Claremont Colleges Scholarship @ Claremont

**CGU Theses & Dissertations** 

CGU Student Scholarship

Fall 2020

# Recidivism among Previously Incarcerated People Enrolled in Riverside County Whole Person Care

Ndifreke Emmanuel Etim Claremont Graduate University

Follow this and additional works at: https://scholarship.claremont.edu/cgu\_etd

Part of the Public Health Commons

#### **Recommended Citation**

Etim, Ndifreke Emmanuel. (2020). *Recidivism among Previously Incarcerated People Enrolled in Riverside County Whole Person Care*. CGU Theses & Dissertations, 267. https://scholarship.claremont.edu/cgu\_etd/267.

This Open Access Dissertation is brought to you for free and open access by the CGU Student Scholarship at Scholarship @ Claremont. It has been accepted for inclusion in CGU Theses & Dissertations by an authorized administrator of Scholarship @ Claremont. For more information, please contact scholarship@cuc.claremont.edu.

# RECIDIVISM AMONG PREVIOUSLY INCARCERATED PEOPLE ENROLLED IN RIVERSIDE COUNTY WHOLE PERSON CARE

by

Ndifreke Emmanuel. Etim

Claremont Graduate University

© Copyright Ndifreke Etim, 2020.

All rights reserved

# **Approval of the Dissertation Committee**

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Ndifreke Emmanuel Etim as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Health Promotion Sciences.

Dr. Paula H. Palmer (Co-chair)

Claremont Graduate University

Associate Professor

Dr. Bin Xie (Co-chair)

Claremont Graduate University

Professor

Dr. Debbie Freund

Claremont Graduate University

Professor

Dr. Judi Nightingale

Riverside University Health Systems

Director of Population Health

#### Abstract

# RECIDIVISM AMONG PREVIOUSLY INCARCERATED PEOPLE ENROLLED IN RIVERSIDE COUNTY WHOLE PERSON CARE

by

Ndifreke Emmanuel Etim

Claremont Graduate University: 2020

The United States continues to policy shift towards reducing the number of incarcerated people; however, many people released from incarceration will be rearrested due to re-entry challenges. Several re-entry programs, such as the Whole Person Care pilot, have been developed to address these challenges and ensure that formerly incarcerated people successfully transition into the community. The primary aim of this project is to explore the determinants of recidivism among previously incarcerated people enrolled in the Whole Person Care pilot in Riverside County.

This study suggests early linkage to services, such as mental health and substance use treatment services, will reduce the likelihood of recidivism within 12 months. It further proposes that housing status at release will increase recidivism risk and reduce the number of days till first rearrests. Finally, the study proposes that early linkage to Medicaid will increase service use, consequently reducing the likelihood of recidivism.

The findings from this project support that hypothesis by showing that engagement in services reduced the likelihood of recidivism. It further identified a lack of housing at release as a significant predictor of recidivism within 12 months. Finally, two indirect pathways through which Medicaid insurance reduces recidivism were identified. These findings have important

implications for policies that aim to reduce the prison population. In addition, the findings have significant implications for program planners who are developing re-entry interventions.

# Dedication

To my parents, Emmanuel and Ema Etim, for their unwavering support and encouragement over the years.

#### Acknowledgments

I received a great deal of support and assistance from many people throughout my doctoral studies and the course of this dissertation.

First and foremost, I would like to thank my mentors, Dr. Paula Palmer and Dr. Bin Xie, for their support and encouragement over the past few years. Without you, none of this would have been possible. Your feedback and encouraging words kept me going when I felt like giving up. You also pushed me to learn new skills and to raise my thinking to a higher level.

I would also like to thank other members of my committee. To Dr. Judi Nightingale, thank you for supporting this project from the onset and ensuring that I had access to the Whole Person Care pilot data. Also, thank you for readily answering any questions I had about the Whole Person Care project. To Dr. Debbie Freund, your expertise has been invaluable in guiding me through this dissertation and thinking beyond the current project.

I want to acknowledge my colleague and dissertation partner Nirshila Chand for informing me about the Whole Person Care. I am glad that I had someone to vent to whenever I was frustrated about the IRB and data cleaning process.

I would also like to acknowledge other people that supported and guided me during my doctoral studies, including Jolanda Lisath, Dr. Nicole Gatto, Dr. Alan Stacy, James Pike, Bree Hemingway, and other SCGH faculty and classmates.

In addition, I would like to thank my friends for providing a happy distraction outside of my research. And thank you to those who took the time to read my work or listen to my practice presentations. I know some of you disagreed with my views or had no idea what I was talking about; however, you listened and offered your honest opinion. Finally, I would like to thank my family for their continued support and challenge to seek more. To my brother Ifiok Etim, my sisters Edidiong Etim, Mbuotidem Etim and Esther Etim, and my parents Emmanuel and Ema Etim, you are always there for me, and I know I am never alone despite the distance between us.

ruble of contents	
LIST OF TABLES	xi
LIST OF FIGURES	xii
LIST OF ABBREVIATIONS	xiii
CHAPTER 1: INTRODUCTION	1
INCARCERATION IN THE UNITED STATES	1
HEALTH OUTCOMES AMONG PEOPLE INVOLVED IN THE JUSTICE SYST	ГЕМ 2
RECIDIVISM FOLLOWING RELEASE FROM INCARCERATION	3
MENTAL HEALTH, SUBSTANCE USE AND RECIDIVISM	5
MEDICAID INSURANCE AND RECIDIVISM	6
HOUSING AND INCARCERATION	
THEORETICAL / CONCEPTUAL FRAMEWORK	9
A socioecological framework to prevent recidivism	9
Risk-Need-Responsivity (RNR)	
PROJECT OVERVIEW	14
Purpose of the Study	14
Riverside University Health System Whole Person Care Pilot	14
Significance	15
Objectives	15
METHODS	16
Data Source	16
Ethical- Human Studies considerations	17
Measures	17
Analysis Plan	19
CHAPTER 2: THE ASSOCIATION BETWEEN EARLY LINKAGE TO TREATM	ENT FOR
MENTAL HEALTH AND SUBSTANCE USE DISORDERS AND RECIDIVISM	30
BACKGROUND	30
METHOD	
Measures	
Analysis	
RESULTS	
Mental health and Substance use Service encounter	
DISCUSSION	

# **Table of Contents**

CHAPTER 3: HOUSING INSTABILITY AND TIME TILL RE-INCARCERATION: A	
SURVIVAL ANALYSIS	42
BACKGROUND	42
METHOD	43
Measures	43
Independent Variable	43
Analysis	44
RESULTS	45
Participants characteristics	45
Time till re-incarceration	45
DISCUSSION	50
CHAPTER 4: THE MEDIATING EFFECT OF MENTAL HEALTH AND SUBSTANCE U SERVICES ON THE RELATIONSHIP BETWEEN MEDICAID AND RECIDIVISM	SE 53
BACKGROUND	53
METHODS	55
Measures	56
Analysis	56
RESULTS	57
Participant Characteristics	57
DISCUSSION	59
CHAPTER 5: CONCLUSION	62
SUMMARY OF STUDIES	62
LIMITATIONS	63
FUTURE DIRECTIONS	64
TABLES	66
ADDITIONAL FIGURES	74
REFERENCES	75

# LIST OF TABLES

Table 1: Study 1 Sample Description	67
Table 2: Predictors of Recidivism using Logistic Regression and Negative Binomial	
Regression	69
Table 3: Study 2 Sample Description	70
Table 4: Test for Proportional Hazard Assumption	72
Table 5: Cox Proportional Hazard Model of Time till First Reincarceration	72
Table 6: Study 3 Sample Description	73
Table 7: Path coefficients, indirect effects, and 95% corrected confidence interval (10,00	0
bootstrapped samples) predicting recidivism	74

# LIST OF FIGURES

Figure 1. The conceptual framework for the current study	14
Figure 2 A simple mediation model	29
Figure 3: Survival Probability of WPC Participants	47
Figure 4: Survival Probability by Housing Status	47
Figure 5: Schoenfeld test for all variables	49
Figure 6: Aalen's plot for the additive regression	51
Figure 7: Conceptual Model for the current study	58
Figure 8: Rootogram showing model fit for the negative binomial regression model	.75
Figure 9: Rootogram showing model fit for the Poisson regression model	75

# LIST OF ABBREVIATIONS

BJS	Bureau of Justice Statistics
CMS	Centers for Medicare and Medicaid Services
DTC	Drug Treatment Court
ED	Emergency Department
HbA1c	Glycohemoglobin
HCV	Hepatitis C
HIV	Human Immunodeficiency Virus
IRB	Institutional Review Board
MHC	Mental Health Court
MI	Mental Illness
NIJ	National Institute of Justice
OR	Odds Ratio
РО	Probation Officer
RN	Registered Nurse
RNR	Risk-Need-Responsivity
RUHS	Riverside University Health System
SMI	SEVERE Mental Illness
SUD	Substance Use Disorder
US	United States
WPC	Whole Person Care

#### **CHAPTER 1: INTRODUCTION**

#### INCARCERATION IN THE UNITED STATES

The United States (US) has a higher incarceration rate than any other country globally; in 2018, there were 1.4 million people incarcerated in the US.<sup>1</sup> According to the National Bureau of Justice Statistics, in 2015 an estimated 6,741,400 adults were under the supervision of the US adult correctional system either through incarceration, probation or parole .<sup>2</sup> Mass incarceration is a public health issue that disproportionately affects the health and health outcomes of minority communities across the US. Blacks and African Americans represented 33% of the prison population, but they constitute only 12% of the US adult population. Similarly, Hispanics accounted for 23% of inmates, compared with 16% of the adult population. In comparison, Whites accounted for 30% of prisoners while making up 63% of the adult population.<sup>3</sup>

In the last few years, a policy shift towards decarceration has led to a reduction in the US prison population, decreasing it by 15% between 2008 and 2018.<sup>1</sup> For example, California has passed laws intended to reduce the state's prison inmate population. In 2014, the state passed the Safe Neighborhoods and Schools Act (Proposition 47). This law, which reclassified certain theft and drug possession offenses from felonies to misdemeanors, allowed people currently serving sentences for felony offenses that would have qualified as misdemeanors under the proposition to petition for resentencing.<sup>4</sup> It authorized defendants who had completed their sentences for felony convictions that would have qualified as misdemeanors under the proposition to apply to reclassify those convictions to misdemeanors.<sup>4</sup> Up to 10,000 people became eligible to return home due to the proposition, and over 200,000 petitions for resentencing have been received.<sup>4,5</sup>

In November 2016, Californians voted to pass The Public Safety and Rehabilitation Act (Proposition 57), which aimed to stop the revolving door of incarceration by emphasizing rehabilitation and increasing opportunities for release on parole for felons convicted of nonviolent crimes.<sup>6(p57)</sup> As a result of such policies, over 600,000 individuals are now being released back into their communities from state and federal prisons in the US annually.<sup>7</sup> In 2016, 1 in 55 nonincarcerated adults were either on probation or parole, this number continues to grow each year.<sup>2</sup> As previously incarcerated people are released back into the community, health professionals must find ways to ensure that they are successfully reintegrated back into their communities.

# HEALTH OUTCOMES AMONG PEOPLE INVOLVED IN THE JUSTICE SYSTEM

Incarceration is a stressful period for incarcerated people, and this stress is likely higher immediately after release.<sup>8</sup> Incarceration is a stressful period for incarcerated people as it may activate stress pathways known to be associated with poor health outcomes.<sup>8</sup> People who are incarcerated have a higher prevalence of hypertension, tuberculosis, viral hepatitis, HIV/AIDS, asthma, syphilis, and cervical cancer than the general population.<sup>9–12</sup> Early data from the COVID-19 pandemic has found a prevalence of COVID-19 correctional settings between 0%-86.8%.<sup>13</sup> In Massachusetts, the COVID-19 rate among incarcerated individuals was nearly three times that of the general population and five times the US rate.<sup>14</sup> People who are incarcerated are disproportionately affected by poor health compared to the general population. Mass incarceration may have significant implications for health disparities as a larger proportion of incarcerated people are Black or Hispanic.

In 1976, the US Supreme Court ruled that health care deprivation for incarcerated people constituted cruel and unusual punishment and violated the Eighth Amendment to the

Constitution.<sup>15</sup> As a result, incarceration is the only time a US citizen is guaranteed healthcare. However, many incarcerated people still lack access to healthcare because they cannot afford the steep co-pay required for medical visits.<sup>16,17</sup> Before 2020, prison inmates in California could pay up to five dollars for medical visits, the equivalent of \$656.25 for non-incarcerated people when adjusted for minimum wage.<sup>16</sup> Such a high co-pay might deter prisoners from seeking healthcare, affecting their health and resulting in increased adverse outcomes.

Previous studies have described higher rates of mortality among previously incarcerated people.<sup>8</sup> For example, Binswanger et al. found that mortality rates post-incarceration were 3.5 times higher overall, and the death rate was 13 times higher among previously incarcerated individuals than the general population within the first two weeks after release.<sup>8,18</sup> Furthermore, life expectancy was 4.2 years less for men and 10.6 years less for women who experienced incarceration than the general population.<sup>19</sup> One study showed a dose-response relationship of incarceration on mortality, reporting that for every year a person is incarcerated, their life expectancy decreases by two years.<sup>20</sup> In general, the stress of reentry and these poor health outcomes may interfere with the process of re-entry into the community, which may lead to re-incarceration or mortality.

# RECIDIVISM FOLLOWING RELEASE FROM INCARCERATION

In general, recidivism refers to relapse to criminal behavior over a specified period.<sup>21</sup> McLean and Ransford (2004) define recidivism as the relapse to criminal activity due to the individual's return to prison for a new offense.<sup>22</sup> They noted that the recidivism rate reflects the degree to which previously incarcerated people have been rehabilitated and the success of reintegration into society.<sup>22</sup> According to the Bureau of Justice Statistics, although recidivism

can be defined in multiple ways, all definitions share the common traits. First, each definition must have a starting event, for example, release from incarceration. Second, each definition must have a measure of failure, such as re-arrests, reconviction, or committing a new crime. Finally, each definition must have a recidivism window (for example, six months, one year, etc.).<sup>23</sup> The National Institute of Justice (NIJ) defines recidivism as criminal acts that result in re-arrests, reconviction or return to prison with or without a new sentence during three years following the prisoner's release.<sup>21</sup> Unfortunately, estimates of recidivism rate will vary depending on the length of follow up and the specific measure selected.<sup>24</sup> When recidivism is only measured from new crimes, the rate will be lower than if all re-arrests or reconviction is used to measure recidivism.

Re-entry from prison to the community is a stressful time for released individuals. Previously incarcerated individuals face numerous barriers such as lack of employment opportunities, family support and housing. In addition, people returning from incarceration may have lower educational attainment, mental health problems, substance abuse, and the fragmentation of treatment services upon release and during re-entry into the community.<sup>25</sup> These barriers place them at an increased risk of returning to prison in the first few years after release. Previous studies suggest that about two-thirds of inmates released from prison are rearrested within three years.<sup>26</sup> A Bureau of Justice Statistics study found that among 401,288 state prisoners released in 2005, about 68% were reincarcerated within three years of release.<sup>26</sup> A more recent 2018 report by the Pew Center found that 38% of previously incarcerated people were sentenced to at least one new prison term within three years of release.<sup>27</sup> The high rates of re-incarceration underscore the need to examine predictors of re-arrests and recidivism among formerly incarcerated people and develop interventions that reduce the barriers to successful reintegration into the community.

