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FROM TREATMENT TO SAFETY:
THE ROLE OF SUBSTANCE USE TREATMENT IN PREVENTING INTIMATE PARTNER VIOLENCE

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From Treatment to Safety: The Role of Substance Use Treatment in Preventing Intimate Partner Violence
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ABSTRACT

Substance use is a well-established driver of intimate partner violence (IPV), with drug-related incidents posing persistent challenges for both public health and criminal justice systems. We examine how expanding access to substance use treatment (SUT) services affects IPV in the United States by leveraging variation in the opening and closing of treatment facilities at the county level. Using administrative data on IPV incidents from the National Incident-Based Reporting System at the agency level from 1998 to 2019 combined with county-level records on treatment facility information, we implement a continuous difference-in-differences research design. Our results show that adding three SUT facilities—the average annual increase per county over the sample period—reduces drug-involved IPV by about 1.5–1.7 percent. We find no evidence of significant effects on alcohol-related or non-substance-related IPV. Staggered event-study analyses confirm parallel outcome trends, across treated and non-treated counties, prior to net facility openings and lend support to a causal interpretation of the estimates. Related evidence from SUT admissions drawn from the Treatment Episode Data Set (TEDS) shows that new centers significantly raise treatment entry, particularly among men, consistent with reduced perpetration driving the observed decline in IPV exposure. Our findings highlight the role of health services infrastructure in shaping violence-related outcomes and underscore the broader public safety benefits of investment in treatment access.

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1 Introduction

Intimate partner violence (IPV) is among the most widespread forms of violence in the United States, encompassing physical and sexual violence, stalking, and psychological aggression perpetrated within romantic or cohabiting relationships (CDC, 2024). Although IPV is prevalent across all socioeconomic strata, women are disproportionately affected (World Health Organization, 2013). According to the National Intimate Partner and Sexual Violence Survey (NISVS), nearly one in two women and more than 40% of men report experiencing IPV during their lifetime, with comparable rates of physical violence across genders but much higher rates of sexual violence and stalking among women (Leemis et al., 2022). The consequences of IPV extend far beyond immediate harm, inflicting substantial physical, mental, and economic burdens on survivors and their families. The lifetime health and economic costs of IPV in the US are estimated at over 4.1 trillion (2021 dollars), including approximately $1.5 trillion in productivity losses and diminished lifetime earnings (Peterson et al., 2018). These staggering figures underscore IPV as both a major public health and socioeconomic challenge.

A substantial body of research identifies substance use—particularly alcohol and illicit drug use—as a major risk factor for IPV perpetration (Cafferky et al., 2018; Leonard and Quigley, 2017). Among men in treatment for substance use disorders, rates of IPV perpetration are far higher than in the general population, with studies estimates ranging from 15 to 40% depending on substance and type of IPV (Easton, 2006; O'Farrell et al., 2003; Stone and Rothman, 2019). Based on data from the National Incident-Based Reporting System (NIBRS) covering 1998–2019, 18.2% of intimate partner violence incidents reported to law enforcement involved a perpetrator who was suspected of using alcohol or other substances. Moreover, while victims of IPV are also more likely to engage in drug use (Ogden et al., 2022; Testa et al., 2003), current substance use has been found to substantially increase the risk of subsequent IPV perpetration and other violent behaviors (Moore et al., 2008; Cunningham et al., 2009; Pallatino et al., 2021; Stith et al., 2004). Substance use can escalate both the prevalence and severity of IPV through multiple channels, including impaired self-control, heightened aggression, and increased household conflict over financial and resource allocation (Giancola and Corman, 2007; Schilbach, 2019; Angelucci and Heath, 2020).

The scale of this public health challenge is substantial. In 2023, approximately 48.5 million Americans aged 12 or older (17.1 percent of the U.S. population) met the criteria for a substance use disorder (Substance Abuse and Mental Health Services Administration, 2024). However, despite this widespread need, substance use disorders remain severely undertreated, with only 14.6 percent (7.1 million people) receiving any substance use treatment in 2023, while 85.4 percent (41.4 million people) did not receive care (Substance Abuse and Mental Health Services Administration, 2024). Given the strong link between substance use and IPV (18.17% of IPV incidents according to our NIBRS sample), an important question is whether expanding access to effective treatment for substance use disorders can mitigate substance-related harm and interpersonal violence. By providing accessible treatment options, substance use treatment (SUT) facilities may help reduce the economic strain that substance use disorders impose on households, alleviating disputes over household finances and spending priorities that may otherwise escalate into aggression (Leonard and Eiden, 2007; Fox et al., 2002). Effective treatment can also counteract the physiological effects of drug use that increase irritability, diminish empathy, and impair emotional regulation, while alleviating withdrawal symptoms such as anxiety, restlessness, and agitation that elevate the risk of violent behavior (Crane et al., 2014; Cafferky et al., 2018). The SUT programs also provide counseling and behavioral therapies that foster impulse control, anger management, and communication skills, which can help de-escalate arguments before they become violent (Reilly and Shopshire, 2019). Moreover, SUT can reduce the prevalence of high discount rates among individuals with substance use disorders, making them less likely to prioritize short-term impulses over long-term relationship stability (Chabris et al., 2008). By addressing these behavioral, physiological, and economic risk factors, SUT facilities have the potential to reduce IPV not only for those directly in treatment but also through spillover effects on partners, families, and the broader community.

While SUT facilities have the potential to reduce IPV by addressing substance abuse, there are also plausible pathways through which their presence could inadvertently raise IPV risk in surrounding communities. One concern–often echoed in "not-in-my-backyard" debates–is that these facilities may attract individuals with elevated rates of IPV perpetration, particularly those with active or partially treated substance use disorders. This could lead not only to a redistribution of IPV incidents across locations but also to a concentration of higher-risk individuals within certain neighborhoods. If drug-dependent men relocate to an area in large numbers to access treatment, their new partners may face a greater risk of IPV than they otherwise would. In addition, SUT programs can influence IPV risk by reshaping the social environments of those in treatment. New peer networks and exposure to high-stress situations associated with recovery could, in some cases, exacerbate tensions in intimate relationships. Finally, treatment engagement may temporarily disrupt employment or daily routines, which for some individuals could increase financial strain or relationship conflict, indirectly contributing to IPV risk. Taken together, these mechanisms point to *a priori* ambiguous effects of treatment access on IPV.

In this study, we provide some of the first empirical evidence on how greater access to substance use treatment, measured by the supply of SUT facilities, influences domestic abuse. Our analyses combine administrative incident-level data from the National Incident-Based Reporting System (NIBRS) measured at the law-enforcement agency level in conjunction with detailed records on SUT facility operations within each county. We exploit plausibly exogenous variation from the staggered timing of facility openings and closures across counties, within a difference-in-differences framework, to estimate the causal impact of treatment access on IPV incidents. The panel structure of the data allows us to incorporate a rich set of fixed effects (agency and state-by-year) and time-varying county-level controls, including demographic composition, economic conditions, and law enforcement presence. We also conduct event-study analyses to assess the validity of the research design, including tests showing that IPV outcomes respond after–but not before–to changes in the number of local SUT facilities. Complementing the lead-lag analyses in a two-way fixed effects (TWFE) design, we also estimate dynamic event-study plots using the Chaisemartin–D'Haultfœuille framework to account for potential heterogeneous treatment effects (de Chaisemartin et al., 2024b).

Our findings reveal consistent evidence that expanding access to SUT through additional treatment facilities reduces violence from intimate partners who are suspected of being under the influence of drugs at the time of the incident. The magnitudes of our estimates indicate that adding three additional SUT centers in a county, which is the annual increase observed for the average county over the sample period, reduces the rate of drug-involved IPV by approximately 1.5 percent. Estimates are robust to the inclusion of state-by-year fixed effects and a wide range of time-varying socioeconomic and policy controls. In contrast, we find no statistically significant effects on alcohol-related or non-substance-related IPV incidents. We also examine whether the composition of IPV cases changed after treatment expansions and find no evidence that the severity of reported cases, as proxied by injuries or arrests, shifted in response to SUT availability. This pattern suggests that the observed declines are not driven by changes in reporting behavior or case composition. A causal interpretation of our findings is supported by the event study analyses, and their robustness across alternate specifications and samples.

Linking these findings to data on SUT admissions, derived from the Treatment Episode Data Set (TEDS), we show that additional facilities significantly increase entry into treatment programs, particularly among men. This provides direct evidence for the proximate mechanism that treatment expansions reduce IPV exposure by addressing substance use disorders among potential offenders and thereby reducing the perpetration of IPV. Combining these results with the reduced-form estimates, we infer that for every five to six additional men entering treatment as a result of increased SUT access, one IPV incident with a suspected drug-using perpetrator is prevented.

We also document some heterogeneity in the treatment responses, with the effects being stronger for female and white victims, and are more pronounced in counties with lower education and income levels, suggesting that treatment expansions are especially effective in reducing IPV among more vulnerable populations. The benefits are also more pronounced in counties with less developed illicit drug markets, compared to areas where illegal markets are more entrenched. When distinguishing across treatment types, we find that outpatient facilities drive nearly all reductions in IPV, suggesting that continuous and accessible care may be having the greatest impact.

Our study contributes to several strands of literature. First, we widen the lens in assessing heretofore under-studied consequences of expanding SUT availability. Prior work has shown that SUT facility openings improve health and crime outcomes at the local level: Swensen (2015) finds that treatment availability reduces drug-induced mortality, and Bondurant et al. (2018) documents declines in overall violent and property crimes following increases in SUT facilities. Similarly, recent studies show that Medicaid expansions increased substance use disorder treatments (Maclean and Saloner, 2019), and reduced criminal activity by lowering substance misuse (Wen et al., 2017; Vogler, 2020). Yet little is known about how SUT infrastructure affects IPV—a distinct and socially costly form of violence. Our study fills this gap by providing the first causal evidence on how investments in reducing substance misuse can have spillover effects on IPV risk.

Second, we build on the broader literature linking substance use policies to violence and crime. Studies show that alcohol access policies, such as beer taxes and minimum legal drinking age restrictions, reduce violence and crime (Markowitz and Grossman, 2000; Carpenter, 2005), and that medical marijuana laws affect risky behaviors including traffic fatalities (Anderson et al., 2013). Similarly, a growing body of work studies the effects of opioid policies on crime and violence, highlighting both intended benefits and unintended substitution effects (Dave et al., 2021; Alpert et al., 2018; Evans et al., 2018; Powell et al., 2020). Building on this literature, our own recent work has examined the direct causal association between opioid policies and IPV outcomes. In (Dave et al., 2025b), we find that the 2010 abuse-deterrent reformulation of OxyContin–a major supply-side shock to prescription opioid misuse–led to declines in IPV in areas with high pre-reformulation prescription opioid use, but increased heroin-involved IPV in places with large illicit opioid markets. Similarly, (Dave et al., 2024) show that mandatory-access Prescription Drug Monitoring Programs reduced women's IPV exposure in early adopting states, while also having some unintended effects on increasing IPV in cases where perpetrators are suspected of using heroin. These findings highlight both the potential for reducing substance misuse to lower IPV and the risk of substitution toward other harmful substances if treatment access is inadequate. By focusing on treatment infrastructure rather than supply restrictions, this study examines whether expanding access to care can achieve sustained reductions in IPV without triggering such adverse spillovers.

