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An Evaluation of Clackamas County's Transition Center Using Propensity Score Modeling

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An Evaluation of Clackamas County's Transition Center
Using Propensity Score Modeling

by

Alicia de Jong McKay

A thesis submitted in partial fulfillment of the
requirements for the degree of

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in
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Portland State University
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Abstract

Part of the purpose of Justice Reinvestment Initiatives (JRIs) involve a focus of funds and effort toward implementing practices that increase the chances of successful reintegration of people recently released from incarceration. Similar to other jurisdictions, Oregon's JRI has taken a number of forms of reintegrative efforts. In 2016, JRI funding opened a services hub and reintegration/reentry center in a rural county. The Center offers a central location for reentry services, such as employment and housing assistance, but is not a requirement of an offender's supervision. Relying on the risk-need-responsivity framework, this program aims to reduce recidivism by mitigating barriers for offenders to access services offered by the county and to target and treat needs. The purpose of this study is to conduct a preliminary evaluation of the Center's effectiveness using propensity score modeling. Data used in this evaluation includes 1,727 people who visited the Center who were compared to 3,486 people from a historical sample by creating matching pairs. Post-matching, this was reduced to an even 1,669 offenders in each group. Further analyses such as binary logistic regression are used to further understand the differences between those who were able to visit the Center, and those from the historical sample who would have been equally likely to choose to visit, had it been available to them. Results show that visiting the Center does have a reducing impact on recidivism. Compared to offenders from the historical sample, those who were able to visit the Center reduced their odds of being rearrested by 80%, their odds of reconviction by 90%, and their odds of reincarceration by 99%. This study contributes to the body of

knowledge on voluntary reentry programs and shows preliminary positive results to Clackamas County's Transition Center.

Dedication

This thesis is dedicated to Aunt Michelle, my service dog Bogart, and to my parents, Bruce McKay and Jacqueline de Jong McKay.

Michelle, Multiple Sclerosis did not stop you from being my fiercest supporter and biggest champion. Thank you for always wearing my college shirts, teaching me how to ride horses, and how to fall off with style. I know you're riding now. I love you.

Bogart, you're my Balto. I would be lost without you. You went to every single class with me (even though you were bored through most of them) and have been the constant I have always needed. I love you.

Dad, you may have passed almost 22 years ago, but you still find ways to reach out and be there for me in your own lucky way. Thank you. I love you.

Finally, and most importantly, Mum. When Dad died you were left with two young girls and a dream. Now, you have the nursing degree you worked so hard for, and both your daughters have Masters (or will soon). It is a credit to your strength and dedication that we have all made it here. I love you.

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Megan, you are the best roommate. Thank you for making sure I ate balanced meals and got enough rest. This would have been a much more painful process without you.

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Introduction

As the nation has begun to shift toward a new era of decarceration (Garland, Hogan, Wodahl, Hass, Stohr, & Lambert, 2014), states are searching for innovative ways to tackle recidivism and cost, among other reverberations of mass incarceration such as overcrowding and reduced access to services within prison (Maurer, 2012). About 95% of people incarcerated in state prisons will be released eventually (Schlager, 2013), making reintegration and the reduction of recidivism an important part of the criminal justice process. Of those 95%, a majority will likely recidivate. The Bureau of Justice Statistics (2018) conducted a national study of 401,288 prisoners released in 2005 from 30 states. Approximately 79% of the releases were rearrested within the first six years in the community, and 83% within nine years. In addition to reducing recidivism rates, many states have taken aim on decreasing correctional expenditures. The rate of corrections spending has risen rapidly with the incarceration binge (Selmon & Leighton, 2010). The United States spent \$15.0 billion on state corrections in 1982, which rose to \$48.5 billion in 2010 (Kyckelhahn, 2012). In the same period, the number of prisoners in state and private prisons grew from 371,522 to 1,316,858, a 254.4% increase.

One method created to combat this excessive spending and resource usage is the Justice Reinvestment Initiative (JRI). The JRI concept originated in 2003 (Tucker & Cadora, 2003) and was enacted in 2006 by the United States Department of Justice's Bureau of Justice Assistance. The JRI is currently used in 35 states (Pew Trusts, 2018) and uses a focus of funds and effort toward improving public safety and controlling for

corrections costs, while still holding offenders accountable (BJA, 2019). Each state uses different methods (La Vigne, Samuels, Bieler, Mayer, Pacifici, Cramer, Peterson & Kotonias et al., 2013). The State of Oregon’s JRI focuses on implementing practices that reduces prison use and recidivism, while still keeping the public safe (CJC, 2019). Although cost savings is not a primary goal, the Oregon JRI attempts to use its resources effectively while still working towards recidivism and prison use reduction.

Oregon focuses their JRI on these goals because their recidivism rates mirror the trends of the nation. The Oregon State Criminal Justice Commission, a state-run commission created to “improve the legitimacy, efficiency, and effectiveness of state and local criminal justice systems” (CJC, 2019), provides a twice-yearly report on statewide recidivism rates. They collect data from the Oregon Department of Corrections on offenders who are starting felon probation and/or offenders starting parole supervision or post-prison supervision¹ in six-month cohorts. These cohorts are followed for three years (CJC, 2019). Overall, these reports note that one-year recidivism rates for the first half of 2017 consisted of 37.4% rearrests, 26.1% reconvictions, and 6.3% reincarcerations. Similar to other states, Oregon has placed many of their reform efforts into JRI. Oregon’s JRI aims to mirror the national JRI objectives with a statewide goal to reduce incarceration, and a county-based effort to invest the associated savings into community-based programs which attempt to reduce recidivism while holding offenders accountable and still keeping the public safe (HB 3194). This has led to the distribution of state grants

¹ Parole offenders are those who were sentenced to Discretionary crimes (committed before 1/20/1977) and Matrix crimes (committed between 1/26/1977 and 10/31/1989). Post-prison supervision is for offenders who committed crimes on or after 11/1/1989 and were given Sentencing Guidelines (Oregon.gov).

to a multitude of programs, including work release projects, re-entry courts, specialty courts, and other effective programs based on empirical evidence (Oregon.gov, 2019).

One such JRI effort is the Clackamas County Transition Center, the focus of this study. The Center was established specifically to address the county's recidivism rates through targeting the many barriers of reintegration. These barriers can include issues like difficulty accessing housing or employment, substance abuse, and mental illness (Gunnison & Helfgott, 2013). The Center offers a variety of services to assist with these barriers by targeting these needs with programs that have been shown to reduce recidivism and assist in the reentry process.

Clackamas County created the Transition Center because it possesses similar recidivism² rates as the state and nation. The county has a rearrest rate of 34.7% within one year of release, 25.8% reconvictions for a new misdemeanor or felony, and 4.5% reincarcerations for a new felony. Under the parameters of JRI, there is a certain expectation of what consists of an "evidence-based" program. It is "evidence-based" if it uses empirical research to direct its creation and implementation (Mears, 2013). However, the prevalence of "evidence-based" programs that are not actually based in evidence has led researchers to posit new methods to determine if a program is truly evidence-based, such as anchoring ranking scopes to credible methodological sources, ensuring the research population matches the served population, and confirming the

² Recidivism as defined by the Criminal Justice Commission, see Dependent Measures for more information.

components being delivered match those being studied (Campbell, Abboud, Hamilton, van Wormer, & Posey, forthcoming).

One of the stipulations for funding from the Oregon JRI is that programs must be evaluated for their effectiveness and cost savings (Oregon.gov, 2019), using randomized controlled trials (RCT) when possible. Although RCTs are considered the gold standard for evaluations (Shaddish, Cook, & Campbell, 2001), they are not always feasible due to ethical concerns or implementation methods. Such is the case with the CTC. Thus, this study is an outcome evaluation of the CTC that employs a quasi-experimental design through propensity score modeling (PSM). Specifically, PSM matches a historical sample from Clackamas County to clients of the CTC to measure the effectiveness of the CTC at reducing recidivism. Propensity score modeling (Rosenbaum & Rubin, 1983) is a statistical method that approximates an RCT. Using PSM allows for an unbiased estimation of the average causal effect³ of the CTC and reduces the risk of confounding variables to internal validity (Austin, 2011).

³ Also known as the average treatment effect, or ATE.

Literature Review

Principles of Effective Intervention

To increase the likelihood that a rehabilitative program like the Clackamas Transition Center is successful, it should adhere to the Principles of Effective Intervention (PEI). These principles are based in meta-analyses, narrative reviews of offender treatment research, and insights from recidivism and reentry scholars (Gendreau, 1996). A program is only as effective as its implementation. The Principles of Effective Intervention help to certify a program is completing its goals of rehabilitation and treatment successfully.

The Principles of Effective Intervention led to the creation of the Core Correctional Practices. There are five dimensions of effective correctional practice - effective use of authority, anticriminal modeling and reinforcement, problem solving, use of community resources, and interpersonal relationships (Andrews & Kiessling, 1980). This was further updated to become the Correctional Program Assessment Inventory (CPAI) (Gendreau & Andrews, 2010), which measures how well a correctional treatment program properly adheres to effective correctional treatment (Labrecque, Schweitzer & Smith, 2013). One method of effective correctional treatment that has consistently been shown to be successful is the use of the risk-need-responsivity model (RNR).

Addressing risks and needs for people on supervision

The RNR model is an approach to using risk assessments to help guide supervision plans via targeting criminogenic needs through a focus on three principles (Andrews, Bonta, & Hoge, 1990). These principles are: Risk, or who should be targeted

for treatment, Need, or what should be targeted, and Responsivity, or how we should target a person's needs and risks. The RNR model is not a specific program. Rather, it is the belief that recommendations for a person's treatment should be based on their specific needs and risk factors. This model has been used frequently in recent offender treatments (Ogloff & Davis, 2006), but has often had issues when it comes to implementation in agencies (Taxman & Marlow, 2006). Even so, the RNR principles have been consistently shown to be an effective approach for targeting treatment and reducing recidivism. For instance, in an analysis of 13,676 offenders from 97 correctional programs found that programs which adhered to the risk principle by targeting their efforts on high-risk offenders were more effective in reducing recidivism than those that did not (Lowenkamp, Latessa, & Holsinger, 2006).

Risk

The Risk principle has two purposes. The first is to determine who is most likely to reoffend. The RNR model uses the 4th generation of risk assessments. These assessments measure an offender's likelihood to reoffend, and all generations are still used to varying degrees. Objective risk assessments, also known as actuarial risk assessments, use statistical algorithms that use empirically proven recidivism measures (Hamilton, Kigerl, Campagna, Barnoski, Lee, van Wormer, & Block, 2015) to predict recidivism. In other words, they calculate a person's likelihood to recidivate based on statistical measures that have been shown to predict recidivism. These recidivism measures have been discovered through meta-analyses of the factors related to criminal

activity (Gottfredson & Moriarty, 2006), or are grounded in criminological theory (Andrews, Bonta, & Wormith, 2006).

