ALTERNATIVE APPROACHES TO CRIMINAL JUSTICE:
PROBLEM-SOLVING COURTS AND INCARCERATED PEER EDUCATION

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I walked out of Lea County Correctional Facility (Hobbs, NM) on February 24, 2008, broken. My life to that point consisted of ingesting mind-altering chemicals, committing crimes to feed that habit (and those that came along with the lifestyle), and doing time for these crimes. I was not a very good criminal. As the guard and I walked to the transportation van that would take us to the Hobbs, NM bus station, he realized he had the wrong set of keys. “Stay here. I'll be right back,” he said before walking back into the prison. I watched him go back in and my focus expanded to the whole prison. The symbol of my foolishness. At that moment I vowed to do whatever it would take to not return. The problem, though, was that I knew of no other life. Two days later I walked into a 12-step fellowship, almost by accident. I only knew that I would not be in danger of relapsing while there, that it would be warm, and that they had coffee. In that and many other meetings I found a new way to live. My core problem had not been alcohol or drugs or crime. It was, and still is, knowing how to live. The approach to life people in these meetings taught me has to do with acknowledging the mistakes of the past, taking responsibility for my part in them, and learning how to live a life of service and altruism, mending this broken world as best I can. This dissertation is a part of that path. I dedicate this work to all those who suffer, as I suffered. To all those coming after me who are confused and baffled and tired of causing so much pain but do not know another way.

You are not alone.
Acknowledgements

I would like to acknowledge all the people and institutions that helped me become a person capable of a dissertation. First, the countless people in 12-step meetings throughout the world and these institutions themselves. You give freely of your time ensuring the lights are on, the coffee is ready, and poor souls like myself can find recovery. I am one of millions of people that 12-step fellowships have saved. I will always live in gratitude for this precious gift, and do my part to ensure the lights are on for those coming after me. I also thank the educational advisors who helped me rise from remedial courses at the Central New Mexico Community College to this dissertation. Dr. Manuel-Julian R. Montoya at the University of New Mexico helped me think critically, in an interdisciplinary way, and showed incredible compassion. Lisa Blomgren Amsler taught me not only about Collaborative Governance and Representative Bureaucracy but also about working for a purpose, working to make the world a better place. Drs. Brad Ray and Eric Grommon showed what a practicing research career looks like, making it look easy. Drs. Sean Nicholson-Crotty and Matthew Baggetta guided me along this dissertation path, showing incredible amounts of patience while imparting from their incredible stores of knowledge. Dr. Coady Wing helped me stay calm while teaching this old dog new statistical tricks. And I would not have survived this PhD program without Dr. Bradley Heim’s math camp in 2017. All of these people, and so many more, deserve credit – I stand on the shoulders of giants. I also am eternally grateful for my partner, my wife, my muse, Kristin Sarette, and my son, Byron Albert Thomas Hibbard. You both are my anchor to this world.
Finally, I have to acknowledge that my ability to attain a PhD, to work on this dissertation, to lead the life I now have, comes because of privilege. As a white male with felony convictions, in the United States I have more opportunities than a black male without this record. One motivation for the work I do is to rectify this injustice. This process starts by directly facing my own bias and how I might perpetuate the US’s heritage of racism.

The destroyers are merely men enforcing the whims of our country, correctly interpreting its heritage and legacy. This legacy aspires to the shackling of black bodies. It is hard to face this. But all our phrasing—race relations, racial chasm, racial justice, racial profiling, white privilege, even white supremacy—serves to obscure that racism is a visceral experience, that it dislodges brains, blocks airways, rips muscle, extracts organs, cracks bones, breaks teeth. You must never look away from this. You must always remember that the sociology, the history, the economics, the graphs, the charts, the regressions all land, with great violence, upon the body... I would not have you descend into your own dream. I would have you be a conscious citizen of this terrible and beautiful world. – Coates (2015)
Decades of punitive criminal justice policies in the United States have depleted public budgets, disrupted families and communities, and fallen short of their intended purpose. By all measures, the War on Drugs and tough-on-crime policies have failed. Contemporary approaches to crime and deviance take a less punitive tack, looking to address conditions leading to crime. This dissertation investigates the effectiveness of two such efforts: problem-solving courts (PSCs) and incarcerated peer education (IPE).

Miami-Dade County began the first PSC in 1989 with their drug treatment court. This policy innovation diffused throughout the US, currently numbering in the thousands, and covering multiple issues (e.g., mental health, veterans’ issues). To date, however, the bulk of research looking at PSCs evaluates participant-level outcomes (e.g., recidivism, drug use), despite having community-level mandates like public safety. Further, the little research into PSC impact on communities indicates increases in crime. I apply a stacked event study design on a purpose-built dataset of extant PSCs in the US to estimate their impact on crime, finding reductions ranging from a 2.06% decrease in theft to, surprisingly, a 6.22% drop in robbery, as well as returns between $1.98 and $2.45 for every dollar spent on PSCs. I also find evidence that these results stem from successful service provision, as I found PSCs reduce drug arrests, and that drug arrests appear to mediate PSC effects on crime.

IPEs train people incarcerated as peer educators to teach others incarcerated on specific subjects. I evaluate the Indiana Peer Education Program, which trains people in the Indiana Department of Corrections to teach on health topics (e.g., chronic diseases).
Findings indicate increases in health knowledge and behavior intentions for both peer educators and their students, and improved attitudes and self-efficacy for peer educators. Qualitative data from peer educators confirms self-efficacy findings and indicates the program helps them gain agency and a sense of purpose.

Taken together, these results show less-punitive policies improve outcomes relative to traditional measures. Expanding these types of programs will improve public safety, keep communities and families more whole, and save tax-payer dollars.
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Abbreviations and Additional Notes

PSC: Problem-solving court
ADC: Adult drug treatment court
JDC: Juvenile drug treatment court
MHC: Mental health treatment court
DWI: DWI/DUI treatment court
HYB: Hybrid drug/DWI court
VET: Veterans’ court
COO: Co-occurring disorder treatment court
RE: Reentry Court
CGR: Collaborative Governance Regime

A Note on Person-First Language:
Throughout this dissertation I use “person-first language.” This terminology stems from efforts begun in the disability field that seeks to describe a condition a person *has* instead of the disability being the entire definition of a person (Wright, 1983). More recently, scholars and practitioners have adapted such terminology for people involved in the criminal justice system (Cox, 2020). I hold with these efforts and make every attempt at describing a person within a certain condition, rather than using the condition to describe a person – avoiding terms like “defendant” and “offender,” instead using “person charged with a crime” and the like. Not one person would like to be described by the worst part of their history, including myself. As a person with lived experience in substance use disorder and the criminal justice system, any description of “convict” or “ex-offender” would be simplistic, reductive, and quite frankly offensive. I adapt this method both to give respect to the individuals represented in my datasets and to push our literature toward such respect.
I. Introduction

Oftentimes have I heard you speak of one who commits a wrong as though he were not one of you, but a stranger unto you and an intruder upon your world.

But I say that even as the holy and the righteous cannot rise beyond the highest which is in each one of you,
So the wicked and the weak cannot fall lower than the lowest which is in you also.
And as a single leaf turns not yellow but with the silent knowledge of the whole tree,
So the wrong-doer cannot do wrong without the hidden will of you all.

(Gibran, 1923/1973)

United States criminal justice policies have shifted away from punitive, “nothing works” doctrines over the past 20 years (Martinson, 1974). The War on Drugs and tough-on-crime era led to mass incarceration, with dubious results (Alexander, 2012; Donohue & Levitt, 2019). More recently, scholars and policymakers have realized that a substantial proportion of crime in the United States exists as a manifestation of underlying conditions, such as substance use disorder (SUD), post-traumatic stress disorder (PTSD) (Rossman, Roman, & Rempel, 2011), and socio-economic conditions (Phillips & Land, 2012). The US criminal justice system recognized this in the late 1980s, following unsustainable growth, and modified institutional structures to address underlying problems these criminal acts indicate (Walker, 1994). This dissertation explores two approaches to addressing precursors to crime and recidivism: problem-solving courts (PSCs) and incarcerated peer education (IPE). Both approaches signify changes in rational premises for criminal justice policy and methods of implementation.

PSCs represent drastic modifications to court structures. Where previously judges reserved authority for all court decisions, save jury adjudication, many PSCs make decisions as a team (Drug Court Administrator A, personal communication, 2019;
Noia et al., 2018). And though traditional criminal justice courts order defendants to certain services (e.g., SUD recovery services), monitoring of and connection to these services was provided by probation departments and other, non-court entities (NADCP, 2018a). PSCs not only monitor these services, and connect participants to them, but include service providers inside the court as decision-making team members (Drug Court Administrator A, personal communication, 2019; NADCP, 2018b). These programs incorporated a Collaborative Governance model long before the literature had formally defined it.

IPE, as represented here, includes training incarcerated individuals (peers) in relevant topics who then teach these topics to others in prison (students). While those who created the programs under review built them to address health concerns (Ross et al., 2006; K. Thornton et al., 2018), recent programming has expanded to include mental health, SUD, and reentry issues (Indiana Peer Education Program Manual, 2019). By empowering incarcerated individuals as authorities on specific topics, these programs disrupt traditional carceral power structures (hierarchical, us-them dichotomies), empowering traditionally marginalized people in the process. Thus, peer education programs serve layered, dynamic outcomes, providing sorely needed educational services and altering criminal justice mechanics (Story, 2019).

This dissertation includes four primary empirical chapters. The first examines PSC impacts on crime within communities. I exploit variation of time and place for PSC implementation to estimate the effects PSCs have on crime over time. This type of analysis usually involves some form of event study, which estimates policy effects before and after implementation within relative time bins (i.e., not calendar time but relative to implementation). This practice, though, includes several drawbacks. For instance, if
relative time bins exhibit heterogenous treatment effects, which is likely in many cases, then these bins will influence each other, creating bias (Sun & Abraham, 2020). To avoid these issues, I use a stacked event study identification (Cengiz et al., 2019; Deshpande & Li, 2019). This method sets up estimation of sub-experiments that provide a “clean” control group and balances the sample in relative time.

To test robustness, I compare predicted and actual values, over time, finding they align well. I also explore potential confounding factors, especially those that indicate higher levels of community public safety proficiency (e.g., law enforcement variables). Though I find some prediction of PSC implementation in rates of housing and community development employees, I do not find these results detract much from core analysis.

The second empirical chapter takes another perspective, exploring the question of Collaborative Governance performance, positioning PSCs as an ideal case. Contemporary theorists define this type of collaboration as cross-boundary organizations collaborating toward a common objective (Thomson & Perry, 2006). As PSCs not only coordinate with service providers, but include representatives within internal decisionmaking structures, these programs align perfectly with such definitions.

Thus far, empirical tests of collaboration performance relative to traditional structures, especially concerning objective measures, have returned mixed results. For example, two papers examining collaboration efforts in law enforcement activities found different results. One found improvements in crime clearances by arrest (Nicholson-Crotty & O’Toole, 2004), while the other found no change despite more positive community perceptions (Smith et al., 2000). Further, much of the literature evaluates
intermediary variables, rather than big-picture goals like improving public safety (an explicit mandate of PSCs and nearly all criminal justice organizations). I fill this gap by investigating the effectiveness and efficiency of PSCs, as Collaborative Governance Regimes (CGRs, Emerson & Nabatchi, 2015a).

I revisit the effectiveness of PSCs reducing five index crimes found in the previous chapter: burglary, theft, motor vehicle theft, robbery, and aggravated assault. Then, I estimate costs associated with this reduction in crime, via counterfactual analysis, relative to costs of PSC operation. I find these CGRs provide cost savings between $3.5 and $5.9 billion, within my sample from 1995 to 2013, a return between $1.78-2.47 for every dollar spent on PSCs.

These results, though, bring up the question of causal mechanisms. PSCs provide no services directly. Toward this end, in the third empirical chapter I explore potential channels between PSCs and reductions in crime. I investigate three general paths: a lack of social disorganization, changes in law enforcement activity, and service provision. Social disorganization describes a dysfunctional community in which socially beneficial facets have broken down (e.g., civic engagement). These breakdowns also occur in individual household. Imagine a home in which one parent has been incarcerated. The now-single parent is left to provide for the entire household, leaving little time for acts that might benefit the community, sometimes even the household. The question, then, is whether PSCs reduce crime by simply not incarcerating people. I address this question by estimating the relationship between adult PSCs and juvenile arrests and between PSCs and unfounded crimes (reported crimes found later to be false). I find no relationship with juvenile arrests but do find PSCs associated with a reduction in unfounded violent crimes. With the latter, though, I find no evidence of mediation.
I operationalize changes in law enforcement behavior by exploring the relationship between PSCs and arrests in the same categories I found significant effects in the Offenses Known database. Arrests represent purely law enforcement behavior. Offenses Known includes these and crimes reported. I found, interestingly, no relationship between PSCs and these categories of arrests.

Toward the issue of service provision, I estimate the relationships PSCs have with the number of employees in relevant public employee categories (social welfare, community and housing development, health, and hospital workers) and drug arrests. I found a relationship with hospital workers (which includes in-patient treatment facilities) but no evidence of mediation. With drug arrests, though, I found a relationship between total, sales, and possession arrests and evidence of mediation. This variable mediated the effects PSCs have on crimes between nine and 14 percent. This points toward PSCs’ crime reducing effect coming through service provision, particularly through the cooperative, collaborative framework unique to PSCs.

The fourth empirical chapter evaluates the Indiana Peer Education Program. This program replicates the New Mexico Peer Education Project (K. Thornton et al., 2018), which trains incarcerated individuals (peers) to teach others in prison about important health issues (e.g., hepatitis C). The present study replicates previous findings and extends evaluation to include more sophisticated methodology. This process replicates previous findings, with improvements in health knowledge and behavior intentions for both peers and their students. Peers show small improvement in their attitudes about issues like substance use disorder and show large increases in their sense of self-efficacy.

Taken broadly, this work contributes to the criminal justice, public management, and public health fields, and highlights the artificial divisions between them. Studying
alternative approaches nudges policy and research in this direction, signaling priorities. Also, a not-insignificant portion of contemporary criminal justice research does not use contemporary methodologies, especially along quantitative lines (Lipsey et al., 2006).

More specifically, nearly all the research on PSCs amounts to non-equivalent comparison group analysis. This perspective not only limits empirical reach but also ignores the socioeconomic milieu in which PSCs operate. Along similar lines, performance measurement of collaborative governance structures often ignores larger-picture questions.

The INPEP evaluation contributes to the corrections literature as well. Though an incredible amount of programming has come online throughout the US over the past few decades, few empower incarcerated individuals in such a way. Also, previous program evaluations assess outcomes using outdated difference-in-means statistical approaches (like much of the corrections, criminal justice programming, and public health education literature).

Before empirically testing these propositions, it would help to know more about the context. First, I introduce problem-solving courts, an innovation in court practices that began in 1989 and diffused across the country rapidly. Then, I introduce incarcerated peer education, rare efforts that train people incarcerated to teach others similarly situated specific topics.
A. Problem-Solving Courts

Since Miami-Dade County created the first drug court in 1989, these specialty courts have expanded in focus and jurisdiction (Strong et al., 2016). Currently, over 3,600 PSCs exist (National Drug Court Resource Center, 2018). While the bulk of these are drug treatment courts, problems addressed have expanded to include issues such as mental health, veterans, parents with SUD (family dependency), and others (Marlowe et al., 2016; NDCRC, 2018).

Little research into the effectiveness of these courts has evaluated community-level outcomes, though scholars have called for more research examining broader, macro-social crime outcomes (Lipsey et al., 2006). PSC research almost universally performs program evaluation examining individual participant outcomes (e.g., recidivism, drug use, employment, attitudinal measures), overwhelmingly finding improvements (GAO, 2005; Rossman, Roman, & Rempel, 2011; Sevigny et al., 2013; Shaffer, 2011). Research evaluating community-level outcomes, on the other hand, has found no effect, or even increases, in relevant arrest and crime rates (Lilley, 2013, 2017; Lilley et al., 2019, 2020; Orrick, 2005; Zafft, 2014). Disparate findings between these two units of analysis beg the questions of why individual participants fare well but arrest and crime rates do not. The answers lie in using state-of-the-art econometric techniques, such as the stacked event study described below, on the most rigorously verified data, with the most up-to-date information on PSCs.

1. The Problem-Solving Court Movement:

When Miami-Dade County created specialty docket courts, including a drug court, they did so as an attempt to manage over-burdened dockets. The Crack Epidemic
and War on Drugs policies flooded their criminal justice system, and it became necessary to organize case types to gain efficiency. These dockets featured judge, prosecutor, and defense attorneys specializing in the topic (in this case, drug crimes; D. Marlowe, personal communication, January 2021). Practices at the time bent toward punitive measures, being the Tough on Crime period of criminal justice policies (Alexander, 2012; D. Marlowe, personal communication, January 2021; Martinson, 1974). The incredible costs associated with this approach – court dockets, jails, and prisons filled well beyond capacity – created substantial incentives to try something different. The War on Drugs was not working (Alexander, 2012). Thus, the Drug Treatment Court model (DTC) was born (D. Marlowe, personal communication, January 2021).

A few similarly situated jurisdictions replicated Miami-Dade County efforts in the years following its implementation, but DTCs gained prominence after being included in federal policy (1994 Crime Bill). Among the many other measures in this bill, it codified DTCs, provided funding, established a drug court program office, and laid the groundwork for the National Association of Drug Court Professionals.

This new prominence and funding created a boom for DTCs. They diffused across the country rapidly. Today, approximately 1,600 DTCs operate in the US. Jurisdictions throughout the US applied the DTC model to address other issues. The most prominent types of PSCs in operation today are:

1. Adult Drug Treatment Courts (ADC)
2. Hybrid Drug Treatment/DWI Courts (HYB)
3. Veterans’ Treatment Courts (VET)
4. Mental Health Courts (MHC)
5. Juvenile Drug Treatment Courts (JDC)
6. Family Dependency Courts (FAM)
7. DWI/OWI Treatment Courts (DWI)
8. Prisoner Reentry Courts (RE)
9. Co-Occurring Disorder Courts (i.e., mental health and substance use disorders; COO)
10. Healing to Wellness Courts (primarily found in Native American jurisdictions; HTW)

Figure 1 displays the number of PSCs implemented per year with a cumulative sum (A), and total PSC type counts as of 2018 (B).\(^1\) PSC implementation continued to increase year over year, dropping off after a peak of 328 new courts in 2007. Adult drug treatment courts represent a plurality of all PSCs, especially considering many evolved into hybrid DWI/drug courts. When put together, adult drug courts and hybrid courts total 1,703, over 46% of total PSCs. See Appendix A for more detailed graphs.

\(^{1}\) These numbers reflect the number of courts and not number of counties covered by these courts.

**FIGURE 1**

**Problem-Solving Courts in the US**

Note: Figure 1.A shows the number of PSCs implemented per year and the cumulative total for all PSCs. Figure 1.B presents total counts of the top seven PSC types as of 2018.
2. Problem-Solving Court Program Evaluations:

Scholars have evaluated participant outcomes for drug courts (Sevigny et al., 2013) and other PSCs (see Stein et al., 2013 for juvenile drug courts; and Tsai et al., 2018 for veterans courts). In addition to The Multi-Site Adult Drug Court Evaluation (Rossman, Roman, Zweig, et al., 2011), researchers have performed several meta-analyses of drug court program evaluations (e.g. Shaffer, 2011). The consensus from these studies is that PSCs, especially drug courts, perform better than traditional structures on individual participant-level outcomes. While effect sizes have varied, whether measuring changes in recidivism or other outcome indicators, reported results have been positive (e.g., lower recidivism and drug relapse).

Most of these evaluations used non-equivalent comparison group designs. Given the ethical implications inherent with human subject research, randomized controlled trials have been rare. Many researchers attempted to control for possible confounding variables (e.g., selection bias) through a variety of statistical techniques (e.g., propensity score matching).

Two problems have tempered knowledge of PSC programs (and their extensions). First, evaluations such as these cannot completely control for confounding factors (e.g., selection bias). Variation in individuals who participate (and graduate), PSC personnel, and jurisdictions that create such courts create an ambiguous environment in which studying individual-level outcomes may not be appropriate.² Gottfredson, et al. (2006) used a randomized trial design, finding reductions in re-arrest in one-, two-, and three-

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² To illustrate this point, the meta-analysis performed by the US Government Accountability Office (2005) used stringent guidelines for which studies were included, based upon research methodology, and found noticeably smaller effect sizes than other meta-analyses; Shaffer (2006) also found smaller effects for studies exhibiting higher levels of scientific quality.
year periods. The study, however, only included one drug court and may not be
generalizable. Further, extensions of this research found conflicting results regarding
long-term recidivism rates and other outcomes (Kearley et al., 2019 found no effect on
drug overdose mortality; Mackin et al., 2009 found no effect on long-term recidivism).

Second, jurisdictions create PSCs to address community-level problems. These
courts manifest as an effort to more effectively respond to local crime challenges and
improve public safety (see Lurigio, 2008). Any analysis of how well PSC participants do
relative to a comparison group may provide an approximation of how well these courts
serve their larger function, but they do not answer the most important question: Do
these courts improve public safety? Studies thus far are limited to effectiveness for those
who participate – or, more specifically, those who graduate – and fail to address
whether these efforts have led to outcomes citizens expect of local legal institutions.

3. Problem-Solving Court Community-Level Research:

The limited research that evaluates community measures of crime relative to the
presence of drug courts found no effect or, surprisingly, increases (Lilley, 2013; Orrick,
2005; Zafft, 2014). One paper offers high participant attrition as a plausible mechanism
contributing to higher crime levels, positing those who participate but do not graduate
may be worse off for the effort (Lilley, 2013, 8-10).

Though work on community-level outcomes may have identified unintended
consequences, it is incomplete for a few reasons. First, authors limited their work in size
and scope of PSCs covered. Lilley (2013) evaluated a limited number of years (1995-
2002) and used drug court grants as a proxy indicator for drug courts in a limited
number of communities. Zafft (2014) restricted her analysis to drug courts that a
previous meta-analysis review covered (i.e., Sevigny et al., 2013). As the growth of drug courts and expansion to other types of PSCs in the US occurred with substantial variability, these samples do not accurately describe general impacts (Strong et al., 2016).

Secondly, over the past decade decisionmakers have recognized the need for quality improvement, explicitly addressing issues with selection, retention, and attrition (e.g. Parker & Smith, 2011; Prince et al., 2013). Along with the growth of PSCs, personnel have grown and adapted processes. Every state in the nation employs personnel that coordinate and assist PSCs (NDCRC, 2018); most require reports outlining program evaluations, best practices, and strategies for improving operations. Recognizing the problems associated with attrition Lilley (2013) mentioned, states have attempted to adjust practices that improve retention, making graduation rates an explicit performance goal. A good illustration of this comes from Idaho’s annual PSC reports, each of which outlines measures of quality improvement, including graduation rates (Thomas, 2020; Tobias, 2010).

B. Incarcerated Peer Education

Incarcerated populations experience higher incidence of chronic diseases and less desirable health outcomes overall (Ferguson, 2018; Sugarman et al., 2020). Several factors influence this phenomenon. For one thing, in the United States social determinants associated with poor health – “being non-white, low-income, undereducated, homeless, and uninsured” (Macmadu & Rich, 2014, 2) – align almost perfectly with those associated with criminal justice system involvement (Ferguson,
Scholars cite an “Epidemic of Incarceration,” intertwining these concepts (Dumont et al., 2012).

Further, groups disadvantaged outside of the carceral system show such health disparities within the criminal justice system. Stark differences exist within incarcerated populations along race and gender lines. Taken from another perspective, those among disadvantaged groups who are also incarcerated experience less desirable health outcomes than those not incarcerated but within the same demographic groups. The intersection of incarceration and demographic disadvantage compounds health issues (Dumont et al., 2012).