## MENTAL HEALTH, SUBSTANCE USE AND RECIDIVISM

Previously incarcerated individuals with substance use disorder (SUD) and mental illness (MI) face even more significant challenges than those without SUD or MI upon release from incarceration due to a lack of access to behavioral health care and improper re-entry and transition planning.<sup>28,29</sup> These individuals face considerable challenges in obtaining appropriate community-based behavioral health services, which results in poor and fragmented care.<sup>30</sup> Furthermore, formerly incarcerated individuals with mental health disorders are more likely to experience homelessness and are less likely to find employment after release from incarceration.<sup>28,31</sup> These challenges, along with improper re-entry and transition planning, place these individuals at an increased risk for recidivism, as shown in previous studies.<sup>28,29,32</sup> For example, a large scale evaluation of recidivism among people with serious mental health conducted in Florida found an average of 4.6 rearrests over the four year period.<sup>33</sup> Similarly, an analysis of over 61,000 prison inmates in Texas showed that those with dual diagnosis (cooccurring psychiatric and substance use disorder) had a significantly higher risk of multiple incarcerations over six years than inmates with mental illness or substance use disorder alone.<sup>29</sup> The presence of a mental health diagnosis or receipt of mental health treatment/services is associated with recidivism or return to incarceration.<sup>34,35</sup> Individuals with serious mental illness may return to prison about 12 months earlier than those without serious mental illness <sup>36</sup>, while participation in mental health treatment has been shown to be associated with a lower risk of incarceration.35

A history of substance use has been consistently reported as a predictor of recidivism among previously incarcerated individuals.<sup>37,38</sup> Individuals with substance use disorders are at a higher risk for recidivism and are likely to have fewer protective resources, such as family,

relationships and skills that protect them from recidivism. Putnins (2003) found that substance use disorder increased the likelihood of re-offending within six months.<sup>39</sup> However, they noted that specific substances differentially predict recidivism. In their study, alcohol and inhalants significantly predicted recidivism. Denney & Connor (2016) also found a statistically significant relationship between specific substances and recidivism among juvenile offenders.<sup>40</sup> Some studies suggest that the presence of mental illness alone does not increase the risk of reincarceration. These studies suggest that it is the co-occurrence of mental illness with substance use that significantly increases the risk for recidivism.<sup>32,41</sup> They argue that the risk of recidivism among individuals with serious mental illness alone is similar to individuals with no mental illness or substance use diagnoses.<sup>32</sup>

## MEDICAID INSURANCE AND RECIDIVISM

A significant barrier to care for individuals returning to the community from incarceration is a lack of access to health insurance and health benefits.<sup>30,42–44</sup> Most previously incarcerated individuals rely on public-sector mental health services supported by Medicaid insurance. Medicaid is an insurance program jointly funded by the federal government and individual states.<sup>45</sup> Medicaid provides healthcare coverage for some low-income people, families and children, pregnant women, the elderly, and people with disabilities; however, eligibility criteria differ by state.<sup>46</sup> In California, this insurance program is known as Medi-Cal. Unfortunately, Medicaid coverage can be suspended or terminated after the individual spends time in jail or prison.<sup>47–49</sup> Also, enrollment in Medicaid can be a burdensome process for most people released from incarceration, making the need to re-enroll or reactivate Medicaid insurance a barrier to care for people released from incarceration.<sup>50</sup>

Some studies have examined the association of expedited Medicaid coverage before or immediately after prison release and the use of community mental health services and substance use treatment, as well as the effect on recidivism.<sup>30,50–55</sup> A previous study found that a discharge planning program for inmates with serious mental illness increased both Medicaid enrollment and mental health service use in three Oklahoma prisons.<sup>55</sup> Another study in Washington State also showed that expediting Medicaid for individuals with severe mental illness was associated with increased Medicaid enrollment by 15% and increased outpatient mental health service use by 13% in the 90 days following release.<sup>51</sup> Gertner et al., 2019 found that referral for expedited Medicaid at release increased Medicaid enrollment and increased community mental health and general medical services immediately after release from incarceration.<sup>30</sup> For substance use disorders, Medicaid enrollment has been associated with an increased probability of utilizing substance use disorder treatment in the three months following release from incarceration.<sup>50</sup>

Increased engagement in treatment would be expected to decrease the likelihood of recidivism. However, previous studies are inconclusive on the effect of Medicaid enrollment on recidivism. The findings from Fry et al., 2020 demonstrates this inconsistency in findings. The study found that Medicaid expansion was associated with decreased recidivism rates in two of the three counties studied.<sup>56</sup> Other studies have found no evidence that expediting Medicaid reduced criminal recidivism.<sup>53,57</sup> In one study, the authors examined whether expediting Medicaid benefits would lead to reduced criminal recidivism for those with severe mental illness. In this study, the authors observed significant increases in enrollment and service use; however, the referral did not reduce criminal recidivism rates.<sup>58</sup> Similarly, another study in Washington State found that expedited Medicaid enrollment resulted in an increase in service use but did not result in a reduction in rearrests.<sup>54</sup> While the findings to date on recidivism are mixed, it is clear

that expedited referral and enrollment in Medicaid increases service use. It is logical to assume that engagement in treatment for mental health and substance use disorders may contribute to reduction in recidivism.

## HOUSING AND INCARCERATION

The disruption in social engagement during incarceration places individuals at an increased risk of housing instability and insecurity immediately upon their release from incarceration.<sup>59,60</sup> In addition, a history of incarceration makes it difficult to obtain housing upon return to the community. Housing is a major risk factor for recidivism, potentially having a more substantial influence on recidivism than most other risk factors.<sup>61</sup> Previously incarcerated people rank housing as one of the top four needs; however, they report having difficulties finding housing due to their previous history of incarceration.<sup>59,62</sup> Previous studies have found that many people experiencing homelessness have a history of incarceration. For instance, Metraux and Culhane found that 23% of the sheltered homeless people in the New York City shelter system had been incarcerated within the previous two-year period.<sup>63</sup> Also, previously incarcerated people with mental illness have higher rates of homelessness and housing insecurity compared to those without mental illness.<sup>64–67</sup> In examining the relationship between homelessness, housing insecurity, and incarceration using longitudinal, administrative data in Michigan, Herbert and Morenoff (2016) found low rates of homelessness but very high rates of housing insecurity among former prisoners.<sup>68</sup>

The success of re-entry for individuals released from incarceration may rely on the availability of stable housing.<sup>69</sup> Without stable housing, formerly incarcerated individuals may have difficulties in finding and maintaining stable employment, receiving necessary physical and mental health care, and avoiding substance use.<sup>70</sup> In this study, we contribute to the literature on

housing and re-entry success by first examining the relationship between housing and time to recidivism.

#### THEORETICAL / CONCEPTUAL FRAMEWORK

#### A socioecological framework to prevent recidivism

The socioecological model emphasizes multiple levels of influence on individual behavior and outcomes.<sup>71,72</sup> The model considers the complex interactions between individual, relationship, community, and societal factors in predicting human behavior.<sup>71</sup> This model may provide a framework for understanding the different ecological factors that put people at risk for recidivism. The following paragraphs discuss the socioecological model in the context of recidivism.

## Individual-level

The individual-level identifies the biological and personal history factors that may increase the risk of recidivism. Previous studies have identified various individual-level factors associated with recidivism; for example, research shows that men, members of minority groups, and younger adults are more likely to be re-arrested.<sup>73,74</sup> In addition, mental health diagnosis and substance use disorders are associated with recidivism or return to incarceration.<sup>35,38</sup> Interventions at the personal level could include various strategies, such as educational programs, support groups, organizational incentives, or peer counseling, to target knowledge, attitude, and skills with the specific goal of changing the behaviors of the individual.<sup>75</sup>

# Interpersonal

The interpersonal level examines the relationships that may protect individuals from recidivism. Incarceration is an isolating experience that socially separates individuals from the sources of social support in their lives.<sup>76</sup> While incarcerated, the impact of social separation may

be subtle. However, such separation is problematic upon release as previously incarcerated individuals may rely on these sources of support, such as family and friends, for stability. Studies have found that returning prisoners relied on family members for housing, financial support, and emotional support.<sup>77</sup> Strong family ties after incarceration may be associated with employment and job stability.<sup>77</sup> In fact, positive family social support has been said to reduce the effect of individual factors known to predict higher recidivism rates, like substance abuse, Black race, and younger age.<sup>78</sup> Unfortunately, in the absence of such positive support, previously incarcerated individuals may return to the negative social networks that are likely to lead to a return to crime and recidivism.

# Community

The community-level explores the settings, such as the neighborhoods that individuals released from incarceration return to, and the characteristics of these settings that place them at a greater risk for recidivism. The community-level also seeks to understand the existing relationships that may be critical in the development and provision of services.<sup>75</sup> Studies have shown that individuals who return to disadvantaged neighborhoods recidivate at a greater rate than those who return to affluent communities<sup>79,80</sup> One study found that particularly among African American populations, those returning to communities where social service providers are within two miles recidivate about 41 percent less than those who did not have social services providers within two miles.<sup>81</sup> In addition, a high concentration of bars and liquor stores in a census tract increased the risk of recidivism for individuals returning to those tracts and surrounding tracts by 26 percent.<sup>81</sup> Such effect of neighborhood characteristics to re-arrests tends to be more pronounced among minority groups than White.<sup>82</sup>

Interventions at the community level should aim to improve economic and housing opportunities and the processes, policies, and social environment in these neighborhoods. Intervention at this level may also targets essential components of the community, such as churches, informal social networks, volunteer and neighborhood associations, and organizations, and seeks to build relationships with them.<sup>75</sup> These organizations may be important sources of social resources and social identity for the formerly incarcerated individual, buffering the effect of other levels of intervention.<sup>75</sup>

# Societal

The social level examines the broader societal factors that may contribute to recidivism, such as health, economic factors, and social policies.<sup>71</sup> To achieve this, public health professionals must seek to make policy and regulatory changes targeted at whole populations or society to improve the health of all.<sup>75</sup> For instance, access to healthcare after release is a significant predictor of recidivism. However, Medicaid coverage can be suspended or terminated during incarceration due to the inmate exclusion statutes, and many individuals returning to the community lack access to health insurance and health benefits.<sup>30,44,47,83</sup> This means that they may forgo important medical care or visit the emergency room for necessary healthcare procedures. With the expansion of the Affordable Care Act, some states have removed some of these barriers and have provided funding dedicated to providing services to some individuals while incarcerated and expanding coverage to almost everyone who meets other eligibility criteria immediately after release.<sup>84</sup> As previously discussed, access to Medicaid increases the use of medical services, such as mental health and substance use treatment services.

Societal level interventions seek to create a society that supports re-entry and provides the stability that formerly incarcerated people need to thrive. A prison policy initiative report

provided policy recommendations that could help the returning individual find work and earn an income.<sup>85</sup> These recommendations include the issuance of a short-term temporary income upon release, implementation of an automatic record expungement procedure, tax benefits for employers hiring formerly incarcerated individuals, a blanket ban on employment discrimination and reform of occupational licensing requirements to be more inclusive of formerly incarcerated people.<sup>85</sup> These policy recommendations target access to employment at the societal level and are guided by previous studies showing that if formerly incarcerated people find stable employment after release, they are less likely to be re-incarcerated.<sup>86,87</sup>

# Risk-Need-Responsivity (RNR)

A common theory that is used to study recidivism is the Risk-Need-Responsivity (RNR) theory. The RNR is thought to be one of the most effective models in assessing the needs and providing treatment for the rehabilitation of previously incarcerated people.<sup>88,89</sup> The theory comprises three principles, risk, need and responsivity. The risk principle states that criminal behavior is preventable if the offender receives adequate treatment based on the level of risk for recidivism.<sup>88</sup> For instance, mental illness and substance use may increase recidivism risk, and a lack of appropriate treatment for individuals with mental illness may lead to engagement in criminal behavior.<sup>90</sup> This theory suggests the importance of identifying the increased risks and appropriately addressing them.

The needs principle focuses on the importance of individual needs and treatment to reduce recidivism <sup>88</sup>. Needs may include factors like mental health treatment, substance use disorders, housing, essential job skills, and education <sup>91</sup>. Although most of these clinical and social service needs are not criminogenic (meaning they are usually not a principal cause of crime), they nevertheless can interfere substantially with other rehabilitation efforts.<sup>91</sup>

Lastly, the responsivity principle focuses on factors that may influence an individual's responsiveness to treatment that help him/her change behaviors.<sup>92</sup> Responsivity needs may include determining factors that interfere with compliance and retention in treatment programs.<sup>91</sup> Lack of stable housing may interfere with how individuals respond to treatment for mental illness and substance use disorder.

This study is guided by the socioecological model and the RNR model. Figure 1 depicts the conceptual model and framework that will for this study. The model proposes that mental illness, substance use disorder and physical health comorbidity are significantly associated with recidivism. The model also suggests that early linkage to services such as Medicaid will promote engagement in treatment services, which would reduce the odds of recidivism. The model further proposes that housing status will directly affect recidivism and moderate the relationship between service use and recidivism. Without housing, participants may be limited in their ability to benefit from the other components of the intervention.



Figure 1. The conceptual framework for the current study

#### PROJECT OVERVIEW

#### Purpose of the Study

The purpose of this study is to evaluate the impact of the Riverside University Health System (RUHS) Whole Person Care (WPC) pilot on recidivism among individuals released from incarceration in Riverside County. This study will specifically focus on the role of housing, physical health, substance use, Medicaid enrollment, and mental health on incarceration recidivism among individuals who participated in the program. The examination of state-funded initiatives such as this is likely to offer recommendations for policy and structural changes that could lead to greater success in reintegrating recently incarcerated people and reducing recidivism rates.

# Riverside University Health System Whole Person Care Pilot

The Whole Person Care (WPC) pilot is a program implemented in California through the Medicaid Section 1115(a) waiver. The program aimed to promote the integrated delivery of care for populations who use costly services in multiple service sectors <sup>93</sup>. The total program budget was \$3 billion, which included a \$1.5 billion investment from participating pilots to implement WPC and \$1.5 billion in matching funds from the Centers for Medicare and Medicaid Services (CMS) <sup>93</sup>. The WPC program is designed to provide participants with care coordination and other services to address medical, behavioral health, and social needs with the aim of improving their health outcomes and overall well-being <sup>93</sup>. Therefore, successful implementation required careful planning and engagement of multiple agencies involved in these individuals' physical, behavioral and social care.

WPC pilots across the state were required to select one or more target populations identified by the state. The Riverside University Health System (RUHS) WPC pilot focused on

people recently released from incarceration. The RUHS WPC Pilot was designed around a complex case management system that sought to support the mission of early recognition and treatment of disease, thereby enhancing the quality of patient management and patient satisfaction.<sup>94</sup> Upon release from incarceration, participants were screened by a Registered Nurse (RN) for physical health, behavioral health, social services, housing and other needs. The RN also performed a screening of the participants' blood pressure and provided referrals for glycohemoglobin levels (HbA1c), as well as Human Immunodeficiency Virus (HIV), Hepatitis C (HCV) and tuberculosis status. Based on screening results, care coordination continued with referral to the appropriate departments to provide services.<sup>94</sup>

# Significance

This study focuses on a vulnerable population that is frequently invisible and understudied in public health research and practice. This study may help prevent recidivism and provide an understanding of the types of linkages, resources, and coordination for health services that may reduce re-incarceration. The specific objectives of this study are outlined below.

# Objectives

- Objective 1. To examine the impact of treatment for substance use disorder on recidivism.
  - a. Hypothesis: Substance use treatment utilization will be negatively associated with the odds of recidivism
- 2. Objective 2. To examine the impact of mental health treatment on recidivism.
  - a. Hypothesis: Mental health treatment utilization will be negatively associated with the odds of recidivism.

- 3. Objective 3. To examine the effect of active Medicaid on recidivism.
  - a. Hypothesis: Active Medicaid insurance will reduce the likelihood of recidivism by increasing the use of mental health and substance use services among participants with mental health or substance use disorders.
- 4. Objective 4. To examine the association of housing status at release with recidivism.
  - a. Hypothesis: Participants who are homeless at baseline will be more likely to be reincarcerated within the first year.
  - b. Hypothesis: Participants who are homeless will have fewer days until the first reincarceration than those who are not homeless.

# METHODS

# Data Source

This study uses secondary data from the Riverside University Health System (RUHS) Whole Person Care (WPC) pilot program. Participants were recruited from their local Probation Department office, where they were generally required to report within 48 hours of release from incarceration. The Probation Officer (PO) introduced the participant to the RN as close to the first probation appointment as possible. The RN provided each participant with an informed consent form describing the types of screening to be conducted. The participant had the right to refuse to participate and share data with any or all departments listed.

Individuals were eligible to participate in the WPC pilot if they had been on probation for at least one full year, were at risk of or experiencing homelessness, currently had a behavioral health diagnosis, and had/or have a physical health diagnosis. All participants had to be 18 years and over. For this study, participants who were enrolled after July 31, 2019, were excluded because they would not have up to 12 months of follow-up data at the time of this study.

Ethical- Human Studies considerations

An initial inquiry for approval was made to the Claremont Graduate University (CGU) Institutional Review Board (IRB). However, the IRB at CGU deferred to Riverside University Health Center IRB because only secondary data belonging to Riverside University Health System was proposed to be used for the study. Approval for the current study was obtained from the Riverside University Health System Institutional Review Board (IRB). The current study analyzes secondary data; therefore, there are no direct risks or benefits to participants in the WPC. The potential risk may include having the patient's privacy or confidentiality compromised. Nevertheless, every reasonable effort will be made to protect privacy while their data is used as part of this study. Data obtained from RUHS were de-identified by RUHS staff using the Safe Harbor Method before sharing with the researchers. In addition, all data and records generated throughout the study will be kept confidential in alignment with the policies of the RUHS Institutional Review Board. Finally, only study personnel will have access to the study data and records to conduct the study.

#### Measures

#### Recidivism

For this study, three different recidivism outcomes were available. First, recidivism will include any re-arrests or re-incarceration for any reason within one year. Data were collected about whether or not the individual had any re-arrests within one year after release from incarceration. In addition, the number of times incarcerated within one year was recorded for participants with an arrest or re-incarceration. Finally, the number of days till the first episode of re-arrests or re-incarceration was also obtained from administrative data obtained from RUHS.

# Mental health and substance use disorder

During the initial assessment, the WPC registered nurse assessed participants for any mental illness or substance use disorder. If any disorder was identified, this information was recorded in the participants' records. Mental health diagnoses included generalized anxiety disorder, major depressive disorder, schizoaffective disorder, among others. Substance use included alcohol dependence, opioid dependence, sedative, hypnotic or anxiolytic abuse, and other substance use disorders. For this study, mental illness and substance use disorders were recategorized to a dichotomous variable (yes/no) that captures any recorded diagnosis for mental illness or substance use disorder.

#### Service use

The data for the utilization of mental health treatment and substance use disorder treatment was obtained from the participants' health records. Health encounter data obtained from the RUHS Department of Behavioral Health was linked to participants using a unique identifier. The number of encounters each participant had was extracted from their health records. Medical care was defined as access to outpatient services during the one year following release. Participants' health encounter data were obtained from the electronic health record at the RUHS.

#### Physical Health comorbidities

Physical health comorbidities were assessed during the initial screening. Participants were asked to select if they had been diagnosed with diabetes, tuberculosis, hepatitis C, HIV, hypertension or any other chronic health disease. For this analysis, physical health comorbidity was recategorized to a dichotomous variable that captured the presence of one or more of these conditions.

# Housing status

Housing status was assessed during the initial screening process by asking participants to identify their current living arrangements. Participants were asked, "What are your living arrangements?" Response options included A) Co-housed; B) Homeless Shelter; C) Not Homeless; D) Street; E) Transitional; F) Vehicle; G) Other (specify). For the current study, participants who identified as "not homeless" were classified as not homeless, while all others were classified as homeless.

# **Covariates**

Participants' demographic variables were obtained using a questionnaire during the initial screening. Demographic variables obtained included sex, race, ethnicity, and age. Sex included male or female. Participants' age was obtained as a continuous variable, then converted to a categorical variable, with categories: 18-26, 27-40, 40-55, 55 and over. Due to small group frequencies, race was recategorized to African American/Black, White and Others/Unknown/Multiple Races. Three categories of ethnicity included in the analysis included Hispanic, Non-Hispanic and Unknown. A single variable was then created to reflect four categories of race/ethnicity, including White or Caucasian, Black or African American, Hispanic or Latino and Others/Unknown/Multiple Races.