An important factor to note is that actuarial risk assessments measure the likelihood of all offenders as an average of particular groups, and not as individuals. This means a person can have a low-risk score and recidivate, or have a high-risk score and not recidivate, because the likelihood of recidivating is based on the individual's domain scores that are associated with the group's statistical averages. In other words, these risk assessments are not able to predict a specific individual's likelihood to recidivate using only their unique risk factors. Rather, it creates the likelihood the person with their risk score will recidivate, based on people with similar characteristics and scores who did or did not recidivate before.

The Risk principle's second purpose is to ensure that the majority of treatment resources and efforts should be focused on offenders who have a higher risk of recidivating than those with a lower risk score (Andrews, Bonta, & Hoge, 1990). Concentrating too-strict treatment on low-risk offenders can have an iatrogenic effect and increases their risk of future offending (Lowenkamp & Latessa, 2005). These negative effects can involve being displaced from a supportive community or coming into contact with high-risk offenders through treatment. Because of this, the Risk Principle also directs that treatment programs should be separated by risk level, so as not to mix low- and high-risk offenders. In other words, this principle states that a person's risk level matches them to the level of service they receive (Bonta & Andrews, 2007).

Risk Assessments used in Clackamas

The RNR model uses the 4th generation of risk assessments. These assessments measure an offender's likelihood to reoffend, and all generations are still used to varying degrees. Objective risk assessments, also known as actuarial risk assessments, use statistical algorithms that use empirically proven recidivism measures (Hamilton, Kigerl, Campagna, Barnoski, Lee, van Wormer, & Block, 2015) to predict recidivism. In other words, they calculate a person's likelihood to recidivate based on statistical measures that have been shown to predict recidivism. These recidivism measures have been discovered through meta-analyses of the factors related to criminal activity (Gottfredson & Moriarty, 2006), or are grounded in criminological theory (Andrews, Bonta, & Wormith, 2006). An important factor to note is that actuarial risk assessments measure the likelihood of all offenders as an average of particular groups, and not as individuals. This means a person can have a low-risk score and recidivate, or have a high-risk score and not recidivate, because the likelihood of recidivating is based on the individual's domain scores that are associated with the group's statistical averages. In other words, these risk assessments are not able to predict a specific individual's likelihood to recidivate using only their unique risk factors. Rather, it creates the likelihood the person with their risk score will recidivate, based on people with similar characteristics and scores who did or did not recidivate before.

The 2nd generation focuses its attention on static measures. Static factors are immutable, such as a person's age at the time of their evaluation and their race. An actuarial risk assessment specific to the State of Oregon, Public Safety Checklist (PSC),

is a 2nd generation tool. It is an automated assessment that solely relies on static risk factors. This quick appraisal (CJC, 2019) is based on an offender's:

- Current age
- Gender
- Age at first arrest
- Total number of statutory, property, and person arrests
- How many of those occurred in the past five years
- Severity of current crime
- Multiple custody cycles
- Prior incarceration(s)
- Prior theft conviction
- Prior revocation
- Previous sentence type (probation or incarceration)

These variables create a composite score of the probability an offender will either be re-convicted or re-arrested for a property or person crime within three years of release. The scoring is then trichotomized into low-risk (score of 20% or lower), medium-risk (21-80%), and high-risk (81-100%) offenders. The assessment has been shown to properly predict a person's risk-level with at least 70% accuracy (CJC, 2019). The PSC is a valuable supplementary tool to other assessments due to its accessibility, as anyone can receive a score without additional evaluative training, and ease of use.

The Level of Service/Case Management Inventory (LS/CMI) is an actuarial 4th generation risk assessment designed to structure offender supervision using the RNR model. It includes a number of static aspects of an offender, such as their incarceration history, social and mental health history, and criminal history (Andrews, Bonta, & Wormith, 2006), as well as dynamic factors. As stated previously, these are factors that can be targeted with treatment and can change over time, such as a current drug or alcohol addiction(s), problems with family, or mental health issues. Not every risk assessment includes dynamic risk factors, but targeting them has been shown to improve

recidivism by supplementing the recommendations made from static risk factors (Serin, Gobeil, Lloyd, Chadwick, Wardrop, & Hanby, 2016). Fourth generation risk assessments also offer plans for how to target a person's risks and needs with treatment. It is referred to as a responsive instrument (Hamilton et al., 2015) because of the inclusion of targeted treatments.

The LS/CMI also measures the "Central Eight" risk factors for recidivism (Andrews, Bonta, & Hoge, 1990). The composite LS/CMI score can range from 0 to 43. Each domain has its own scoring, and these individual scores are added together to create an overall score. A person can have an overall low score but be at a high risk in a particular domain. These specific domains can be targeted with treatment, although there is currently some debate on specific domain targeting can be successful or not for females (Vitopoulos, 2012). The LSCMI has been shown to have high reliability and validity. A study of its predictive validity found the combined total score correctly predicted male recidivism 74.6% of the time, and females 82.7% of the time (Andrews, Guzzo, Raynor, Rowe, Rettinger, Brews, & Wormith, 2012). Risk assessments, and the LS/CMI specifically, are shown to be something that "works" in reintegration, and are frequently used in reintegration programs.

Need

The Need principle decides "what" to treat to improve an offender's likelihood of recidivism. It does this by determining an offender's criminogenic needs. These needs, also known as dynamic risk factors, are those that can be changed and can be predictive of reoffending (Latessa & Lovins, 2010). The most predictive of these are the "Central

Eight” risk factors,⁴ which were determined via meta-analyses (Andrews & Bonta, 1998) of varied offender groups. These are:

- Antisocial or procriminal behavior, personality and cognition
- Procriminal associations and distance from prosocial associations
- History of antisocial behavior
- Family concerns
- Personality factors such as impulsivity
- Lack of achievement in work or school
- Lack of prosocial leisure and recreational activities
- Substance abuse

Once an offender’s needs have been determined, they can be targeted with treatment and potentially reduce future crime. These treatments should focus on criminogenic needs, such as the Central Eight listed above, or with other factors associated with criminal conduct (Latessa & Lovins, 2010), including but not limited to housing or employment instability, mental illness, or lack of an education (Travis, 2005).

Responsivity

The final principle, responsivity, answers how treatment should be implemented; it is determining how the treatment should be delivered in a way that considers the offender’s learning style and abilities (Bonta & Andrews, 2016). There are two forms of responsivity: general and specific. General responsivity refers to the prevailing forms of influencing antisocial behavior: the cognitive-behavioral and cognitive social learning methods (Bontas & Andrews, 2016). The second form of responsivity, specific, is ensuring treatment matches an offender’s characteristics and their specific needs. It

⁴ All of these risk factors are dynamic (i.e. criminogenic) except for the history of antisocial behavior, which is a static risk factor.

argues for differential treatment, meaning that offenders are matched to treatment that is based on their own abilities.

The use of RNR has been shown to work in rehabilitative efforts and in the reintegration process (Bontas & Andrews, 2016). However, it is not the only aspect necessary for an effective intervention.

“What Works” in Reintegration

The argument that “nothing works” in corrections (Martinson, 1974) has been largely replaced by the question of “what works?” (Petersilia, 2003). Many reentry programs follow the RNR principles by addressing an offender’s criminogenic needs while also considering their risk during the transition process. While there are numerous program methods, from intermediate sanctions such as boot camps to educational programs in prisons (Aos & Drake, 2012), this review will focus on concepts that have been proven to assist in the reentry process – continuum of care and cognitive behavioral treatment, and two programs which use these methods: Day Reporting Centers and Community Justice Centers

A concept shown to be integral to the reentry process is the use of a continuum of care. First used in the healthcare system (Evashwick, 1989), the continuum of care refers to the unbroken assistance during a patient’s movement between treatment stages. In criminal justice, continuum of care refers to maintaining a focus on addressing criminogenic needs while the individual is incarcerated, and maintained after the person is released. Services begin while the offender is still incarcerated, and continue post-release with outpatient services that assist with the transition process (Taxman, 1998). In

this context, the continuum of care increases the amount of time an offender is able to receive treatment through multiple stages of the criminal justice system (i.e., from prison to parole). Having continuum of care treatment options for offenders both while still in prison and once released offers more stability and reduces the likelihood of recidivism. An in-prison therapeutic community combined with residential aftercare was found to decrease recidivism (Wormith & Olver, 2002).

Continuum of care also increases treatment retention, and treatment attrition has been linked to recidivism. A meta-analysis of 114 studies on treatment programs reported a positive relationship between treatment attrition and recidivism, with recidivism rates between 10-23% higher for program dropouts than program completers (Olver, Stockdale, & Wormith, 2011). Treatment attrition is also most likely to occur for the most high-risk participants, meaning that the people who are in most need of assistance are the least likely to receive it (Olver et al., 2011). The continuum of care works as a protective factor for these participants by involving unbroken access to services.

Another concept linked to successful reentry is the use of rehabilitative methods, such as cognitive behavioral treatment (CBT). CBT falls under the responsivity principle by treating offender's dysfunctional thought processes by teaching problem solving, pro-social skills, and improving self-efficacy (Mpofu, Athanasou, Rafe, & Belshaw, 2018). A review of adult correctional programs' ability to reduce recidivism by the Washington State Institution for Public Policy (2001) found that cognitive behavioral treatment (for the general offender population) reduced recidivism by 8.2%. A specific method of CBT is moral reconnection therapy (MRT). This method works to strengthen an offender's use of

“conation”, the psychological term for actively making moral decisions (Ferguson & Wormith, 2012). A meta-analysis of MRT outcome studies showed that, while the use of MRT was more successful for institutionalized adults than institutionalized juveniles, it had an overall small but significant impact on recidivism reduction (Ferguson & Wormith, 2012).

As previously mentioned, there are numerous programs that are available for offenders during the reentry process. A common approach used by many states to aid the reintegration process by addressing criminogenic risks and needs are the use of Day Reporting Centers. These can be described as “one-stop shops” (DRP, 2018) where clients can access a host of services to aid in their reintegration, such as employment assistance, drug and alcohol abuse treatment, and family counseling. A client is assigned to a Day Reporting Centers by their probation or parole officer and required to report in on a regular basis. Clients can receive sanctions for failing to check in or complete the tasks assigned to them by the Day Reporting Center. These programs are considered an intermediate sanction due to their involuntary nature (Marciniak, 2000).

There have been multiple evaluations of Day Reporting Centers (Ostermann, 2009; Boyle, Ragusa-Salerno, Lanterman, Marcus, 2013; Ostermann, 2013) with mixed results, which could be partially attributed to program fidelity. Boyle et al. (2013) recommended against the use of Day Reporting Centers, while Ostermann (2013) finds them to be effective at reducing the rates of reconvictions and reincarcerations post-release, but not rearrests. However, it is important to note that each Day Reporting Center is run based on its own standards and procedures, so no one study can evaluate all

variations of them (Ostermann, 2009). Because of this, it is difficult to compare Day Reporting Centers to each other. Along with this, their mandatory nature does not help to explain the processes involved in voluntary reentry programs, and thus leaves a research gap.