The literature lists disparities for chronic diseases such as hypertension, asthma, and cancer (Binswanger et al., 2012); infectious diseases like tuberculosis (Baussano et al., 2010; MacNeil et al., 2005), HIV (Freudenberg, 2011), and hepatitis C (Varan et al., 2014); and psycho-social issues including substance use disorder, psychiatric disorders, and victimization (Binswanger et al., 2012). At the time of writing this article, the COVID-19 pandemic is highlighting these grim facts with disturbing rates of transmission (including among prison officials and guards) and frantic calls to address the problem (Kinner et al., 2020). Beyond the immediate ethical necessity of examining the health of incarcerated populations, such outcomes have ramifications for communities and society, as the recent pandemic demonstrates.

These disparities align with another social determinant of health and criminal justice system involvement: power dynamics (Harrison, 1995; Pratto & Pitpitan, 2008). Generations of a punitive system have prolonged a power structure that disadvantages minorities, women, and others, that both precedes criminal justice involvement and ensures disadvantage, making criminal desistance much more difficult (Weaver &
Geller, 2019). Programming offered to improve underlying issues associated with crime, be they toward education or mental health interventions, presents a traditional power structure dichotomy: some authority providing programming content (them) and those receiving the programming (us).

Over 600,000 people are released from US state and federal prisons each year (Carson, 2020). The predisposition for negative health status, poor level of health engagement within carceral systems, stigma and collateral consequences formerly incarcerated people experience upon release, and disparities in knowledge of relevant health practices conspire to undermine any progress returning citizens aspire toward (Tyler & Brockmann, 2017). Further, such elements impact the families, communities, and society people return to (Travis & Waul, 2003). More concisely, carceral health is public health.

The Indiana Peer Education Program (INPEP) approaches this issue along two lines. The fist, and more direct perspective provides accurate and helpful learning engagement through training and education sessions. The second, and somewhat indirect has to do with self-efficacy. The program seeks to empower peers, as educators in their own right, hopefully improving their individual sense of agency. On one hand, scholars have demonstrated that self-efficacy impacts health and health behavior (Strecher et al., 1986). One the other, agency and self-efficacy have been associated with criminal desistance (Johnston et al., 2019). Further, in training incarcerated peer educators, INPEP disrupts traditional carceral power dynamics (Story, 2019). Peers become leaders within their carceral community and, as such, do not fit within the usual dichotomy.
Together, PSC and IPE programs exemplify innovative approaches to crime and delinquency. They offer alternatives to the usual punitive, hierarchical structures. Each professes effectiveness and efficiency at achieving both short- and long-term outcomes, though the evidence has yet to prove such claims. This dissertation addresses this lack of evidence, proving the assertions accurate – both PSCs and IPEs achieve their goals.
II. Problem-Solving Courts and Community-Level Crime

This chapter explores the impact problem-solving courts (PSCs) have on community-level crime. Created in response to overcrowded dockets, these programs seek to address underlying conditions antecedent to criminal offense (e.g., substance use disorder). Since Miami-Dade County implemented the first drug treatment court in 1989 this model has diffused throughout the United States, covering several issues (e.g., mental health disorders, veterans’ issues), with close to 4,000 courts currently covering nearly every jurisdiction in the United States. Most research to-date, however, measures individual participant effects (usually substance use relapse or criminal recidivism). The few studies examining community-level outcomes found increases in crime and drug arrests, creating conflict between individual and community levels of analysis. I rectify this disparity by estimating the effects PSCs have on known offenses using a stacked event study design, finding substantial and significant reductions in total, property, and violent crime indexes, as well as several of the crime categories that comprise these. Crime reductions range from a 2.06% reduction in theft to, surprisingly, a 6.22% drop in robbery. These results stand up to several robustness checks, indicating PSCs provide an outsized reduction in community-level crime, considering their limited footprint within the criminal justice system.
A. Introduction

As a deputy sheriff with the Cache County Sheriff’s Office, Mark served several roles. For ten years he worked as a detention officer in the jail, then transferring to bailiff with the local court (Dupree et al., 2017b). He found his time at the jail disheartening, “I have lost my love for my fellow man... I’m not a better person for having served there” (Dupree et al., 2017a, 8). This experience contrasts with his more recent post as bailiff for the Cache County Drug Court.

...to come to Drug Court and to see people that had been in there, not very long ago or that I’d seen come through [jail] a number of times and to see the change that they’re going through outside of the jail was huge! I mean, some of them I looked at and thought, ‘I would never have thought in a million years you could have done this from the dealings that we had in the jail.’ I just, I was amazed. – (Dupree et al., 2017a, 8)

Mark’s experience represents an interesting shift in the construction of crime, deviance, and how society should address these. And, as compelling as his story may be, it represents the scale of most research evaluating PSCs. Changes in attitudes, graduation rates, and participant recidivism show promising outputs and outcomes for these programs but beg the question of community-level impacts. Do these intermediary results translate to larger benefits?

Research has yet to establish PSC effects on public safety, despite over three decades of operation and an explicit mandate. Early adopters created the intervention as a response to incredible growth in numbers of people arrested and charged in the 1980s, which clogged court dockets – especially with low-level drug charges. Big-picture outcomes, then, provide logical measures. This chapter examines the effectiveness of PSCs to address community-level outcomes. The most prominent directive for criminal
justice courts includes public safety, making crime a logical starting point. I exploit variation in PSC implementation across the US to assess the question of their impact on crime at the county level. As a check for robustness, I compare estimated outcomes with actual data.

Also, as PSCs represent substantial changes in court structures, which require substantial changes in local attitudes and construction of certain concepts (e.g., crime and criminality, the role of a court), several factors likely threaten validity. These communities might simply feature more resources than those without PSCs. To explore this, I estimate the predictive nature of variables likely to indicate confounding factors. Communities capable of implementing a PSC may also exhibit higher capacity for other criminal justice efforts. I evaluate law enforcement activity to determine whether these factors confound results, finding little dissuading evidence. Similarly, communities with PSCs may consist of actors more inclined to a service-oriented approach to crime. I perform similar estimation of the predictiveness of variables that might indicate such communities. Specifically, I examine the relationship between PSCs and public employee groups that reflect local policy priorities (e.g., social welfare workers). Total and housing and community development public employee categories show some prediction, that PSCs select a bit on these factors, muddying causal inference. This element, though, requires a slight alteration of language, rather than completely confounding results. Communities more prone to a service orientation – that possess and expend resources necessary for this approach – show reductions in crime.

Estimation indicates overall reduction in index offenses, though total and property indexes show some pre-trends, potentially biasing post-implementation estimates. Interestingly, these programs show the largest, most robust crime-reducing
effect on the violent index. Over the five years after PSC implementation, the total crime index drops by an average of 2.71% (with a maximum of 3.48% in the fourth year after implementation), the property index by 2.71% (3.42% max in the fourth year), and the violent index by 2.92% (max of 4.33% in the fourth year).

Evaluating the individual crime categories used to compose these indexes indicates significant and substantial reduction effects on burglary (-3.76% average), theft (-2.13% average), motor vehicle theft (-5.39% average), robbery (-3.99% average), and aggravated assault (-2.64% average). Predictably, I found no effects for the arson, murder, and rape categories. In addition to event study graphs below, I present a table of crime category effect sizes by relative year, as well as post-implementation averages, in Appendix A. I also performed sensitivity tests by running the same analyses on more stringently specified crime data, finding similar patterns of effect sizes.

It appears that treating underlying factors that lead to criminality provide substantial returns. The previous 30 years have taught us that enforcement and punitive policy levers come with untenable financial and social costs (Alexander, 2012). Programming like PSCs offer layered benefits with appeal across the political continuum: they save taxpayer dollars and avoid socially disruptive outcomes like incarceration.

B. Setting and Data
1. Problem-Solving Courts:
   a. The Model

   The PSC model stems from that developed for adult drug treatment courts, based upon the Ten Key Components that early PSC professionals set down as the standard (Bureau of Justice Assistance, 2004; NADCP, 2018a). These include (1) integrating
treatment services into court case processing systems, (2) non-adversarial internal operations, (3) early criminal career intervention, (4) access to a continuum services for participants, (5) monitored abstinence from drugs and alcohol, (6) coordinated strategies between court actors governing responses to participant compliance or non-compliance (i.e., all actors provide input), (7) ongoing judicial interactions (usually frequent meetings with presiding judges in their courtroom), (8) ongoing program evaluation, (9) ongoing professional development of court actors, and (10) building relationships with community stakeholders (BJA, 2004). Every other type of PSC includes some iteration of these elements (Marlowe et al., 2016).

The PSC model altogether represents innovative practice. Some elements, though, align with other criminal case outcomes. Those whose cases terminate with probation or incarceration also experience drug and alcohol use monitoring, as well as some connection with services like SUD counseling (see e.g., Kelly et al., 2005). The call for a continuum of service for those involved in the criminal justice system also includes non-PSC options, though it does not appear other areas have achieved the levels of program adherence seen in PSCs (Behavioral Sciences & the Law printed a double issue on the subject; Pinals & Felthous, 2017). Similar calls for cross-boundary collaboration within and without the criminal justice system (including courts) have also seen spotty implementation (e.g., Morrissey et al., 2009).

b. The Process

Following arrest and charges alleging criminal offense, individuals participate in traditional criminal justice processes, including plea negotiations. PSCs come into play
as one option within the set of alternatives prosecutors might offer in exchange for a guilty plea (Public Defender, personal communication, 2018).

Most PSCs focus on people who have committed first-time, non-violent offenses, though recent developments have opened this up a bit (Marlowe et al., 2016; Saum et al., 2001). Often, plea agreements include sentence deferral, in which a guilty plea is thrown out upon successful completion (Noia et al., 2018; Rossman, Zweig, Kralstein, et al., 2011).

The typical program length for PSCs varies from 12 to 24 months, with the average being roughly 18 months (Rossman, Zweig, Kralstein, et al., 2011). Participants experience a tiered program that involves higher levels of supervision and task requirements (e.g., number of SUD meetings to attend) during early periods, and less as they progress. Sanctions for noncompliance, like failing a drug test, also increase in phases. Some courts provide incentives for reaching benchmarks as well, like graduating from one phase to the next, beyond those inherent to the program (e.g., sentence deferral), though these tend to be nominal and non-increasing (Rossman, Zweig, Kralstein, et al., 2011).

c. Treatment and Control Conditions

Those facing criminal charges generally face four paths, whether through plea negotiations or a trial: (1) no punishment (due to acquittal or technical dismissal), (2) incarceration, (3) community supervision, or (4) a diversion program like PSCs. Though

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3 This is another area in which scholars and practitioners state the need for change – PSCs lowering admission standard to include more people, like violent offenses – but organizations act slowly or not at all. Few PSCs have changed requirements for participation.

4 Deferral itself, though, is also not uncommon for probation supervision sentences (Mueller-Smith & Schnepel, 2017).
each of these involves more complexity than I have space for, we must establish counterfactual conditions prior to analysis, so I cover them briefly.

Incarceration incapacitates individuals from committing crimes (in the communities of interest) for the duration of imprisonment, so can be set aside. It stands to reason that acquittals, and other non-punishment outcomes, are evenly distributed (i.e., as good as random), so we can also set these aside (Gramlich, 2019). Therefore, the primary counterfactual condition to PSC participation is some form of community supervision.

Community supervision ranges from unsupervised probation to house arrest. As mentioned in section II.B.1.a, many features of community supervision overlap with PSCs. Probationers and PSC participants both submit to frequent drug tests, meetings with an authority (probation officer or PSC judge), adhere to specific requirements like employment, and are referred to services. PSCs, though, not only monitor service and general program adherence, but do so in a cooperative, collaborative environment. Service providers serve on PSC teams with influence on policies and decisions. Probation and other community supervision types feature no such arrangement.

A 2008 report estimated the average number of participants per PSC at 93.\textsuperscript{5} Multiplying this figure by the number of PSCs in 2018 (National Drug Court Resource Center, 2018) – 3,681 – we get roughly 342,333 participants (Bhati et al., 2008). That same year, reports the Bureau of Justice Statistics, about 3.5 million people were on probation (Kaebel, 2020). Even if we assume authorities double count PSC participants as on probation, general supervision outnumbers PSC participation ten-fold. Given that

\textsuperscript{5} As I cover in Chapter III below, this figure has been debated. 93 is the largest estimate I could find so I use it as a conservative assessment of the difference between PSC participants and people on probation.
every jurisdiction includes probation as an outcome for criminal justice cases, the two conditions investigated in this study amount to counties with probation and without a PSC, and those with both probation and a PSC.⁶

2. Data:
   a. Problem-Solving Courts

   I downloaded a dataset⁷ offered by the National Drug Court Resource Center⁸ (NDCRC) that listed all of the problem-solving courts in the US according to a survey the NDCRC administered to 55 state coordinators (National Drug Court Resource Center, 2018). Original data variables included court name, court type, location, and implementation date.

   I improved the data by specifying counties of jurisdiction each court covered and implementation dates that the original download did not include. I found these variables in publicly available digital information (e.g., court websites), contact with state and court administrators, and the National Association of Drug Court Professionals (NADCP).⁹ The original dataset included 59.42% implementation dates. Though some courts listed their main county of jurisdiction under Court Name, many did not. Further, this information did not indicate whether a court covered more than one county (common in rural areas).

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⁶ Practitioners and researchers have attempted to make probation and supervision generally more effective, closing the gap between treatment and control conditions (see Lattimore et al., 2021, chapters 4-12). These improvements would bias estimates on PSC performance toward zero.
⁷ The NDCRC changed hands from American University to the University of North Carolina – Wilmington and after the transition this dataset was rescinded. It is no longer publicly available.
⁸ https://ndcrc.org/
⁹ https://www.nadcp.org/ -- I must thank Dr. Doug Marlowe and Carolyn Hardin at the NADCP for their assistance.
Currently, my dataset includes 4,423 observations representing 3,698 courts. Many rural courts cover more than one county, making more observations than courts. The current dataset includes 89.51% implementation dates. Since adult drug treatment courts (ADCs) serve as the prototype for all other PSCs, I exclude any counties that indicate the presence of an ADC but no implementation date. Similarly, since some hybrid DWI/drug courts evolved from ADCs, I also exclude counties with a hybrid court but no implementation date.

Some spatial concerns arise from variation in jurisdictions, especially between urban and rural counties. Many urban counties contain several PSCs (Los Angeles County has roughly 50) and many rural courts cover several counties. To deal with this, I include an indicator variable coded one if a county includes a court that covers multiple counties, and zero otherwise. The ideal strategy for this issue would be to create “super counties” that combine all rural counties covered by the same court.\textsuperscript{10} Unfortunately, the efforts necessary to clean the UCR data (described below) exclude such construction.

b. The Uniform Crime Reporting Program

I use the Uniform Crime Reporting (UCR) program data for Offenses Known, Arrests, and Law Enforcement Personnel. Though one may be tempted to use the UCR county-level data imputed by the FBI, many scholars have pointed out fatal flaws in imputation strategies (Maltz & Targonski, 2002, 2003; see Lott & Whitley, 2003 for a

\textsuperscript{10} Many thanks to Dr. Aaron Chalfin for offering this solution.
counter-point). Jacob Kaplan\textsuperscript{11} has, in fact, retired his county-level files from ICPSR.\textsuperscript{12} For this reason, I opted to use his publicly available concatenated files of yearly known offenses, arrests, and law enforcement personnel (Kaplan, 2021d, 2021c).

These data, however, also come with complications. As the UCR program is voluntary, law enforcement agencies report data inconsistently. This inconsistent reporting is unpredictable between agencies and over time, so do not present random error. Though recent federal policy efforts have improved incentives for accurate and consistent reporting, much of the program’s history features flawed data. To address this, I balance data quality with generalizability to formulate inclusion criteria.

I use two included variables as measures of data quality: number of months reported per calendar year and population group. An agency that reports more months in a year likely signifies concern toward accurate reporting. Population covered by a reporting agency has been associated with both the consistency (i.e., number of months) and quality of reporting. Restricting inclusion to those agencies most likely to be consistent and accurate, though, presents issues with generalizability.

I assess optimal inclusion criteria by iterating across three population cutoffs – 2,500+, 10,000+, and 50,000+ – and four months-reported minima – 9, 10, 11, and 12. For population groups, I consider whether an agency reports that group (or higher) at any point between 1990 and 2018. The months reported figure, however, applies to the entire study period. I compared descriptive statistics of independent and control variables between each of these iterations to those presented in the underlying datasets.

\textsuperscript{11} I appreciate all the help Dr. Jacob Kaplan provided in this work. This dissertation would not have been possible without his help.

\textsuperscript{12} https://www.openicpsr.org/openicpsr/project/108164/version/V4/view
Since the question under review pertains to the quality of crime data, using these variables for generalizability comparison makes the most sense. Variables included are law enforcement agencies per county; law enforcement personnel grouped by total, officers, and civilians (per 1,000); problem-solving courts per county; percentages age 15-24, male, and white; and percentage of Republican and Democratic Party presidential votes.

Figure 2 presents overall averages of standard differences between variable means in the 12 dataset iterations and source data. This figure shows quite a difference between population groups, with the datasets allowing inclusion of agencies covering at least 2,500 population showing the least standardized difference. Surprisingly, these differences come out lower for more stringent months reported criteria in the 2,500+ population group iterations, and partially in the 10,000+ iterations.

FIGURE 2
Standard Differences of Data Iterations

Note: This figure reports average standard differences between descriptive statistics between the listed data iterations and underlying data.
Thus, I find the inclusion criteria most likely to offer data most accurately representing the entire US, while providing the most reliable crime figures to be agencies that:

1. Cover at least 2,500 population at any point within the study period; and
2. Report all 12 months each year within the study period.

The FBI adjusts some agency population counts to correct for overlap within counties (FBI, 2004). To account for this, I deleted any agency completely from the dataset that returned a zero-population figure at any point in the study period. I also collapsed these data using Federal Information Processing Standards (FIPS) codes to the county level. Since the data are fully balanced, this made the unit of analysis the super-agency (i.e., not individual agencies but also not full counties). For ease of discussion, and since I use county FIPS codes to identify super-agency units, I stick with the term “county” throughout this study (“county-year” for individual observations).

Agencies occasionally correct for previous reports – say, when several crimes were judged unfounded – so a few observations include negative values. My estimation strategy involves Poisson transformation, which cannot include negative values. I set a floor of zero for all values, though this only adjusted a maximum of five observations (violent index) with the most adjustment needed for one agency reporting -5 violent crimes.

The Offenses Known dataset includes variables used to evaluate offenses cleared by arrest and unfounded crimes, which come with their own issues. Arrests for reported crimes, and determinations of unfoundedness, may not occur in the same year as the underlying offense, introducing additional measurement error. Some county-years presented rates over 100%. I created a ceiling of 100% with the realization that these
issues make interpretation more difficult. Further correction, however, is beyond the scope of this paper; these variables do not constitute core analysis data.

c. Control Variables
i. Population

UCR data included population covered figures. I also merged county size data, obtained from the USDA, to calculate population density, which provides a proxy variable for access to services (Allard, 2004; USDA, 2021). As described above, I excluded any observations that indicated zero population at any point in the study.

ii. County Demographics

In keeping with previous work that shows association between community demographics and crime, I pulled longitudinal data from the National Institutes of Health – Surveillance, Epidemiology, and End Results Program (SEER) and included county-year percentages of age 15-24, male, and white (NIH | SEER, 2021). I expressed these as 0-100 percentages to make interpretation easier. Some counties in the master dataset were not covered by using data. I excluded counties that did not match at any point in the study period.

iii. Unemployment

For similar reasons, I included county-year unemployment rate, 0-100 range as well, that I pulled from the Bureau of Labor Statistic’s Local Area Unemployment Statistics website (Bureau of Labor Statistics, 2021). As with SEER data merging procedures, I excluded counties that did not merge from the master dataset at any point in the study period.
iv. Presidential Vote Proportions

As a proxy measure of local construction of issues like crime, substance use disorder, and veterans, I merged county-level data indicating the proportion of Republican and Democrat votes (Allard, 2004). John Stavick and Justin Ross pulled these data together and interpolated them for non-election years, weighting by proximity to an election year (Stavick & Ross, 2020). The pulled original data from the CQ Press Voting and Elections Collection.13

v. Annual Survey of Public Employment and Payroll

I analyze potential confounding variables using the Annual Survey of Public Employment and Payroll data (Kaplan, 2021a). The US Census Bureau asks various levels of government to report numbers of personnel and payroll figures. As payroll presents high variation in interpretation, due to disparate costs of living across geographic and temporal space, I use full time equivalent employee numbers per 1,000 population for analysis. I include county and local government data, aligning with the county-year unit level of my core analysis.

3. Descriptive Statistics:
   a. Problem-Solving Courts

Table 1 provides summary statistics for PSCs per county (by FIPS code), and their individual types, as well as multiple county courts. I also include the number and percentages of counties that ever have a PSC (treated) and those that do not (control), collapsed to the county (i.e., not by county-year).

