can be used to match records to both GDC and DCS data. Those datasets supplied information on whether any booked person **with a felony offense history** had been in a mental health program or scored highly on a mental health screener.

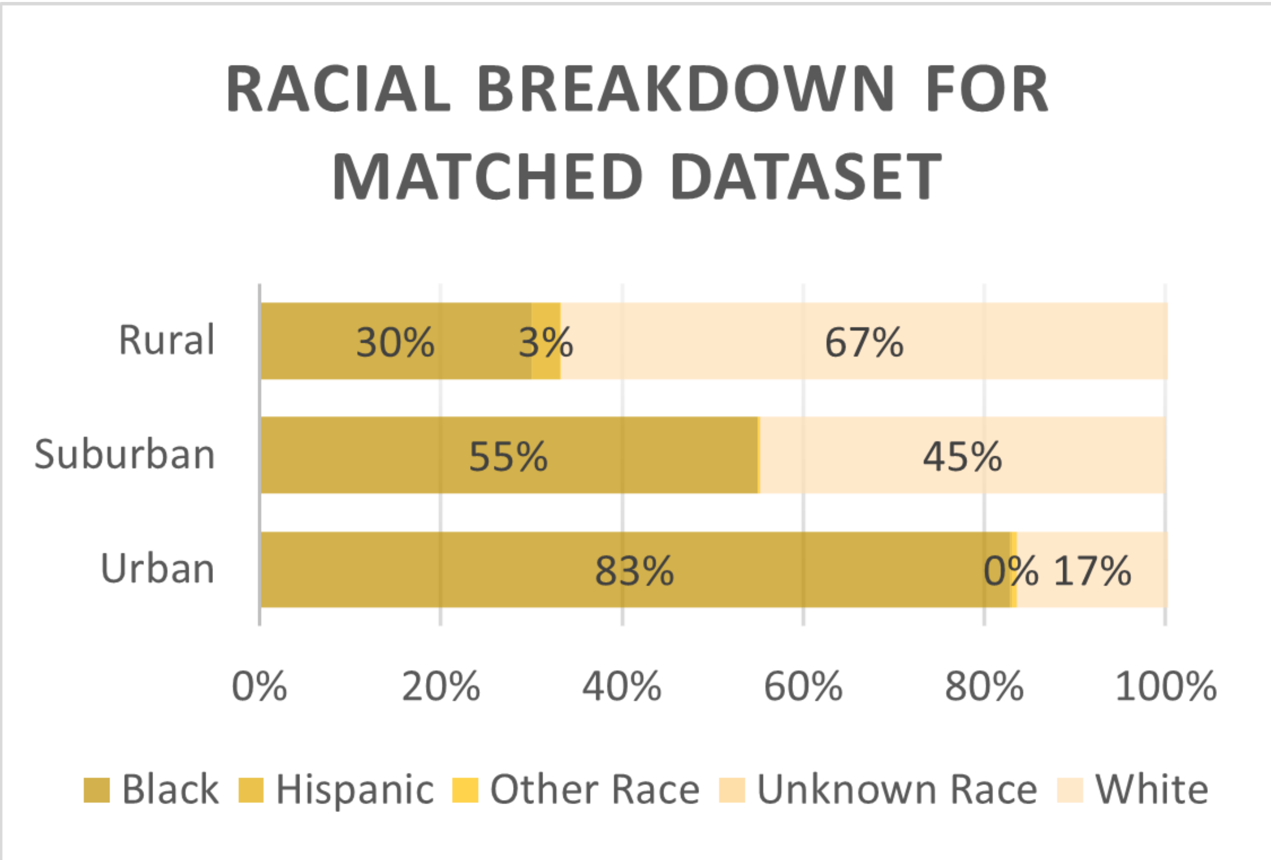
Only one jail provided clean SIDs. The match rate for that jail was upwards of 90% of booking episodes. The other two jails that provided SID information did so in an open text field with multiple SID, and SID-like numbers in the field. Those had to be parsed, cleaned, and each number was tried against the CCH database for a match.

Below is a summary of the number of persons and booking episodes in the dataset. Overall, ARS was able to find SID's for 71% of the people in the dataset representing 69% of the booking episodes in the dataset.