Our study also relates to the extended literature on how public policy interventions and economic shocks affect the prevalence of domestic abuse. This body of work spans the impacts of unilateral divorce reforms (Stevenson and Wolfers, 2006), mandatory arrest laws (Chin and Cunningham, 2019; Iyengar, 2009), conditional cash transfers (Bobonis et al., 2013), educational reforms (Erten and Keskin, 2018), and women's political representation (Anukriti et al., 2025; Stern and Erten, 2024) on IPV risk. Recent studies further highlight the effects of economic and other health shocks, including trade and labor market disruptions (Erten and Keskin, 2021, 2024), the COVID-19 pandemic (Erten et al., 2022; Bullinger et al., 2021), as well as contextual triggers including major sporting events (Card and Dahl, 2011) and college party culture (Lindo et al., 2018).

The remainder of the paper is structured as follows. Section 2 provides background on substance use treatment facilities in the US. Section 3 describes the data sources, including incident-level law enforcement records and facility operations data, and explains the construction of our key measures. Section 4 presents our empirical strategy. Section 5 reports our results, and Section 6 concludes.

2 Institutional Background

Substance use treatment in the United States is delivered through a large but decentralized system of providers that differ in ownership, financing, and services. According to the 2023 National Substance Use and Mental Health Services Survey (N-SUMHSS), there are approximately 14,600 stand-alone substance use treatment facilities and nearly 3,800 centers that provide both substance use and mental health services nationwide (SAMHSA, 2024). Private nonprofit organizations operate about half of these facilities, while private for-profit providers have expanded rapidly in recent years to account for roughly one-third. Public facilities, typically administered by county or state agencies, remain particularly important in rural or medically underserved regions where the reach of the private sector is particularly limited (SAMHSA, 2024; Bondurant et al., 2018). This mix of nonprofit, public, and for-profit providers shapes not only treatment availability but also the financial stability of the sector.

Outpatient programs dominate the treatment landscape, representing over 80 percent of all facilities (SAMHSA, 2024). These programs deliver counseling, detoxification, and medication-assisted treatment (MAT) such as methadone or buprenorphine maintenance, and frequently offer specialized tracks for adolescents, or criminal-justice-involved individuals. Residential facilities, including inpatient detoxification units and longer-term therapeutic communities, serve patients with more severe or chronic substance use disorders or without stable housing. Although treatment philosophies vary widely, from medication-assisted to abstinence-based approaches, the shared goal across all models is to reduce the harms of substance use, promote recovery, and minimize relapse risk (Swensen, 2015).

The financial foundations of the treatment system have changed substantially over the past two decades. Historically, SUT providers relied heavily on federal block grants, such as the Substance Abuse Prevention and Treatment (SAPT) Block Grant, and on state and local subsidies. Subsequent legislative reforms, particularly the Mental Health Parity and Addiction Equity Act and the Affordable Care Act (ACA), integrated substance use services into the broader health-insurance system, expanded Medicaid coverage, and increased parity between behavioral and physical health benefits (Buck, 2011; Beronio et al., 2014). As a result, Medicaid has become the single largest payer for substance use disorder (SUD) treatment, with coverage expansions directly influencing provider entry, capacity, and financial stability (Maclean and Saloner, 2019).[1]

Despite these policy advances, access to treatment remains limited relative to need. National surveys show that more than 80 percent of individuals with a substance use disorder receive no formal treatment in a given year (Bondurant et al., 2018).[2] On the margin, many of these patients are deterred from entering treatment programs due to supply-side constraints.[3] Geographic disparities persist: rural counties often face sparse coverage, long travel distances, and shortages of MAT prescribers, whereas urban centers, though more densely served, encounter long waiting lists and excess demand. Even where facilities exist, additional barriers such as cost-sharing, insurance acceptance, transportation, childcare, and stigma continue to limit utilization (Appel et al., 2004; Friedmann et al., 2003; Office of National Drug Control Policy, 2014).

The economic structure of the industry significantly influences the fragility of treatment access. Most facilities operate on thin margins, and fluctuations in public funding or insurance reimbursement can trigger closures or consolidation. The average annual cost of operating a treatment facility is estimated to approximately cost $1-1.2 million (Bondurant et al., 2018; NCDAS, 2024). Federal initiatives, such as Medicaid expansions and opioid-response grants, can influence both entry and survival (Swensen, 2015). In recent years, corporate acquisitions have accelerated, as large behavioral-health companies purchase regional systems and rebrand facilities (Park, 2024). While consolidation may improve administrative efficiency, it can also erode local accessibility and reduce responsiveness to community needs.

Beyond these broader policy and market forces, facility openings and closings often occur for idiosyncratic reasons—such as management turnover, licensing delays, or shifts in state contracting—creating short-run changes in treatment capacity that are only loosely connected to underlying substance use trends. These fluctuations generate meaningful geographic and temporal variation in treatment access, which we exploit to examine how changes in treatment availability influence IPV risk.

[1] Park (2024) further documents that the survival of SUT facilities is closely tied to reimbursement rates and the predictability of Medicaid payments, with for-profit providers being especially responsive to changes in revenue incentives.

[2] Recent data from the 2024 National Survey of Drug Use and Health show that 86.2 percent of young adults (ages 18-25) and 76.3 percent of older adults (ages 26+) who were in need of SUT over the past year did not receive any treatment or support group services.

[3] Among individuals who needed but did not receive treatment, 15 percent cited the lack of openings in treatment programs, and 29 percent cited not being able to find programs that they wanted as reasons underlying the unmet need (2023 NSDUH).

3 Data

3.1 National Incident-Based Reporting System (NIBRS)

We use data from the National Incident Based Reporting System (NIBRS) covering the years 1998 to 2019 to measure the prevalence of IPV and whether the police suspected the perpetrator to be under the influence of any substances during the incident. NIBRS is an administrative dataset based on detailed crime reports submitted by law enforcement agencies across the US. Each record contains information about the victim, including age, sex, race, ethnicity, and relationship to the offender, as well as information about the offender such as demographic characteristics and whether substance use was suspected. The data also include details about the incident itself, including the date, presence of injuries, and whether an arrest occurred. Because the information is drawn from official administrative reports, it provides consistent documentation of IPV incidents over time and allows us to directly examine the role of drug use and alcohol in reported cases.

We study IPV incidents involving both male and female victims aged 15 and above where the victim and offender had a current or former romantic or sexual relationship, including spouses, common-law partners, dating partners, same-sex partners, and ex-partners. For each reporting law enforcement agency, we aggregate all qualifying incidents across offense categories including aggravated assault, simple assault, intimidation, and sexual offenses, then normalize these counts by the agency's population coverage to calculate annual IPV rates per 10,000 residents at the agency level.

One important limitation of the NIBRS data is that not all law enforcement agencies participated consistently across years. Following Yörük et al. (2025), we apply two main restrictions. First, agencies must have reported for at least six months in each year (or at minimum, have data for December) to ensure partial-year reporters do not skew the results. Second, following Bondurant et al. (2018), we restrict our analysis to agencies that service only one county, which allows us to precisely match treatment facility data to agency jurisdictions. This process yields an unbalanced panel of 6,952 agencies from 1998 to 2019 for our analysis. We, however, note that our results remain consistent across different samples and data restrictions as summarized in the robustness section later.

We construct our primary outcome measures as follows. First, the drug-involved IPV rate captures the number of incidents in which the offender was suspected of being under the influence of drugs at the time of the offense, divided by the reporting agency's population (in 10,000s). Second, the alcohol-involved IPV rate measures incidents where the offender was suspected of using alcohol during the incident, normalized by agency population. Third, the non-substance-involved IPV rate represents incidents in which law enforcement reported no suspected involvement of drugs or alcohol, again expressed per agency population. Lastly, the IPV rate refers to total IPV incidents per 10,000 population at the agency-year level.

Figure 1 presents aggregate trends in IPV rates over the sample period. Panel (A) shows a steady decline in the overall IPV rate beginning in the early 2000s. In contrast, Panel (B) reveals that the drug-involved IPV rate has risen over most of the sample period, aside from a brief decline between 2005 and 2009. Specifically, the average number of drug-involved IPV incidents more than doubled, increasing from 0.5 incidents per 10,000 individuals in 1998 to 1.2 incidents in 2019. This upward trend stands in stark contrast to the declining patterns observed for alcohol-involved and non-substance-involved IPV rates (Appendix Figure A1). Together, these trends suggest a growing role of drug use in IPV incidents, even as overall IPV rates have fallen.

Table 1 presents summary statistics for IPV outcomes. Over the full analysis period, the mean IPV rate was 46.3 reported incidents per 10,000 individuals, comprising 0.91 drug-involved incidents, 9.47 alcohol-involved incidents, and 34.46 non-substance-involved incidents per 10,000 individuals.[4]

3.2 Treatment Facilities Data

Our data on treatment facilities are drawn from the County Business Patterns (CBP), an annual dataset compiled by the U.S. Census Bureau that reports the number and characteristics of business establishments by county and industry.[5] The CBP provides consistent county-level counts of facilities by year, which we use to track the evolution of the treatment sector between 1998 and 2019. To identify establishments providing substance use treatment services, we focus on two key industry classifications: Specialty Outpatient Facilities (SIC 8093) and Residential Care Facilities (SIC 8361).[6] Although residential and outpatient programs are reported as separate categories in the CBP data, in practice many treatment providers operate both under the same organizational structure, with more than 85-90% of admissions taking place in an outpatient setting (SAMHSA, 2024, 2015). Because a large share of facilities deliver multiple levels of care, the distinction between residential and outpatient services is often blurred. To capture the overall availability of treatment resources at the county level, we therefore aggregate both categories and use the total number of establishments as a summary indicator of the local supply of substance use treatment services.

[4]A very small share of IPV incidents involve suspected use of both drugs and alcohol (0.34% of substance-involved incidents); consequently, the sum of drug-involved, alcohol-involved, and non-substance-involved IPV rates does not equal the total IPV rate.

[5]The Substance Abuse and Mental Health Services Administration (SAMHSA) maintains data from the National Survey of Substance Abuse Treatment Services (N-SSATS) covering 1997-2020. While this voluntary survey includes detailed information on client counts and treatment options, it has significant limitations for our analysis: facility identifiers are only available for 1997-2011, and county identifiers are not included in the dataset. Given these data constraints, we rely on CBP data instead.

[6]Consistent with Park (2024), we map these to the North American Industry Classification System (NAICS) codes 621420 (outpatient mental health and substance abuse centers) and 623220 (residential mental health and substance abuse facilities).

Table 1 shows that the average county contains of 14.24 total SUT facilities. Notably, the number of facilities fluctuated substantially over time: on average, counties experienced 3 net openings and 2.6 net closures between 1998 and 2019. A net opening refers to an increase in the number of facilities from one year to the next, and a net closure is defined analogously. Figure 2 illustrates the spatial distribution of the change in SUT facilities across counties, grouped into quantiles, over the sample period. Darker shaded areas indicate counties with larger expansions in SUT facility availability due to openings and lighter shaded areas indicate smaller expansions/larger contractions due to closures, highlighting the substantial spatial variation across the United States.