13 library.cqpress.com
**TABLE 1**

*Problem-Solving Courts*

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>S.D.</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem-solving courts</td>
<td>0.19</td>
<td>0.47</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Adult drug treatment courts</td>
<td>0.08</td>
<td>0.3</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Hybrid DWI/drug courts</td>
<td>0.04</td>
<td>0.2</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>DWI courts</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Family courts</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Juvenile drug courts</td>
<td>0.02</td>
<td>0.16</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Mental health courts</td>
<td>0.02</td>
<td>0.15</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Veterans’ courts</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Reentry courts</td>
<td>0</td>
<td>0.05</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Co-occurring disorder courts</td>
<td>0</td>
<td>0.05</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Healing-to-wellness courts</td>
<td>0</td>
<td>0.03</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ADC+HYB</td>
<td>0.12</td>
<td>0.35</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>JDC+FAM</td>
<td>0.04</td>
<td>0.21</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>MHC+COO</td>
<td>0.02</td>
<td>0.16</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Mult County (if PSC &gt;= 1)</td>
<td>0.22</td>
<td>0.41</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Perc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ever PSC</td>
<td>1,130</td>
<td>50.6%</td>
</tr>
<tr>
<td>Never PSC</td>
<td>1,103</td>
<td>49.4%</td>
</tr>
</tbody>
</table>

**b. Crime and Other Variables**

Table 2 provides descriptive statistics for the total sample, as well as the treatment (i.e., counties with a PSC) and control groups. I also included p-values for a difference in means test between these, as well as standardized differences. Though many t-tests show highly significant differences, the standardized differences show most below 0.3 standard deviations, with the exception of population.
### TABLE 2
**Descriptive Statistics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total Mean (N = 52,275)</th>
<th>Treat Mean (N = 14,474)</th>
<th>Cont Mean (N = 37,801)</th>
<th>T-Test of difference</th>
<th>Standardized difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Known Offenses (per 100k)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>4,356.93</td>
<td>4,875.87</td>
<td>4,158.23</td>
<td>&lt;0.001</td>
<td>0.26</td>
</tr>
<tr>
<td>Total Index</td>
<td>3,370.67</td>
<td>3,762.22</td>
<td>3,220.75</td>
<td>&lt;0.001</td>
<td>0.25</td>
</tr>
<tr>
<td>Prop Index</td>
<td>3,022.40</td>
<td>3,366.20</td>
<td>2,890.76</td>
<td>&lt;0.001</td>
<td>0.24</td>
</tr>
<tr>
<td>Violent Index</td>
<td>351.03</td>
<td>398.62</td>
<td>332.81</td>
<td>&lt;0.001</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>Arrests (per 100k)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>6,804.73</td>
<td>6,917.96</td>
<td>6,751.61</td>
<td>0.318</td>
<td>0.01</td>
</tr>
<tr>
<td>Total Index</td>
<td>941.71</td>
<td>933.21</td>
<td>945.69</td>
<td>0.192</td>
<td>-0.02</td>
</tr>
<tr>
<td>Prop Index</td>
<td>751.16</td>
<td>734.96</td>
<td>758.76</td>
<td>&lt;0.001</td>
<td>-0.04</td>
</tr>
<tr>
<td>Violent Index</td>
<td>193.21</td>
<td>202.17</td>
<td>189.43</td>
<td>&lt;0.001</td>
<td>0.06</td>
</tr>
<tr>
<td><strong>Law Enforcement (per 1k)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tot LE/ik</td>
<td>2.59</td>
<td>2.70</td>
<td>2.55</td>
<td>&lt;0.001</td>
<td>0.11</td>
</tr>
<tr>
<td>Officers/ik</td>
<td>1.85</td>
<td>1.93</td>
<td>1.81</td>
<td>&lt;0.001</td>
<td>0.11</td>
</tr>
<tr>
<td>Civ/ik</td>
<td>0.77</td>
<td>0.79</td>
<td>0.76</td>
<td>&lt;0.001</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>Officers Killed/Assaulted (per 100k)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off Kill/Felony</td>
<td>0.02</td>
<td>0.01</td>
<td>0.02</td>
<td>0.238</td>
<td>-0.01</td>
</tr>
<tr>
<td>Off kill/Accident</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
<td>0.313</td>
<td>-0.01</td>
</tr>
<tr>
<td>Off Assaulted</td>
<td>12.60</td>
<td>15.24</td>
<td>11.59</td>
<td>&lt;0.001</td>
<td>0.14</td>
</tr>
<tr>
<td><strong>Clearance by Arrest (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>33.38</td>
<td>31.93</td>
<td>33.93</td>
<td>&lt;0.001</td>
<td>-0.13</td>
</tr>
<tr>
<td>Total Index</td>
<td>25.34</td>
<td>24.11</td>
<td>25.81</td>
<td>&lt;0.001</td>
<td>-0.13</td>
</tr>
<tr>
<td>Prop Index</td>
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<td>20.58</td>
<td>22.09</td>
<td>&lt;0.001</td>
<td>-0.12</td>
</tr>
<tr>
<td>Violent Index</td>
<td>58.81</td>
<td>55.68</td>
<td>60.01</td>
<td>&lt;0.001</td>
<td>-0.18</td>
</tr>
<tr>
<td><strong>Unfounded Crimes (%)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>1.98</td>
<td>1.73</td>
<td>2.07</td>
<td>&lt;0.001</td>
<td>-0.07</td>
</tr>
<tr>
<td>Total Index</td>
<td>2.06</td>
<td>1.82</td>
<td>2.15</td>
<td>&lt;0.001</td>
<td>-0.06</td>
</tr>
<tr>
<td>Prop Index</td>
<td>2.03</td>
<td>1.80</td>
<td>2.13</td>
<td>&lt;0.001</td>
<td>-0.06</td>
</tr>
<tr>
<td>Violent Index</td>
<td>2.55</td>
<td>2.25</td>
<td>2.66</td>
<td>&lt;0.001</td>
<td>-0.06</td>
</tr>
<tr>
<td><strong>Socio-Economic</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>87,654</td>
<td>162,294</td>
<td>59,073</td>
<td>&lt;0.001</td>
<td>0.38</td>
</tr>
<tr>
<td>Age 14-25 (%)</td>
<td>13.65</td>
<td>14.45</td>
<td>13.46</td>
<td>&lt;0.001</td>
<td>0.20</td>
</tr>
<tr>
<td>Male (%)</td>
<td>49.60</td>
<td>49.48</td>
<td>49.64</td>
<td>&lt;0.001</td>
<td>-0.09</td>
</tr>
<tr>
<td>Female (%)</td>
<td>50.40</td>
<td>50.52</td>
<td>50.36</td>
<td>&lt;0.001</td>
<td>0.09</td>
</tr>
<tr>
<td>White (%)</td>
<td>87.22</td>
<td>86.04</td>
<td>87.68</td>
<td>&lt;0.001</td>
<td>-0.11</td>
</tr>
<tr>
<td>Black (%)</td>
<td>10.03</td>
<td>10.05</td>
<td>10.02</td>
<td>0.779</td>
<td>0.00</td>
</tr>
<tr>
<td>Unemployment Rate (%)</td>
<td>6.35</td>
<td>6.22</td>
<td>6.41</td>
<td>&lt;0.001</td>
<td>-0.07</td>
</tr>
<tr>
<td>Republican Vote Proportion (%)</td>
<td>53.87</td>
<td>53.96</td>
<td>53.83</td>
<td>0.332</td>
<td>0.01</td>
</tr>
</tbody>
</table>
c. Crime Trends

Figure 3 shows trend lines for total, property, and violent crime indexes between counties that ever adopt a PSC and those that never do. I include these visualizations to get an idea of trends, not toward any real analysis. With thousands of counties, in all 50 states, over such a long period, the high number of shifting factors makes visual analysis unreliable. These figures help, though, build confidence in the common trends between treatment and control counties over time. Given the issues mentioned above with UCR data, I filtered data through the same inclusion criteria, which limited the number of PSCs reported (in green). I provide these figures to get a sense of PSC implementation over time relative to crime trends.
FIGURE 3
Crime Trends

A. Total Index

B. Property Index

C. Violent Index

Notes: These graphs present crime trends for Total, Property, and Violent crime indexes, and include the number of PSCs implemented per year (green bars, right axis).
C. Study Description and Results

1. Empirical Strategy:

In a study such as this, a researcher would normally employ an event study design that evaluates the dynamic effects of a policy (“treatment”) over time. This method allows estimation of pre-treatment trends, which would bias post-treatment estimates (Wing et al., 2018), as well as dynamic impact over time. To implement an event study, one creates indicator variables for relative years before and after policy implementation and whether a specific observation (county-year) has the policy in place during that relative period. Note that the term “relative” time period differs from calendar years. In this study, the relative time bin for “0” (the year of PSC implementation) would include a court implemented in any calendar year. For example, the first adult drug treatment court created in Miami in 1989 and one created in Indiana in 2018 would both fall into the zero bin. Formally, this method is defined as:

\[
Y_{ct} = \sum_{\tau = -K, \tau \neq -1}^{T} \sigma_{\tau} D_{ct}^{T} + \sum_{\tau = -K, \tau \neq -1}^{T} \pi_{\tau}(PSC_{ct} \times D_{ct}^{T}) + \omega_{c} + \zeta_{t} + \kappa_{ct} + \epsilon_{ct} \tag{1}
\]

\(Y_{ct}\) is the outcome for county \(c\) in calendar year \(t\). Relative time periods are indexed \(\tau = -K, ...,-2,0,...L\), with \(\tau = 0\) representing the year of implementation. Following convention, I exclude \(\tau = -1\). \(D_{ct}^{T}\) is an indicator variable for each relative time bin, representing main (control) effects, with \(\sigma_{\tau}\) estimating average effects for that relative time bin. I also include an interaction term for each time bin and whether county \(c\) has any PSC\(^{14}\) for that year. \(\pi_{\tau}\) indicates the average treatment effect for relative time period

\(^{14}\) We can take this treatment as absorbing (i.e., non-decreasing over time) for three reasons. First, the rate of closure for PSCs is very low (Marlowe et al., 2016). Second, the original dataset came from a survey of state coordinators in 2018 — those presented existed in 2018; any courts opened and closed prior to then would not appear. This presents some measurement error, in that counties coded as not having a
\( \tau \) – Callaway and Sant’Anna’s (2018) cohort-specific average treatment effect. County – \( \omega_c \) – and calendar year – \( \zeta_t \) – are also included, as well as controls described above – \( \kappa_{ct} \).

This method, though, comes with stringent assumptions. These include parallel trends, that those areas with and without the treatment “share the same evolution of baseline outcomes,” and likely would if the treatment were not implemented (Sun & Abraham, 2020, 7). Similarly, the assumption of non-anticipatory behavior dictates that those impacted by the policy do not change their behavior in anticipation of the new policy (e.g., individuals shifting capital around in anticipation of a new tax law). The third, and most germane, assumption is treatment effect homogeneity. Since event study estimates amount to an average treatment effect within each relative time bin, heterogeneity would bias these in unpredictable ways.

Considering the same two courts mentioned above, between Miami in 1989 and Indiana in 2018, I cannot justify the latter assumption. Thus, a traditional event study design would likely return biased estimates. The high degree of non-random implementation variation in time and space, and the variation in local conditions this represents, means that there would be composition bias and heterogenous treatment effects. Variation in number and content of each relative time bin creates composition bias in that estimates change depending on which relative time bins are specified. Variation in the courts within each time bin creates treatment effect heterogeneity as different courts, implemented in different areas at different times, have different effects.

---

PSC in a certain year may have had one that closed prior to 2018. This would likely bias estimates toward zero, though. Finally, most specification strategies here consider the case of counties ever having a PSC, so they are absorbing by construction.
Heterogeneity of this type means that relative time bins contaminate each other, whether included in specification or not (Sun & Abraham, 2020).

To address these issues, I use an event-specific, stacked event study design presented in Cengiz et al. (2019). Like a traditional event study, I set up relative time bins indicating the year of implementation (zero again) and relative years prior and after. For this analysis, though, I create individual sub-experiment datasets (termed “stacks”) for each year in the study period, which includes counties that implement a PSC in that year and counties that have no PSC for five years prior and after. Given that my study period is 1990-2018, this limits PSC counties to 1995-2013 to allow for pre- and post-periods.

Consider Figure 4 below. The first row represents a stack for 1995, which includes counties that implemented a PSC in that year and those that do not have a PSC for that year, five years before (1990-1994), and five years afterward (1996-2000) – a “clean” control group. This stack is now balanced in relative time, eliminating composition bias, and is much less likely to exhibit heterogenous treatment effects, satisfying the third assumption above. To evaluate the average treatment effect over multiple stacks, I append all available, creating a stacked dataset. Figure 4 also shows five stacks together, with relative year time bins indicated in the bottom row. The present study period goes from 1990 to 2018, which allows inclusion of implementation years 1995 to 2013. Thus, the final dataset includes 19 stacks (see Appendix A for a table listing total observations in each stack). Finally, below this figure I included an example event study graph with enlarged relative year numbers. All stacked event study graphs below exhibit the same pattern of relative year bins, which align with the stacked datasets as displayed here.
FIGURE 4
Stacked Event Study Data Process

<table>
<thead>
<tr>
<th>Controls</th>
<th>Treat</th>
<th>Controls</th>
</tr>
</thead>
</table>

-5 -4 -3 -2 -1 0 1 2 3 4 5

Example Graph

![Graph showing stacked event study data process with years and control periods identified.](image-url)
We can formally define event-specific evaluation of each stack as

$$ Y_{cth} = \sum_{\tau=-5, \tau \neq -1}^{5} \delta_{\tau} I^e_{cth} + \sum_{\tau=-5, \tau \neq -1}^{5} \alpha_{th}(PSC_{ch} \times I^e_{cth}) + \mu_{ch} + \rho_{t} + \Omega_{ct} + u_{ct}. \tag{2} $$

Most terms here reflect those in Equation (1), with the addition of stacks being indicated by $h$, with $\alpha_{th}$ providing an event-specific estimation of each stack's effect for each relative time period. Evaluating average treatment effects across all stacks can be defined as

$$ Y_{cth} = \sum_{\tau=-5, \tau \neq -1}^{5} \delta_{\tau} I^e_{cth} + \sum_{\tau=-5, \tau \neq -1}^{5} \alpha_{t}(PSC_{ch} \times I^e_{cth}) + \mu_{ch} + \rho_{t} + \Omega_{ct} + u_{ct}. \tag{3} $$

Here, $\alpha_{t}$ estimates the average treatment effect across all stacks – my core analysis below.

2. Core Analysis:

My primary analysis for community-level public safety involves PSC impacts on county-level offenses known from the UCR database. Figure 5 displays control (main effects in blue) versus treatment (main plus interaction effects in red) for total, property, and violent crime indexes. While all results indicate crime reductions after PSC implementation, estimates for the total crime index shows pre-implementation effects, which indicates some selection of treatment (PSC implementation) on this outcome variable, possibly biasing results. Property crime appears to drive this trend, as shown in graph 5.B. Post-implementation estimates look promising, providing evidence of reductions in crime, especially considering pre-trends show higher crime, but not reliably enough to make casual claims or rely on effect sizes. Such prediction makes sense, given the motivations for implementing PSCs have to do with backlogs in court dockets,
this backlog came primarily through increased law enforcement of low-level offenses, and lower-level offenses outnumber violent crimes quite a bit.

Violent crimes, on the other hand, do not indicate pre-trends and show substantial and significant reductions beginning the second year after implementation. These results may point to divergence in theoretical associations between drug use and crime between criminology and crime economics theories. Substantial criminological work associates substance use disorder, and drug use in general, with property crimes (e.g., Ball et al., 1983; Bean, 2008; Sutherland et al., 2015). Crime economists, however, have attributed property crimes to other factors, such as changes in law enforcement behavior (Benson et al., 1992); and connected violent crime directly to prohibition-type policies (Miron, 1999; Miron & Zwiebel, 1995; M. Thornton, 2014). The largest reduction in property crime associated with PSCs is 3.42% in the fourth year after implementation, violent crime drops by over 4.33% in the same relative year. See Appendix A for a detailed graph of effect sizes.
FIGURE 5
Dynamic Impact of PSCs On Crime Indexes

Notes: These graphs show point estimates, and 95% confidence intervals of the effect PSCs have on total, property, and violent crime indexes. Blue lines represent main effects (coefficient $\delta_T$ from Equation [3]), and the red lines include main and interaction effects (coefficients $\delta_T + \alpha_T$ from Equation [3]).

To get a more detailed look at crimes, Figures 5 and 6 show similar analysis on individual crimes comprising indexes. The property crime index consists of burglary, theft, motor vehicle theft, and arson. Murder, rape, robbery, and aggravated assault make up the violent crime index.
Results for individual property crimes do not exhibit the same pre-trends as above. Given the lower counts of each, results may lack the power necessary for reliable estimation. Having said that, results continue to show promise. While arson indicates no effect, burglary, theft, and motor vehicle theft indicate reductions after PSC implementation, with the latter offering the most notable results. Motor vehicle theft estimates show an immediate drop of 3.56%, and a maximum reduction of 6.86% in the fourth year after implementation.

Within violent index crimes, murder and rape show essentially no effects. Robbery and aggravated assault seem to drive estimates shown in Figure 4 above. Robbery drops by approximately 6.22% in the fifth year after implementation, and aggravated assault by 4.39% in the fourth.
FIGURE 6
Dynamic Impact of PSCs on Individual Property Index Crimes

Notes: These graphs display point estimates and 95% confidence intervals for individual property index crimes. Red lines show estimates for PSC effects, blue effects of relative time bins alone.
**FIGURE 7**

*Dynamic Impact of PSCs on Individual Violent Index Crimes*

- **A. Murder**
- **B. Rape**
- **C. Robbery**
- **D. Agg. Assault**

*Notes:* These graphs report point estimates and 95% confidence intervals for individual violent index crimes. Blue points and lines show effects of time bins by themselves (i.e., without PSCs). PSC treatment effects show in red.
3. Robustness:
   a. Actual vs Predicted Values

   To assess how well the stacked event study model performed, I place actual crime rate (per 100,000) data against model-predicted values. As estimates for arson, murder, and rape are not reliable, I include graphs below (Figure 8) for burglary, theft, motor vehicle theft, robbery, and aggravated assault.
FIGURE 8
Actual and Predicted Values for Select Crimes

Notes: These graphs show average annual crime rates per 100,000 and predicted values for the same period for Burglary, Theft, Motor Vehicle Theft, Robbery, and Aggravated Assault.
In all cases, predicted and actual values align well but not perfectly, showing the model sufficient.

*b. Law Enforcement Personnel*

Communities with the means to create a PSC may also have better resourced law enforcement agencies. War on Drugs policies, those that created the backlog in court dockets that gave birth to the PSC movement, provided substantial law enforcement funding and training. I apply the same stacked event study methodology to explore whether the number of law enforcement personnel, rates of law enforcement personnel (precent officers and civilians, and ratio of officer to civilians), and known offenses cleared by arrest predict PSC implementation.

Figure 9 presents stacked event study point estimates of PSCs on total law enforcement personnel, officers, and civilians, as well as percentages of officers and civilians, and the ratio of officers to civilians. Officers, as defined in the Law Enforcement Officers Killed or Assaulted dataset (LEOKA; Kaplan, 2021a), have the power of arrest, civilian personnel do not. These do not predict PSC implementation.
c. Clearances by Arrest

Though the size of law enforcement agencies may not predict PSC implementation (by personnel numbers), those agencies may simply be more effective. Funding from the War on Drugs not only went to hiring more personnel, but also to training and equipment. Figure 10 explores this question by estimating the pre- and post-trends of PSCs on clearances by arrest. Here, we see a bit of prediction two years prior to implementation for clearance rates of total, total index, and property index crimes, but no effect for violent index crimes. These results provide some confirmation.
of core analysis results above. PSCs seem to have a differing relationship with violent crimes than others, with a significant relationship at four and five years prior to implementation. The negative correlation bears further investigation, but I save that for another time, as this dissertation does not have the room. The negative relationship leans in the opposite direction I would expect of communities exhibiting more proficient law enforcement agencies that also implement PSCs. It points toward communities with less proficient agencies, thus negating any worry about this factor confounding results above.

**FIGURE 10**  
*PSCs and Clearances by Arrest*

![Graph showing clearance rates by arrest for different crime types over time](image)

*Note:* This graph shows estimates for effects PSCs have on rates of clearance by arrest including total crimes, as well as total, property, and violent index crimes. See Appendix A for detail graphs with confidence intervals.

*d. Law Enforcement Activity*

A consideration for causal inference, here, involves whether other activity in these communities, that may align with PSCs, caused crime reductions, rather than
PSCs. One such confounding factor may be law enforcement activity. If communities that implemented PSCs took a multi-pronged approach to addressing crime, law enforcement agencies would be included, with some change in policy or behavior. As an example, previous work associates increases in arrests with drug courts (Lilley, 2017; Lilley et al., 2020), especially of minority community members (Lilley et al., 2019). Toward this end, I evaluate the effects PSCs have on arrests at the county-level (Figure 11). There does not appear to be any impact on arrests, including total, property, and violent index crimes.

**FIGURE 11**

*Crime Index Arrests*

*Note:* This graph displays point estimates and 95% confidence intervals for PSC effects on total, property, and violent crime indexes.
e. Law Enforcement and Community Interaction

Another consideration has to do with how well a community and its law enforcement agencies interact. Along with funding for personnel, training, and equipment, many federal, state, and local funding initiatives sought to improve relationships between agencies and the communities they serve. Though not a direct measure, rates of officers killed and assaulted provides some measure of this relationship. Better relationships would likely come through in these data as lower rates. Figure 12 looks at this question, finding no significant relationship nor pattern.

FIGURE 12
PSCs and Officers Killed or Assaulted

Note: This figure displays estimates of PSC impacts on officers killed by felony, killed by accident, and assaulted per 100,000 population. I do not include confidence intervals for brevity. See Appendix A for detail graphs with confidence intervals.
Another way to explore law enforcement and community interaction is by looking at the rate of unfounded crimes, though it has more to do with the community than agencies themselves. These include crimes that were reported to agencies but were found to be false or baseless (FBI, 2004). A healthier community would likely report less baseless crimes, so I evaluated relative effects PSCs have on unfounded total, total index, property index, and violent index crimes (Figure 13). Analysis indicates no pre-trends, though the reductions after implementation point toward interesting future work.

Note: This figure displays estimates for the effect PSCs have on unfounded crimes. See Appendix A for detail graphs with confidence intervals.
f. Public Employees

Beyond law enforcement agencies, communities that implement PSCs may also better resource other agencies. The Annuals Survey of Public Employment and Payroll (ASPEP; Kaplan, 2021a) provides data to investigate this question. I estimated PSC effects for total employees, and relevant categories: Judicial and Legal, Housing and Community Development, Social/Welfare, and Education (all measuring full time equivalent personnel). If communities that include PSCs coincide with higher levels of employees in these categories, then results might indicate communities with better resources for addressing crime, confounding causal interpretation. As Figure 14 shows, the total employee category returns significant estimates in the -3 relative time bin. It appears that Housing and Community Development drives these results. None of the other categories proved reliable. We should take these results, however, with a grain of salt. ASPEP is a voluntary survey with less-than-perfect response rates. Also, data at the county level only include the years 1993-1995, and 1997-2016, which limited stacked event study analysis to 1998-2011, with some missing bins (and a missing 1996 stack).

Having said that, the selection of PSCs on communities with more Housing and Community Development employees does not appear too out of place here. A community that implements a PSC would likely approach crime and this type of community development in the same way. Further, these results push the discussion toward the present analysis showing results for communities willing and capable to implement PSCs. This interpretation does not detract from results altogether but widens the focus a bit.
D. Discussion, Interpretation, and Implications

I find these results reliably indicate PSCs reduce crime. Despite rigorous analysis methods and a bevy of robustness checks, these positive effects shine through. While the final check against public employees seems to indicate communities with PSCs might also embody other social efforts, such as housing and community development, the slight alteration of language to state communities that approach crime from a service provision perspective, rather than PSCs themselves, show crime reductions continues to make a good case for this program. Programs like these do not occur in a vacuum.

Returning to the discussing in section II.B.1.c regarding the number of PSC participants compared to those on probation, the PSC footprint is small. Even if reporting agencies double count participants as probationers, the former represents one

---

**FIGURE 14**

*PSCs and ASPEP Categories*

*Notes:* These graphs display point estimates and 95% confidence intervals for estimation of the effect PSCs have on public employee numbers (per 1,000). See Appendix A for graphs of all public employee categories.
tenth of the latter. Thus, PSCs must have substantial impacts on community-level crime for analysis to yield any effects, which is the present case.

The effect that these courts have on violent crime provides interesting results. It appears true that those who commit crimes do not pay special attention to any crime category, that they are generalists, not specialists. This line of reasoning provides further weight to a fundamental PSC premise: treat underlying conditions that lead to crime and crime will decrease. That is, treat people with dignity, assuming that they are not bad but sick people in need of treatment, and they will make better decisions in the future.

Results in this chapter suggest efforts to increase public safety that match and provide people who commit crimes with services, rather than punitive measures, lead to desirable results. Not only does this likely spend public money more effectively (explored below in Chapter III) but builds trust and legitimacy, something lacking in the current environment. Applying this practice more broadly will likely continue to reduce crime. Avinash Singh Bhati and colleagues (2008) recommended expanding such programs in size and opening access by reducing barriers to participation (e.g., violent offenses). I concur. Bhati cites an additional 1.47 million potential participants, with capacity in that year reaching approximately 55,000. Making demand for programming like PSCs much larger than supply. While reaching all potential participants does not seem likely, expanding capacity for programs like PSCs will reduce crime effectively.

Critiques of PSCs include the amount of fines participants face (Drug Policy Alliance, 2011; Shumm et al., 2009; Walsh, 2011). Though some courts provide access to services free of charge, most force participants to pay for program elements (e.g., drug testing). Recent developments, especially in mental health courts, recommend tapping
into Medicare and Medicaid funding, especially following the 2010 Affordable Care Act expansions (NADCP, 2018b, 12). These criticisms suggest a model that requires less from participants financially would likely increase effectiveness, whether by lowering fees or finding alternative sources to pay them.

Other scholars question the equity of these programs, citing underrepresentation of minorities, especially compared to overrepresentation in other parts of the criminal justice system (Nicosia et al., 2013). Explicit efforts have curbed this a bit, with more recent representation being closer to equity (Marlowe et al., 2016; NADCP, 2018a). One other important critique posits that PSCs, especially adult drug treatment courts, treat those who commit crimes as specialists when the bulk of criminological research indicates, rather, generalization and opportunism (Pratt & Turanovic, 2019).

Results above show the latter criticism to be correct, though from a different perspective. Treating antecedents to committing crime prevents more than just drug or property crime. My analysis indicates PSCs also reduce violent crime, especially robbery and aggravated assault. Thus, expanding PSC capacity and access would likely lower rates in several crime categories.