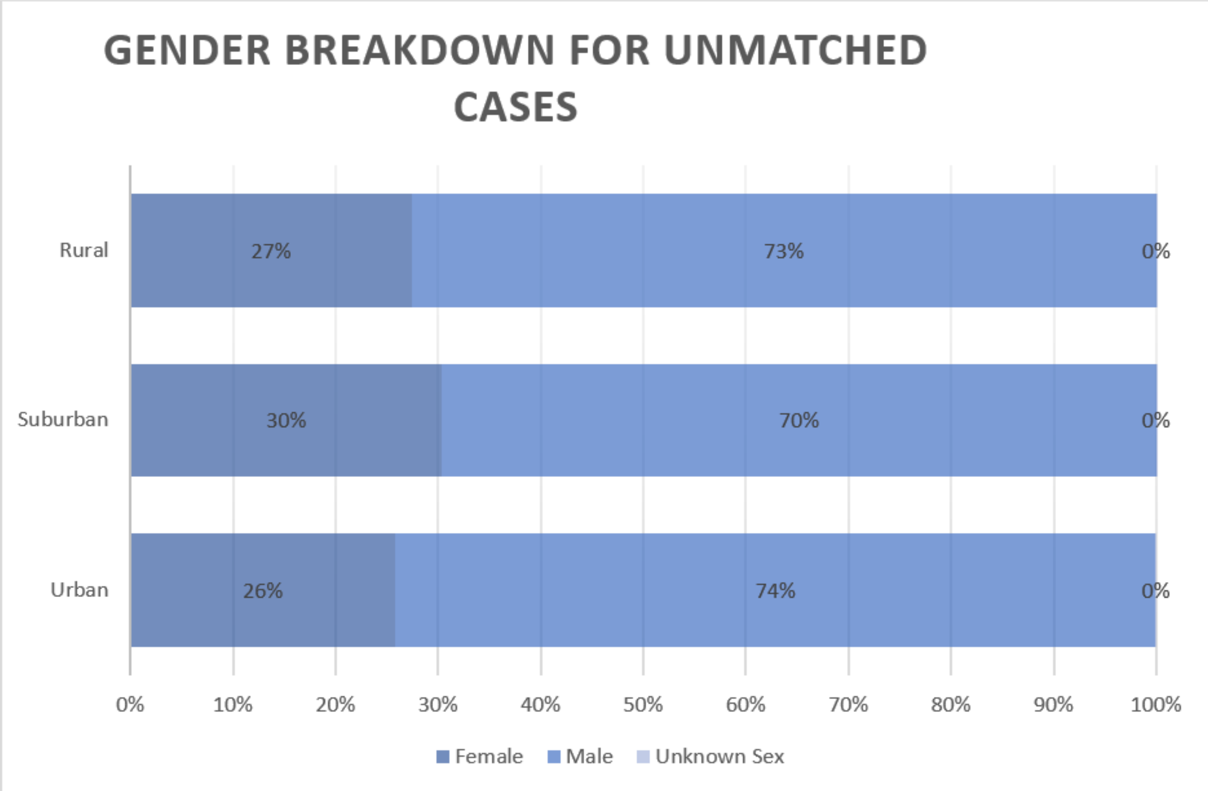
Number of People Booked (369,748)	**Urban (203,998)**	**Suburban (142,416)**	**Rural (23,334)**
Number of Booking Episodes (611,432)	**Urban (384,115)**	**Suburban (217,504)**	**Rural (45,813)**
SID Matches (71%)	**Urban (61%)**	**Suburban (86%)**	**Rural (68%)**

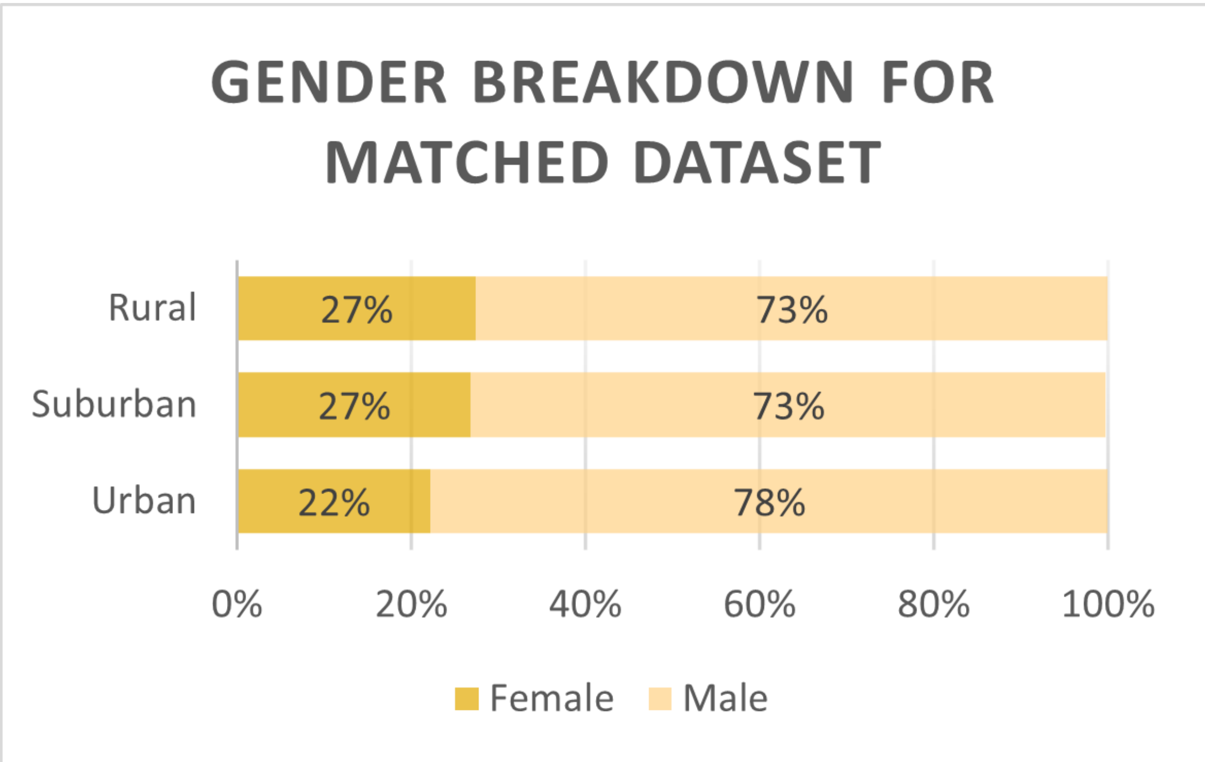
The charts below demonstrate that the demographic breakdown for the matched dataset versus the full dataset.





