Mental Health Courts and their Effects on Repeat Offending and Suicidality: Evidence from Randomized Therapists *

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Abstract

As many as 20 percent of inmates in jails reportedly suffer from a serious mental illness. In an effort to divert the mentally ill out of jails and prisons, many counties assign mentally ill defendants into "mental health courts". Using administrative data from a large urban county's correctional complex, we use a leniency design with randomized therapists to estimate the causal effect of mental health court on recidivism and mental health outcomes. We find that mental health court increases repeat offending by as much as 47 percent which we suggest is due to the negation of incapacitation effects associated with traditional courts. Idiosyncratic features of the county also allow us to evaluate the relative effects of being assigned to a public defender versus a private indigent defense attorney. We show that public defenders have no effect on recidivism relative to private attorneys but do improve mental health including reductions in suicidal ideation and suicide attempts.

Keywords: mental health court; diversion; recidivism; suicidality; leniency design; instrumental variables.

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1 Introduction

A significant number of individuals with mental illnesses are in jail or in prison on any given day. Such individuals are therefore overrepresented in criminal justice settings in the United States (Prins, 2014). More specifically, the prevalence estimates for individuals with mental illnesses within criminal justice settings are 64% or up to 12 times higher than the general community (Prins, 2014). Consequently, jails have become the de facto mental hospital of last resort. As a result of the growth in the correctional facility populations, criminal justice now holds the sober responsibility of protecting the health and safety of its inmate population. But due to the growth in mentally ill inmates, suicide has become the most common cause of death in correctional facilities. A previous study found a 77% prevalence rate of mental illness among inmates who attempted suicide (Goss, 2002). As inmates exit these facilities, many counties have sought to address the lack of coordination and continuity of care for mentally ill offenders by investing in specialty courts which disentangle the mentally ill from criminal justice altogether. These courts are called mental health courts and exist in over 600 US counties as of 2016.

Frank and McGuire (2010) note that a serious mental illness is associated with a 58% higher lifetime risk of arrest conditional on age, gender and race. They report the results of several evaluations of mental health courts and note that the results are mixed. The most common result appears to be a reduction in recidivism, but as the designs are usually matching on observables methodologies, it is unclear if these declines in repeat offending are causal or due to selection.

We present new evidence on the causal effect of mental health courts on repeat offending, mental health symptoms and suicidality using a popular design in criminal justice called the leniency design. The leniency design is also often referred to as a judge fixed effects design because the design ordinarily uses randomized courts for identification. To the degree that judges exhibit systematic tendencies in recommending a treatment, then instrumental variable based estimators can recover local average treatment effects. To the degree the identifying assumptions for our instrumental variables designs hold, then we will estimate the local average treatment effect of mental health court on recidivism, mental health symptoms and suicidality

Mental health courts are often too small to have randomized judges, though, as there may be as few as one judge handling the entire docket. Instead, we use a separate form of randomized leniency – the randomization of therapists that occurs at the point of booking in our large urban correctional complex. These therapists interview each inmate and then rate the severity of their mental illness symptoms on a scale of 0 (high functioning) to 3 (lowest functioning). Because therapists have a high degree of discretion when rating inmates, and have different thresholds and tendencies to rate the severity of an inmate's mental illness, we are able to use therapists' average propensity to recommend mental health court as an instrument for a particular inmate's mental health court recommendation.

We show that the effect of mental health court on inmate outcomes is a mixed blessing. First, we show that random assignment of mental health court causes recidivism to increase by 47%. These effects were larger for inmates with a prior record (63% versus 38%). Because we find no differences in recidivism for public defenders versus private indigent defense attorneys, we believe that the cause of the increase in repeat offending is due to mental health courts inability to incapacitate defendants awaiting trial and upon disposition. We tentatively suggest that mental health court increases recidivism by mechanically negating incapacitation effects associated with typical courts.

But beyond an increase in repeat offending, we find evidence of heterogeneous beneficial effects depending on whether an inmate was assigned to a private attorney or a public indigent defense attorney appointed by the court. While public defenders have no differential impact on repeat offending, they do have dramatic impacts on mental health symptoms and suicidality. Conditional on returning to jails, those who had previously been assigned a public defender showed lower probabilities of suicidality, including suicide attempts, and showed considerable improvements in their functioning. This suggests that the bulk of negative effects due to mental health courts were caused by the "wheel" of private indigent defense attorneys.

We find that if assigned a private attorney, then compared to those individuals who had just missed qualifying for mental health court (receiving a mental health score of 1), then suicide attempts conditional on returning to jail increased. This effect is concentrated among those who have prior mental health problems. Furthermore, private attorneys do not lead to improvements in mental health. So, the overall effect of being assigned a private attorney shows no evidence of improved mental health; if anything, mental health deteriorates for this group.

These findings have implications for understanding both the causal effect of mental health courts on communities as well as whether differences in how communities interpret and comply with the Sixth Amendment guaranteeing counsel regardless of ability to pay impact the mentally ill. While the Sixth Amendment requires compliance in providing indigent defense, it does not specify how those rights will be financed or sourced. We find that this matters, suggesting that through a combination of negative selection and perverse incentives, private indigent attorneys perform considerably worse at helping the mentally ill than public defenders. Mental health court is a mixture of costs and benefits that must be addressed by administrators if these courts are to continue to function as a first line effort at helping mentally ill defendants disentangle from the criminal justice system.

The manuscript is organized as follows. Section two discusses the history of mental health care, including mental health courts, in the US. The third section discusses our data and research design. The fourth section reports our findings, including heterogeneity analysis. And the final section concludes with a discussion of the implications of our findings.

2 Background

The concentration of mental illness within correctional justice facilities has not always been as high as it is today. Due to the US transition towards community-based mental health care while arrests, sentencing and imprisonment grew at the same time, growing correctional populations selectively drew in more mentally ill inmates than had been the case in the early to mid 20th century (Harcourt, 2006; Western, 2006; Raphael and Stoll, 2013). Here we discuss that history, including the emergence of mental health courts and the problem of suicides in jails and prisons.

2.1 History of Mental health care Within Jails and Prisons

Prior to the 1960s, the US depended intensively on state funded mental hospitals to treat severe mental illness. These hospitals were primarily staffed with custodians, in poor condition, and employed few psychiatrists. As such, there were complaints about human rights violations within them, which led to state defunding. This was seen as possible since alternatives to hospitalization had become more available.

As training in mental health improved at medical schools and graduate programs, different options became available, and in 1963, President Kennedy established the first community mental health centers which improved options for treating mental health disorders. Combined with the establishment of Medicare and Medicaid in the 1960s, mental health care expanded in the US which caused a decrease in mental health hospital populations. The creation of Section 8 housing only intensified this process as many of the mentally ill, when symptoms are severe, experience homelessness. The advent of several pharmacological breakthroughs for treating schizophrenia (Clozaril), bipolar disorder (Lithium), and depression (selective serotonin reuptake inhibitors (SSRIs)) only furthered the deinstitutionalization of US mental health hospitals and replaced it with more heterogeneous outpatient options.

But as the movement towards community based treatment for mental illness occurred, the US began its intensive war on crime. From the mid 1970s to 2000, the number of US citizens housed in correctional facilities grew from 100 individuals per 100,000 to over 500 per 100,000 (Patillo, Weidman and Western, 2004; Western, 2006). Raphael and Stoll (2013) show that the causal effect of this expansion in US imprisonment additionally caused a decline in the number of mentally ill individuals living openly in society. Torrey et al. (2014) estimates that today as much as twenty percent of inmates in jails suffer from a serious mental illness.

2.2 Mental Health Courts

The mental health court movement emerged out of recognition of inequities in the experiences of mentally ill offenders within criminal justice, along with the therapeutic jurisprudence and drug court movements (Watson et al., 2001). Admission into mental health courts is complicated and often a variable decision-making process that involves multiple parties, such as therapists, clinicians, judges, defense attorneys, and victims, all of whom represent different expertise and interests (Wolff, 2002b; Wolff and Pogorzelski, 2005). Over the last 30 years, problem-solving courts have shifted the criminal court's focus from criminal processing to therapeutic healing (Rottman and Bowman, 2014).

The first mental health courts began in Broward County, Florida in 1997 and the Psychiatric Assertive Identification and Referral (PAIR) Program in Marion County, Indiana in 1996. A Broward County circuit judge established a mental health task force which found that the mentally ill were cycling through jails. These individuals were often picked up for low-level offenses, sat in jail untreated for days after being unable to make bond, pled guilty or no contest, released, and then rearrested. This process would repeat over and over for the most severely mentally ill and became a burden on communities both in the form of using scarce criminal justice resources, as well as emergency departments.

Mental health courts were created as a diversion intervention to engage defendants with mental illnesses in treatment in lieu of incarceration (Wolff, 2002a). These courts are specialty courts adopted by counties to care for the growing mentally ill population caught in criminal justice institutions in their communities. They have grown in popularity in recent years, with over 600 county-level mental health courts across the country as of 2016, and only continue to grow.

Mental health courts receive a variation of cases, and since the criteria and capacity constraints of these courts differ by county, it is impossible to say just exactly how individuals are selected. Nonetheless, we know that these individuals differ from those in typical courts based on observed and unobserved selection bias. The mere reason that a defendant has a combined criminal charge and mental illness that falls within the court's eligibility criteria is not sufficient to determine admission into the court given capacity constraints within that county. But the opposite is also true; the fact that a criminal charge and/or mental illness (of a defendant) falls outside the court's eligibility criteria is not sufficient to preclude admission. To the extent that the eligibility criteria of mental health courts are more suggestive than deterministic, selection bias can be expected (Luskin, 2002). For example, particularly low-risk individuals, or those exhibiting mental illness symptoms that are misdemeanor offenders, may be offered the intervention but not necessarily be appropriate for it.[1]

The mental health court intervention can only be expected to work for a select and specific class of defendants with mental illnesses. This is especially problematic when the decision rule process (i.e. mental health scoring upon entry to jail/prison) generating the mental health court class of defendants cannot be readily replicated because it relies on hard-to-measure factors, such as a clinician's/therapist's initial evaluation of an inmate (Wolff, 2002b; Wolff and Pogorzelski, 2005). Very little research has rigorously focused on the selection processes underpinning mental health courts even though such processes may influence the performance of such interventions.

Mental health courts mostly focus on misdemeanor offenses, though there are exceptions. The judge, prosecutor, defense attorney, and other court staff often have special training in and are familiar with community mental health services. Oftentimes, court staff collaborate with community providers to implement a therapeutic intervention that may include medication management, substance abuse treatment, housing, job training, and psychosocial rehabilitation, although this is mostly true only for individuals receiving public defenders via the mental health court. Overall, mental health courts aim to defer charges or jail sentences if defendants agree to participate in services. The ultimate goal of such courts is to prevent recidivism by providing critical mental health services that defendants otherwise would not receive (Watson et al., 2001).

In general, mental health courts have several defining characteristics including: (1) a specialized docket of cases of defendants with a mental illness; (2) a collaborative and

[1] It is important to note that insofar as performance outcomes are driven by idiosyncratic case selection processes, then research designs such as differences-in-differences combining heterogeneous courts into one treatment variable violate the stable unit treatment value assumption (SUTVA) assumption which assumes homogenous dosages in addition to no spill-overs.

non-adversarial team comprised of a judge, prosecuting and defense attorneys, and a mental health representative; (3) a link to a local mental health system; and (4) compliance monitoring with sanctions for non-compliance (Wolff, 2002b). Clients of mental health courts may forgo criminal processing (i.e., they are not prosecuted) altogether, undergo criminal processing (i.e., they are prosecuted on criminal charges) but forgo sentencing, or receive an alternative favorable sentence for participating and completing the mental health court program (Goldkamp and Irons-Guynn, 2001; Steadman, Davidson and Brown, 2001; Watson et al., 2001).

The eligibility criteria for mental health courts typically require that defendants have a mental illness (serious, chronic, or persistent) and non-violent criminal charges that are most often classified as a misdemeanor (Wolff, 2002b; Wolff and Pogorzelski, 2005). Potential defendants could be referred to the mental health court by a prosecutor, defense attorney, family member, treatment provider, judge, jail personnel, police officer, and so forth (Goldkamp and Irons-Guynn, 2001; Redlich et al., 2010). They may be screened formally by the court team or a case coordinator with mental health training using a screening protocol (Wolff, 2002b).

The confluence of all these factors on selection easily predicts variation in client pools among and between mental health courts. Variation in the client pools may occur because of eligibility requirements mandated by criminal justice personnel or the court itself, poor or inconsistent program identification or recruitment practices, mixed or variable support among team members, improper matching of services to the target population, or other forms of structural rigidities or flexibilities that restrict or expand the identification, recruitment, or selection of seemingly eligible clients. In addition, courts may use different incentives and disincentives to encourage participation in the court and, as such, introduce selection bias (Redlich et al., 2010). These motivational inducements may foster or hinder the interests of potential clients and the support from defense attorneys (Wolff, 2002b).

2.3 Suicide in Jails

Self-harm and suicide attempts in prison represent a double tragedy: human life is jeopardized or lost and the correctional facility failed to protect the inmate. There are various mental health treatment and prevention methods utilized by correctional facilities to decrease self-harm and suicide attempts. Suicide is complex, and predicting or evaluating suicide risk is even more complex (Turecki and Brent, 2016). The World Health Organization explains that suicide is a serious public health problem (WHO, 1999), yet the feasibility of suicide prevention must involve many moving parts, including effective treatment of mental disorders and environmental control of risk factors (WHO, 2007).

Many factors that may influence suicide risk are varying factors between correctional settings, including: short-term detainees, pre-trial offenders, sentenced prisoners, harsh sentencing practices, overcrowding (Huey and McNulty, 2005), purposeful activity (Leese, Thomas and Snow, 2006), times spent locked up, sanitation, sociocultural conditions, levels of stress, and access to basic health and mental health services, among other aspects. Further, after Sandra Bland's tragic suicide in 2015, which led to Texas passing its Sandra Bland Act, cells have become more suicide-resistant (i.e. without protrusions of any kind that may enable individuals to harm themselves).

Suicidal behaviors are more common among those who get imprisoned, resulting in pre-trial detainees having a suicide attempt rate of almost 8 times compared to those in the general population (Jenkins et al., 2005). The causes of suicide to persons in custody is difficult to understand since those who break the law inherently have many risk factors for suicide before, during, and after release (Pratt et al., 2006). Any combination of individual and environmental factors may account for the higher rates of suicide in correctional facilities, such as the psychological impact of arrest and incarceration, symptoms of withdrawal experienced by drug addicts, expected long prison sentences, the overall stress of being associated with prison life, poor or no access to mental health professionals or treatments, lack of formal policies and procedures to identify and manage inmates at risk of suicide, individuals with mental disorders, substance or alcohol abuse, socially isolated or socially disenfranchised individuals, among many other factors (WHO, 2007).

Environmental factors and interventions are critical to consider when assessing risk of self-harm and suicide attempt within prisons (Marzano et al., 2016). One study found that the importance of talking with someone was helpful in decreasing self-harm and suicide attempts. For example, more time out of cell and sharing a cell with another prisoner both were discussed as helpful remedies (Borrill, 2002). One case-control study from Austria identified four specific individual factors (previous suicide attempts, psychiatric diagnosis, psychotropic medication prescribed during imprisonment, and highly violent index scores) and one environmental factor (single-cell accommodation) that may be used to better understand who may be at risk for suicide (Fruehwald et al., 2004).

Situational factors that contribute to suicide in correctional facilities are isolation or segregation cells and times when staffing is low, such as nights and weekends. Several factors affect housing assignments/arrangements within correctional facilities, such as capacity, staffing, availability of appropriate facilities, and more. Housing is also widely used as a measure of supervision. For example, certain housing arrangements facilitate specific supervision from officers so that inmates are checked periodically. Also, most suicides occur by hanging in prison. Housing arrangements have a strong association with inmate suicide, especially when an inmate is placed somewhere they are unable to cope and when such housing assignments result in an inmate being inside the cell for 23 hours per day for significant periods of time (WHO, 2007). Poor social and family support, history of psychiatric illness and emotional problems, and a prior history of suicidal behavior are all common among inmate suicides. Individual stressors and vulnerabilities, resulting from bullying (Blaauw and Winkel, 2001), recent inmate-to-inmate conflicts, adverse information (Way et al., 2005), or disciplinary infractions, lead to inmates feeling hopeless, with narrowing future prospects, and loss of coping options, which ultimately leads to suicide attempts. Furthermore, as length of stay increases, so does suicide rates for long-term inmates (Frottier et al., 2002), with “lifers” having especially high-risk for suicide (Borrill, 2002; Liebling and Ludlow, 2016).

2.4 Mental Health Housing in our Large Urban Correctional Complex

Behavioral health and psychiatry staff review and make housing recommendations to classifications each time an assessment is completed with a patient. Recommendations for mental health housing are made primarily to ensure the safety of the inmate as well as provide needed treatments. As housing options progress, they become more restrictive for the patient’s and others’ safety. Housing options are divided in to four categories Psychiatric Outpatient (POP), Psychiatric Inpatient (PIP), Vulnerable (VUL), and Psychiatric Intensive Care (PIC)) starting with general population and increasing in restrictiveness and monitoring.

POP describes the general population inmate unit where patients have the ability to independently manage and monitor their mental health symptoms with minimal intervention from staff including the ability to self-advocate for their needs when symptoms or situations become overwhelming. PIP describes the inmate unit where patients have difficulty managing and monitoring mental health symptoms without support from staff. There are two housing options in PIP units: Open Psych (Open) and Psych Lockdown (PsyLD). Corrections officers have the ability to manage patients between Open and PsyLD housing. To be recommended for PIP housing, the patient must be enrolled in psychiatry services (PSY). VUL describes a cell for inmates in need of special care, support, or protection because of factors such as age, disability, or risk of abuse. Admittance to this unit requires treatment team approval. Lastly, PIC describes the inmate unit where patients are engaging in behaviors or cognitive processes that are dangerous to self. There are two housing options in PIC units: Psychiatric Observation (OBS) and Full Safety Precautions (FSP).

3 Data and Estimation

Given the heterogeneity across courts, research designs such as differences-in-differences inevitably combine many different types of treatments into a single treatment variable. Given both the endogenous adoption of courts in response to changing criminality and mental illness populations within their communities, as well as the combination of heterogenous courts into single categories, both the parallel trends assumption and SUTVA assumptions may be challenging assumptions to defend. As an alternative, we acquired administrative data from a large urban county's correctional complex and used a leniency design to estimate the causal effect of mental health court, as well as differences between public and private representation, on both repeat offending and mental health outcomes, including suicide attempts and suicidal ideation.

As said earlier, the design we use is sometimes referred to as the "judge fixed effects" design and sometimes as the "leniency design". These terms are synonymous albeit with randomized therapists in our application, not judges. As there is no variation in mental health court judges within our county, we utilize the randomization of therapists upstream, prior to court and disposition, to identify the local average treatment effect of mental health court and its elements on our outcomes of interest. This design can help us better understand the role of mental health court attributes in improving the lives of both mentally ill defendants and residents within their community.

3.1 Research Design: Therapist Fixed Effects

The leniency design was first proposed by Imbens and Angrist (1994).[2] It is ingenious in the way that it solves the problem of selection bias. Assume that an individual is moving through a pipeline but before he or she can be assigned to some treatment, the inmate must first meet with a randomly assigned decision-maker drawn from a wheel of many different decision-makers. If decision-makers are randomly assigned to each inmate, possess discretion in assigning treatments, and have systematic tendencies to recommend treatments, then the random assignment of decision-makers might function as a randomizing device mimicking a randomized experiment.

Given both its potential to isolate causal effects and the increased availability of large administrative datasets, the leniency design has exploded in popularity. It has been used to study the consequences of Chapter 13 bankruptcy on future financial events (Dobbie, Goldsmith-Pinkham and Yang, 2017), racial bias among bail judges (Arnold, Dobbie and Yang, 2018), pretrial detention having higher rates of guilty pleas, conviction, recidivism and worsened labor market outcomes (Leslie and Pope, 2018; Dobbie, Goldin and Yang,

[2] In this classic instrumental variables paper decomposing IV estimates into the local average treatment effect, the authors write "Suppose applicants for a social program are screened by two officials. The two officials are likely to have different admission rates, even if the stated admission criteria are identical. Since the identity of the official is probably immaterial to the response, it seems plausible that Condition 1 [independence] is satisfied. The instrument is binary so Condition 3 is trivially satisfied. However, Condition 2 [monotonicity] requires that if official A accepts applicants with probability $P(0)$, and official B accepts people with probability $(P1) > P(0)$, official B must accept any applicant who would have been accepted by official A. This is unlikely to hold if admission is based on a number of criteria. Therefore, in this example we cannot use Theorem 1 to identify a local average treatment effect nonparametrically despite the presence of an instrument satisfying Condition 1 [independence]"

2018; Stevenson, 2018), juvenile incarceration on high school completion and adult crime (Aizer and Doyle, 2015), and more.