E. Conclusion

This chapter asked whether PSCs reduce crime at the community level, answering in the affirmative. Not only do these programs reduce the expected property crimes but show substantial impact on violent crimes as well. These results prove robust, though analysis may also pick up effects of well-resourced communities, in that results indicate selection on Housing and Community Development public employees.
To interpret these findings, though, we must consider what this study measures. What exactly is the difference between a community with a PSC and another without it? Both conditions attempt to lower crime through direct supervision of people convicted of a crime, usually non-violent offenses and early in the person’s criminal career. Both conditions steer participants toward services and feature requirements such as consistent employment and housing. The difference, it seems, amounts to the cooperative, collaborative environment found in PSCs not found in probation offices (i.e., business as usual). Thus, it seems that communities and organizations who approach criminal justice issues in such a cooperative, collaborative way perform better than those who do not; especially those functioning from a service orientation.

These results indicate a few paths for future research. One obvious question is cost effectiveness. Implementing and operating PSCs cost money, which begs the question of whether this serves as a good investment. Another open question comes from the high levels of variation in effects between different types of PSCs (e.g., drug treatment courts vs mental health courts), implemented in different areas at different times. Future work might look at differential impacts between these dimensions.
III. Collaborative Governance Performance: The Problem-Solving Court Context

The past four decades brought a fundamental shift in how US governments do their business, evolving from isolated and direct service provision to more networked, collaborative arrangements. Though researchers have performed substantial work developing theory and empirical tests of these new arrangements, the literature has yet to establish effectiveness or efficiency, especially on objective, community-level outcomes. Problem-solving courts (PSCs) present an ideal case for evaluating Collaborative Governance. The difference between these programs and the status quo, some other type of community supervision (e.g., probation), amounts to the very definition of collaboration: meaningful, cooperative engagement between cross-boundary organizations aimed at a shared goal. In this chapter I explore cost-benefits of PSCs as a method for understanding Collaborative Governance generally, building upon a stacked event study design and performing counterfactual analysis to estimate total number of crimes prevented and associated cost savings. I find these programs effective at reducing crime at the community level, conservatively estimating returns between $1.98 and $2.47 for every dollar invested, for a total savings between $3.5 and 5.5 billion between 1995 and 2013. These results indicate PSCs, and collaboration, provide outsized benefits for communities.
A. Introduction

The Albuquerque, NM organization Mission: Graduate\(^5\) formed using the Collective Impact Model, pulling together collaborative partners that serve distinct needs dimensions along a “cradle to career” timeline (Gonzalez, 2012; see, generally, Kania & Kramer, 2011). In explaining how he convinced dozens of independent organizations to cooperate, then-Executive Director Angelo Gonzalez cited finding a common goal of 60,000 new graduates with college degrees by 2020. This focus on a larger goal, especially an accessible and measurement one, allowed disparate, independent organizations to focus on how their participation in the collaboration contributed, and worry less about conflicting priorities. While many collaborations do not begin with such clearly defined overarching goals, most organize around a larger vision, some better version of the world used as a guiding principle for operations. Such a big-picture perspective, what Gonzalez (2012) called a “Hairy Audacious Goal,” frames this chapter.

Since the 1980s, most western governments have fundamentally changed how they operate, especially concerning service provision. Where traditional bureaucracies functioned from silos, with distinct boundaries between types of services and levels of government (see, generally, Kettl 2006), contemporary government service provision commonly occurs through a maze of formally and informally connected organizations; variously termed service networks, Collaborative Governance, Collaborative Governance Regimes (CGR), or Joined-Up Government\(^6\) (6, 2004; Ansell & Gash, 2007; Bingham & O’Leary, 2008; Emerson & Nabatchi, 2015; Frederickson, 1999). As public needs have

\(^5\) https://uwcnm.org/mission-graduate
\(^6\) I use these terms interchangeably, though some semantic differences exist. The literature has yet to unify terms.
become more demanding – “wicked” problems deemed “complex, unpredictable, openended, or intractable” (Head & Alford, 2015, 712) – and public sentiment veered toward less direct government provision – decentralization, privatization, disarticulated government (Frederickson, 1999; Marini, 1971; Osborne & Gaebler, 1992) – public service implementation evolved to meet public demands and sentiment.

Researchers have attempted to keep up with these developments positing useful theory (e.g., Ansell & Gash, 2007), developing conceptual frameworks (e.g., Emerson et al., 2012; and Emerson & Nabatchi, 2015a), establishing management practices (e.g., O’Leary & Bingham, 2009), performing empirical analysis (e.g., Andrews & Entwistle, 2010; Jimenez et al., 2004), and exploring performance measurement (e.g., Bixler et al., 2016; Emerson & Nabatchi, 2015b; Koontz & Thomas, 2012). The field, however, has yet to establish whether these arrangements generally perform more effectively than traditional models.

Problem-Solving Courts (PSCs) serve as an ideal case for examining CGR effectiveness. This policy innovation exhibits many features found in other settings, such as community supervision. The primary difference comes from courts directly supervising participants (rather than ordering them to services and tasking probation departments with supervision), in a cooperative courtroom environment (as opposed to traditional adversarial structures), through a collaborative network including service providers and other stakeholders (e.g., local or state political leaders, private-sector actors). These programs provide fertile ground to investigate the performance of Collaborative Governance.

Though this chapter explores the question of effectiveness in a specific setting – PSCs – I propose we may generalize results more broadly. Few situations present a case
in which the counterfactual context amounts to such similar sets of service provision, save a collaborative structure. Having established the general effectiveness of PSCs to reduce crime, I now approach the question as one of public management. I build upon the previous chapter to assess cost effectiveness for PSC operation. To get at this question, I estimate the number of crimes PSCs prevent using a counterfactual analysis, calculate gross cost savings of these, then deduct costs of PSC operation to determine net savings and cost-benefit ratios. I find these programs return between $1.98 and 2.35 for every dollar invested, totaling between $3.5 and 5.5 billion savings in the period running 1995 and 2013, depending on the crime costs being considered.

This chapter contributes to public management research generally as a test of Collaborative Governance in an ideal case: PSCs. I also expand current conceptions and practices around measuring performance of collaborations, showing a means of performing top-down, retrospective cost analysis. Finally, I contribute to PSC research by incorporating public management theory and research methods, providing evidence of their fiscal benefits.
B. Collaborative Governance Performance
1. Measuring Performance:

As theorists have attempted to keep pace with rapid shifts in government, and how government performs, empiricists have attempted to evaluate whether the new arrangements perform better than the previous, with mixed results. Though the literature has yet to settle on specific theoretical bases or conceptual frameworks, and though I use the various terms for collaborative arrangements for public service delivery interchangeably, I couch discussion in Collaborative Governance Regimes and the Integrative Framework for Collaborative Governance terms (Emerson, Nabatchi, and Balogh 2012; Kirk Emerson and Nabatchi 2015a). With this foundation, I investigate performance starting with conceptual categories proposed by Kirk Emerson and Tina Nabatchi (2015b).

First, we must explore the question of what to measure. Desired outputs and outcomes prove as numerous and complex as the issues CGRs attempt to address. Driving forces behind collaboration implementation, according to Kirk Emerson and colleagues (2012, 9-10; see also Emerson & Nabatchi, 2015a) include leadership, internal or external consequential incentives (e.g., funding), and a desire to share risk in uncertain environments. These motivations indicate a variety of ways to measure performance. For instance, emergency management collaborations, whether addressing large-scale disasters (Getha-Taylor, 2007) or day-to-day emergencies (Nohrstedt, 2016), occur in a context of harm reduction, formed as a way to spread risk in uncertain environments, so it makes sense to gauge efficiency. Natural conservation efforts, though, form with explicit goals in mind (i.e., conserving some natural resource; usually occurring around either leadership or incentive drivers, or both), which indicates
effectiveness, though other concerns include issues of efficiency and equity – likely channels between operations and effectiveness. Other types of collaborations aim toward public and civic engagement, such as those enacted by 1990s Seattle Mayor Norman Rice (Page, 2010), and look at issues like trust and legitimacy (Sirianni, 2009). To complicate matters further, few collaborations exist in an environment suitable for a single performance metric.

Measuring performance also necessitates discussing unit of analysis. Collaborations involve nested action arenas, to use Elinor Ostrom’s term (Polski & Ostrom, 1999). Each arrangement includes individuals (service recipients, personnel, etc.), each of whom bring their own individual characteristics, and social and professional networks to the table. These individuals interact within and across organizations, performing the functions of each organization and the CGR. Commonly, collaborations consist of both formally and informally, directly and indirectly connected organizations. That is, an array of formally and informally tied organizations, along a spectrum of distance from the collaboration along functional lines (having an array of influences on a CGR and desired outcomes). These arrangements function within larger contexts, such as the physical world and socio-economic conditions. Within each nest, rules and norms vary. Finally, collaborations operate with unique sets of goals, from proximate outputs like number of meetings, to grand notions of public value.

Emerson and Nabatchi (2015b, 723) propose three performance dimensions along three units of analysis to create a three-by-three matrix. This construction proposes researchers might measure productivity regarding actions/outputs, outcomes, and adaptation, at the participant organization, CGR, and target goal levels. I follow their lead beginning with the larger question of effectiveness: How effective are CGRs, in
the form of PSCs, at reducing crime at the community level? An explicit goal of PSCs, and nearly any section of the criminal justice system, is to improve public safety.

I explore effectiveness by appraising the number of crimes prevented by PSCs, and the return on investment. I calculate the approximate savings in dollars for total crime prevented and compare this figure to approximate PSC expenditures, all done at the national, per-annum level.

2. Collaborative Governance Performance Research:

The breadth of research evaluating CGR performance is too large to cover here but some highlights prove telling. One difficulty comes from the complexity and disparate nature of CGRs. The term, and attendant research, includes a broad range of issues, tackled at a variety of levels, with different motivations and goals. All this notwithstanding, Collaborative Governance performance continues to show mixed results, even in the same fields.

Take, for instance, collaborations geared toward conservation, sustainability, and environmental issues generally (see Gerlak et al., 2012). This sub-field provides a consistent analogy, as they usually present logical objective outcomes (e.g., conserving a watershed) and ask traditionally adversarial groups to cooperate. Some research indicates improvements in desired outcomes (e.g., sustainability), including through intermediate social outcomes (Bjärstig, 2017). Tyler A. Scott (2016) evaluated return on investments into Oregon Watershed Councils, finding improvements in objective outcomes, tying council actions and dynamics to these results. On the other hand, some research finds missing internal dynamics like power balance between actors lead to
failures, such as efforts to preserve US pronghorn sheep in Wyoming (Kretser et al., 2018).

More generally, work in the United Kingdom finds spotty results in collaborations for public service delivery, especially considering the mix between public and private partner organizations (Andrews & Entwistle, 2010). The bulk of research into non-environmental, and non-emergency management collaborations, though, focuses on more upstream issues, with little research into downstream, objective outcomes (Sørensen & Torfing, 2021). I hold with Eva Sørensen and Jacob Torfing that “the real problems might emerge ‘downstream’ rather than ‘upstream’ in the collaborative governance process” (2, citing Agranoff & McGuire, 2001).

Empirical work looking at collaborations in the criminal justice system also have a mixed record. Sean Nicholson-Crotty and Laurence J. O’Toole (2003) indicate law enforcement agencies improve clearance-by-arrest by increasing external management efforts, such as networking and community policing. Their paper importantly distinguishes between the common practice of measuring citizen satisfaction, something of an intermediate outcome, and broader variables like clearances (12-13). Other research on drug task forces, though, found communities that implemented them improved community perceptions but failed to find any effect on objective outcomes like arrests (Smith et al., 2000).
C. Problem-Solving Courts as Collaborative Governance Regime

A substantial proportion of crime in the United States exists as a manifestation of underlying conditions, such as substance use disorder (SUD) or post-traumatic stress disorder (PTSD) (Rossman, Roman, & Rempel, 2011). The US criminal justice system recognized this trend in the 1980s and 90s, following unsustainable growth in incarceration, and thus modified institutional structures to address underlying problems these criminal acts indicate (Walker, 1994). Problem-solving courts serve as one such adaptation.

Though PSCs did not explicitly form using Collaborative Governance designs – they had not yet been envisioned as such – their current form embodies identical structures and ideals. These programs signify drastic changes in how courts function. Where previously judges reserved authority for all court decisions (save jury adjudication), many PSCs make decisions as a team (Drug Court Administrator A, personal communication, 2019; NADCP, 2018a). And though traditional criminal justice courts would order defendants to certain services (e.g., SUD recovery services), monitoring of and connection to these services was provided by probation departments and other, non-court entities (Lurigio, 2008). PSCs not only monitor these services, and connect participants to them, but include service providers inside the court as decision-making team members.

PSC judge roles resemble public managers much more than their judicial counterparts. They manage a team consisting of traditionally adversarial parties, relying upon their cooperation and assistance in making decisions (NADCP, 2018a). In some instances these teams include members with direct SUD recovery and criminal justice experience (Drug Court Administrator A, personal communication, 2019).
These structural changes run parallel to similar shifts in public service provision over the past several decades toward collaboration. As public organizations shifted from isolated roles, connecting to external organizations in networked and collaborative structures, courts connected with service providers and community stakeholders. The structural arrangements of PSCs – networking with service providers and other stakeholders and including them in day-to-day court operations (including decision-making) – fits the Collaborative Governance definition which “suggests a higher-order level of collective action than cooperation or coordination” (something seen in the PSC counterfactual, community supervision) (Thomson & Perry, 2006, 23).

To make the claim explicit: problem-solving courts represent Collaborative Governance Regimes in-and-of-themselves. Using Ostrom’s construction of nested action arenas, described in section III.B.1, and pairing it with above definitions of collaboration, the PSC action arena includes individuals from disparate organizations (some previously adversaries, like prosecution and defense attorneys) cooperatively engaging in a larger vision, all contributing to substantive action situations (Polski, 1999, 23-15).17

Several sets of guidelines govern the rules-at-play within PSCs. The most pertinent to this discussion involve local and state adaptation of standards set by national institutions, especially the National Association of Drug Court Professionals. Almost universally, these jurisdictions have adopted the Ten Key Components presented in section II.B.1.a above; most notably, those listing internal cooperation and external collaboration. Not only do these components form the basis of my claim for

17 Though I could write much about the internal PSC action arena, and attendant multiple-play action situations, the present study only requires understanding that these actors contribute cooperatively toward the larger goal and that they cross boundaries to do so.
PSCs as CGR, but the uniformity of their adoption allows for broad analysis of CGR performance (Marlowe, Hardin, and Fox, 2016).

I am not the first to propose PSCs as Collaborative Governance. Kathleen Hale (2011) explored the role information plays in policy innovation and diffusion via networks. This book took a different tack, looking at how non-governmental actors within policy networks influence innovation and adaptation, but sets a similar stage.

Though these programs operate in highly variable contexts – the biophysical/material and community attributes Ostrom envisions as “exogenous variables” (Polski & Ostrom, 1999, 17, 19-23) – my use of fixed-effects analysis (see section II.C.1 above) implicitly controls for these.

1. The Ideal Case:

As discussed in Chapter II.B.1.c above, the most logical counterfactual outcome for criminal cases is community supervision (e.g., probation). This counterfactual includes many elements found in PSCs: probation and PSCs both require participants report regularly, order and monitor programming participation (e.g., SUD services), and offer similar incentives for compliance. Therefore, PSCs embody three distinct innovations: altering internal structures from adversarial to cooperative, shifting decision structures from strictly hierarchical to cooperative, and expanding organizational connections from those within the criminal justice system to include service providers and other stakeholders. These factors fit perfectly within the CGR framework (Emerson et al., 2012; Emerson & Nabatchi, 2015a).

Kirk Emerson, Tina Nabatchi, and Stephen Balogh (2012, 2) define Collaborative Governance as “the processes and structures of public policy decision
making and management that engage people constructively across the boundaries of public agencies, levels of government, and/or the public, private and civic spheres in order to carry out a public purpose that could not otherwise be accomplished.”

Decisions in PSCs occur cooperatively, with many courts making major decisions (e.g., whether to issue sanctions for non-compliance) by consensus of the PSC team (Drug Court Administrator A, personal communication, 2019; D. Marlowe, personal communication, January 2021; NADCP, 2018a). These teams consist of representatives from across government and non-government organizations.

To phrase this argument a bit differently, PSCs present an opportunity to measure variation in rules-in-use that define a CGR. Given the wide adoption of NADCP standards for internal cooperation and external collaboration, positioning PSCs as Collaborative Governance structures, and that these components constitute the primary difference between communities with PSCs (treatment group) and those without (control group), analysis of these programs amounts to direct measurement of CGR performance.

2. Problem-Solving Courts and Theory

Researchers specializing in criminal justice programs like PSCs have called for more dynamic, objective evaluations for (at least) the past 15 years (Heck & Thanner, 2006; D. B. Marlowe et al., 2006). More recently, Kristen E. DeVall and colleagues (2012) recommend more substantive application of social science theory when researching PSCs. I agree with these perspectives, taking a sophisticated look at PSCs through the Collaborative Governance lens.
Scholars have attempted to keep up with PSC implementation, much as with Collaborative Governance, along empirical and theoretical lines. A section of researchers (generally from the Law and Society field) position PSC operation within Therapeutic Jurisprudence theory (Wexler et al., 2016; Winick, 2003). James L. Nolan’s (2003) book Reinventing Justice approaches drug courts from a social-psychological perspective, looking at the new courtroom drama – roles, narratives, and logics of action being quite different from previous judicial systems – that evolved in this movement.

Though most theoretical work involving PSCs deals with judicial and psycho-social theories, some does look at organizational and management factors. Chad Michael McPherson and Michael Sauder (2013) applied institutional theory, especially institutional logics (see, generally, P. H. Thornton et al., 2012). They report results from a 15-month ethnographic study of drug courts, finding actors have wide latitude in bringing extra-local institutional influences (e.g., professional networks) into local decision- and policymaking. Researchers have also examined PSCs through Dispute Resolution lenses. For instance, Cassandra Atkin-Plunk and colleagues (2019) find substantial differences in perceptions of procedural justice along racial and ethnic lines. This Chapter extends these efforts, looking at larger structures – collaborations, larger networks, and communities – and broader outcomes.

3. Problem-Solving Courts and Performance Measurement

To synthesize empirical work evaluating PSCs and collaborative governance theory, I place extant PSC research into the matrix for CGR performance measurement discussed above, using the same three units of analysis and performance levels (Emerson and Nabatchi 2015b). Table 3 conceptualizes this process. Some elements of
PSC operation do not fit perfectly into this framework, as this context makes differentiation between the PSC and the collaboration difficult. Most collaborating organizations have a representative serving on the PSC team, making the boundaries between these units of analysis indistinct.

**Level 1: Actions/Outputs**

The impetus for creating the first PSCs came from overloaded court dockets, so early evaluations measured outputs like cases processed and numbers of service recipients connected to providers (Goldkarnp & Weiland, 1993; Marshall et al., 2004; Monchick et al., 2006). Another early, and continuing, evaluation metric looked at graduation rates (Olson et al., 2001; Wolf et al., 2003). More recently, scholars criticized PSCs for provided inequitable access (relative to other criminal justice institutions, like jails, and their distributions of race and ethnicity) and treatment (Nicosia et al., 2013). Thus, PSCs made explicit efforts to rectify these failings, which seems to be the trend (D. B. Marlowe et al., 2006; NADCP, 2018a, 2018b).

**Level 2: Outcomes**

The bulk of literature on PSCs measures participant level outcomes, which we can classify into both Participant Organization and Target Goals units of analysis. The overwhelming consensus from this literature finds positive results at these levels, whether considering participant recidivism or drug use relapse (GAO, 2005; Latimer & Chretien, 2006; Mitchell et al., 2012). My work in Chapter II looked at community-level outcomes, finding reductions in many crime categories, which falls into both the CGR and Target Goals units of analysis. The present work, performing cost-benefit analysis, also falls into the Target Goals category, but may also fit with the CGR unit of analysis.
Issues like trust and legitimacy at the community level would be easier to obtain with proof that these programs spend public moneys wisely, providing a return on investment. This work might also help influence policy and public sentiment as communicating these improvements provide evidence for future considerations. The concepts of trust and legitimacy and influencing public policy and sentiment involve more than the present study, though; discussions of which I save for another time.

**TABLE 3**

*Performance Dimensions of Collaborative Governance Regimes*

<table>
<thead>
<tr>
<th>Performance Level:</th>
<th>Participant Organization</th>
<th>Collaborative Governance Regime</th>
<th>Target Goals</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level 1:</strong> Actions/Outputs</td>
<td><strong>Efficiency</strong></td>
<td><strong>Efficacy</strong></td>
<td><strong>Equity</strong></td>
</tr>
<tr>
<td></td>
<td>- Cases processed</td>
<td>- Graduation rates/attrition</td>
<td>- Equitable access &amp; treatment</td>
</tr>
<tr>
<td></td>
<td>- Number of service recipients</td>
<td>- Coordinated service goals</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Personnel training</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Level 2:</strong> Outcomes</td>
<td><strong>Effectiveness</strong></td>
<td><strong>External Legitimacy</strong></td>
<td><strong>Effectiveness</strong></td>
</tr>
<tr>
<td></td>
<td>- Participant outcomes</td>
<td>- Community-level outcomes</td>
<td>- Participant- and community-level outcomes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Influencing policy and public sentiment</td>
<td>- Cost-benefit analysis</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- Trust &amp; legitimacy</td>
<td></td>
</tr>
<tr>
<td><strong>Level 3:</strong> Adaptation</td>
<td><strong>Equilibrium</strong></td>
<td><strong>Viability</strong></td>
<td><strong>Sustainability</strong></td>
</tr>
<tr>
<td></td>
<td>- Ability of PSC/organizations to iterate and learn</td>
<td>- Ability of entire CGR to iterate and learn</td>
<td>- Long-term operational improvement</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>- Broadening collaborative network</td>
</tr>
</tbody>
</table>

*Source: Adapted from Emerson & Nabatchi 2015b*
Level 3: Adaptation

The likely next wave for PSC research looks at adaptation. Some extant work looks at potential expansion of PSCs, and treatment in general (Bhati et al., 2008). Two key components of PSCs, built on the Adult Drug Treatment Court model, deal directly with the Adaptation level (Bureau of Justice Assistance, 2004; NADCP, 2018a): those recommending ongoing professional development of key actors within the collaboration and cultivating relationships with key community stakeholders. Though a few scholars have looked at program adherence to these, little work takes an empirical perspective evaluating how such adherence leads to specific outcomes (Marlowe, Hardin, and Fox 2016; Rossman, Roman, and Rempel 2011). Hale (2011) also provides a roadmap for further exploration, showing the role non-governmental actors have on diffusion of policy innovations like PSCs. Though such considerations do not fit into the current study, these elements are ripe for research.

D. Measuring Problem-Solving Court Performance

1. Empirical Strategy:

For analysis of the question of PSC effectiveness I revisit analysis found in Chapter II. Having established the effectiveness of PSCs to reduce certain index crimes, I then turn to the question of efficiency, operationalized as cost surpluses or deficits relative to PSC implementation. Reductions in costs, that savings from crime prevented outweigh moneys spent operating PSCs, would indicate efficiency. This process includes predicting crime values, per county-year, like that found in section II.C.3.a (Figure 8) above. Here, though, I use the policy effects found through Equation (4) to create a counterfactual projection by subtracting them from predicted values:
\[
\hat{y}_{\text{counter}} = \hat{y}_{\text{predicted}} - \sum_{\tau = -K, \tau = -1}^{T} \hat{a}_\tau (PSG_{ch} \times I_{cht})
\]

\( \hat{y}_{\text{predicted}} \) represents predicted crime rates using Stata’s built-in post-estimation commands, and \( \hat{y}_{\text{counter}} \) counterfactual predictions. The summation term shows estimated policy effects from Equation (4). As I performed a Poisson monotonic transformation of outcomes for analysis, I approximated the original crime rates by taking the exponent of both predicted and counterfactual values.