3.3 Treatment Episode Data Set

We use data from the Treatment Episode Data Set (TEDS), an administrative database compiled by the Substance Abuse and Mental Health Services Administration (SAMHSA) that provides detailed information on admissions to substance use treatment programs, to examine first-order effects on admission flows into treatment facilities. TEDS aggregates data collected through state administrative systems on all facilities receiving public funding for treatment services. Each record in the dataset corresponds to the initiation of a new treatment episode at a non-hospital facility, capturing admissions for approximately two million individuals annually. For each admission, TEDS includes information on the patient's demographic and socioeconomic characteristics, and substances reported as the primary, secondary, and tertiary causes for treatment. While TEDS is not a complete census of all treatment admissions, coverage is comprehensive for publicly-funded facilities, a group that comprises the majority of treatment centers in the U.s. and about two-thirds of the census of all treatment admissions across all known providers Dave and Mukerjee (2011).

We define three sets of admissions outcomes for adults above the age of 18, separately for men and women. The first measures total admissions per 10,000 population at the state-level. The second involves the rate of admissions for which the primary cause for treatment was drug-related substance use disorder (SUD). Finally, we also define a commensurate measure for the alcohol-related admissions rate as the sum of admissions for which alcohol is the primary substance underlying the SUD, normalized by 10,000 population at the state-level.

3.4 State and County Level Data

In our analysis, we account for time-varying demographic and economic factors that may influence IPV outcomes over time and across jurisdictions by combining information from multiple data sources. At the county level, we use population characteristics from the SEER County Population Files, including the share of residents who are female, Black, white, or Hispanic, as well as the share of population across different age groups. We complement these data with socioeconomic indicators from the Bureau of Labor Statistics, including the county unemployment rate and labor force participation rate, as well as firm births from the U.S. Census Bureau's Business Dynamics Statistics (BDS). Firm births are defined as the number of firms with age zero (new entries) in a given year.

At the state level, we incorporate data on a number of state policy changes over time. These include information on whether a state has enacted a medical marijuana law (MML), and whether a state has any prescription drug monitoring program (PDMP) aimed at reducing doctor shopping and excessive prescribing of opioids. We also use data on the number of police officers per capita to capture differences in law enforcement capacity. We use data from Evans et al. (2022) and Dave et al. (2025a) to determine and cross-reference the adoption dates of mandatory-access PDMPs across states. Data on MML adoption is compiled from a web search of state legislation. Data on police employment per capita are drawn from the U.S. Department of Justice Bureau of Justice Statistics.

Table 1 provides summary statistics for county demographics, socioeconomic indicators, and state controls used in our analysis. For heterogeneity analyses, we use data from a fixed baseline period - the earliest year available - on indicators for educational attainment, rural share of population, and median income level at the county level to stratify areas across these characteristics. Specifically, we use data on the share of the population with more than a high school education in 1998 from the American Community Survey; the share of population living in a rural county in 2000 from the Population Census, and median household income at the county in 1998 from the American Community Survey.

For our robustness analyses, we draw on one additional county-level indicator from the U.S. Census Bureau's BDS, that is net job creation. Net job creation is defined as the difference between gross job gains (from establishment openings and expansions) and gross job losses (from establishment closings and contractions). Because net job creation can take negative values when job destruction exceeds job creation, this measure captures both periods of local economic growth and economic distress. Lastly, we draw on state-level data from the Kaiser Family Foundation on Medicaid rates for the year 2008, in order to assess the interaction between supply availability and demand-side insurance coverage.

4 Empirical Strategy

We leverage changes in the number of SUT facilities across counties and over time using a difference-in-differences (DID) framework. Specifically, we aggregate the data to agency-year level and implement a continuous treatment difference-in-differences (DID) research design using the spatial and temporal variation in treatment access proxied by the number of available SUT facilities (Callaway et al., 2024). We estimate the following two-way fixed effects (TWFE) specification:

$$y_{acst} = \beta_0 + \beta_1 facilities_{(cs,\,t-1)} + \beta_2 \mathbf{X_{cst}} + \delta_a + \delta_{st} + \epsilon_{acst} \tag{1}$$

where Y_{acst} is the rate of IPV, defined as the number of reported IPV incidents per 10,000 (respective) population covered by agency a in county c in state s in year t. The treatment variable, $facilities_{(cs,t-1)}$, represents the number of SUT facilities in county c in state s in the previous year $(t-1)$. The lagged number of SUT facilities serves as a proxy for access to substance use treatment services, with increased number of available treatment facilities from $t-1$ to t within a county representing greater access to treatment availability for agencies located in that county in time period t. The coefficient β_1 represents our parameter of interest: the average causal response on the treated (ACRT), which is the continuous-treatment analogue of the average treatment effect (ATE). It captures the average change in IPV outcomes associated with an incremental increase in the local supply of substance use treatment (SUT) facilities.

The vector $\mathbf{X_{cst}}$ includes time-varying county demographic and socioeconomic characteristics and state policies. County characteristics include the shares of the population categorized by race/ethnicity, gender, and age groupings, unemployment rate, and labor force participation rate. The time-varying state controls include the number of law enforcement officers per 100,000 population, and indicators for whether a state has a medical marijuana law, and any prescription drug monitoring program (PDMP) in place.

All models include agency fixed effects, δ_a, to control for unobserved, time-invariant agency characteristics that may influence IPV rates, and year fixed effects, δ_t, to account for nationwide shocks or trends in IPV outcomes that affect all counties uniformly over time. We replace year fixed effects with state-by-year fixed effects δ_{st} in more saturated specifications.[7] The state-by-year fixed effects capture all common shocks at the state level, including changes in law enforcement and reporting practices, health policy changes such as expansions in health insurance, other statewide policy shifts, and economic and labor market conditions, in addition to aggregate shocks affecting all agencies in a given year, including aggregate trends in IPV reported to the police, or national economic conditions. We cluster standard errors at the county level - the level of the treatment - to account for serial correlation in errors within counties (Bertrand et al., 2004), and weight all regressions with initial agency population.

[7]The time-varying state controls drop out in this specification.

Our empirical strategy builds on Swensen (2015) and Bondurant et al. (2018), who conduct multiple validity tests to support the identifying assumptions in the DID design. Estimates of β_1 in Equation (1) will be biased in the presence of reverse causality and unobserved factors differentially affecting the counterfactual counties from the treated counties. Specifically, changes in IPV in a local area could drive the opening or closing of SUT facilities in that area. For example, counties with rising IPV might invest more in treatment centers, especially if a rising share of IPV incidents are perpetrated by offenders who are suspected of using certain substances. To address these concerns, we test whether IPV outcomes change before facility openings/closings, and validate that effects appear only after treatment access changes. We implement a TWFE specification similar to Eq. (1) that incorporates leads and lags of the facility numbers by taking into account the current, prior, and subsequent number of SUT facilities in a given county.

Recent advances in the DID literature highlight that TWFE estimates in Equation (1) may be biased when treatment effects vary over time or across treated cohorts (Goodman-Bacon, 2021; Sun and Abraham, 2021). To address this concern, we also employ the dynamic estimator proposed by de Chaisemartin et al. (2024b) (dCDH), which allows us to assess dynamics while also providing evidence on pre-treatment parallel outcome trends across treated and non-treated counties. This approach is not only robust to biases from heterogeneous and dynamic treatment effects, but it also adjusts for compositional changes in the identifying counties over time, ensuring that the same counties contribute variation in identifying each post-treatment effect. A limitation, however, is that the treatment needs to be binned (rather than allowed to be fully continuous) in order to form appropriate counterfactuals whose treatment intensity remains unchanged over the sample period. For our binned treatments, we group them in increments of ten SUT facilities; the treatment intensity is therefore equivalent to a movement from one bin to the next or approximately ten additional SUT facilities.

5 Results

Our key findings are reported in Tables 2 through 9 and Figures 3 and 4. Supplemental analyses and robustness checks are presented in Table 10 and in the appendix. All regression models are weighted by the baseline agency population, and reported standard errors are clustered at the county (treatment) level to account for arbitrarily correlated errors across agencies and over time within each county (Bertrand et al., 2004).

We begin with our main estimates, reported in Table 2, of the effects of increased access to SUT facilities on the incidence of IPV. Panel A considers drug-involved IPV incidents, Panel B reports results for alcohol-involved IPV, and Panel C presents corollary findings for non-substance-involved IPV. We assess the sensitivity of these estimates across four specifications that capture increasing saturation with time-varying controls. In interpreting our results, we standardize the effect sizes to correspond to a treatment dose of three additional SUT facilities, which is the annual net facility openings observed for the average county (Table 1), and translates into a treatment dose of approximately 21 percent relative to the mean number of facilities for the average county. In the most parsimonious model (column 1), which controls only for the agency and year fixed effects, we find that three additional SUT facilities in the county on the net significantly reduces the rate of drug-involved IPV by 0.011 incidents (per 10,000 persons) or about 1.5 percent. This effect remains largely unchanged with the addition of state policy controls (column 2), county-level socio-economic factors (column 3), or state-by-year fixed effects (column 4), with the latter non-parametrically accounting for any observed and unobserved time-varying state-specific shocks. In this most saturated model as with the sparsest one, the coefficient estimate continues to indicate a similar reduction in drug-involved IPV incidents by approximately 2 percent (0.015 incidents per 10,000 persons).[8]

Turning to IPV incidents that involve alcohol (reported in Panel B), while the coefficients are consistently negative, they are imprecisely estimated and not statistically distinguishable from zero. The magnitude of the point estimate in the extended specification prima facie indicates that three additional SUT centers, on the net, are associated with a reduction in alcohol-involved IPV by about 0.038 incidents (per 10,000 persons), which represents only about a 0.50 percent decline relative to the mean. In contrast, Panel C shows that SUT facility expansion has no meaningful effect on IPV incidents where no substance has been flagged by law enforcement. The point estimates are small in magnitude and statistically insignificant across all specifications, with coefficients fluctuating around zero (ranging from -0.0073 to 0.0091 in the most restrictive and saturated models, respectively). Distinguishing between drug-related IPV and other IPV incidents turns out to be important as these differential patterns are masked when we analyze all IPV incidents (Appendix Table A1).

Taken together, the findings in Table **??** suggest that the most prominent beneficial effects of expanded access to SUT centers materialize for IPV incidents by perpetrators suspected of consuming illicit drugs. For other IPV incidents, notably those involving alcohol, while there is some weak indication that additional treatment centers may also deter such incidents, the relative declines and the implied elasticity estimates (-0.01 $\sim$ -0.02) are orders of magnitude smaller, and not statistically significant. In light of this finding that the most precise and salient effects are concentrated for drug-involved IPV, we focus our discussion on this outcome for the rest of our analyses; in supplementary analyses, though, we also present relevant findings for other IPV components for comparison as warranted.

[8] The estimated elasticity of drug-involved IPV with respect to SUT centers ranges from -0.05 to -0.09 across these models.