Most of the applications use randomized judges, but there are exceptions such as Joseph J. Doyle (2007, 2008) who use randomized case workers to estimate the causal effect of removal from the home and placement into foster care on future adult outcomes, such as crime, as well as teen pregnancy. This is the first project, though, that uses randomized therapists to assign individuals into any type of treatment. We use it for mental health courts because in our setting, therapists both score the severity of each inmate's mental illness and have considerable discretion in assigning those scores.[3] As these therapists never meet with the inmate again, either in the jail or when they exit, the exclusion restriction is trivially satisfied. And since therapists are randomly assigned, it also trivially meets the independence assumption.

Interestingly, leniency designs are often the rare situations with instrumental variables designs where exclusion and independence may hold trivially because of the structure of the design, and yet monotoncity fail for reasons that Imbens and Angrist (1994) note. Strict monotonicity in this context requires therapists who are systematically more likely to rate symptoms higher to never "criss cross" with those therapists who tend to downplay symptoms. This might happen if each type of therapist suddenly recalibrate their tendencies when confronted with certain demographics. We were told, for instance, by the director of inmate mental health in our jail that Black inmates tend to be over-identified as mentally ill. While this does not violate strict monotoncity in principle, it is reasonable to be skeptical as to whether strict monotonicity holds in the sample later in the article.

One consequence of a monotoncity violation is that the weights in the LATE become unstable and may cease to have a causal interpretation. Such a violation ultimately undermines our ability, also, to calculate marginal treatment effects. But, we can still estimate the local average treatment effect to the degree that average monotonicity holds even though the ability to calculate marginal treatment effects disappears. We discuss our evidence for both strict and average monotonicity in our data.

[3]While the scoring of inmates by severity of mental illnes creates a running variable, regression discontinuity is not possible as the running variable is too coarse with only four possible values.

What is also intriguing about our context, though, is the unusual way in which this county finances indigent defense. Most counties in this state do not have a designated public defenders office. But this county is unusual in that while it does not have a general public defenders office, it does for the mental health court. This county uses both a public defenders office as well as a "wheel" of private indigent defense attorneys who moonlight for extra money as well as due to altruism. Inmates are assigned to either a public defender or a private "wheel" attorney depending on whether the inmate's score exceeds a particular threshold. The randomization of therapists ensures that observable and unobservable characteristics of inmates are distributed equally across all treatment groups.

The way in which this assignment occurs is explained as follows. Upon booking, inmates in this correctional complex are met by an officer who makes a cursory check about whether an inmate has any signs or history of mental illness. This decision is based on such questions as whether the individual has a history of mental illness, has ever taken medication, or whether the officer believes the person is showing signs of mental illness. If any of these criteria are met, the officer recommends that the inmate meet with a randomized therapist who will evaluate their symptoms. As a large number of inmates are believed to suffer from some form of mental illness, a large number of inmates are ultimately assigned to a therapist for evaluation. At any point in time, the correctional complex employs approximately 60 therapists. The vast majority of these therapists are clinical social workers and professional counselors. Their interest in working for the correctional complex is sometimes due to the generous benefits of the county, as well as seeking the hours needed for licensure in the state.

Using a structured survey as well as their own professional judgment, therapists rate the severity of the inmate's symptoms on a scale of 0 to 3, with 3 being the most severe and lowest functioning score possible. Inmates with a 0 (no symptoms) or 1 (mild symptoms) do not meet criteria for the county mental health court and so remain on the normal track into typical courts. Inmates with a 2 (moderate symptoms) are assigned to a private attorney appointed by the court for indigent defense. These private attorneys are paid a nominal flat fee of $750 which does not vary with the number of hours devoted to the defendant's case.[4] Inmates with a 3 (severe symptoms) are perceived as unusually low functioning and are redirected to the county public defender's office.

Public and private defenders differ with regards to unobserved selection as well as with regards to the resources that each bring to a case. Private moonlighting indigent defense attorneys are paid a flat fee financed by the county, and while they receive extra mental health training for this work, they are not provided with additional support such as social workers. The Mental Health Public Defenders office, on the other hand, provides resources in addition to indigent defense. The office employs social workers, for instance, who help defendants make their appointments as well as sign up for disability, housing, and other relevant social services.

3.2 Our setting: A Large Urban Correctional Complex

County jails around the nation have become frequent temporary homes for millions of individuals suffering from mental illness or a substance use disorder thanks to gaps in health coverage, limited access to behavioral health care and many more reasons (Center for Substance Abuse Treatment, 2005). In most states, there is at least one jail or prison that houses more mentally ill individuals than the largest psychiatric hospital in the area (Torrey et al., 2014). Within every county of this nation that has both a county jail and a county psychiatric facility, more seriously mentally ill individuals are incarcerated than hospitalized (Torrey et al., 2014). Consequently, ten times more individuals with serious mental illness are in jails and state prisons than in the remaining state mental hospitals (Torrey et al., 2014). Approximately 20 percent of the inmate population at our large urban correctional complex requires treatment for mental illness.[5] On any given

[4]Theoretically, since payment is a fixed and low nominal fee, private indigent defense attorneys appointed by the court have distorted incentives associated with representation. For instance, they are not paid for each hour of effort, and since effort is costly, they may seek to minimize their costs by exerting the minimum effort above some personal reservation effort. Furthermore, given the low nominal rate, it is more likely that the labor supply would consist of lawyers whose main practices have low demand, thus creating the need to moonlight. And while altruistic highly competent defense attorneys are likely part of the labor supply of private indigent defense, reduced demand linked to the need to moonlight as well as the perverse incentives at the intensive margin implies at least some negative selection may be present in the wheel pool of private indigent defense attorneys.

[5]We have chosen note to name our county at the request of the correctional complex. But we can say that this is one of the largest counties in its state.

day, approximately seven percent of inmates with mental illness are experiencing severe symptoms such as psychosis, delusions or suicidal thoughts. The jail is a highly sensitive and unusual work environment that requires extensive training and a very unique skill set. It is incumbent upon the large urban county's Sheriff's office to make every effort possible to ensure their employees are equipped to serve this vulnerable population.

The purpose of the Misdemeanor Mental Health Diversion Docket is to provide court supervision for defendants diagnosed with mental illness who have entered an agreement with the State to have their criminal case dismissed after a period of treatment and stability. Defendants are released on personal bond with conditions that are agreed to by the State and are supervised by specialized pretrial service officers. Defendants report monthly until their case is dismissed. The eligibility criteria includes: mental health diagnosis, pending misdemeanor offense, and approval by prosecution (Misdemeanor Mental Health Diversion Docket). For our county, eligibility criteria includes that the defendant is also experiencing significant challenges due to mental health, intellectual, or developmental disabilities.

The County Mental Health Public Defender office is operated in connection with County Justice Planning. Its staff includes a director, three full time attorneys, four social workers, three caseworkers, and three support staff. Referrals are made for a variety of social services. Follow-up case management services are also provided.[6]

Our administrative data is from a large urban county's correctional complex administrative records on every inmate seen between 2016 and 2019. This urban county is home to over 1.2 million residents. These data were collected as routine mental and physical health assessments on inmates.[7] These administrative data include information on each inmate's offense type (felony, misdemeanor), demographics, mental health records, charges, suicide attempt, suicide ideation, and more. A unique inmate ID and unique booking ID is utilized for each inmate.

We begin with a sample of over 40,000 unique inmate bookings. But we do not use all of these because we were informed that the only way in which the randomization was

[6]These eligibility criteria and staffing information were collected from qualitative interviews with the head of the Mental Health Public Defender Office, as well as documentation provided by the county.

[7]Institutional review board (IRB) approval was granted from Baylor University in April 2019.

violated was in instances where a therapist would endogenously select a client who he or she had seen before. As this automatically selects on individuals who are reoffending, this can create issues for our randomization. We investigated the degree to which this may be occurring by comparing the distribution of clinician assignment against a randomized simulation. This is shown in Appendix Figure 8.1. As can be seen, there are fewer singleton visits (40,808 versus 35,974) than would occur at random, and more multiple visits than would be predicted in our simulation. Thus in order to eliminate all such instances where randomization may not occur, we use only those instances where a therapist-client match was unique. This drops our sample from 40,808 to 31,501.

Table 1 reports summary statistics for our sample for both our typical court and our mental health court groups. These courts differ considerably along observable dimensions. The mental health court, for instance, has fewer White and Hispanic inmates, and more Black inmates. There are fewer males in mental health court, and individuals tend to be about 2.5 years older. Individuals in mental health court typically have more priors. They also are more likely to have received mental health treatment prior to this visit.

3.3 Instrumental Variable Calculation

The correctional complex randomly assigns therapists to inmates from which we construct a residualized leave-one-out mean measure of each therapist's tendency to recommend mental health court. As mental health court only occurs when a score is 2 or greater, we convert the scores into a binary treatment variable with 1 being mental health court (combining public and private defense attorneys) and a 0 being typical courts. We use the residualized leave-one-out mean as an instrument for a therapist's own recommendation of an inmate to mental health court.

First, we show that there is a considerably strong relationship between a therapist's average tendency to recommend mental health court and their judgment on any particular inmate's symptom level. Given the wide discretion that therapists have in making rulings, this is not surprising to the degree that any portion of a recommendation is due to systematic professional opinions. Many therapists, in other words, have "tendencies" when interpreting an inmate's presentation of symptoms. Some tend to consistently recommend mental health court due to perceiving higher mental illness regardless, whereas others are systematically less likely to recommend it, ceteris paribus. We use the following two-stage least squares (2SLS) model for estimation.

$$mental\_health\_court_{dct} = \beta \widetilde{Z}_{cl} + \psi X_{dct} + \varpi_{dct} \tag{1}$$

$$Y_{dct} = \delta \widehat{mental\_health\_court}_{dct} + \gamma X_{dct} + \varepsilon_{dct} \tag{2}$$

where $\widetilde{Z}_{cl}$ is the constructed instrument for each therapist discussed below, X_{dct} is a matrix of inmate pre-treatment characteristics, and both ϖ_{dct} and ε_{dct} are error terms. We estimate equations (1) and (2) using 2SLS with standard errors clustered two-way by clinician and inmate.[8]

Following Arnold, Dobbie and Yang (2018) and Aizer and Doyle (2015), we construct our instrument, the residualized leave-one-out mean, using the following steps. First, we regress an observed mental health court indicator variable onto a vector of time controls (day of year time fixed effects).[9] This was done as a balancing act between having enough power within each fixed effect to estimate parameters, and wanting to restrict identification to periods in time that control for both seasonality and scheduling. Next, we calculate the residual, $\tilde{D}_{dkt}$, from this regression. Finally, we use the residualized mental health court propensity rate to calculate the therapist recommendation instrument, $\tilde{Z}_{cl}$, as a residualized leave-one-out mean rate of mental health court recommendation associated with each randomly assigned therapist l and inmate c.

To calculate the leave-one-out mean, we use the following formula which is the same as used by Aizer and Doyle (2015) and others.

[8]We also estimate the same models using, not the residualized leave-one-out-mean in a just-identified model, but using the jackknife instrumental variables estimator (JIVE) (Angrist, Imbens and Krueger, 1999). Researchers often use the residualized leave-one-out-mean as it is typically simpler than inverting a multidimensional matrix in 2SLS. But it can be shown that 2SLS with the residualized leave-one-out-mean as an instrumental variable is comparable to using JIVE with therapist fixed effects as instruments. We have, therefore, done the analysis both ways, and results do not change when using JIVE. We present the 2SLS results with the residualized leave-one-out-mean as an instrument in a just identified model, which is consistent with approaches taken by others such as Aizer and Doyle (2015) and Arnold, Dobbie and Yang (2018).

[9]We experimented with different time-based fixed effects, but our results never change much.

$$
\begin{aligned}
\widetilde{Z}_{cl} &= \left(\frac{1}{n_l - n_c}\right)\left(\sum_{k=0}^{n_l} \widetilde{D}_{dkt} - \sum_{k\in\{c\}} \widetilde{D}_{dkt}\right) \\
&= \frac{1}{n_l - 1}\sum_{k\neq c}^{n_l - 1} \widetilde{D}_{dkt} \qquad (3)
\end{aligned}
$$

We overlaid the residualized leave-one-out with the share of individuals assigned to mental health court and present it in Figure 3. As can be seen, there is a strong correlation between the average tendency of a therapist to recommend mental health court and whether they do so in the inmate's own case. Furthermore, there is a large spread in recommendation rates in the first place ranging from -0.5 (normalized) to 0.5.[10]

Table 2 shows the strength of the first stage. A one point change in the leave-one-out mean is associated with a 0.9 increase in probability of recommending mental health scores. We present conventional F statistics on the excludability of our instrumental variable from the first stage. Unlike the earlier rules of thumb by Stock and Yogo (2005) recommending an F of 10 as the lower bound needed for first stage strength, recent work by Lee et al. (2020) show that a true 5 percent test requires an F greater than 104.7. Table 2 presents the Cragg-Donald F statistic. All of our specifications have an F greater than 104.7. For instance, our main just-identified specification using the residualized leave-one-out mean has an F of 1,655. Other subsamples have F greater than 200.

Key to our identification strategy, though, is that the instrument is balanced across observable inmate characteristics. To the degree that it is, we have some ad hoc evidence that unobservables may also be. In Table 3, we present a table of inmate characteristics across the distribution of the residualized leave-one-out-mean instrumental variable with p-values on differences in means for the bottom and middle tercile of the instrument, as well as the difference between top and bottom. For the most part, the data is balanced. When it is not, for instance for number of offenses per booking, the magnitude differences are trivial (1.51 vs 1.56). It is probable that at least one difference can be significant,

[10] We also present evidence for systematic differences in Figure 2 and Figure 3, which show effect sizes on therapist fixed effects as well as the distribution of t-statistics. There is considerable variation in effect sizes, consistent with what is shown in Figure 4, as well as evidence for a strong first stage.

though, so it's noteworthy that these are effectively relatively precise zeroes.

Finally, in Table 4, we present evidence on the independence of the instrument from inmate characteristics. The observable difference between inmates in mental health court and those in typical courts is stark, which we saw also in Table 1. But once we construct the instrument, the differences shrink to small zeroes, most of which are not statistically significant.

3.4 Monotonicity

One of the key insights discovered by Imbens and Angrist (1994) and Angrist, Imbens and Rubin (1996) was that instrumental variables models, when cast using the potential outcomes notation, had additional assumptions not previously known. The one we focus on in this paper is non-trivial: the monotonicity assumption.[11] As noted in footnote 2, Imbens and Angrist (1994) note that monotonocity requires that if therapst A recommends inmates to mental health court with probability P(0), and therapist B recommends inmates to mental health court with probability P(1)>P(0), then therapist B must accept any inmate who would have been accepted by therapist B. This may be violated if therapists criss-cross in their recommendations based on observable or unobservable inmate characteristics. But, it may also be violated when there is heterogenous differences in therapist skill level (Chan, Gentzkow and Yu, 2019).

Frandsen, Lefgren and Leslie (2019) provide a test for the sort of strict monotonocity described above. We implement this test, but are able to reject strict monotonicity in every sub-sample examined. This test can only evaluate excludability and monotonicity together, but since we are confidence given the nature of the experiment that excludability holds, it is likely that the Frandsen, Lefgren and Leslie (2019) test is rejecting strict monotonicity. As said, this may be because of the sort of criss-crossing in therapist evaluations based on observable or unobservable inmate characteristics, or due to heterogenous skills in therapists themselves.

Since strict monotonicity can be rejected in our sample, we turn to evaluating whether

[11] The other is SUTVA which we argue is satisfied trivially because mental health court is a homogenous treatment and spillovers between inmates is unlikely given inmates most likely do not exist in one another's social network and therefore are unlikely to interact post treatment.

average monotoncity might hold. Average monotoncity is sufficient for estimate the local average treatment effect, but is not sufficient for estimating marginal treatment effects (Joseph J. Doyle, 2008). We present evidence for average monotonicity in Table 2 columns 3-7 along the top row. In all race and age subsamples, our instrument is significant and qualitatively in the same direction. Interestingly, the one demographic subsample in which the sign on the instrument is considerably different from other demographic subsamples is the subsample consisting only of Hispanic inmates. Here we see that the coefficient on the instrument is statistically different from that of the Black and White subsamples. While the effect is qualitatively the same and similar in magnitude, there is nonetheless evidence for such differences between young and old inmates as well.[12]

3.5 Sample selection and collider bias

Our administrative data is rich in both outcomes and controls as well providing opportunities for identification using randomized therapists. For instance measuring recidivism is straightforward since the administrative data assigns each resident in the county with a unique inmate ID. If John Doe was arrested twice, the same inmate ID will be assigned to him. And this makes measuring recidivism very easy, because insofar as all offenders are equally likely to be caught and remain in the county, then anytime someone reoffends, they will be arrested and appear in our data.

Another interesting feature of our dataset is that we have various mental health measurements, such as the therapist reviews of each inmate upon subsequent booking, as well as records as to whether the inmate attempted suicide or displayed any suicidal ideation. But because we only observe suicidality and mental health scores within the administrative data, it means we only observe mental health outcomes for those inmates who reoffend. This is a potential problem because insofar as recidivism is endogenous to mental health court, then our sample – which is based on recidivism – may suffer from what is sometimes called “collider bias” (Pearl, 2009; Morgan and Winship, 2014; Schnei-

[12]Due to amount of work required to investigate the source of these differences by demographics, we are reluctant to include it in this manuscript given the manuscript is already lengthy. The authors are currently analyzing the heterogenous first stage factors for a different study examining the behavior of randomized thereapists altogether.

der, 2020) and other times called "bad controls" (Angrist and Pischke, 2009). We will illustrate this problem in Figure 1 which shows a directed acyclic graphical (DAG) that describes a plausible data generating process creating complex relationships within our administrative data.[13]

Assume that mental health court (MHC) has some causal effect on recidivism (R). Assume, too, that mental health court can affect mental health outcomes, such as suicidality (Y). This effect of mental health court on suicidality can happen both for those who reoffend (the mediated edge, $MHC \to R \to Y$) as well as for those who do not reoffend ($MHC \to Y$). We instrument for MHC with the residualized leave-one-out mean (Z), which alone is sufficient to block the backdoor path between MHC and Y via controls ($ZMHC \leftarrow X \to Y$). This is because MHC when instrumented by Z is a "collider" and colliders by design always block backdoor paths (Schneider, 2020; Cunningham, 2021).

But notice the unobserved variables, U, which cause a person to reoffend for reasons other than mental health court. Insofar as these U unobserved variables also cause mental health outcomes in the jails, then working with an administrative dataset consisting only of reoffending individuals, R, will create collider bias between MHC and Y along a backdoor path represented by a chain of variables, $MHC \to R \leftarrow U \to Y$ (Morgan and Winship, 2014).

Such situations only occur, though, if MHC does cause recidivism. If mental health court has no effect on recidivism, then there is no collider problem because $MHC \to R$ does not exist. In such a situation, the direct edge $MHC \to Y$ will capture potentially the general effects of mental health court on mental health, including suicidality. The implications of this DAG, though, is that insofar as there are ever any recidivism results, it is not feasible to estimate the effect of mental health court on mental health outcomes using the administrative data because the administrative data suffers from a type of sample selection version of collider bias. But, if there is no effect, then such analysis could be informative as it would not suffer from this type of bias.

[13]Our problem resembles the problem identified by Knox, Lowe and Mummolo (2020) in their critique of Fryer (2019). Sometimes administrative data can suffer from collider bias insofar as certain conditions hold.

4 Results

We examine two main types of outcomes depending on the subsample: recidivism and mental health. When there is an effect of mental health court on recidivism, we do not analyze the impact of mental health court on mental health for the reasons given in the previous section. But when there is no such relationship, we do.

But within each, we look at several dimensions of these variables. For instance, for recidivism, we examine whether an inmate re-entered the correctional complex (the most common definition of reoffending used by researchers), whether they did so within a year of booking, the number of times they committed another offense, the days to returning, and whether the next offense was a felony. For mental health, we have three measures: the mental health score upon re-entry, whether a suicide attempt was recorded upon re-entry, as well as whether the inmate expressed any suicidal ideations upon re-entry.

4.1 Main effects of mental health court on recidivism

We present results for our main specification of the effects of mental health court on recidivism in Table 5. Note that our mental health court variable is an indicator as to whether the inmate had either a score of 2 or 3. This is mixes two potentially very different treatments as it combines the return to private indigent and public defense attorneys. Any heterogeneity in causal effects, though, will necessarily create complications for interpretations. We explore these heterogeneities in subsequent analysis using various subsamples of the data.

It is noteworthy that in Table 5, the 2SLS results differ so considerably from that of the OLS results. Comparisons between these two are not warranted, though, since OLS is a biased estimate of the ATE, whereas 2SLS is a consistent estimate of the LATE. Nevertheless, we find using 2SLS that mental health assignment increases recidivism by almost 50%. The effect on recidivism within a year of booking is roughly the same, and the number of future offenses is around 1.3.