I convert both predicted and counterfactual values back to total counts per county year from the analyzed rate per 100,000 population: \( \hat{y}^{\text{count}}_{\text{counter}} = \hat{y}^{\text{rate}}_{\text{counter}} \times \left( \frac{\text{Population}}{100,000} \right) \). Then, I subtract counterfactual values from predicted to approximate total crime prevented per county year. I average these figures by year, then calculate costs/benefits by multiplying these by the tangible, quality-of-life, and total costs found in a recent work by Ted R. Miller and colleagues (2021) (Table 4). Given the wide variation between these costs – from $4,780 to $43,768 – I calculate each category for each year, then add them together, rather than taking an average of them all. These numbers also show that three of the five crime categories under consideration do not include quality-of-life costs. Their work fit crime costs into two categories: tangible and quality-of-life, both of which deal with costs to victims. Tangible costs refer to “out-of-pocket monetary costs per criminal offense,” while “pain and suffering” fall into the quality-of-life figures (38). The authors include these latter costs for “personal” crimes (those falling under Part I of the FBI crime categorization scheme). Given the wide

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18 Scholars continue to debate costs of crime. I use Miller, et al. (2021) as state-of-the-art estimations, though the debate rages on (see Clear & Austin, 2021; and Cohen & Farrington, 2021 for a response).
variation between these crime category costs – from $4,780 to $43,768 – I calculate each category for each year, then add them together, rather than taking a total average.

<table>
<thead>
<tr>
<th>TABLE 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated Costs* of Crime</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tangible</th>
<th>Quality Of Life</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burglary</td>
<td>$5,369</td>
<td>$0</td>
</tr>
<tr>
<td>Theft</td>
<td>$4,780</td>
<td>$0</td>
</tr>
<tr>
<td>Mot. Veh. Theft</td>
<td>$10,783</td>
<td>$0</td>
</tr>
<tr>
<td>Robbery</td>
<td>$29,112</td>
<td>$14,656</td>
</tr>
<tr>
<td>Agg Assault</td>
<td>$17,635</td>
<td>$21,149</td>
</tr>
</tbody>
</table>

*All amounts expressed in (original) 2017 dollars

The literature has yet to settle on PSC costs. Estimates range from $6,008 (Marlowe, Hardin, and Fox 2016) to $14,269 (Steadman et al., 2014) per participant. These costs differ from traditional court cases since participation lasts between 9 months and two years. All reports express costs per participant, necessitating estimation of participants per court. This figure also proves to be a moving target, ranging from 34 to 102. To establish appropriate costs for analysis, I reviewed several sources and put together a list of studies to calculate an average. The list includes reports from research organizations, states, and courts themselves, as well as peer-reviewed literature. I sought to include a range of sources to establish robust figures. Table 5 lists sources, their figures, and my average of them for participants per court, and Table 6 shows costs. To make averaging costs equivalent, and keep them consistent with crime costs, I converted all reported figures to 2017 dollars before averaging.
### TABLE 5
\textit{PSC Participants per Court}

<table>
<thead>
<tr>
<th>Source</th>
<th>Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cissner et al. (2013)</td>
<td>102</td>
</tr>
<tr>
<td><em>Collaborative Justice Court Roster</em> (2020)</td>
<td>55</td>
</tr>
<tr>
<td>Malsch et al. (2013)</td>
<td>51</td>
</tr>
<tr>
<td>Florida Office of the State Courts Administrator (2020)</td>
<td>34</td>
</tr>
<tr>
<td>Florida OSCA (2021)</td>
<td>65</td>
</tr>
<tr>
<td>Herrera Allen et al. (2015)</td>
<td>42</td>
</tr>
<tr>
<td>Marlowe et al. (2016)</td>
<td>41</td>
</tr>
<tr>
<td>Mackin et al., (2009)</td>
<td>57</td>
</tr>
<tr>
<td>Bhati et al. (2008)</td>
<td>93</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>60</strong></td>
</tr>
</tbody>
</table>

### TABLE 6
\textit{PSC Costs per Participant}

<table>
<thead>
<tr>
<th>Source</th>
<th>Cost/Participant</th>
<th>2008 Dollars</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malsch et al. (2013)</td>
<td>$9,242</td>
<td>$8,471</td>
</tr>
<tr>
<td>D. B. Marlowe et al. (2016)</td>
<td>$6,008</td>
<td>$5,421</td>
</tr>
<tr>
<td>Burrus et al. (2011)</td>
<td>$7,272</td>
<td>$6,970</td>
</tr>
<tr>
<td>Mackin et al., (2009)</td>
<td>$7,151</td>
<td>$7,149</td>
</tr>
<tr>
<td>Steadman et al. (2014)</td>
<td>$14,269</td>
<td>$12,876</td>
</tr>
<tr>
<td>Cheesman &amp; Kunkel (2012)</td>
<td>$11,051</td>
<td>$10,291</td>
</tr>
<tr>
<td>Bhati et al. (2008)</td>
<td>$9,315</td>
<td>$9,315</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>$8,642</strong></td>
<td></td>
</tr>
</tbody>
</table>
2. Data:

Other than cost and participant figures mentioned above, I use stored estimates from analysis in **Chapter II**. Thus, this chapter includes the same PSC independent variable, crime outcome variables, and controls.

3. Descriptive Statistics:

Table 7 shows the number of PSCs in my study sample, the number of participants, costs per PSC in 2017 dollars, and total costs. Note that the number of PSCs is not cumulative. The stacked event study sampling strategy (see section II.C.1 above) creates a situation in which counties with a PSC may enter the time series at certain points but not others.
TABLE 7

PSCs, Participants, and Costs

<table>
<thead>
<tr>
<th>Year</th>
<th>Participants per PSC</th>
<th>PSC Counts</th>
<th>Total Participants</th>
<th>Cost per Participant</th>
<th>PSC Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>60</td>
<td>25</td>
<td>1,500</td>
<td>$6,154</td>
<td>$9.2 million</td>
</tr>
<tr>
<td>1996</td>
<td>60</td>
<td>54</td>
<td>3,240</td>
<td>$6,321</td>
<td>$20.5 m</td>
</tr>
<tr>
<td>1997</td>
<td>60</td>
<td>114</td>
<td>6,840</td>
<td>$6,514</td>
<td>$44.6 m</td>
</tr>
<tr>
<td>1998</td>
<td>60</td>
<td>162</td>
<td>9,720</td>
<td>$6,616</td>
<td>$64.3 m</td>
</tr>
<tr>
<td>1999</td>
<td>60</td>
<td>227</td>
<td>13,620</td>
<td>$6,727</td>
<td>$91.6 m</td>
</tr>
<tr>
<td>2000</td>
<td>60</td>
<td>314</td>
<td>18,840</td>
<td>$6,911</td>
<td>$130.2 m</td>
</tr>
<tr>
<td>2001</td>
<td>60</td>
<td>387</td>
<td>23,220</td>
<td>$7,169</td>
<td>$166.5 m</td>
</tr>
<tr>
<td>2002</td>
<td>60</td>
<td>453</td>
<td>27,180</td>
<td>$7,251</td>
<td>$197.1 m</td>
</tr>
<tr>
<td>2003</td>
<td>60</td>
<td>443</td>
<td>26,580</td>
<td>$7,439</td>
<td>$197.7 m</td>
</tr>
<tr>
<td>2004</td>
<td>60</td>
<td>476</td>
<td>28,560</td>
<td>$7,582</td>
<td>$216.5 m</td>
</tr>
<tr>
<td>2005</td>
<td>60</td>
<td>512</td>
<td>30,720</td>
<td>$7,808</td>
<td>$239.9 m</td>
</tr>
<tr>
<td>2006</td>
<td>60</td>
<td>496</td>
<td>29,760</td>
<td>$8,119</td>
<td>$241.6 m</td>
</tr>
<tr>
<td>2007</td>
<td>60</td>
<td>582</td>
<td>34,920</td>
<td>$8,287</td>
<td>$289.4 m</td>
</tr>
<tr>
<td>2008</td>
<td>60</td>
<td>575</td>
<td>34,500</td>
<td>$8,642</td>
<td>$298.2 m</td>
</tr>
<tr>
<td>2009</td>
<td>60</td>
<td>601</td>
<td>36,060</td>
<td>$8,645</td>
<td>$311.7 m</td>
</tr>
<tr>
<td>2010</td>
<td>60</td>
<td>593</td>
<td>35,580</td>
<td>$8,872</td>
<td>$315.7 m</td>
</tr>
<tr>
<td>2011</td>
<td>60</td>
<td>584</td>
<td>35,040</td>
<td>$9,016</td>
<td>$315.9 m</td>
</tr>
<tr>
<td>2012</td>
<td>60</td>
<td>575</td>
<td>34,500</td>
<td>$9,280</td>
<td>$320.1 m</td>
</tr>
<tr>
<td>2013</td>
<td>60</td>
<td>487</td>
<td>29,220</td>
<td>$9,428</td>
<td>$275.5 m</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>7,660</td>
<td>459,600</td>
<td>$3,746.2 m</td>
<td></td>
</tr>
</tbody>
</table>
E. Analysis
1. Results:
   a. PSCs Effects on Crime

   Figure 15 pulls together results in Chapter II showing reductions in select crimes relative to implementation of a PSC, including burglary, theft, motor vehicle theft, robbery, and aggravated assault. As shown previously, the largest relative impacts (i.e., percentage of crime reduction rather than number) occur for motor vehicle theft, robbery, and aggravated assault.

   ![Figure 15: PSCs’ Reductions in Crime](image)

   **Notes:** These graphs display point estimates of the effect PSCs have on known offenses. For more detail, and 95% confidence intervals, consult Figures 6 and 7.
b. Number of Crimes Prevented

As described in section III.D.1, I estimate number of crimes prevented per category. To ensure accuracy, I conservatively use only the crime categories found in Chapter II to have significant, robust reductions: burglary, theft, motor vehicle theft, robbery, and aggravated assault. Figure 16 shows these values, over time, operationalized as the difference between predicted and counterfactual values. One interesting element of this graph comes from variation between percentages of crime reduction shown above and total crimes prevented. Many more thefts occur in the US than other crimes. Thus, even though we see a lower crime reducing effect above for motor vehicle theft, the number of thefts prevented is larger.

FIGURE 16
Predicted vs Counterfactual Values

Notes: This graph approximates number of crimes prevented in the five categories shown in Chapter II to have significant effects. These figures represent the difference between predicted and counterfactual values. For detailed graphs showing predicted and counterfactual values see Appendix A.
c. Cost-Benefit Analysis

Table 8 presents savings in crime costs relative to PSC operations. I calculated savings per crime category using the figures listed above but include total amounts per year for brevity (see Appendix A for a detailed table). Results indicate a total gross savings of nearly $6 billion in tangible and over $9 billion in total (tangible plus quality-of-life) costs, resulting from the prevention of over one million crimes.

<table>
<thead>
<tr>
<th>Year</th>
<th>Net Crimes (Predicted – Counterfactual)</th>
<th>Gross Tangible Savings (millions)</th>
<th>Gross Total Savings (Tang. + QOL; millions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>11,242</td>
<td>-$49.5</td>
<td>-$82.5</td>
</tr>
<tr>
<td>1996</td>
<td>-9,347</td>
<td>-$4.0</td>
<td>$51.8</td>
</tr>
<tr>
<td>1997</td>
<td>-30,629</td>
<td>$137.3</td>
<td>$228.5</td>
</tr>
<tr>
<td>1998</td>
<td>-48,275</td>
<td>$209.9</td>
<td>$351.7</td>
</tr>
<tr>
<td>1999</td>
<td>-62,027</td>
<td>$313.5</td>
<td>$483.8</td>
</tr>
<tr>
<td>2000</td>
<td>-73,907</td>
<td>$394.7</td>
<td>$600.8</td>
</tr>
<tr>
<td>2001</td>
<td>-71,150</td>
<td>$359.4</td>
<td>$589.5</td>
</tr>
<tr>
<td>2002</td>
<td>-77,207</td>
<td>$404.7</td>
<td>$632.2</td>
</tr>
<tr>
<td>2003</td>
<td>-73,430</td>
<td>$376.8</td>
<td>$584.3</td>
</tr>
<tr>
<td>2004</td>
<td>-65,805</td>
<td>$320.7</td>
<td>$509.4</td>
</tr>
<tr>
<td>2005</td>
<td>-68,237</td>
<td>$357.4</td>
<td>$578.5</td>
</tr>
<tr>
<td>2006</td>
<td>-60,215</td>
<td>$321.6</td>
<td>$557.3</td>
</tr>
<tr>
<td>2007</td>
<td>-64,193</td>
<td>$401.7</td>
<td>$629.1</td>
</tr>
<tr>
<td>2008</td>
<td>-52,514</td>
<td>$353.7</td>
<td>$538.3</td>
</tr>
<tr>
<td>2009</td>
<td>-47,527</td>
<td>$293.5</td>
<td>$446.6</td>
</tr>
<tr>
<td>2010</td>
<td>-55,383</td>
<td>$360.5</td>
<td>$519.2</td>
</tr>
<tr>
<td>2011</td>
<td>-67,148</td>
<td>$411.9</td>
<td>$604.9</td>
</tr>
<tr>
<td>2012</td>
<td>-72,536</td>
<td>$479.8</td>
<td>$714.8</td>
</tr>
<tr>
<td>2013</td>
<td>-70,313</td>
<td>$471.0</td>
<td>$696.3</td>
</tr>
<tr>
<td>Total</td>
<td>-1,058,601</td>
<td>$5,914.5</td>
<td>$9,234.5</td>
</tr>
<tr>
<td>Average</td>
<td>-55,716</td>
<td>$311.3</td>
<td>$486.0</td>
</tr>
</tbody>
</table>
Net savings associated with PSC operation (Table 9) – gross savings (Table 8) minus annual PSC costs (Table 7) – indicate a total savings of roughly $3.5 billion tangible and $5.5 billion total costs. Tangible savings range from loss of $58.8 million in 1995 to a savings of $338.5 million in 2000. The same years show a loss of $91.7 million in tangible (1995) and savings of $470.6 million total (2000) costs. Ratios range dramatically with 1995 showing a loss of $5.36 in tangible criminal costs for every dollar spent to a return of $4.44 per dollar in 1998, with total cost returns ranging from losing $8.94 per dollar spent in 1995 to returning $5.47 in 1998. Average returns on investment over this period show a 98% return tangible and 135% total costs. Total tangible criminal costs divided by total PSC costs shows a return of $1.94 in tangible and $2.35 in total costs per dollar spent. Needless to say, these results show incredible promise.
<table>
<thead>
<tr>
<th>Year</th>
<th>Net Tangible Savings (millions)</th>
<th>Net Total Savings (millions)</th>
<th>Tangible to PSC Cost Ratios</th>
<th>Total to PSC Cost Ratios</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>-$58.8</td>
<td>-$91.7</td>
<td>-5.36</td>
<td>-8.94</td>
</tr>
<tr>
<td>1996</td>
<td>$33.4</td>
<td>$31.3</td>
<td>2.63</td>
<td>2.53</td>
</tr>
<tr>
<td>1997</td>
<td>$142.2</td>
<td>$184.0</td>
<td>4.19</td>
<td>5.13</td>
</tr>
<tr>
<td>1998</td>
<td>$221.2</td>
<td>$287.3</td>
<td>4.44</td>
<td>5.47</td>
</tr>
<tr>
<td>1999</td>
<td>$288.2</td>
<td>$392.1</td>
<td>4.15</td>
<td>5.28</td>
</tr>
<tr>
<td>2000</td>
<td>$338.5</td>
<td>$470.6</td>
<td>3.60</td>
<td>4.61</td>
</tr>
<tr>
<td>2001</td>
<td>$296.8</td>
<td>$423.0</td>
<td>2.78</td>
<td>3.54</td>
</tr>
<tr>
<td>2002</td>
<td>$302.7</td>
<td>$435.1</td>
<td>2.54</td>
<td>3.21</td>
</tr>
<tr>
<td>2003</td>
<td>$274.6</td>
<td>$386.6</td>
<td>2.39</td>
<td>2.96</td>
</tr>
<tr>
<td>2004</td>
<td>$198.6</td>
<td>$292.8</td>
<td>1.92</td>
<td>2.35</td>
</tr>
<tr>
<td>2005</td>
<td>$218.7</td>
<td>$338.7</td>
<td>1.91</td>
<td>2.41</td>
</tr>
<tr>
<td>2006</td>
<td>$193.0</td>
<td>$315.7</td>
<td>1.80</td>
<td>2.31</td>
</tr>
<tr>
<td>2007</td>
<td>$195.7</td>
<td>$339.7</td>
<td>1.68</td>
<td>2.17</td>
</tr>
<tr>
<td>2008</td>
<td>$115.6</td>
<td>$240.2</td>
<td>1.39</td>
<td>1.81</td>
</tr>
<tr>
<td>2009</td>
<td>$33.5</td>
<td>$134.8</td>
<td>1.11</td>
<td>1.43</td>
</tr>
<tr>
<td>2010</td>
<td>$88.0</td>
<td>$203.6</td>
<td>1.28</td>
<td>1.64</td>
</tr>
<tr>
<td>2011</td>
<td>$147.1</td>
<td>$288.9</td>
<td>1.47</td>
<td>1.91</td>
</tr>
<tr>
<td>2012</td>
<td>$229.1</td>
<td>$394.7</td>
<td>1.72</td>
<td>2.23</td>
</tr>
<tr>
<td>2013</td>
<td>$261.0</td>
<td>$420.8</td>
<td>1.95</td>
<td>2.53</td>
</tr>
<tr>
<td>Total</td>
<td>$3,519.1</td>
<td>$5,488.3</td>
<td>1.94</td>
<td>2.47</td>
</tr>
<tr>
<td>Average</td>
<td>$185.2</td>
<td>$288.9</td>
<td>1.98</td>
<td>2.35</td>
</tr>
</tbody>
</table>
2. Discussion:

These results indicate problem-solving courts reduce crime and not only prevent the costs associated with them but do so at a net savings, yielding a high return on investment. These results prove surprising for a few reasons. First, the relatively small footprint of PSCs would generally make detecting community-level effects difficult. Each program functions within a complex milieu of competing and complimentary factors. The number of people on probation in the US far outnumbers PSC participants, discussed in more detail below.

Another surprising element comes from cost savings and returns on investment. Remember that I limit analysis to those crime categories that returned significant, reliable estimates. Not finding reliable estimates from other crime categories does not mean PSCs have no effect on them, just that I could not disprove the null hypothesis.

Further, costs of crime, by themselves, provide highly conservative analysis. These do not consider other costs, or benefits, such as increased income for those who would have otherwise committed crimes, the collateral consequences associated with the attendant criminal record, or the impact criminal involvement has on family members. It is likely PSCs offer additional benefits.
3. Implications and Future Research:

a. Theory

This chapter indicates that Collaborative Governance Regimes improve big-picture, objective outcomes. Given that PSCs present an ideal case for studying collaborative structures, we can conclude that collaborating in the criminal justice system provides results that improve public safety cost effectively. By organizing previously loosely connected elements – prosecutor, defense, service providers – into a collaboration, aimed at a common goal, PSCs present a compelling case for collaborating.

I posit these results inform Collaborative Governance generally. Though analysis would certainly vary across policy areas, results here provide compelling evidence for the effectiveness and efficiency of cross-boundary collaboration.

This study also pulls a new context into the Collaborative Governance discussion. Though some researchers have examined criminal justice and courtroom issues, the author is unaware of substantial lines of inquiry into these issues generally and no work looking at PSCs as a test case. PSCs and the criminal justice system offer fertile ground to improve theory further.

b. Research

Examining Collaborative Governance performance presents several issues, especially concerning objective measures. The work presented here displays methods for looking into the question of long-term outcomes and how collaborations impact communities. This type of measurement not only helps make the case for collaboration in the literature, appealing to researchers, but offers another channel for gaining
support from policymakers, practitioners, and the public. Such efforts circle back to intermediary goals, such as increasing trust and legitimacy.

Further, this work applies Emerson and Nabatchi’s (2015b) performance measurement theory in a practical way, showing its usefulness. Though PSC elements do not fit perfectly into their matrix, the present work shows this method has heuristic value at a minimum.

c. Policy and Practice

These results also indicate expansion of programs like PSCs will yield substantial returns, both financially and socially. My analysis looks at a sample of extant PSCs, so actual benefits likely exceed those presented above. Additionally, these programs serve a fraction of potential participants. Communities can, therefore, likely scale PSCs quite a bit before reaching a point of saturation – where costs equal returns. Such a scaling process would also lower costs per participant, since many costs are fixed (e.g., courtroom, judge, and administrator salaries), providing economies of scale.

The sample used in this study covers 2,125 of the 3,006 US counties – roughly 70.69%. Thus, we can extrapolate results a bit and approximate net savings of nearly $5 billion in tangible ($3.519 b/0.7069) and $7.8 b in total ($5.488 b/0.7069) costs, while preventing something like 1.5 million crimes.

Taking another perspective, as of 2018 approximately 3,600 PSCs served about 216,000 participants. Compare this figure to the 3.5 million people on probation that same year (Kaeble, 2020) – PSC participants comprise about 6 percent of this population. Estimations vary widely of the proportion of people in the criminal justice system with the types of issues PSCs address (e.g., substance use or mental health
disorder), which we do not have room to fully discuss here. But a very broad, very conservative assumption of half those on probation exhibiting these issues indicates about 1.75 million potential participants – pointing toward the potential for PSCs to expand to roughly eight times current capacity. I will not venture to extrapolate my analysis to these figures, given all the variation in economies of scale and capacity, but we can see incredible potential for PSCs to impact their communities more broadly.

d. Future Research

Having established big-picture, objective outcome improvements for PSCs (and CGRs in general) here, and considering other work establishing short-term improvements, it makes sense to look further into the connections between these two units of analysis. Program evaluations, and several meta-analyses of these, have found reductions in drug relapse, recidivism, and other relevant outcomes (e.g., employment and housing).

Another line of future inquiry includes using the wealth of Collaborative Governance literature to better understand how PSCs function, and which elements lead to better outcomes. Not only would theoretical work, such as Kirk Emerson and colleagues' (2012) Integrative Framework for Collaborative Governance, provide tractable framing for understanding PSCs, but this work would further CGR theory. For instance, the judge (and court) preserve authority over the PSC collaboration, with final decisionmaking power. Though most judges include their team in final decisions, final authority rests with them. How does this authority fit within the CGR framework? What leadership styles might these judges exhibit, and which tend to improve operations?
One other element to consider comes from the number of crimes prevented relative to the number of PSC participants. I estimate PSCs prevented about 1.087 million crimes between 1995 and 2013. During this period my sample of PSCs saw about 459,000 participants, making each participant responsible for two fewer crimes. This back-of-the-envelope calculation assumes all PSC participants graduate, which is not the case. One 2016 report cited graduation rates between 50 and 75 percent (Marlowe, Hardin, and Fox 2016). If we take the high end of these figures, 75 percent, then each graduating PSC participant is responsible for three fewer crimes. All this is to say that PSCs seem to prevent more crime than their participants are likely to be responsible for, that some knock-on effects might be present. This could come from the aforementioned lack of disorganization seen in other, non-PSC contexts, or it might be some other factor entirely. This points toward future work looking at both collaboration and community causal channels leading to reductions in crime. The next chapter explores a few possibilities.
F. Conclusion

This study evaluated the performance of Collaborative Governance Regimes, using problem-solving courts as an ideal case. Results indicate that these structures improve long-term, objective outcomes (i.e., crime) and provide a strategic investment of public money. There also appears to be much more capacity, and demand, for these programs than current efforts fulfill. Therefore, expanding PSCs to include more participants would likely yield higher returns on investment, through economies of scale, and improve public safety. The most efficient use of public dollars would scale these programs to the point at which costs equal returns.