In Appendix Table A3, we examine whether the share of drug-involved IPV incidents that result in an injury or arrest change in response to improved access to SUT facilities. The results presented in columns 1 and 2 show null effects on these outcomes; point estimates are close to zero and not statistically significant. These findings suggest that expanding access to SUT centers did not alter the composition of IPV cases in terms of severity. If access to better treatment options had an impact on reporting patterns either through encouraging victims to report only the most serious incidents or by increasing reports of less severe cases, we would expect to detect changes in the proportion of incidents involving injuries or arrests. We interpret these findings as indicating that the access to SUT centers did not shift the severity of IPV incidents on the margin. Alternately, if there was a shift in the reporting of IPV incidents towards or away from more severe incidents (as proxied by those involving an injury or resulting in the arrest of the offender), then we would have observed significant effects on these shares. That we do not find any effects here also implies that the treatment is not associated with more severe incidents being reported to the police, which is ex post reassuring in terms of ruling out any potential reporting bias driving our estimates.

The above estimates can be construed as plausibly causal under the identifying assumption that outcome trends would have evolved similarly between the "treated" areas that experienced changes in the supply of SUT facilities and those that did not, in the absence of those supply changes. As noted earlier, our estimated parameter of interest reflects the average causal response on the treated (ACRT), the continuous equivalent of the average treatment effect (ATE) and that captures the impact of incremental changes in the supply of SUT facilities in the local area. In the context of this continuous treatment, identification requires a more generalized "parallel trends" assumption, that is absent SUT supply shifts, counties with different "doses" of the treatment (in our case, different net changes in the supply of SUT facilities) would have followed similar trends in IPV. While not directly testable, we provide indirect evidence by evaluating outcome trends prior to the supply-side shift via two approaches.

First, following Swensen (2015) and Bondurant et al. (2018), we expand on the main specification (equation 1) to include the measure of SUT facilities contemporaneously along with its one-year lag and lead. We would expect the coefficient of the lead to be null in the absence of differential pre-treatment trends. Results reported in Table 3 show that: a) the coefficient on the lead is indeed small (and if anything, positive), and statistically indistinguishable from zero; b) the inclusion of the contemporaneous and lead effects does not materially affect the main coefficient of SUT facilities at $t-1$; and c) declines in IPV appear to materialize after net increases in SUT facilities, as evidenced by the negative and significant lagged effects. We qualify this discussion by noting that continuous measures of the supply of SUT centers are expectedly highly correlated within areas over time, leading standard errors on the main treatment effect to inflate as more terms are added to the specification and thus precluding us from further extending the dynamics in this manner. We therefore view these results as only weakly corroborating, and turn to an event study approach to further evaluate pre-treatment trends and dynamics.

Figure 3 visually presents estimates from the event study analysis for drug-involved IPV incidents, based on the approach proposed by de Chaisemartin and D'Haultfoeuille (De Chaisemartin et al. (2024a)), which has the advantage of being robust to potential biases from heterogeneous and dynamic treatment effects as discussed in Section 4. The dCDH event study analyses underscore three points. First, estimates in the pre-treatment period do not indicate any discernible deviation in trends between the treated and control counties, and support the parallel trends assumptions; all lead effects are close to zero, and individually as well as jointly insignificant. Second, declines in drug-related IPV materialize only after the increase in the supply of SUT facilities. Third, assuming linear effects and normalizing to a treatment dose of 3 additional SUT centers (approximately a 21 percent increase, and as discussed in relation to the results reported in Table 2), the effect sizes in the dCDH analyses are larger than those derived from the standard TWFE DID estimator. This is consistent with standard DID estimates potentially being understated in the presence of dynamic heterogeneity, and we therefore interpret the standard estimates as conservative. Specifically, dCDH point estimates (reported in Appendix Table A4) suggest that an additional three SUT facilities deters drug-involved IPV by as much as 0.05 incidents (per 10,000 persons); this translates to a seven percent decline relative to the mean, and an elasticity of -0.33. Corollary event study analyses for alcohol-involved IPV (shown in Figure 4, with point estimates reported in Appendix Table A4) show a highly similar pattern; the effects, however, are imprecisely estimated and do not achieve statistical significance at conventional levels.

Access to treatment is likely to matter most in areas that are completely under-served. Table **??** presents the extensive-margin effects of treatment facility openings and closures on drug-involved IPV. This analysis focuses on "SUT deserts", counties that initially had zero treatment facilities and later experience a net opening, allowing us to isolate the impact of introducing treatment capacity where none previously existed. In addition to net openings, we also study net closures. Net openings is a binary indicator that switches to 1 when an agency goes from zero to a positive number of SUTs and remains 1 in all subsequent years until a net closure occurs. Net closures is a binary indicator that switches to 1 when an agency goes from a positive number of SUTs to zero and remains 1 in all subsequent years until a net opening occurs. Thus, the treatment group consists of these previously under-served counties that gain at least one SUT facility during the sample period, and alternately counties that previously had some access to SUT but then subsequently lose all access due to net closures. For both analyses, the control group comprises counties that never have any facilities ("never-adopters"). Results indicate that under-served counties that experience a net opening of SUT facilities experience a statistically significant decline in drug-involved IPV. The effect magnitudes point to a reduction of 0.10 IPV incidents (per 10,000), or approximately a 13 percent reduction relative to the sample mean; notably, this effect is considerably larger than our main findings. Conversely, net closures are associated with significant increases in drug-involved IPV, on the order of 0.06 to 0.12 incidents (per 10,000), implying an increase of roughly 8 to 16 percent relative to the sample mean. These results underscore three points. First, with respect to net additions in SUT facilities, there is strong evidence of non-linearity such that effects are stronger at the extensive margin. Second, relatedly, largest benefits with respect to beneficial spillover impacts on drug-involved interpersonal violence accrue when SUT deserts gain facilities and treatment access. And, largest detriments accrue as well when areas that previously had some access to treatment centers lose this access altogether. Third, the effects of gaining access vs. losing access at the extensive margin are largely symmetric; we cannot reject the null of equality in absolute effect magnitudes between net openings and closures.

The most plausible link in the causal chain connecting the presence of SUT centers to IPV operates through expanded access to needed treatment for substance use disorder (SUD) patients and the resulting mitigation of their substance abuse and related harms. We assess this mediating pathway in Appendix Table A5 [9] as a further validation check on the plausibility of our findings and to frame the magnitudes of our reduced-form effects. Specifically, we provide direct evidence on the "first stage" effects on how additional SUT facilities in the local area affect total admission inflows for SUD treatment, based on data from the TEDS. If this link is absent, then this would cast doubt on a causal interpretation of the reduced-form results. To the contrary, we find strong evidence of this proximate pathway, that is net expansion of SUT treatment facilities in a given state significantly raises admission flows for treatment. The effect is much more pronounced and significant for males; for females, effects are very small and not statistically different from zero. One implication of this gender-based heterogeneity is that the decrease in IPV that we document appears to be largely driven, on the margin, by a decrease in perpetration among substance-

[9] We estimate the following specification:

$$Admissions_{st} = \beta_0 + \beta_1 Facilities_{s,\,t-1} + \beta_2 \mathbf{X_{st}} + \delta_s + \delta_t + \gamma_s \cdot t + \epsilon_{st} \tag{2}$$

where $admissions_{st}$ is the rate of treatment admissions, defined as the number of admissions to alcohol or drug treatment facilities per 10,000 population in state s in year t. The treatment variable, $facilities_{s,t-1}$, represents the total number of SUT facilities in state s in the previous year $(t-1)$. The coefficient β_1 represents the effect of an additional SUT facility on treatment admissions. The vector $\mathbf{X_{st}}$ includes time-varying state controls, including the number of law enforcement officers per 1,000 residents, and indicators for whether a state has a medical marijuana law, and whether it has any prescription drug monitoring program (PDMP). All models include state fixed effects, δ_s, to control for unobserved, time-invariant state characteristics that may influence admission rates, and year fixed effects, δ_t, to account for nationwide shocks or trends that affect all states uniformly over time. We also include state-specific linear trends, $\gamma_s \cdot t$, to control for unobserved differential trends in treatment admissions across states. We cluster standard errors at the state level to account for serial correlation in errors within states.

using male offenders induced into treatment rather than a decrease in the risk of victimization among substance-using females.

Combining the first-stage effects (Table A5, Panel A) with the reduced-form main effects (Table 2, Panel A), we can impute the implied structural "treatment on the treated" (TOT) effect of SUD treatment on the incidence of IPV. For drug-involved IPV, these estimates range from 0.14 to 0.24, which imply that for every five to six drug users who are induced into treatment on the margin, as a result of expanded SUT supply and access, one additional drug-involved IPV incident is prevented.[10] TOT effects imputed in this manner should be interpreted with caution since they would be sensitive to small underlying changes in the first-stage or reduced-form effects. This exercise also makes the presumption (albeit one that is defensible) that all of the downstream effects on drug-involved IPV are realized through diversion of drug users into SUD treatment. These qualifications notwithstanding, that this implied marginal response (0.14 to 0.24) is ballpark-similar to the observed average prevalence of IPV perpetration among SUD patients (0.15 to 0.40; Stone and Rothman (2019)) is ex post validating.

Next, we explore whether the effects of SUT supply are heterogeneous across various salient dimensions that vary by victim and county characteristics, treatment modality, illicit drug markets, and public insurance coverage. We start with individual-level victim socio-demographics in Table 5. Here we find that a net expansion in the number of SUT facilities significantly lowers drug-involved IPV incidents for both female and male victims, though the effect is larger (in both absolute and relative terms) for females than for males. With more than 4 out of 5 drug-involved IPV incidents involving female victims, and the significant and more pronounced first-stage response for SUT admissions for male drug users (Table A5), these gender differentials are consistent with treatment expansion lowering the incidence of IPV exposure for female victims through its impact on deterring perpetration among male drug offenders. We also find significant beneficial effects on drug-related IPV among both white and black victims [11]. The decline is stronger among whites, in both absolute and relative terms; an additional three SUT centers reduces the reported incidence of drug-involved IPV among whites by about 1.1 percent (relative to the race-specific population-adjusted mean) compared to 0.5 percent for blacks. These differences suggest notable racial disparities in access to treatment, treatment modality conditional on entering treatment, and treatment completion (Center for Behavioral Health Statistics and Quality, 2021; Saloner and Cook, 2013; Lê Cook

[10]Technically, in forming this TOT imputation, we should be using reduced-form effects specifically on IPV incidents reported by female victims since the first-stage response was concentrated among male SUD patients. We show later (results reported in Table 5) that restricting IPV incidents to female victims results in very similar effect sizes. This is not surprising since the vast majority of reported IPV incidents (>80 percent) involve female victims.

[11]Since population demographics are not available at the agency level, the IPV rates for race-specific samples are constructed using total agency population. As a result, the difference in the IPV rates across racial groups reflects both differences in incidence as well as differences in the underlying population shares. If we apply the national population shares from the 2000 Census to the reported means in Table 5, the approximate drug-related IPV rate per 10,000 black individuals is 0.819, and that among white individuals is somewhat higher at 1.003 per 10,000 white individuals

and Alegría, 2011). Thus, treatment expansion appears to be eliciting a somewhat weaker response on these and related margins for blacks. Among Hispanics, the point estimate is negative, though highly statistically under-powered. Turning to effects over the life-course, our results point to a concave age-based gradient, with the effects on drug-involved IPV becoming progressively larger with victim's age into their 20s and 30s – the age group which experiences the highest rate of IPV – before starting to decline. Reported drug-involved IPV incidents among older individuals (ages 50+) are rare, and we also do not find any discernible effects for these victims. Panel C of Table 5 further shows that the treatment effects are mostly occurring through reductions in simple assaults, and less so through aggravated assaults and intimidation incidents, and we find no evidence of a significant impact on incidents involving sexual violence.