This is admittedly a surprising result. After speaking with public defense, we suspect that the reason for this increase in repeat offending is due, not so much because mental health court harms defendants, but rather because mental health court does not possess the incapacitation effect associated with typical courts. In other words, we suspect this positive effect is driven more by changes in recidivism in the control group as other papers have found incapacitation effects associated with typical courts (Mueller-Smith, 2015). Mental health court releases offenders on personal bond while seeking dismissal of the original charges, and by disentangling defendants from the criminal justice system, it may be mechanically eliminating any incapacitation effects associated with typical courts. This is problematic given we find that when they reoffend, they are 13% more likely to have committed a felony. These effects are driven primarily by those individuals with prior offenses, though, and not those who had previously shown problems with mental illness (Table 6).

4.2 Public vs private indigent defense attorneys

As we said earlier, one of the unique features of this large county is that despite not having a general public defender's office, they do have a public defender's office for the mental health court. Defendants are assigned to mental health court based on whether they have a 2 or a 3 in their mental health score, but if they are assigned a 2, they will be assigned to a private indigent defense attorney appointed by the court. And if they are scored a 3, they will be assigned to the public defender's office. This allows us to explore a relatively understudied area within law and criminal justice on the relative merits of these two types of defenders (and more specifically the way in which the Sixth Amendment is satisfied by the county).

We limit our sample to only the public and private defenders, because we are interested in studying the relative effects of being assigned to either type of attorney. Table 8 shows the differences between these groups on observables. There are more people in our "wheel" group than our public defense group because severe symptoms are less common in this correctional complex. After that, though, most of the differences are the same with some exceptions. Public defenders on average have clients whose mental health scores improve upon re-entry, for instance.

Table 9 shows the strength of the first stage. We also have evidence for a strong first strong with an F between 129 and 136 in our main sample (column 1 and 2). Qualitatively, we see that the residualized leave-one-out-mean is of the same sign across all subsamples suggesting average monotonicity holds in the data.

There is also no longer any unique differences in observable characteristics once we examine the instrument's relationship with inmate characteristics. Tables 10 and 11 present evidence that our instrument is balanced. Across the distribution of the residualized leave-one-out-mean instrumental variable, the mean characteristics of inmates remains virtually the same. The only significant difference is that those with the highest recommendation rate are different from those with the lowest with regards to prior offenses (0.42 versus 0.38), but the effects are only significant at the 10% level. Observable individual covariates are also independent of the residualized leave-one-out-mean as well (Table 11).

In Table 12, we re-examine the same outcomes shown in Table 5, only this time the treatment variable is a public defender and the control is a private indigent defense attorney from the wheel. Insofar as recidivism had occurred for mental health court due to the negation of incapacitation effects, then there should be no difference in recidivism for these two types of defense attorneys. And in fact, we do not find significant differences between the two. This is stands somewhat in contrast to Shem-Tov (2021) who found that public defenders reduced the probability of a prison sentence by 22% and also the length of prison by 10%. But this may be because Shem-Tov (2021) examined a more antagonistic court than ours is here since the sole purpose of mental health court is to avoid punishment in the first place. That presumably would hold for any defense attorney in the court, public or private.

Given that there is no difference between public and private indigent defense attorneys on recidivism, then the problem of collider bias as shown in Figure 1 disappears. Public and private are both equally likely to have inmates reoffend, but that does not mean that they are equally likely to have identical mental health outcomes given the differences in resources that public defenders access for their clients. In the bottom three rows of Table 12, we present evidence that public health defenders compared to the wheel of private indigent defense attorneys cause mental health to improve. For instance, public defenders cause nearly a one point improvement (on a four point scale) in mental health symptoms.

Since public defenders only see people with a 3 (lowest functioning), this is a sizeable improvement in symptoms and functionality.

But perhaps more encouraging is the effects that public defenders have on suicidality. Assigned to a public defender, a mentally ill defendant is 12-16% less likely to attempt suicide in their next booking, and 1-2% less likely to exhibit suicidal ideation. With some exception, it appears that these improvements are driven by those people who had not previously had treatment for their mental illness (Table 13). It is also concentrated among those who were not homeless or unemploymed (Table 14).

4.3 Private attorneys compared to bare misses

Given what we found when comparing the public defenders to the private "wheel" attorneys, we sought to study the efficacy of being assigned a wheel attorney to those inmates who just barely missed the criteria for mental health court with a score of 1. As before, the first stage is strong. But, covariates are much less balanced (Table 17) than we had found in earlier subsamples. We also see a correlation between our instrumented mental health court and covariates in column 2 of Table 18. Thus, we are less confident in this analysis and caution the reader to not make too much of this analysis as idiosyncratic factors in the correctional complex which are poorly understood may in fact be clouding the ability to detect the causal effect of private defense in mental health court's impact on the relevant outcomes.

In Table 19, we find that wheel attorneys cause recidivism to increase by between 16 and 29% when we compare those who just barely made it into mental health court and those who missed. The number of future offenses is smaller than what we had previously found, though, but conditional on returning, the wheel defendants are more likely to come in having committed a felony than those in typical courts. Since we found no difference between public and private attorneys along recidivism outcomes, we believe that the most likely explanation for higher rates of recidivism is the negation of the incapacitation effect associated with typical courts (Mueller-Smith, 2015). That said, though, the increase in felony probabilities is worrisome.

Given that we find increases in recidivism for this sample, the issue of collider bias shown in Figure 1 makes it impossible to estimate the causal effect of private indigent defense attorneys on mental health outcomes, such as suicidality. Further analysis would be needed using non-administrative data (such as linked coroners reports) to better understand what effect, if any, mental health court had on suicides.

5 Discussion

The causal effect of mental health court on defendants is complex. When dismissal and personal bond are used, and longterm treatment cannot be enforced, then mental health court increases repeat offending. The most likely mechanism is the negation of incapacitation effects. Collider bias makes it impossible to evaluate the effect of mental health court on mental health outcomes, though, due to the endogeneity of the administrative data itself (Figure 1).

But we do not face this collider bias problem when evaluating the relative returns to public defense within the mental health court itself, because public defenders are no more likely to cause recidivism compared to private indigent defense attorneys. As such, collider bias is not triggered as the sample ceases to be a "bad control" (Angrist and Pischke, 2009). This allows us to evaluate the impact that public defense has on jail mental health, including suicidality. Across the board, public defenders cause considerable improvements in mental health relative to that of private "wheel" attorneys. Their mental health scores improve by almost a full point, which suggests that their functioning has improved since daily functioning is the main reason that a therapist assigns a 3 instead of a 2.

But perhaps even more hopeful is the effect that public defense has on suicidality. Both suicidal ideation and suicide attempts fall drastically as a result of being assigned to a public defender instead of the private "wheel" attorneys in our sample. This may be a result of several factors. For one, public defenders have more staff, which include numerous social workers and administrative staff. Social workers work very hard to sign defendants up for disability, as well as other social support services. They also help defendants meet the criteria needed for dismissal. And since they do not have differential recidivism rates, this suggests that the higher rates of recidivism observed as a consequence of mental health court assignment are due, not by the resources or investments made in inmates by court attorneys, but a feature of the court itself – most likely the negation of the incapacitation effect.

There are several implications of this study. For one, our findings suggest that counties who adopt mental health courts should be aware that recidivism is possible. This may be because typical courts unknowingly incapacitate offenders (Mueller-Smith, 2015). Thus, adopting mental health courts should be done with this risk in mind. Counties should simultaneously create a court that simultaneously remedies problems created by eliminating incapacitation effects.

This problem is not related to county's decision to comply with the Sixth Amendment using a wheel or public defender option, though, as there is no noticeable difference in recidivism between the two. This is good news in that it implies that while private indigent defense attorneys face blunt incentives to exert themselves at the margin for their clients due to the fixed and small fee they are paid for representation, it does not ultimately matter with regards to recidivism. This may be because, though, mental health court is de facto designed to disentangle the defendant from the criminal justice system, and so the cards are in the favor of the defense attorneys from the start.

Where we do find differences in attorney outcomes is when we examine the effect of public defenders on mental health. We find that public defenders improve mental health, including a reduction in suicidality, when compared to private indigent defense attorneys. We suspect that this may be because the public defenders have access to more resources than the wheel attorneys in this county, which is an issue that counties should have in mind when adopting a system that complies with the Sixth Amendment.

The high burden of mentally ill within the criminal justice system has caused counties to experiment with a variety of programs, including mental health courts. These courts are likely to become even more interesting to counties if jurisdictions seek to shift resources away from police departments and towards social services. We find that the mechanisms used matter a lot. Absent efforts to incapacitate defendants while awaiting trial, mental health courts can have a perverse effect of increasing repeat offending. Reliance on a wheel system, which is very common across the country, may also be sub-optimal given the higher returns to using public defenders.

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6 Tables and Figures

Table 1 Descriptive Statistics by MH Court (unique clinician/inmate) Assignation

	Typical Court	Mental Health Court
Mental Health Needs		
None	0.754	0.000
Mild	0.246	0.000
Moderate	0.000	0.822
Severe	0.000	0.178
Outcomes		
Recid after current booking	0.322	0.454
Recid within 1 year	0.411	0.516
Count of future recidivism	0.573	0.928
Days to recidivism	244.321	218.646
Next offense felony	0.091	0.127
Next booking mental health score improves	0.104	0.453
Suicide attempt in next booking	0.019	0.047
Suicide ideation in next booking	0.002	0.006
Inmate Characteristics		
White	0.763	0.726
Asian	0.014	0.009
Black	0.223	0.263
Race other	0.001	0.001
Hispanic	0.302	0.210
Male	0.718	0.643
Age at booking	33.362	35.929
Prior offense w/in 365 days	0.296	0.391
Number of offenses per booking	1.522	1.607
First time in jail	0.062	0.018
Prior treatment	0.110	0.131
Prior medications	0.103	0.122
Prior hospitalization	0.050	0.099
Homeless	0.032	0.052
Jobless	0.070	0.070
Clinician Characteristics		
Clinician Male	0.150	0.188
Clinician White	0.793	0.852
Clinician Black	0.137	0.072
Clinician Hispanic	0.065	0.069
Observations	26,279	5,222

Table 2 First Stage Regressions for MH Court (unique clinician/inmate)

	Residualized Leave-Out		Residualized Leave-Out Sub-Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z: Clinician's Leave-Out Mean Mental Health Score Rate	0.963***	0.897***	0.870***	0.921***	0.689***	0.746***	0.908***
	(0.017)	(0.024)	(0.029)	(0.047)	(0.046)	(0.054)	(0.044)
Asian		-0.044**	-0.042*	0.000	-0.037	0.013	-0.050
		(0.019)	(0.021)	(0.000)	(0.031)	(0.039)	(0.036)
Black		0.005	-0.004	0.000	0.011	-0.003	0.030*
		(0.006)	(0.008)	(0.000)	(0.055)	(0.015)	(0.017)
Race other		0.093	0.078	0.000	0.000	0.113	0.501
		(0.077)	(0.078)	(0.000)	(0.000)	(0.131)	(0.335)
Hispanic		-0.047***	-0.044***	-0.029	0.000	-0.043***	-0.029*
		(0.009)	(0.011)	(0.050)	(0.000)	(0.012)	(0.016)
Male		-0.046***	0.000	-0.079***	-0.031***	-0.031***	-0.088***
		(0.007)	(.)	(0.017)	(0.011)	(0.010)	(0.018)
Age at booking		0.002***	0.002***	0.003***	0.002***	-0.002	-0.000
		(0.000)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Prior offense w/in 365 days		0.052***	0.048***	0.057***	0.041***	0.022*	0.064***
		(0.011)	(0.011)	(0.014)	(0.015)	(0.011)	(0.017)
Number of offenses per booking		0.009***	0.007***	0.004	0.005	0.005	0.002
		(0.002)	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)
First time in jail		-0.055***	-0.051***	-0.051***	-0.042***	-0.063***	-0.105***
		(0.009)	(0.011)	(0.017)	(0.013)	(0.011)	(0.015)
Prior treatment		-0.016	-0.014	-0.011	0.014	-0.005	-0.062*
		(0.012)	(0.016)	(0.026)	(0.022)	(0.019)	(0.033)
Prior medications		-0.021*	-0.016	-0.020	-0.014	0.035*	0.019
		(0.011)	(0.017)	(0.031)	(0.025)	(0.020)	(0.032)
Prior hospitalization		0.141***	0.162***	0.161***	0.090***	0.073**	0.158***
		(0.014)	(0.022)	(0.036)	(0.033)	(0.027)	(0.024)
Homeless		0.043**	0.025	0.029	-0.002	0.032	0.056**
		(0.018)	(0.020)	(0.034)	(0.026)	(0.031)	(0.027)
Jobless		-0.029**	-0.023	-0.035	-0.031***	-0.028*	-0.067**
		(0.013)	(0.016)	(0.021)	(0.010)	(0.015)	(0.029)
Cragg-Donald F	1655.24	1440.39	981.60	313.32	341.13	263.79	225.80
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample			Male	Black	Hispanic	Under 25	Over 45
Observations	31,498	31,498	22,230	7,227	9,047	7,743	5,540

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 3 Instrument v. Inmate Characteristics for MH Court (unique clinician/inmate)

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out Mean Mental Health Score Rate	-0.082	-0.017	0.099	(0.001)	(0.000)
Inmate Characteristics					
Asian	0.013	0.013	0.013	(0.976)	(0.935)
Black	0.224	0.237	0.227	(0.326)	(0.781)
Race other	0.001	0.001	0.001	(0.468)	(0.199)
Hispanic	0.300	0.285	0.277	(0.156)	(0.163)
Male	0.721	0.715	0.682	(0.684)	(0.065)
Age at booking	33.219	33.751	34.393	(0.178)	(0.014)
Prior offense w/in 365 days	0.288	0.335	0.313	(0.325)	(0.343)
Number of offenses per booking	1.511	1.542	1.556	(0.407)	(0.045)
First time in jail	0.083	0.053	0.028	(0.296)	(0.034)
Prior treatment	0.115	0.110	0.116	(0.900)	(0.892)
Prior medications	0.111	0.101	0.107	(0.806)	(0.969)
Prior hospitalization	0.050	0.055	0.071	(0.858)	(0.440)
Homeless	0.031	0.036	0.040	(0.720)	(0.543)
Jobless	0.072	0.072	0.065	(0.973)	(0.929)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4 Test of Randomization for MH Court (unique clinician/inmate)

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	-0.040*	0.005
	(0.020)	(0.005)
Black	0.002	-0.003*
	(0.006)	(0.001)
Race other	0.077	-0.018
	(0.081)	(0.015)
Hispanic	-0.050***	-0.004*
	(0.009)	(0.002)
Male	-0.057***	-0.013**
	(0.009)	(0.005)
Age at booking	0.002***	0.000***
	(0.000)	(0.000)
Prior offense w/in 365 days	0.052***	-0.001
	(0.011)	(0.002)
Number of offenses per booking	0.010***	0.001***
	(0.002)	(0.000)
First time in jail	-0.089***	-0.039***
	(0.012)	(0.012)
Prior treatment	-0.016	-0.000
	(0.012)	(0.008)
Prior medications	-0.033**	-0.014**
	(0.014)	(0.007)
Prior hospitalization	0.159***	0.020***
	(0.014)	(0.004)
Homeless	0.047**	0.005
	(0.019)	(0.009)
Jobless	-0.044**	-0.017
	(0.017)	(0.015)
Time fixed effects	Yes	Yes
F-test	32	5
Observations	31,501	31,498

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 5 Assignation to MH Court (unique clinician/inmate) and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.132***	0.110***	0.490***	0.469***	0.379***	0.630***
	(0.012)	(0.009)	(0.146)	(0.119)	(0.121)	(0.123)
Recid within 1 year	0.104***	0.112***	0.467***	0.513***	0.537***	0.490***
	(0.011)	(0.011)	(0.100)	(0.104)	(0.146)	(0.091)
Count of future recidivism	0.355***	0.304***	1.334***	1.336***	0.844***	2.201***
	(0.039)	(0.033)	(0.411)	(0.352)	(0.278)	(0.472)
Days to recidivism	-26.506***	-20.246***	77.978	62.346	91.316	39.332
	(8.050)	(7.859)	(77.913)	(59.704)	(73.013)	(57.136)
Next offense felony	0.036***	0.032***	0.127***	0.136***	0.093***	0.213***
	(0.005)	(0.005)	(0.041)	(0.036)	(0.031)	(0.054)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 6 Assignation to MH Court (unique clinician/inmate) and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Recid after current booking	0.456***	0.356	0.458***	0.312	0.467***	0.282
	(0.119)	(0.233)	(0.119)	(0.191)	(0.120)	(0.378)
Recid within 1 year	0.488***	0.780	0.501***	0.445	0.516***	0.161
	(0.098)	(0.616)	(0.101)	(0.337)	(0.103)	(0.611)
Count of future recidivism	1.347***	0.535	1.350***	0.483	1.353***	0.209
	(0.353)	(0.418)	(0.353)	(0.382)	(0.352)	(0.623)
Days to recidivism	53.838	557.725	52.409	742.940	53.977	-227.300
	(60.167)	(1216.127)	(59.826)	(1300.780)	(59.948)	(269.216)
Next offense felony	0.132***	0.162	0.134***	0.128	0.132***	0.260
	(0.038)	(0.173)	(0.038)	(0.142)	(0.038)	(0.244)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7 Assignation to MH Court (unique clinician/inmate) and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1)	(2)	(3)	(4)
	No	Yes	No	Yes
Recid after current booking	0.465***	0.174	0.455***	0.278
	(0.119)	(0.328)	(0.119)	(0.414)
Recid within 1 year	0.508***	0.528	0.500***	1.128
	(0.102)	(0.570)	(0.101)	(1.794)
Count of future recidivism	1.329***	0.673	1.311***	0.739
	(0.349)	(0.711)	(0.353)	(1.020)
Days to recidivism	58.906	11.391	60.631	-288.134
	(59.271)	(423.362)	(60.102)	(384.792)
Next offense felony	0.140***	-0.182	0.139***	-0.357
	(0.039)	(0.186)	(0.039)	(0.338)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 8 Descriptive Statistics by Public Defender (unique clinician/inmate) Assignation

	Wheel	Public Defender
Mental Health Needs		
None	0.000	0.000
Mild	0.000	0.000
Moderate	1.000	0.000
Severe	0.000	1.000
Outcomes		
Recid after current booking	0.445	0.495
Recid within 1 year	0.511	0.536
Count of future recidivism	0.904	1.038
Days to recidivism	222.642	202.020
Next offense felony	0.129	0.117
Next booking mental health score improves	0.431	0.547
Suicide attempt in next booking	0.051	0.030
Suicide ideation in next booking	0.006	0.004
Inmate Characteristics		
White	0.731	0.704
Asian	0.009	0.011
Black	0.259	0.284
Race other	0.001	0.001
Hispanic	0.218	0.177
Male	0.630	0.702
Age at booking	35.653	37.204
Prior offense w/in 365 days	0.379	0.449
Number of offenses per booking	1.597	1.654
First time in jail	0.019	0.014
Prior treatment	0.140	0.087
Prior medications	0.129	0.089
Prior hospitalization	0.103	0.080
Homeless	0.055	0.042
Jobless	0.073	0.052
Clinician Characteristics		
Clinician Male	0.185	0.200
Clinician White	0.841	0.903
Clinician Black	0.079	0.042
Clinician Hispanic	0.074	0.045
Observations	4,294	928

Table 9 First Stage Regressions for Public Defender (unique clinician/inmate)

	Residualized Leave-Out		Residualized Leave-Out Sub-Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z: Clinician's Leave-Out Mean Mental Health Score Rate	0.635***	0.619***	0.562***	0.899***	0.556***	0.598**	0.568***
	(0.152)	(0.150)	(0.164)	(0.179)	(0.200)	(0.254)	(0.170)
Asian		0.034	-0.021	0.000	0.000	-0.011	0.206
		(0.055)	(0.065)	(0.000)	(0.000)	(0.065)	(0.148)
Black		0.009	0.004	0.000	-0.102	-0.022	-0.050*
		(0.015)	(0.017)	(0.000)	(0.064)	(0.029)	(0.026)
Race other		-0.074	-0.024	0.000	0.000	-0.204***	0.596***
		(0.143)	(0.153)	(0.000)	(0.000)	(0.061)	(0.126)
Hispanic		-0.034**	-0.033*	-0.223***	0.000	-0.047	-0.036
		(0.015)	(0.019)	(0.060)	(0.000)	(0.028)	(0.036)
Male		0.038***	0.000	0.012	0.042**	0.022	0.013
		(0.011)	(0.000)	(0.028)	(0.018)	(0.022)	(0.037)
Age at booking		0.001**	0.001*	0.001	0.001	0.008	0.007**
		(0.001)	(0.001)	(0.001)	(0.001)	(0.007)	(0.003)
Prior offense w/in 365 days		0.035***	0.025	0.044**	0.021	0.043	0.084**
		(0.013)	(0.017)	(0.021)	(0.027)	(0.027)	(0.037)
Number of offenses per booking		0.005	0.004	-0.009	-0.014	-0.001	0.006
		(0.005)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)
First time in jail		0.054*	0.043	0.090	-0.085*	0.016	0.081
		(0.031)	(0.055)	(0.073)	(0.044)	(0.066)	(0.111)
Prior treatment		-0.145***	-0.141***	-0.023	-0.081**	-0.150**	-0.177**
		(0.036)	(0.046)	(0.080)	(0.034)	(0.067)	(0.084)
Prior medications		0.059	0.065*	-0.023	-0.058	0.122**	0.029
		(0.037)	(0.038)	(0.087)	(0.052)	(0.052)	(0.088)
Prior hospitalization		0.049*	0.041	0.030	0.071	-0.039	0.132**
		(0.025)	(0.038)	(0.063)	(0.044)	(0.091)	(0.057)
Homeless		-0.003	0.021	-0.005	0.065	-0.140***	-0.005
		(0.029)	(0.033)	(0.029)	(0.071)	(0.047)	(0.045)
Jobless		-0.003	-0.011	-0.064	0.025	0.120**	-0.034
		(0.016)	(0.021)	(0.043)	(0.068)	(0.056)	(0.054)
Cragg-Donald F	135.84	128.68	68.91	55.63	30.97	29.31	22.49
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample			Male	Black	Hispanic	Under 25	Over 45
Observations	5,215	5,215	3,355	1,371	1,097	1,031	1,219