Results also indicate PSCs, and possibly collaborations generally, punch above their weight, providing improvements in public safety despite serving but a portion of potential participants. These programs are also associated with improvements beyond what we might expect from their operations alone. It is likely that some community factors interact with PSCs creating some knock-on effects to reduce crime at the community level.
IV. Potential Causal Mechanisms for Problem-Solving Court Reductions in Crime

Having established problem-solving courts (PSCs) reduce crime, and that they do so at a substantial cost savings, this chapter turns to the question of why PSCs reduce crime. These programs provide no services directly, doing so through a collaboration of service providers. Thus, they do not likely impact crime directly. I explore potential mediating factors that would indicate whether these lower crime rates occur due to a lack of social disorganization (by not taking individuals out of their community for incarceration), changes in law enforcement behavior relative to PSC implementation, and effective service provision. Specifically, I look at the relationships between PSCs and crime with unfounded crimes, juvenile arrests, arrests in the same categories found significant above, drug arrests, and relevant public employee categories. I found a relationship between PSCs and unfounded violent index crimes, drug arrests, and public hospital workers. Of these, only drug arrests indicate a mediating effect. All drug arrest types (total, sales, and possession) appear to mediate PSC impact on the total, property, and violent indexes.
A. Introduction

February 25, 2008, I walked out of prison broken. This was not the first time I walked out of prison. It was the first time I felt this broken, though. At 33-years-old my life had consisted of practicing substance use disorder (SUD) and the consequences associated with this malady, including a criminal career. I had no idea how to move forward in life. I did not want to continue hurting people. I did not want to continue the cycle of incarceration. But I did not know any other life.

My parole officer, and the system I found myself in, seemed concerned with reporting at the right times, providing clean urinalyses, getting a job... I found no help there. Two days after my release I found myself walking around Albuquerque, New Mexico lost, hopeless. Then, I remembered a 12-step club where I had attended meetings during previous terms of supervision – getting my attendance paper signed so I could stay out of jail. At this club they would have coffee, it would be warm, I could smoke indoors. In this hopeless state, I found the help I needed in 12-step programs. The people in that club taught me how to deal with my substance use disorder, how to become a productive member of society, how to repair the damage I had caused. Nearly 14 years later I write this dissertation as a direct result of the way of life those people taught me.

The New Mexico Department of Corrections did not help me solve my problem, nor did their Probation and Parole Department. These government agencies directed me toward potential services that, eventually, did help. That is, a basic analysis might indicate I desisted from crime, and achieved sobriety, following incarceration and parole. This analysis would only tell a part of the story, though. The current chapter
takes this perspective: looking at potential causal channels for the crime- and cost-reducing effects I found above for problem-solving courts (PSCs).

I explore variables likely to mediate PSC impact on crime relative to less social disorganization (unfounded crimes and juvenile arrests), law enforcement behavior changes (arrests), and service provision (drug arrests and public employees in relevant categories). While I find PSCs influence unfounded violent index crimes, I do not find a mediating effect. Drug arrests, however, who potential mediation. I found decreases in total, sales, and possession arrests, over time, relative to PSC implementation, as well as evidence of a mediating effect of all drug arrest categories between PSCs and their impact on all three crime indexes. Public hospital workers do seem to increase relative to PSC implementation, but their impact on crime in a covariate model (Equation 7 below) does not return significant results, though PSC indirect effects in the same model return the largest sign of mediation.

B. Background

As PSCs provide no services directly, doing so through a network of collaborating service providers, the question remains of how they reduce crime. Previous work has shown the eroding effects incarceration can have on communities, creating social disorganization (Kubrin & Weitzer, 2003; see also Burch, 2013). So, the simple fact that PSCs provide an alternative to incarceration may benefit communities, keeping people home. Though this explanation, though, would fit with the control condition mentioned above (community supervision), and the relatively small footprint PSCs have in any given community makes community-level impacts difficult to discern, I take an initial look at this potential channel. First, I revisit the impact PSCs have on unfounded crimes
seen in Chapter II. Also, an element of social disorganization operates within a household. Studies indicate children of incarcerated parents experience long-term consequences, including delinquency (Uggen & McElrath, 2014). Thus, PSCs may reduce crime by allowing parents to remain in the household. This reasoning may help explain the outsized impact PSCs have on crime discussed in Chapter III. I explore this channel by estimating the relationship between adult PSCs and juvenile arrests.

As briefly explored in Chapter II, communities capable of implementing a PSC might also have the wherewithal to improve other public safety measures, such as law enforcement activity. Previous work found increases in drug arrests relative to implementation of drug treatment courts (Lilley, 2017; Lilley et al., 2019, 2020). One interpretation of such an increase, a change in law enforcement activity upon PSC implementation, would posit police officers serve a selection service by arresting those who might benefit from PSCs. Given previous results show the increased arrests impact minorities more substantially, I find such an argument unlikely (if not immoral). I investigate PSCs’ relationship with arrests in the categories shown to be statistically significant and substantial in Chapter II.

Another straightforward explanation of PSCs reducing crime would be that the services they connect participants to have their intended effect: they address the underlying conditions (e.g., SUD) successfully. While the counterfactual condition, community supervision, also includes referral to similar services, the integrated nature of these services in PSC structures makes the connection more substantial (as explained in Chapter III). To put a finer point on the argument, if the method by which PSCs connect participants with services has its intended effect, then this may present a causal channel through which they reduce crime. To explore this channel, I look at PSCs and
drug arrests, as well as public employee numbers in categories likely to indicate community service provision.

C. Analysis
1. Empirical Strategy:

While causal analysis of mediation (and/or moderation) of PSC impact on crime presents setup and analysis beyond the scope of this dissertation, it behooves me to investigate a few possibilities as directions for future work. Toward this end, I perform traditional mediation analysis (Baron & Kenny, 1986). The usual strategy looks at a series of equations such as:

\[ M_i = \theta_1 + aX_i + \epsilon_{i1} \]  
\[ Y_i = \theta_2 + cX_i + \epsilon_{i2} \]  
\[ Y_i = \theta_3 + c'X_i + bM_i + \epsilon_{i3} \]

Where \( Y_i \) refers to an outcome variable (various crime categories in the current study), \( X_i \) is the independent variable (PSCs), and \( M_i \) a mediating variable. We can calculate the amount of mediated effect either \( c - c' \) of \( ab \), provided all of these coefficients return statistically significant. This strategy comes with several issues, such as the necessary assumption of sequential ignorability (Imai et al., 2010). Both the treatment (PSC implementation here) and the mediator must be statistically independent potential confounder (4-5). Many of the limitations with this approach require more room than I have in this study to overcome, so I will use the traditional method as a guide toward future work, not to make causal inference.

Having said that, I apply the same stacked event study design above to look at Equation (5). With these, I assess whether PSCs impact a potential mediator and if there
is any evidence of pre-trends. Then, I turn to the other two Equations, (6) and (7), to determine if inclusion of the mediator in a model (Equation 7) lowers the effect PSCs have on crime outcomes.

I explore the question of social disorganization, and lack thereof, by looking at the relationships between PSCs and relevant variables. My general strategy consists of estimating the effects PSCs have on each variable using the same stacked event study design described in Chapter II, looking at heterogeneity of treatment effects for those variables’ PSCs impact, and concluding with analysis of the mediation these have between PSCs and crime.

To look at social disorganization I explore the relationships between PSCs and unfounded crimes, and between adult PSCs and juvenile crime (i.e., excluding juvenile drug treatment and family treatment courts). I explore the PSC-law enforcement relationship using the arrest categories PSCs reduce in the Offenses Known dataset. I look at the question of whether the services PSCs connect participants with have their intended effect by exploring their relationship with drug arrests, as well as relevant public employee categories.

2. Data:

I explained the data used in this study in Chapters II and III. I use the same PSC dataset, as well as crime and public employees (ASPEP).

3. Social Disorganization:

If PSCs indicate less social disorganization in a community, we expect to see fewer unfounded crimes reported. Toward this end, Figure 17 revisits the stacked event
study shown in Chapter II (Figure 13) estimating the impact PSCs have on unfounded crimes, breaking them out into individual crime categories. Where the previous chapter included these to explore potential confounding factors, looking at estimates to the left of implementation (year 0), here I am concerned with coefficients after implementation. I also expanded analysis to individual graphs for each crime category. With no substantial pre-trends, results indicate a significant and substantial reduction in unfounded violent crimes three to five years and non-significant reductions in the other categories.
FIGURE 17
PSCs and Unfounded Crimes

Note: This figure displays estimates for the effect PSCs have on unfounded crimes for those categories PSCs have a significant and substantial impact on in Chapter II.
Figure 18 shows a stacked event study estimating the effects adult PSCs have on juvenile crime. Though these show no pre-trends, post-implementation results do not show the expected reductions but, rather, *increases* in total and property indexes in the fourth year after implementation. Rather than attribute these to crime reduction, that increased arrests of juveniles somehow reduces adult crimes, I consider results coincidental.

Figure 18: Adult PSCs and Juvenile Arrests

*Notes:* This graph displays point estimates and 95% confidence intervals for the effect adult PSCs have on juvenile crime index arrests.

4. Law Enforcement Activity:

Figure 19 displays stacked event studies estimating the effects PSCs have on arrests in crime categories shown to be affected using the Offenses Known dataset. Though we see a consistent reduction in theft arrests, these are not significant.
Otherwise, these results do not indicate PSCs have an effect on the crime categories. While these results may seem surprising – many consider the two datasets I use, Offenses Known and Arrests, as synonymous – some research indicates police change their behavior relative to policies and other indirect factors, meaning that arrests alone cannot be relied upon to reflect crime in the community (Crank et al., 2007; Lilley, 2017). Take, for instance, Table 10, which estimates the correlations between Arrest and Offenses Known in the same categories. Here we see total and property offenses correlate strongly but violent indexes do not.

<table>
<thead>
<tr>
<th>TABLE 10</th>
<th>Known Offenses and Arrest Dataset Comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Known Offenses</strong></td>
<td><strong>Total</strong></td>
</tr>
<tr>
<td>Arrests</td>
<td>0.9166***</td>
</tr>
<tr>
<td>(0.0855)</td>
<td>(0.0798)</td>
</tr>
<tr>
<td>Within-R2</td>
<td>0.0926</td>
</tr>
<tr>
<td>N</td>
<td>200,929</td>
</tr>
</tbody>
</table>

*Standard Error in Parentheses
*p < 0.05, **p < 0.01, ***p < 0.001
FIGURE 19  
PSCs and Arrests (Detailed Graphs)

Note: This figure shows point estimates and 95% confidence intervals for arrests in the categories PSCs impact known offenses: burglary, theft, motor vehicle theft, robbery, and aggravated assault.
5. Service Provision:

To look at whether the services PSCs connect participants with I estimate the effects these programs have on drug arrests and relevant categories of public employees. Figure 20 indicates no pre-trends for drug arrests and significant reductions post-implementation, especially for sales. Figure 21, on the other hand, shows results for PSCs and public employees in the health, hospital, housing and community development, and welfare categories. No other categories showed significant results (see Appendix A for all results).

FIGURE 20
PSC Effects on Drug Arrests

Notes: This graph reports point estimates and 95% confidence intervals for the effect PSCs have on total, sales, and possession drug arrests.
6. Direct vs. Indirect Effects:

Table 11 looks at the mediating effect variables PSCs influence above (satisfying Equation 5) by comparing direct (Equation 6) and indirect (Equation 7) effects. For these models, I lagged the PSC variable by two years, as this presents the most likely timeline for them to have any impact. The table reports indirect effects by category, as well as the difference between that category’s PSC coefficient and that from the direct model.

While results showing lower rates of unfounded violent index crimes associated with PSCs (Figure 17), and as much as this factor provides a worthy outcome in-and-of itself, we see a minimal difference between direct and indirect effects – showing, in fact, a very slight increase. I estimate indirect effects for all three drug arrest categories (total, sales, and possession) as PSCs showed impact on all of them above (Figure 20).
Here, it appears that all three categories mediate PSC effects on all three indexes, showing a difference of -0.003 in coefficients (~0.03% crime reduction). This figure, if we were to take it at face value, indicates mediation roughly between 9 and 15%. Public hospital employees show the biggest difference between direct and indirect effects, but the mediator coefficient is insignificant, making interpretation difficult.

<table>
<thead>
<tr>
<th></th>
<th>Unfounded Violent</th>
<th>Total Drug Arrests</th>
<th>Sales Drug Arrests</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
<td>Indirect</td>
<td>Difference</td>
</tr>
<tr>
<td>Total Idx</td>
<td>-0.021***</td>
<td>-0.021***</td>
<td>8.9E-05</td>
</tr>
<tr>
<td>Mediator</td>
<td>-0.001***</td>
<td>3.40E-06***</td>
<td>4.50E-06**</td>
</tr>
<tr>
<td>Property Idx</td>
<td>-0.020***</td>
<td>-0.020***</td>
<td>2.70E-05</td>
</tr>
<tr>
<td>Mediator</td>
<td>-2.3E-04</td>
<td>3.10E-05***</td>
<td>3.90E-06*</td>
</tr>
<tr>
<td>Violent Idx</td>
<td>-0.033***</td>
<td>-0.033***</td>
<td>1.8E-04</td>
</tr>
<tr>
<td>Mediator</td>
<td>-0.008***</td>
<td>6.50E-05***</td>
<td>1.2E-04***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Possession Drug Arrests</th>
<th>Public Hospital Workers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
<td>Indirect</td>
</tr>
<tr>
<td>Total Idx</td>
<td>-0.021***</td>
<td>-0.018***</td>
</tr>
<tr>
<td>Mediator</td>
<td>3.70E-06***</td>
<td>6.00E-06</td>
</tr>
<tr>
<td>Property Idx</td>
<td>-0.020***</td>
<td>-0.017***</td>
</tr>
<tr>
<td>Mediator</td>
<td>3.40E-06**</td>
<td>6.01E-06</td>
</tr>
<tr>
<td>Violent Idx</td>
<td>-0.033***</td>
<td>-0.030**</td>
</tr>
<tr>
<td>Mediator</td>
<td>6.40E-06***</td>
<td>2.18E-06</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001
D. Discussion and Conclusion

Keeping in mind that these results serve as preliminary investigation, results around drug arrests prove promising, especially if we consider I performed this analysis on a relatively weak proxy variable. While more work is needed to test the robustness of these analyses, finding such a proxy variable mediates PSCs impact on crime 9-15% provide evidence that the services PSCs connect participants with serve their intended purpose. Incorporating Chapter III’s discussion, that the difference between communities with and without PSCs amounts to cooperation and collaboration, these results point toward integrated collaboration between service providers and courts provide substantial returns.
V. Incarcerated Peer Education: The Indiana Peer Education Program

Incarcerated peer education (IPE) seeks to disseminate critical knowledge to people in prison by training others who are incarcerated as educators. These programs offer layered goals – increasing health knowledge, improving health outcomes, enhancing participants’ sense of self-efficacy, and improving criminogenic outcomes like recidivism. This chapter evaluates the Indiana Peer Education Program, an IPE program that trains people incarcerated in Indiana prisons to teach their fellows health topics. Peers undergo a 40-hour training, who then facilitate 10-hour trainings. I estimate the effect these trainings have on pre- and post-training surveys, as well as analyze qualitative data provided from peer educators via the Indiana prison email system. Results indicate improvements in health knowledge, attitudes about health, behavior intentions, and peer educators’ self-efficacy. Qualitative data affirms these findings, with many peer educators citing the program as improving their confidence and ability to navigate their lives effectively.

A. Introduction

Josh19 received a prison sentence in 2012 for drug related charges. He spent years feeding substance use disorder. He spent years without hope. Prison would be another hopeless place.

While in prison, though, Josh signed up for training to be a peer educator. The New Mexico Peer Education Project (NMPEP) taught him about chronic diseases and health-related topics, as well as how to teach these subjects to people incarcerated with

---

19 This is a pseudonym to protect the individual’s privacy.
him. He worked in this capacity for three of the four years spent behind bars, also attending college courses and gaining an associate degree.

When he left prison in 2016, he was a college graduate and had a feeling he had never felt before: hope. Josh found a job helping others getting out of prison and continued his education, obtaining both bachelor’s and master’s degrees. He now works in a field helping others at a professional level, cleared in several states to work with the most vulnerable people.

Though several factors led to Josh’s success, he attributes NMPEP participation as an important element: “It was an opportunity to do something productive in a place where there isn’t a lot of those... it made me believe I could do something meaningful,” which he continued after release from prison. Interestingly, Josh described self-efficacy as a product of being useful to others – that he found purpose and meaning in service, which led to a sense of self-worth, of confidence, of hope. “I was able to make meaning out of the experience [prison] and turn it into something purposeful” (Josh, personal communication, 2021).

The Indiana Peer Education Program (INPEP) replicates NMPEP. Not only does the program address the need for accurate health knowledge in Indiana Prisons but also attempts to improve participants’ sense of self-efficacy, which evaluation has shown NMPEP to do (K. Thornton et al., 2018). Beyond replicating evaluation results from the preceding program, this study applies more robust statistical techniques to ask the question of effectiveness. Quantitative evaluation of peer and student pre- and post-training surveys shows significant, substantial increases in health knowledge, health attitudes, behavior intentions, and peer self-efficacy. Analysis of qualitative data affirms the latter element, with peer educators indicating participation improved confidence
and their ability to contribute to their communities. Peer educators also indicated INPEP efforts will likely have lasting, expansive effects throughout Indiana prisons and communities that participants eventually re-join.

B. Literature Review

Incarcerated populations experience higher incidence of chronic diseases and less desirable health outcomes overall (Ferguson, 2018; Sugarman et al., 2020). Several factors influence this phenomenon. For one thing, in the United States social determinants associated with poor health – “being non-white, low-income, undereducated, homeless, and uninsured” (Macmadu & Rich, 2014, 2) – align almost perfectly with those associated with criminal justice system involvement (Ferguson, 2018; Sugarman et al., 2020). Some scholars cite an “Epidemic of Incarceration,” intertwining these concepts (Dumont et al., 2012).

Further, groups disadvantaged outside of the carceral system show such health disparities within the criminal justice system. Stark differences exist within incarcerated populations along race and gender lines. Taken from another perspective, those among disadvantaged groups who are also incarcerated experience less desirable health outcomes than those not incarcerated but within the same demographic groups. The intersection of incarceration and demographic disadvantage compounds health issues (Dumont et al., 2012).

The literature lists disparities for chronic diseases such as hypertension, asthma, and cancer (Binswanger et al., 2012); infectious diseases like tuberculosis (Baussano et al., 2010; MacNeil et al., 2005), HIV (Freudenberg, 2011), and hepatitis C (Varan et al., 2014); and psycho-social issues including substance use disorder, psychiatric disorders,
and victimization (Binswanger et al., 2012). At the time of writing this article, the coronavirus disease 2019 pandemic is highlighting these grim facts with disturbing rates of transmission (including among prison officials and guards) and frantic calls to address the problem (Kinner et al., 2020). Beyond the immediate ethical necessity of examining the health of incarcerated populations, such outcomes have ramifications for communities and society as a whole, as the COVID-19 pandemic demonstrates.

These disparities align with another social determinant of health and criminal justice system involvement: power dynamics (Harrison, 1995; Pratto & Pitpitan, 2008). Generations of a punitive system have prolonged a power structure that disadvantages minorities, women, and others, that both precedes criminal justice involvement and ensures disadvantage, making criminal desistance much more difficult (Weaver & Geller, 2019). Even programming offered to improve underlying issues associated with crime, be they toward education or mental health interventions, presents a traditional power structure dichotomy: some authority providing programming content and those receiving the programming.

Over 600,000 people are released from US state and federal prisons each year (Carson, 2020). The predisposition for negative health status, poor level of health engagement within carceral systems, stigma and collateral consequences the formerly incarcerated experience upon release, and disparities in knowledge of relevant health practices conspire to undermine any progress returning citizens aspire to (Tyler & Brockmann, 2017). Further, such elements impact the families, communities, and society people return to (Travis & Waul, 2003). More concisely, carceral health is public health.
The Indiana Peer Education Program (INPEP) approaches this issue along two lines. The first, and more direct perspective provides accurate and helpful learning engagement through training and education sessions. The second, and somewhat indirect has to do with self-efficacy. Peer educators are empowered as educators in their own right, hopefully improving their individual sense of agency. On one hand, scholars have demonstrated that self-efficacy impacts health and health behavior (Strecher et al., 1986). On the other, agency and self-efficacy have been associated with criminal desistance (Johnston et al., 2019). Further, in training incarcerated peer educators, INPEP disrupts traditional carceral power dynamics (Story, 2019). Peer educators become leaders within the carceral community and, as such, do not fit within the usual dichotomy.

1. Project ECHO and the Indiana Peer Education Program:

The Indiana Peer Education Program replicates earlier efforts by the New Mexico Peer Education Program (NMPEP; K. Thornton et al., 2018), which adapted processes developed in Texas prisons that dealt with HIV (Ross et al., 2006). INPEP trains peer educators in health education content and methods for teaching through 40-hour trainings. These peer educators, in turn, conduct 10-hour training sessions teaching others in prison a range of health topics. Though INPEP staff perform monthly site visits assuring the quality of 10-hour sessions, peer educators themselves perform all tasks associated with the sessions.

Peer educators also participate in periodic teleECHO sessions. These sessions take their format from the highly successful Expanding Community Health Options movement (see Zhou et al., 2016). This model democratizes specialized knowledge of
chronic diseases (e.g., hepatitis C) by bringing together primary care physicians (non-experts) with experts in these diseases, insurance issues, pharmacology, etc. in electronic, case-based learning modules. INPEP peer educators learn from experts in much the same way, making them a source of new and relevant information for their incarcerated peer educators and, at times, individuals traditionally more of an authority (e.g., medical or correctional personnel; Thornton et al., 2018). The ECHO model uses the analogy of a wheel – experts generally form the hub and primary care physicians the spokes. For INPEP, peer educators constitute the hub and those they teach the spokes; they are a central source of information.

B. Research Design

Evaluating a program like INPEP at this stage proves difficult. Where longer-running programs (like PSCs analyzed above) involve operations established enough in their communities that researchers can look at their impact on long-term and objective measures. INPEP has not operated long enough for such evaluation. Thus, I look at intermediary variables in a quasi-experimental design to test efficacy and likely to indicate long-term outcomes. Health knowledge, behavior intentions, and attitudes around health topics allude to health outcomes like disease transmission, preventative health involvement, and treatment adherence (e.g., voluntary vaccination). Self-efficacy and serving as a peer educator may also point toward seemingly tangential outcomes like criminal desistance and long-term quality of life.

Proximate analysis like this also has to deal with the question of robustness – that results might be spurious, especially. Thus, I integrate qualitative assessment
toward validation of quantitative results, particularly concerning self-efficacy. I also employ several models, with increasing fixed-effects strictures.

Finally, INPEP works toward layered, interlocking outputs and outcomes, that make full analysis difficult. The program serves two sets of individuals: peer educators and students. While expectations for the latter group generally amount to improved health knowledge and behavior, peer educators participate in a much more in-depth way, with more sophisticated expectations like empowerment and leadership qualities. I examine qualitative data for themes that indicate such outcomes.

1. Data:

This study examines both quantitative and qualitative data. Quantitative data comes from surveys peer educators and students take before and after trainings (see above for a description and Appendix B for the instrument itself). Qualitative data comes from prison-system email responses peer educators provided to INPEP staff geared toward quality improvement. Specifically, peer educators were asked:

- Can you tell me your general opinion of INPEP? What would you say are our successes?
- Do you think there has been any impact on your facility generally?
- How about with people specifically (like yourself)?
- Are there any skills you have gained from being a part of the INPEP team?
- What challenges or barriers have you faced as a peer educator?
- Do you have any suggestions for us to do better?
- Is there anything you would like to share that isn’t covered in these questions?
a. Quantitative Analysis:
Independent Variable

The primary independent variable for examining survey scores is whether the scores come from a pre- or post-training survey.