Since the NIBRS lacks information on the victim's socio-economic status (SES), we draw on information from the ACS to investigate if there are differential effects across areas based on educational attainment and/or income levels. The pattern of estimates reported in Table 6 suggests that a net increase in SUT facilities results in stronger declines in drug-related IPV in low SES areas.[12] As both IPV and rates of substance use are higher among low-SES individuals and in economically-vulnerable areas, these findings imply that treatment expansions may be particularly effective in mitigating harms related to SUDs for these populations. We also find stronger effects in more urban areas. Urban counties not only have a higher density of SUT centers at any point in time but also experience more facility openings over our study period, expanding access to treatment more rapidly than rural areas. This greater concentration and growth of facilities likely reduce logistical and financial barriers to care (e.g., travel distance, wait times), thereby facilitating earlier entry and sustained engagement in treatment (Appel et al., 2004; Lister et al., 2020). In addition, urban areas often have a more developed support infrastructure, including counseling services, mental health providers, and peer networks, which can complement treatment and amplify its effects on reducing drug-involved IPV (Friedmann et al., 2003). These results also complement our earlier findings which pointed to strong effects at the extensive margin for SUT deserts newly gaining treatment centers, to paint a complex picture on how treatment supply can interact with other salient factors (under-served areas; support networks; illicit drug markets; costs and coverage) in effectively expanding treatment access to varying degrees for patients with SUDs.

Following Gupta and Mazumder (2023) and Dave et al. (2025b), we proxy for the illicit market share by the ratio of deaths due to illicit or synthetic opioids to deaths from prescription opioids. This ratio proxies for the potential substitution rate from prescription to illicit opioids, which is a function of how

[12] When counties are classified by high school completion rates, significant effects are observed among those below the 25th percentile.

well-developed the illicit drug market is in the area. Results reported in Table 7 confirm that the beneficial spillovers on drug-involved IPV of expanding treatment centers are indeed much weaker in areas where the illicit drug market is more developed. This weaker reduced-form response may reflect a weaker first-stage, that is treatment expansions may be less effective in inducing drug users to seek treatment in these markets, and/or a weaker structural response, that is the marginal drug user who does seek treatment in these areas is less deterred in their perpetration of IPV, perhaps due to treatment non-completion or future relapse. We acknowledge that these hypotheses are speculative and require further inquiry that is not feasible with the data at hand.

In all of our analyses up to this point, our main "treatment" measure has aggregated all SUT facilities since many facilities deliver multiple modalities of care, including detoxification and medication-assisted treatment, intensive and non-intensive outpatient care, and rehabilitation and residential programs. The majority ($\sim$ 80 percent) of SUD treatment admissions takes place at outpatient and detoxification service settings. SUD patients, however, who receive treatment at inpatient service settings are observationally different in ways that indicate more severe dependence; they are more likely to present with mental health and psychiatric disorders in addition to SUDs, they are more likely to be users of multiple substances, and they are also more likely to have had a prior SUD treatment admission. In Table 8, we separately estimate the effects of net increases in residential vs. outpatient SUT centers, noting the caveat that although residential and outpatient programs are reported as separate categories in the CBP data, in practice many treatment providers operate both and the separation is not as distinct as suggested by the data. This qualification notwithstanding, the results suggest that the beneficial spillovers into lower incidence of drug-involved IPV are concentrated almost solely with respect to the supply of outpatient centers. An increase of three additional centers is predicted to reduce these incidents of IPV by about 3.8 percent relative to the mean. Point estimates associated with expansions in residential programs also point to declines in drug-involved IPV, but these estimates are much weaker and not statistically distinguishable from zero.

Barriers to SUD treatment, such as lack of insurance and inability to pay, suggest that the effectiveness of expanding treatment facilities may depend on public coverage, particularly for low-SES populations who may lack other means to pay for treatment. Before the Affordable Care Act (ACA), private insurance covered only a minority of specialty SUD patients (Maclean and Saloner, 2019), and states with lower baseline Medicaid coverage likely faced greater obstacles in translating new facilities into actual treatment. The ACA Medicaid expansion may have amplified the impact of facility openings in these historically low-coverage states. Table 9 examines whether the effects of expanding SUT facilities vary with states' baseline Medicaid coverage (measured using 2008 Medicaid rate) and with states' decisions to expand Medicaid under the ACA. The triple interaction between SUT , below-median baseline Medicaid coverage, and ACA expansion is negative and statistically significant. Specifically, the effect of 3 additional facilities in below-median Medicaid states that adopted the ACA is approximately a decrease of 0.0315 drug-involved IPV incidents (per 10,000 population), or 4 percent of the sample mean outcome. These results suggest that within expansions in public coverage, particularly in states that had low levels of baseline coverage, reinforced the effects of expansions in treatment supply and convert the new treatment capacity into real reductions in drug-related IPV.

Finally, we conduct various sensitivity analyses to check whether the results are robust to alternate specifications and sample restrictions. In Table 10, we report our main results for: 1) alternate samples (Panel A), including expanding the agencies in our sample to any that reported in a given year (column 1), restricting the sample to larger counties (population $\geq$ 10,000) (column 2), winsorizing the top 10% and bottom 10% of counties in terms of number of SUT facilities (columns 3 and 4), and dropping never-treated counties from the sample (column 5), and 2) alternate empirical specifications (Panel B), including estimating the same regression unweighted (column 1); using alternate functional forms including a Poisson regression model and transforming the IPV outcomes to an inverse hyperbolic sine (columns 2 and 3), controlling for net job creation (column 4). Across all of these models, our estimates – both in terms of magnitude and precision – remain largely robust.

6 Conclusion

While most forms of IPV have declined rapidly in recent decades, incidents in which perpetrators were suspected of using illicit drugs have increased markedly over the same period in the US. In this study, we provide evidence of statistically and economically significant effects of expanding the supply of SUT centers on drug-involved IPV. We find robust and consistent evidence that increases in the number of SUT facilities significantly reduce the incidence of drug-involved IPV.

The estimated effects are meaningful. On average, an increase of three SUT net openings per county—which is the average annual change observed during our sample period—reduces the rate of drug-involved IPV by approximately 1.5 to 2 percent. The benefits are even more pronounced at the extensive margin; when counties that previously did not house any SUT facilities ("SUT deserts") newly gain treatment facilities, the spillover declines in drug-involved IPV exposure are larger, on the order of 13 percent, and vice versa for symmetric detrimental effects accruing to counties that lose all availability of treatment and turn into SUT deserts. Heterogeneity analyses reveal stronger effects for female and white victims and in counties with lower income and education levels, underscoring that treatment expansions are especially effective among economically vulnerable and underserved areas. Our results also show weaker effects in counties with more developed illicit drug markets, where substitution toward untreated substances may offset gains.

Event study analyses add a degree of confidence regarding the validity of the counterfactuals, confirming that declines in drug-involved IPV materialize only after increases in SUT availability, and support a causal interpretation of the estimates. To probe mechanisms, we directly link SUT center expansions to treatment admissions data, showing that new facilities significantly increase treatment inflows, particularly among men with SUDs. This suggests that the decline in IPV that we find is driven predominantly by reduced perpetration among male offenders with SUDs who, on the margin, are diverted into treatment (as opposed to a reduced risk of victimization among female patients with SUDs). Combining the estimates across the reduced-form and first-stage analyses implies that for every five to six additional men induced into treatment, one drug-involved IPV incident is prevented.

Spatial disparities in treatment access remain persistent, with particularly large shortfalls in availability in rural areas.[13] On average, the top quintile of counties - largely urban areas - contained about 12.8 SUT facilities (per 100,000 population) compared to the bottom four quintiles, which housed over 80 percent fewer facilities (2.3 SUT centers per 100,000 individuals); the lowest quintile of counties did not contain any SUT facilities. To frame the effect magnitudes implied by our findings, one thought experiment would be to simulate changes in drug-involved IPV incidents if these geographic disparities in SUT supply were narrowed. For the bottom four quintiles to achieve parity with the top quintile in terms of SUT availability, the average county in the lower quintiles would need to add approximately 10 SUT facilities (per 100,000 population). Doing so would prevent approximately 591 drug-involved IPV incidents annually, amounting to national cost savings of $66.2 million.[14] To further inform the cost-effectiveness of expanding SUD treatment supply in relation to the spillover benefits derived from the declines in IPV incidence, we note that the average annual costs of providing treatment for an SUT facility is approximately $1-1.2 million (Bondurant et al., 2018; NCDAS, 2024). For the average locality, adding one SUT

[13]Beyond supply, shortfalls in accessibility also extend to coverage of costs. Among SUD treatment facilities, almost 30 percent do not accept Medicaid and almost 60 percent do not accept Medicare as forms of payment (Cantor et al., 2022). And, combining both supply and payment coverage, over a third of counties in 2021 had no treatment facilities or had facilities that did not accept Medicaid as a form of payment (Cantor et al., 2022).

[14]The estimated lifetime cost per female IPV victim is $112,060 (deflated to 2019$, based on (Peterson et al., 2018)). We note that these estimates are back-of-the-envelope given the inherent uncertainty underlying many of the input parameters. On the one hand, our cost-savings estimates are potentially under-stated due to various considerations. First, these estimates do not include intangible costs to victims and family members (i.e., pain and suffering), which can amount to more than double the tangible costs (Zhang et al., 2012). Second, our imputation of the IPV incidents deterred does not include IPV incidents that are not reported to law enforcement. Our focus on IPV incidents reported to law enforcement likely captures more serious and/or frequent incidents (i.e. 55 percent of all such reported incidents involve physical injury), though many incidents do not get reported; even for serious incidents of IPV, about half go unreported Morgan and Truman (2018). On the other hand, the monetized cost savings may be over-stated since the cost estimates in Peterson et al. (2018) correspond to the lifetime costs per victim, which may involve multiple incidents, as opposed to the cost per incident.

facility would result in approximately 0.05 fewer drug-involved IPV incidents, at a societal cost saving of $5,600, with this indirect spillover benefit offsetting about 0.5 percent of the annual operating cost of the facility. This offset is substantially higher - approximately 10 percent of the annual facility cost, when an under-served county - a previously SUT desert - newly gains SUD treatment availability.

These findings highlight that SUT facilities not only play a critical role in addressing substance use disorders but can generate important spillover benefits by reducing substance-related violence within households. Efficient deployment of public resources to support treatment expansion depends, in part, upon a careful cost-benefit calculus that includes, not just the direct benefits of treatment but also, any societal cost savings accruing from such downstream effects on IPV (and other harms associated with SUDs). By mitigating drug dependence and improving engagement with treatment and support systems, SUT expansion can help reduce one of the key proximate risk factors for IPV.