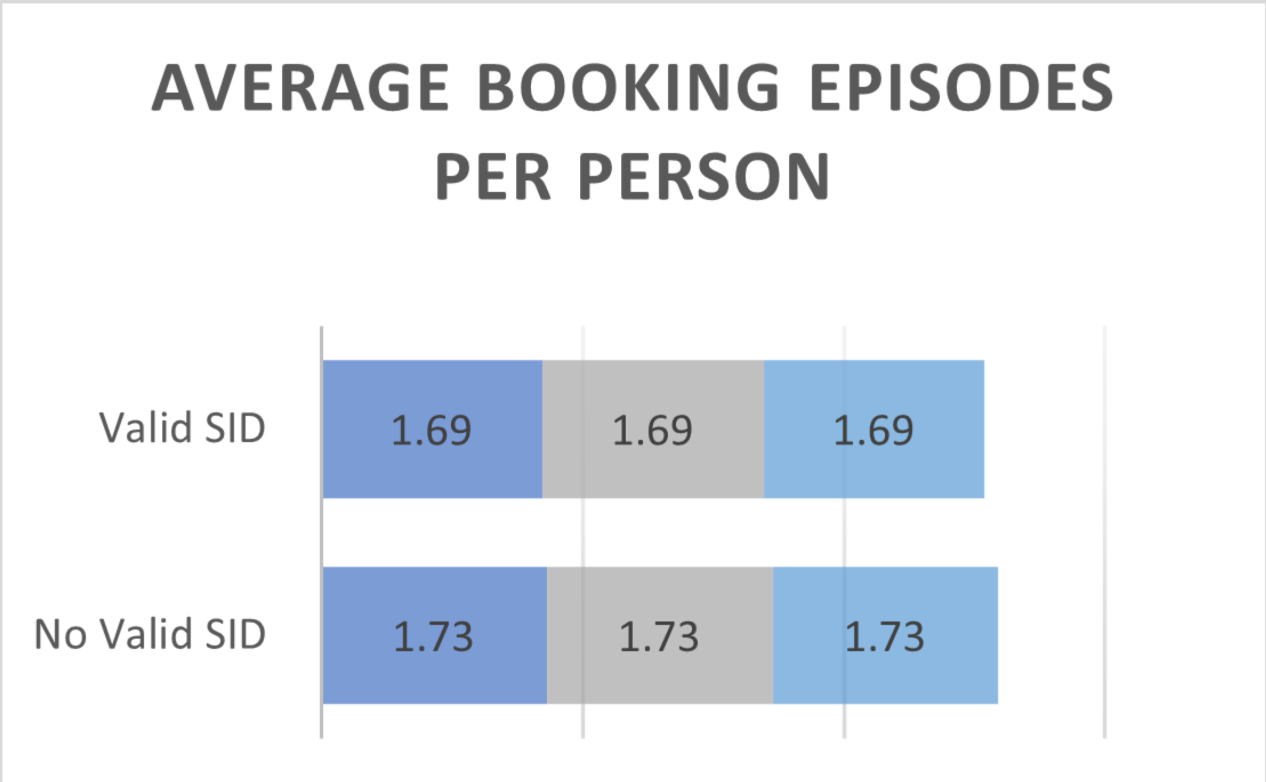
As compared to urban and suburban jails, the population in rural jails was substantially whiter. With respect to gender breakdown, almost three quarters of the overall and matched samples for all jails were male.





Finally, with respect to age, the overall population was 35 on average. The matched sample was 34 on average and the non-matched sample was between 36 and 34.

Whether someone's record successfully matched CCH did not seem to be dependent on booking frequency either. Across the three jail types, the average number of bookings per person was 1.7 for those with and without a Valid SID.



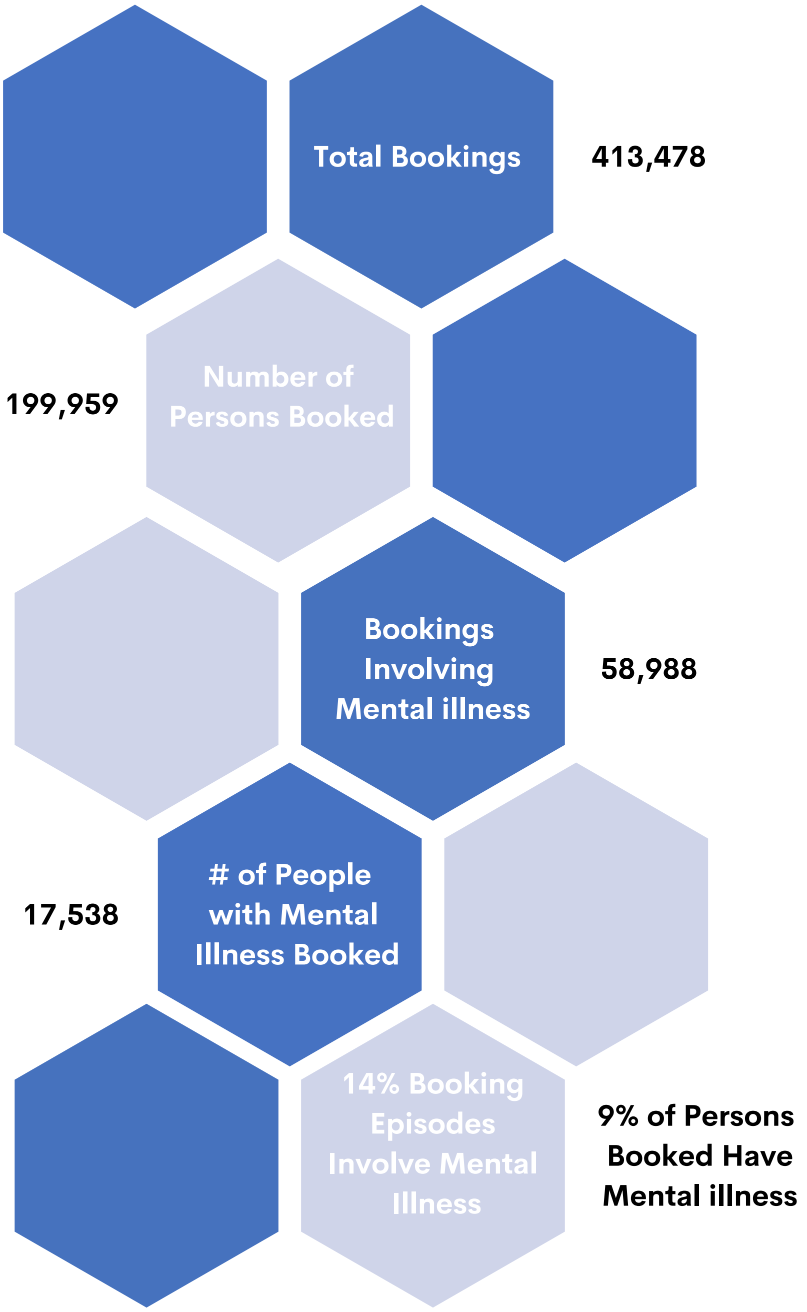
Given the basic demographic breakdowns of the matched and non-matched data, and that we were able more than two-thirds of the people in the original datasets, we are confident that the missing records from non-matches are not likely to bias our findings.