Dependent Variables

Our outcomes of interest come from survey scores. Peer educator surveys contain four categories:

- **Knowledge**: 20 multiple choice knowledge questions (with one correct answer out of four to five choices) about HCV, sexually transmitted infections (STIs), addiction and skin infections
- **Attitudes**: five attitude questions using a five-point Likert scale (strongly agree to strongly disagree) to assess attitudes about drug use, HCV and syringe services
- **Behavioral intention**: five behavioral intention questions using a five-point Likert scale (very likely to very unlikely) to assess the likelihood that peer educators, upon release, would: find a primary health care provider, use condoms every time they have sex, get a tattoo using shared ink or equipment, talk to their sex partner(s) about sexually transmitted infections (STIs) and consistently wash their hands before meals and after using the bathroom
- **Self-efficacy**: Seven self-efficacy questions using a five-point Likert scale (strongly agree to strongly disagree) to assess ability to teach, retain necessary information and overall ability to be a peer educator

Student surveys include 10 knowledge and five behavioral intentions questions (see Appendix B for a sample of the survey instruments).
Control Variables

Surveys, for both peer educators and students, include questions about individual demographics that include race, ethnicity, gender, age, and education level.

b. Qualitative Analysis:

Our primary source of data for qualitative analysis comes from email responses by peer educators to questions about INPEP. Since the COVID-19 pandemic severely limited contact between INPEP staff and peer educators, the Indiana Department of Corrections allowed staff to communicate with peer educators using the prison email system. During these communications, peer educators were asked about their views on the INPEP program, what it means for them personally, and what it means for others (both inside prisons and the broader community). After de-identification, we downloaded these data into the NVIVO qualitative software system for analysis.

2. Empirical Strategy:

a. Quantitative Model

To examine survey outcomes, I use the model:

$$
\log(\text{Score}_{its}) = \beta_0 + \text{Post}_{its}\beta_1 + \text{X}_{its}\beta_2 + \theta_s + \delta_t + \rho_{st} + \sigma_i + \epsilon_{it} \quad (6)
$$

Where:

- Individuals are indexed $i = 1... N$
- Time (cohort survey date) is indexed $t = 1... T$
- $\text{Score}_{it}$ indicates survey score for individual $i$ at time $t$
  - Using natural log as monotonic transformation
- $\text{Post}_{it}$ indicates if the survey is post-training and is our variable of interest
- $\text{X}_{ct}$ is a vector of individual-level controls
- $\theta_s$ are facility fixed effects
- $\delta_t$ are training date fixed effects
- $\rho_{st}$ represents facility by date fixed effects
- $\sigma_i$ are individual participant fixed effects
I cluster standard errors at the facility level. Further, I present models below that include graduating fixed effects. Since the sample of peer educators is much smaller (57) than students (857), I cannot use the date of assessment as a fixed effect and the Post variable as they introduce multicollinearity. Thus, I present two models for peer educators that present facility fixed effects and all control variables and another with facility and individual fixed effects. I present four models for students that show graduating levels of fixed effects.

b. Qualitative Assessment

We perform theme analysis of qualitative data, using a synthesis of phenomenological approach and grounded theory, looking for common constructions of peer experiences with INPEP (Creswell, 2007). The process involves approaching analysis agnostically, without preconceived notions, letting the data dictate theory development. Our reasoning stems from two premises. (1) The reality experienced by peer educators may be much different than our ideas about that reality. Who better to define that experience than a group of peer educators? Any overlapping themes provide an accurate account of INPEP’s influence. (2) Crediting peer educators with constructing this reality continues the explicit goal of the program to empower participants.

Three authors reviewed data independently, with a goal of 80% intercoder reliability, returning approximately 85% agreement.
3. Descriptive Statistics:

Currently, INPEP operates in four Indiana prisons. The program has trained 64 peer educators, who have taught approximately 2,000 students. Table 12 shows descriptive statistics for both peer educators and students included in this study. Student surveys did not include self-efficacy or attitude questions, so do not have scores in these categories. Also, this study does not include peer surveys from the Plainfield Correctional Facility.

| TABLE 12 |

**INPEP Descriptive Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Peers</th>
<th>Students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>Knowledge Scores</td>
<td>11.5/20</td>
<td>15.37/20</td>
</tr>
<tr>
<td>Self-Efficacy</td>
<td>27.52/35</td>
<td>32.96/35</td>
</tr>
<tr>
<td>Behavior Intentions</td>
<td>23.95/25</td>
<td>24.32/25</td>
</tr>
<tr>
<td>Attitudes</td>
<td>23.78/25</td>
<td>24.87/25</td>
</tr>
<tr>
<td>Age</td>
<td>37.93</td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>36.52%</td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>31.30%</td>
<td></td>
</tr>
<tr>
<td>Native American</td>
<td>6.96%</td>
<td></td>
</tr>
<tr>
<td>Pac Islander</td>
<td>1.74%</td>
<td></td>
</tr>
<tr>
<td>Other/No Answer</td>
<td>23.48%</td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>3.48%</td>
<td></td>
</tr>
<tr>
<td>Facility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IWP</td>
<td>32.23%</td>
<td></td>
</tr>
<tr>
<td>CIF</td>
<td>36.67%</td>
<td></td>
</tr>
<tr>
<td>Pendleton</td>
<td>49.59%</td>
<td></td>
</tr>
<tr>
<td>Plainfield</td>
<td>No Data</td>
<td></td>
</tr>
</tbody>
</table>
C. Analysis
1. Results:
   a. Quantitative

Peer educators

Table 13 reports results for peer surveys. Model (1) includes control variables and facility fixed effects. Model (2), on the other hand, includes both facility and individual fixed effects but no control variables, as they would introduce multicollinearity. I include the coefficients for the Post variable as well as percent change. Since the outcome variable is log transformed and Post is an indicator variable, I calculate percent change: $e^{\beta_1} - 1$.

Results indicate no significant results for behavior intentions, but significant and robust improvements for knowledge score, self-efficacy, and attitudes. An interesting finding comes from the scores showing more improvement when I individual-level fixed effects in the model. Knowledge scores increase by 31.56%, attitudes by 10.4%, and self-efficacy by 24.8%. This last improvement aligns well with qualitative findings (below).
### TABLE 13  
**Peer Scores**

<table>
<thead>
<tr>
<th>Knowledge Scores</th>
<th>(1) Post Coefficient</th>
<th>(2) Post Coefficient</th>
<th>Post Percent</th>
<th>Post Percent</th>
<th>Within-R2</th>
<th>Within-R2</th>
<th>N</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Scores</td>
<td>0.217* (0.0758)</td>
<td>0.2743*** (0.0269)</td>
<td><strong>24.23%</strong></td>
<td><strong>31.56%</strong></td>
<td>0.4108</td>
<td>0.6730</td>
<td>57</td>
<td>45</td>
</tr>
<tr>
<td>Self-Efficacy</td>
<td>0.1908* (0.0773)</td>
<td>0.2216* (0.0924)</td>
<td><strong>21.02%</strong></td>
<td><strong>24.8%</strong></td>
<td>0.1912</td>
<td>0.3184</td>
<td>57</td>
<td>45</td>
</tr>
<tr>
<td>Behavior Intentions</td>
<td>0.0128 (0.0089)</td>
<td>0.008 (0.0187)</td>
<td>1.29%</td>
<td>0.08%</td>
<td>0.1636</td>
<td>0.0073</td>
<td>57</td>
<td>45</td>
</tr>
<tr>
<td>Attitude</td>
<td>0.029 (0.0318)</td>
<td>0.099** (0.0164)</td>
<td>2.94%</td>
<td><strong>10.4%</strong></td>
<td>0.1461</td>
<td>0.1185</td>
<td>57</td>
<td>45</td>
</tr>
<tr>
<td>Control Variables</td>
<td>All</td>
<td>Limited</td>
<td>Facility</td>
<td>Facility, ID Number</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Facility</td>
<td>Facility, ID Number</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Standard Error in Parentheses*  
*p < 0.05, **p < 0.01, ***p < 0.001*

Students

Table 14 lists results for models presented above. These indicate a modest increase in behavior intentions and a dramatic increase in knowledge scores. Further, results are robust to all specifications, including (4) which includes individual identification numbers. Students’ behavior intentions improved by 6% and their knowledge scores increased by almost 59%.
TABLE 14
Student Scores

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Scores</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Coefficient</td>
<td>0.4422**</td>
<td>0.4566***</td>
<td>0.4620***</td>
<td>0.4633***</td>
</tr>
<tr>
<td></td>
<td>(0.0717)</td>
<td>(0.0051)</td>
<td>(0.0001)</td>
<td>(0.0733)</td>
</tr>
<tr>
<td>Percent</td>
<td>55.62%</td>
<td>57.87%</td>
<td>58.73%</td>
<td>58.93%</td>
</tr>
<tr>
<td>Within-R2</td>
<td>0.127</td>
<td>0.095</td>
<td>0.093</td>
<td>0.185</td>
</tr>
<tr>
<td>N</td>
<td>1,714</td>
<td>1,686</td>
<td>1,678</td>
<td>1,644</td>
</tr>
<tr>
<td>Behavior Intentions</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post Coefficient</td>
<td>0.0550**</td>
<td>0.0700***</td>
<td>0.0667***</td>
<td>0.0583***</td>
</tr>
<tr>
<td></td>
<td>(0.0058)</td>
<td>(0.0024)</td>
<td>(0.00003)</td>
<td>(0.0008)</td>
</tr>
<tr>
<td>Percent</td>
<td>5.65%</td>
<td>7.25%</td>
<td>6.90%</td>
<td>6%</td>
</tr>
<tr>
<td>Within-R2</td>
<td>0.058</td>
<td>0.056</td>
<td>0.053</td>
<td>0.050</td>
</tr>
<tr>
<td>N</td>
<td>1,712</td>
<td>1,684</td>
<td>1,676</td>
<td>1,640</td>
</tr>
<tr>
<td>Control Variables</td>
<td>All</td>
<td>All</td>
<td>All</td>
<td>Limited</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>Facility</td>
<td>Facility, Date, Date</td>
<td>Facility, Date, Facility x Date</td>
<td>Facility, Date, Facility x Date, ID number</td>
</tr>
</tbody>
</table>

Standard Error in Parentheses
*p < 0.05, **p < 0.01, ***p < 0.001

b. Qualitative

Broadly, we can classify peer comments into two categories: personal and community impact. Over half of the respondents commented on the benefits of health knowledge directly. “My general opinion of INPEP would be that it saves people’s lives. Whether it be with harm prevention tools we share [or] how important it is to get tested” (3). Qualitative data reflect quantitative results along these lines, with students showing substantial improvements in health knowledge.
Regarding personal impact, peer educators indicated improved communication skills, and a stronger sense of confidence and leadership; they feel empowered: “... I am not just an inmate but play an important role in helping people...” (2). Essentially, while learning about health and how to teach these topics, they gained a sense of self-efficacy – results that quantitative analysis confirms. One participant put it “[INPEP] aids in building our self-worth... it adds to our skillset, it helps us and lends hope to the lost, forgotten, overlooked, and marginalized” (16).

Peer educators expressed their belief that INPEP improved health knowledge and outcomes for both their incarcerated peer educators and communities outside of prisons: “we’re educating our communities... now they [incarcerated peer educators] are able to have conversations with their family, friends, etc.”

Finally, the theme of shifting power dynamics came up as well. One peer discussed “... working with professional who treat us as co-workers.” Another stated INPEP participation “helped me shake some of the stereotypes that have been placed on me.” The similarity in the last remark with that above regarding empowerment allude to the intertwined nature of individual agency and contextual constructions of their roles. That is, in taking part in the INPEP program, peer educators gain confidence and self-efficacy, helping them take a place of more authority within the carceral setting, which erodes traditional power dynamics. Pair these themes with the incredible jump in self-efficacy scores above and a picture of empowerment comes into focus.

2. Implications and Future Research:

Quantitative results indicate INPEP achieves the goals of increasing health knowledge, behavior intentions, attitudes, and self-efficacy. This last finding aligns well
with qualitative results. Though originally designed to increase health knowledge in prisons, and thereby decrease the transmission of deadly diseases like hepatitis C, the model quickly adapted to early results to include more content and aim toward increasing self-efficacy (K. Thornton et al., 2018).

From a purely practical perspective, the costs associated with chronic disease – especially within incarcerated populations – present a case in which the break-even point for investing in program like INPEP come quickly. For instance, hepatitis C in people incarcerated costs facilities approximately $15,000 to treat in early stages, or as high as $42,000 if it progresses to liver cancer (Tan et al., 2008). Thus, increased health education that nudges people with such an illness toward treatment lowers costs by roughly $27,000 for each case. Avoiding an infection altogether provides savings somewhere between early- and late-stage treatment costs. Considering annual costs for INPEP run approximately $162,000 annually, it would take six people choosing early treatment or between four and 10 avoided cases. I present conservative estimates here to illustrate how quickly returns come from investment.

Normatively speaking, improving confidence and sense of self-efficacy in this population presents its own desired outcome. Providing peer educators and their students with an opportunity to learn and grow builds hope. Given that negative outcomes (e.g., substance use relapse or recidivism) correlate with constructs like low self-efficacy, programs like INPEP address underlying issues that precede such negative outcomes.

All this indicates further investment into Incarcerated Peer Education. Not only will money spent avoid direct costs associated with chronic illness, but improvements in issues like confidence and self-efficacy will likely positively impact downstream
outcomes. As returns on these investments come in so quickly, and at such a high rate, saturation – the point at which costs equal returns – will not likely be reached any time soon. Further, many costs are fixed, meaning that economies of scale can be obtained by expanding to this saturation point.

The above recommendations also indicate further research, though. Results presented above amount to intermediate outcomes. While immediate improvement in health knowledge may imply better health outcomes, examination of health and criminogenic outcomes is necessary to make the case. If such assumptions about objective outcomes prove correct – that future research shows lower rates of infection, higher treatment rates, or lower recidivism rates – then cost-benefit analysis becomes simple.

D. Conclusion

Programs like INPEP aim toward layered goals. Those directly associated with the program (health knowledge in this case) and improving normative notions of confidence and self-efficacy. Further, these programs hope to leverage such outcomes in participants into more general, community-wide outcomes. This study shows improvements in health knowledge, attitudes about health topics, behavior intentions, and self-efficacy, which offers early evidence that INPEP is achieving its goals. Qualitative data duplicate quantitative results, lending weight to this argument. Given the costs associated with chronic disease and negative criminogenic outcomes (e.g., recidivism), investment into these programs offers substantial investment. Scaling these programs to serve more people in prison would likely increase savings, at an increasing rate (economies of scale).
My findings add to previous literature evaluating NMPEP by applying more robust quantitative methods and incorporating qualitative analysis as validation of quantitative findings, in addition to interesting data for exploration. This study also adds to the more general incarcerated peer education literature by finding application in a specific setting (health education training) has general benefits.
VI. Conclusion

The United States’ criminal justice policies have vacillated between punitive and rehabilitative efforts over its history. The most recent swing toward punishment, though, pushes far beyond any other similar period (Muenster & Trone, 2016). Politicians from the Nixon Administration forward grasped onto the notion that “nothing works” using work by Edward Martinson (1974) (and, it must be noted, many other sociologists on the same project) to justify cutting rehabilitation programs and expanding of punitive measures. The 1970’s through 90’s saw both major US political parties attempting to outdo each other in tough-on-crime stance. Even the US Supreme Court weighed in on the subject, stating rehabilitation to be “an unattainable goal for most cases” (*Mistretta v. United States*, 1989). The sheer inertia of these widespread efforts created something of a new equilibrium (see, generally, Baumgartner & Jones, 1993). Despite mountains of evidence to the contrary, including by the very researcher that politicians quoted so often (e.g., Martinson, 1979),20 and despite the mathematical reality of the racist and classist nature of these policies, a tone had been set. Academics, practitioners, and advocates found their efforts fruitless, for the most part.

Fighting such a tide required power not imbued upon those normally in such policy domains. These attributes underlie the alternative approaches presented above. On one hand, problem-solving courts gained prominence because powerful players pushed for them. Janet Reno helped create the first adult drug treatment court in Miami 1989, then went on to serve as Attorney General, when the model became enshrined into federal law (*1994 Crime Bill*). Further, this period of punitive policy also created an

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20 The National Academy of Sciences conducted a panel revisiting the quoted “nothing works” papers, stating, "When it is asserted that 'nothing works,' the Panel is uncertain as to just what has even been given a fair trial" (J. G. Miller, 1989).
appetite for mandatory minimum sentences, which took control out of judges’ hands. Many judges fought the tide on this front unsuccessfu

lly. A few, though, saw the new drug court model as a way to regain some authority in their own courtrooms (D. Marlowe, personal communication, January 2021). Certainly, some judges truly believed in the model, and in rehabilitation generally, but the incentive to regain control played a not insignificant role. Thus, PSCs had powerful champions: judges. Their authority trumped any previous efforts by other, less powerful parties.

Incarcerated peer education sprang from alarming rates of infectious diseases in prisons. From The Walls program in Texas, which addressed HIV issues, to the New Mexico and Indiana efforts, these programs gained entrée under the premise of health concerns (K. Thornton et al., 2018). IPE’s, though, also serve rehabilitative purposes. As the work above alludes to, participating in this type of program helps people in prison gain a sense of self-efficacy.

Thus, efforts to provide services which address conditions preceding criminal acts seems to be on the rise. The punitive-rehabilitative pendulum appears to swing toward services. We can thank the unsustainable financial and social costs of punishment, and the efforts of countless individuals, this dissertation included.

Findings presented above illustrate that providing access to services not only effectively addresses issues like public safety but does so at a savings. It turns out that the most self-interested measures coincide with the most humanitarian. Treating people with compassion, in this case, creates a safer society for much less money.

Another overall implication of these findings has to do with the complex, interconnected nature of social phenomena. The struggle within criminal justice policy mirrors the battle between simplistic, heuristic knowledge most human beings default
toward and more nuanced, challenging concepts. We live in a world better adjusted to soundbites and slogans than sophisticated, critical thought. Is it any wonder the War on Drugs has had such lasting effects?

The application of layered services in both PSCs and IPEs illustrates not only the complexity of issues like criminality but also offers hope. While such complexity and nuance present difficult areas of research and practice, understanding how personal, interpersonal, organizational, institutional, and social elements interact provides potential methods for gaining synergistic outcomes. PSCs reduce pressure on court dockets, improve public safety, and save money. IPEs increase health knowledge, likely improving health outcomes, and cultivate self-efficacy in participants, likely reducing recidivism and improving long-term life quality.

There is hope.

A. Extensions and Future Work

Results in chapters II and III point toward several extensions and future work. Below, I classify them by theoretical base, starting with applied economics extensions, then describing public policy and public administration directions. I also discuss further efforts evaluating the Indiana Peer Education Program.

Economics:

Two directions follow well from this dissertation. First, funding for problem-solving courts does not occur randomly, especially grants from the federal government. This money correlates very strongly with PSC implementation, and operation, but not perfectly. Further, these funds do not affect crime except through PSCs. These facts
make PSC funding a well-suited instrumental variable. This method controls for endogeneity between an outcome variable (crime in this case) and the treatment under review (Angrist & Krueger, 2001).

Getting a dataset of PSC funding and merging it with those used above will provide solid causal inference and lay the groundwork for more nuanced questions like dose (i.e., how the number and type of PSCs impact crime rates). I also discuss below how I can use results from this method to investigate questions in the public policy and administration fields.

Next, the question of individuals making a decision to commit a crime continues unanswered, satisfactorily, in the literature. PSCs attempt to address antecedents to crime, rather than use traditional policy levers. Consider Becker’s canonical crime supply \( O_j \) equation,

\[
O_j = O_j(p_j, f_j, u_j)
\]  \hspace{1cm} (7)

in which individual \( j \) weighs the decision to offend based upon the probability of conviction \( p_j \), the punishment for the offense \( f_j \), and a range of other personal influences \( u_j \). The first and same second derivatives for \( p_j \) and \( f_j \) are all less than zero, and cross-second derivatives are roughly equal to zero (to avoid a corner solution). That is, as the probability of conviction and punishment severity increase, the number of offenses will go down, with decreasing marginal returns. Traditional approaches focus on \( p_j \) and \( f_j \), reflecting the “nothing works,” tough-on-crime sentiment. PSCs, on the other hand, focus on \( u_j \); at least, in part.

An argument can be made that PSC supervision increases the probability of getting caught for any new crimes, that the punishments are greater for failing a PSC
program, or that participation increases awareness of such factors (possibly clarifying perceived probabilities and punishments). The counterfactual to PSC operation, though, is not simply a lack of supervision or punishment. Given that 90-95% of criminal cases in the US terminate with a negotiated plea deal (Devers, 2011), nearly all non-PSC criminal cases conclude with some alternative type of supervision (e.g., probation) or incarceration. Thus, we can expect little difference in these factors between PSCs and traditional approaches.

This argument extends to the notion of punishment type. Becker, and others, also argue that switching the type of punishment – for instance, from a fine to imprisonment – will also impact the supply of crime. While PSCs can be seen as a punishment, in-and-of themselves, the best confounding argument has to do with the consequences of failing. A few studies have indicated that those who drop out of PSCs fare worse than if they had never began the program (Lilley, 2013). If this is the case, estimates for PSC effects on crime will trend upward, biasing analysis presented above toward zero.

Tackling the $u_j$ term comes with ambiguity and complexity. This term has not been well-defined, though a fair amount of policy and research work contends with elements within it. The direction of influence varies depending on the element. Consider, for instance, the opportunity costs associated with a decision to offend. Lower socio-economic factors, such as lack of employment or social connections, would increase the likelihood of a decision to offend – the person would have less to lose – while increases in these would lower it (by increasing the opportunity cost). Even more slippery, a person physically and/or psychologically dependent on a substance would weight the expected utility from an offense much higher, and the expected consequences much lower, as well as the probability of conviction. I delve into these elements more
below, first answering the reduced-form question of whether addressing this term (i.e., not the probability of conviction or level of punishment) impacts known offenses.

Researchers have attempted to chip away at the “something else” term over the past few decades, even during the “nothing works” era. Philip Cook (1975, 14) cited a “well-documented failure of the ‘therapeutic approach,’” while laying the groundwork for labor participation as a potential way to reduce recidivism for people returning from prison (though the cited article found no effects). He began refinement of Becker’s equation, especially expected utility, by positing “that the deterrent effect of a threatened prison term increases with wealth” (note 38), and noting that at least one observable characteristic, marriage, will likely show decreases in expected utility for any given crime – the person has more to lose if caught. Importantly, Cook alludes to the malleability of factors within a decision array, that expectations are influenced throughout the criminal justice process, and in a subsequent paper associates interventions lowering availability of alcohol with reductions in violent crime (Cook & Moore, 1993).

Becker points out that empirical evidence indicates those who commit crimes prefer risk, that increases in surety of conviction will have a greater impact on reducing crime than severity of punishment. Though much of the economic literature assumes risk preference stable (including Becker himself; Stigler & Becker, 1977), contemporary work questions whether it might be malleable (Schildberg-Hörisch, 2018). I propose PSC participation may influence risk attitudes and, thus, expected utility. It will be

---

21 It should be noted that this term exists as a political fiction. Even Robert Martinson, whom policy makers attribute this “doctrine,” pushed back against the notion that only enforcement and punishment “work.” Martinson attempted to clarify his position in later works, stating “contrary to my previous position, some treatment programs do have an appreciable effect on recidivism, (Martinson, 1979, 244). Such complex reasoning, though, does not fit well in a campaign slogan or sound bite.
difficult to discern, though, whether this change comes from opportunity cost increases, increased awareness of the surety and severity of punishment, or fundamental changes in utility function.