Taken together, the results underscore the broader social value of investments in addiction treatment infrastructure. Expanding SUT access has the potential to reduce not only the individual and public health costs of substance use but also the far-reaching social harms associated with drug-involved violence. Strengthening this system—particularly in underserved and rural communities—represents a promising avenue for improving both public health and family well-being.

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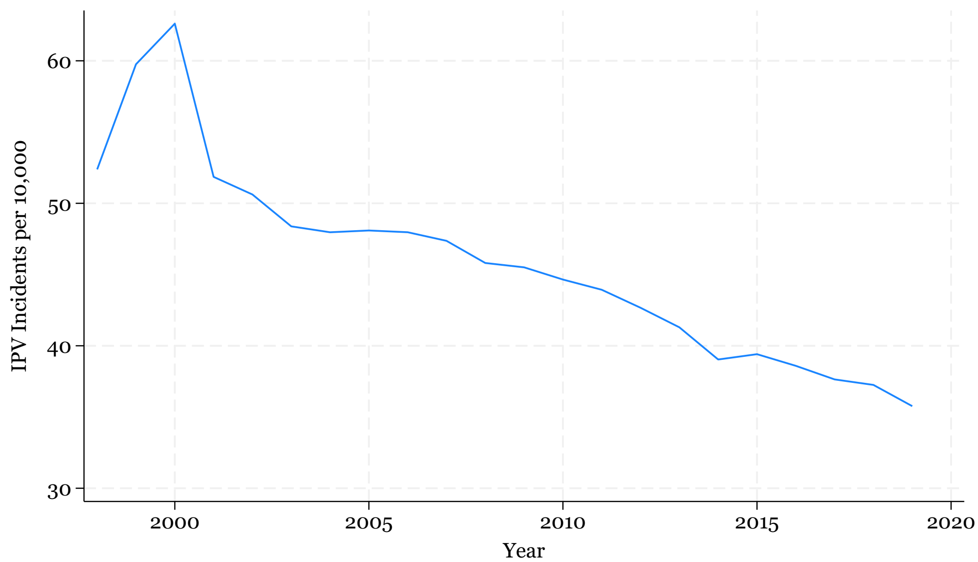
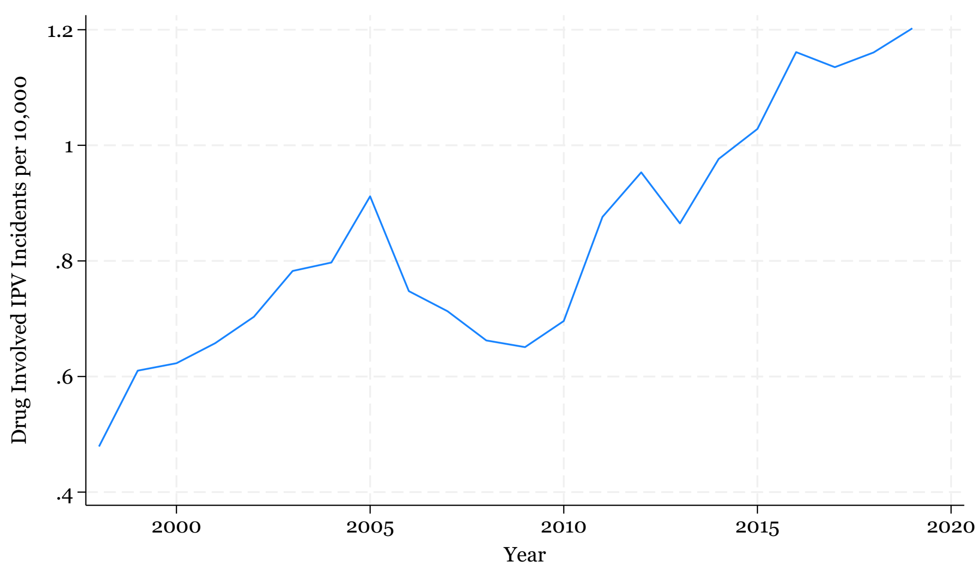
Figures and Tables

FIGURE 1: TRENDS IN INTIMATE PARTNER VIOLENCE RATES, 1998-2019

(a) IPV Rate

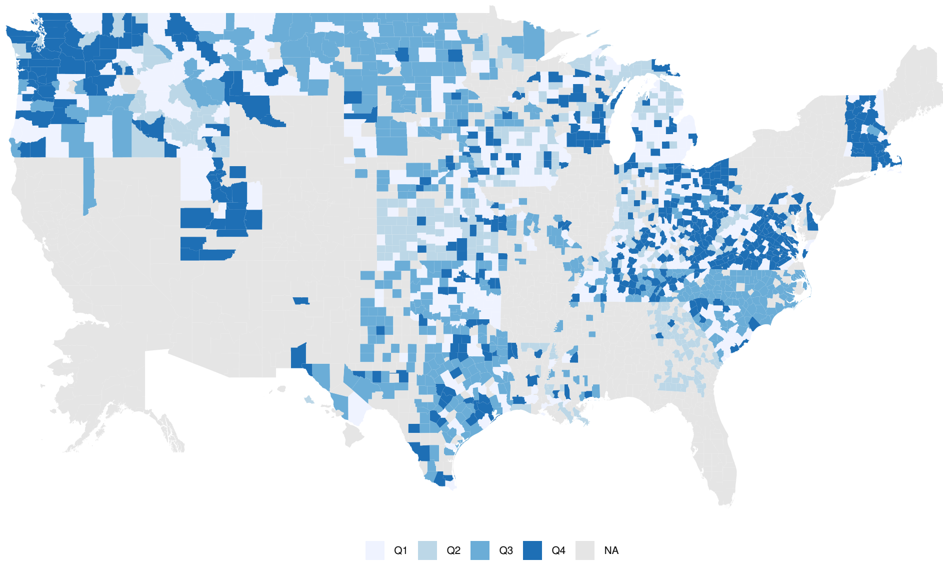


(b) Drug-Involved IPV Rate



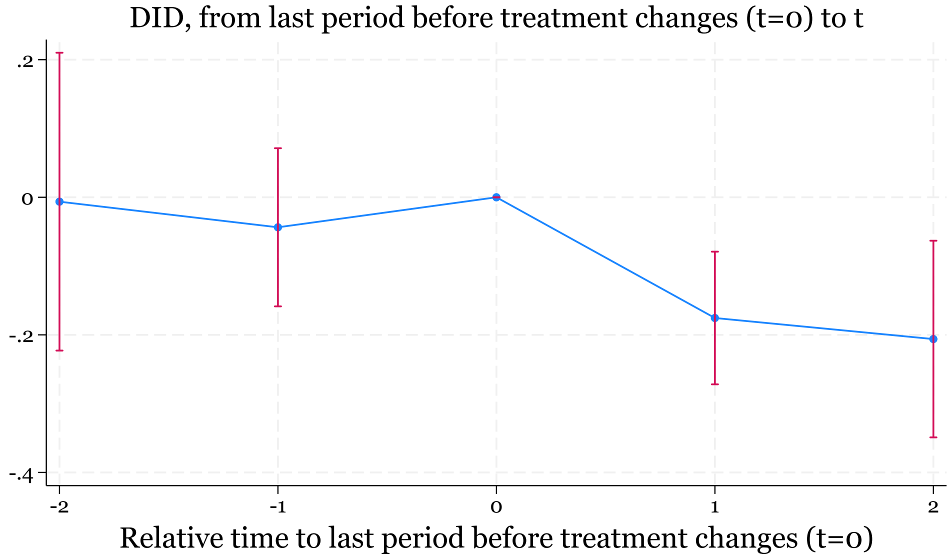
Notes: The figures plot annual average IPV rate per 10,000 at the agency year level. Panel (a) plots total IPV rate, Panel (b) plots drug-involved IPV rate, which includes the sum of incidents where law enforcement suspects the perpetrator was under the influence of drugs, normalized by 10,000 population. The data comes from National Incident-Based Reporting System (NIBRS) covering 1998-2019.

FIGURE 2: VARIATION IN THE CHANGE IN SUBSTANCE USE TREATMENT FACILITIES ACROSS COUNTIES



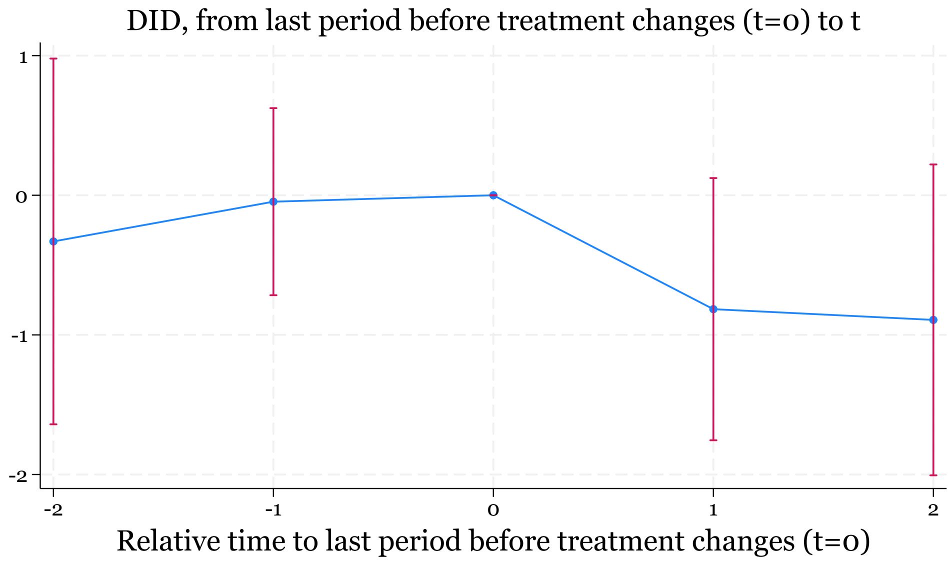
Notes: The map plots the variation in the change in the number of SUT facilities across counties from the earliest to latest year in the sample (1998–2019). Counties are colored by quartile based on the long difference (last year minus first year): Q1 (largest decreases, lightest blue), Q2 (small decreases), Q3 (no change to small increases), and Q4 (largest increases, darkest blue). Counties in gray (NA) either have missing treatment facilities or are missing in the NIBRS dataset. The map displays the spatial distribution of changes in treatment facility availability, with darker blue shades indicating counties with the largest increases in facilities. The data comes from the County Business Patterns (CBP) data from the Census Bureau. The total SUT facilities represent the sum of the outpatient and residential facilities (NAICS codes 621420 and 623220, respectively).

FIGURE 3: EVENT STUDY ESTIMATES FOR THE EFFECTS OF SUT FACILITIES ON DRUG-INVOLVED IPV RATE



Notes: The figure plots event study estimates from the dynamic difference-in-difference estimator proposed by de Chaisemartin et al. (2024b). Event time is relative to the first treatment year for each county (-10 to +10). To implement the event-study specification, we recode facility counts into increments of 10, and treat each increment as a "treatment event." The regression includes two pre-treatment placebo periods and two post-treatment periods, using 95% confidence intervals. The regression includes agency and year fixed effects, and is weighted by initial agency population. Standard errors are clustered at the county level.