Findings

Conservative Estimate of Prevalence of Mental Illness in County Jails

The indicator for mental illness in our dataset is derived from an 11-point mental health screener that DCS conducts, and GDC's mental health classification for inmates.

A person in our dataset must have a felony conviction history to be found in either GDC or DCS datasets. Therefore, the estimate below is **conservative** and likely **understates** the percent of people who have mental illness, and by extension total bookings involving mental illness.



These prevalence estimates are conservative because a substantial portion of our matched sample had no felony conviction history, and thus their mental health status is completely unknown, since jails did not give us these data. These prevalence estimates are based on known mental health flags as denoted in DCS and GDC data.

Nevertheless, even with these conservative estimates persons with mental illness are represented in county jails at twice the rate that they are in the general population. According to the National Institutes of Mental Health, 5.6% of the U.S. population has serious mental illness.xiv

No Felony Booking Episodes

Number of Booking Episodes
(162,615)

Percent Total Booking Episodes:
(39%)

People Booked with No Felony History

Number of People Booked
(98,022)

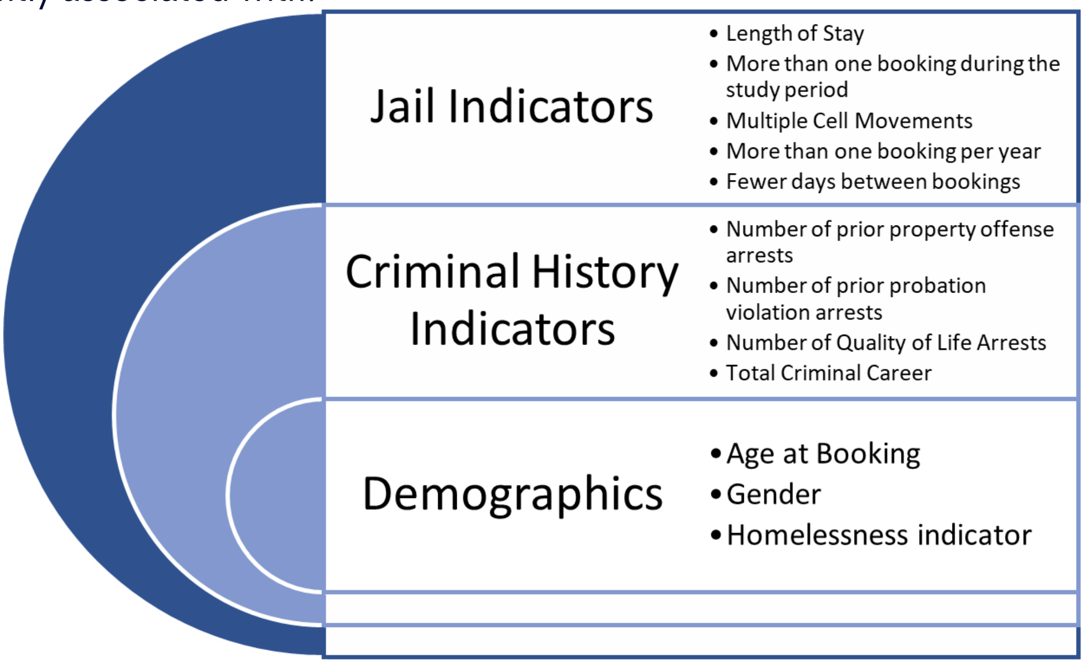
Percent of Total Number of Persons Booked:
(49%)

Almost half of all people booked into the jails in our sample during the study period had no felony conviction history. That means they would never had gotten screened at either DCS or GDC for mental illness, and thus their mental health status is effectively unknown in the administrative datasets at our disposal. This fact presents a substantial limitation to the current study and to our prevalence estimate.