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 10 Instrument v. Inmate Characteristics for Public Defender (unique clinician/inmate)

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out Mean Mental Health Score Rate	-0.088	-0.020	0.107	(0.000)	(0.000)
Inmate Characteristics					
Asian	0.010	0.009	0.009	(0.717)	(0.679)
Black	0.279	0.256	0.253	(0.069)	(0.003)
Race other	0.001	0.001	0.002	(0.365)	(0.768)
Hispanic	0.202	0.227	0.202	(0.248)	(0.795)
Male	0.643	0.639	0.649	(0.976)	(0.892)
Age at booking	36.445	35.793	35.523	(0.372)	(0.133)
Prior offense w/in 365 days	0.380	0.372	0.421	(0.706)	(0.082)
Number of offenses per booking	1.606	1.581	1.637	(0.820)	(0.467)
First time in jail	0.025	0.018	0.011	(0.434)	(0.174)
Prior treatment	0.176	0.118	0.098	(0.420)	(0.363)
Prior medications	0.163	0.112	0.092	(0.451)	(0.380)
Prior hospitalization	0.136	0.089	0.073	(0.413)	(0.339)
Homeless	0.062	0.050	0.045	(0.658)	(0.688)
Jobless	0.090	0.074	0.045	(0.745)	(0.293)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 11 Test of Randomization for Public Defender (unique clinician/inmate)

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	0.030	-0.006
	(0.054)	(0.008)
Black	0.004	-0.007**
	(0.014)	(0.003)
Race other	-0.067	0.011
	(0.144)	(0.017)
Hispanic	-0.035**	-0.002
	(0.015)	(0.004)
Male	0.040***	0.004
	(0.011)	(0.003)
Age at booking	0.001**	-0.000
	(0.001)	(0.000)
Prior offense w/in 365 days	0.036***	0.003
	(0.013)	(0.003)
Number of offenses per booking	0.005	0.000
	(0.005)	(0.001)
First time in jail	0.041	-0.018
	(0.031)	(0.012)
Prior treatment	-0.141***	-0.014
	(0.041)	(0.018)
Prior medications	0.046	-0.004
	(0.037)	(0.012)
Prior hospitalization	0.048**	0.001
	(0.024)	(0.008)
Homeless	-0.007	-0.005
	(0.029)	(0.010)
Jobless	-0.014	-0.018
	(0.018)	(0.013)
Time fixed effects	Yes	Yes
F-test	6	2
Observations	5,222	5,215

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 12 Assignation to Public Defender (unique clinician/inmate) and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.053***	0.024	0.123	-0.016	0.056	-0.257
	(0.020)	(0.019)	(0.182)	(0.145)	(0.114)	(0.276)
Recid within 1 year	0.029	0.023	0.006	-0.064	-0.010	-0.198
	(0.022)	(0.023)	(0.156)	(0.143)	(0.118)	(0.273)
Count of future recidivism	0.135*	0.043	0.700	0.278	0.243	0.132
	(0.082)	(0.083)	(0.589)	(0.469)	(0.255)	(1.086)
Days to recidivism	-20.884*	-18.330	29.171	-17.727	-3.769	12.697
	(12.060)	(11.705)	(90.727)	(77.893)	(135.021)	(126.284)
Next offense felony	-0.011	-0.020*	0.034	-0.020	0.039	-0.098
	(0.010)	(0.010)	(0.083)	(0.075)	(0.058)	(0.146)
Next booking mental health score improves	0.115***	0.136***	0.964***	0.981***	1.060***	1.021**
	(0.036)	(0.037)	(0.274)	(0.249)	(0.304)	(0.415)
Suicide attempt in next booking	-0.020***	-0.016***	-0.158**	-0.122**	-0.095**	-0.198
	(0.006)	(0.006)	(0.064)	(0.060)	(0.041)	(0.140)
Suicide ideation in next booking	-0.002	-0.002	-0.019**	-0.014*	0.005	-0.065***
	(0.003)	(0.003)	(0.008)	(0.008)	(0.009)	(0.022)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 13 Assignation to Public Defender (unique clinician/inmate) and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Recid after current booking	0.047	0.807	0.063	0.989	0.069	0.737
	(0.123)	(0.693)	(0.126)	(0.802)	(0.128)	(0.594)
Recid within 1 year	-0.029	0.744	-0.017	1.012	0.010	0.759
	(0.110)	(0.898)	(0.108)	(1.075)	(0.109)	(0.909)
Count of future recidivism	0.395	0.789	0.414	0.969	0.458	1.027
	(0.444)	(1.076)	(0.442)	(1.111)	(0.446)	(0.890)
Days to recidivism	-32.014	-2339.871	-20.452	34.928	-38.706	-144.906
	(72.814)	(27452.092)	(79.433)	(587.633)	(70.849)	(301.394)
Next offense felony	-0.031	-0.133	-0.020	-0.076	-0.022	-0.101
	(0.069)	(0.294)	(0.070)	(0.261)	(0.067)	(0.246)
Next booking mental health score improves	0.907***	-5.577	0.909***	-4.620	0.878***	-10.576
	(0.230)	(20.219)	(0.228)	(19.928)	(0.232)	(38.930)
Suicide attempt in next booking	-0.084*	0.486	-0.074	0.592	-0.089*	0.271
	(0.048)	(0.501)	(0.048)	(0.574)	(0.048)	(0.330)
Suicide ideation in next booking	-0.013**	0.054	-0.012**	0.060	-0.012**	0.041
	(0.006)	(0.086)	(0.006)	(0.094)	(0.005)	(0.068)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 14 Assignation to Public Defender (unique clinician/inmate) and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1) No	(2) Yes	(3) No	(4) Yes
Recid after current booking	0.009	0.168	-0.019	-0.246
	(0.124)	(0.473)	(0.119)	(0.509)
Recid within 1 year	-0.065	0.104	-0.075	0.528
	(0.113)	(0.778)	(0.120)	(1.161)
Count of future recidivism	0.350	0.305	0.272	-1.285
	(0.437)	(0.811)	(0.425)	(1.496)
Days to recidivism	-33.538	-671.394	-28.151	-72.249
	(68.436)	(1249.923)	(77.305)	(449.843)
Next offense felony	-0.012	0.021	0.006	0.425
	(0.068)	(0.166)	(0.070)	(0.419)
Next booking mental health score improves	0.952***	-1.509	0.928***	0.463
	(0.227)	(1.492)	(0.226)	(1.112)
Suicide attempt in next booking	-0.117**	-0.062	-0.105**	0.042
	(0.052)	(0.132)	(0.053)	(0.261)
Suicide ideation in next booking	-0.012*	0.065	-0.017**	-0.089
	(0.006)	(0.068)	(0.007)	(0.074)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 15 Descriptive Statistics by MH Score 1s vs. 2s (unique clinician/inmate) Assignation

	0	1
Mental Health Needs		
None	0.000	0.000
Mild	1.000	0.000
Moderate	0.000	1.000
Severe	0.000	0.000
Outcomes		
Recid after current booking	0.368	0.445
Recid within 1 year	0.445	0.511
Count of future recidivism	0.671	0.904
Days to recidivism	241.022	222.642
Next offense felony	0.107	0.129
Next booking mental health score improves	0.327	0.431
Suicide attempt in next booking	0.040	0.051
Suicide ideation in next booking	0.003	0.006
Inmate Characteristics		
White	0.772	0.731
Asian	0.010	0.009
Black	0.217	0.259
Race other	0.001	0.001
Hispanic	0.244	0.218
Male	0.626	0.630
Age at booking	34.474	35.653
Prior offense w/in 365 days	0.326	0.379
Number of offenses per booking	1.538	1.597
First time in jail	0.045	0.019
Prior treatment	0.197	0.140
Prior medications	0.192	0.129
Prior hospitalization	0.098	0.103
Homeless	0.038	0.055
Jobless	0.085	0.073
Clinician Characteristics		
Clinician Male	0.193	0.185
Clinician White	0.849	0.841
Clinician Black	0.061	0.079
Clinician Hispanic	0.082	0.074
Observations	6,454	4,294

Table 16 First Stage Regressions for MH Score 1s vs. 2s (unique clinician/inmate)

	Residualized Leave-Out		Residualized Leave-Out Sub-Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z: Clinician's Leave-Out Mean Mental Health Score Rate	0.945***	0.890***	0.911***	0.875***	0.809***	0.929***	0.847***
	(0.032)	(0.034)	(0.046)	(0.077)	(0.093)	(0.068)	(0.070)
Asian		-0.011	-0.005	0.000	-0.233***	0.052	0.136
		(0.051)	(0.056)	(0.000)	(0.076)	(0.106)	(0.160)
Black		0.036***	0.031*	0.000	0.093	0.070**	0.087***
		(0.012)	(0.017)	(0.000)	(0.119)	(0.027)	(0.027)
Race other		0.218*	0.171	0.000	0.000	0.325	0.000
		(0.115)	(0.109)	(0.000)	(0.000)	(0.256)	(0.000)
Hispanic		-0.017	0.001	0.075	0.000	-0.007	-0.000
		(0.017)	(0.017)	(0.118)	(0.000)	(0.027)	(0.035)
Male		-0.003	0.000	-0.036	0.039*	0.019	-0.028
		(0.011)	(0.000)	(0.028)	(0.020)	(0.023)	(0.026)
Age at booking		0.001***	0.001**	0.002**	0.002	-0.002	-0.002
		(0.000)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
Prior offense w/in 365 days		0.039***	0.034***	0.042*	0.047*	0.016	0.006
		(0.011)	(0.011)	(0.022)	(0.025)	(0.025)	(0.027)
Number of offenses per booking		0.006	0.001	0.008	-0.006	0.004	-0.007
		(0.005)	(0.006)	(0.011)	(0.007)	(0.008)	(0.010)
First time in jail		-0.053*	-0.076**	0.024	-0.038	-0.079**	-0.115**
		(0.027)	(0.031)	(0.061)	(0.036)	(0.033)	(0.054)
Prior treatment		-0.020	-0.023	-0.032	0.007	0.007	-0.091
		(0.030)	(0.032)	(0.049)	(0.056)	(0.052)	(0.082)
Prior medications		-0.135***	-0.143***	-0.122*	-0.137**	-0.074	-0.065
		(0.025)	(0.038)	(0.068)	(0.059)	(0.044)	(0.065)
Prior hospitalization		0.145***	0.166***	0.150**	0.109**	0.104**	0.135***
		(0.015)	(0.024)	(0.057)	(0.050)	(0.046)	(0.034)
Homeless		0.118***	0.082**	0.080	0.013	0.078	0.179***
		(0.022)	(0.034)	(0.068)	(0.043)	(0.060)	(0.032)
Jobless		0.013	0.046	0.029	-0.017	-0.043	0.027
		(0.023)	(0.036)	(0.048)	(0.023)	(0.035)	(0.049)
Cragg-Donald F	629.11	542.58	352.08	114.21	122.46	123.00	97.07
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample			Male	Black	Hispanic	Under 25	Over 45
Observations	10,747	10,747	6,746	2,513	2,511	2,354	2,223

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 17 Instrument v. Inmate Characteristics for MH Score 1s vs. 2s (unique clinician/inmate)

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out					
Mean Mental Health Score Rate	-0.142	-0.005	0.147	(0.000)	(0.000)
Inmate Characteristics					
Asian	0.010	0.009	0.010	(0.403)	(0.799)
Black	0.225	0.244	0.233	(0.063)	(0.657)
Race other	0.001	0.001	0.001	(0.613)	(0.357)
Hispanic	0.245	0.225	0.231	(0.059)	(0.478)
Male	0.630	0.636	0.617	(0.642)	(0.495)
Age at booking	34.323	35.375	35.138	(0.024)	(0.049)
Prior offense w/in 365 days	0.317	0.371	0.354	(0.028)	(0.029)
Number of offenses per booking	1.508	1.587	1.591	(0.005)	(0.003)
First time in jail	0.067	0.017	0.021	(0.004)	(0.010)
Prior treatment	0.257	0.148	0.117	(0.233)	(0.058)
Prior medications	0.247	0.143	0.111	(0.246)	(0.057)
Prior hospitalization	0.126	0.102	0.073	(0.677)	(0.193)
Homeless	0.057	0.043	0.034	(0.613)	(0.232)
Jobless	0.127	0.065	0.049	(0.140)	(0.053)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 18 Test of Randomization for MH Score 1s vs. 2s (unique clinician/inmate)

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	-0.005	0.006
	(0.051)	(0.004)
Black	0.034***	-0.003
	(0.011)	(0.003)
Race other	0.195	-0.026
	(0.119)	(0.023)
Hispanic	-0.020	-0.004
	(0.017)	(0.004)
Male	-0.010	-0.008*
	(0.012)	(0.004)
Age at booking	0.002***	0.000
	(0.000)	(0.000)
Prior offense w/in 365 days	0.041***	0.001
	(0.011)	(0.004)
Number of offenses per booking	0.008*	0.003**
	(0.005)	(0.001)
First time in jail	-0.093***	-0.045***
	(0.031)	(0.015)
Prior treatment	-0.044	-0.027*
	(0.034)	(0.016)
Prior medications	-0.164***	-0.032*
	(0.034)	(0.017)
Prior hospitalization	0.171***	0.028***
	(0.018)	(0.010)
Homeless	0.126***	0.009
	(0.021)	(0.011)
Jobless	-0.018	-0.034
	(0.032)	(0.022)
Time fixed effects	Yes	Yes
F-test	40	5
Observations	10,748	10,747

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 19 Assignation to MH Score 1s vs. 2s (unique clinician/inmate) and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.079***	0.050***	0.288***	0.159**	0.160**	0.153
	(0.014)	(0.010)	(0.107)	(0.073)	(0.079)	(0.114)
Recid within 1 year	0.064***	0.057***	0.205**	0.144*	0.216*	0.066
	(0.014)	(0.012)	(0.085)	(0.076)	(0.112)	(0.094)
Count of future recidivism	0.237***	0.166***	0.797***	0.501**	0.382**	0.711
	(0.043)	(0.035)	(0.293)	(0.207)	(0.178)	(0.454)
Days to recidivism	-18.073*	-16.147*	83.344	31.124	27.293	63.098
	(10.497)	(9.210)	(81.658)	(54.092)	(63.767)	(62.308)
Next offense felony	0.023***	0.016***	0.091**	0.066*	0.042	0.120
	(0.007)	(0.006)	(0.043)	(0.039)	(0.036)	(0.080)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 20 Assignation to MH Score 1s vs. 2s (unique clinician/inmate) and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Recid after current booking	0.116	0.320***	0.129	0.308**	0.135*	0.496***
	(0.084)	(0.124)	(0.086)	(0.126)	(0.081)	(0.185)
Recid within 1 year	0.065	0.589**	0.086	0.457**	0.100	0.697**
	(0.073)	(0.231)	(0.073)	(0.227)	(0.073)	(0.292)
Count of future recidivism	0.447*	0.549*	0.477*	0.488*	0.477**	0.736*
	(0.250)	(0.281)	(0.250)	(0.278)	(0.237)	(0.401)
Days to recidivism	27.699	97.864	26.128	211.447	29.432	-402.663
	(58.158)	(94.664)	(58.195)	(220.000)	(55.932)	(1261.787)
Next offense felony	0.071	0.035	0.074	0.043	0.062	0.198***
	(0.053)	(0.051)	(0.052)	(0.053)	(0.048)	(0.070)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 21 Assignation to MH Score 1s vs. 2s (unique clinician/inmate) and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1) No	(2) Yes	(3) No	(4) Yes
Recid after current booking	0.148*	0.397	0.146*	0.286**
	(0.078)	(0.315)	(0.082)	(0.136)
Recid within 1 year	0.109	1.014	0.096	0.828***
	(0.073)	(0.781)	(0.068)	(0.295)
Count of future recidivism	0.481**	0.805	0.492**	0.391
	(0.225)	(0.608)	(0.234)	(0.321)
Days to recidivism	31.839	-43.112	41.155	-159.920
	(53.898)	(364.281)	(59.691)	(140.657)
Next offense felony	0.071	-0.012	0.067	0.052
	(0.046)	(0.128)	(0.047)	(0.106)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

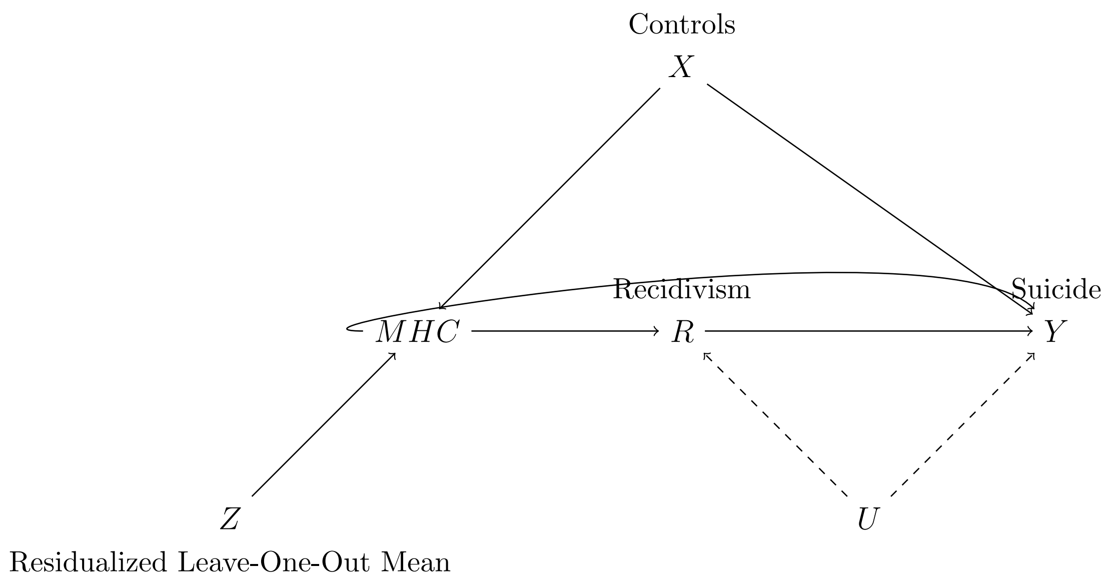

Figure 1 DAG showing sample based collider bias connecting mental health court to suicide

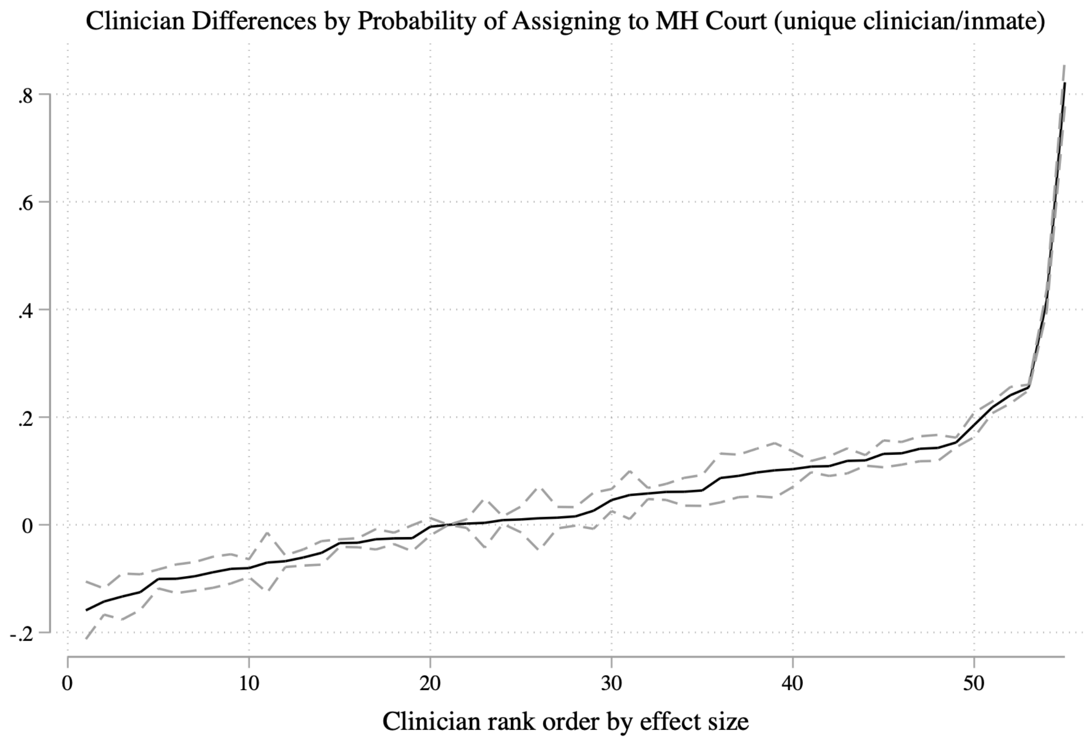

Figure 2 Clinician fixed effects with unique clinician sample for individuals assigned to mental health court