Figure 4: Event Study Estimates for the Effects of SUT Facilities on Alcohol-Involved IPV Rate



Notes: The figure plots event study estimates from the dynamic difference-in-difference estimator proposed by de Chaisemartin et al. (2024b). Event time is relative to the first treatment year for each county (-10 to +10). To implement the event-study specification, we recode facility counts into increments of 10, and treat each increment as a "treatment event." The regression includes two pre-treatment placebo periods and two post-treatment periods, using 95% confidence intervals. The regression includes agency and year fixed effects, and is weighted by initial agency population. Standard errors are clustered at the county level.

TABLE 1: SUMMARY STATISTICS

	Mean	S.D.	Min.	Max.	N
SUT Facilities					
Total treatment facilities	14.24	27.86	0.00	209.00	53,292
Net openings	3.04	3.88	1.00	44.00	53,292
Net closures	2.56	3.36	1.00	52.00	53,292
IPV Outcomes (per 10,000 population)					
IPV rate	46.27	67.84	0.39	6256.98	50,688
Drug-involved IPV rate	0.91	2.93	0.00	322.58	50,688
Alcohol-involved IPV rate	9.47	13.97	0.00	1290.32	50,688
Non-substance-involved IPV rate	34.46	58.97	0.00	6256.98	50,688
Demographics (% of county population)					
Female share	0.50	0.02	0.25	0.57	53,206
Black share	0.09	0.12	0.00	0.75	53,206
White share	0.88	0.13	0.19	1.00	53,206
Hispanic share	0.06	0.08	0.00	0.97	53,206
Population 0–19	0.26	0.03	0.12	0.45	53,206
Population 20–44	0.32	0.04	0.16	0.58	53,206
Population 45–64	0.27	0.03	0.09	0.42	53,206
Population 65+	0.15	0.04	0.03	0.37	53,206
Socioeconomic Indicators					
Unemployment rate	5.95	2.66	1.10	25.70	52,143
Labor force participation rate	49.15	5.56	20.64	99.60	52,089
Firm births	328.46	593.91	0	6863	52,001
State Indicators					
Police per capita	2.31	0.53	0.74	5.71	53,292
Medical marijuana (MML)	0.31	0.46	0.00	1.00	53,292
Any PDMP	0.80	0.40	0.00	1.00	53,292

Notes: The table presents the means, standard deviations, minimum and maximum values, and the number of observations in our sample covering the period 1998-2019 at the agency-year level.

TABLE 2: EFFECT OF TOTAL SUT FACILITIES ON IPV RATE

Panel A: Drug-involved IPV rate	(1)	(2)	(3)	(4)
Total Facilities$_{t-1}$	-0.0038***	-0.0034***	-0.0028*	-0.0050***
	(0.0013)	(0.0013)	(0.0016)	(0.0018)
Observations	48,356	48,356	47,170	47,132
Mean	0.7516	0.7516	0.7627	0.7598
Panel B: Alcohol-involved IPV rate				
Total Facilities$_{t-1}$	-0.0070	-0.0061	-0.0104	-0.0126
	(0.0184)	(0.0148)	(0.0130)	(0.0104)
Observations	48,356	48,356	47,170	47,132
Mean	7.5962	7.5962	7.6837	7.6345
Panel C: Non-substance-involved IPV rate				
Total Facilities$_{t-1}$	-0.0039	-0.0073	0.0002	0.0091
	(0.0321)	(0.0318)	(0.0347)	(0.0304)
Observations	48,356	48,356	47,170	47,132
Mean	35.3776	35.3776	35.6280	35.4914
Agency fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	No
Demographic and economic controls			Yes	Yes
State$\times$year fixed effects				Yes

Notes: Data comes from NIBRS covering 1998-2019. Estimates of the effects of lagged SUT facilities on the drug-involved IPV rate, alcohol-involved IPV rate, and non-substance-involved IPV rate per 10,000 population at the agency level. Panel A shows estimates for drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense. Panel B shows estimates for alcohol-involved IPV incidents where the offender was suspected to be under the influence of alcohol. Panel C shows estimates for IPV incidents for which no substance was suspected. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), county-level economic controls (unemployment rate, labor force participation rate, and firm births), and state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). The regressions are weighted by initial agency population (first year of observation). Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 3: EFFECT OF TOTAL SUT FACILITIES ON DRUG-INVOLVED IPV RATE

	(1)	(2)	(3)
Total Facilities$_{t-1}$	-0.0050***	-0.0054**	-0.0046*
	(0.0018)	(0.0024)	(0.0025)
Total Facilities$_{t}$		0.0005	-0.0016
		(0.0019)	(0.0010)
Total Facilities$_{t+1}$			0.0013
			(0.0016)
Observations	47,132	47,132	40,712
Mean	0.7598	0.7598	0.7497

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions include agency, year, and state$\times$year fixed effects, and are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 4: EFFECT OF NET SUT FACILITIES ON DRUG-INVOLVED IPV RATE, EXTENSIVE MARGIN

Panel A: Net Openings[1]	(1)	(2)	(3)	(4)
Net opening	-0.1050*	-0.1044*	-0.0968*	-0.1014*
	(0.0539)	(0.0539)	(0.0560)	(0.0547)
Observations	25,317	25,317	25,317	25,317
Mean	0.7833	0.7833	0.7833	0.7833
Panel B: Net Closures[2]				
Net closure	0.1219***	0.1169***	0.1052***	0.0608*
	(0.0351)	(0.0349)	(0.0337)	(0.0344)
Observations	25,317	25,317	25,317	25,317
Mean	0.7833	0.7833	0.7833	0.7833
Agency fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	No
Demographic and economic controls			Yes	Yes
State×year fixed effects				Yes

Notes: Data comes from NIBRS covering 1998-2019. This table presents estimates from the extensive margin analysis examining the effect of treatment facility openings and closures on drug-related intimate partner violence (IPV) rates using the same sample as the main analysis (Table 2 column 4). The treatment group consists of counties that transition from having zero facilities to one or more facilities during the sample period. The control group consists of counties that never have treatment facilities throughout the sample period. Net Openings[1] is a binary that switches to 1 when an agency goes from zero to a positive number of SUTs and remains 1 in all subsequent years until a net closure occurs. Net Closures[2] is a binary that switches to 1 when an agency goes from a positive number of SUTs to zero and remains 1 in all subsequent years until a net opening occurs. The dependent variable is the rate of drug-related IPV incidents per capita. All regressions include agency and year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), county-level economic controls (unemployment rate, labor force participation rate, and firm births), and state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). The regressions are weighted by initial agency population (first year of observation). Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 5: HETEROGENEITY BY VICTIM, COUNTY AND CRIME CHARACTERISTICS

Panel A: Gender and Race					
	(1) Female	(2) Male	(3) White	(4) Black	(5) Hispanic
Total Facilities$_{t-1}$	-0.0043***	-0.0007**	-0.0036***	-0.0013**	-0.0002
	(0.0015)	(0.0004)	(0.0013)	(0.0006)	(0.0003)
Observations	47,132	47,132	47,132	47,132	47,132
Mean	0.7504	0.1716	0.7536	0.1007	0.0341

Panel B: Age						
	(1) Age 15–19	(2) Age 20–29	(3) Age 30–39	(4) Age 40–49	(5) Age 50–59	(6) Age 60+
Total Facilities$_{t-1}$	-0.0005**	-0.0015**	-0.0016***	-0.0010**	-0.0002	-0.0001
	(0.0002)	(0.0006)	(0.0006)	(0.0005)	(0.0002)	(0.0001)
Observations	47,132	47,132	47,132	47,132	47,132	47,132
Mean	0.0659	0.3527	0.2778	0.1550	0.0507	0.0120

Panel C: Types of Drug-Involved IPV Crimes				
	(1) Simple assault	(2) Aggravated assault	(3) Intimidation	(4) Sexual violence
Total Facilities$_{t-1}$	-0.0036***	-0.0008**	-0.0012***	-0.0001
	(0.0014)	(0.0004)	(0.0004)	(0.0001)
Observations	47,132	47,132	47,132	47,132
Mean	0.5500	0.1475	0.0816	0.0183

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. *White* and *Black* categories refer to non-Hispanic individuals. All outcome variables are measured per 10,000 population within each agency, and represent cases where the offender was under the influence of drugs at the time of the offense. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 6: HETEROGENEITY BY COUNTY CHARACTERISTICS

	Sample split by the following county characteristic:					
	A. More than HS Education		B. Rural Share		C. Household Income	
	Above median (1)	Below median (2)	Above median (3)	Below median (4)	Above median (5)	Below median (6)
Total Facilities$_{t-1}$	-0.0032	-0.0071	0.0111	-0.0044**	-0.0033*	-0.0163**
	(0.0021)	(0.0050)	(0.0112)	(0.0019)	(0.0019)	(0.0069)
Observations	23,820	23,274	23,011	24,107	23,975	23,128
Mean	0.7821	1.0661	1.0243	0.8241	0.6902	1.1623

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, normalized by 10,000 population within each agency. "More than HS Education" refers to the share of adults with above high school education. County-level education and household income are measured using their baseline 1998 values, while rural population share is measured as of 2000. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 7: HETEROGENEITY BY SIZE OF ILLICIT OPIOID MARKET ACTIVITY

	(1) Below median	(2) Above median
Total Treatment Facilities$_{t-1}$	-0.0114***	-0.0029
	(0.0026)	(0.0023)
Observations	20,107	27,025
Mean	0.8077	1.0071

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. Following Dave et al. (2025b), illicit market share is proxied by the ratio of deaths due to illicit or synthetic opioids to deaths from prescription opioids. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 8: HETEROGENEITY BY FACILITY TYPE ON DRUG INVOLVED IPV PER 10,000

	(1)	(2)	(3)	(4)
Outpatient Facilities$_{t-1}$	-0.0075**	-0.0071**	-0.0049	-0.0096**
	(0.0037)	(0.0035)	(0.0037)	(0.0041)
Observations	48,356	48,356	47,287	47,249
Mean	0.7516	0.7516	0.7627	0.7598
Residential Facilities$_{t-1}$	-0.0018	-0.0015	-0.0014	-0.0016
	(0.0015)	(0.0015)	(0.0015)	(0.0016)
Observations	48,356	48,356	47,287	47,249
Mean	0.7516	0.7516	0.7627	0.7598
Agency fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	No
Demographic and economic controls			Yes	Yes
State$\times$year fixed effects				Yes

Notes: Data comes from NIBRS covering 1998-2019. Substance use treatment facility data is collected from County Business Patterns (CBP). NAICS codes that represent outpatient and residential facilities are 621420 and 623220, respectfully. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. All regressions include include agency and year fixed effects, and column 4 includes state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), county-level economic controls (unemployment rate, labor force participation rate, and firm births), and state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 9: HETEROGENEITY BY INSURANCE COVERAGE

	(1) Drug-Involved IPV
Total Facilities$_{t-1}$ $\times$ Below-median Medicaid $\times$ ACA Adopters	-0.0218*
	(0.0121)
Total Facilities$_{t-1}$ $\times$ Below-median Medicaid	0.0136
	(0.0109)
Total Facilities$_{t-1}$ $\times$ ACA Adopters	0.0110
	(0.0108)
Total Facilities$_{t-1}$	-0.0133
	(0.0107)
Observations	47,170
Mean	0.7627