One of the few opt-in services are Community Justice Centers. The Washington State Department of Corrections describes them as a “nonresidential facility...in which recently released offenders may access services necessary to improve their successful reentry into the community (WADOC, 2019). Services provided include employment assistance, mental health treatment, and parenting classes. Unfortunately, at the time of this writing, little research has been done to evaluate these voluntary centers and their reduction of recidivism. An evaluation of San Francisco Community Justice Centers (Kilmer & Sussell, 2014) measured recidivism for one year in districts that included a Community Justice Center. The researchers were able to measure both before and after the Centers were implemented. After controlling for a number of factors, the researchers found the Centers reduced the likelihood of rearrest within one year between 8.9 and 10.3%. This study, although promising in demonstrating the effectiveness of voluntary reentry assistance programs, is specific to the San Franciscan Community Justice Center model and consequently more studies are needed to replicate their results elsewhere.

The Use of Propensity Score Modeling in Criminology

Propensity Score Modeling has been used widely throughout the criminal justice system and has been successfully applied in the field of reentry program evaluation.

Criminologists use PSM to measure the treatment effect of discrete events on a person’s

criminal behavior (Apel & Sweeten, 2010). The ability to create a quasi-experimental study that approximates the results of a randomized controlled trial has been used to study prison segregation (Clark, 2018), juvenile programming (van Wormer & Campbell, 2016), and incarceration effects (Jolliffe & Hedderman, 2015).

PSM has also been used to study recidivism, but the general focus has been on prison treatments and their effects post-release. Bales & Piquero (2011) used the method to study the effects of imprisonment on reoffending, Duwe & Johnson (2015) found that visits from community volunteers reduced recidivism through PSM, and a study of Dutch prisoners used PSM to report that offenders recidivated less if they participated in community service rather than being incarcerated (Wermink, Blockland, Nieuwbeerta, Nagin, & Tollenaar, 2010). There are a small but strong number of studies that use PSM to evaluate reentry programs. One of the closest studies involves therapeutic communities and recidivism, but placement in the communities was assigned by the Department of Corrections (Jensen & Kane, 2012).

Some of the few studies that use PSM to study community corrections, such as Hamilton's halfway house placement evaluation and Ostermann's study of Day Reporting Centers, do provide support to the use of PSM for rehabilitative measures. Hamilton and Campbell (2014) used propensity score modeling to match participants who received a halfway house placement to offenders who did not receive a halfway house placement. Their results showed that halfway house placement was able to reduce the likelihood of returning to incarceration via parole revocations and other returns to prison, but had nonsignificant findings for the typical recidivism measures of rearrest,

reconviction, and reincarceration for a new crime. Their matching process and results exhibit the usefulness in PSM for non-randomized placement procedures.

Ostermann (2011) used PSM to determine if there was a significant difference in recidivism between inmates who voluntarily refused parole in lieu of serving their entire prison sentence and released unconditionally to those assigned to mandatory six-months of parole post-release, regardless of unconditional release status. Although the results suggested there was a significant difference between discretionarily released parolees and mandatorily supervised parolees, the between-group difference was minor. In other words, although the results did show there was a significant difference between the two groups, the actual effect size was small. This study does consider voluntary decisions, but because the treatment group was assigned to mandatory supervision, more research about non-mandatory treatment programs are needed.

Even with these successful PSM efforts, continued research is required; particularly on non-assigned, voluntary reentry programs that are able to have opt-in biases controlled for with PSM. In addition, both Hamilton and Ostermann's studies were completed using New Jersey data, and so it would be beneficial to replicate their results in other states.

Gaps in the Literature and Current Study

The lack of literature on voluntary reentry programs, coupled with the nascent existence of the CTC, means that there is a dearth of research on opt-in programs that are able to control for selection biases, as this study can. The use of PSM has grown considerably since its creation in 1983, and its use in measuring the effects of recidivism

and rehabilitative programs can help to even better determine “what works”. It also provides additional examinations of the RNR principle and the LS/CMI and PSC risk assessments.

Previous research has demonstrated that reentry programs and risk assessments can work to reduce recidivism. However, more research is needed, especially considering America’s high recidivism rates. The creation of the Justice Reinvestment Initiative and its dedication to funding practices that assist with the reentry process speaks to the nation’s continued focus on reducing recidivism and improving practices. Additionally, part of the funding offered by the JRI is dedicated to the evaluation of their programs for efficiency and effectiveness. This study contributes to the JRI’s requirement of program evaluation at the preliminary level.

Setting

Clackamas County possessed a rate of 97 prison intakes per 100,000 in 2017. This was further broken down into drug, driving, and property crimes (52.6% of prison intakes), person crimes (18.5%), other (16.5%), and sex crimes (11.3%). In comparison, the State of Oregon had a rate of 118 prison intakes per 100,000 citizens, with drug, driving and property crime making up 50.8% of their intakes, followed by person (24.5%), other (13.5%), and sex crimes (11%). Even though below the state average, Clackamas County was looking to further reduce their imprisonment and recidivism rates by implementing the CTC through Justice Reinvestment.

The CTC is located in Oregon City, the county seat of Clackamas. It was established using JRI funds in 2015, and officially opened to clients in February 2016. Clackamas County received \$2,407,093 of the \$37,537,822 allocated to counties utilizing the Justice Reinvestment Grant Funding. Of this, 56.4% went to Transition Services, with \$130,000 going to housing assistance, and \$1,228,769 specifically to reentry programs. The CTC is similar to Day Reporting Centers due to also being a centralized location for resources for clients. However, it differs, as it is not an alternative to incarceration (Rhyne & Hamblin, 2010), and does not use surveillance on its clients (Marciniak, 2000). Rather, it is an opt-in service that offers services and resources without being linked to a client's release conditions or treatment.

The Transition Center can be best described as a "hub" which connects clients to local resources in the community and offers access to services. These services include:

- Cognitive therapy
- Mental health and substance abuse assessments
- Housing assistance
- Peer mentors
- Employment assistance
- Parenting classes
- On-site healthcare
- GED courses from the local community college
- Basic needs/hygiene items

Many of the services offered in the CTC are from community partners who contribute their resources and experience. These partners offer cognitive behavioral programs, substance abuse treatment, and healthcare assistance, among other services. Between its opening in February 2016 and the end of 2017, over 3,000 unique visitors have accessed the Center in some form.

The CTC focuses on assisting its medium- to high-risk visitors (as designated by the LS/CMI scores). However, it also attempts to decrease the number of individuals entering jail in the first place by allowing walk-ins from the community and people who have had contact with law enforcement (Clackamas, 2016). These lower-risk individuals are also offered services and support with their needs as an attempt to preclude them from the criminal justice system, but per the Principles of Effective Intervention are separated from high-risk offenders. The main goal of the CTC is to “break patterns and change lives” (Clackamas County, 2018).

In its goal to break patterns and change lives, it has three main distinctive characteristics. The first is its accessible location. The Center is housed in a building that is within walking distance of the Clackamas County Jail, the two separated only by a parking lot. The second is the ability of probation officers to “reach-in” to clients while they are still incarcerated in prison or jail. Officers can connect to people currently

incarcerated and complete risk assessments, begin CTC referrals, and work on release plans. In this way, there is a continuum of care from pre- to post-release. The Center provides this continuum of care for many of its clients by having the opportunity for probation officers being creating release plans and making referrals for many clients prior to leaving incarceration, and by allowing for unlimited visits to the Center for assistance post-release. Finally, citizens in the county have the option of “walking in” to the CTC and receive support without the requirement of being under supervision. Thus, the CTC is accessible to the population as well as those who have been in custody or are on supervision. Although the CTC is not mandatory, many POs make it a part of a client’s case plan to achieve goals that can be assisted by the CTC, such as gaining employment or housing.

Upon an offender’s first visit to the Center, Probation/Parole Officers (PO) begins documenting their experience. POs catalogue the date a person visited the CTC, and a visitor’s State Identification Number (SID, which was changed to RID before analysis), and what services they were referred to.⁵ POs can also conduct an LS/CMI. These can occur either before they are released from prison or jail or within 60 days of their release. Although the CTC is not mandatory, many POs make it a part of a client’s case plan to achieve goals that can be assisted by the CTC, such as gaining employment or housing. It could be argued that offenders who are assigned conditions in their case plan that can be accessed at the Transition Center are not choosing to access the Center entirely

⁵ These services are not mandatory; they are suggestions for resources they can access at the CTC. These were not included in the analysis because POs did not specify whether or not a person accessed the services they were referred to and thus were not a reliable measure of services received.

voluntarily and are coerced to. Although the Center is not the only location in Clackamas County that provides the condition requirements, and they are not required to go to specifically choose to visit the Center, due to the ease of access to the Center it is possible this has an effect on how entirely voluntary visiting is. That being said, it still differs from other non-voluntary reentry assistance programs, such as Day Reporting Centers, as an offender is not penalized for not specifically visiting the Center. Instead, they are sanctioned only for not accessing the treatment at any location.

Methodology

The JRI has several requirements in order for a program to receive funding. Its initial requirement is that the program(s) funded must be evidence-based. The CTC meets this condition by employing the risk-need-responsivity principle of focusing on high-risk offenders (Andrews, Bonta, & Hoge, 1990) and its use of the validated risk assessment tool, the Level of Service/Case Management Inventory (LS/CMI). The JRI also requires programs can demonstrate they are effective. The JRI sets aside 3% of its funds for the research and evaluation of its sponsored programs. This evaluation is a preliminary examination of the effectiveness of the CTC in order to determine if it meets this JRI standard.

Research Question and Hypothesis

This study is an examination of the CTC's effectiveness in reintegration assistance. As such, the research question is as follows:

To what extent does the Clackamas Transition Center influence supervision outcomes of recently released offenders?

Based on previous works evaluating Day Reporting Centers and reentry programs (Ostermann, 2009; Rhyne et al., 2010, Severson, Veeh, Bruns, & Lee, 2012), I have the following hypothesis:

H1: Visiting the Transition Center will reduce a participant's likelihood to recidivate as measured by rearrest, reconviction, and/or reincarceration.

Because this type of voluntary center has received little attention in the literature, my research question suggests a two-tailed test in that it possesses equal chances of succeeding and failing to reduce recidivism. I am able to explore whether the CTC had any influence at all, either positively or negatively.

The current study uses data from the Clackamas County Community Corrections department and the State of Oregon Criminal Justice Commission (CJC). The county collected CTC observations' information at their first visit, which typically coincided with their release from prison or jail, although walk-ins were also possible.

Sample Data

The historical sample was obtained from the Criminal Justice Commission for any offender released to Clackamas County from 1/1/2012 to 12/31/2015. It includes the same demographic information available for CTC visitors. The only difference is that they have no CTC visit information. To ensure confidentiality, all data was de-identified prior to analysis and disseminated at the aggregate level to ensure no individual could be identified. In other words, their original State Identification Number (SID) was replaced with a Random Identification Number (RID). The RID ensured confidentiality, as offender's names were not included, and meant the project was marked exempt from the Institutional Review Board.