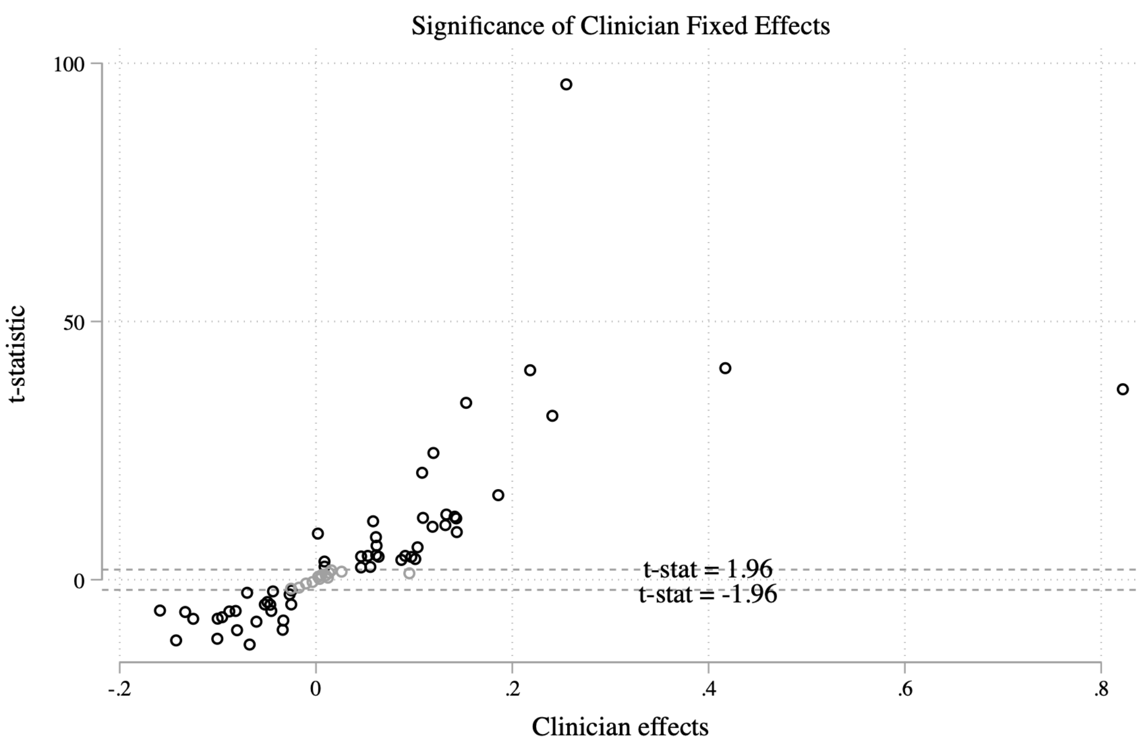

Figure 3 Distribution of t-statistics on individual therapist fixed effects for unique clinician sample for individuals assigned to mental health court

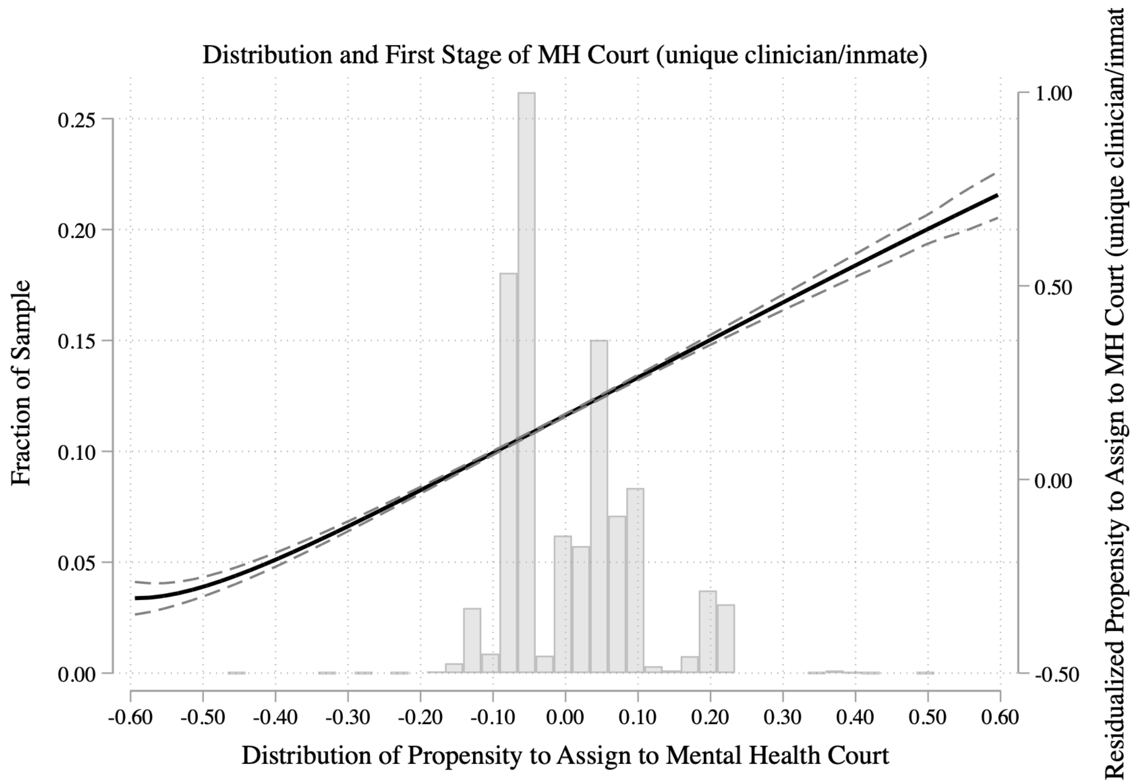

Figure 4 Smoothed fan regression of residualized leave one out against the share of individuals assigned to mental health court

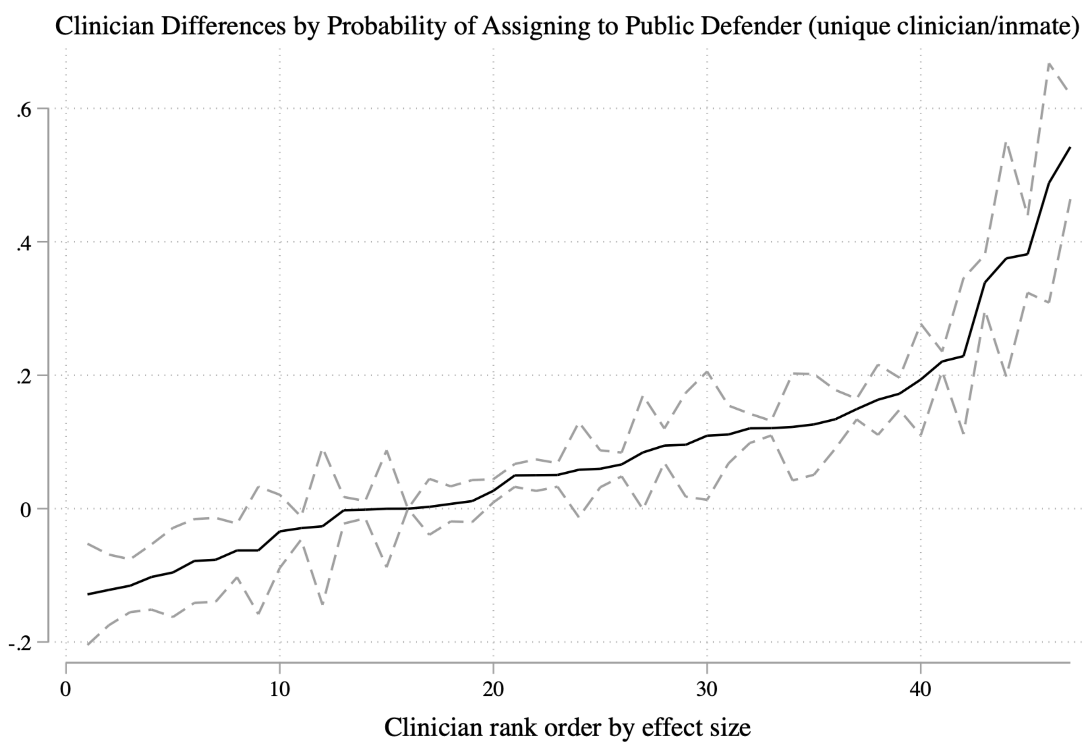

Figure 5 Clinician fixed effects with unique clinician sample for individuals assigned to public defender

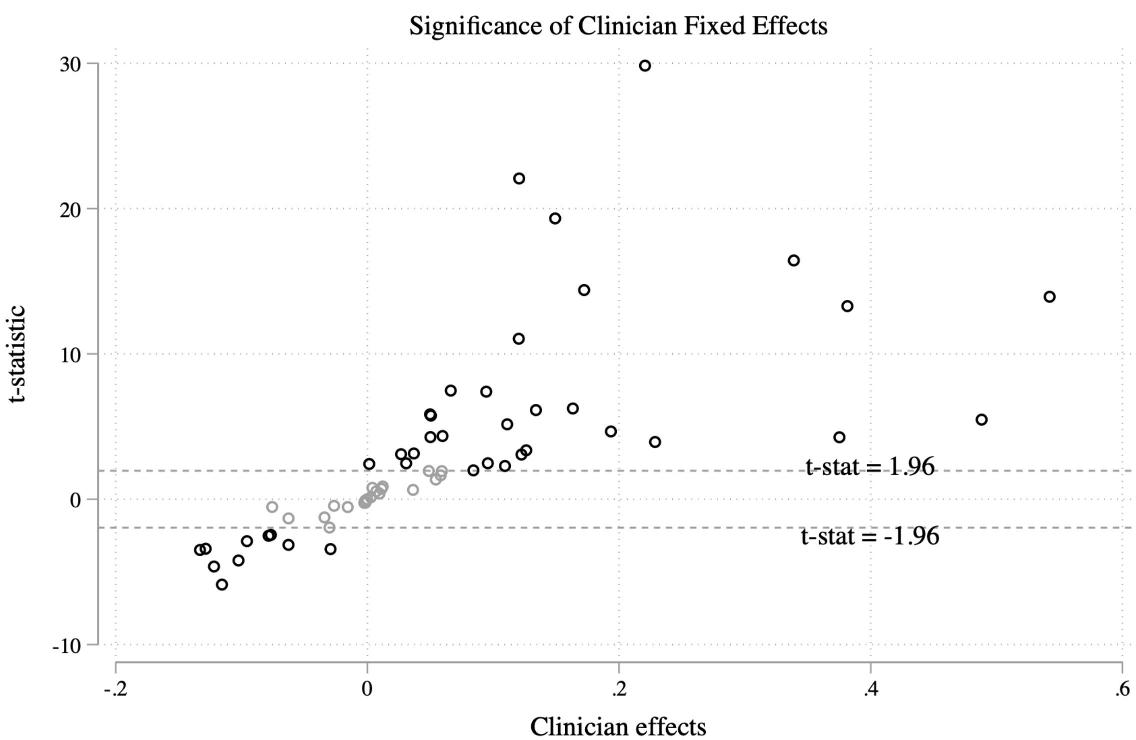

Figure 6 Distribution of t-statistics on individual therapist fixed effects for unique clinician sample for individuals assigned to public defender

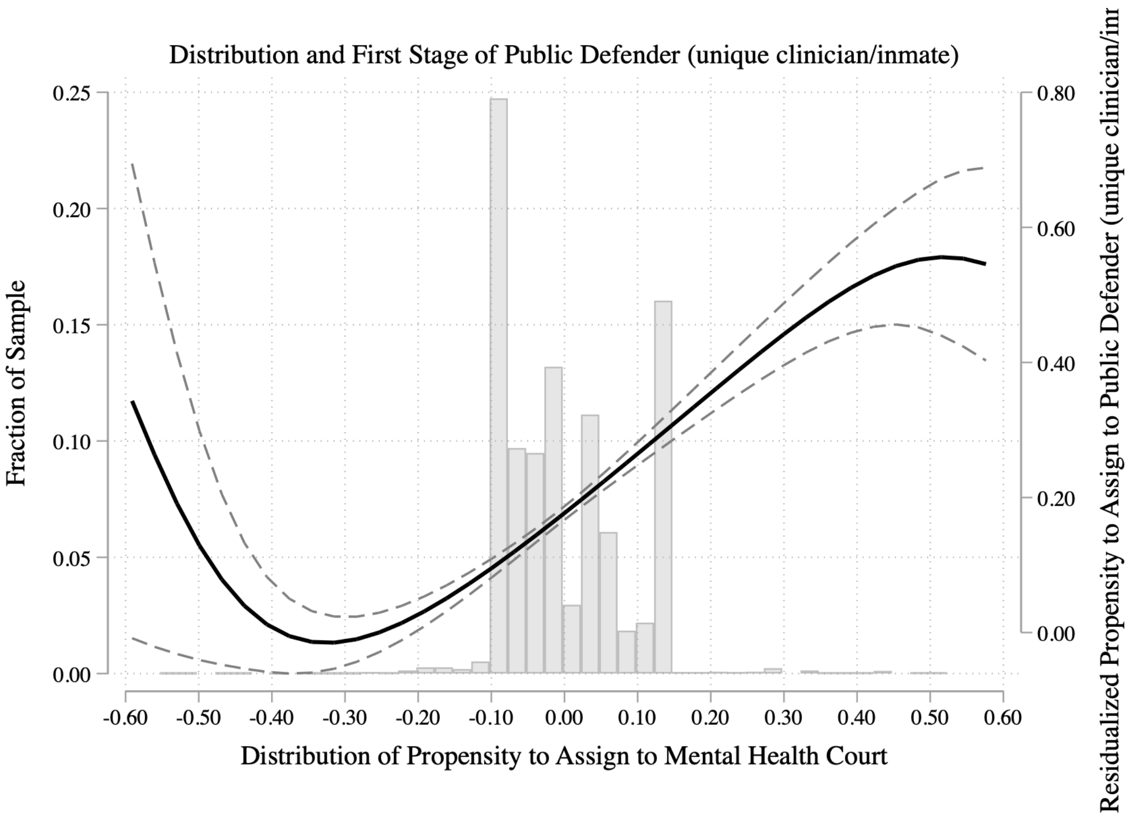

Figure 7 Smoothed fan regression of residualized leave one out against the share of individuals assigned to public defender

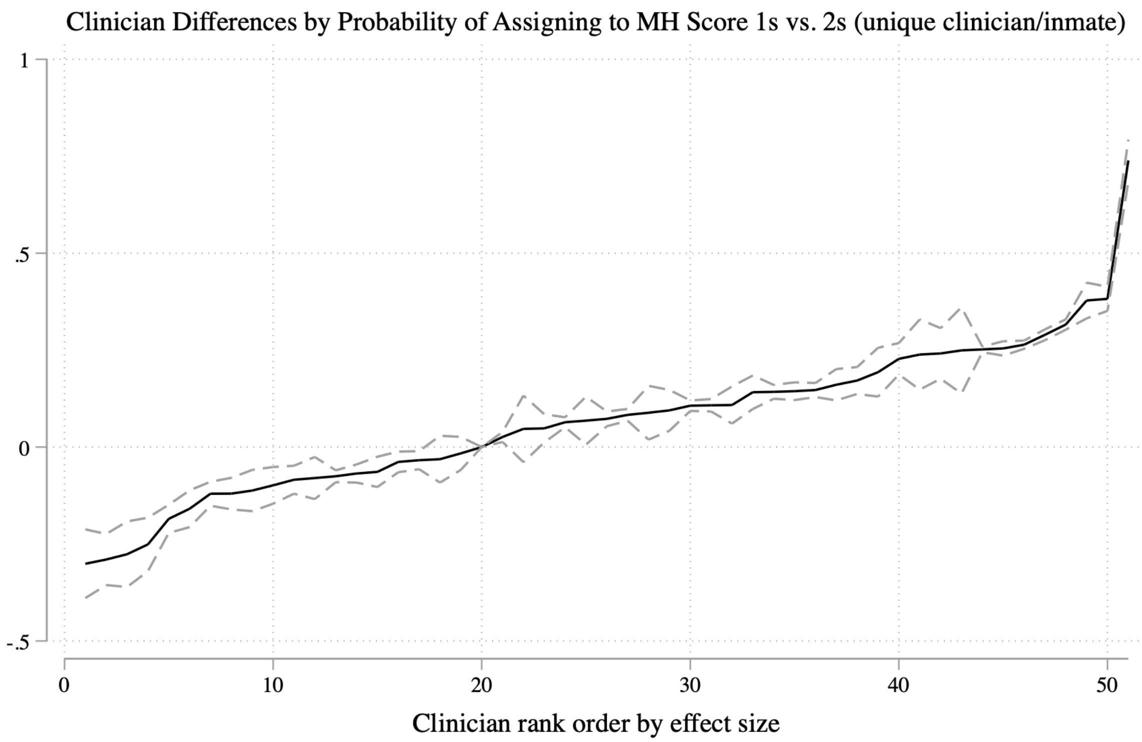

Figure 8 Clinician fixed effects with unique clinician sample for 1s vs 2s

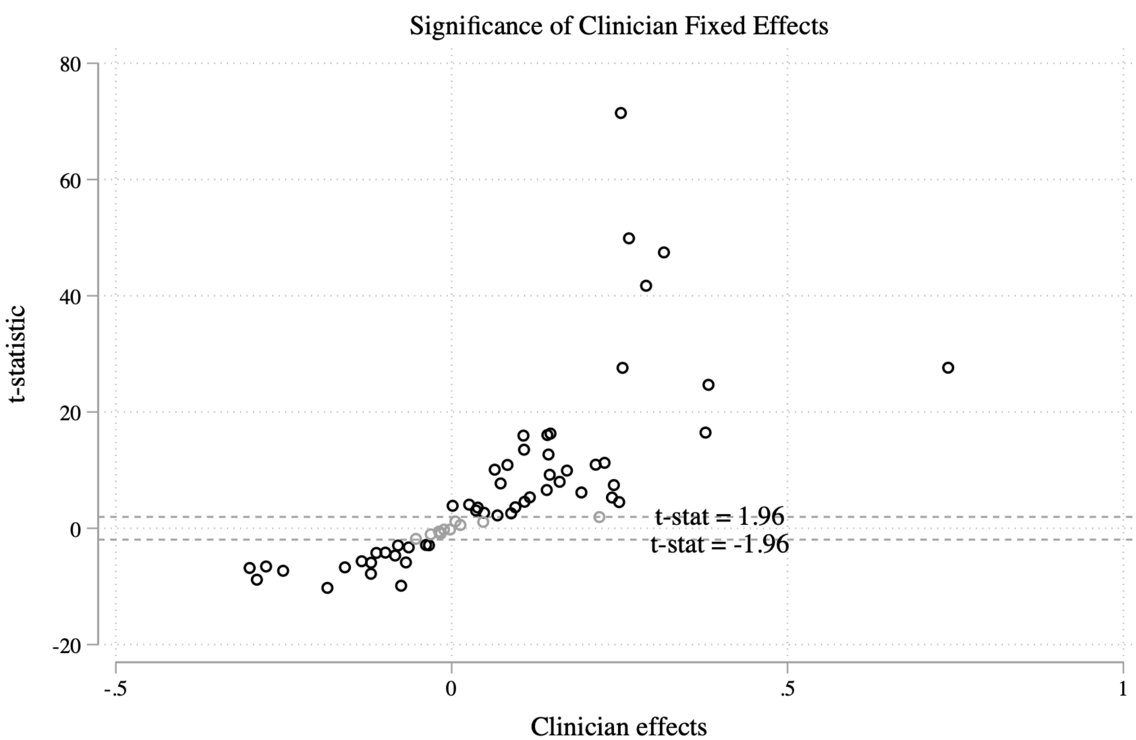

Figure 9 Distribution of t-statistics on individual therapist fixed effects for unique clinician sample for 1s vs 2s