#### Analysis Plan

## Preliminary analysis

Data analysis were conducted using Tableau prep, R version 4.0.2. Mplus version 8.3 and SAS® software, version 9.4.<sup>95,96</sup> Descriptive statistics (e.g., frequencies, mean, range, standard deviation, etc.) were performed on demographics and other variables to describe the sample. For the descriptive analysis, the data were stratified by gender, ethnicity, and age. The distribution of

continuous outcome variables were examined for parametric assumptions. Participants' Medicaid status was recorded as active or inactive. Each hypothesis was tested using appropriate modeling techniques such as logistic regression, negative binomial logistic regression, survival analysis or mediation analysis.

#### Logistic Regression

# Overview

Chapter one examines the predictors of recidivism using binary logistic regression and negative binomial regression models. The logistic regression model is a type of generalized linear model (GLM) where the outcome variable (Y) is categorical. In the case of logistic regression used in the first paper, the outcome variable is a dichotomous, nominal variable measuring recidivism (return to incarceration or not). Given a binary outcome such as this, we assume a binomial distribution for the random component of the GLM.<sup>97</sup> Binary logistic regression also requires the logit link function. The link function specifies the functional transformation required to relate the mean of the probability distribution of the outcome variable ( $\mu$ ) to the linear combination of the predictor variables.<sup>97</sup>

In linear regression, the equation for the expected mean of the probability distribution is given by:

$$\mu = E(Y|x) = \beta_0 + \beta_I x \tag{1}$$

The expression above allows for E(Y | x) to take on any value as x ranges between  $-\infty$  and  $+\infty$ .<sup>98</sup> In logistic regression with a dichotomous outcome variable, the conditional mean must be greater than or equal to zero and less than or equal to one  $(0 \le E(Y | x) \le 1)$ ,<sup>98</sup> thus requiring the logit transformation. As noted by Agresti, while the conditional mean of a logistic regression

model  $\pi$  is restricted to the values between zero and one, the logit can be any real number that can be modeled using the linear expression above.<sup>97</sup> The equation of the logistic regression then becomes:

$$\operatorname{Logit}(\pi(x)) = \ln(\frac{\pi(x)}{1 - \pi(x)}) = \beta_0 + \beta_1 X$$
(2)

Where

$$\pi = P(Y = 1|X)$$
 probability of success (recidivate),  
 $1 - \pi(x) = P(Y=0)$  or probability of failure (did not recidivate),  
 $\beta_0 =$ intercept or predicted average logit, and  
 $\beta_1 =$ predicted change in logit for a unit increase in  $X$ 

Assumptions

Logistic regression is generally considered a nonparametric technique. This means that it does not require any particular distributional assumptions like other methods such as Analysis of Variance (ANOVA) and Ordinary Least Squares (OLS) regression.<sup>99</sup> However, certain assumptions must be met to use logistic regression and for the result of logistic regression to be valid. First, binary logistic regression, as used in the first paper, requires the dependent variable to be binary. Second, logistic regression assumes that there is little or no correlation among the independent variables<sup>99</sup> Here, logistic regression requires that independent variables included in the model are not too correlated with each other. When variables are highly correlated but conceptually different, it is recommended that one of the variables is removed from the model, or a latent variable modeling technique is used for the analysis.<sup>99</sup> Third, logistic regression requires a large sample size. The general guideline is that a minimum of 10 events per independent

variable is required to fit a logistic regression model reliably from the results of previous simulation studies.<sup>98–100</sup> For instance, if the number of cases with the less frequent outcome divided by the total number of independent variables is less than 10, then the estimate of the regression coefficient, the confidence interval, and the sample variance of the model coefficients will be unreliable.<sup>100,101</sup> Fourth, logistic regression requires that continuous predictors have a linear relationship with the log odds of the outcome.<sup>101</sup> This assumption does not hold for categorical predictors.<sup>101</sup>

## Interpretation of results

The regression coefficient in logistic regression is the log odds of the outcome occurring given the change in the predictor, that is,  $\beta_l$  coefficient indicates the effect of a unit change in X on the log odds of the event occurring.<sup>97</sup> However, logistic regression results are better interpreted in terms of odds. The regression coefficients are converted from logit to odds by exponentiating the coefficients.<sup>97</sup> The odds of an event occurring is the probability of the event occurring divided by the probability of that event not occurring. This is represented in the formula below:

$$Odds = \frac{\pi(x)}{1 - \pi(x)} = \mathbf{e}^{\beta 0 + \beta 1 X}$$
 (3)

For a dichotomous predictor, such as any mental health encounter, where x = 1 when there is an encounter and x = 0 when there is no encounter:

$$Odds \ Ratio = \frac{Odds_1}{Odds_0} = \frac{e^{\beta 0 + \beta * 1}}{e^{\beta 0 + \beta * 0}} = e^{\beta}$$
(4)
The odds ratio compares the odds of the outcome occurring in one state of the predictor to another.

# Negative Binomial Regression

# Overview

In modeling outcomes that result from counting the occurrence of an event where the outcome variable can take any nonnegative integer value, for example, the number of re-arrests in a year, the generalized linear model (GLM) with a *Poisson distribution* for the random component may be used.<sup>97</sup> The Poisson model has a single parameter  $\mu > 0$ , which is both the mean and variance of the distribution.<sup>97,102,103</sup> That is:

$$E(Y) = Var(Y) = \mu$$

$$\sigma(Y) = \sqrt{\mu}$$
(5)
(6)

Unfortunately, many datasets contain some form of overdispersion, where the mean and the variance are not equal, often due to unobserved heterogeneity in the data.<sup>104</sup> Such data can be modeled by an additional shape parameter to account for the difference between the mean and variance. The negative binomial regression is also one of the generalized linear models used for count data with two parameters, the mean ( $\mu$ ) and dispersion (*D*) parameters.<sup>97</sup> Negative binomial regression models the expected log count of the outcome to the linear combination of the predictor variables. The negative binomial distribution does not assume equal mean and variance and has the following form:

$$E(Y) = \mu \tag{7}$$

$$Var(Y) = \mu + D\mu^2$$
(8)

Assumptions of negative binomial regression.

The negative binomial regression shares similar assumptions as the Poisson and linear regression models, such as linearity in model parameters and independence of individual observations. The linearity assumption means that the relationship between the independent and dependent variables is linear.<sup>99,103,105</sup> With the assumption of independence of observations, all observations in the model are independent of each other and the errors in the model are not related.<sup>105</sup>

#### Interpretation of results

Model fit can be examined using the goodness of fit statistics such as the log-likelihood, Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). In addition, the model fit can also be visually examined using rootograms.<sup>102,104</sup> The rootogram displays the theoretical Poisson distribution as red lines. Hanging from the lines at each point is a bar representing the difference between expected and observed counts.<sup>104</sup> A bar hanging below zero indicates underfitting. A bar hanging above zero indicates overfitting.<sup>104</sup> Figure 8 in the appendix shows the rootogram for the negative binomial regression model of re-incarceration, while figure 9 shows the rootogram for the Poisson model. The rootogram shows that the negative binomial model fits the data better than the Poisson model.

As previously stated, the model estimates the expected log count of the outcome given the predictor. This estimate can be exponentiated to obtain an Incidence Rate Ratio (IRR) for ease of interpretation.<sup>102,103</sup> The result is interpreted as a comparison of the incidence rate in two categories: the ratio rate of occurrence of the outcome in one group compared to the reference group. An IRR of one would mean no difference in the incidence rate in the two groups being compared. An IRR greater than one indicates a greater incidence in the selected group compared to the reference group. In comparison, an IRR less than one indicates a lower incidence in the selected group than the reference group.

#### Survival Analysis

Chapter 3 uses survival analysis to examine the effect of housing on time until recidivism. Survival analysis is the study of survival time and the factors that influence it, where survival does not exclusively mean death but any event of interest.<sup>106</sup> There are two major characteristics of survival data. First, the outcome variable must be a non-negative discrete or continuous variable representing the time from a clearly defined time origin to a clearly defined event.<sup>106</sup> The second characteristic of survival data, known as censoring, occurs when the starting and ending events are not precisely observed. In right censoring, which is the most common, the exact time of the ending event is unknown; however, it is known to exceed a particular value.<sup>106</sup> Two major survival analysis strategies will be described here, Kaplan-Meier survival analysis and the Cox proportional hazard model. Finally, a brief description of Aalen's Additive model, which is used as a supplement of the Cox model, is provided.

#### Kaplan-Meier survival estimate

The Kaplan-Meier (KM) method is a nonparametric method used to estimate the survival probability from observed survival times.<sup>107</sup> The Kaplan-Meier estimate is the simplest way of computing the survival time. It can be used to produce a survival curve (Kaplan-Meier curve), which shows the probability of survival at a given time.<sup>108</sup> The survival probability at each time (*t*) can be computed as:

$$S(t) = \frac{\text{Number of subjects at start-number of subjects with event at time t}}{\text{Number of subjects at start}}$$
(9)

There are three assumptions in the Kaplan-Meier estimate. Firstly, we assume that at any given time, participants who are censored have the same survival probability as those who continue to be followed. Secondly, we assume that the survival probabilities are the same for subjects regardless of when they were recruited into the study. Finally, we assume that the event happens at the time specified.<sup>108</sup>

# Cox proportional-hazards model

The Cox proportional-hazards model is a regression model that is used to estimate the association between survival time and one or more predictor variables.<sup>109</sup> The Cox model is expressed by the hazard function denoted by h(t) and can be estimated as follow:

$$\mathbf{h}_{(t)} = \mathbf{h}_0(t) * \exp(\beta_1 X_1 + \beta_2 X_2) \tag{10}$$

Where:

- *t* = survival time,
- $h_{(t)}$  = the hazard function determined by a set of covariates (X1, X2),
- $\beta$  coefficients = the hazard of the covariate, and
- $h_0 =$  the baseline hazard

#### Model Interpretation

The regression coefficients produced from the Cox model indicate the direction and magnitude of each predictor's change in hazard. This value can be positive or negative. A more intuitive interpretation can be obtained by taking the exponential of the regression coefficient to obtain the hazard ratio. Interpretation of the hazard ratio is similar to the odds ratio in that it gives an estimate of the effect size.

Model Assumptions

A major assumption of the Cox proportional hazard model is that of proportional hazard.<sup>106,109</sup> The assumption requires that the hazard ratio of each explanatory variable remains constant over time.<sup>109–111</sup> A second assumption states that covariates are multiplicatively related to the hazard, as seen in the Cox regression formula above.<sup>111</sup> In the Cox model, the Cox-Snell residuals can be used to assess the overall fit of the model and the scaled Schoenfeld residuals can be used to assess proportional hazard assumptions.<sup>111</sup>

# Aalen's Additive Hazard Model

Aalen's additive model is also a survival regression model that defines the hazard rate as an additive instead of a multiplicative linear model.<sup>112</sup> Unlike the Cox model, this model does not assume a proportional hazard. This model can be used to circumvent the proportional assumption and characterize the nature of the time-varying effects of covariates through the cumulative regression function plots.<sup>112</sup> This model is given by the equation:

$$\mathbf{h}(\mathbf{t}|\mathbf{X}\mathbf{i}) = \mathbf{h}\mathbf{0}(\mathbf{t}) + \mathbf{X}\boldsymbol{\gamma}(\mathbf{t}) \tag{11}$$

Where:

- h0 = baseline hazard function
- γ= vector of time-varying regression coefficients, which may change in magnitude and even sign over time.

# Mediation Analysis

# Overview

In chapter 4, a multiple mediation analysis with probit regression is used to examine the role of mental health services and substance use disorder treatment as mediators of the relationship between Medicaid enrollment and recidivism. The direct effect and mediated effect were examined using a 95% bias-corrected confidence interval based on 10,000 bootstrapped samples.

Mediation analysis seeks to answer the question of "how." For example, how does Medicaid enrollment reduce recidivism?<sup>113</sup> See figure 2 below for a simple mediation model. Mediation analysis can be used to identify the pathway through which an independent variable affects an outcome by showing how the independent variable affects a mediator variable (*a path*) and the mediator variable affects a dependent variable (*b path*).<sup>114,115</sup> The indirect effect is the effect of the independent variable on the outcome through this chain of relations among the specified variables. In contrast, the direct effect (*c*') does not pass through this pathway.<sup>116</sup> Mediation analysis has been extended to allow for the inclusion of multiple mediators or pathways arranged in series or parallel.<sup>117</sup>



Figure 2 A simple mediation model

After conducting the mediation analysis, the product of the effect in both *path a* and *path* b is the estimate of the indirect effect (*ab*). A statistical significance test can be conducted using the Sobel test to compute this estimate's standard error.<sup>118</sup> The ratio of the estimated indirect effect (*ab*) to its standard error, calculated using the Sobel method, is used as a test statistic for

the null hypothesis that the "true" indirect effect is zero; the p-value is then obtained from the standard normal distribution.<sup>117–119</sup> This assumption that the underlying distribution of the indirect effect follows a normal distribution has been found to be flawed as the distribution of *ab* tends to be asymmetrical, with nonzero skewness and kurtosis.<sup>117,119</sup> An alternative method that makes no distributional assumption is the bootstrapping method.

Bootstrapping is a process where the data is repeatedly resampled a given number of times, with replacement, to generate an empirical representation of the sampling distribution of  $ab^{119,120}$ . This process involves randomly drawing cases from the original data, replacing the drawn case and drawing randomly again to create the specified number of samples (for example, 10,000), each size equal to the original sample size. For each sample, the value of ab is estimated and recorded. After this process, the distribution of the estimates is examined to obtain the required confidence interval. The 2.5 percentile and the 97.5 percentile of this distribution represent the 95% percentile confidence limits. These limits can be corrected depending on the skewness of the distribution to obtain a 95% bias-corrected confidence interval.<sup>117,120</sup> The bias-corrected bootstrap has been shown to have the least biased confidence intervals, greatest power to detect nonzero effects, and the most accurate overall Type I error.<sup>120</sup>

# CHAPTER 2: THE ASSOCIATION BETWEEN EARLY LINKAGE TO TREATMENT FOR MENTAL HEALTH AND SUBSTANCE USE DISORDERS AND RECIDIVISM. BACKGROUND

Over 600,000 individuals are released back into their communities from state and federal prisons annually<sup>1</sup>. Many of these people have either a mental health disorder, substance use disorder or both co-occurring at the same time. About two-thirds of people incarcerated in the United States have been reported to meet the criteria for at least one mental health disorder<sup>121</sup>. In addition, between 17% to 34% are diagnosed with a severe mental illness compared to 4.6% of the general population. <sup>121–123</sup> In addition to mental health disorders, incarcerated individuals also have a high burden of substance use disorders. About 58% of people incarcerated in state prisons and 63% of sentenced jail inmates met the criteria for drug dependence or abuse.<sup>124</sup> A previous study found that up to 82% have reported lifetime use of any drugs among people detained in jails.<sup>125</sup> Many of these people have co-occurring mental health and substance use disorders. Another study of prison inmates showed that 74% of individuals with a mental health disorder also had substance use disorders. In comparison, 54% of those with no mental health disorder had a substance use disorder.<sup>126</sup>

Unfortunately, many of the people released from incarceration will return to prison or jail due to the significant barriers they face upon release. For instance, previously incarcerated individuals face barriers such as lack of employment opportunities, family support and housing.<sup>25</sup> These barriers place them at an increased risk of returning to prison in the first few years after release. A Bureau of Justice Statistics study found that among 401,288 state prisoners released in 2005, about 68% were reincarcerated within three years of release.<sup>26</sup> Among previously

incarcerated women, severe mental disorder (SMD) significantly increases the likelihood of recidivism by 16% over an eight-year follow period.<sup>127</sup>

Research suggests that people with mental health and substance use disorders experience greater recidivism rates partly due to difficulties accessing community-based treatment services upon release. <sup>28–30,38</sup> Perhaps the most common diversion to the treatment program is the mental health court (MHC). Studies have shown that MHC participants have better criminal justice outcomes than those who do not participate in the program. Dirks-Linhorst and Linhorst (2012) found a lower re-arrest rate for people who completed the MHC program than those who chose not to participate.<sup>128</sup> A 2019 literature review showed some evidence that mental health courts help reduce recidivism rates; however, it was unclear if it affected police contact.<sup>129</sup> Furthermore, this review suggested that effective MHC programs should address other essential needs, such as providing access to vocational and housing services.<sup>129</sup>

A few re-entry programs have focused on engaging people with mental health and substance use disorders in treatment in order to reduce recidivism. Theurer and Lovell (2008) examined the Washington State Mentally III Offender Community Transition Program (MIOCTP).<sup>130</sup> They found that those in the program had an average of 2.3 days to contact mental health services compared to 185 days in a matched control group and had more hours of contact with mental health staff both in prison and the community.<sup>130</sup> Previous studies show that when people with mental health or substance use disorders have access to treatment, they are likely to have better outcomes. For example, Kelly et al. (2017) showed that assertive community treatment for people with serious mental illness reduces the number of arrests and incarceration in the nine months following release.<sup>131</sup> A study that examined the impact of New York State's program to divert youths with mental health and substance use disorder found a significant

reduction in re-arrests for those who received mental health services and other wrap-around services.<sup>132</sup> Engagement in treatment services through mental health court has been shown to increase medication compliance and reduce recidivism.<sup>34</sup> Other studies support the claim that engagement in treatment may reduce the risk of recidivism in this population.<sup>133–135</sup> Increasing access to outpatient treatment, particularly for mental health services, may reduce the likelihood of re-arrests and reduce recidivism.<sup>53,136</sup>

Treatment for substance use disorders is also likely to reduce recidivism and reincarceration. Just like MHC, drug treatment courts (DTC) have also been used to examine the impact of diversion to treatment rather than incarceration. Wilson (2017) found that participants in a DTC program were more likely to abstain from substances.<sup>137</sup> Among the program participants, they found that older age and employment reduced the likelihood of re-arrested.<sup>137</sup> This finding is further supported by a study that randomly assigned participants into a DTC or treatment as usual group. The study found that those in the DTC group were less likely to recidivate over two years than the control and untreated groups.<sup>138</sup> An evaluation of Access to Recovery (ATR), an initiative funded by the Substance Abuse and Mental Health Services Administration (SAMHSA) that offers a mix of clinical and supportive services for previously incarcerated people with substance use disorders, found that differential effect of the type of service and recidivism. The evaluation noted that participating agencies with more resources and a focus on prisoner re-entry had better recidivism outcomes than those focusing only on substance abuse services.<sup>139</sup> A modified therapeutic community (TC) program serving probationers with substance use disorders found that treatment graduates were slightly less likely to be arrested within two years of leaving the program.<sup>140</sup>

The purpose of this study was to examine the effect of mental health and substance use treatment on recidivism among participants of the Whole Person Care pilot in Riverside County. It was hypothesized that participants who had mental health or substance use treatment encounter in the first 90 days after release would be less likely to be reincarcerated than those who did not have a service encounter. In addition, the study hypothesized that those with early linkage to treatment would have fewer rearrests in the 12 months.