A person is eligible for the study if they have a commitment offense, an LS/CMI score and was over the age of 18 at the time of their commitment offense or CTC visit,⁶

⁶ Please see Appendix A for more detailed information about the differences between eligible and ineligible offenders.

depending on if they were part of the historical or CTC samples. The commitment offense is the crime that led to their incarceration or supervision prior to the collection of CTC data. This also excludes visitors who were “walk-ins” from the community who were not involved with the criminal justice system, as this study’s goal is to study recidivism. If the “walk-ins” commit a crime after visiting the CTC, it would be classified as a “new” crime instead of as recidivism. The historical sample does not include any people without a commitment offense because it is based on official data from the State of Oregon. The LS/CMI score is required because it is one of my main independent variables. As this study considers the Center’s use of RNR procedures, it was important to include a risk assessment that considered dynamic factors as independent variables, as well as the PSC score that considered static factors. Finally, juveniles are excluded because the juvenile justice system handles cases differently than adult courts, and the juvenile aftercare differs from adult parole (NCJJ, 2014).

Ultimately, the pre-match sample⁷ examined in this study includes people released to Clackamas County Community Corrections between 2012 and 2017. The data was pulled in July of 2018, allowing for at least 6 full months of follow-up, with the shortest follow-up for CTC visitors from December of 2017. The majority of the historical sample were followed for over three years. I control for this disparity in follow-up time in the outcome analyses.

⁷ The term Pre-Match describes the sample before PSM, but after removing ineligible offenders.

Measures

Independent Measures

The main independent variable is contact with the Center's services in some way, which was dichotomously coded as 0 (no) or 1 (yes) for visiting the Center at any point since its creation. The Transition Center sample received the "treatment" of visiting the CTC, and the historical sample was the "control". The number of visits a person made to the Center was recorded, but the complexity of analyzing recidivism rates per number of visits, as opposed to a yes/no variable, was beyond the scope of this current project.

POs record the bulk of information about an offender's CTC visit, including independent measures such as a client's LS/CMI scores (both as their combined total score and each domain's score). As noted in the literature review, these measures (in some form) are commonly used in evaluations of reentry programs (Ostermann 2009; Spence & Haas, 2015). The Criminal Justice Commission, who provided more detailed information obtained from the Oregon Department of Corrections based on an offender's SID, supplemented this information. This additional information includes **demographics** such as an offender's gender and race, age at time of release, and PSC score. All of these demographic factors were used both in the creation of the propensity score and as a control for the binary logistic regression.

Age at release

Prior research on reentry across 30 states (Durose et al., 2014) found that in five years, post-release, 84.1% of offenders released at age 24 or younger had been rearrested

for a new offense. Subsequently, age was viewed as a critical measure for this study. Age was recorded by the Oregon DOC at the time of release, and is measured in years.

Gender

Gender has also been shown to be predictive of recidivism, in that males consistently demonstrate a higher likelihood to reoffend. The same longitudinal study of prisoners released from 30 states reported males were arrested post-release with more frequency than females. In their first year post-release, 44.5% of males had been arrested compared to 34.4% of females (Durose et al., 2014). For this study, gender is coded as a dichotomous variable (0 = not male, 1 = male).

Race

Race has been shown to be a predictor of recidivism, as non-Hispanic whites are rearrested at a lower rate (39.7%) in the one year after release from prison as compared to non-Hispanic blacks (45.8%) and Hispanics (46.3%). This difference could be partially attributed to the inherent disadvantages faced by non-whites in the criminal justice system and in the reentry process, making it an important control measure for my study. Clackamas County is predominately white, with 89.4% identifying as such in the 2018 census estimates (Census.gov, 2019). The remaining 10.6% is made up of Hispanic or Latino residents (8.7%), African American residents (1.1%), Asian Americans (4.6%), indigenous persons (1.1%) and Native Hawaiian or Pacific Islander (.3%). 3.5% are noted as two or more races. Due to the overabundance of White citizens, and

underrepresentation of other races, I code race into a dichotomous variable where 0 = non-white and 1 = white.

Risk Assessments

A study of a sample of offenders found the PSC was able to predict recidivism correctly in 72.9% of felony reconvictions, 69.5% of arrests for a person crime, and 76.1% of property arrests (Gibbons, 2012). For this study, the PSC score is left as a continuous variable gauging risk from one's criminal history, with scores between 0 and 1. A lower score indicates a lower risk of recidivism, and vice versa. This is included as an independent variable because of its predictive validity and this score, alongside the LS/CMI, can be used in determining the level of supervision someone receives. These scores were used to some capacity in both the propensity score creation and the binary logistic regression.

LS/CMI information was given by the CJC in both its raw number scores for each domain⁸ and in pre-determined classifications of their recidivism risk as *very high*, *high*, *medium*, *low*, and *very low*. These classifications collapse ranges of domain raw numbers into easily determined and comparable scores. Depending on the domain, a raw numerical score could have a max of 2 for leisure and recreation to a max of 9 for education and employment (Davidson, Haas, Spence, & Arnold, 2015). Because of this variability, I use the pre-determined classifications instead of the raw numbers because the uniformity of rankings is easier to compare and understand. These allow for an easier

⁸ The eight domains mirror the Central Eight risk factors noted on page 9.

at-a-glance review of a person's risk. Future iterations of this study would benefit from using the raw scores, but because of the preliminary nature of this evaluation the dichotomization of the LS/CMI scores was deemed acceptable.

All LS/CMI levels (overall and by domain) were recorded into dummy variables (e.g. 1 = high overall risk, 0 = any other overall risk level). This meant that each of the eight domains had dummy variables for each level of severity: *very high risk*, *high risk*, *medium risk*, *low risk*, and *very low risk*. The exceptions to this were recreation, which had no responses in the *very high* and *low* ranges, and my total LS/CMI score combined *low and very low* into one dichotomous variable, due to the small base-rates for *very low*, which could have affected results.

Type of Release

Instead of relying upon self-reporting from offenders, their type of release was recorded by the CJC with the following options: Released from jail/local control, prison, and post-prison supervision (PPS) or parole. I include this measure because the difficulties of reentry are amplified for offenders who were recently released from incarceration as compared to those allowed to remain in their communities on supervision (Travis, 2005), in numerous aspects. It has been shown that finding and maintaining employment is integral to reentry success (Baer et al, 2006), but people returning from incarceration may or may not have a job waiting for them post-release (Travis, 2005). If they do not, their chances of obtaining a job significantly reduce due to their criminal history and the stigma accompanying it (Durose, Cooper, & Snyder, 2014). These types of release are coded in dichotomous no (0) and yes (1) variables for each of the three

options. These variables are included both in the propensity score creation and as controlling variables for the binary logistic regression.

A person is unable to have multiple release types recorded. While the CJC also provided the most serious commitment offense, the most serious charge for the offense that led to their incarceration or supervision, it was not used in this study due to its breadth of options that would divide my samples into too small groups.

Days between Admission and Release

A second method to determine the type of release was the number of days between being sentenced and being released. This was included to add more in-depth information about how much time an offender was either incarcerated or on some form of supervision prior to their release. I calculated this by subtracting the date an offender was convicted from the date they were released. This was used to create the propensity score because it offered more detailed information about the amount of time a person was incarcerated or under supervision than type of release did alone, but not as a controlling factor in the binary logistic regression. This was a continuous variable measured in days.

Time at Risk

The binary logistic regression model included a continuous measure of length in time out in the community measured in days as a control variable. This variable shows how long a person was at-risk in the community before they “failed” with a recidivating action or succeeded (no recidivism as of collection date), to control any difference between the historical and CTC samples in time at-risk. This was calculated by

subtracting the date a person was released from either the soonest date post-release they came back into contact with the criminal justice system for a recidivating event (e.g. rearrest, reconviction, or reincarceration), or from the day the data was pulled for those who did not recidivate.

Dependent Measures

The dependent measures for this study took the definition of recidivism according to the state of Oregon,⁹ which includes multiple types. These comprise any new arrest, conviction, or incarceration, which are dichotomized and coded as 1 = occurred, 0 = did not occur. Typically, an evaluation of a reentry program or policy measures recidivism by whether or not an offender was reconvicted and/or reincarcerated (Boyle et al., 2013, Ostermann, 2011). However, as previously stated, House Bill 3194 (2013) also includes rearrest for a new felony or misdemeanor in its definition of recidivism (CJC, 2019). I include all three measures because all are relevant to the study. Rearrest information is a broad measure that allows for a generous estimate of reengagement with criminal activity. Incorporating reincarceration allows for probation/parole revocations as well as new convictions, which captures those returned to prison from supervision but who did not receive a new sentence. Finally, the inclusion of reconviction is useful because it is the most conservative estimate of recidivism: to be reconvicted a person must go through the entire court process.

The CJC provided these outcomes measures by documenting recidivism data as of July 2018. The CJC created new variables for rearrest, reconviction, and reincarceration.

⁹ The State of Oregon also measures these recidivism markers for 3 years following release.

If a person committed a new offense, the date of the offense was added to the corresponding variables. If the person continued through the criminal justice system towards reconviction and/or reincarceration, the disposition date(s) are added. If a person did not recidivate, or did not go through the entire criminal justice system to being reincarcerated, there is no date available. Thus, a person could have a date for a rearrest, but not for a reconviction if they had not been reconvicted. I coded these dates into dichotomous variables by creating a new variable that had a score of 1 (yes) if there was a date, and 0 (no) if there was not, for each of the three recidivism measures of rearrest, reconviction, and/or reincarceration. Finally, a continuous measure of length in time out in the community is measured in days is included as a control variable

If an offender had a score of 1 for any of the preceding variables, I gave them a score of 1 in a dichotomous measure of any form of recidivism. This is an overarching measure of recidivism combines all three forms – rearrest, reconviction, and reincarceration.

Analytic Plan

As previously mentioned, a randomized controlled trial is not feasible for the CTC. It was not possible to randomly assign people to visiting the CTC or a control group retroactively since its creation in 2016, and it would involve denying support to people seeking help. Because attending the CTC allowed for participants to opt-in, there is inherent selection bias (Rosenbaum & Rubin, 1983). In other words, there could be something qualitatively different about those who self-selected, or opted-in, to attend the CTC as compared to those who did not. This is important because these same traits (e.g. motivation) that led someone to choosing to visit the CTC could also lead to differing recidivism outcomes than those who did not choose to go.

PSM reduces selection bias of the opt-ins by matching those who visited the CTC to a historical sample of offenders released in Clackamas County between 2012 and 2015 who may or may not have opted into visiting the CTC, had it been available. It can find counterfactual cases from the historical sample (control) who have similar characteristics to people who visited the CTC (treatment). By matching comparison cases to the CTC participants on all available and theoretically relevant measures, the observable selection bias created by the opt-in process can be reduced. This allows me to see what characteristics, if any, are qualitatively different between people who would choose treatment and those would not, and control for them. PSM allows for an unbiased estimate of the average causal effect of the CTC and reduces the risk of confounding variables (Lambert 2014, Austin, 2011). While it is able to reduce the risk, it cannot entirely eliminate it, as the PSM is only able to match on observable characteristics. Any

unobserved differences cannot be accounted for. This is a limitation of PSM, but as its ability to simulate a randomized controlled trial has been demonstrated (Campbell & Labrecque, 2018), it is not insurmountable.