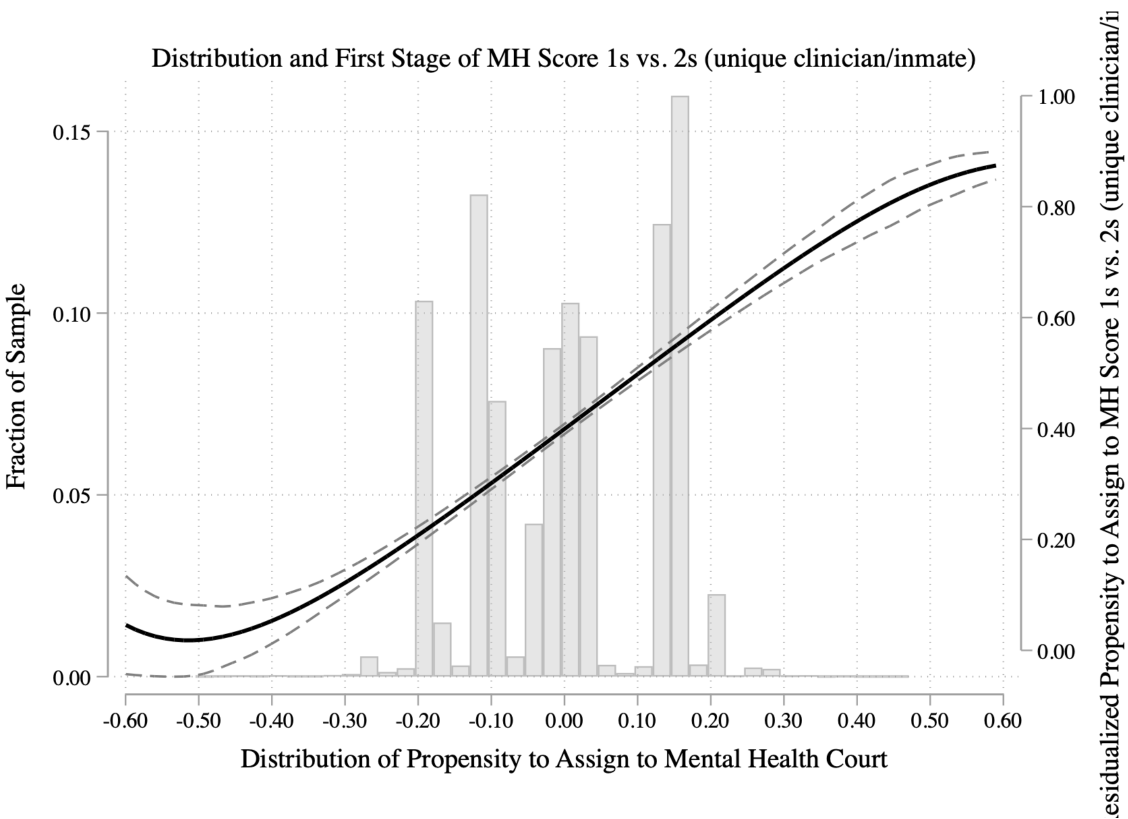

Figure 10 Smoothed fan regression of residualized leave one out against the share of individuals with 1s vs 2s

7 Appendix

Table 22 Descriptive Statistics by Mental Health Court Assignation

	Typical Court	Mental Health Court
Mental Health Needs		
None	0.732	0.000
Mild	0.268	0.000
Moderate	0.000	0.754
Severe	0.000	0.246
Outcomes		
Recid after current booking	0.421	0.671
Recid within 1 year	0.519	0.720
Count of future recidivism	1.229	3.888
Days to recidivism	193.055	125.354
Next offense felony	0.119	0.139
Next booking mental health score improves	0.095	0.323
Suicide attempt in next booking	0.028	0.063
Suicide ideation in next booking	0.003	0.008
Inmate Characteristics		
White	0.744	0.694
Asian	0.012	0.011
Black	0.243	0.294
Race other	0.001	0.001
Hispanic	0.298	0.189
Male	0.737	0.691
Age at booking	33.761	37.121
Prior offense w/in 365 days	0.396	0.632
Number of offenses per booking	1.557	1.630
First time in jail	0.051	0.010
Prior treatment	0.118	0.143
Prior medications	0.111	0.136
Prior hospitalization	0.058	0.117
Homeless	0.044	0.075
Jobless	0.079	0.083
Clinician Characteristics		
Clinician Male	0.155	0.188
Clinician White	0.791	0.855
Clinician Black	0.136	0.063
Clinician Hispanic	0.068	0.074
Observations	32,449	9,912

Table 23 First Stage Regressions for Mental Health Court

	Residualized Leave-Out		Residualized Leave-Out Sub-Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z: Clinician's Leave-Out Mean Mental Health Score Rate	0.896***	0.792***	0.779***	0.891***	0.683***	0.733***	0.795***
	(0.038)	(0.040)	(0.043)	(0.048)	(0.032)	(0.044)	(0.059)
Asian		-0.007	0.013	0.000	-0.076*	0.015	0.168
		(0.037)	(0.048)	(.)	(0.043)	(0.032)	(0.116)
Black		0.000	-0.003	0.000	0.023	0.020	0.015
		(0.009)	(0.011)	(.)	(0.060)	(0.017)	(0.021)
Race other		0.033	0.042	0.000	-0.146**	0.107	0.093
		(0.073)	(0.071)	(.)	(0.060)	(0.113)	(0.285)
Hispanic		-0.072***	-0.072***	-0.052	0.000	-0.039***	-0.061***
		(0.010)	(0.013)	(0.054)	(.)	(0.013)	(0.019)
Male		-0.052***	0.000	-0.065***	-0.039***	-0.037***	-0.091***
		(0.009)	(0.000)	(0.017)	(0.014)	(0.012)	(0.020)
Age at booking		0.003***	0.002***	0.003***	0.002***	0.003	-0.000
		(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)
Prior offense w/in 365 days		0.150***	0.146***	0.150***	0.099***	0.072***	0.173***
		(0.018)	(0.018)	(0.021)	(0.018)	(0.017)	(0.026)
Number of offenses per booking		0.005**	0.004	-0.003	0.006*	0.002	-0.000
		(0.002)	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)
First time in jail		-0.055***	-0.051***	-0.052***	-0.036**	-0.062***	-0.093***
		(0.012)	(0.014)	(0.019)	(0.015)	(0.014)	(0.020)
Prior treatment		-0.047**	-0.033	-0.062*	-0.021	-0.022	-0.086**
		(0.020)	(0.022)	(0.033)	(0.021)	(0.022)	(0.032)
Prior medications		-0.025*	-0.028	-0.011	-0.000	0.030	0.004
		(0.014)	(0.019)	(0.028)	(0.023)	(0.021)	(0.031)
Prior hospitalization		0.185***	0.210***	0.227***	0.157***	0.098***	0.205***
		(0.014)	(0.021)	(0.020)	(0.030)	(0.029)	(0.026)
Homeless		0.040***	0.017	0.031	0.029	0.021	0.026
		(0.013)	(0.014)	(0.033)	(0.019)	(0.028)	(0.024)
Jobless		-0.048***	-0.039***	-0.056***	-0.041***	-0.044***	-0.084***
		(0.012)	(0.014)	(0.014)	(0.013)	(0.015)	(0.028)
Cragg-Donald F	2245.04	1833.87	1311.17	519.41	527.74	386.09	323.03
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample			Male	Black	Hispanic	Under 25	Over 45
Observations	42,357	42,357	30,747	10,813	11,542	9,531	8,232

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 24 Instrument v. Inmate Characteristics for Mental Health Court

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out Mean Mental Health Score Rate	-0.111	-0.009	0.118	(0.000)	(0.000)
Inmate Characteristics					
Asian	0.011	0.013	0.011	(0.449)	(0.823)
Black	0.254	0.262	0.249	(0.417)	(0.604)
Race other	0.001	0.001	0.000	(0.293)	(0.145)
Hispanic	0.282	0.269	0.266	(0.566)	(0.448)
Male	0.743	0.719	0.716	(0.177)	(0.159)
Age at booking	33.714	34.703	35.225	(0.099)	(0.018)
Prior offense w/in 365 days	0.423	0.472	0.459	(0.029)	(0.293)
Number of offenses per booking	1.559	1.571	1.592	(0.767)	(0.059)
First time in jail	0.062	0.048	0.015	(0.525)	(0.012)
Prior treatment	0.113	0.165	0.094	(0.402)	(0.794)
Prior medications	0.109	0.154	0.087	(0.462)	(0.722)
Prior hospitalization	0.054	0.098	0.063	(0.277)	(0.753)
Homeless	0.041	0.071	0.041	(0.259)	(0.962)
Jobless	0.076	0.104	0.059	(0.485)	(0.731)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 25 Test of Randomization for Mental Health Court

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	-0.005	0.003
	(0.037)	(0.006)
Black	-0.003	-0.004***
	(0.010)	(0.001)
Race other	0.015	-0.023
	(0.075)	(0.020)
Hispanic	-0.076***	-0.005*
	(0.010)	(0.003)
Male	-0.062***	-0.012***
	(0.010)	(0.005)
Age at booking	0.003***	0.001***
	(0.000)	(0.000)
Prior offense w/in 365 days	0.155***	0.006*
	(0.017)	(0.003)
Number of offenses per booking	0.006**	0.001*
	(0.002)	(0.000)
First time in jail	-0.094***	-0.049***
	(0.012)	(0.016)
Prior treatment	-0.046**	0.001
	(0.018)	(0.011)
Prior medications	-0.033**	-0.011
	(0.016)	(0.008)
Prior hospitalization	0.205***	0.025***
	(0.014)	(0.006)
Homeless	0.047***	0.009
	(0.017)	(0.010)
Jobless	-0.064***	-0.020
	(0.018)	(0.020)
Time fixed effects	Yes	Yes
F-test	56	3
Observations	42,361	42,357

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 26 Assignation to Mental Health Court and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.251***	0.168***	0.503***	0.433***	0.373***	0.476***
	(0.014)	(0.010)	(0.133)	(0.116)	(0.129)	(0.113)
Recid within 1 year	0.202***	0.184***	0.479***	0.500***	0.543***	0.470***
	(0.011)	(0.010)	(0.101)	(0.110)	(0.153)	(0.099)
Count of future recidivism	2.661***	2.088***	4.101***	3.637***	1.118**	5.557***
	(0.261)	(0.212)	(1.242)	(1.143)	(0.434)	(1.765)
Days to recidivism	-68.549***	-45.344***	-56.202	-40.063	27.976	-67.408**
	(5.823)	(4.824)	(51.763)	(35.518)	(54.961)	(28.492)
Next offense felony	0.021***	0.005	0.064**	0.063**	0.095**	0.039
	(0.005)	(0.005)	(0.029)	(0.027)	(0.037)	(0.026)
Next booking mental health score improves	0.228***	0.244***	0.284***	0.309***	0.473***	0.226**
	(0.024)	(0.024)	(0.085)	(0.090)	(0.096)	(0.096)
Suicide attempt in next booking	0.036***	0.023***	0.065	0.053**	0.073***	0.037
	(0.006)	(0.004)	(0.043)	(0.025)	(0.025)	(0.033)
Suicide ideation in next booking	0.005***	0.005***	0.008**	0.007**	0.009**	0.006
	(0.001)	(0.001)	(0.004)	(0.003)	(0.004)	(0.006)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 27 Assignation to Mental Health Court and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Recid after current booking	0.455***	0.494	0.454***	0.513	0.476***	0.155
	(0.121)	(0.433)	(0.122)	(0.340)	(0.123)	(0.645)
Recid within 1 year	0.490***	0.822	0.494***	0.596	0.517***	-0.046
	(0.105)	(0.744)	(0.107)	(0.404)	(0.109)	(0.948)
Count of future recidivism	4.248***	-4.509	4.027***	0.635	4.257***	-13.227
	(1.203)	(6.738)	(1.223)	(1.278)	(1.183)	(19.785)
Days to recidivism	-55.165	-239.482	-55.690	-113.318	-52.437	1089.312
	(39.170)	(411.865)	(39.240)	(126.636)	(38.442)	(8765.072)
Next offense felony	0.066**	0.275	0.068**	0.226	0.071**	0.347
	(0.029)	(0.299)	(0.029)	(0.202)	(0.029)	(0.377)
Next booking mental health score improves	0.327***	-0.350	0.330***	-0.285	0.316***	-1.796
	(0.079)	(1.569)	(0.083)	(0.769)	(0.083)	(12.005)
Suicide attempt in next booking	0.037	0.498	0.038	0.423*	0.044*	0.659
	(0.024)	(0.372)	(0.023)	(0.254)	(0.024)	(0.661)
Suicide ideation in next booking	0.009**	-0.009	0.008**	-0.002	0.009***	-0.038
	(0.003)	(0.031)	(0.003)	(0.031)	(0.003)	(0.049)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 28 Assignation to Mental Health Court and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1)	(2)	(3)	(4)
	No	Yes	No	Yes
Recid after current booking	0.472***	0.141	0.472***	-0.616
	(0.123)	(0.321)	(0.123)	(1.318)
Recid within 1 year	0.508***	0.347	0.509***	-0.059
	(0.109)	(0.398)	(0.108)	(1.383)
Count of future recidivism	3.981***	0.966	4.219***	-30.470
	(1.195)	(1.502)	(1.191)	(44.811)
Days to recidivism	-50.574	-208.497	-51.652	-1283.079
	(39.247)	(169.977)	(38.176)	(5610.931)
Next offense felony	0.077**	-0.122	0.075***	-0.122
	(0.030)	(0.220)	(0.029)	(0.563)
Next booking mental health score improves	0.320***	0.278	0.330***	-1.401
	(0.089)	(0.272)	(0.082)	(7.985)
Suicide attempt in next booking	0.049*	0.184	0.052**	0.447
	(0.025)	(0.165)	(0.025)	(0.488)
Suicide ideation in next booking	0.006**	0.059	0.006*	0.138
	(0.003)	(0.094)	(0.003)	(0.191)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 29 Descriptive Statistics by Public Defender Assignation

	Wheel	Public Defender
Mental Health Needs		
None	0.000	0.000
Mild	0.000	0.000
Moderate	1.000	0.000
Severe	0.000	1.000
Outcomes		
Recid after current booking	0.644	0.755
Recid within 1 year	0.699	0.780
Count of future recidivism	3.425	5.302
Days to recidivism	136.279	96.858
Next offense felony	0.147	0.115
Next booking mental health score improves	0.302	0.378
Suicide attempt in next booking	0.071	0.042
Suicide ideation in next booking	0.008	0.006
Inmate Characteristics		
White	0.700	0.674
Asian	0.008	0.020
Black	0.291	0.305
Race other	0.001	0.000
Hispanic	0.201	0.152
Male	0.686	0.707
Age at booking	36.471	39.107
Prior offense w/in 365 days	0.595	0.748
Number of offenses per booking	1.625	1.648
First time in jail	0.012	0.005
Prior treatment	0.158	0.097
Prior medications	0.149	0.097
Prior hospitalization	0.125	0.090
Homeless	0.080	0.060
Jobless	0.091	0.059
Clinician Characteristics		
Clinician Male	0.188	0.187
Clinician White	0.842	0.895
Clinician Black	0.073	0.034
Clinician Hispanic	0.078	0.061
Observations	7,469	2,443

Table 30 First Stage Regressions for Public Defender

	Residualized Leave-Out		Clinician Fixed Effects
	(1)	(2)	(3)
Z: Clinician's Leave-Out Mean Mental Health Score Rate	0.497***	0.487***	
	(0.164)	(0.158)	
Asian		0.201**	0.194**
		(0.094)	(0.092)
Black		-0.002	-0.001
		(0.017)	(0.016)
Race other		-0.078	-0.079
		(0.171)	(0.171)
Hispanic		-0.047***	-0.046***
		(0.016)	(0.017)
Male		-0.003	-0.004
		(0.018)	(0.018)
Age at booking		0.003***	0.003***
		(0.001)	(0.001)
Prior offense w/in 365 days		0.117***	0.116***
		(0.015)	(0.015)
Number of offenses per booking		-0.000	-0.001
		(0.005)	(0.005)
First time in jail		0.039	0.049
		(0.032)	(0.030)
Prior treatment		-0.139***	-0.135***
		(0.039)	(0.036)
Prior medications		0.031	0.032
		(0.039)	(0.041)
Prior hospitalization		0.052**	0.055**
		(0.024)	(0.025)
Homeless		-0.006	-0.009
		(0.021)	(0.021)
Jobless		-0.024*	-0.012
		(0.013)	(0.012)
Time fixed effects	Yes	Yes	Yes
Adjusted F-test			
Observations	9,907	9,907	9,912

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 31 Instrument v. Inmate Characteristics for Public Defender

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out Mean Mental Health Score Rate	-0.097	-0.023	0.116	(0.000)	(0.000)
Inmate Characteristics					
Asian	0.011	0.011	0.011	(0.987)	(0.680)
Black	0.310	0.289	0.284	(0.087)	(0.000)
Race other	0.001	0.000	0.001	(0.221)	(0.702)
Hispanic	0.173	0.204	0.190	(0.000)	(0.025)
Male	0.684	0.695	0.694	(0.311)	(0.795)
Age at booking	37.426	37.222	36.716	(0.579)	(0.240)
Prior offense w/in 365 days	0.655	0.617	0.625	(0.113)	(0.240)
Number of offenses per booking	1.638	1.603	1.651	(0.119)	(0.995)
First time in jail	0.013	0.015	0.003	(0.711)	(0.019)
Prior treatment	0.162	0.205	0.062	(0.555)	(0.093)
Prior medications	0.156	0.196	0.056	(0.570)	(0.073)
Prior hospitalization	0.133	0.169	0.048	(0.548)	(0.093)
Homeless	0.085	0.104	0.036	(0.574)	(0.167)
Jobless	0.105	0.121	0.022	(0.610)	(0.044)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 32 Test of Randomization for Public Defender

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	0.203**	-0.003
	(0.096)	(0.007)
Black	-0.005	-0.006**
	(0.016)	(0.002)
Race other	-0.074	0.007
	(0.173)	(0.017)
Hispanic	-0.046***	0.003
	(0.016)	(0.003)
Male	-0.001	0.004
	(0.018)	(0.003)
Age at booking	0.003***	-0.000
	(0.001)	(0.000)
Prior offense w/in 365 days	0.116***	-0.002
	(0.015)	(0.004)
Number of offenses per booking	-0.000	0.000
	(0.005)	(0.001)
First time in jail	0.019	-0.042**
	(0.031)	(0.019)
Prior treatment	-0.142***	-0.005
	(0.042)	(0.019)
Prior medications	0.016	-0.030**
	(0.040)	(0.014)
Prior hospitalization	0.055**	0.006
	(0.022)	(0.007)
Homeless	-0.006	0.001
	(0.022)	(0.009)
Jobless	-0.032*	-0.018
	(0.017)	(0.012)
Time fixed effects	Yes	Yes
F-test	10	.
Observations	9,912	9,907