# METHOD

#### Measures

#### Recidivism

For this study, recidivism will include any re-arrests or re-incarceration for any reason within one year. Data were collected about whether or not the individual had any re-arrests within one year after release from incarceration. In addition, the number of times incarcerated within one year was also recorded for participants with an arrest. This variable will also be used in the analysis of re-incarceration.

#### Mental health and substance use disorder

During the initial assessment, participants were assessed for any mental illness or substance use disorder by the RN. If any disorder was identified, this information was recorded in the participants' records. For this study, mental illness and substance use disorders were combined into a single variable that reflects a mental health diagnosis alone, substance use disorder alone, co-occurring disorder and none. Those with no diagnosis were used as the reference group for all analyses.

#### Service use

Service use for mental health treatment and substance use disorder was obtained from the participants' health records. Health encounter data obtained from the RUHS Department of Behavioral Health was linked to participants using a unique identifier, and the number of encounters for each participant was extracted from their health records. Service use was defined as any treatment encounter for mental health or substance use service during the first 90 days following initial assessment after release from incarceration. Participant's health encounter data was obtained from the electronic health record at the Riverside University Health Systems (RUHS).

#### Physical health comorbidities

Physical health comorbidities were assessed during the initial screening. Participants were asked to select if they had been diagnosed with diabetes, tuberculosis, hepatitis C, HIV, hypertension or any other chronic physical illness. For this analysis, physical health comorbidity will be recategorized to a dichotomous variable that captures the presence of one or more of these comorbidities.

#### Analysis

#### Preliminary analysis

Data analysis was conducted using Tableau prep and R version 4.0.2. Descriptive statistics were performed on demographics and other variables to describe the sample. Two Logistic regression models were used to test the hypothesis in this study while controlling for other covariates and potential confounders. First, a binary logistics regression, using any re-arrest within one year as the dependent variable, with mental health or substance use diagnosis, mental health or substance use treatment, housing instability, physical health comorbidity, self-rated

physical and emotional health, race, ethnicity, Medi-Cal status and age included as predictor variables. Secondly, a negative binomial logistic regression was used to model the number of times the participant was incarcerated within one year with the same set of independent variables as in the binary logistic regression above.

#### RESULTS

Data from 6,347 individuals recruited in 2017, 2018 and 2019 were included in this analysis. Table 1 shows the descriptive statistics of the sample. The majority of participants in the sample were male (80.9%). After categorizing the participants' age into groups, 22.5% were between 18-26 years, 31.7% were 27-34 years, 25.4% were 35-44 years, 13.2% were 45-54 years and 7.2% were 55 years and over. The sample was also comprised 33.4% White or Caucasian, 12.0% Black or African American, 27% Hispanic or Latino(a) and 27% Others, Multiple Races and Unknown. The majority of the participants had active Medi-Cal (67.8%) within 90 days of the initial screening. The majority of the participants rated their physical health (79.8%) and emotional health (78.2%) as good. Similarly, the majority did not have a mental health or substance use diagnosis, while 8.6% had a substance use diagnosis, 10.0% a mental health disorder and 5.6% a co-occurrence of mental health and substance use disorders. Finally, 13.9% reported having one or more of the physical health comorbidities that were listed during the initial screening.

#### Mental health and Substance use Service encounter

While only 18.8% of the total sample of participants were referred to behavioral health and 15.1% to substance use disorder treatment, 13.3% of participants had a mental health encounter and 12.3% had a substance use treatment encounter within 90 days of the initial screening. Among those with a referral to behavioral health, 36.8% had a mental health

encounter, while 18.5% had a substance use encounter. Among those with a referral to substance use treatment, 18.3% had a mental health encounter and 26.6% had a substance use encounter.

The results of the logistic regression model showed that participants with a mental health disorder alone (OR: 1.88, p < .001), substance use alone (OR: 3.16, p < .001) and those with co-occurring mental health and substance use (OR: 3.67, p < .001) were more likely to be reincarcerated within one year following release compared to those with no diagnosis after controlling for all other variables in the model. Participants with a mental health diagnosis had almost twice the odds of re-incarceration within one year, while participants with substance use disorder had three times the odds of recidivism compared to those without any mental health or substance use disorder. Similarly, a co-occurring mental health and substance use disorder increased the odds of recidivism by over three and a half times compared to those with no diagnosis.

Any mental health service was associated with a 64% reduction in the odds of recidivism (OR: 0.46, p<.001) compared to those with no mental health service encounter after controlling for all other variables. Similarly, having any substance use encounter within 90 days of the initial screening was associated with a 50% reduction in the odds of recidivism when compared to those with no substance use encounter (OR: 0.50, p<.001).

Other significant predictors of re-incarceration in the model included housing instability (OR: 2.01, p <.001), having an emergency department visit (OR: 1.62, p <.001) and having active Medicaid (OR: 1.29, p < .001). All three predictors were associated with an increase in the odds of recidivism. Age showed an inverse relationship with re-incarceration such that the odds of re-incarceration decreased with increasing age. Table 3 displays the result of the logistic regression model.

A second regression model was used to examine the association between the same set of predictors and the number of times individuals were re-arrested in the 12 months following the initial screening. The results of the negative binomial regression were mostly consistent with the findings from the logistic regression model. Participants with any mental health disorder had a higher rate of re-arrests than those with no mental health or substance use disorder (Rate Ratio: 1.83, p < .001). Participants with any substance use disorder alone also had a higher rate of re-arrests than those with no substance use disorder (Rate Ratio: 1.63, p < .001). Finally, those with co-occurring mental health and substance use disorder had an incarceration rate over twice as much as participants with no mental health or substance use disorder (Rate Ratio: 2.25, p < .001).

When examining the association between mental health and substance use service encounters and the rate of re-arrests, those with any mental health encounter had a reduction in the frequency of re-arrests compared to those with no mental health service encounter (Rate Ratio: 0.51, p < .001). Those with any substance use treatment encounter also had a reduction in the rate of re-arrests within 12 months (Rate Ratio: 0.78, p < .001).

As was found in the logistic regression model, housing status at baseline (Rate Ratio: 1.64, p < .001) and having any emergency department visit (Rate Ratio: 1.21, p < .001) were associated with an increase in the frequency of re-arrests. However, there was no statistically significant association between active Medicaid insurance and the frequency of re-arrests (Rate Ratio: 1.07, p = .171).

#### DISCUSSION

This study examined the impact of early linkage to mental health and substance use treatment on recidivism among participants of the Whole Person Care pilot, controlling for other potential confounders such as age, sex, race/ethnicity, housing status, diagnosis for mental health or substance use, Medicaid insurance and emergency department use. The results showed that linkage to care is associated with a reduction in the odds of recidivism, as well as the number of rearrests within 12 months. The results also showed that other significant predictors of recidivism in this sample included age, sex, housing status, mental health or substance use diagnosis, emergency department use and Medicaid insurance.

The primary results of this study showed that mental health and substance use encounters were associated with lower odds of reincarceration and a lower rate of re-arrest over the 12 month follow-up. Mental health service encounter was associated with a 54% reduction in the odds of recidivism and a 49% reduction in the rate of re-arrests compared to not having an encounter. Although the measures and types of treatment vary, this finding is consistent with previous studies.<sup>128,131,132,141</sup> Some studies have shown that the use of assertive community treatment for people with serious mental illness reduces the number of arrests and incarceration following release.<sup>131</sup> Sullivan et al. (2007) found that receiving community-based mental health services reduced the likelihood of recidivism by 32%.<sup>132</sup>

Substance use service encounter was associated with a 50% reduction in the odds or recidivism; however, no statistically significant reduction in the rate of rearrests was found. This finding is consistent with previous studies that showed an association between substance use treatment and recidivism.<sup>132,142</sup> A study that examined the impact of New York State's program to divert youths with mental health and substance use disorder found a significant reduction in re-arrests for those who received mental health services and other wrap-around services.<sup>132</sup> A similar study by Robertson et al. (2020) using administrative data found that diversion to treatment was associated with reductions in incarceration risk.<sup>142</sup> Gottfredson et al. (2003) found

that participants who were referred to a drug treatment court were significantly less likely to recidivate than were both untreated drug court subjects and control subjects.<sup>138</sup> A 2018 review also supports the findings in this study, showing that treatment for substance use after release is effective in reducing recidivism.<sup>143</sup>

Several studies show that certain characteristics associated with incarceration and criminal justice involvement may be more prevalent among people with mental health or substance use disorders. These studies suggest that people with mental health or substance use disorder may show cognitive and neuropsychological problems, personality disorders, risktaking behavior, aggression, lack of coping skills and impulsive behaviors.<sup>32,141,144,145</sup> Engagement in and adherence to treatment for mental health and substance use disorders may allow participants to receive the necessary care that addresses these risk factors.<sup>141</sup> Given the stress associated with re-entry, persons with serious mental illness who do not receive adequate treatment may act in an inappropriate and often aggressive manner, resulting in arrest or incarceration.<sup>146</sup> On the other hand, people with mental health disorders generally have a lower level of support, which increases the impact of stress; this may be more salient immediately following release from incarceration.<sup>32</sup> Engaging with treatment may help the individual recognize the stressors they face and provide them with the strategies to utilize formal and informal support that are available to them. For individuals with substance use disorders, recidivism may be associated with environmental factors such as the procurement of illegal substances or violation of community supervision terms.<sup>32</sup>

This study also finds other variables that are associated with reincarceration and re-arrest. First, we find an inverse relationship between age and both re-arrest and reincarceration. This finding is consistent with findings in the literature showing that older individuals are less likely

to recidivate than younger individuals.<sup>147,148</sup> Secondly, we find a higher odds or recidivism for males than females in the sample. Males had a 70% higher odds of reincarceration and a 60% higher rate of re-arrest than women. This finding is also consistent with the findings in previous studies.<sup>148</sup> Third, the results showed that when compared to participants who had no mental health or substance use disorder, the odds of re-incarceration were highest for those with co-occurring mental health and substance use disorder (COD). Participants with COD had 3.67 times the odds of re-incarceration and 2.25 times the re-arrest rate as those with no diagnosis. The finding here is consistent with the literature as people with COD disorders have been shown to have the highest recidivism rates in previous studies.<sup>32</sup>

Surprisingly, we find a higher odd of recidivism for participants with active Medicaid. It is logical to assume that participants enrolled in Medicaid would be less likely to be reincarcerated. Previous studies have found mixed results, with most finding no association between Medicaid and recidivism. <sup>54,58</sup> From this study, it is unclear why active Medicaid would increase the odds of reincarceration. Future studies are needed to explore this relationship further. Finally, the results show that housing status was significantly associated with the odds of reincarceration and the rate of re-arrests. Specifically, being homeless or lacking stable housing at baseline was associated with a 100% increase in the odds of reincarceration and a 64% increase in rearrests rate. This finding consistent with the results of other studies that showed that a lack of stable housing is a significant risk factor for recidivism. For example, Jacobs and Gottlieb (2020) found a significant increase in recidivism risk for people who were homeless or lacked a stable living situation, respectively.<sup>149</sup> Steiner et al. (2015) found a statistically significant effect of homelessness on re-arrests.

The findings of this study have several implications. With respect to prevention and intervention efforts, the results suggest a model of care for people returning from incarceration that may be used to prevent recidivism and rearrests. Other systems may find that early linkage to care during release from incarceration or at entry into community supervision may prevent recidivism and rearrests. Furthermore, it is essential to consider other potential risk factors, such as housing, to design these interventions. From a policy perspective, as the criminal justice system continues a move towards demarcation, policies that ensure successful re-entry are needed. It may be necessary for criminal justice settings to collaborate with health systems to ensure that individuals leaving prisons and jails are linked to the care that they need. In addition, increased funding towards reentry interventions, such as the Whole Person Care, may be cost-effective by reducing the number of people who return to incarceration and increasing access to healthcare, thereby reducing the costs associated with poor health outcomes.

# CHAPTER 3: HOUSING INSTABILITY AND TIME TILL RE-INCARCERATION: A SURVIVAL ANALYSIS

# BACKGROUND

One barrier that has been cited as a determinant of recidivism is the lack of housing. Previous studies have found that a previous episode of incarceration negatively affects the ability to obtain stable housing.<sup>59</sup> Previously incarcerated people may have difficulties finding housing after release because private landlords hesitate to rent to people with a criminal record.<sup>61,67</sup> On the other hand, public housing availability is limited and the waitlist can be very long.<sup>61,67</sup> These challenges mean that many previously incarcerated people cannot find housing after release. Up to two-thirds of formerly incarcerated people have some form of housing instability, while 10% to 20% are homeless.<sup>61,62,67</sup>

Many people experiencing homelessness also have a history of incarceration. For instance, Metraux and Culhane found that 23% of the sheltered homeless people in the New York City shelter system had been incarcerated within the previous two-year period.<sup>63</sup> In examining the relationship between homelessness, housing insecurity, and incarceration, Herbert and colleagues found that housing insecurity among former prisoners was associated with re-incarceration.<sup>68</sup> They also found that housing insecurity was linked to return to prison and absconding. Furthermore, they identify mental illness and substance use as risk factors of housing insecurity.<sup>68</sup> Steiner et al. (2015) found that although homelessness had a substantial effect on re-arrest, it was unrelated to felony re-arrest.<sup>150</sup> For people coming out of incarceration, lack of housing may result in unsuccessful re-entry, resulting in recidivism.

It is important to note that being homeless may not be directly responsible for reincarceration or re-arrests. Being homeless complicates all other risk factors of recidivism and all

other intervention targets to help previously incarcerated people with re-entry. Housing provides the foundation for successful re-entry by providing a stable base from which individuals can find employment and access need services like mental health and substance use treatment.<sup>67</sup> In addition, the effect of homelessness and housing insecurity may be stronger for low-risk people and low severity offenders than for high-risk individuals.<sup>149</sup> This may result in high recidivism rates among individuals who otherwise would not have recidivated. This study examines the effect of housing status on time until recidivism among individuals released from incarceration. It was hypothesized that homeless participants at baseline would have fewer days until the first recidivism compared to participants who were not homeless.

# METHOD

# Measures

#### Time till first re-incarceration

For this study, the dependent variable is defined as the number of days until the first episode of recidivism, which includes re-arrests or re-incarceration for any reason within one year.

#### Independent Variable

#### Housing Status

During the initial assessment, participants were assessed for housing instability. Participants were asked, "What are your living arrangements?". Responses included "Cohoused"; "Homeless Shelter"; "Not Homeless"; "Street"; "Transitional"; "Vehicle"; "Other". Responses were categorized into a dichotomous variable (yes/no) that reflects homeless status. Homeless status was coded as "no" for participants who selected not homeless, while all other responses were classified as "Yes."

#### Mental health and substance use disorder

For this study, mental illness and substance use disorders were combined into a single variable that reflects a mental health diagnosis alone, substance use disorder alone, co-occurring disorder and none. Those with no diagnosis were used as the reference group for all analyses.

#### Service use

Service use was defined as any treatment encounter for mental health or substance use service during the first 90 days following the initial assessment. Participant's health encounter data was obtained from the electronic health record at the Riverside University Health System.

#### Physical health comorbidities

Physical health comorbidities were assessed during the initial screening. Participants were asked to select if they had been diagnosed with diabetes, tuberculosis, hepatitis c, HIV or hypertension. For this analysis, physical health will be recategorized to a dichotomous variable that captures the presence of one or more of these conditions.

#### Analysis

#### Preliminary analysis

Data analysis was conducted using Tableau prep and R version 4.0.2. Descriptive statistics were performed on demographics and other variables to describe the sample. Chi-square tests were used to examine whether there were significant differences in the sample by housing status. The Kaplan–Meier method was used to conduct a survival analysis on the number of days until first rearrest and housing status. A log-rank test was used to examine the difference in survival by housing status.<sup>151</sup> Cox proportional hazard regression model was used to examine the impact of housing status on the risk of re-incarceration among this sample, controlling for socio-demographic variables and other potential confounders such as age, race,

gender, mental illness and substance use disorder. Finally, Aalen's additive regression model was fitted to the same predictors and outcomes as the Cox model. This regression model was used to supplement the Cox model as it results in informative plots regarding the effect of covariates on survival probability. All models were conducted using the survival package in R.<sup>152</sup>

#### RESULTS

#### Participants characteristics

Data from a total of 6,279 individuals recruited between 2017and 2019 were included in this analysis. Table 3 shows the descriptive statistics of the sample, stratified by housing status. The Chi-square test shows significant differences between homeless participants and those who were not homeless in most demographic and clinical variables except gender and substance use treatment service. Participants who were homeless were generally older. A higher percentage of homeless participants had a mental health diagnosis or co-occurring diagnosis with substance use, at least one physical health comorbidity rated their physical and emotional health poorly, and utilized mental health treatment. Among participants without stable housing at baseline, 16.6% were African American/Black, 35.7% were white or Caucasian, 28.3% were Hispanic or Latino and 19.4 % were classified as Others, Multiple Races or Unknown. For participants with stable housing, 10.8% were African American/Black, 32.8% were white or Caucasian, 26.7% were Hispanic or Latino and 29.7 % were classified as Others, Multiple Races or Unknown.