Although some concern has been raised regarding how reliable PSM can be and how it can create additional imbalances (King & Nielsen, 2018), others have demonstrated the opposite. For instance, a recent cross validation meta-analysis comparing the performance of PSM to match RCT findings found that PSM can be a reliable and valid replacement to estimate causal inference if RCT is not available (Campbell & Labrecque, 2018).

The matching process starts with the creation of a “propensity score” for all participants from the treated (CTC visit) and control (historical) samples. In essence, this is a score that calculates the likelihood a person would or would not have participated in a treatment, had it been available to them. A score ranges from 0 (no possibility of treatment) to 1 (absolute certainty of treatment opt-in). This score is calculated by a logistic regression with the dependent variable being the odds of receiving treatment. The independent variables included are any that could influence a person’s likelihood of treatment based on the standardized percent difference between the pre-matched groups’ means for scores.

The standardized percent difference is calculated by completing cross tabulations for dichotomous independent variables and independent t-tests for continuous variables (Austin, 2008). The mean percent and standard deviation for the historical and CTC groups were entered, gained from independent t-tests and cross-tabulations. These inputs

were used to compute the standardized percent bias for continuous variables by subtracting the mean of the historical sample from the mean of the CTC sample, then dividing by the square root of their combined sample variances divided by two. Dichotomous variables were calculated by the subtraction of the historical mean from the CTC mean, divided by the square root of the (CTC mean (1- CTC mean) plus historical mean (1- historical mean)) divided by two. Dichotomous variables do not have sample variance, hence the change in the denominator (Austin, 2011). This creates a percentage score of the standardized difference in the groups' means between 0-100%. A standardized percent bias below 20% is needed to consider the variable in the propensity score, but a score over 10% is considered ideal (Campbell & Labrecque, 2018). Thus, a standardized percent bias over 10% was considered large enough to show there was a significant imbalance between the historical and CTC groups.

Before running the PSM, but after calculating the standardized percent biases, I estimated a binary logistic regression to determine how well the pre-match model could predict whether or not someone visited the CTC. The dependent variable was whether or not someone visited the CTC, and all the variables with a score over 10% (discussed in the results) were entered as covariates. The option to save predicted probabilities was selected to show the pre-match propensity scores. Once these were calculated it was possible to create an Area Under the Curve (AUC) score.¹⁰ The closer the AUC score is

¹⁰ The AUC assesses the ability of the propensity score to predict whether or not someone was in the treatment group (Rice & Harris, 2005). Before the match, a high AUC (preferably .715 or higher) means the propensity score was able to predict when someone received treatment (in this case, visiting the CTC) with 71% accuracy.

to .5 after the matching process means what made the treatment group unique is no longer predictable, thus simulating a randomized controlled trial.

Once these required steps were completed, it was possible to create a propensity score. Using the SPSS function for propensity scores with the fuzzy matching add-on,¹¹ the same covariates entered into the prior binary logistic regression are added to the propensity score calculation. The add-on requires there to be a match tolerance, also known as the caliper.¹² An appropriate caliper is $\frac{1}{4}$ of the standard deviation.¹³

Once a propensity score has been created, there are several options for how to “match” the treated and control groups. There are seven main propensity score models to measure counterfactuals, including propensity score weighting, kernel-based matching, and Heckman’s sample selection (Guo & Fraser, 2015, p 35). Each method has its own advantages and disadvantages. This study will use a 1-1 (read one-to-one) greedy matching with a caliper. A 1-1 greedy match with a caliper allows for matching between samples as long as they fall within the caliper range. Greedy matching breaks up the matching process into smaller designations, determined by the caliper. The treatment and control groups are compared to find similar propensity scores between a pair, and the pair is then removed from the potential matching pool.

The other matching style that can be used is optimal matching. This is a multi-stage process that can involve backtracking and relies on complete matched-pair samples.

¹¹ An extension command that performs case-matching of two datasets and allows the match to be exact or fuzzy (IBM, 2019).

¹² The caliper tells the program how large the difference between the group indicator’s propensity scores can be while still being matched.

¹³ As decided by Rosenbaum and Rubin (1983).

It requires matching all treated and untreated participants, instead of having an uneven number of treated and untreated options (which greedy matching can handle) (Guo & Fraser, 2005). Optimal matching develops matched sets where the total sample distance is minimized and pairs can be broken up to rematch to create more equal pairings. No pair is removed as they are in greedy matching, because they could be broken up and re-matched to new partners if the new pairing is more ideal (that is, less distance between the two).

Although the optimal matching method does give the opportunity for better-matched pairs, as optimal can allow for re-matching and greedy matching cannot, this does not mean that optimal is always the better choice. Both optimal matching and 1-1 with a caliper are capable of replicating an RCT (Campbell & Labrecque, 2018), but a comparison of model balance found the 1-1 with a caliper had an AUC of .539, compared to the optimal's score of .650. The goal after matching is to get an AUC as close as possible to .5, meaning that the likelihood of being in one group or another is a 50-50 chance. With the closer AUC score, the 1-1 with a caliper has been shown to be an effective matching method.

Following the PSM procedures, I use other statistical analyses to compare the groups on recidivism measures. These include cross-tabulations and independent t-tests to compare the means of the groups, and a binary logistic regression to gauge the predictive power of the CTC variable on recidivism. The cross-tabulations and independent t-tests are necessary to determine if there is a significant difference in means between CTC visitors and historical samples in their recidivism rates. Cross-tabulations

are used to show the relationship between two variables when they are discrete, and independent t-tests can determine if there is a statistically significant difference between two groups when one distinction is continuous. This is important because it allows me to view the interaction between my dependent variables (recidivism) and my independent variable (visiting the CTC). If the results are significant (denoted by a chi-square of $p < .05$), it means there is a measurable difference between the samples' recidivism that can be accounted for by the CTC variable. I also measured the Cohen's d effect size to compare how much of an effect the CTC had on the outcome variables. This measure calculates the standardized difference between the means for each group. I used the Campbell Collaboration's effect size calculator (Wilson, n.d.) to create my scores. The generally accepted effect size ranges are $d = .2$ for a small effect size, $d = .5$ for a medium effect size, and $d = .8$ for a large effect size. My pre-match Cohen's d analysis (see Table 2) revealed a small effect for all four outcomes, with a max d of .44.

The binary logistic regression is a predictive analysis that gives greater detail to the relationship between the dependent variables of recidivism and any controlling variables included and is able to estimate the probability that the predicted variable occurs or not based on the values of the explanatory variables (Field, 2013). Binary logistic regressions are used when the dependent variable is dichotomous, as my recidivism measures are, because linear regressions are not able to handle a dichotomous predicted outcome. It is an extension of linear regressions.

Results

Assessing the standardized percent bias between the historical (i.e., control) and CTC (i.e., treatment) samples' independent variables was the first step to create the propensity scores for the current study. I ran each cross-tabulation to see if there was a significant difference between whether or not someone visited the CTC (0 = no, 1 = yes) with the percent within each group calculated. Their significance was calculated with a chi-square test, where $p < .05$ being significant. I also used Independent T-Tests to compare the means between groups for continuous variables. Their significance was determined with the Levene's Test for Equality of Variances. These can be seen on the pre-match side of Table 1.

I included variables that exceeded a 10% standardized percent bias in my propensity score creation. It is preferable to have standardized percent biases below 20% post-match, but it is preferred to have a score over 10% to include it in the creation as it shows there are significant differences between the two groups (Campbell & Labrecque, 2018). Thus, a standardized percent bias over 10% pre-match was considered large enough to show there was a significant imbalance between the historical and CTC groups and was included in the propensity score creation. These were: whether or not someone had been sentenced to prison before starting their supervision (% bias 20.8), whether or not they were sentenced to jail or local control prior to starting their supervision (% bias 26.1), if their total LSCMI score was very high (10.6), and if they had specific LSCMI scores of very low for family (10.4), drug use (11), attitude (10.7), and antisocial (13.1).

Finally, the continuous variables of age (12.4), PSC score (26.1), and days between their admission to their sentence and their supervision began (23.4).

I also included one 9.5% score, a *very-low* LSCMI score for Leisure/Recreation, because it was .5% away from 10. Research shows how a person spends their free time could influence whether they would want to receive treatment (Schmidt, Lien, Vaughan & Huss, 2017). Although there were several standardized percent differences from the historical domain had a standardized percent bias over 10%, these were not included. This is due to the inclusion of an offender's PSC score, which measures the same historical information. To avoid duplication of historical bias, I opted to remove the LSCMI history scores and only include a person's PSC score to control for historical differences.

Once the standardized percent bias was calculated for all 50 measures, I calculated the average percent significant differences. Pre-match, this value was an average of 48% difference between the historical and CTC groups. This meant that approximately half of my variables were significantly different before the match. The mean standardized percent difference was 6.9%. The AUC for the pre-match was .711, indicating that the results were not random. The caliper, as previously mentioned, is calculated as the $\frac{1}{4}$ the standard deviation. With a standard deviation of .1558, the caliper was entered at .0389.

Once SPSS estimated the propensity scores using logistic regression for likelihood of visiting the Center, it created a new dataset that only included a balanced number of CTC and historical participants who were matched to each other by having

similar propensity scores. This reduced my sample size from 5,213 to 3,338. Prior to matching, there were 3,486 historical samples, and 1,727 from the CTC. After matching, there were an even 1,669 people in each. After the match, the average percent of significant differences went from 48% to 22%, meaning that approximately 11 of the variables were significantly different post-match compared to about half of the pre-match variables. The percent of covariates with bias over 10% was 20% for the pre-match, and 16% post-match. The AUC reduced from .711 to .510, thereby making the chances of the model accurately predicting if a person was in the CTC or historical group down to 51%, suggesting a much more randomized model.

Table 1 depicts the model balance summary for pre- and post-matching, as well as the bivariate breakdown across the independent measures. Prior to matching, the samples were relatively even for gender and race.