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 33 Assignation to Public Defender and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.112***	0.042***	0.011	-0.077	0.130	-0.200
	(0.018)	(0.014)	(0.126)	(0.098)	(0.110)	(0.126)
Recid within 1 year	0.083***	0.058***	-0.110	-0.152	0.043	-0.220
	(0.015)	(0.015)	(0.117)	(0.112)	(0.111)	(0.150)
Count of future recidivism	1.899***	0.973***	0.324	-1.102	0.660	-2.282
	(0.370)	(0.313)	(2.725)	(2.280)	(0.532)	(3.401)
Days to recidivism	-39.500***	-28.206***	102.758	37.404	14.262	48.633
	(7.296)	(5.700)	(69.089)	(44.641)	(81.817)	(51.316)
Next offense felony	-0.032***	-0.038***	-0.007	-0.036	0.062	-0.079
	(0.006)	(0.006)	(0.071)	(0.064)	(0.062)	(0.076)
Next booking mental health score improves	0.076***	0.111***	0.825***	0.756***	0.927***	0.726***
	(0.025)	(0.023)	(0.196)	(0.167)	(0.230)	(0.180)
Suicide attempt in next booking	-0.029***	-0.025***	-0.144*	-0.045	-0.093**	-0.010
	(0.007)	(0.006)	(0.082)	(0.062)	(0.037)	(0.098)
Suicide ideation in next booking	-0.002	-0.002	-0.019**	-0.008	-0.001	-0.015
	(0.001)	(0.002)	(0.009)	(0.009)	(0.014)	(0.013)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 34 Assignation to Public Defender and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1) No	(2) Yes	(3) No	(4) Yes	(5) No	(6) Yes
Recid after current booking	-0.145	0.317	-0.134	0.163	-0.129	0.215
	(0.106)	(0.715)	(0.105)	(0.769)	(0.107)	(0.760)
Recid within 1 year	-0.237**	0.370	-0.238**	0.311	-0.203*	0.042
	(0.119)	(0.544)	(0.115)	(0.590)	(0.119)	(0.583)
Count of future recidivism	-1.548	0.157	-1.533	0.989	-1.432	-0.333
	(2.623)	(4.232)	(2.599)	(4.147)	(2.613)	(5.028)
Days to recidivism	65.552	-39.676	68.845	-107.544**	67.224	-34.883
	(60.916)	(82.704)	(61.866)	(54.480)	(61.544)	(80.437)
Next offense felony	-0.063	0.213	-0.061	0.317	-0.064	0.320
	(0.072)	(0.360)	(0.074)	(0.465)	(0.074)	(0.490)
Next booking mental health score improves	0.865***	-0.382	0.863***	-0.663	0.849***	-0.459
	(0.205)	(0.432)	(0.201)	(0.409)	(0.197)	(0.487)
Suicide attempt in next booking	-0.027	-0.534	-0.022	-0.656*	-0.040	-0.466*
	(0.068)	(0.350)	(0.067)	(0.384)	(0.066)	(0.267)
Suicide ideation in next booking	-0.009	-0.166	-0.009	-0.175	-0.009	-0.202
	(0.010)	(0.129)	(0.010)	(0.131)	(0.009)	(0.142)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 35 Assignation to Public Defender and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1)	(2)	(3)	(4)
	No	Yes	No	Yes
Recid after current booking	-0.116	0.860	-0.136	2.188
	(0.108)	(1.992)	(0.109)	(4.941)
Recid within 1 year	-0.192	0.637	-0.206*	1.769
	(0.121)	(1.389)	(0.123)	(4.155)
Count of future recidivism	-1.188	-3.828	-1.125	-5.402
	(2.541)	(7.369)	(2.579)	(9.924)
Days to recidivism	57.213	-113.977	58.165	-255.160
	(56.110)	(643.095)	(58.001)	(927.977)
Next offense felony	-0.035	-0.444	-0.036	-0.334
	(0.061)	(0.619)	(0.063)	(0.669)
Next booking mental health score improves	0.813***	-6.922	0.784***	-0.685
	(0.190)	(72.585)	(0.187)	(4.086)
Suicide attempt in next booking	-0.040	-0.389	-0.038	-0.305
	(0.062)	(0.551)	(0.065)	(0.727)
Suicide ideation in next booking	-0.005	-0.411	-0.012	-0.076
	(0.007)	(0.690)	(0.009)	(0.413)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 36 Descriptive Statistics by MH Score 1s vs. 2s Assignation

	MH Score 1	MH Score 2
Mental Health Needs		
None	0.000	0.000
Mild	1.000	0.000
Moderate	0.000	1.000
Severe	0.000	0.000
Outcomes		
Recid after current booking	0.498	0.644
Recid within 1 year	0.582	0.699
Count of future recidivism	1.733	3.425
Days to recidivism	175.856	136.279
Next offense felony	0.136	0.147
Next booking mental health score improves	0.275	0.302
Suicide attempt in next booking	0.053	0.071
Suicide ideation in next booking	0.003	0.008
Inmate Characteristics		
White	0.741	0.700
Asian	0.009	0.008
Black	0.250	0.291
Race other	0.001	0.001
Hispanic	0.240	0.201
Male	0.663	0.686
Age at booking	34.981	36.471
Prior offense w/in 365 days	0.460	0.595
Number of offenses per booking	1.582	1.625
First time in jail	0.035	0.012
Prior treatment	0.193	0.158
Prior medications	0.188	0.149
Prior hospitalization	0.104	0.125
Homeless	0.051	0.080
Jobless	0.089	0.091
Clinician Characteristics		
Clinician Male	0.200	0.188
Clinician White	0.847	0.842
Clinician Black	0.061	0.073
Clinician Hispanic	0.085	0.078
Observations	8,701	7,469

Table 37 First Stage Regressions for MH Score 1s vs. 2s

	Residualized Leave-Out		Residualized Leave-Out Sub-Samples				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z: Clinician's Leave-Out Mean Mental Health Score ate	0.659***	0.606***	0.572***	0.836***	0.838***	0.925***	0.609***
	(0.176)	(0.163)	(0.205)	(0.070)	(0.074)	(0.080)	(0.188)
Asian		-0.000	0.002	0.000	-0.295***	0.062	0.178
		(0.041)	(0.048)	(0.000)	(0.070)	(0.095)	(0.143)
Black		0.018	0.010	0.000	0.029	0.064**	0.032
		(0.011)	(0.015)	(0.000)	(0.109)	(0.030)	(0.025)
Race other		0.113	0.141	0.000	0.000	0.290	-0.539***
		(0.133)	(0.109)	(0.000)	(0.000)	(0.249)	(0.084)
Hispanic		-0.040***	-0.037***	-0.032	0.000	-0.007	-0.041
		(0.013)	(0.014)	(0.107)	(0.000)	(0.023)	(0.026)
Male		-0.002	0.000	-0.019	0.024	0.007	-0.018
		(0.010)	(0.000)	(0.025)	(0.019)	(0.025)	(0.024)
Age at booking		0.002***	0.001***	0.002*	0.001	0.003	-0.002
		(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.002)
Prior offense w/in 365 days		0.111***	0.114***	0.099***	0.087***	0.057***	0.091***
		(0.013)	(0.015)	(0.021)	(0.020)	(0.020)	(0.026)
Number of offenses per booking		0.003	-0.003	-0.002	-0.006	0.001	-0.003
		(0.003)	(0.004)	(0.006)	(0.006)	(0.008)	(0.009)
First time in jail		-0.074**	-0.102***	-0.003	-0.041	-0.094**	-0.039
		(0.029)	(0.032)	(0.050)	(0.041)	(0.038)	(0.056)
Prior treatment		-0.062**	-0.041*	-0.106**	-0.033	-0.020	-0.132*
		(0.028)	(0.024)	(0.051)	(0.046)	(0.042)	(0.075)
Prior medications		-0.129***	-0.163***	-0.076	-0.125**	-0.078*	-0.060
		(0.022)	(0.029)	(0.051)	(0.048)	(0.045)	(0.057)
Prior hospitalization		0.175***	0.209***	0.201***	0.163***	0.118**	0.174***
		(0.017)	(0.026)	(0.041)	(0.040)	(0.045)	(0.047)
Homeless		0.118***	0.077***	0.075*	0.073**	0.036	0.158***
		(0.018)	(0.023)	(0.039)	(0.033)	(0.049)	(0.042)
Jobless		0.008	0.035	0.038	-0.006	-0.033	0.011
		(0.022)	(0.028)	(0.028)	(0.027)	(0.025)	(0.041)
Cragg-Donald F	545.82	469.95	296.48	171.83	164.65	146.02	95.49
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample			Male	Black	Hispanic	Under 25	Over 45
Observations	16,169	16,169	10,890	4,352	3,591	3,146	3,591

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 38 Instrument v. Inmate Characteristics for MH Score 1s vs. 2s

	Bottom Tercile	Middle Tercile	Top Tercile	Middle v. Bottom P-Value	Top v. Bottom P-Value
Z: Clinician's Leave-Out Mean Mental Health Score Rate	-0.140	-0.001	0.137	(0.000)	(0.000)
Inmate Characteristics					
Asian	0.008	0.008	0.009	(0.738)	(0.527)
Black	0.263	0.277	0.268	(0.105)	(0.926)
Race other	0.001	0.001	0.001	(0.624)	(0.887)
Hispanic	0.226	0.215	0.225	(0.368)	(0.650)
Male	0.670	0.681	0.669	(0.457)	(0.944)
Age at booking	35.024	36.082	35.903	(0.008)	(0.079)
Prior offense w/in 365 days	0.487	0.541	0.539	(0.006)	(0.001)
Number of offenses per booking	1.562	1.617	1.626	(0.026)	(0.012)
First time in jail	0.049	0.014	0.010	(0.008)	(0.001)
Prior treatment	0.253	0.167	0.111	(0.401)	(0.041)
Prior medications	0.244	0.161	0.105	(0.399)	(0.037)
Prior hospitalization	0.140	0.123	0.078	(0.837)	(0.170)
Homeless	0.078	0.064	0.051	(0.758)	(0.326)
Jobless	0.141	0.071	0.057	(0.153)	(0.083)

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 39 Test of Randomization for MH Score 1s vs. 2s

	(1) Mental Health Court	(2) Z: Mental Health Court
Asian	0.005	0.008
	(0.042)	(0.007)
Black	0.019	0.001
	(0.011)	(0.003)
Race other	0.109	-0.007
	(0.134)	(0.018)
Hispanic	-0.039***	0.002
	(0.013)	(0.004)
Male	-0.005	-0.005*
	(0.011)	(0.003)
Age at booking	0.002***	0.000*
	(0.000)	(0.000)
Prior offense w/in 365 days	0.113***	0.003
	(0.014)	(0.004)
Number of offenses per booking	0.003	0.001
	(0.003)	(0.001)
First time in jail	-0.105***	-0.051***
	(0.031)	(0.016)
Prior treatment	-0.078**	-0.026
	(0.029)	(0.016)
Prior medications	-0.143***	-0.023*
	(0.026)	(0.013)
Prior hospitalization	0.196***	0.034**
	(0.018)	(0.013)
Homeless	0.129***	0.019**
	(0.019)	(0.009)
Jobless	-0.007	-0.024
	(0.032)	(0.026)
Time fixed effects	Yes	Yes
F-test	23	5
Observations	16,170	16,169

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 40 Assignation to MH Score 1s vs. 2s and Recidivism Outcomes

	OLS results		2SLS results		2SLS by Prior Offense	
	(1)	(2)	(3)	(4)	(5)	(6)
Recid after current booking	0.148***	0.084***	0.260**	0.124*	0.165**	0.078
	(0.015)	(0.009)	(0.113)	(0.075)	(0.079)	(0.102)
Recid within 1 year	0.116***	0.095***	0.182*	0.126	0.225**	0.051
	(0.012)	(0.010)	(0.103)	(0.094)	(0.109)	(0.104)
Count of future recidivism	1.697***	1.203***	1.661	0.673	0.354	1.039
	(0.216)	(0.169)	(1.428)	(1.115)	(0.320)	(2.129)
Days to recidivism	-39.342***	-25.588***	34.481	6.858	-3.044	24.953
	(8.972)	(6.879)	(73.572)	(40.912)	(54.878)	(42.665)
Next offense felony	0.012**	0.000	0.071**	0.054*	0.061**	0.053
	(0.006)	(0.006)	(0.032)	(0.029)	(0.028)	(0.050)
Next booking mental health score improves	0.027	0.048***	0.052	0.047	0.213	-0.059
	(0.019)	(0.017)	(0.181)	(0.163)	(0.144)	(0.176)
Suicide attempt in next booking	0.018***	0.011**	0.020	0.042	0.057*	0.025
	(0.006)	(0.004)	(0.055)	(0.029)	(0.030)	(0.050)
Suicide ideation in next booking	0.005***	0.005***	0.005	0.008	0.003	0.011*
	(0.001)	(0.001)	(0.004)	(0.005)	(0.007)	(0.006)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	Yes	Yes
Subsample					No prior offense	Prior offense

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 41 Assignation to MH Score 1s vs. 2s and Heterogeneity in Outcomes

	Prior treatment		Prior medications		Prior hospitalization	
	(1)	(2)	(3)	(4)	(5)	(6)
	No	Yes	No	Yes	No	Yes
Recid after current booking	0.100	0.263**	0.112	0.234*	0.134	0.207
	(0.089)	(0.133)	(0.090)	(0.132)	(0.088)	(0.217)
Recid within 1 year	0.080	0.348**	0.097	0.264	0.124	0.154
	(0.103)	(0.174)	(0.103)	(0.168)	(0.101)	(0.239)
Count of future recidivism	0.713	0.192	0.788	-0.131	0.888	-1.008
	(1.392)	(1.023)	(1.382)	(1.067)	(1.291)	(1.798)
Days to recidivism	8.134	-4.630	8.790	-7.967	8.793	-73.513
	(52.796)	(51.308)	(52.838)	(44.829)	(49.554)	(105.726)
Next offense felony	0.064*	0.055	0.070*	0.042	0.060*	0.130
	(0.036)	(0.058)	(0.037)	(0.053)	(0.032)	(0.082)
Next booking mental health score improves	0.108	0.032	0.097	0.047	0.089	0.170
	(0.182)	(0.241)	(0.184)	(0.240)	(0.173)	(0.534)
Suicide attempt in next booking	0.019	0.230***	0.022	0.234***	0.042	0.158
	(0.030)	(0.074)	(0.028)	(0.070)	(0.028)	(0.102)
Suicide ideation in next booking	0.008*	0.009	0.009*	0.000	0.011**	-0.029
	(0.005)	(0.019)	(0.005)	(0.017)	(0.005)	(0.022)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Table 42 Assignation to MH Score 1s vs. 2s and Heterogeneity in Outcomes

	Homeless		Jobless	
	(1) No	(2) Yes	(3) No	(4) Yes
Recid after current booking	0.133	0.108	0.131	0.160
	(0.086)	(0.159)	(0.089)	(0.106)
Recid within 1 year	0.114	0.265	0.109	0.287*
	(0.101)	(0.198)	(0.100)	(0.158)
Count of future recidivism	0.815	0.772	0.844	-0.245
	(1.254)	(0.757)	(1.332)	(1.163)
Days to recidivism	13.022	-75.599	12.008	-86.861
	(49.375)	(52.074)	(53.171)	(55.762)
Next offense felony	0.054*	0.053	0.055*	0.097
	(0.031)	(0.128)	(0.033)	(0.072)
Next booking mental health score improves	0.082	0.248	0.106	0.019
	(0.180)	(0.191)	(0.174)	(0.240)
Suicide attempt in next booking	0.029	0.190**	0.036	0.163***
	(0.029)	(0.087)	(0.031)	(0.050)
Suicide ideation in next booking	0.006	0.025	0.005	0.021
	(0.004)	(0.037)	(0.005)	(0.023)
Time fixed effects	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes

Data is from a large county correctional complex.

Time fixed effects include day-of-week-month fixed effects.

Clinician and inmate two-way clustered standard errors shown in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

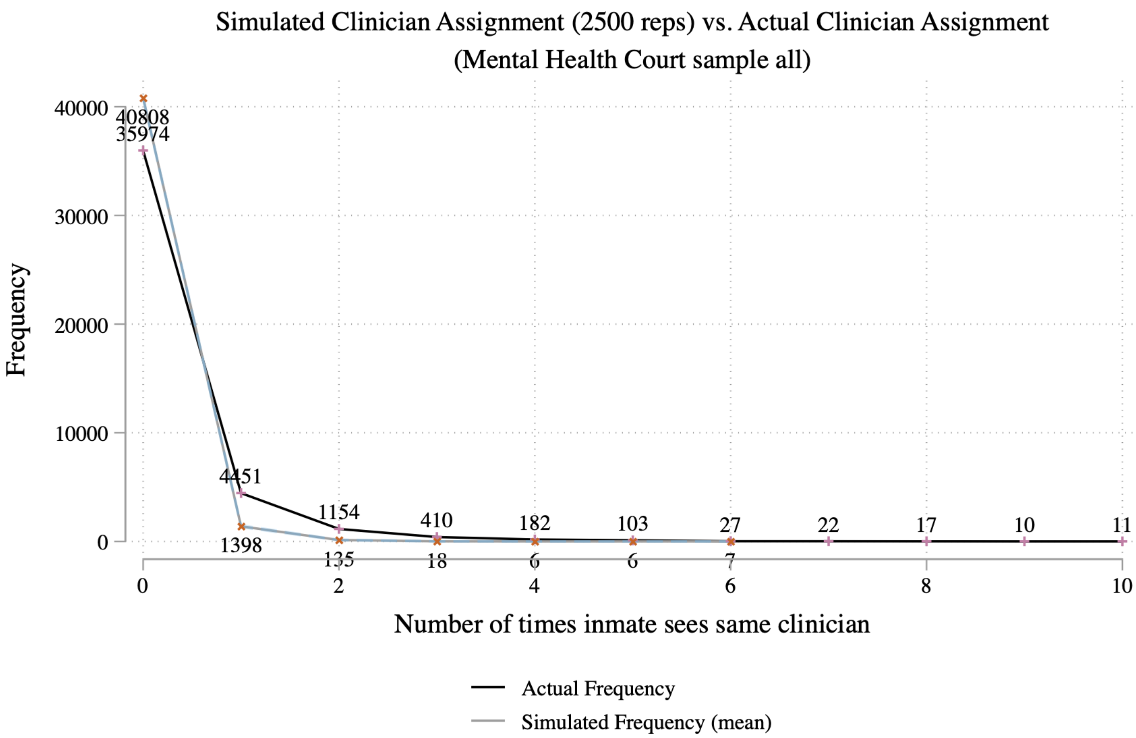

Figure 11 Simulated Clinician Assignment Compared to Actual Assignment

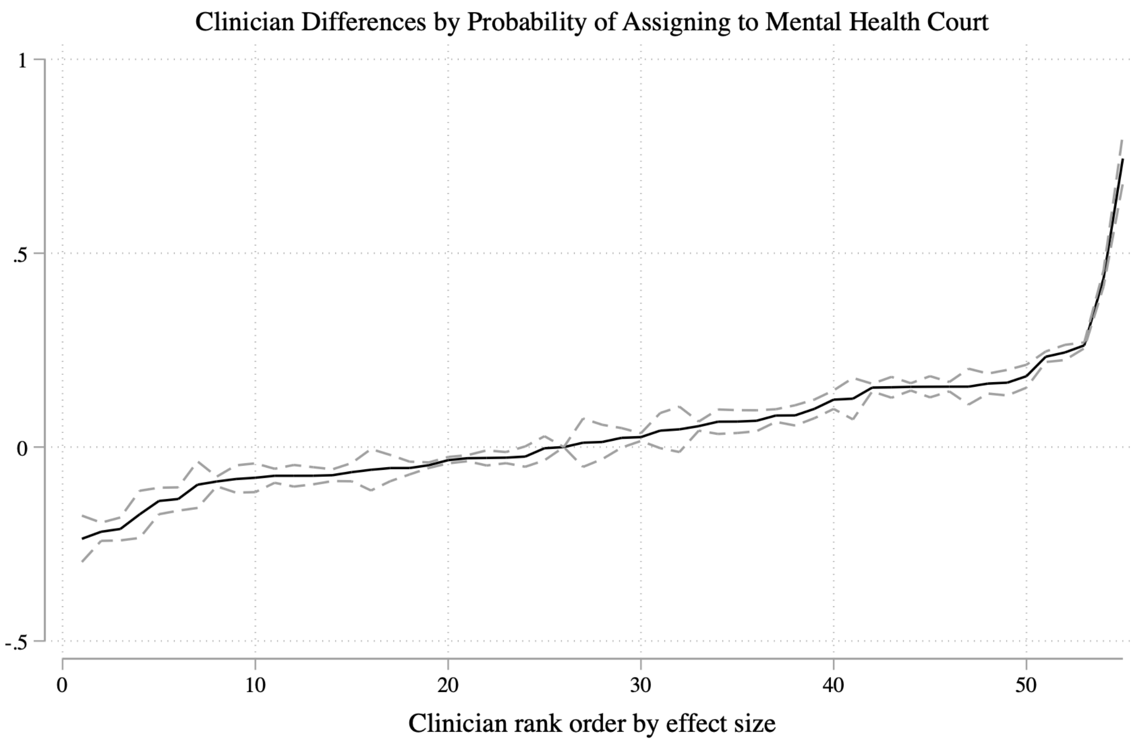

Figure 12 Clinician fixed effects with full sample for mental health court assignment