#### Time till re-incarceration

Figure 2 displays the Kaplan–Meier curve showing the number of days to first reincarceration amongst all participants, while Figure 3 displays Kaplan–Meier curve of the number of days to first re-incarceration for by housing status. The plot shows a difference in the curve associated with both groups. The curve associated with people who were homeless drops more quickly from the beginning of the follow-up period. It remains significantly lower than the curve associated with individuals with housing. The log-rank test for difference in survival gives a chi-square (1) = 142, p < 0.001, indicating that the housing groups differ significantly in survival. Overall, this analysis shows that homeless participants spent fewer days in the community before re-incarceration than individuals with housing.



Figure 3: Survival Probability of WPC Participants





Figure 4: Survival Probability by Housing Status

Table 5 displays the Cox regression model results that examine the impact of housing status on the risk of re-incarceration over the follow-up period while controlling for demographic factors and other potential confounders. The results found that the model test statistic was significant (LRT = 437, df = 14, p < .001), which supports rejecting the global null hypothesis in this analysis. A Schoenfeld test was conducted to examine the proportional hazard assumption.<sup>153</sup> Figure 5 displays the plot of the Schoenfeld test for all variables. The global test suggested that the proportional hazard assumption was met (Chi-square (14) = 14.89, p = .390). Additionally, all variables met the proportional hazard assumption as shown by the p-values of tests based on the scaled Schoenfeld and cumulative residuals for non-proportional hazard assessment in figure 5 and table 4. Because age is known to be significantly associated with recidivism, as shown in

the previous study, and significantly different by housing status (see table 3), we were unable to exclude it from the analysis.



Figure 5: Schoenfeld test for all variables

Examining the adjusted hazard ratios for housing status shows that the hazard of reincarceration for people without stable housing was significantly higher than those with housing (HR: 1.63, 95% CI: 1.46, 1.83). The results suggest a 63% increase in the hazard of reincarceration for those who were homeless. As expected, participants with mental health disorder alone (HR: 1.52, 95% CI: 1.22, 1.89), substance use disorder alone (HR: 2.01, 95% CI: 1.63, 2.48) and co-occurring disorder (HR: 2.11, 95% CI: 1.63, 2.74) had a higher risk of reincarceration compared to those with no diagnosis. In addition, those with any mental health encounter (HR: 0.59, 95% CI: 0.46, 0.75) and those with any substance use encounter (HR: 0.70, 95% CI: 0.85, 0.89) had a statistically significant reduction in the risk of recidivism over the oneyear follow-up. The results also showed that those with any emergency department visit had a statistically significant increase in recidivism risk (HR: 1.36, 95% CI: 1.22,1.52). Interestingly, active Medicaid insurance was also associated with a statistically significant increase in recidivism risk (HR: 1.19, 95% CI: 1.08,1.32).

Aalen's additive model result provides the cumulative regression function plots or Aalen's plot. This plot shows the constant or time-dependent effect of covariates on survival; that is, how the effect changes over time.<sup>112</sup> Figure 6 displays the plot of the cumulative regression coefficient for Aalen's model. The results show a linear increase in the hazard of recidivism for housing status and its 95% confidence interval does not include zero. This indicates that housing status has a significant effect on recidivism hazard over the one year follow up. The plot for any mental health encounter shows a negative relationship, with statistical significance, with recidivism. It decreases gradually below zero over the follow-up period. The effect of substance use encounter remains at or around zero until about day 150. At this point, it starts to decrease, and the upper limit of its confidence interval falls below zero after day 200, suggesting that the substance use treatment encounter may have a late effect on recidivism. Active Medicaid did not affect the risk of recidivism, remaining insignificant past day 150. It then began a gradual increase that suggested a late effect on the risk of recidivism. Participants who had an emergency department use had a statistically significant increase in recidivism risk over the follow-up. Figure 6 displays the effect of the other variables in the model.



Figure 6: Aalen's plot for the additive regression

# DISCUSSION

This study examined whether housing status at release will predict time till recidivism. It was hypothesized that participants who were homeless or did not have stable housing at the initial screening time would have fewer days till recidivism. The results of all three survival models examined consistently support this hypothesis by showing an increased risk of recidivism for people without stable housing at release. The Cox proportional hazard model suggests a 63% increase in the risk of recidivism over the 12-month follow-up, while Aalen's plot shows that the effect is consistent throughout the follow-up period. This finding is consistent with previous studies on housing and recidivism.<sup>66,68,149,150</sup> A longitudinal study using a similar administrative dataset in San Francisco, Jacobs and Gottlieb (2020) found that housing insecurity is associated with an increased risk of recidivism among people on probation beyond other recidivism risk factors.<sup>149</sup>

There are several reasons why people who are homeless may be more at risk for recidivism. First, housing provides the platform for reentry among previously incarcerated people. Without stable housing, individuals returning from incarceration cannot find employment, participate in social activities, or adhere to mental health or substance use disorders treatment.<sup>67,154</sup> Previously incarcerated people who are homeless often have complex behavioral health needs requiring access to coordinated care.<sup>155</sup> However, being homeless means that they are unable to access or adhere to care. By this logic, homelessness itself is not directly responsible for recidivism, but homelessness complicates the other risk factor leading to a higher risk of recidivism. On the other hand, previous studies suggest that homeless people may be arrested due to their visibility on the street. Because of this, people who are homeless are more likely to be arrested for nonviolent, minor, and victimless offenses (e.g., public intoxication, theft/shoplifting, violation of city ordinances) than the general population.<sup>156</sup>

A few studies have examined the effectiveness of providing housing for people returning from incarceration. In a randomized control trial using a Housing First model, Sommers and Rezansoff (2013) found that participants with mental health disorders that were assigned to the housing first intervention had significantly lower sentences than the treatment as usual group.<sup>157</sup> They conclude that housing first programs for individuals with mental health disorders returning from incarceration reduce reoffending and reconviction. A study examining the impact of the Mecklenburg County Frequent User Systems Engagement (FUSE) Initiative, which provided supportive housing to previously incarcerated people who were homeless, found that the FUSE group had fewer arrests and remained in the community for a longer time than those who did not participate in the FUSE initiative over a four year period.<sup>158</sup> These studies demonstrate the effectiveness and feasibility of using providing housing for people returning to incarceration.

The findings in this study have several implications for policy and practice. First, the results add to the literature showing that homelessness is a significant risk factor. In planning reentry programs, it is essential to attend to the housing needs of previously incarcerated people. It may be necessary for the corrections department and re-entry staff to assist the client in finding housing arrangements before release from incarceration. In addition, policies that make it easier for people returning from incarceration to find housing may be needed. Previous studies have shown that people returning from incarceration may not be able to afford housing.<sup>31</sup> In addition, people with a criminal record may find it challenging to find housing due to the stigma associated with their prior history of incarceration. Future studies should examine the challenges and barriers to implementing housing first models in other settings. In addition, cost-effectiveness analysis may demonstrate the value of such interventions to the individual and society.

# CHAPTER 4: THE MEDIATING EFFECT OF MENTAL HEALTH AND SUBSTANCE USE SERVICES ON THE RELATIONSHIP BETWEEN MEDICAID AND RECIDIVISM. BACKGROUND

Incarceration is a stressful period for incarcerated people, and this stress is likely higher immediately after release.<sup>8</sup> People who are incarcerated experience poorer health than the general population. Incarcerated individuals have a higher risk for several health conditions, such as tuberculosis, hepatitis, HIV, sexually transmitted infections, cardiovascular disease, weight gain, hypertension, and cancer compared with the general population.<sup>8</sup> While incarcerated, healthcare is guaranteed and everyone has access to some level of health care, according to the US Supreme Court case Estelle v. Gamble, which ruled that denial of health care constituted cruel and unusual punishment and in violation of the Eighth Amendment.<sup>159,160</sup> However, upon release, many previously incarcerated people lack health insurance and housing and must deal with other factors that may significantly negatively impact their health status. Previous studies have described higher rates of mortality among previously incarcerated people.<sup>8</sup> For example, Binswanger et al. found that mortality rates post-incarceration were 3.5 times higher overall, and the death rate was 13 times higher among previously incarcerated individuals than the general population within the first two weeks postrelease.<sup>8,18</sup> These poor health outcomes may interfere with the process of re-entry into the community, which may lead to re-incarceration.

A significant barrier to care for individuals returning to the community from incarceration is a lack of access to health insurance and health benefits.<sup>30,42–44</sup> Most previously incarcerated individuals rely on Medicaid insurance for health coverage.<sup>161,162</sup> Medicaid is an insurance program jointly funded by the federal government and individual states.<sup>45</sup> A study by the Urban Institute that tracked the Medicaid services used by those who entered and left jail

with Medicaid coverage intact found that 90% of these individuals received some outpatient services.<sup>161</sup> Most people returning from incarceration are eligible for Medicaid insurance because Medicaid provides healthcare coverage for some low-income people, families and children, pregnant women, the elderly, and people with disabilities; however, eligibility criteria differ by state.<sup>46</sup> The study also found that although half the population needed substance use treatment, only 18 percent used Medicaid-funded substance abuse treatment services after release.<sup>161</sup>

Some studies have examined the association of expedited Medicaid coverage before or immediately after prison release and the use of community mental health services and substance use treatment, as well as the effect on recidivism.<sup>30,50–55</sup> A previous study found that a discharge planning program for inmates with serious mental illness increased both Medicaid enrollment and mental health service use in three Oklahoma prisons<sup>55</sup>. Another study in Washington State also showed that expediting Medicaid for individuals with severe mental illness was associated with increased Medicaid enrollment by 15% and increased outpatient mental health service use by 13% in the 90 days following release from incarceration.<sup>51</sup>

While studies showed that Medicaid coverage increases service use, its impact on recidivism and reincarceration is unclear and complex. Some studies have found no association between expedited Medicaid enrollment and criminal justice indicators. Morrissey et al. (2016) found that expedited Medicaid enrollment was not associated with a reduction in arrests, but that participants who received expedited Medicaid enrollment had higher incarceration levels in jail or state prisons compared to those in the usual process group.<sup>54</sup> Similarly, Canady (2016) found significant increases in enrollment and service use following expedited medical enrollment; however, it did not reduce recidivism rates.<sup>58</sup>

In contrast, some studies have found a statistically significant reduction in crime and recidivism rates following Medicaid enrollment. Using a difference in difference design, Vogler (2020) found a statistically significant reduction in annual reported violent crime rates when comparing states that expanded Medicaid to non-expansion states.<sup>163</sup> Cuddleback and Cuelar (2019) found that having Medicaid resulted in a 30% reduction in the odds of returning to prison within 36 months among individuals who have committed sex offenses and that have severe mental illnesses.<sup>148</sup> Aslim et al. (2020) show that offering previously incarcerated people access to treatment reduces recidivism. The authors found that in states with Medicaid expansion following the Affordable Care Act, the increased access to health insurance reduces recidivism for violent crimes.<sup>164</sup> This reduction was attributed to an increase in SUD treatment among newly insured previously incarcerated people.<sup>164</sup>

The current study contributes to the literature by examining the effect of early enrollment in Medicaid and recidivism. However, unlike in previous studies, this study examines the role of mental health services and substance use disorder treatment as mediators of the relationship between Medicaid enrollment and recidivism. The current study hypothesized that mental health and substance use services would mediate the association between Medicaid and recidivism among participants with mental health or substance use disorders. Here we propose an indirect effect of Medicaid enrollment on recidivism.

## **METHODS**

In this study, data from WPC participants who had a mental health or substance use disorder were analyzed. The analytical sample comprised 1,525 participants.

#### Measures

#### Recidivism

For this study, recidivism will include any re-arrests or re-incarceration for any reason within one year. Data were collected about whether or not the individual had any re-arrests within one year after release from incarceration.

# Service use

Service use was defined as care access to appropriate services (mental health or substance use) during the 90 days following release. Participants' health encounter data was obtained from the electronic health record at the Riverside University Health System.

#### Mental health and substance use disorder

For this study, mental illness and substance use disorders were combined into a single variable that reflects a mental health diagnosis alone, substance use disorder alone, co-occurring disorder and none. Those with no diagnosis were used as the reference group for all analyses.

# Physical Health

Participants were asked to select if they had been diagnosed with diabetes, tuberculosis, hepatitis C, HIV, hypertension, or other chronic health conditions. For this analysis, physical health will be recategorized to a dichotomous variable that captures the presence of one or more of these conditions.

#### Analysis

# Preliminary analysis

Data analysis was conducted using Mplus **version 8.3**.<sup>165</sup> Descriptive statistics were performed on demographics and other variables to describe the sample. Participants' age was

converted to a categorical variable, with categories created for participants between 18-26, 27-40, 40-55, 55 and over. Participants' Medi-Cal status was recorded as active or inactive. Mediation analysis was conducted using Mplus version 8 with maximum likelihood estimation with 10,000 bootstrapped confidence intervals. A probit regression model with mean- and variance-adjusted weighted least squares (WLSMV) estimator was used to estimate the direct effect of Medicaid on recidivism and the indirect effect through mental health and substance use services, as shown in figure 7. All models included mental health or substance use diagnosis, housing status, physical health comorbidity, sex, race, and age included as covariates.



Figure 7: Conceptual Model for the mediation analysis

# RESULTS

#### Participant Characteristics

The results of the descriptive analysis showed that the majority of participants were male (74.8%). After categorizing the participants' age into groups, 18.8% were between 18-26 years, 31.3% were 27-34 years, 27.2% were 35-44 years, 15.3% were 45-54 years and 7.5% were 55 years and over. The sample was also comprised of 40.7% White or Caucasian, 13.1% Black or African American, 31.4% Hispanic or Latino(a) and 14.8% Others, Multiple Races and

Unknown. Only 38.5% had active Medi-Cal within 90 days of the initial screening. Regarding mental health or substance use disorder, 64.3% of the sample had mental health disorders, while 58.8 had substance use disorder. For mental health encounters, 36.1% of the participants had at least one encounter within 90 days. For substance use encounters, 29% had an encounter within 90 days. The majority of the participants were not homeless at baseline (74.8%). Finally, 17.4% reported having one or more of the physical health comorbidities that were listed during the initial screening.

This model evaluated whether substance use treatment encounters and mental health service encounters would mediate the relationship between having Medicaid insurance and recidivism among participants with mental health or substance use disorders. Multiple fit indices were examined to evaluate model fit, with Comparative Fit Index (CFI) of 1.00, Tucker-Lewis Index(TLI) of 1.00, Root Mean Square Error Of Approximation (RMSEA) of .000 (p <.001), and Standardized Root Mean Square Residual (SRMR) of 0.00. Overall, the model fit statistics suggest that the proposed model was a satisfactory fit for the data.

From the values given in Table 7, we see that substance use treatment encounters and mental health service encounters significantly mediated the relationship between Medicaid insurance and recidivism because the bootstrap CI was below zero while controlling for demographic variables. The indirect effect of Medicaid on recidivism through substance use treatment encounters was statistically significant, as indicated by the confidence limits ( $a_1b_1 = -0.04, 95\%$  CI: -0.11, -0.01). Similarly, the indirect effect of Medicaid on recidivism through mental health service encounter was statistically significant ( $a_2b_2 = -0.10, 95\%$  CI: -0.18, -0.04). Finally, the total indirect effect of Medicaid insurance and recidivism through substance use treatment encounters and mental health service encounters was statistically significant (Total
indirect effect = -0.14, 95% CI: -0.21, -0.08). The direct effect (c') of Medicaid in recidivism was not statistically significant (c' = -0.02, 95% CI: -0.17, 0.13). These findings suggest that in our sample, Medicaid enrollment was not directly associated with recidivism but reduced recidivism by increasing service use. All models controlled for age, sex, race/ethnicity, mental health or substance use diagnosis, physical health comorbidity and housing status.

#### DISCUSSION

The present study investigated a hypothesized pathway through which enrollment in Medicaid insurance is associated with recidivism among previously incarcerated people with mental health or substance use disorders. Specifically, the analysis examines the role of mental health and substance use encounters as mediators of the relationship between Medicaid and recidivism. The results indicated that enrollment in Medicaid within 90 days of release was associated with an increased likelihood of mental health and substance use service encounters, which then reduced recidivism rates. Before discussing the findings in this study, several limitations are discussed.

Several limitations should be considered in this study. This study analyzed a large administrative dataset from a county health system. Due to privacy and confidentiality issues, several variables were computed by RUHS staff before providing the data to the research team. This meant that the researchers had no control over the reliability and validity of the data. For example, a variable was computed to determine if the participants had any re-incarceration within one year. The researchers were unable to determine the reasons for re-arrests, such as if the re-arrest was due to a new crime or violation of probation terms. Previous studies have shown that when recidivism is only measured from new crimes, the rate will be lower than if all re-arrests or reconvictions are used to measure recidivism.<sup>24</sup> Similarly, the researchers relied on

clinical diagnoses obtained from the participants' electronic health records to determine a mental illness or substance use disorder. There is likely some heterogeneity in the assessment method depending on the clinician or health center that may affect the reliability of this measure.