Table 1. Bivariate and continuous descriptives pre- and post-match (part 1 of 3)

	Pre-Match			Post-Match		
Model Fit Summary						
Percent significant differences			48.0			22.0
Mean standardized percent difference or bias			6.9			6.0
Maximum percent bias			26.1			40.4
Percent with bias over 20			8.0			6.1
Percent with bias over 10			20.0			16.0
Area under the curve (AUC)			0.711			0.510
Domain/Measure (50 total measures compared)			%CTC			%CTC
			%Hist			%Hist
			%Bias			%Bias
Demographics						
Sample size			1,727			1,669
Male		3,486	**79.7		78.1	79.1
Race - white		87	88.2		87.3	88.1
Age (continuous)		34.0(10.6)	***35.83 (10.3)		35.4(10.4)	35.4 (10.3)
Original Sentence Prior to Supervision and PSC						
Prison sentence		25.1	***16.7		32.8	***15.8
Jail or local control sentence		20	***31.3		24.3	***30.7
Probation/post-prison supervision		54.9	*52.1		42.9	***53.6
Days between admission and release (continuous)		223.4 (616.8)	***430.6 (769.3)		332.5(767.2)	***385.3 (695.1)
Public Safety Checklist (PSC) Score (continuous)		32.45 (18.0)	***38.91 (21.2)		38.2(20.1)	38.26(20.8)
LS/CMI Scores						
Combined LS/CMI Score						
	Very high	13.2	***17		17.3	16.6
	High	40.2	41.4		43.1	41.2
	Medium	33	*30.3		31.2	30.7
	Very/low & low	13.5	*11.2		8.5	**11.5
						10.0

Table 1. Bivariate and continuous descriptives pre- and post-match (Continued, part 2 of 3)

		%Hist	%CTC	%Bias	%Hist	%CTC	%Bias
<i>History</i>	<i>Very high</i>	2.7	2.5	1.3	4.3	**2.5	9.9
	<i>High</i>	26.3	26.1	.5	33.6	***25	19.0
	<i>Medium</i>	31.6	32.2	1.3	33.1	32.4	1.5
	<i>Low</i>	22.6	*25.2	6.1	18.9	***25.8	16.6
<i>Family</i>	<i>Very low</i>	16.9	**14	8.0	10.2	***14.4	12.8
	<i>Very high</i>	8.1	8.4	1.1	9.3	8.4	3.2
	<i>High</i>	17	*19.3	6.0	18.2	19.2	2.6
	<i>Medium</i>	23.8	25.2	3.3	24.7	25.2	1.2
<i>Education</i>	<i>Low</i>	29.9	30	0.2	31.9	29.7	4.8
	<i>Very low</i>	21.1	***17.1	10.4	15.9	17.4	4.0
	<i>Very high</i>	8.5	**11.1	8.8	8.8	10.8	6.7
	<i>High</i>	31.7	31.7	0.0	31.9	31.7	0.4
	<i>Medium</i>	24.8	22.6	5.2	25.6	*22.6	7.0
	<i>Low</i>	12.8	12.4	1.2	13.1	12.2	2.7
<i>Recreation</i>	<i>Very low</i>	22.2	22.2	0.0	20.6	22.6	4.9
	<i>High</i>	54	56.6	5.2	40.9	56.3	31.2
	<i>Medium</i>	20.6	22	3.4	19.5	22.1	6.4
	<i>Very low</i>	25.4	**21.4	9.5	21.4	21.6	.5
<i>Associates</i>	<i>Very high</i>	33.2	34.5	2.7	37.1	34.6	5.2
	<i>High</i>	14	**16.9	8.0	14.7	16.5	5.0
	<i>Medium</i>	21.2	21	0.5	21.4	20.8	1.5
	<i>Low</i>	20.8	18.6	5.5	18.6	18.8	0.5
<i>Drug</i>	<i>Very low</i>	10.8	9.1	5.7	8	9.3	4.6
	<i>Very high</i>	15.5	17.7	5.9	16.8	17.5	1.9
	<i>High</i>	34.5	**38.2	7.7	36.2	38.3	4.3
	<i>Medium</i>	18.8	17.5	3.4	17.3	17.7	1.1
	<i>Low</i>	20.2	18.8	3.5	22.6	**18.6	9.9
	<i>Very low</i>	11	**7.8	11.0	7.1	8	3.4

Table 1. Bivariate and continuous descriptives pre- and post-match (Continued, part 3 of 3)

		%Hist	%CTC	%Bias	%Hist	%CTC	%Bias
<i>Attitude</i>	<i>Very high</i>	9.2	*11	6.0	11.9	10.8	3.5
	<i>High</i>	9.7	*11.8	6.8	10.9	11.6	2.2
	<i>Medium</i>	15.9	17.5	4.3	17.1	17.6	1.3
	<i>Low</i>	19.3	19.1	0.5	20.7	19.2	3.8
	<i>Very/low</i>	45.8	**40.5	10.7	39.4	40.8	2.9
<i>Antisocial</i>	<i>Very high</i>	3	3.8	4.4	3.8	3.8	0.0
	<i>High</i>	144	**17.3	7.9	17.4	17	1.1
	<i>Medium</i>	269	**30.9	8.8	28.2	30.7	5.5
	<i>Low</i>	289	26.8	4.7	28.8	26.8	4.5
	<i>Very/low</i>	269	**21.3	13.1	21.8	21.7	0.2

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

The distribution of type of release was highly biased prior to matching, and stayed so afterward, with approximately a quarter of the historical sample released from a prison sentence, a fifth from jail or local control, and over half released on probation or post-prison supervision. The CTC sample consisted of approximately a sixth of the sample released from prison, a third from jail or local control, and about half from parole or post-prison supervision. After matching, the historical sample was made up of a third released from prison, a quarter from jail or local control, and about two-fifths probation or post-prison supervision. The CTC sample had roughly one-fifth released from prison, a third from jail or local control, and half from parole or post-prison supervision. Although the standardized percent bias post-matching was still large (40.4% for the prison sentence between the two groups), the improvement of the overall model's standardized percent bias allowed for such differences.

LS/CMI scores experienced more homogeneity post-matching overall. The historical sample was made up of 13.2% *very high*, 40.2% *high*, 33% *medium*, and 13.5% *low* and *very low* scores, and the CTC sample was composed of 17% *very high*, 41.4% *high*, 30.4% *medium*, and 11.2% *low and very low*. Post-match the historical and CTC samples were approximately equal to each other. The individual breakdowns of LS/CMI domains pre- and post-match can be viewed in table 1. Having similar LS/CMI scores, which have been shown to be predictive of treatment and recidivism outcomes, was an important goal of the matching procedure and was achieved.

Continuous variable matchings were as follows: before matching, the average historical PSC score was 32.5% with a standard deviation of 18.0, and the CTC sample

was 38.9% with a standard deviation of 21.2%. This was improved by the PSM to 38.2 (20.1 SD) and 38.3 (20.8) in post-match. The average age of the historical sample was roughly 34 years old with 10.5 years standard deviation, and the CTC was 35.5 years old with a standard deviation of 10.3 years. Post-match this changed to 35.4 with a 10.3 SD for the historical sample, and 35.4 for the CTC sample with a SD of 10.3 years, reducing the bias from 12.4% to 0%. The days between their admission and release began with 23% standardized percent bias, with 223.4 days for the historical sample and 430.6 days for the CTC sample, and this bias was reduced to 6% post-match with 332.4 days and 385.3 days, respectively. Age and time at risk are both important predictors of recidivism nationwide, and the PSC score has been shown to work in Oregon. Thus, these post-match results are highly encouraging and suggest that the confounding of these variables has been largely controlled for.

Although there were some variables which remained highly biased post-match, this was still considered a successful matching process. The reduction in the average percent of significant differences from 48 to 22% and the AUC from .711 to .510 point towards a more evenly matched sampling of CTC and historical offenders. This success permitted me to run a simple bivariate analysis of my outcome variables using cross-tabulations, as can be seen in Table 2. All four outcomes – rearrest for a new misdemeanor or felony, reconviction for a new misdemeanor or felony, reincarceration for a new felony, or any form of recidivism showed that CTC visitors were less likely to have recidivated. These results were all significant at that $p < .001$, which shows that there is a meaningful difference between CTC visitors and the historical sample. Results

show a Cohen’s *d* growth post-PSM for all categories except for reincarceration. This improvement shows that the matching procedure provides an unbiased estimate of the treatment effect between the two groups on their outcomes. Post-match had medium effect sizes for rearrest, reincarceration, and any form of recidivism, with a max *d* of .41, and conviction had a large effect of *d* = .53.

Table 2. Breakdown of recidivism outcome measures pre- and post-match

Recidivism	Pre-match			Post-match			
	Sample size	%Hist	%CTC	<i>d</i>	%Hist	%CTC	<i>d</i>
		3,486	1,727		1,669	1,669	
Rearrest		54.2	***43.2	.22	57.8	***42.7	.31
Reconviction		47.2	***26.0	.29	50.7	***25.8	.53
Reincarceration		19.2	***8.6	.44	23.1	***8.6	.41
Any form of recidivism		58.4	***46.9	.23	61.4	***46.4	.30

One potential concern was the difference in the lack of follow-up time between CTC and historical samples. This was an unavoidable issue because of the preliminary nature of the CTC data. As previously mentioned, some CTC participants only had about six months of follow-up time between their visit to the CTC and when the data was collected, as compared to the historical sample, who had a minimum of 1.5 years. To determine if this was a cause for concern, I ran a cross tabulation that calculated whether or not a person experienced a recidivating event within 365 days of their release. These results showed a relatively similar proportion of historical and CTC participants recidivated within one year of release: 32.17% and 38.1%, respectively, although the chi-square was significant at $p < .001$. Needing to control for the length of time out in the

community (i.e., time at risk) supported the necessity of the binary logistic regression, where it could be properly controlled as a confounding measure.

The final analyses used binary logistic regressions to isolate the effect of visiting the CTC on recidivism likelihood while controlling for the covariates that were still unbalanced post-match. Any covariates with a standardized percent bias greater than 9.5% post-PSM were included. These were their sentence type (prison or jail and local control), a *medium* risk score for recreation, and *low* drug risk. I also included a *very high*, *high*, and *medium* total risk score for the LS/CMI due to its proven predictive abilities in prior research. However, I excluded the probation- post-prison supervision and the *low* and *very low*-risk variables because the posterior probabilities of release type and total LS/CMI in each group would add to 1 for any offender. If I included all options for release type or LS/CMI, they would be completely correlated (Field, 2013).

I also included the theoretical predictors of crime such as their age, race, and gender. Finally, I added a person's PSC score. Although there was not a significant difference between groups for any of these, prior research has shown them to be predictive of recidivism, as seen in my Independent Measures section. Finally, I included a continuous variable for total time at risk to control for the follow-up time between groups.

Before running the analysis, it was necessary to test the assumptions of a binary logistic regression. All four regressions involved a dichotomous dependent variable and independent variables that are independent of each other. I also tested for multicollinearity by running a collinearity diagnostic testing the Variance of Inflation

(VIF). A score above 4 typically indicates that indicators are highly related to each other and should be cause for concern (Field, 2013). VIF scores ranged from 1.057 to 2.152, so my independent variables were not unduly influenced by other variables in the equation.

Lastly, I tested if there was a linear relationship between the continuous predictors and the logit of the outcome variable (Field, 2013). This assumption tests if there is an association between my three continuous variables (age, PSC score, and time at risk) and my outcome variables. To test this assumption I computed the log of each of my three continuous variables. I then ran a logistic regression that compared the log of each variable to its original output while still controlling for my other independent variables. Finally, I checked the p-scores for variables within the equation for significance. A significant p-score ($p < .05$) means that there is a nonlinear relationship between my continuous variables and their log transformation (Field, 2013), meaning the assumption is violated. The interaction between age and the log age was $p > .05$ for all four outcomes, but the interactions between time at risk and log time at risk and PSC score and log PSC score were all $p < .05$. Although this final assumption failed in two of my three continuous variables, the overall robustness of my models could withstand this assumption being violated. Thus, I was able to run my analyses.