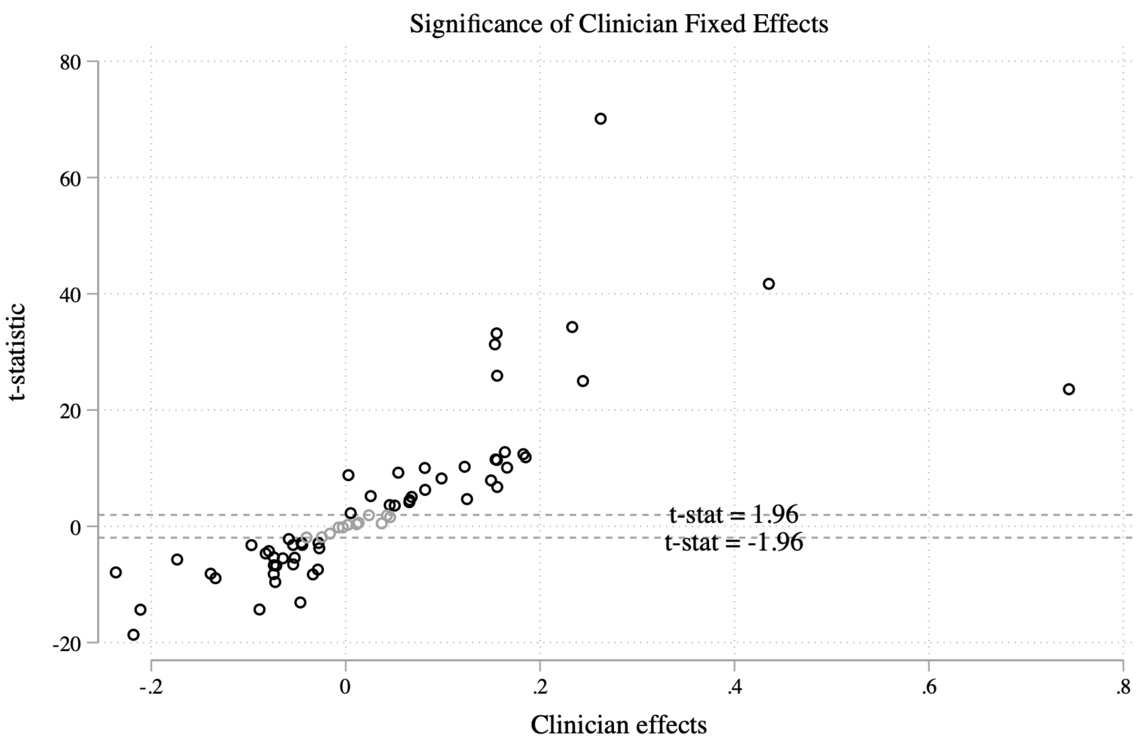

Figure 13 Distribution of t-statistics on individual therapist fixed effects for full sample

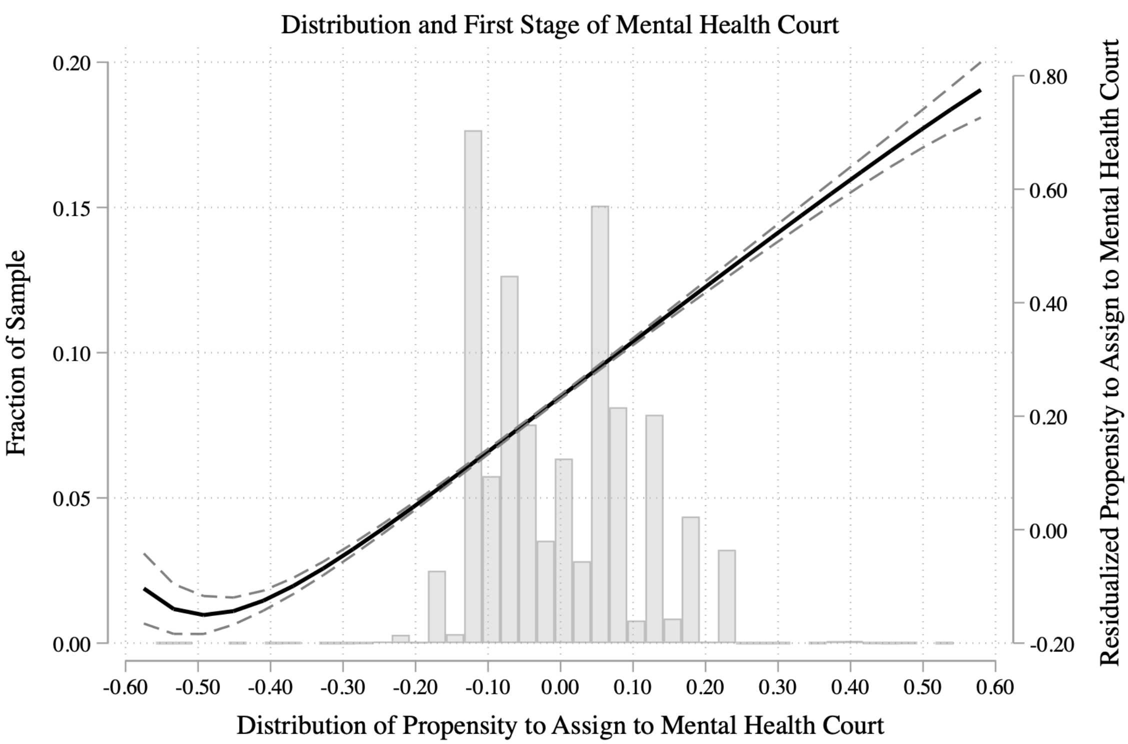

Figure 14 Smoothed fan regression of residualized leave one out against the share of individuals in mental health court

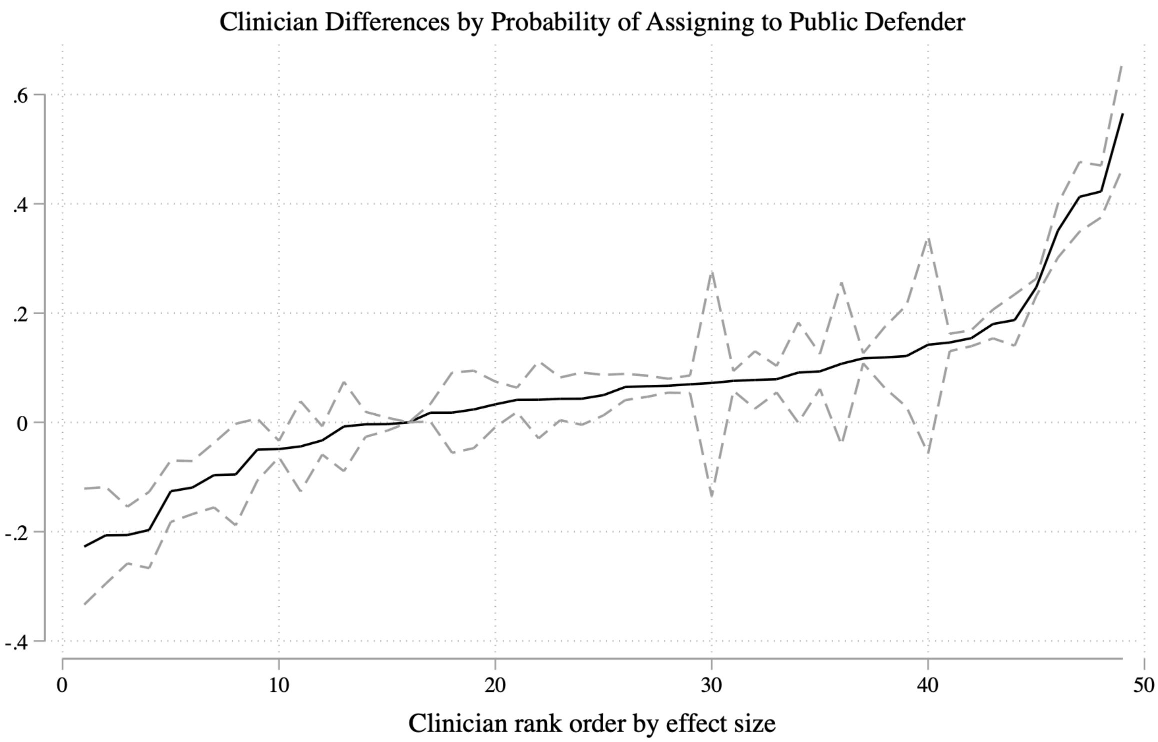

Figure 15 Clinician fixed effects with full sample for public defender assignment

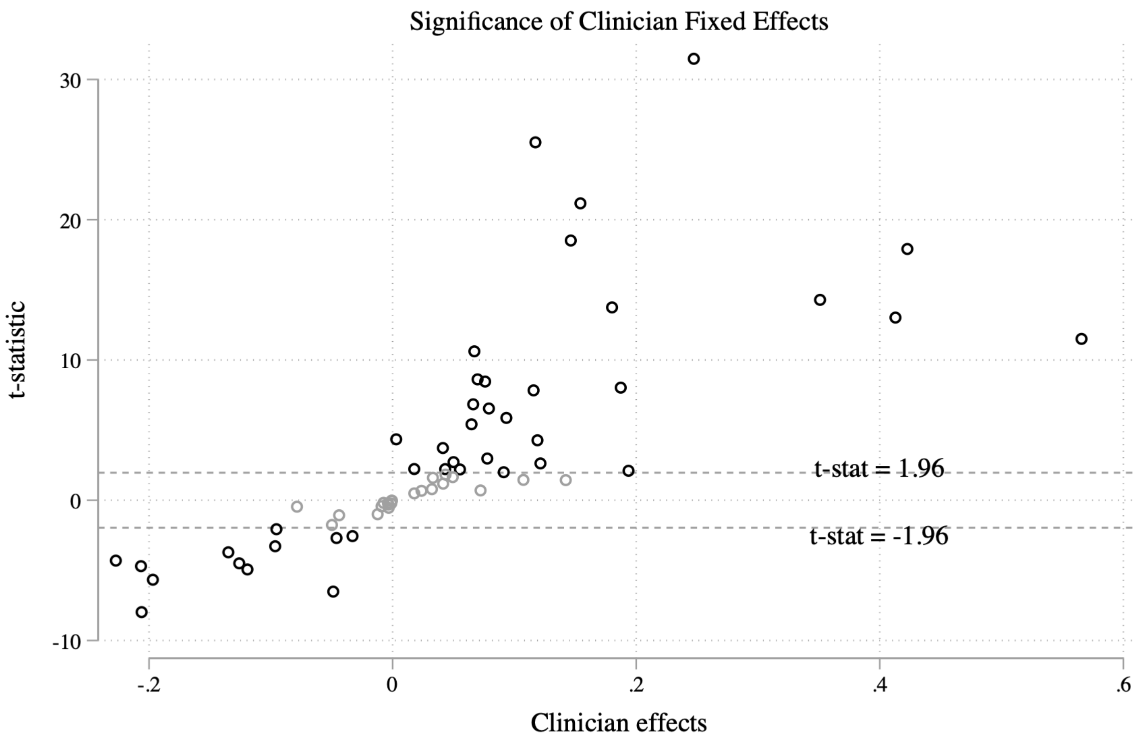

Figure 16 Distribution of t-statistics on individual therapist fixed effects for full sample for public defender assignment

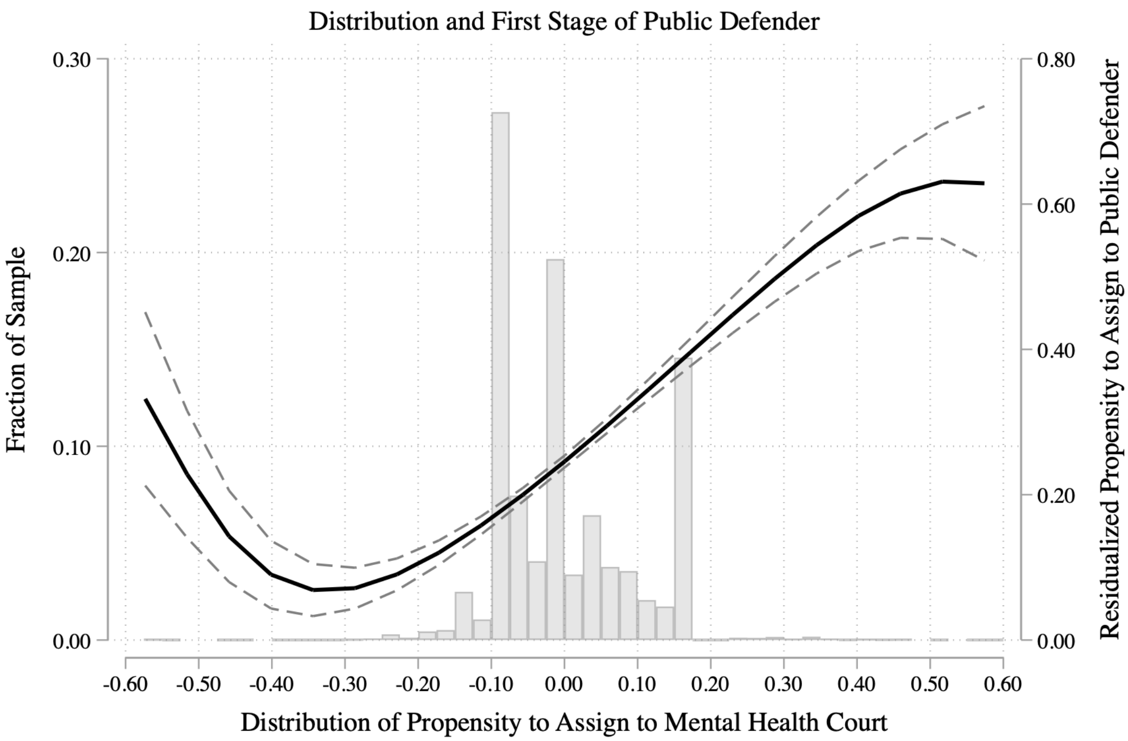

Figure 17 Smoothed fan regression of residualized leave one out against the share of individuals with public defender assignation

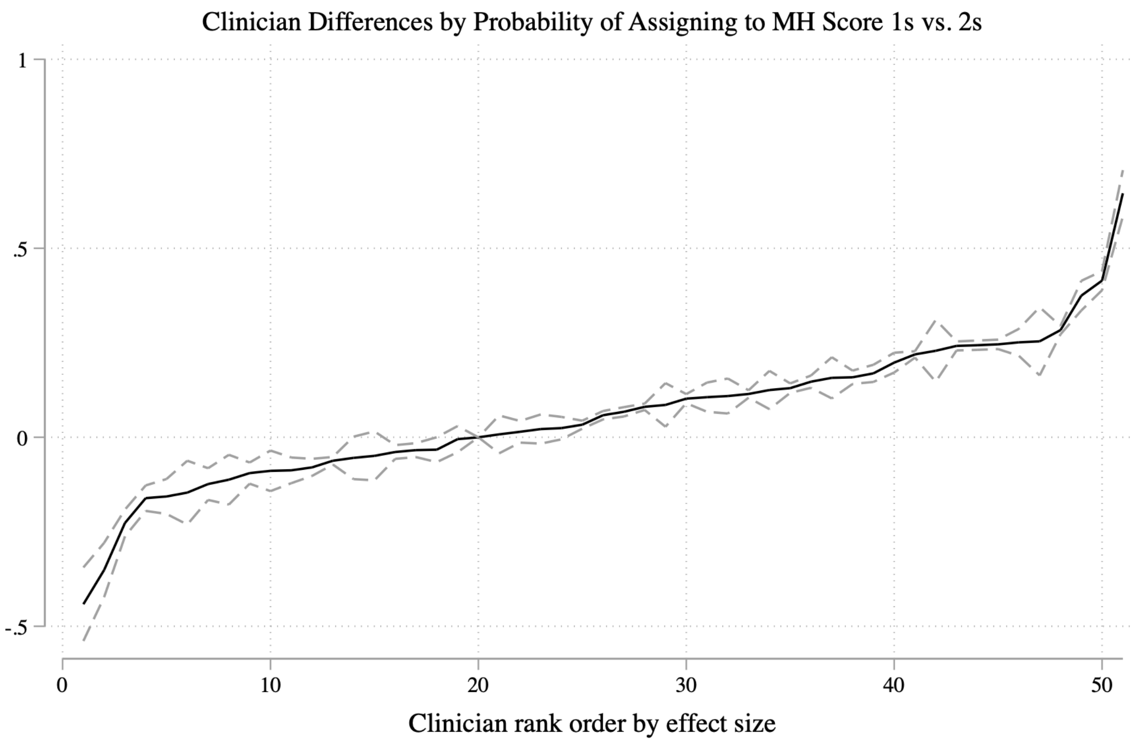

Figure 18 Clinician fixed effects with full sample for 1s vs 2s

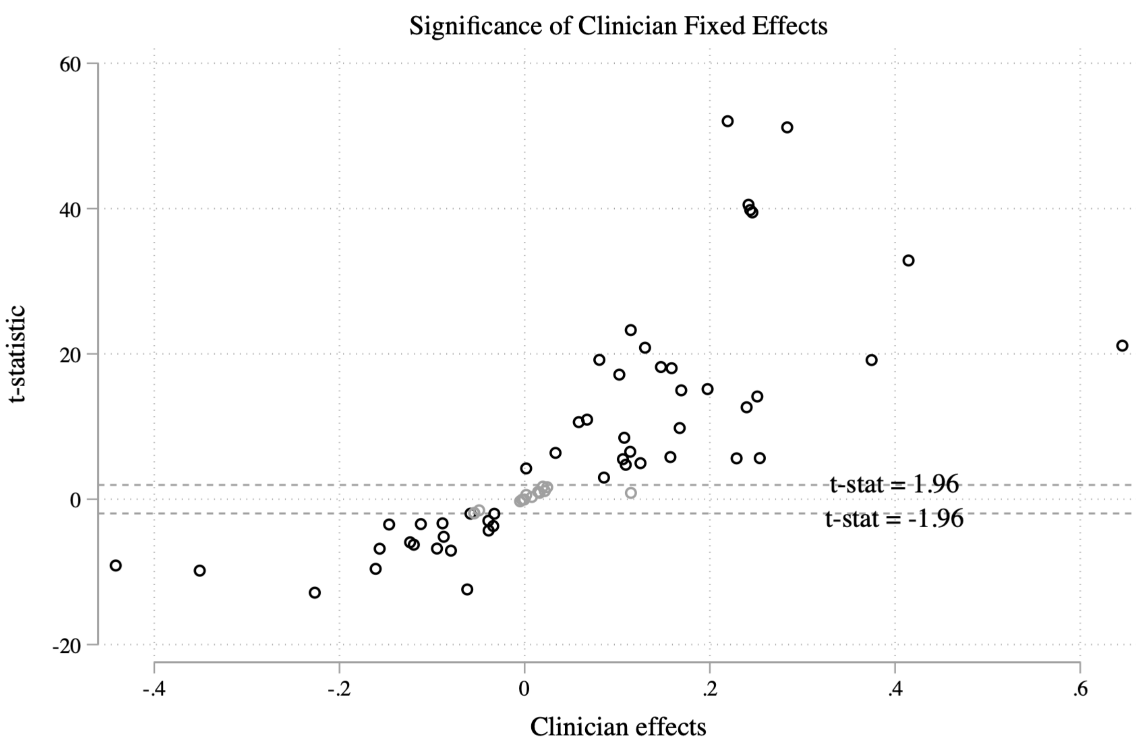

Figure 19 Distribution of t-statistics on individual therapist fixed effects for full sample for 1s vs 2s

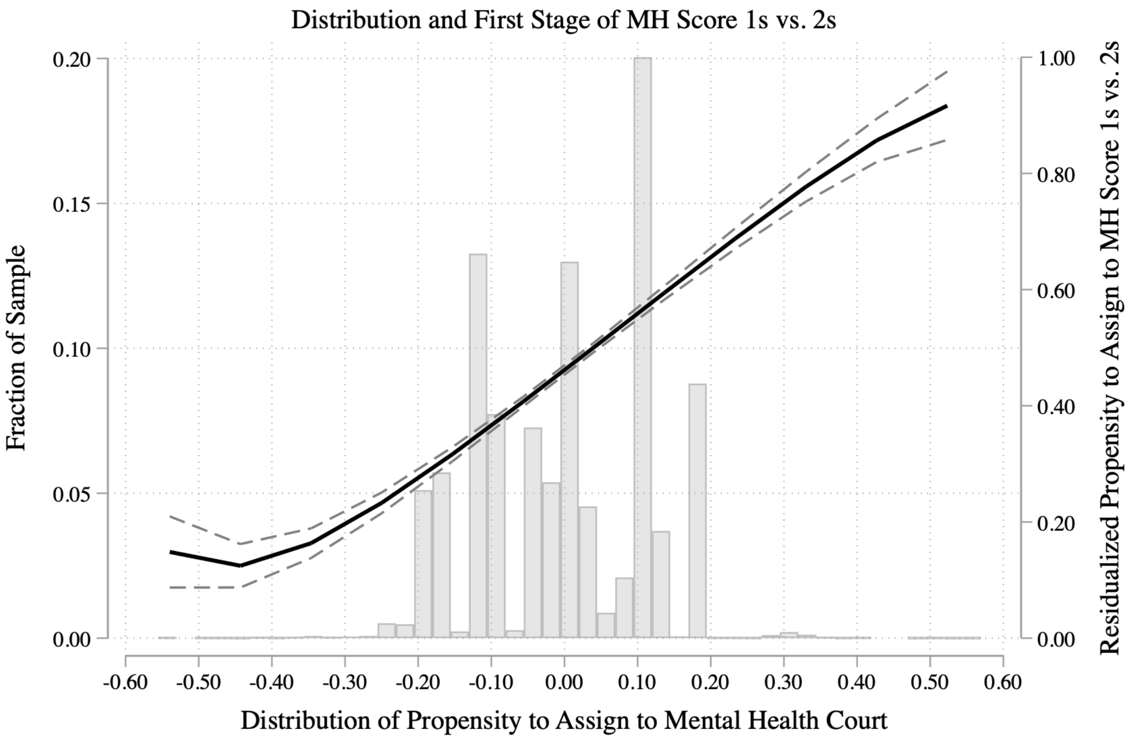

Figure 20 Smoothed fan regression of residualized leave one out against the share of individuals with 1s vs 2s