Murat C. Mungan and Jonathan Klick (2016, note 50) make an important distinction in their extension of Becker’s expected utility function \( U \) – by including a current monetary equivalent position variable, \( w \),

\[
U(w) < pU(w + b - f) + (1 - p)U(w + b).
\]  

(8)

Here, \( b \) represents the gain a person expects from committing a crime, \( f \) continues to represent the criminal sanction, and \( p \) the probability of getting caught. A convex \( U \) implies risk preference (increasing marginal returns), concave risk aversion (decreasing marginal returns). Since the counterfactual situation to PSCs is most likely some other type of supervision (e.g., probation), any changes to the distributions and variances of \( p \) and \( s \) would be nominal. This model points toward a few suspects that may alter the decision to offend, other than increasing surety or severity.

If a person’s starting position is improved, they will have more to lose. Also, if risk preference changes, then elements will be weighted differently. First, though, it makes sense to alter this model a bit. The first adjustment is to include some portion of starting position lost as a function of punishment:

\[
U(w) < pU(w^k + b - f(w^l, s)) + (1 - p)U(w + b).
\]  

(9)

Here, \( w^k \) denotes the portion of a person’s starting position that would be kept if caught, \( w^l \) would be lost. \( s \) indicates sanctions over-and-above \( w^l \). For example, if a person is caught, current job and some social connections would be lost \( (w^l) \), while capital not
subject to fines and other social connections would not \( (w^k) \). Additional punishments, like incarceration, would add to the loss.

PSCs provide an interesting context to look into the decision to commit a crime in this way. Further, it provides fertile ground for comparing economic theories like Becker’s rational approach and behavioral approaches like Prospect Theory (Kahneman & Tversky, 1979).

Public Policy and Public Administration:

The unique conditions found in PSCs offer an interesting context to evaluate public policy and public administration theories, which will also add to understanding of PSCs. The PSC movement occurred in the face of countervailing forces. Despite the inertia of punitive criminal justice policy, this program spread across the US. This constitutes an interesting Policy Diffusion story. As in, how did a service-oriented program diffuse across the US concurrent with adverse, even antagonistic, other policies and sentiment? I suspect the influence of the judicial branch had something to do with it – that judges’ advocacy moved this mountain – but such supposition bears investigation.

As described in Chapter III, PSCs embody Collaborative Governance structures. A look into how specific elements within these collaborative structures function will illuminate elements with the Collaborative Governance literature heretofore not well known. Specifically, the connection between intermediate outcomes (e.g., public trust and legitimacy) influence long-term measures. Though the work above points toward collaboration offering more effective and efficient operations, relative to traditional
arrangements, elements within and between organizations surely connect to these results. The question is which and how?

Along similar lines, PSCs might provide fertile ground for empirically testing organization. Organizational ecology theory works well in the private sector, in which competition between organizations for customer dollars dictates which organizations survive (Hannan & Freeman, 1977). While researchers have begun applying this theoretical foundation to collaboration (e.g., Scott & Thomas, 2017), looking at the survival of PSCs, especially in light of other efforts that failed, will provide insight into how public organizations survive. Internal, interpersonal, and inter-organizational facets of PSCs offer prime areas to look at institutional theories like how institutional logics interact (P. H. Thornton et al., 2012) and how individuals carry extra-local logics into play within their PSC roles – their “inhabited institutions” (Hallett & Ventresca, 2006).

Finally, PSCs provide a context to extend the representative bureaucracy (see Bishu & Kennedy, 2019 for a review) and political representation (Pitkin, 1967). Toward the latter, PSCs represent a fundamental shift in whose interests courts represent. Whereas traditional courts serve higher-order notions of justice and public safety (Pitkin’s “trustee” type representation), PSCs focus on individual interests (participants).

Representative bureaucracy generally measures ascribed characteristics like race and gender, yet human identity comprises more sophistication. Contemporary efforts in this field attempt to look at more experiential elements of individual identity, like veteran status (Gade & Wilkins, 2013). Some PSCs include team members with
substance use disorder recovery and/or criminal justice experience. Such conditions could be exploited to determine if such parts of identity translate into better outcomes.

INPEP:

While the results in Chapter IV offer hope for the Indiana Peer Education Program, outcomes measured may or may not translate to long-term impact. The questions regarding improved health and criminogenic outcomes bear asking. Toward this end, assessment of more objective measures are called for. The evaluation team are currently engaged with the Indiana Department of Corrections to attain data on objective outcomes like commissary purchases, disciplinary reports, and health-related issues (e.g., voluntary vaccine uptake). Most participants, especially peer educators, have agreed to being contacted in the future by the INPEP team, which will provide long-term evaluation of the topics addressed during participation, and other outcomes like quality of life and recidivism.

Further, the finding regarding self-efficacy also points toward future work. The participant quoted at the beginning of Chapter IV, Josh, indicated participation in NMPEP showed him that being of service to others in prison helped him gain a sense of self-efficacy. The notion of generative behavior comes up in criminal desistance theory but has yet to be substantively tested (Laub & Sampson, 2001; McAdams, 2006). INPEP might serve well in this capacity.
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https://doi.org/10.1016/j.ssresearch.2012.01.001


https://doi.org/10.1097/ACM.0000000000001328
FIGURE A.1
PSC implementation over time and by type

Notes: These graphs show PSC implementation numbers by year and by type. Graph A.1.a includes the top seven types of PSCs, A1.b groups similar types together.
FIGURE A.2
PSC implementation over time and by type (individual time series)

Notes: These graphs display PSC implementation patterns over time, showing individual types in each. I grouped together similar types of PSCs for brevity.
### TABLE A.1

*Observations per Sub-Experiment (“Stack”)*

<table>
<thead>
<tr>
<th>Stack</th>
<th>Observations Per Stack</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>1,113</td>
<td>12,243</td>
</tr>
<tr>
<td>1996</td>
<td>1,062</td>
<td>11,682</td>
</tr>
<tr>
<td>1997</td>
<td>1,046</td>
<td>11,506</td>
</tr>
<tr>
<td>1998</td>
<td>1,012</td>
<td>11,132</td>
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<tr>
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<td>977</td>
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</tr>
<tr>
<td>2000</td>
<td>911</td>
<td>10,021</td>
</tr>
<tr>
<td>2001</td>
<td>894</td>
<td>9,834</td>
</tr>
<tr>
<td>2002</td>
<td>847</td>
<td>9,317</td>
</tr>
<tr>
<td>2003</td>
<td>831</td>
<td>9,141</td>
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<tr>
<td>2004</td>
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<td>9,548</td>
</tr>
<tr>
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<td>938</td>
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<tr>
<td>2006</td>
<td>904</td>
<td>9,944</td>
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</tr>
<tr>
<td>2008</td>
<td>939</td>
<td>10,329</td>
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<tr>
<td>2009</td>
<td>948</td>
<td>10,428</td>
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<td>2010</td>
<td>980</td>
<td>10,780</td>
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<td>1,160</td>
<td>12,760</td>
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<tr>
<td>Total</td>
<td>18,501</td>
<td>203,511</td>
</tr>
</tbody>
</table>

*Note: This table lists observations (county-years) included in each sub-experiment (“stack”).*

This table lists the numbers of observations in each sub-experiment dataset (“stack”) described in section II.C.1, including counts within each relative year bin for each stack, as well as totals per relative bin, sub-experiment, and overall.
Figure A.3 shows detailed graphs of stacked event studies exploring the impact PSCs have on law enforcement personnel. While we see no significant prediction of PSCs, there does appear to be lower rates of officers in the third year after implementation (A.3.b) and a trade-off in year five between the percentage of officers and civilians (A.3.d/e).
FIGURE A.3
Law enforcement personnel detailed event studies

Notes: These graphs display point estimates, and 95% confidence intervals of the effect PSCs have on law enforcement personnel; including total, officers, civilians, percent officers, percent civilians, and ratio of officers to civilians.
Figure A.4 displays detailed graphs of the relationship between PSCs and clearances by arrest. There is some evidence of prediction of PSCs on clearances for all crimes and the total index, which seems to be driven by the property index.

**Notes:** The graphs here show point estimates and 95% confidence intervals for PSC effects on clearances by arrest; including all crimes, as well as total, property, and violent indexes.
Figure A.5 shows detailed graphs of stacked event studies of the effects PSCs have on law enforcement officers killed or injured. There appears to be no effect.

Notes: These graphs show point estimates and 95% confidence intervals of the effect PSCs have on officers killed by felony and by accident, as well as officers assaulted.
FIGURE A.6
Public employees and PSC event studies
Figure A.6 displays event studies of PSC impact on number of public employees in specific categories.

Notes: These graphs show point estimates and 95% confidence intervals for PSC effects on public employee categories. Data come from the Annual Survey of Public Employment and Payroll.
FIGURE A.7
Predicted vs counterfactual values

Notes: These graphs show predicted and counterfactual values (left axes) and differences between them (right axes).
Figure A.7 shows detailed graphs of predicted and counterfactual crime counts per year on the left-hand y-axis, and the difference between these on the right. Table A.2 also reports the latter counts of net crimes (predicted – counterfactual) in each category per year.

TABLE A.2
Net Crimes (Detail)

<table>
<thead>
<tr>
<th>Year</th>
<th>Burglary</th>
<th>Theft</th>
<th>Motor Vehicle Theft</th>
<th>Robbery</th>
<th>Aggravated Assault</th>
</tr>
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<tbody>
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<td>1995</td>
<td>4543.04</td>
<td>16512.24</td>
<td>4501.78</td>
<td>-885.79</td>
<td>2200.11</td>
</tr>
<tr>
<td>1996</td>
<td>987.21</td>
<td>7057.82</td>
<td>-556.65</td>
<td>-1311.86</td>
<td>651.58</td>
</tr>
<tr>
<td>1997</td>
<td>-3014.23</td>
<td>-2039.58</td>
<td>-7232.81</td>
<td>-2651.60</td>
<td>-1611.22</td>
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<td>1998</td>
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<td>-6902.11</td>
<td>-10782.17</td>
<td>-2860.81</td>
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<td>1999</td>
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<td>-15191.88</td>
<td>-13727.77</td>
<td>-3915.39</td>
<td>-4986.16</td>
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TABLE A.3 (continued)

Gross Crime Savings (Detail; in millions of dollars)

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Table A.3 displays gross crime savings per crime category, per year, in millions of dollars.
INPEP ECHO Post-Training Survey

Appendix B: Indiana Peer Education Program Peer Educator Post-Training Survey

INPEP ECHO 40-Hour Post-Test

Today’s Date: ___/___/____  Your initials and year of birth (example – br1963): __________________________

Location of Training: ______________________ What is your age? _______

Please fill in the appropriate bubble for each answer.

For example if your answer is “B”: ☐ ☐ ☐ ☐

Knowledge about HCV/HIV/other health issues
(Please fill in one bubble for each answer)

1) Approximately what percent of people incarcerated in Indiana state are infected with hepatitis C?
   ______________________

2) Hepatitis C can be spread in all of the following ways EXCEPT:
   ☐ Sharing tattoo ink
   ☐ Injecting drugs with an unused needle
   ☐ Sexual intercourse
   ☐ Sharing a toothbrush

3) Approximately what percent of people exposed to hepatitis C will develop chronic hepatitis C infection?
   ☐ Less than 5%
   ☐ About 25%
   ☐ 50%
   ☐ 75 – 85%
   ☐ 100%
4) Hepatitis C primarily affects what organ?

☐ Liver
☐ Kidneys
☐ Heart
☐ Brain

5) Which of the following is TRUE regarding hepatitis C symptoms?

☐ People immediately know they have hepatitis C because they always become jaundiced (skin turns yellow).
☐ Most people can live for many years with hepatitis C before they have any symptoms.
☐ Within the first year of getting hepatitis C, everyone experiences flu-like symptoms.
☐ One can always tell whether or not they have hepatitis C by the way they feel.

6) Cirrhosis is the medical word for:

☐ Liver cancer
☐ Early stage of hepatitis C
☐ A lot of scarring in the liver
☐ Internal bleeding

7) What is the function of the liver?

☐ Removes toxins from the body
☐ Converts food into energy
☐ Aids in the digestion of food
☐ All of the above
8) Which of the following conditions increase scarring of the liver for people who have hepatitis C:

- □ Infection with HIV
- □ Alcohol use
- □ Being overweight
- □ All of the above

9) Chronic hepatitis C sometimes leads to:

- □ Pneumonia
- □ Cirrhosis (scarring of the liver)
- □ Liver cancer
- □ HIV/AIDS
- □ Both b and c

10) Which of the following is TRUE about hepatitis C treatment:

- □ There is no cure for hepatitis C
- □ Only a small minority of people getting treatment will be cured
- □ Over 70% of those getting treatment will be cured
- □ It generally takes one month to treat someone for hepatitis C
11) The following is a good way to prevent getting hepatitis C:

- Get the hepatitis C vaccine
- Wash your hands regularly
- Use clean needles
- Eat a nutritious diet
- All of the above

12) You can tell you have HIV/AIDS by:

- Symptoms such as swollen lymph nodes, fatigue, and flu-like symptoms
- Loss of appetite
- Getting tested
- Serious weight loss for no apparent reason

13) HIV can be found in all of the following body fluids EXCEPT:

- Blood
- Saliva
- Breast milk
- Vaginal fluid or semen

14) A good way to prevent the spread of MRSA/ Staph infection is:

- Get lots of exercise
- Get a MRSA vaccine (shot)
- Wash your hands frequently
- Avoid fatty foods
15) There is a cure for all of the following sexually transmitted infections EXCEPT:

- Gonorrhea
- Syphilis
- Herpes Simplex
- Chlamydia

16) Which of the following is TRUE about gonorrhea and syphilis?

- If you do not have any symptoms, you cannot pass it on to others.
- There is a vaccine that can prevent you from getting them.
- These are both diseases that can be transmitted from a mother to her baby during childbirth.
- Only the person that has gonorrhea or syphilis needs to be treated, not their sex partner.

17) HPV, the virus associated with genital warts, causes:

- Cirrhosis
- Cervical cancer
- Enlarged lymph nodes
- Frequent urination (peeing)

18) People misuse drugs and alcohol because:

- It is a choice people make
- It is an attitude
- It is a personality characteristic
- It is a medical disorder
- Of a combination of factors
19) The following can help prevent diabetes:

☐ Get a vaccination (shot)
☐ Lots of physical activity and a healthy diet
☐ Wash your hands often
☐ Quit smoking
☐ All of the above

20) Which of the following sexually transmitted infections can be prevented by a vaccine?

☐ HIV
☐ Syphilis
☐ Human Papilloma Virus (HPV)
☐ Chlamydia

Attitude Questions:
Please fill in one bubble for each answer that best describes your attitude:

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<th>Agree</th>
<th>Strongly Agree</th>
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<td>21) People who inject drugs should have access to unused needles on the outside.</td>
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<td>☐</td>
<td>☐</td>
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<td>22) It is important to me to know whether or not I have hepatitis C.</td>
<td>☐</td>
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<tr>
<td>23) People who misuse drugs or alcohol have poor morals and values.</td>
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<td>☐</td>
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<td>24) People who get hepatitis C through sharing needles deserve what they get.</td>
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<td>25) If I had hepatitis C, I would want to get treatment.</td>
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Behavioral Intentions Questions:

Please fill in one bubble for each answer that best describes your attitude:

Once you are released, how likely are you to:

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<td>27) Use condoms every time you have sex</td>
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<td>28) Get a tattoo using shared ink or equipment</td>
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<td>29) Talk to your sex partner about sexually transmitted infections</td>
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<td>30) Consistently wash your hands before meals and after using the bathroom</td>
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</table>
Appendix C: Data Availability Statement

The majority of data used in this dissertation came from publicly available sources, including: UCR Offenses Known, UCR Arrests, UCR LEOKA, Unemployment, County-level demographics, and public employees. Anybody interested can access these through the same sources.

I will provide data on PSCs upon reasonable request for replication of this work alone.

Data on INPEP comes from protected information and is not available for use by anybody other than staff.

I will also provide the Stata code used for all analysis upon reasonable request (whether for replication or general interest).
CURRICULUM VITAE

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The Oregon Social Learning Center
patrickh@oslc.org

EDUCATION

December 2021  Ph.D., Public Affairs, Indiana University—O’Neill School of Public and Environmental Affairs
                Minor: Social Science Research Methods
                Committee: Matthew Baggetta (co-chair), Sean Nicholson-Crotty (co-chair), Lisa Blomgren Amsler, Coady Wing

December 2014  M.B.A., University of New Mexico—Anderson School of Management
                Concentrations: Nonprofit and International Management

July 2013      B.B.A. University of New Mexico—Anderson School of Management
                Concentration: Entrepreneurial Studies

RESEARCH EXPERIENCE

August 2021  Research Assistant III/Post-Doctoral Fellow (once PhD is issued) at the Oregon Social Learning Center
             - Research into substance use disorder and criminal justice issues; initial program involvement: Juvenile and Emerging Adult Populations

2019 — Present  Program Evaluator for the Indiana University-Purdue University Indianapolis Project ECHO Indiana Peer Educator Program
                 - Responsible for the evaluation design, institutional review, data and instrument development, implementation, analysis, and dissemination

2018 — 2019  Research Assistant for Eric Grommon, Ph.D. and Brad Ray, Ph.D., O’Neill School of Public and Environmental Affairs, Indiana University-Purdue University Indianapolis

2017 — 2018  Research Assistant for Lisa Blomgren Amsler, J.D., O’Neill School of Public and Environmental Affairs, Indiana University-Bloomington
2013 Graduate Assistant for Manuel Montoya, Ph.D. (UNM—Anderson)
- Special assignment building out new International Business Students Global infrastructure

RESEARCH IN PROGRESS

Hibbard, P., Amsler, L.B., Jackman, M.S. “Representative Bureaucracy and Organizational Justice in Mediation.”
Accepted to the Journal of Public Administration Research and Theory


Hibbard, P., Visher, C.A. “Re-Entry Program Timing Effects: Using Qualitative Comparative Analysis, Machine Learning, and Matching Pre-Processing to Test Program Type and Timing Effects on Recidivism”

Hibbard, P., Duwve, J., Janota, A. “Carceral Health is Public Health: the Indiana Peer Education Program.”

McGee, C., Hibbard, P., Rowan, D., Janota, A. “Long-Term Effects of the New Mexico Peer Education Project.”

TEACHING EXPERIENCE

2019 — 2020 Associate Instructor at the O’Neill School of Public and Environmental Affairs, Indiana University-Bloomington
- Instructor of Record, V236 “Managing and Leading Organizations”
2018 Guest Lecturer, Negotiation and Dispute Resolution for Public Affairs (graduate and masters)
- Three lectures on negotiation and alternative dispute resolution

PROFESSIONAL PRESENTATIONS
2019 Hibbard, P. “Substance Use Disorder Policy Space Analysis.” University Network for Collaborative Governance, Indiana University- Bloomington


PROFESSIONAL EXPERIENCE
2015—2017 Sales Director, National Event Publications, Clearwater, FL
- Directed advertising sales in professional sports publications.

2014 — Present Senior Consultant, Social Enterprise Ventures, LLC, Albuquerque, NM (remotely)
- Develop, market, and facilitate social enterprise training and consulting for nonprofits.

2013 — Present Owner/Operator, Patrick Hibbard Consulting, LLC, Logan, UT
- Business and organizational strategy for small to medium enterprises and nonprofits.
2013 — 2014  **Owner/Operator, $1.00 Clearance, Albuquerque, NM**
- Arranged purchase contracts for thrift store rags; transported, stored, sorted, hung, and arranged all clothes; set-up, ran, and broke-down flea market venue; tracked and analyzed all business operations; managed financial and operational obligations; earned 55% net profit margin throughout summer 2014.

**SERVICE**

<table>
<thead>
<tr>
<th>Year</th>
<th>Position</th>
<th>Details</th>
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</thead>
<tbody>
<tr>
<td>2021</td>
<td><em>Journal Referee</em>, Journal of Substance Abuse Treatment</td>
<td></td>
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<tr>
<td>2021</td>
<td><em>Journal Referee</em>, Journal of Health and Justice</td>
<td></td>
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<tr>
<td>2021</td>
<td><em>Journal Referee</em>, Journal of Public Administration Research and Theory</td>
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<tr>
<td>2019</td>
<td><em>Volunteer Nonprofit Consulting</em>, Indiana Recovery Alliance</td>
<td>Facilitated two-day strategy retreat after change of leadership</td>
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<tr>
<td>2018</td>
<td><em>Journal Referee</em>, International Journal of Public Sector Management</td>
<td>Peer reviewer of articles submitted for publication</td>
</tr>
<tr>
<td>2018</td>
<td><em>Volunteer Consultant</em>, 12/24 Club, Inc., Bloomington, IN</td>
<td>Consulted nonprofit board as volunteer</td>
</tr>
<tr>
<td>2017 – Present</td>
<td><em>Convening Committee Member</em>, Formerly Incarcerated College Graduates Network</td>
<td>Helping arrange regional and national conventions</td>
</tr>
<tr>
<td>2015</td>
<td><em>Volunteer Business Incubator Resource</em>, Santa Fe College Center for Innovation and Economic Development, Gainesville, FL</td>
<td>Provided consulting services to CIED incubating companies in business strategy, social entrepreneurship, social enterprise, and other issues.</td>
</tr>
<tr>
<td>2014</td>
<td><em>Community Consultant</em>, Social Entrepreneur Corps (Guatemala)</td>
<td>Consulted with community entrepreneurs who sell products with high social impact (e.g. water filters, reading glasses).</td>
</tr>
<tr>
<td>2014</td>
<td><em>Treasurer</em>, International Business Students Global, Albuquerque, NM</td>
<td>Tracked all revenues and expenses; created and submitted budget and appropriations proposals; recruitment and development of IBSG executive leadership; growth strategy.</td>
</tr>
<tr>
<td>Year</td>
<td>Position and Company</td>
<td>Description</td>
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<tr>
<td>2010 – 2011</td>
<td>Board Member At-Large, Desert Club, Inc., Albuquerque, NM</td>
<td>Board duties including organizational oversight, finance and expenditure monitoring, future board recruitment, and bylaws/policy review.</td>
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</table>

**TRAINING AND CONSULTING**

<table>
<thead>
<tr>
<th>Year</th>
<th>Company</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>2014-2016</td>
<td>Greenleaf Joint Ventures, Orlando, FL</td>
<td>Market research and analyses of proposed venture investments; feedback loop development, tracking, and analyses (Lean Startup methodology); business model proposals; organization structures; and business plan creation.</td>
</tr>
<tr>
<td>2015</td>
<td>Hippodrome State Theater, Gainesville, FL</td>
<td>Analysis of board structures and recommendations for board recruitment and motivation, creating Board Policy Manual and Operations Manuals.</td>
</tr>
<tr>
<td>2014-2015</td>
<td>Meals on Wheels Plus, Inc., Abilene, TX</td>
<td>“Expedition” Social Enterprise Training for Nonprofits (through Social Enterprise Ventures). Fully developed Social Enterprise training for nonprofits including asset inventory, excess capacity analysis, market research (primary and secondary), customer segmentation, trend detection and analysis, competitive landscape analysis, leadership development, organizational structures, feasibility study, pricing and promotions strategy, finance and accounting for social enterprise, business plan development, and implementation.</td>
</tr>
<tr>
<td>2015</td>
<td>Central Florida Community Action Agency, Gainesville, FL</td>
<td>Facilitated board training introducing them to Social Enterprise training.</td>
</tr>
<tr>
<td>Year</td>
<td>Event</td>
<td>Location</td>
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<tr>
<td>2014</td>
<td><strong>International Business Students Global</strong>, Albuquerque, NM</td>
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<tr>
<td>2014</td>
<td><strong>Various New Mexico Nonprofits</strong>, Albuquerque, NM</td>
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**PRACTITIONER PRESENTATIONS**

<table>
<thead>
<tr>
<th>Year</th>
<th>Title</th>
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<tbody>
<tr>
<td>2015</td>
<td>“Nonprofit or Tax-Exempt Business?” Santa Fe Center for Innovation and Economic Development, Gainesville, FL.</td>
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</tbody>
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