Among participants in this study, which included those with mental health or substance use disorders, 58% were re-incarcerated within one year. Despite the difference in the methods and definition of recidivism used in other studies that may make direct comparisons difficult, this finding is similar to other findings in other studies. Over a 36 month follow-up, Zgoba et al. (2020) found that 52.3%, 38.2% and 29.8% of participants were rearrested, reconvicted, and reincarcerated, respectively.<sup>133</sup> Jaffe et al. (2012) found an overall recidivism rate greater than 50%, with a significant difference between those with severe co-occurring mental health and substance use disorder over 12 months.<sup>166</sup> Over four years, Wilson et al. (2011) found that 54% of people with severe mental illness had recidivated. In addition, they found that 66% of those witsubstance use disorders and 68% of those with co-occurring disorders also experienced recidivism.<sup>32</sup>

The main finding showed that enrollment in Medicaid significantly reduced recidivism through its effect on mental health and substance use service encounters. To our knowledge, no study has examined this pathway among previously incarcerated people with mental health and substance use disorders; however, this finding is consistent with current assumptions about a possible pathway through which Medicaid may reduce recidivism.<sup>53,57,58,164</sup> A similar finding using state-level data showed that Medicaid expansion reduces recidivism and increases access to substance use disorder treatment.<sup>164</sup> The authors here showed that individuals covered by Medicaid and referred to SUD treatment by the criminal justice system had much lower recidivism rates, thus attributing the effect of Medicaid enrollment on recidivism to increased

treatment access. A few studies that found no relationship between Medicaid enrollment and recidivism have used a different design from this study.<sup>54,57,58</sup> Although these studies find that Medicaid enrollment increases service use, their finding of no relationship with recidivism may be because they did not examine the relationship as a pathway from Medicaid enrollment to recidivism through service use.

Our findings have clear implications for policy and practice. First, given the inconsistencies in previous studies, our finding suggests that enrollment in Medicaid by itself is not associated with recidivism, but that the access to services that come with Medicaid enrollment reduces recidivism. In planning expedited Medicaid programs, the program planner should include expedited Medicaid enrollment and ensure that individuals are referred to needed services, such as mental health and substance use treatment. Secondly, the findings suggest that policies to increase Medicaid insurance to previously incarcerated people may have implications beyond improving health and wellbeing. Such policies may contribute to a reduction of the US prison population by preventing recidivism. This study joins a growing body of studies that suggest that Medicaid is associated with criminal justice outcomes, such as recidivism. Future studies are needed to assess the consistency of this finding. In examining this relationship between Medicaid and recidivism, it may be more appropriate for future studies to conceptualizing this relationship as a pathway.

#### **CHAPTER 5: CONCLUSION**

#### SUMMARY OF STUDIES

The current study examines factors associated with recidivism among recently released incarcerated individuals participating in the Riverside University Health System Whole Person Care Pilot. Study one showed that early linkage to mental health and substance use services might reduce recidivism. A logistic regression model showed a statistically significant reduction in recidivism rates for participants who had an encounter for mental health service or treatment for substance use disorder. Furthermore, a negative binomial logistic regression model indicated a statistically significant reduction in the number of re-arrests for participants who had an encounter for mental health service. However, the reduction in re-arrests frequency due to substance use disorder treatment was not significant.

This study also examined the effect of housing status on recidivism. First, in study one, the effect of housing on recidivism was assessed using binary and negative-binomial logistic regression models. The binary logistic regression results showed a statistically significant increase in the odds of recidivism for homeless participants. The negative binomial model results supported this finding by showing a statistically significant increase in re-arrest rates for homeless people compared to those who were not homeless. In study two, Cox proportional hazard model showed that participants who were homeless at baseline returned to incarceration faster than those who were not homeless. In addition, Aalen's additive model showed that the effect of homelessness at baseline was consistent throughout the study period.

Finally, this study explored the path through which providing linkage to Medicaid insurance may reduce recidivism. Study three examined a parallel mediation model of mental health service encounters and substance use treatment encounters as mediators of the relationship

between Medicaid and recidivism. The study found a statistically significant indirect effect of Medicaid on recidivism through both mediators. However, there was no direct effect of Medicaid enrollment on recidivism. This finding clarifies some of the inconsistencies in the literature by showing the pathway through which Medicaid enrollment reduces recidivism.

Some of the findings in this study confirm previous studies' results; for example, the finding that people with co-occurring mental health and substance use disorder have the highest risk of recidivism has been widely documented.<sup>133</sup> Similarly, male participants were more likely to return to incarceration than female participants. Some unexpected findings were also observed; for example, the logistic regression model indicated an increase in recidivism rates for participants with active Medicaid insurance compared to those without Medicaid insurance.

### LIMITATIONS

There are several limitations to consider in this study. First, this study was conducted in Riverside County and participants were not randomly sampled. Participants were able to choose to participate or not. This means that the findings of this study may not be generalizable beyond the participants in this study. Second, all physical health and behavioral health service records were obtained from Riverside University Health systems. This study cannot determine if participants received any medical and behavioral services received from other health systems. However, RUHS and the Department of Behavioral Health is a public healthcare system that comprises an integrated network of providers serving the county's most diverse population.<sup>94</sup> Third, this study relied on administrative data that was linked and compiled by RUHS before being provided to researchers for confidentiality reasons. This made it difficult for the researchers to judge or validate the reliability of the measures and the data linkage process.<sup>167</sup> Furthermore, the data was lacking the details of crucial variables like incarceration. For example,

a variable was computed to show participants who had been re-incarcerated in the year following release. The researchers were unable to determine why participants were re-incarcerated. The study was also unable to control for other know confounders, such as education, social support, and employment following release. Despite the challenges, the availability of these kinds of data has the potential to contribute to research with significant impact for society.<sup>168</sup> Fourth, because of a high number of missing data on subsequent housing status, this study relied on the baseline housing status. Participants may likely have had transitions in housing status throughout the follow-up period. Previous studies suggest that housing instability, measured by the number of moves, may have a small positive effect on recidivism.<sup>149</sup>

### FUTURE DIRECTIONS

Future studies should employ a person-centered analysis, like Latent Class Analysis (LCA), to identify subgroups of WPC participants. LCA may provide vital information on the characteristics of participants who were and were not successful in the WPC program. This information may be relevant to the design of future interventions to prevent recidivism. In addition, the role of housing should be explored further. For example, the potential pathway through which housing status affects recidivism may help guide the development of interventions. Future studies should examine housing as a dynamic factor rather than a static one. It is likely that the participants' housing status changed over the 12 months follow up and that this change may be associated with recidivism. Unfortunately, this study was unable to examine this due to a lack of data. Also, the interaction of housing and other factors such as mental health and substance use treatment may shed more light on how lack of housing increases the risk of recidivism. Finally, this study only found a small indirect effect of Medicaid on recidivism. Future studies should explore other pathways linking Medicaid insurance and recidivism. For

example, active Medicaid insurance may allow individuals to access physical health services besides the emergency room. This may play a role in criminal justice outcomes such as recidivism and re-arrest.

	Overall (N=6347)
Gender	
- Female	1215 (19.1%)
- Male	5132 (80.9%)
Age	
- 18-26	1430 (22.5%)
- 27-34	2009 (31.7%)
- 35-44	1612 (25.4%)
- 45-54	838 (13.2%)
- 55+	458 (7.2%)
Mental Health and Substance Use Diagnosis	
- None	4811 (75.8%)
- Co-Disorder	353 (5.6%)
- MH Alone	635 (10.0%)
- SUD Alone	548 (8.6%)
Chronic Condition	
- No	5464 (86.1%)
- Yes	883 (13.9%)
Housing status (homeless)	
- No	5014 (79.9%)
- Yes	1265 (20.1%)
Race	
- White or Caucasian	2121 (33.4%)
- Black or African American	759 (12.0%)
- Others/Unknown/Multiple Races	1752 (27.6%)
- Hispanic or Latino	1715 (27.0%)
Any Mental Health Encounter	
- No	5790 (91.2%)
- Yes	557 (8.8%)
Any Substance Use Encounter	
- No	5899 (92.9%)
- Yes	448 (7.1%)

TABLES Table 1: Study 1 Sample Description

Medi-Cal	
- Active	2100 (52.6%)
- Not Active	1893 (47.4%)
Any Emergency Department Visit	
- No	4519 (71.2%)
- Yes	1828 (28.8%)

			Negati	ve Bind	omial			
	Logi	stic Re	egressio	n	Regress	sion		
-	0.7	959	% CI	-	Rate	95%	o CI	
Parameter	OR	LL	UL	Р	Ratio	LL	UL	р
Constant	0.44	0.34	0.56	0.001	0.52	0.44	0.63	<.001***
Male	1.70	1.42	2.04	<.001***	1.60	1.40	1.83	<.001***
Age (ref: 18-26)								
27-34	1.04	0.87	1.25	0.667	1.09	0.96	1.23	0.188
35-44	0.81	0.67	0.99	0.036*	0.87	0.76	0.99	0.041*
45-54	0.56	0.44	0.72	<.001***	0.70	0.59	0.83	<.001***
55+	0.42	0.31	0.58	<.001***	0.49	0.39	0.62	<.001***
Any Physical Health Condition	0.91	0.74	1.11	0.36	0.94	0.82	1.09	0.435
Housing Instability	2.01	1.70	2.39	<.001***	1.64	1.47	1.84	<.001***
Race (ref: White or Caucasian)								
Black or African American	0.89	0.71	1.12	0.327	0.96	0.82	1.13	0.613
Others/Unknown/Multiple	0.50	0.42	0.60	< 001***	0.54	0.47	0.62	< 001***
Races	0.50	0.72	0.00	<.001	0.54	0.47	0.02	<.001
Hispanic or Latino	1.03	0.87	1.23	0.732	0.96	0.85	1.08	0.484
Mental Health or Substance Use								
(ref: none)								
Co-Disorder	3.67	2.29	5.86	<.001***	2.25	1.72	2.96	<.001***
MH Alone	1.88	1.32	2.66	<.001***	1.63	1.31	2.03	<.001***
SUD Alone	3.16	2.20	4.55	<.001***	1.83	1.46	2.28	<.001***
Any Mental Health Encounter	0.46	0.31	0.67	<.001***	0.51	0.40	0.66	<.001***
Any Substance use Encounter	0.50	0.33	0.75	<.001***	0.78	0.61	1.00	0.054
Any Emergency Department Encounter	1.62	1.38	<.001	<.001***	1.21	1.08	1.35	<.001***
Medi-Cal	1.29	1.12	1.48	<.001***	1.07	0.97	1.19	0.171

Table 2: Predictors of Recidivism using Logistic Regression and Negative Binomial Regression

\* p < .05, \*\* p < .01, \*\*\* p < .001

Homeless				
		YES	Total	
	NO (N=5014)	(N=1265)	(N=6279)	p value
Gender				0.032
- Female	933 (18.6%)	269 (21.3%)	1202 (19.1%)	
- Male	4081 (81.4%)	996 (78.7%)	5077 (80.9%)	
Age				< 0.001
- 18-26	1188 (23.7%)	231 (18.3%)	1419 (22.6%)	
- 27-34	1608 (32.1%)	381 (30.1%)	1989 (31.7%)	
- 35-44	1249 (24.9%)	341 (27.0%)	1590 (25.3%)	
- 45-54	625 (12.5%)	203 (16.0%)	828 (13.2%)	
- 55+	344 (6.9%)	109 (8.6%)	453 (7.2%)	
Mental health and Substance use				< 0.001
diagnosis				
- None	3874 (77.3%)	880 (69.6%)	4754 (75.7%)	
- Co-Disorder	245 (4.9%)	107 (8.5%)	352 (5.6%)	
- MH Alone	458 (9.1%)	171 (13.5%)	629 (10.0%)	
- SUD Alone	437 (8.7%)	107 (8.5%)	544 (8.7%)	
Chronic Condition				0.008
- NO	4343 (86.6%)	1059 (83.7%)	5402 (86.0%)	
- YES	671 (13.4%)	206 (16.3%)	877 (14.0%)	
Self-Reported Physical Health				< 0.001
- Good	3996 (80.8%)	955 (75.9%)	4951 (79.8%)	
- Poor	949 (19.2%)	303 (24.1%)	1252 (20.2%)	
Self-Reported emotional health				< 0.001
- Good	3989 (80.8%)	853 (68.0%)	4842 (78.2%)	
- Poor	950 (19.2%)	402 (32.0%)	1352 (21.8%)	
Race				< 0.001
- White or Caucasian	1645 (32.8%)	452 (35.7%)	2097 (33.4%)	
- Black or African American	541 (10.8%)	210 (16.6%)	751 (12.0%)	
- Others/Unknown/Multiple Races	1490 (29.7%)	245 (19.4%)	1735 (27.6%)	
- Hispanic or Latino	1338 (26.7%)	358 (28.3%)	1696 (27.0%)	

Table 3. Study 2 Sample Description

Any Mental Health Encounter				< 0.001
- No	4627 (92.3%)	1100 (87.0%)	5727 (91.2%)	
- Yes	387 (7.7%)	165 (13.0%)	552 (8.8%)	
Any Substance use Encounter				< 0.079
- No	4673 (93.2%)	1161 (91.8%)	5834 (92.9%)	
- Yes	341 (6.8%)	104 (8.2%)	445 (7.1%)	
Any ED Visit				< 0.001
- No	3693 (73.7%)	774 (61.2%)	4467 (71.1%)	
- Yes	1321 (26.3%)	491 (38.8%)	1812 (28.9%)	
Medi-Cal				< 0.001
- Active	1607 (50.3%)	264 (34.8%)	1871 (47.3%)	
- Not Active	1589 (49.7%)	495 (65.2%)	2084 (52.7%)	

	chisq	df	P value
Male	0.73	1	0.39
Age	1.87	1	0.17
Any Physical Health Condition	0.11	1	0.74
Housing Instability	0.12	1	0.73
Race/Ethnicity	5.16	3	0.16
Mental Health and Substance use	3.55	3	0.31
Any Mental Health Encounter	2.26	1	0.13
Any Substance use Encounter	0.54	1	0.46
Any ED Encounter	1.94	1	0.16
Medi-Cal	1.58	1	0.21
GLOBAL	14.89	14	0.39

Table 4. Test for Proportional Hazard Assumption

# Table 5: Cox Proportional Hazard Model of Time Till First Reincarceration

Parameter	Hazard ratio	95% CI		P-value
		Lower	Upper	
Male	1.46	1.28	1.67	0.001
Age	0.98	0.98	0.99	0.001
Any Physical Health Condition	0.96	0.83	1.11	0.58
Housing Instability	1.63	1.46	1.83	0.001
Race/Ethnicity				
Black or African	0.9	0.76	1.06	0.192
American				
Hispanic	1.01	0.9	1.14	0.813
Others/Unknown/Multip	0.59	0.51	0.68	0.001
le Races				
Mental Health and Substance				
use				
Co-Disorder	2.11	1.63	2.74	0.001
MH Alone	1.52	1.22	1.89	0.001
SUD Alone	2.01	1.63	2.48	0.001
Any Mental Health Encounter	0.59	0.46	0.75	0.001
Any Substance use Encounter	0.7	0.55	0.89	0.004
Any ED Encounter	1.36	1.22	1.52	0.001
Medi-Cal	1.19	1.08	1.32	0.001

\* p < .05, \*\* p < .01, \*\*\* p < .001

Table 6: Study 3 Sample Description

Overall (N=1,525) N (%) Variable Race/Ethnicity Black or African American 200 (13.1%) Hispanic 479 (31.4%) White 620 (40.7%) Others/Unknown/Multiple Races 226 (14.8%) Medicaid Not Active 938 (61.5%) Active 587 (38.5%) Age Category 18-26 286 (18.8%) 27-34 477 (31.3%) 35-44 415 (27.2%) 45-54 233 (15.3%) 55 +114 (7.5%) Substance Use Disorder No 629 (41.2%) Yes 896 (58.8%) Mental Illness No 544 (35.7%) Yes 981 (64.3%) Any Substance Use Encounter No 1083 (71.0%) Yes 442 (29.0%) Any Mental Health encounter No 975 (63.9%) Yes 550 (36.1%) Homeless No 1140 (74.8%) Yes 385 (25.2%) Physical Health comorbidity No 1260 (82.6%) Yes 265 (17.4%) Sex Female 384 (25.2%) Male 1141 (74.8%) Incarcerated with one year 640 (42.0%) No Yes 885 (58.0%)

Path	Effect	95% CI	
		Lower	Upper
Direct effect (c')	-0.02	-0.17	0.13
Medicaid -> SUD Treatment Encounter (a <sub>1</sub> )	0.24	0.08	0.42
Medicaid -> MH Service Encounter (a <sub>2</sub> )	0.40	0.23	0.56
SUD Treatment Encounter -> Recidivism (b <sub>1</sub> )	-0.18	-0.32	-0.02
MH Service Encounter -> Recidivism (b <sub>2</sub> )	-0.24	-0.38	-0.10
Medicaid to Recidivism, through SUD Treatment (a1b1) Medicaid to Recidivism, through MH Service Encounter (a2b2)	-0.04 -0.10	-0.11 -0.18	-0.01 0.04
Indirect effects Total indirect effect	-0.14	-0.21	-0.08

Table 7: Path coefficients, indirect effects, and 95% corrected confidence interval (10,000 bootstrapped samples) predicting recidivism (N=1,525)<sup>a</sup>

CFI = 1.00, RMSEA =.00, TLI = 1.00, SRMR = 0.00

<sup>*a</sup></sup>All models controlled for housing status, physical health comorbidities, sex, race, and age*</sup>