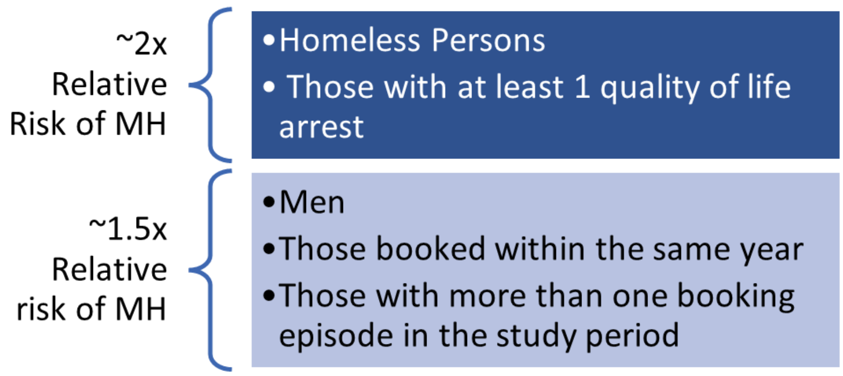
Significant Difference on Multiple Jail Episode Indicators between Persons with Mental Illness and those Without

The second focus of the present study is to identify proxy indicators within jail management system and criminal history data that may predict mental illness. While there are at least two validated xv, short-form screening tools for mental illness available to jails, identifying predictors that can be calculated on, and potentially programmed into, jail management systems would be a time-savings for intake officers. As stated previously, persons with mental illness tend to differ in their jail experiences from those without mental illness on such factors as length of stay and number of times booked to the same (or different) jails.

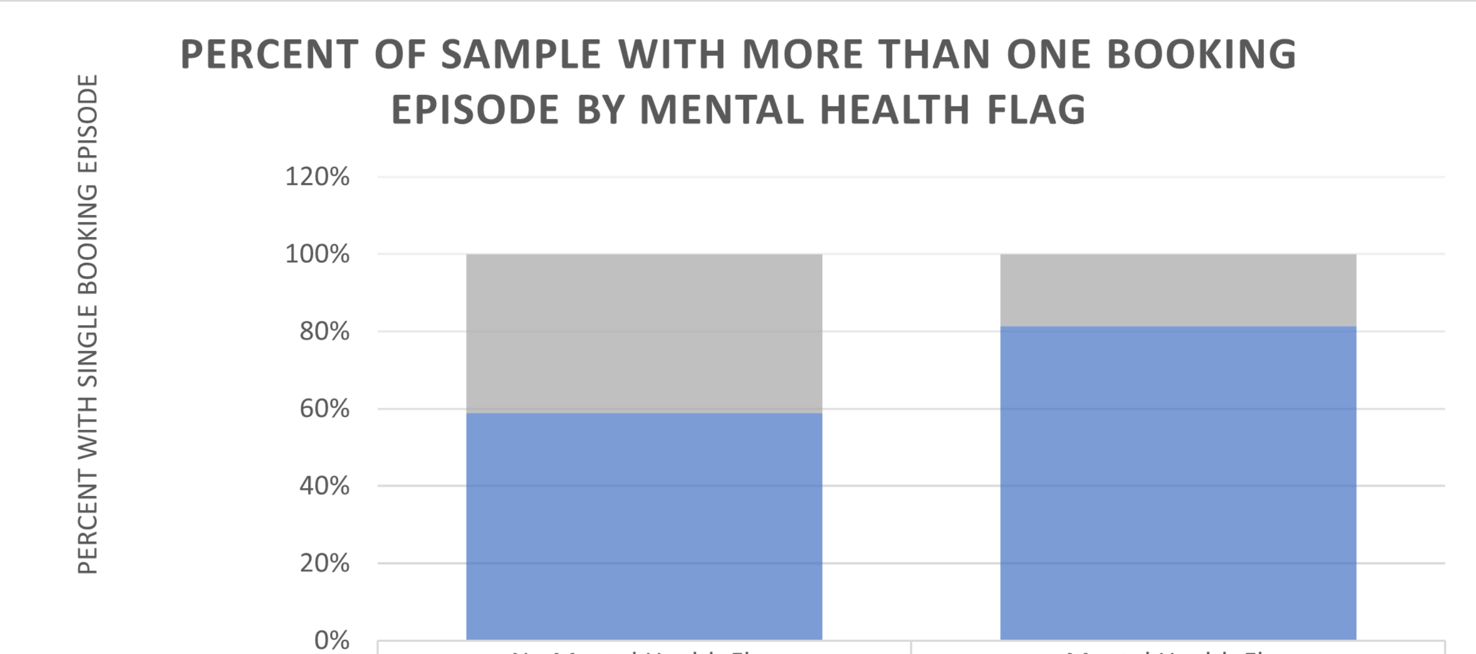
We used t-tests and chi-square analysis to determine whether mental illness was significantly associated with:



In brief, we find significant relationships between our mental illness flag and the following indicators:

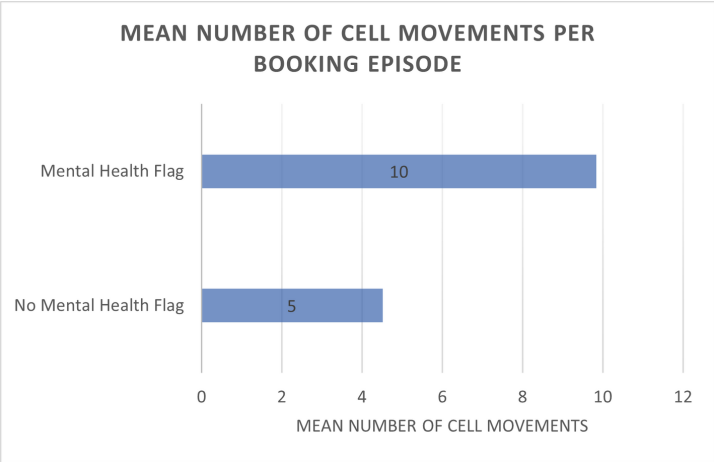


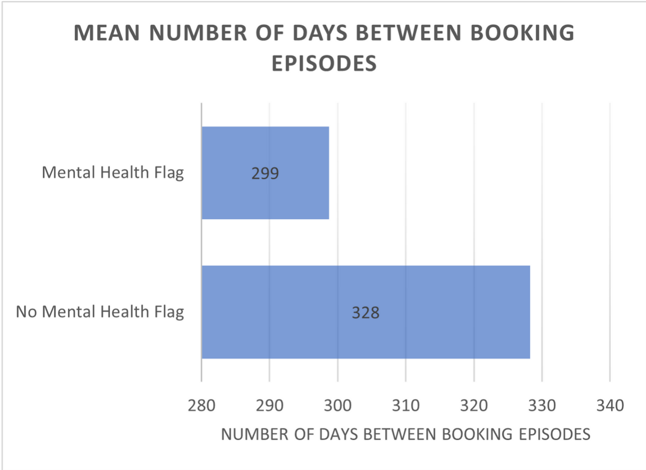
Indeed, while those with no mental health involvement where just slightly more likely to have more than one booking episode during the study period, only 20% of those with a mental health flag had a single booking episode in the five-year study period.

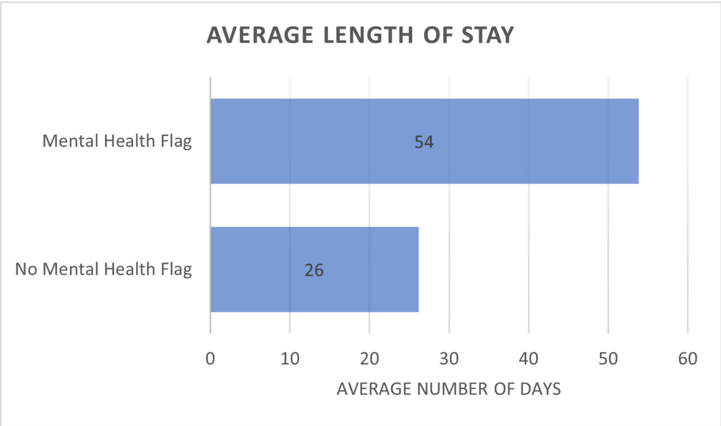


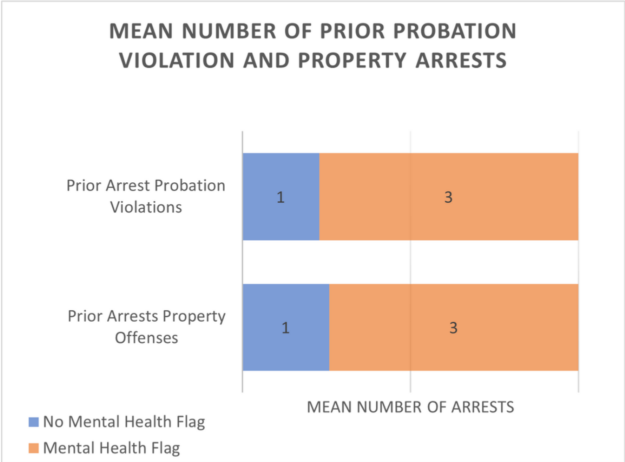
	No Mental Health Flag	Mental Health Flag
Single Booking	41%	19%
More than one Booking	59%	81%

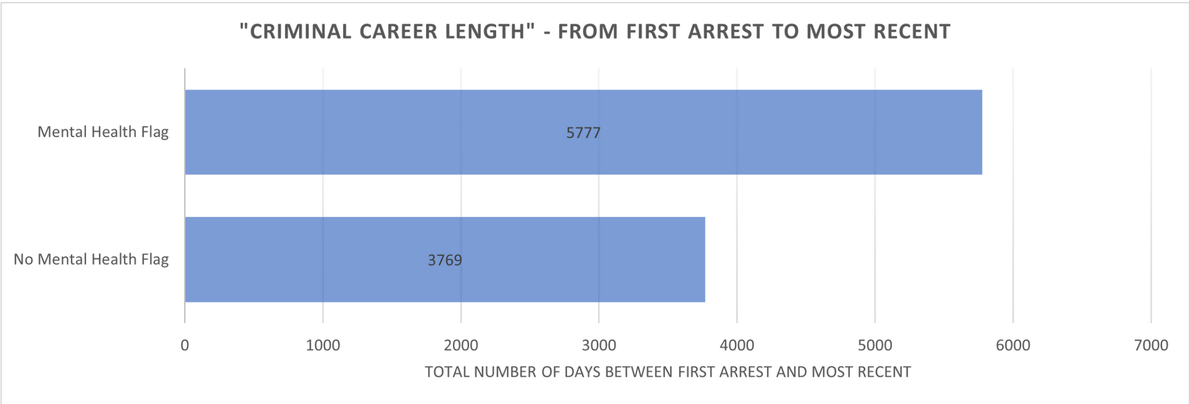
We have similar findings on our t-tests for differences in means for our quantitative indicators. On every single quantitative indicator of interest, persons with mental illness had an average double or triple of that for those without mental illness. These differences are all statistically significant at the $p<0.05$ level and below.











Those with mental illness had been "active" criminally for almost twice as long as those without mental illness. When they were booked into our study jails, they stayed twice as long as those without mental illness. While they were booked, they moved around within the jail twice as many times as those without mental illness. They had three times as many arrests for property offenses and probation or parole violations. The only indicator on which persons with mental illness seemed to have some parity as those without is on number of days between booking episodes. Those without mental illness stayed out of jail approximately 30 days longer on average than those with mental illness.

Assessing Proxy Indicators for Mental Illness

We conducted two types of inferential analysis to determine whether we could derive a set of predictive factors for mental illness from jail management system data. First, we conducted k-means cluster analysis to assess whether having a mental illness substantially differentiated those without such that we could estimate the proportion of those without a felony history who might have a mental illness, based on which cluster they fell into.