Table 3 displays the results of the logistic regressions for all four forms of recidivism. The baseline only considers a visit with the CTC as the only predictor for the outcomes, and the following model includes all additional variables.

Table 3. Logistic regression predicting subsequent recidivism outcomes (part 1 of 2)

Baseline model n=3,338	Rearrest		Reconviction	
	O R	[95% CI] p	OR	[95% CI] p
Historical = 0; CTC = 1	.54	[.47-.62] <.001	.34	[.29-.39] <.001
Constant	1.37	<.001	1.03	.54
Main effects model n=3,338				
Historical = 0; CTC = 1	.20	[.16-.26] <.001	.10	[.08-.13] <.001
Theoretical covariates				
Age	.99	[.98-.99] <.001	.99	[.98-.996] .003
Race – white or not	1.17	[.94-1.47] .17	1.18	[.93-1.5] .16
Gender	1.19	[.996-1.43] .055	1.12	[.92-1.36] .26
PSC score	11.1	[7.06-17.49] <.001	10.14	[6.3-16.1] <.001
Total time at risk	.999	[.999-.999] <.001	.999	[.999-.999] <.001
LS/CMI covariates				
Total score – very high	2.8	[1.96-3.98] <.001	2.73	[1.85-4.02] <.001
Total score – high	1.94	[1.44-2.61] <.001	1.87	[1.34-2.61] <.001
Total score – medium	1.38	[1.04-1.82] .02	1.36	[.98-1.87] .062
Recreation domain – high	.91	[.76-1.08] .27	1.13	[.93-1.36] .19
Drug domain – low	1.06	[.87-1.29] .6	1.14	[.92-1.4] .22
Other unbalanced covariates				
Release type – prison	.67	[.55-.82] <.001	.53	[.43-.65] <.001
Release type – jail or local control	.97	[.80-1.19] .81	.87	[.71-1.07] .19
Constant	2.02	.02	1.9	.04
-2 Log Likelihood	4092.77		3743.52	
Likelihood-ratio χ^2	***534.58 (13df)		***699.0 (13df)	
Nagelkerke R ²	.20		.26	
Cox & Snell R ²	.15		.19	

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

Table 3. Logistic regression predicting subsequent recidivism outcomes (continued, part 1 of 2)

Baseline model n=3,338	Reincarceration			Any recidivism		
	OR	[95% CI]	p	OR	[95% CI]	p
Historical = 0; CTC = 1	.31	[.26-.39]	<.001	.55	[.48-.63]	<.001
Constant	.30		<.001	1.59		<.001
Main effects model n=3,338						
Historical = 0; CTC = 1	.009	[.006-.01]	<.001	.21	[.16-.27]	<.001
Theoretical covariates						
Age	.99	[.97-.1.00]	.19	.99	[.98-.998]	.01
Race – white or not	1.2	[.82-1.74]	.35	1.17	[.93-1.46]	.18
Gender	1.89	[1.33-2.69]	<.001	1.15	[.96-1.37]	.14
PSC score	12.4	[6.18-24.86]	<.001	16.1	[10.1-25.7]	<.001
Total time at risk	.996	[.995-.996]	<.001	.999	[.999-.999]	<.001
LS/CMI covariates						
Total score – very high	1.67	[.88-3.17]	.11	2.72	[1.91-3.87]	<.001
Total score – high	16.1	[.91-2.85]	.10	1.89	[1.41-2.53]	<.001
Total score – medium	.98	[.57-.1.74]	.98	1.33	[1.00-1.75]	.045
Recreation domain – high	1.12	[.82-1.53]	.46	.99	[.83-1.18]	.90
Drug domain – low	1.24	[.88-1.75]	.22	1.11	[.91-1.35]	.3
Other unbalanced covariates						
Release type – prison	1.25	[.91-1.72]	.17	.56	[.46-.68]	<.001
Release type – jail or local control	1.17	[.84-1.62]	.36	.86	[.70-1.05]	.15
Constant	17.47		<.001	1.8		.047
-2 Log Likelihood	1693.85			4049.95		
Likelihood-ratio χ^2	***1227.82 (13df)			***556.92 (13df)		
Nagelkerke R ²	.53			.20		
Cox & Snell R ²	.31			.15		

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

The model fit improved with the addition of the unbalanced and theoretical covariates for all four models. Nagelkerke R^2 showed that anywhere from 20 to 53% of the variance explained the model (Field, 2013).

Baseline models showed that visiting the CTC was a significant predictor of all recidivism outcomes, all with $p < .001$. The predictive strength remained with the inclusion of all other variables. Visiting the CTC was also a significant predictor of all four recidivating measures in the full models. The odds ratios (with $p < .001$) with 95% confidence intervals showed that likelihood of rearrest reduced by 80% visiting the CTC. Their likelihood of reconviction reduced by 90%, followed by reconvicted odds reduced by about 99%. Overall, any form of recidivism reduced by 21%, all with p being significant at less than .001.

These results do not compare outcomes of people who chose to visit the CTC versus those who did not choose to go. Instead, it compares the differences between people who were able to visit the CTC and those who would have been similarly likely to visit the CTC from the historical sample, had it been available to them.

Some variables with odds ratios that went from less than one to over one were a person's race and having a *high* recreation score or a *low* drug score. Interestingly, this was true for the gender covariate except for the odds of reincarceration, where being male increased their odds by 89%. Age had a mitigating effect on the odds of all forms of recidivism, with each additional year older reducing their odds by approximately 1%. Race was not significant in any model, but this was unsurprising due to the low base rates of non-white offenders.

The reincarceration model had the fewest significant results. Visiting the CTC was significant, but should be interpreted with caution due to its low base-rate. Because only 8.6% of the CTC was reincarcerated, compared to 23.1% of the historical sample (as seen in Table 2), it is best to consider the predictive validity of this model as possible, but may wane in accuracy.

The LS-CMI scores for *very high*, *high*, and *medium*-risk increased the odds of an offender's likelihood of being rearrested or any recidivism, all with $p < .05$. A *medium* score increased their odds of rearrest by 38%, and a *very high* score increased their odds by 180%. A *very high* and *high* score was a significant predictor of reconviction, but a *medium* score did not achieve significance. A *medium* score increased their odds of rearrest by 38%, and a *very high* score increased their odds by 180%. These results provide additional support to the use of actuarial risk assessments that target needs.

Interestingly, if an offender released from prison it appeared to lower their odds of rearrest, reconviction, or any recidivism, all with $p < .001$. Their odds decreased 33% for rearrest, 47% for reconviction, and 44% for any recidivism. The results were unable to show if there was an effect for release from jail or local control, and none of their results reached significance.

When considering the other covariates, several key results must be addressed. The first is the predictive ability of PSC scores. With every increase in a person's PSC score their likelihood of recidivating increased exponentially. A higher PSC increased the odds of rearrest approximately 10.1 times, reconviction 9.14 times, reincarceration 11.4 times, and any recidivism 15.1 times, all with $p < .001$. The second factor is the small effect of

total time an offender was at risk. No matter what measure studied, the total time the offender was in the community reduced their odds of recidivism by 1% per each day out. While this has a negligible effect for those recently released from incarceration, over time it can have a considerable effect on their likelihood of recidivating.

Discussion

This study's objective was to complete a preliminary evaluation of the Clackamas County Transition Center. My research question was "*To what extent does the Clackamas Transition Center influence supervision outcomes of recently released offenders?*" My hypothesis was that visiting the CTC would have a reducing effect on an offender's likelihood of recidivism. This hypothesis was chosen for a number of factors about the Transition Center, including its centralized location of programs and services that attempt to reduce the risk of future recidivism by ameliorating reentry concerns through risk assessments and targeted treatments and how it is a largely voluntary experience, making it different from traditional Day Reporting Centers and other rehabilitation programs. This study also adds to the literature on voluntary reentry programs and how they can be used to connect offenders to the appropriate services to fit their risks and needs.

The results from this study are promising. Following the quasi-experimental design, using PSM followed by logistic regression, the findings suggest that visiting the CTC may reduce the odds of recidivating anywhere from 79 to 99% for people equally likely to choose to access such treatment, had it been available to them. For the broadest recidivism measure, rearrest, visiting the CTC reduced their odds of rearrest by 80%. It also adds to previous research on the predictive validity of risk assessments, with the LS/CMI and PSC performing well. These results lend support to my hypothesis: the Transition Center does appear to have a reducing effect on recidivism outcomes for offenders who would be interested in attending, had it been available.

The Center's effectiveness at reducing the likelihood of recidivism for interested offenders is likely due to a number of factors. First and foremost is its usage of the risk-need-responsivity principle. By targeting both an offender's criminogenic needs and addressing them the Center is able to effectively offer support where offenders need it most. The LS/CMI risk assessment that the Center uses also assists with this targeted treatment, as well as being predictive of recidivism. One of the services it offers is Cognitive Behavioral Therapy, which also has been shown to reduce recidivism. Finally, the ability of an offender to make unlimited visits to the Center, combined with the possibility of parole officers being able to reach-in to incarcerated offenders, offers the continuum of care that has been shown to reduce treatment attrition and improve recidivism outcomes. While there are likely many reasons for these preliminary positive results, and many of these are suggested in the next section, the use of RNR, CBT, and a continuum of care are all likely influencers.

Based on the overall analyses, I reject the null hypothesis that the CTC would have no impact on a participant's likelihood to recidivate as measured by rearrest, reconviction, and/or reincarceration. Thus, it appears that the CTC does reduce a participant's likelihood of recidivating as compared to people who would be equally likely to visit the CTC, but did not have it available to them.

Limitations, future research ideas, and policy implications

There are a number of limitations inherent in the use of secondary data. The first is in what information was originally collected by the county. The CTC was created without replicating any previous services or models, meaning their data collection

methods were more reactionary than arranged. As the Center grew, the county added more types of data to its repository. Due to this non-linear process, I was unable to collect information about which clients had experienced a “reach-in” while they were still incarcerated, or received more detailed information about the services they received to create a more nuanced understanding of what aspects of the CTC are the most effective at reducing recidivism for all clients.

I was also unable to test the program’s fidelity, or how well it adhered to its principles. Therefore, I could not measure how successful the CTC is at assisting with the reentry process according to their goals of focusing on high-risk offenders, targeting needs with referrals to services, or if treatment properly addresses those needs. This can also be seen in the lack of data about what services offenders actually received, as POs only recorded what services a person was referred to, and not if they accessed them. This lack of information about the actual services received is a serious consideration that could impact a person’s recidivism outcomes. Future research should consider all aspects of the program in its evaluation, from its implementation to outcomes.