# ADDITIONAL FIGURES



Figure 8: Rootogram showing model fit for the negative binomial regression model



Figure 9: Rootogram showing model fit for the Poisson regression model

### REFERENCES

- 1. Bureau of Justice Statistics (BJS), US Dept of Justice, Office of Justice Programs, United States of America. Prisoners in 2018. Published online 2020.
- 2. Kaeble D, Cowhig M. Correctional Populations in the United States, 2016. Published online 2016:14.
- NW 1615 L. St, Suite 800Washington, Inquiries D 20036USA202-419-4300 | M-857-8562 | F-419-4372 | M. Black imprisonment rate in the U.S. has fallen by a third since 2006. Pew Research Center. Accessed October 18, 2020. https://www.pewresearch.org/facttank/2020/05/06/share-of-black-white-hispanic-americans-in-prison-2018-vs-2006/
- 4. Proposition 47: The Safe Neighborhoods and Schools Act criminal\_justice. Accessed October 18, 2020. https://www.courts.ca.gov/prop47.htm
- 5. Outcomes of California's Proposition 47 | Prison Legal News. Accessed October 18, 2020. https://www.prisonlegalnews.org/news/2016/sep/2/outcomes-californias-proposition-47/
- 6. Proposition 57. California Department of Corrections and Rehabilitation. Accessed October 18, 2020. https://www.cdcr.ca.gov/proposition57/
- 7. Kaeble D, Alper M, Bureau of Justice Statistics (BJS), US Dept of Justice, Office of Justice Programs. Probation and Parole in the United States, 2017–2018. Published online 2020.
- 8. Massoglia M, Remster B. Linkages Between Incarceration and Health. *Public Health Rep.* 2019;134(1\_suppl):8S-14S. doi:10.1177/0033354919826563
- 9. Binswanger IA, Krueger PM, Steiner JF. Prevalence of chronic medical conditions among jail and prison inmates in the USA compared with the general population. *J Epidemiol Community Health*. 2009;63(11):912-919. doi:10.1136/jech.2009.090662
- Ly KN, Xing J, Klevens RM, Jiles RB, Ward JW, Holmberg SD. The increasing burden of mortality from viral hepatitis in the United States between 1999 and 2007. *Ann Intern Med*. 2012;156(4):271-278. doi:10.7326/0003-4819-156-4-201202210-00004
- 11. Massoglia M, Pridemore WA. Incarceration and health. *Annual Review of Sociology*. 2015;41:291-310.
- 12. Blank S, Sternberg M, Neylans LL, Rubin SR, Weisfuse IB, St. Louis ME. Incident Syphilis among Women with Multiple Admissions to Jail in New York City. *J Infect Dis*. 1999;180(4):1159-1163. doi:10.1086/315038
- Jiménez MC, Cowger TL, Simon LE, Behn M, Cassarino N, Bassett MT. Epidemiology of COVID-19 Among Incarcerated Individuals and Staff in Massachusetts Jails and Prisons. JAMA Netw Open. 2020;3(8):e2018851. doi:10.1001/jamanetworkopen.2020.18851

- 14. Abraham LA, Brown TC, Thomas SA. How COVID-19's Disruption of the U.S. Correctional System Provides an Opportunity for Decarceration. *Am J Crim Justice*. Published online June 19, 2020:1-13. doi:10.1007/s12103-020-09537-1
- 15. U.S. Reports: Estelle v. Gamble, 429 U.S. 97 (1976). Library of Congress, Washington, D.C. 20540 USA. Accessed October 18, 2020. https://www.loc.gov/item/usrep429097/
- 16. Initiative PP. The steep cost of medical co-pays in prison puts health at risk. Accessed October 18, 2020. https://www.prisonpolicy.org/blog/2017/04/19/copays/
- 17. Charging Inmates a Fee for Health Care Services. Accessed October 18, 2020. https://www.ncchc.org/charging-inmates-a-fee-for-health-care-services
- Binswanger IA, Stern MF, Deyo RA, et al. Release from Prison A High Risk of Death for Former Inmates. *New England Journal of Medicine*. 2007;356(2):157-165. doi:10.1056/NEJMsa064115
- 19. Kouyoumdjian FG, Kiefer L, Wobeser W, Gonzalez A, Hwang SW. Mortality over 12 years of follow-up in people admitted to provincial custody in Ontario: a retrospective cohort study. *CMAJ Open.* 2016;4(2):E153-161. doi:10.9778/cmajo.20150098
- 20. Patterson EJ. The Dose–Response of Time Served in Prison on Mortality: New York State, 1989–2003. *Am J Public Health*. 2013;103(3):523-528. doi:10.2105/AJPH.2012.301148
- 21. Recidivism. National Institute of Justice. Accessed July 20, 2020. https://nij.ojp.gov/topics/corrections/recidivism
- 22. McKean L, Ransford C. *Current Strategies for Reducing Recidivism*. Center for Impact Research Chicago, IL; 2004.
- 23. BJS. The Measures of Recidivism. Accessed July 20, 2020. https://www.bjs.gov/recidivism/templates/definition.cfm
- 24. Ostermann M, Salerno LM, Hyatt JM. How different operationalizations of recidivism impact conclusions of effectiveness of parole supervision. *Journal of Research in Crime and Delinquency*. 2015;52(6):771-796. doi:10.1177/0022427815580626
- 25. Rakis J. Improving the employment rate of ex-prisoners under parole. *Fed Probation*. 2005;69:7.
- 26. Durose MR, Cooper AD, Snyder HN. *Recidivism of Prisoners Released in 30 States in 2005: Patterns from 2005 to 2010.* Vol 28. US Department of Justice, Office of Justice Programs, Bureau of Justice ...; 2014.
- 27. Gelb A, Velazquez T. The changing state of recidivism: fewer people going back to prison. *The Pew Charitable Trusts*. Published online 2018.

- 28. Baillargeon J, Hoge SK, Penn JV. Addressing the Challenge of Community Reentry Among Released Inmates with Serious Mental Illness. *Am J Community Psychol.* 2010;46(3):361-375. doi:10.1007/s10464-010-9345-6
- Baillargeon J, Penn JV, Knight K, Harzke AJ, Baillargeon G, Becker EA. Risk of Reincarceration Among Prisoners with Co-occurring Severe Mental Illness and Substance Use Disorders. *Adm Policy Ment Health*. 2010;37(4):367-374. doi:10.1007/s10488-009-0252-9
- Hoge SK. Providing Transition and Outpatient Services to the Mentally Ill Released from Correctional Institutions. In: Greifinger RB, ed. *Public Health Behind Bars: From Prisons* to Communities. Springer; 2007:461-477. doi:10.1007/978-0-387-71695-4\_26
- 31. Roman CG. Taking stock: Housing, homelessness, and prisoner reentry. Published online 2004.
- 32. Wilson AB, Draine J, Hadley T, Metraux S, Evans A. Examining the impact of mental illness and substance use on recidivism in a county jail. *International Journal of Law and Psychiatry*. 2011;34(4):264-268. doi:10.1016/j.ijlp.2011.07.004
- 33. Abracen J, Langton CM, Looman J, et al. Mental Health Diagnoses and Recidivism in Paroled Offenders. *Int J Offender Ther Comp Criminol*. 2014;58(7):765-779. doi:10.1177/0306624X13485930
- 34. Han W, Redlich AD. The Impact of Community Treatment on Recidivism Among Mental Health Court Participants. *PS*. 2015;67(4):384-390. doi:10.1176/appi.ps.201500006
- 35. Solomon P, Draine J, Marcus SC. Predicting Incarceration of Clients of a Psychiatric Probation and Parole Service. *PS*. 2002;53(1):50-56. doi:10.1176/appi.ps.53.1.50
- 36. Cloyes KG, Wong B, Latimer S, Abarca J. Time to Prison Return for Offenders With Serious Mental Illness Released From Prison: A Survival Analysis. *Criminal Justice and Behavior*. Published online January 4, 2010. doi:10.1177/0093854809354370
- 37. Bonta J, Law M, Hanson K. The prediction of criminal and violent recidivism among mentally disordered offenders: a meta-analysis. *Psychological bulletin*. 1998;123(2):123.
- Håkansson A, Berglund M. Risk factors for criminal recidivism a prospective follow-up study in prisoners with substance abuse. *BMC Psychiatry*. 2012;12(1):111. doi:10.1186/1471-244X-12-111
- 39. Putniņš AL. Substance use and the prediction of young offender recidivism. *Drug & Alcohol Review*. 2003;22(4):401-408.
- 40. Denney AS, Connor DP. Serious juvenile offenders who have experienced emerging adulthood: Substance use and recidivism. *Children and Youth Services Review*. 2016;67:11-19. doi:10.1016/j.childyouth.2016.05.014

- 41. Walter M, Wiesbeck GA, Dittmann V, Graf M. Criminal recidivism in offenders with personality disorders and substance use disorders over 8 years of time at risk. *Psychiatry research*. 2011;186(2-3):443-445.
- 42. Hammett TM, Roberts C, Kennedy S. Health-Related Issues in Prisoner Reentry: *Crime & Delinquency*. Published online September 4, 2016. doi:10.1177/0011128701047003006
- 43. Lee J, Vlahov D, Freudenberg N. Primary care and health insurance among women released from New York City jails. *J Health Care Poor Underserved*. 2006;17(1):200-217. doi:10.1353/hpu.2006.0028
- 44. Visher CA, Mallik-Kane K. Reentry Experiences of Men with Health Problems. In: Greifinger RB, ed. *Public Health Behind Bars: From Prisons to Communities*. Springer; 2007:434-460. doi:10.1007/978-0-387-71695-4\_25
- 45. Financial Management | Medicaid. Accessed October 7, 2020. https://www.medicaid.gov/medicaid/financial-management/index.html
- 46. Enroll in Medicaid or CHIP any time of year. HealthCare.gov. Accessed October 7, 2020. https://www.healthcare.gov/medicaid-chip/getting-medicaid-chip/
- Albertson EM, Scannell C, Ashtari N, Barnert E. Eliminating Gaps in Medicaid Coverage During Reentry After Incarceration. *Am J Public Health*. 2020;110(3):317-321. doi:10.2105/AJPH.2019.305400
- 48. Rosen DL, Dumont DM, Cislo AM, Brockmann BW, Traver A, Rich JD. Medicaid Policies and Practices in US State Prison Systems. *Am J Public Health*. 2014;104(3):418-420. doi:10.2105/AJPH.2013.301563
- 49. Wakeman SE, McKinney ME, Rich JD. Filling the Gap: The Importance of Medicaid Continuity for Former Inmates. *J GEN INTERN MED*. 2009;24(7):860-862. doi:10.1007/s11606-009-0977-x
- 50. Gertner AK, Grabert B, Domino ME, Cuddeback GS, Morrissey JP. The effect of referral to expedited Medicaid on substance use treatment utilization among people with serious mental illness released from prison. *Journal of Substance Abuse Treatment*. 2019;99:9-15. doi:10.1016/j.jsat.2019.01.010
- Cuddeback GS, Morrissey JP, Domino ME. Enrollment and Service Use Patterns Among Persons With Severe Mental Illness Receiving Expedited Medicaid on Release From State Prisons, County Jails, and Psychiatric Hospitals. *Psychiatr Serv.* 2016;67(8):835-841. doi:10.1176/appi.ps.201500306
- 52. Domino ME, Gertner A, Grabert B, Cuddeback GS, Childers T, Morrissey JP. Do timely mental health services reduce re-incarceration among prison releasees with severe mental illness? *Health Serv Res.* 2019;54(3):592-602. doi:10.1111/1475-6773.13128

- 53. Morrissey JP, Cuddeback GS, Cuellar AE, Steadman HJ. The Role of Medicaid Enrollment and Outpatient Service Use in Jail Recidivism Among Persons With Severe Mental Illness. *PS*. 2007;58(6):794-801. doi:10.1176/ps.2007.58.6.794
- 54. Morrissey JP, Domino ME, Cuddeback GS. Expedited Medicaid, Mental Health Service Use, and Criminal Recidivism among Released Prisoners with Severe Mental Illness. *Psychiatr Serv.* 2016;67(8):842-849. doi:10.1176/appi.ps.201500305
- 55. Wenzlow AT, Ireys HT, Mann B, Irvin C, Teich JL. Effects of a discharge planning program on Medicaid coverage of state prisoners with serious mental illness. *Psychiatr Serv.* 2011;62(1):73-78. doi:10.1176/ps.62.1.pss6201\_0073
- 56. Fry CE, McGuire TG, Frank RG. Medicaid Expansion's Spillover to the Criminal Justice System: Evidence from Six Urban Counties. *RSF: The Russell Sage Foundation Journal of the Social Sciences*. 2020;6(2):244-263. doi:10.7758/RSF.2020.6.2.11
- 57. Grabert BK, Gertner AK, Domino ME, Cuddeback GS, Morrissey JP. Expedited Medicaid Enrollment, Service Use, and Recidivism at 36 Months Among Released Prisoners With Severe Mental Illness. *PS*. 2017;68(10):1079-1082. doi:10.1176/appi.ps.201600482
- 58. Canady VA. Medicaid access for inmates with SMI doesn't lower recidivism. *Mental Health Weekly*. 2016;26(12):5-6. doi:https://doi.org/10.1002/mhw.30548
- 59. Geller A, Curtis MA. A sort of homecoming: Incarceration and the housing security of urban men. *Social Science Research*. 2011;40(4):1196-1213.
- 60. Metraux S, Roman CG, Cho RS. Incarceration and homelessness. In: *National Symposium on Homelessness Research*. US Department of Housing and Urban Development Washington, DC; 2007.
- 61. Predicting Two Types of Recidivism Among Newly Released Prisoners: First Addresses as "Launch Pads" for Recidivism or Reentry Success - Valerie A. Clark, 2016. Accessed November 12, 2020. https://journals.sagepub.com/doi/abs/10.1177/0011128714555760?journalCode=cadc
- 62. Dong KR, Must A, Tang AM, Beckwith CG, Stopka TJ. Competing priorities that rival health in adults on probation in Rhode Island: substance use recovery, employment, housing, and food intake. *BMC Public Health*. 2018;18(1):289. doi:10.1186/s12889-018-5201-7
- 63. Metraux S, Culhane DP. Recent incarceration history among a sheltered homeless population. *Crime & Delinquency*. 2006;52(3):504-517.
- 64. Aidala AA, McAllister W, Yomogida M, Shubert V. Frequent Users Service Enhancement "FUSE" Initiative: New York City FUSE II evaluation report. *New York, NY: Columbia University Mailman School of Public Health.* Published online 2014.

- 65. Couloute L. Nowhere to go: Homelessness among formerly incarcerated people. *Prison Policy Initiative*. Published online 2018.
- 66. McNiel DE, Binder RL, Robinson JC. Incarceration associated with homelessness, mental disorder, and co-occurring substance abuse. *Psychiatric Services*. 2005;56(7):840-846.
- 67. Roman CG, Travis J. Where will I sleep tomorrow? Housing, homelessness, and the returning prisoner. *Housing Policy Debate*. 2006;17(2):389-418.
- 68. Herbert CW, Morenoff JD, Harding DJ. Homelessness and Housing Insecurity Among Former Prisoners. *RSF: The Russell Sage Foundation Journal of the Social Sciences*. 2015;1(2):44-79.
- 69. Bradley KH, Oliver RB, Richardson NC, Slayter EM. No place like home: Housing and the ex-prisoner. *Issue brief Boston, MA: Community Resources for Justice*. Published online 2001.
- 70. Lutze FE, Rosky JW, Hamilton ZK. Homelessness and reentry: A multisite outcome evaluation of Washington State's reentry housing program for high risk offenders. *Criminal Justice and Behavior*. 2014;41(4):471-491.
- 71. The Social-Ecological Model: A Framework for Prevention |Violence Prevention|Injury Center|CDC. Published January 28, 2020. Accessed October 17, 2020. https://www.cdc.gov/violenceprevention/publichealthissue/social-ecologicalmodel.html
- 72. Bronfenbrenner U. Toward an experimental ecology of human development. *American Psychologist.* 1977;32(7):513-531. doi:10.1037/0003-066X.32.7.513
- 73. Alper M, Durose MR, Markman J. 2018 Update on Prisoner Recidivism: A 9-Year Followup Period (2005-2014). US Department of Justice, Office of Justice Programs, Bureau of Justice ...; 2018.
- 74. Hunt KS, Dumville R. *Recidivism among Federal Offenders: A Comprehensive Overview*. United States Sentencing Commission; 2016.
- McLeroy KR, Bibeau D, Steckler A, Glanz K. An ecological perspective on health promotion programs. *Health Educ Q*. 1988;15(4):351-377. doi:10.1177/109019818801500401
- 76. Pettus-Davis C, Howard MO, Murugan V, et al. Acceptability of a Social Support Intervention for Re-entering Prisoners. *Journal of the Society for Social Work and Research*. 2015;6(1):51-89. doi:10.1086/680340
- 77. Berg MT, Huebner BM. Reentry and the Ties that Bind: An Examination of Social Ties, Employment, and Recidivism. *Justice Quarterly*. 2011;28(2):382-410. doi:10.1080/07418825.2010.498383

- Spjeldnes S, Jung H, Maguire L, Yamatani H. Positive Family Social Support: Counteracting Negative Effects of Mental Illness and Substance Abuse to Reduce Jail Exinmate Recidivism Rates. *Journal of Human Behavior in the Social Environment*. 2012;22(2):130-147. doi:10.1080/10911359.2012.646846
- 79. Kubrin CE, Stewart EA. Predicting Who Reoffends: The Neglected Role of Neighborhood Context in Recidivism Studies\*. *Criminology*. 2006;44(1):165-197. doi:10.1111/j.1745-9125.2006.00046.x
- Stahler GJ, Mennis J, Belenko S, Welsh WN, Hiller ML, Zajac G. Predicting Recidivism for Released State Prison Offenders: Examining the Influence of Individual and Neighborhood Characteristics and Spatial Contagion on the Likelihood of Reincarceration. *Criminal Justice and Behavior*. 2013;40(6):690-711. doi:10.1177/0093854812469609
- Hipp JR, Petersilia J, Turner S. Parolee Recidivism in California: The Effect of Neighborhood Context and Social Service Agency Characteristics\*. *Criminology*. 2010;48(4):947-979. doi:10.1111/j.1745-9125.2010.00209.x
- 82. McNeeley S. Do Ecological Effects on Recidivism Vary by Gender, Race, or Housing Type? *Crime & Delinquency*. 2018;64(6):782-806. doi:10.1177/0011128717714425
- 83. Fiscella K, Beletsky L, Wakeman SE. The Inmate Exception and Reform of Correctional Health Care. *Am J Public Health*. 2017;107(3):384-385. doi:10.2105/AJPH.2016.303626
- 84. How and When Medicaid Covers People Under Correctional Supervision. Accessed October 18, 2020. http://pew.org/2amleU0
- 85. Initiative PP. Out of Prison & Out of Work. Accessed October 18, 2020. https://www.prisonpolicy.org/reports/outofwork.html
- 86. Schnepel KT. Good Jobs and Recidivism. *Econ J*. 2018;128(608):447-469. doi:10.1111/ecoj.12415
- Ramakers A, Nieuwbeerta P, Van Wilsem J, Dirkzwager A. Not Just Any Job Will Do: A Study on Employment Characteristics and Recidivism Risks After Release. *Int J Offender Ther Comp Criminol.* 2017;61(16):1795-1818. doi:10.1177/0306624X16636141
- 88. Bonta J, Andrews DA. Risk-need-responsivity model for offender assessment and rehabilitation. *Rehabilitation*. 2007;6(1):1-22.
- 89. Ward T, Melser J, Yates PM. Reconstructing the Risk–Need–Responsivity model: A theoretical elaboration and evaluation. *Aggression and violent behavior*. 2007;12(2):208-228.
- Morgan RD, Flora DB, Kroner DG, Mills JF, Varghese F, Steffan JS. Treating Offenders with Mental Illness: A Research Synthesis. *Law Hum Behav*. 2012;36(1):37-50. doi:10.1037/h0093964