Next, we incorporated the indicators we found to have a significant relationship to mental illness on bivariate analysis into a logistic regression model to predict mental health involvement. The findings for both are reported below.

Grouping Those With and Without Mental Illness into Separate Groups

We conducted two types of inferential analysis to determine whether we could derive a set of predictive factors for mental illness from jail management system data. First, we conducted k-means cluster analysis to assess whether having a mental illness substantially differentiated those without such that we could estimate the proportion of those without a felony history who might have a mental illness, based on which cluster they fell into.

Next, we incorporated the indicators we found to have a significant relationship to mental illness on bivariate analysis into a logistic regression model to predict mental health involvement. The findings for both are reported below.

Urban

- [ ] Number of Dsys B/W Episodes
- [ ] Age at Booking
- [ ] Total Booking Episodes
- [ ] Criminal Career Days
- [ ] # Prior Property Arrests
- [ ] # Prior Probation Violation Arrests
- [ ] Length of Stay

Suburban/Rural

- [ ] Number of Dsys B/W Episodes
- [ ] Age at Booking
- [ ] Cell Movement Count
- [ ] Total Bookings
- [ ] Criminal Career Days
- [ ] # Prior Property Arrests
- [ ] # Prior Probation/Parole Violation Arrests

As the figure above indicates, we excluded length of stay from the Suburban/Rural cluster because one of the largest jails in that grouping did not provide release dates. On the Urban clusters, we only received cell movement from a single jail, so we could not use those data. The tables below provide a summary of the final cluster centers.

Urban Jail Cluster Centers		
	Cluster Number	
Variable	1	2
Number of Days b/w Bookings	339	281
Age At Booking	31	42
Total Bookings	3	4
Criminal Career Days	1920	8509
# Prior Property Arrests	1	4
# Prior Probation/Parole Violation Arrests	1	2
Length of Stay	21	28
Number of Cases in each Cluster		
Cluster	1	144,458
	2	55,511
Valid		199,969
Missing		0.000

Suburban/Rural Jail Cluster Centers		
	Cluster Number	
	1	2
Number of Days b/w Bookings	327	300
Age At Booking	29	40
Cell Movement Count	6	5
Total Bookings	4	10
Criminal Career Days	2176	9047
# Prior Property Arrests	1	3
# Prior Probation/Parole Violation Arrests	1	3
Number of Cases in each Cluster		
Cluster	1	142,556
	2	70,953
Valid		213,509
Missing		0.000

Chi-square tests revealed a significant relationship between cluster membership and mental health flag status.

Urban Jails Mental Health Flag by Cluster Number		**Cluster 1**	**Cluster 2**	**Total**
No Mental Health Flag	Count	127,033.00	39,021.00	166,054.00
	Expected Count	122,882.70	43,171.30	166,054.00
	% Within MH_flag	76.50%	23.50%	100.00%
Mental Health Flag	Count	12,082.00	9,853.00	21,935.00
	Expected Count	16,232.30	5,702.70	21,935.00
	% Within MH_flag	55.10%	44.90%	100.00%
Total	Count	139,115	48,874	187989

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	4620.728a	1	0.000
N of Valid Cases	187,989.00		

Those with mental illness were almost evenly split between the clusters, but they were almost twice as likely to be in Cluster 2 as those without mental illness. Looking at the Expected versus Observed counts in the table above (cells highlighted in gray), there are almost 75% more persons with mental illness in Cluster 2 than what is expected. Assessing the center of the means for Cluster 2 reveals why – the center for the Number of Days indicator is roughly thirty days lower than for cluster 1; criminal career days is almost 7 times larger than Cluster 1; and the ratio for number of prior property and probation violations is maintained in Cluster 2.

The same pattern holds true in suburban/rural jails.

Suburban/Rural Jails Mental Health Flag by Cluster Number		Cluster1	Cluster 2	Total
No Mental Health Flag	Count	122,979	53,477	176,456
	Expected Count	117,816	58,640	176,456
	% Within MH_Flag	69.69%	30.31%	82.60%
Mental Health Flag	Count	19,577	17,476	37,053
	Expected Count	24,740	12,313	37,053
	% Within MH_Flag	52.84%	47.16%	17.40%
Total	Count	142,556	70,953	213,509
	Value	df	Asymptotic Significance (2-sided)	
Pearson Chi-Square	3922.560a	1	0	
N of Valid Cases	213,509.00			

There are 42% more people with mental illness in cluster 2 than what would be expected by random chance. Those with mental illness are 1.5 times as likely as those without to be in cluster 2. With the exception of Cell Movement counts, the centers for cluster 2 are substantially higher than those for Cluster 1, so this pattern makes sense. Those without mental illness are more likely to be in Cluster 1. This makes the k-means clustering too imprecise a tool to use for estimating the percentage of the population without a felony history, for whom we have no mental health indicator in the administrative data.

Testing Predictors of Mental Illness in a Logistic Regression Model

We then broke the jails into three groups – Rural, Urban, and Suburban to run logistic regression models assessing the degree to which the variables for which we found significant relationships to mental illness might be predictive of illness. Below we report only the predicted versus observed classification table and the odds ratio table. The predictive value for the variables that seem promising on bivariate analysis falls apart when inserted in a model.