While these are limitations, they are not insurmountable. My results were able to show that visiting the CTC, regardless of what services they received, appears to reduce the odds of recidivism. Future research can involve a more detailed data collection method that accounts for all aspects of a client’s visit to gain a deeper understanding of all the services the CTC can provide, as well as if there are any interaction effects between them.

A second limitation was the unevenly balanced types of release used in my propensity score. Post-matching the standardized percent difference between the historical and CTC samples for type of release was anywhere from 14.4% to 40.4%, which is high. Running three separate PSMs for each of the release types could mitigate this. However, I chose not to do this due to the preliminary nature of this evaluation. Having three datasets would potentially overcomplicate the recidivism results by having all outcomes measured and recorded thrice. Future research would benefit from isolating the effect of the Center for each release type, but as this study's focus is on whether or not the Center has an effect at all, I chose to create one single post-match dataset.

Another limitation was that I was unable to differentiate between Technical Violations (TVs), rearrests, and revocations. TVs occur when an offender who placed on community supervision fails to follow the conditions of their release, which may or may not be considered criminal (Drake & Aos, 2012). These could include visiting a bar when they are ordered not to, being in possession of drugs, or breaking a restraining order. These violations can be punished with sanctions ranging from verbal reprimands to confinement (Drake & Aos, 2012). The CJC does not account for TVs when it measures recidivism. However, this is less of a concern for this study because I was measuring all recidivating actions, as they are defined by the State of Oregon. While I do not have anything that was not documented as a new crime classification, this is an area rich for future research, and a more targeted future study could collect information about TVs as well as new recidivating actions.

The legalization of marijuana, which began with the approval of Measure 91 in 2014 (Oregon.gov, 2019), is a small consideration that should be noted. It is possible that the lower recidivism rates were due to the legalization of marijuana, and thus not controlled for. However, due to the low historical sample rates of arrests for marijuana usage and sales in my study, it is unlikely to have a significant impact on my results. A more in-depth study of the aftereffects of marijuana legalization would be beneficial for this concern. This limitation ties in with the issues associated with comparing groups from different time periods, as crime trends or additional law changes could have affected my results (UCR, 2019). This limitation can be controlled for in a future evaluation that is able to compare visitors and non-visitors from the same time frame.

Another limitation was the overrepresentation of male offenders. This can be partially attributed to the State of Oregon's implementation of the Women's Risk Need Assessment (WRNA) for women offenders. Women who received a WRNA score did not receive an LSCMI score. This risk assessment was introduced in March 2015 to the Oregon Department of Corrections, and was fully implemented on August 31st, 2017 (ODOC, 2017). I elected not to use the WRNA for this analysis because it was not introduced until near the end of my historical sample's collection date, and was not completely implemented until my Transition Center sample was almost concluded. Future research could compare male recidivism and use of the Treatment Center to female's, to see if there is a gender difference in program adherence or success.

The average difference between the historical sample and the CTC sample for the total time they were in the community (i.e., at risk), should be considered. Although I

controlled for this in my binary logistic regression, the differences between the two groups are large enough to be a concern. This limitation is largely due to the relatively new nature of the Transition Center. The State of Oregon prefers to follow offenders for a minimum of three years post-release (CJC, 2019), but three years had not passed from the inception of the CTC when this study began, thus the time at risk difference. It could have been possible to introduce a cap on both samples to truncate their time at risk to six-month or one year intervals. However, I would have lost any data beyond the truncation, so I chose to maintain the larger gap between groups for time at risk in order to have more recidivism data. This study could be replicated with more equal time at risk data once more time has passed from the release of CTC visitors to data collection.

Finally, the lack of information about the motivating factors that influenced a person to choose visiting the CTC could have affected my results. There are innumerable external and internal motivations that could lead to a person choosing treatment (Parhar, Wormith, Derkzen, & Beauregard, 2008), including wanting to resume mothering children (Robbins, Martin, Surratt, 2007), avoiding further sanctions (Eschbach et al., 2018), and receiving treatment for substance addictions (Robbins et al., 2007). This lack of motivational information also highlights a limitation of most restorative justice research: it is difficult to determine the true reentry effects of the Center and what effects were due to the largely voluntary nature of participation. The PSM was able to control for observed selection biases, such as age or gender, but not the unobserved, like a person's motivation. It also was unable to account for how voluntary visiting the Center actually was for all the participants, as previously mentioned.

To further research motivations and mitigate these limitations, a replication of this study would benefit from a mixed-methods approach instead of a purely quantitative one. People leaving incarceration or being placed on community supervision could complete a survey or interview about their motivations for treatment (if any), and answer further information about the number of dependent children they have, if they have a prosocial partner, or interest in receiving treatment. It should also ask participants how coercive attending the Center felt to assess how voluntary it actually is. This could also be achieved by placing more of an emphasis on the PO's case plan to access services available at the Center. This qualitative approach combined with the quantitative data analysis would provide a richer understanding of the motivations for visiting the CTC, as well as what services they were most likely to access. Future studies should also consider program fidelity and how well it adheres to the Principles of Effective Intervention. This could be done by evaluating the Center against the Correctional Program Assessment Inventory (Gendreau & Adams, 2010).

The results of this study do hold some policy implications. First, the reduced odds of recidivism after visiting the Center suggest this centralized location appears to be effective in the largely rural Clackamas County. The difference between substance abuse treatment participation between urban and rural prisoners (Warner & Leukefeld, 2001) found rural participants had a decreased probability of ever participating in a treatment program as compared to urban participants, even after controlling for the number of years using substances and race. The centralized location of the Center in a rural and large county may be part of its success, though more research is needed.

Second, the overall predictive power of the LS/CMI and PSC scores in this study builds upon previous research about their effectiveness in the reentry process and lends credit to their continued use in the county. The use of the LS/CMI is of considerable interest because it targets and attempts to treat an offender's needs. A follow-up study could measure an offender's overall and individual domain scores from before their visit to the CTC and after, to see if there is any score improvement because of the CTC. It could also determine which domain scores are the most prevalent in CTC visitors, and see if post-visit these domains are improved.

Finally, this study adds to the body of knowledge about the reduction of likelihood to recidivate that is possible with reentry services such as rehabilitation. Policy makers can consider a wide range of studies, including this one, which demonstrate the importance of rehabilitation in the reentry process. Due to the wide variation in program design, any additional research that this evaluation's program's methods can provide to future rehabilitative program implementers is a benefit.

Conclusion

Reentry barriers will continue to exist for the thousands of people being released from incarceration each year. The continued study and use of rehabilitation and reentry services can only improve the reentry process. Offenders may “all come back” (Travis, 2005), but with additional support this transition may become easier for the offenders and their communities. This preliminary examination of the Clackamas County Transition Center suggests its effectiveness at reducing recidivism for those who would choose to visit. It has also demonstrated the relevance of propensity score modeling in community supervision research to remove selection bias as it exists in an opt-in program. At the time of this report, three years have officially passed since its February 2016 opening. When the county begins conducting its own evaluation research, this study can be used as a supplement to inform their data collection process and analysis.

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Appendix A – Ineligible Participants

There were 11,771 offenders in the sample at its onset – 7,957 in the historical sample and 3,814 in the CTC sample. This was reduced to 5,213 offenders after the ineligible offenders were removed; a loss of over 6,000 participants.¹⁴ In order to ensure the removal of the ineligible participants did not negatively affect my results, I ran comparative analyses on the ineligible and eligible samples on variables both samples had,¹⁵ as well as simple cross-tabulations on the differences in outcomes. As can be seen in Table 4, the ineligible and eligible offenders had roughly equal distributions on their independent variables, as well as on the outcome variables. There was a higher percentage of ineligible offenders who were reincarcerated compared to the eligible, but a higher number of eligible offenders reconvicted than ineligible. Future research should consider the differences between eligible and ineligible participants more closely, as well as analyze why these outcomes are different.

¹⁴ Some of the participants were duplicates who were removed prior to checking for eligibility – hence why the sample size for the ineligible is 6,029 and not 6,558.

¹⁵ The majority of the ineligible participants did not have LS/CMI scores, so they were not compared on these measures.

Table 4. Bivariate and continuous descriptives – ineligible & eligible

Domain		Ineligible		Eligible	
		%Hist	%CTC	%Hist	%CTC
Demographics	<i>Sample size</i>	4,471	1,558	3,486	1,727
Male		76	74.4	76.5	**79.7
Race - white		85.5	*88.1	87	88.2
Age (continuous)		35.4	*36.1	34.0	***35.6
		(11.6)	(11.2)	(35.6)	(10.3)
Original Sentence Prior to Supervision and PSC					
Prison sentence		24.3	***14.5	25.1	***16.7
Jail or local control sentence		17.9	***32.7	20	***31.3
Parole/post-prison supervision		23.7	***14.8	54.9	*52.1
Public Safety Checklist (PSC) Score (continuous)		29.7	***39.2	32.5	***35.6
		(17.5)	(22.0)	(18.0)	(10.3)

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

Table 5. Breakdown of recidivism outcome measures – ineligible & eligible

Recidivism		Ineligible		Eligible	
		%Hist	%CTC	%Hist	%CTC
	<i>Sample size</i>	4,471	1,558	3,486	1,727
Rearrest		47.3	**42.4	54.2	***43.2
Reconviction		15.7	***9.4	47.2	***26.0
Reincarceration		40.4	***29.1	19.2	***8.6

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

Appendix B – Unmatched Participants

Between the pre-match sample of 5,213 participants and the post-match reduction to 3,338, a total of 1,875 participants were removed from the study. I compared those unmatched to those matched on their differences in the same manner I did with the ineligible and eligible samples and found that including the unmatched variables would not have changed my outcomes. However, the percentage differences between groups should be considered with caution because of the extremely low base rate of unmatched CTC participants (58), compared to the unmatched historical sample (1,817).

Table 6. Bivariate and continuous descriptives – unmatched & matched

Domain	Unmatched		Matched	
	%Hist	%CTC	%Hist	%CTC
<i>Sample size</i>	1,817	58	1,669	1,669
Demographics				
Male	75	***94.8	78.1	79.1
Race - white	86.7	91.4	87.3	88.1
Age (continuous)	32.7 (10.6)	***41.3 (8.9)	35.4 (10.4)	35.4 (10.3)
Original Sentence Prior to Supervision and PSC				
Prison sentence	18	***43.1	32.8	***15.8
Jail or local control sentence	16	***48.3	24.3	***30.7
Parole/post-prison supervision	66	***8.6	42.9	***53.6
Public Safety Checklist (PSC) Score (continuous)	27.2 (13.9)	***57.4 (24.2)	38.2 (20.1)	38.3 (20.8)

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

Table 7. Breakdown of recidivism outcome measures – unmatched & matched

Recidivism	Unmatched		Matched	
	%Hist	%CTC	%Hist	%CTC
<i>Sample size</i>	1,817	58	1,669	1,669
Rearrest	50.9	56.9	57.8	***42.7
Reconviction	43.9	31	50.7	***25.8
Reincarceration	15.6	8.6	23.1	***8.6

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