- 91. The Most Carefully Studied, Yet Least Understood, Terms in the Criminal Justice Lexicon: Risk, Need, and Responsivity. Policy Research Associates. Published July 17, 2018. Accessed July 20, 2020. https://www.prainc.com/risk-need-responsitivity/
- 92. Bonta J, Andrews DA. The Psychology of Criminal Conduct. Taylor & Francis; 2016.
- 93. Chuang E, Pourat N, Haley LA, O'Masta B, Albertson E, Lu C. Integrating Health And Human Services In California's Whole Person Care Medicaid 1115 Waiver Demonstration: An overview of a California demonstration program focused on improving the integrated delivery of health, behavioral health, and social services for certain Medicaid beneficiaries. *Health Affairs*. 2020;39(4):639-648.
- 94. Whole Person Care Pilot Project Program Narrative. Published online July 2016.
- 95. Institute S. SAS/STAT (Version 9.4) Computer Software. Published online 2014. http://www.sas.com/
- 96. R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing; 2020. https://www.R-project.org/
- 97. Agresti Alan. An Introduction to Categorical Data Analysis. 2nd ed. Wiley-Interscience; 2007. http://search.ebscohost.com/login.aspx?direct=true&scope=site&db=nlebk&db=nlabk&AN =190561
- 98. Hosmer DW, Lemeshow S, Sturdivant RX, Hosmer DW Jr. Applied Logistic Regression. John Wiley & Sons, Incorporated; 2013. http://ebookcentral.proquest.com/lib/claremont/detail.action?docID=1138225
- 99. Osborne JW. Best Practices in Logistic Regression.; 2020. doi:10.4135/9781483399041
- 100. Peduzzi P, Concato J, Kemper E, Holford TR, Feinstein AR. A simulation study of the number of events per variable in logistic regression analysis. *Journal of clinical epidemiology*. 1996;49(12):1373-1379.
- 101. Bagley SC, White H, Golomb BA. Logistic regression in the medical literature:: Standards for use and reporting, with particular attention to one medical domain. *Journal of Clinical Epidemiology*. 2001;54(10):979-985. doi:10.1016/S0895-4356(01)00372-9
- 102. Beaujean AA, Grant MB. Tutorial on Using Regression Models with Count Outcomes using R. doi:10.7275/PJ8C-H254
- 103. HOFFMANN JP. Regression Models for Categorical, Count, and Related Variables. 1st ed. University of California Press; 2016. Accessed October 16, 2020. http://www.jstor.org.ccl.idm.oclc.org/stable/10.1525/j.ctv1wxrfr
- 104. Visualizing Count Data Regressions Using Rootograms: The American Statistician: Vol 70, No 3. Accessed September 16, 2020.

https://www.tandfonline.com/doi/abs/10.1080/00031305.2016.1173590?journalCode=utas20

- 105. Poole MA, O'Farrell PN. The Assumptions of the Linear Regression Model. *Transactions* of the Institute of British Geographers. 1971;(52):145-158. doi:10.2307/621706
- 106. Moore DF. Applied Survival Analysis Using R. Springer International Publishing; 2016. doi:10.1007/978-3-319-31245-3
- 107. Kaplan EL, Meier P. Nonparametric Estimation from Incomplete Observations. Journal of the American Statistical Association. 1958;53(282):457-481. doi:10.1080/01621459.1958.10501452
- 108. Goel MK, Khanna P, Kishore J. Understanding survival analysis: Kaplan-Meier estimate. *Int J Ayurveda Res.* 2010;1(4):274-278. doi:10.4103/0974-7788.76794
- 109. Cox DR. Regression models and life-tables. *Journal of the Royal Statistical Society: Series B* (*Methodological*). 1972;34(2):187-202.
- 110. Abadi A, Saadat S, Yavari P, Bajdik C, Jalili P. Comparison of Aalen's additive and Cox proportional hazards models for breast cancer survival: analysis of population- based data from British Columbia, Canada. *Asian Pac J Cancer Prev.* 2011;12(11):3113-3116.
- 111. Kleinbaum DG, Klein M. Survival Analysis: A Self-Learning Text, Third Edition. 3rd ed. Springer-Verlag; 2012. doi:10.1007/978-1-4419-6646-9
- 112. Aalen OO. A linear regression model for the analysis of life times. *Statistics in Medicine*. 1989;8(8):907-925. doi:10.1002/sim.4780080803
- 113. MacKinnon DP, Luecken LJ. How and for whom? Mediation and moderation in health psychology. *Health psychology*. 2008;27(2S):S99.
- 114. Baron RM, Kenny DA. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology*. 1986;51(6):1173.
- 115. MacKinnon DP. Introduction to Statistical Mediation Analysis. Routledge; 2008.
- 116. MacKinnon DP. Integrating mediators and moderators in research design. *Research on social work practice*. 2011;21(6):675-681.
- 117. Hayes AF. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. Guilford Publications; 2017.
- 118. Sobel ME. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological methodology*. 1982;13:290-312.

- 119. Hayes AF. Beyond Baron and Kenny: Statistical Mediation Analysis in the New Millennium. *Communication Monographs*. 2009;76(4):408-420. doi:10.1080/03637750903310360
- 120. Williams J, MacKinnon DP. Resampling and Distribution of the Product Methods for Testing Indirect Effects in Complex Models. *Struct Equ Modeling*. 2008;15(1):23-51. doi:10.1080/10705510701758166
- 121. Grella CE, Greenwell L, Prendergast M, Sacks S, Melnick G. Diagnostic profiles of offenders in substance abuse treatment programs. *Behavioral Sciences & the Law*. 2008;26(4):369-388. doi:10.1002/bsl.825
- 122. Steadman HJ, Osher FC, Robbins PC, Case B, Samuels S. Prevalence of serious mental illness among jail inmates. *Psychiatric services*. 2009;60(6):761-765.
- 123. Abuse S. Mental Health Services Administration.(2018). Key substance use and mental health indicators in the United States: Results from the 2017 National Survey on Drug Use and Health (HHS Publication No. SMA 18-5068, NSDUH Series H-53). Rockville, MD: Center for Behavioral Health Statistics and Quality. *Substance Abuse and Mental Health Services Administration Retrieved from https://www samhsa gov/data*. Published online 2019.
- 124. Bronson J, Stroop J, Zimmer S, Berzofsky M. Drug use, dependence, and abuse among state prisoners and jail inmates, 2007–2009. *Washington, DC: United States Department of Justice, Office of Juvenile Justice and Delinquency Prevention*. Published online 2017.
- 125. Lurigio AJ. Co-occurring Disorders: Mental Health and Drug Misuse. In: Leukefeld C, Gullotta TP, Gregrich J, eds. *Handbook of Evidence-Based Substance Abuse Treatment in Criminal Justice Settings*. Issues in Children's and Families' Lives. Springer; 2011:279-292. doi:10.1007/978-1-4419-9470-7\_16
- 126. Karberg JC, James DJ. Substance Dependence, Abuse, and Treatment of Jail Inmates, 2002. US Department of Justice, Office of Justice Programs, Bureau of Justice ...; 2005.
- 127. King EA, Tripodi SJ, Veeh CA. The Relationship Between Severe Mental Disorders and Recidivism in a Sample of Women Released from Prison. *Psychiatr Q*. 2018;89(3):717-731. doi:10.1007/s11126-018-9572-9
- 128. Dirks-Linhorst PA, Linhorst DM. Recidivism Outcomes for Suburban Mental Health Court Defendants. *Am J Crim Just*. 2012;37(1):76-91. doi:10.1007/s12103-010-9092-0
- 129. Loong D, Bonato S, Barnsley J, Dewa CS. The Effectiveness of Mental Health Courts in Reducing Recidivism and Police Contact: A Systematic Review. *Community Ment Health* J. 2019;55(7):1073-1098. doi:10.1007/s10597-019-00421-9
- 130. THEURER G, LOVELL D. Recidivism of Offenders with Mental Illness Released from Prison to an Intensive Community Treatment Program. *Journal of Offender Rehabilitation*. 2008;47(4):385-406. doi:10.1080/10509670801995023

- 131. Kelly BL, Barrenger SL, Watson AC, Angell B. Forensic Assertive Community Treatment: Recidivism, hospitalization, and the role of housing and support. *Social Work in Mental Health.* 2017;15(5):567-587. doi:10.1080/15332985.2016.1261754
- 132. Sullivan CJ, Veysey BM, Hamilton ZK, Grillo M. Reducing out-of-community placement and recidivism: diversion of delinquent youth with mental health and substance use problems from the justice system. *Int J Offender Ther Comp Criminol*. 2007;51(5):555-577. doi:10.1177/0306624X06296237
- 133. Zgoba KM, Reeves R, Tamburello A, Debilio L. Criminal Recidivism in Inmates with Mental Illness and Substance Use Disorders. *Journal of the American Academy of Psychiatry and the Law Online*. Published online February 12, 2020. doi:10.29158/JAAPL.003913-20
- 134. McNiel DE, Binder RL. Effectiveness of a Mental Health Court in Reducing Criminal Recidivism and Violence. AJP. 2007;164(9):1395-1403. doi:10.1176/appi.ajp.2007.06101664
- 135. INCIARDI SSM CLIFFORD A BUTZIN, CHRISTINE A SAUM, JAMES A. Three-Year Outcomes of Therapeutic Community Treatment for Drug-Involved Offenders in Delaware: From Prison to Work Release to Aftercare - STEVEN S. MARTIN, CLIFFORD A. BUTZIN, CHRISTINE A. SAUM, JAMES A. INCIARDI, 1999. *The Prison Journal*. Published online November 16, 2016. Accessed October 5, 2020. http://journals.sagepub.com/doi/10.1177/0032885599079003002
- 136. Gilbert AR, Moser LL, Van Dorn RA, et al. Reductions in arrest under assisted outpatient treatment in New York. *Psychiatric Services (Washington, DC)*. 2010;61(10):996-999. doi:10.1176/ps.2010.61.10.996
- 137. Wilson JL, Bandyopadhyay S, Yang H, Cerulli C, Morse DS. Identifying Predictors of Substance Use and Recidivism Outcome Trajectories Among Drug Treatment Court Clients. *Criminal Justice and Behavior*. 2018;45(4):447-467. doi:10.1177/0093854817737806
- 138. Gottfredson DC, Najaka SS, Kearley B. Effectiveness of Drug Treatment Courts: Evidence from a Randomized Trial\*. *Criminology & Public Policy*. 2003;2(2):171-196. doi:https://doi.org/10.1111/j.1745-9133.2003.tb00117.x
- 139. Ray B, Grommon E, Buchanan V, Brown B, Watson DP. Access to Recovery and Recidivism Among Former Prison Inmates: *International Journal of Offender Therapy and Comparative Criminology*. Published online September 17, 2015. doi:10.1177/0306624X15606688
- 140. Hiller ML, Knight K, Simpson DD. Recidivism Following Mandated Residential Substance Abuse Treatment for Felony Probationers. *The Prison Journal*. 2006;86(2):230-241. doi:10.1177/0032885506287951

- 141. Mulder E, Brand E, Bullens R, van Marle H. Risk Factors for Overall Recidivism and Severity of Recidivism in Serious Juvenile Offenders. *Int J Offender Ther Comp Criminol*. 2011;55(1):118-135. doi:10.1177/0306624X09356683
- 142. Robertson AG, Easter MM, Lin H-J, et al. Gender-specific participation and outcomes among jail diversion clients with co-occurring substance use and mental health disorders. *Journal of Substance Abuse Treatment*. 2020;115:108035. doi:10.1016/j.jsat.2020.108035
- 143. de Andrade D, Ritchie J, Rowlands M, Mann E, Hides L. Substance Use and Recidivism Outcomes for Prison-Based Drug and Alcohol Interventions. *Epidemiol Rev.* 2018;40(1):121-133. doi:10.1093/epirev/mxy004
- 144. Gaum G, Hoffman S, Venter JH. Factors That Influence Adult Recidivism: An Exploratory Study in Pollsmoor Prison. *South African Journal of Psychology*. 2006;36(2):407-424. doi:10.1177/008124630603600212
- 145. Farrington DP, Loeber R, Ttofi MM. Risk and Protective Factors for Offending. The Oxford Handbook of Crime Prevention. doi:10.1093/oxfordhb/9780195398823.013.0003
- 146. Lamb HR, Weinberger LE, Marsh JS, Gross BH. Treatment prospects for persons with severe mental illness in an urban county jail. *Psychiatr Serv.* 2007;58(6):782-786. doi:10.1176/ps.2007.58.6.782
- 147. Trupin E, Wood PN, Harris VL. Mentally Ill Offenders and Community Transitions: Resource Acquisition and Recidivism. J Correct Health Care. 1999;6(1):27-40. doi:10.1177/107834589900600103
- 148. Cuddeback GS, Grady M, Blank Wilson A, Van Deinse T, Morrissey JP. Persons With Severe Mental Illnesses and Sex Offenses: Recidivism After Prison Release. *Int J Offender Ther Comp Criminol.* 2019;63(12):2157-2170. doi:10.1177/0306624X19842994
- 149. Jacobs LA, Gottlieb A. The Effect of Housing Circumstances on Recidivism: Evidence From a Sample of People on Probation in San Francisco. *Criminal Justice and Behavior*. 2020;47(9):1097-1115. doi:10.1177/0093854820942285
- 150. Steiner B, Makarios MD, Travis LF. Examining the Effects of Residential Situations and Residential Mobility on Offender Recidivism. *Crime & Delinquency*. 2015;61(3):375-401. doi:10.1177/0011128711399409
- 151. Mantel N. Evaluation of survival data and two new rank order statistics arising in its consideration. *Cancer Chemother Rep.* 1966;50(3):163-170.
- 152. Therneau T. A package for survival analysis in R. :95.
- 153. Grambsch PM, Therneau TM. Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*. 1994;81(3):515-526. doi:10.1093/biomet/81.3.515

- 154. Fontaine J, Biess J. Housing as a platform for formerly incarcerated persons. *Washington, DC: Urban Institute*. Published online 2012.
- 155. Mitchell JN, Clark C, Guenther CC. The Impact of Criminal Justice Involvement and Housing Outcomes Among Homeless Persons with Co-occurring Disorders. *Community Ment Health J.* 2017;53(8):901-904. doi:10.1007/s10597-017-0089-8
- 156. Snow DA, Baker SG, Anderson L. Criminality and homeless men: An empirical assessment. *Social Problems*. 1989;36(5):532-549. doi:10.1525/sp.1989.36.5.03x0010j
- 157. Housing First Reduces Re-offending among Formerly Homeless Adults with Mental Disorders: Results of a Randomized Controlled Trial. Accessed November 16, 2020. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0072946
- 158. Listwan SJ, Hartman JL, LaCourse A. Impact of the MeckFUSE Pilot Project: Recidivism Among the Chronically Homeless. *Justice Evaluation Journal*. 2018;1(1):96-108. doi:10.1080/24751979.2018.1478236
- 159. Medicaid Enrollment Programs Offer Hope To Formerly Incarcerated Individuals And Savings For States | Health Affairs. Accessed October 7, 2020. https://www.healthaffairs.org/do/10.1377/hblog20200218.910350/full/
- 160. U.S. Reports: Estelle v. Gamble, 429 U.S. 97 (1976). Library of Congress, Washington, D.C. 20540 USA. Accessed October 7, 2020. https://www.loc.gov/item/usrep429097/
- 161. Lisa KM-KAL, Tiry DE. Using Jail to Enroll Low-Income Men in Medicaid. Published online 2016.
- 162. Grodensky CA, Rosen DL, Blue CM, et al. Medicaid Enrollment among Prison Inmates in a Non-expansion State: Exploring Predisposing, Enabling, and Need Factors Related to Enrollment Pre-incarceration and Post-Release. J Urban Health. 2018;95(4):454-466. doi:10.1007/s11524-018-0275-1
- 163. Vogler J. Access to Healthcare and Criminal Behavior: Evidence from the ACA Medicaid Expansions. *Journal of Policy Analysis and Management*. 2020;39(4):1166-1213. doi:https://doi.org/10.1002/pam.22239
- 164. Aslim EG, Mungan MC, Navarro C, Yu H. *The Effect of Public Health Insurance on Criminal Recidivism.* Social Science Research Network; 2020. doi:10.2139/ssrn.3425457
- 165. Muthén LK, Muthén B. Mplus. *The comprehensive modelling program for applied researchers: user's guide*. 2018;5.
- 166. Jaffe A, Du J, Huang D, Hser Y-I. Drug-abusing offenders with co-morbid mental disorders: Problem severity, treatment participation, and recidivism. J Subst Abuse Treat. 2012;43(2):244-250. doi:10.1016/j.jsat.2011.12.002

- 167. Harron K, Dibben C, Boyd J, et al. Challenges in administrative data linkage for research. *Big Data Soc.* 2017;4(2). doi:10.1177/2053951717745678
- 168. Connelly R, Playford CJ, Gayle V, Dibben C. The role of administrative data in the big data revolution in social science research. *Social Science Research*. 2016;59:1-12. doi:10.1016/j.ssresearch.2016.04.015