Urban Jails Logistic Regression		Predicted		
		Mental Health Flag		
	Observed	No	Yes	Percentage Correct
Mental Health Flag	No	163,734	2,317	98.6%
	Yes	19,315	2,588	11.8%
		Overall Percentage		88.5%

Variables in the Equation and Odds Ratios			
Variable Name	*B*	*Sig.*	*Odds Ratio*
Age At Booking	-0.047	0.00	0.954
Total Bookings	0.021	0.00	1.022
Criminal Career Days	0	0.00	1
# Prior Property Arrests	0.069	0.00	1.071
# Prior Probation/Parole Violation Arrests	0.252	0.00	1.287
Male	0.506	0.00	1.659
Constant	-1.968	0.00	0.14
***Significance at the 0.0 level indicates p<0.01, or the 99th Percentile**			

The model predicted only 12% of the mental health flags in the urban jail dataset correctly. The remaining 88% were incorrectly classified. A look at the Odds Ratios tells us why. While those with mental illness have almost twice as many booking episodes, a criminal career that is twice as long, the odds ratios for those with or without mental illness is equal. The only variables in this model that predict greater odds of having a mental illness are being male and having a prior arrest for probation violations.

The models for suburban and rural jails performed only marginally better. The predictive power of the individual variables was not great, but they were slightly better at accurately classifying cases with mental illness. This model for suburban jails correctly predicted 15% of mental health cases.

Suburban Jail Logistic Regression Output		Predicted		
		Mental Health Flag		
	Observed	No	Yes	Percentage Correct
Mental Health Flag	No	85,352	2,928	96.7%
	Yes	24,183	4,174	14.7%
		Overall Percentage		76.8%

Variables in the Equation and Odds Ratios			
Variable Name	B	Sig. *	Exp(B)
Age At Booking	-0.027	0.00	0.973
Cell Movement Count	0.025	0.00	1.025
Total Bookings	0.004	0.00	1.004
Criminal Career Days	0	0.00	1
# Prior Property Arrests	0.066	0.00	1.069
# Prior Probation/Parole Violation Arrests	0.118	0.00	1.125
Male	-0.137	0.00	0.872
Constant	-0.928	0.00	0.395
***Significance at the 0.0 level indicates p<0.01, or the 99th Percentile**			

Again, the odds ratios do not clearly distinguish between those with mental illness and those without. Of note, being male is a significant predictor of mental illness in the Urban jails, but in suburban and rural jails, being female is a significant predictor of mental illness. Males are 87% as likely as females to have mental illness.

The model performed best on the rural jail sample – but only marginally so. Here, the variables correctly classified 17% of mental health flags.

Rural Jail Logistic Regression Output		Predicted		
		Mental Health Flag		
	Observed	No	Yes	Percentage Correct
Mental Health Flag	No	14,088	406	97.2%
	Yes	2,475	513	17.2%
		Overall Percentage		83.5%

Variable Name	*B*	*Sig.**	*Exp(B)*
Age At Booking	-0.044	0.00	0.957
Cell Movement Count	0.02	0.00	1.02
Total Bookings	0.025	0.00	1.025
Criminal Career Days	0	0.00	1
# Prior Property Arrests	0.118	0.00	1.125
# Prior Probation/Parole Violation Arrests	0.362	0.00	1.437
Male	-0.714	0.00	0.49
Constant	-0.892	0.00	0.41
*Significance at the 0.0 level indicates p<0.01, or the 99th Percentile			

Three variables here have some viable predictive power. Males in rural jails are *half* as likely as women to have a mental illness. Those with prior arrests for probation or parole violations are 1.5 times as likely to have mental illness. And those with prior property arrests are slightly more likely to have mental illness. While these odds are better for crafting a probability-based screener, they still do not provide sufficient accuracy given how many booking episodes the model classified correctly.

Discussions and Limitations

We set out to do three things:

1. Estimate the prevalence of people with mental illness in county jails;
2. Identify proxy indicators for mental illness in jail management system data;
3. Assess the degree to which those indicators could be used to predict mental illness.

Our findings are promising on all fronts, but precise on two. We have a conservative estimate of the proportion of jail booking episodes, and the percentage of those booked, who have mental illness. Such an analysis using criminal justice administrative data had never been done in Georgia. Moreover, the fact that we have 142 jails with almost as many different jail management systems presents a unique challenge at obtaining statewide data. However, the selection of 9 jails from which we obtained data demonstrate that the data jails collect is consistent and provides a good foundation for assessing the degree to which persons with mental illness interface with the criminal justice system.

We have identified promising proxy indicators for mental illness, but we could not achieve robust predictability once those were put into a logistic regression model. Data missingness meant that we could not use all variables we collected information on in all models, nor could we assess how viable they are for predicting mental illness. While the need for differing models for rural, urban, and suburban jails is evident given our preliminary findings, we cannot ascertain which factors should be included in which models.

One of our more promising indicators seemed to be the homeless flag, but only 992 out of over 400,000 booking episodes could be identified as involving someone who is homeless. This is because we did not receive a reliable flag from the jails for homelessness and were thus relying upon text analysis of address fields. Moreover, we received address information for the active population (not booked) for two of the jails, so those data were incomplete.

There is also the problem of whether mental illness predicts many of the items we are trying to use to predict mental illness. The issue of simultaneity is a difficult one to control for in a limited dataset and with incomplete data.

Next Steps

Our journey does not end here. We have partnered with four of the 9 jails in this study to further assess the proxy measures we have identified. We plan to use a pen and paper screening tool to collect information about all people booked into our partner jails for a short period. The screener tool will give us information about persons without a felony conviction who would never have been assessed for mental illness by either DCS or GDC. These screener results can be compared with jail administrative data, DCS, and GDC data to more accurately classify all persons booked. We can then assess the performance of our identified indicators against the screener to develop a tool based on administrative data.

Endnotes

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