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. Total Facilities measures the number of substance abuse treatment facilities in the county at $t-1$. Medicaid is an indicator for whether the state had below-median Medicaid coverage in 2008, based on state-level Medicaid enrollment rates. ACA Adopter is an indicator for states that adopted the ACA Medicaid expansion in our time period. The regression includes agency and year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), county-level economic controls (unemployment rate, labor force participation rate, and firm births), and state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE 10: ROBUSTNESS CHECKS

Panel A: Different sample restrictions

	Any reporting (1)	Population $\geq$ 10,000 (2)	Remove counties with top 10% SUTs (3)	Remove counties with bottom 10% SUTs (4)	Remove never treated (5)
Total Facilities$_{t-1}$	-0.0052***	-0.0050***	-0.0144***	-0.0050***	-0.0050***
	(0.0018)	(0.0018)	(0.0045)	(0.0019)	(0.0018)
Observations	67,606	44,744	38,149	35,454	41,242
Mean	0.7264	0.7579	0.8240	0.7644	0.7705

Panel B: Alternative empirical specifications

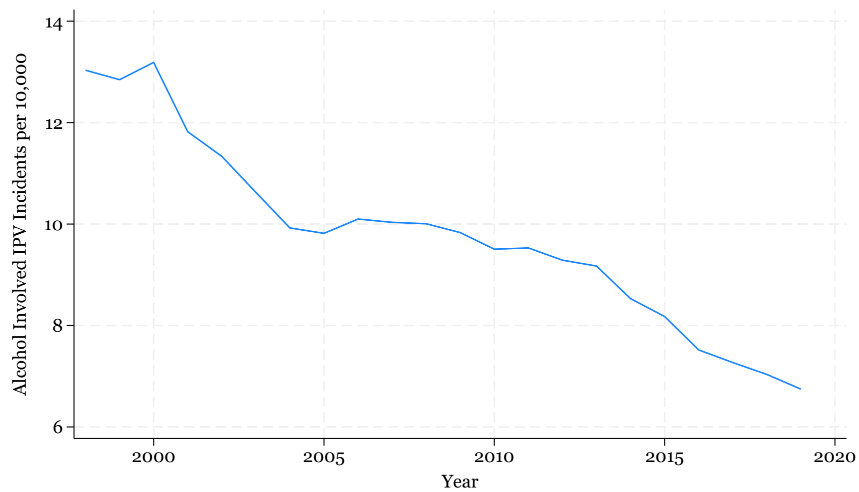
	Unweighted (1)	Poisson (2)	IHS (3)	Controlling for net job creation (4)
Total Facilities$_{t-1}$	-0.0038**	-0.0072***	-0.0020**	-0.0051***
	(0.0019)	(0.0024)	(0.0010)	(0.0018)
Observations	48,802	43,687	47,132	47,132
Mean	0.9189	9.4880	0.7598	0.7598

Notes: Data comes from NIBRS covering 1998-2019. The outcome is drug-involved IPV incidents where the offender was suspected to be under the influence of drugs during the offense, and is normalized by 10,000 population within each agency. Panel A presents alternate samples: (1) includes agencies with any crime reporting in a given year; (2) restricts the sample to counties with population $\geq$ 10,000; (3) and (4) drop counties with the highest 10% and lowest 10% of SUT facilities; (5) excludes counties that never had an SUT opening during the sample period. Panel B presents alternate weighting and functional forms: (1) estimates an unweighted regression; (2) uses a Poisson model; (3) inverse hyperbolic sine transformation of the drug-involved IPV variable; (4) includes net job creation (count) at the county-level as an additional control, where net job creation is calculated as job gains from new establishments and expanding businesses minus job losses from closing establishments and contracting businesses. The variable takes negative values when job destruction exceeds job creation, as reported by the U.S. Census 2023 Business Dynamics Statistics Datasets. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions are weighted by initial agency population in all regressions other than Panel B, column 1. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

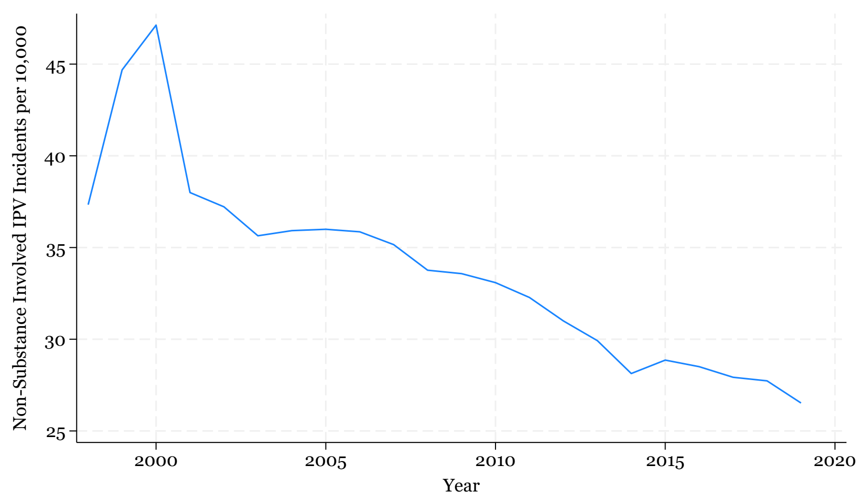
Appendix Figures and Tables

FIGURE A1: OTHER IPV INCIDENTS OVER TIME, 1998-2019

(a) Alcohol Involved IPV Rate



(b) Non-Substance Involved IPV Rate



Notes: The figures plot annual average IPV rate per 10,000 at the agency year level. Panel (a) plots alcohol-involved IPV incidents where the offender was suspected to be under the influence of alcohol during the offense. Panel (b) plots non-substance involved IPV incidents where the offender was not suspected of being under the influence of any substance. Both outcomes are normalized by 10,000 population within each agency. The data comes from National Incident-Based Reporting System (NIBRS) covering 1998-2019.

TABLE A1: EFFECT OF TOTAL SUT FACILITIES ON IPV RATE PER 10,000

	(1)	(2)	(3)	(4)
Total Facilities$_{t-1}$	-0.0062	-0.0073	-0.0054	-0.0064
	(0.0359)	(0.0354)	(0.0394)	(0.0316)
Observations	48,356	48,356	47,170	47,132
Mean	45.1148	45.1148	45.4596	45.2632
Agency fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State controls		Yes	Yes	No
Demographic and economic controls			Yes	Yes
State$\times$year fixed effects				Yes

Notes: Data comes from NIBRS covering 1998-2019. The outcome is all IPV incidents normalized by 10,000 population within each agency. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), county-level economic controls (unemployment rate, labor force participation rate, and firm births), and state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE A2: Normalized Differences Between NIBRS and Non-NIBRS Counties

	NIBRS (1)	Non-NIBRS (2)	Norm. Diff. (1) – (2)
Percent female	50.11	50.01	0.0336
Percent Black	7.97	9.98	-0.1012
Percent White	88.88	86.11	0.1270
Percent Hispanic	6.19	8.54	-0.1404
Percent age 0–19	26.08	26.68	-0.1159
Percent age 20–44	30.87	30.97	-0.0138
Percent age 45–64	26.94	26.16	0.1651
Percent age 65 and up	16.10	16.19	-0.0158
Percent above high school	44.18	42.10	0.1288
Household income	56,384	53,444	0.1549
Percent rural	54.98	61.85	-0.1620
Unemployment rate	5.81	5.95	-0.0352
Labor force participation rate	48.59	47.94	0.0707
Police per capita	2.31	2.57	-0.3197
Firm births	150.29	140.71	-0.0132
Medical marijuana law	0.23	0.19	0.0655
Any PDMP	0.77	0.61	0.2523
Illicit opioid mortality share	77.16	67.07	0.2122
Total treatment facilities	5.39	4.78	0.0271

Notes: Table reports means for NIBRS and non-NIBRS counties over the sample period 1998–2019. Observations: Non-NIBRS = 3,148 counties; NIBRS = 1,389 counties. Given the unequal sample sizes, we follow Imbens and Wooldridge (2009) in our comparison and focus on normalized differences:

$$\Delta_X = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{S_1^2 + S_2^2}},$$

rather than on the t-statistics, since they are independent of the sample size. Imbens and Wooldridge (2009) suggest using 0.25 as the rule of thumb in these comparisons.

TABLE A3: ROBUSTNESS CHECKS RELATED TO REPORTING BIAS

	(1) Arrest probability	(2) Injury probability
Total Facilities$_{t-1}$	0.0001	0.0003
	(0.0006)	(0.0009)
Observations	47,132	47,132
Mean	0.4425	0.4052

Notes: Data comes from NIBRS covering 1998-2019. The arrest probability is the ratio of drug-involved IPV arrest rates to drug-involved IPV incident rates. The injury probability is the ratio of drug-involved IPV injury rates to drug-involved IPV incident rates. The drug-involved arrest and injury rates represent intimate partner violence cases in which the offender was suspected of being under the influence of drugs at the time of the offense, per 10,000 population within each agency. All regressions include agency, year, and state-year fixed effects. Controls include county-level demographic variables (percent female, percent Black, percent White, percent Hispanic, and population shares in four age groups: 0-19, 20-44, 45-64, and 65+), and county-level economic controls (unemployment rate, labor force participation rate, and firm births). The regressions are weighted by initial agency population. Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the county level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.

TABLE A4: AVERAGE TREATMENT EFFECTS USING AN ALTERNATIVE ESTIMATOR

	(1) Drug-involved IPV rate	(2) Alcohol-involved IPV rate
Panel A: Dynamic Treatment Effects		
One year after treatment	-0.176***	-0.816
	(0.049)	(0.479)
Two years after treatment	-0.206***	-0.893
	(0.073)	(0.568)
Panel B: Average Treatment Effect on the Treated		
A.T.T.	-0.176***	-0.786
	(0.048)	(0.464)

Notes: This table reports staggered difference-in-differences estimates using the estimator proposed by de Chaisemartin et al. (2024b). Drug-involved IPV are incidents where the offender was suspected to be under the influence of drugs during the offense, normalized by 10,000 population within each agency. Alcohol-involved IPV are incidents where the offender was suspected to be under the influence of alcohol during the offense, normalized by 10,000 population within each agency. Event time is relative to the first treatment year for each county (-10 to +10). To apply event-study logic, we recode facility counts into increments of 10, and treat each increment as a "treatment event." The regression includes two pre- and two post-treatment placebo periods, using 95% confidence intervals. The regression is weighted by initial agency population, include agency and year fixed effects, and cluster standard errors at the county level. Statistical significance is indicated as follows: * p < .10, ** p < .05, *** p < .01.

TABLE A5: EFFECT OF TOTAL SUT FACILITIES ON ADMISSIONS

	(1) Total	(2) Drug-related	(3) Alcohol-related
Panel A: Male Sample			
Total Facilities$_{t-1}$	0.0373**	0.0205*	0.0168**
	(0.0177)	(0.0120)	(0.0065)
Observations	1,037	1,037	1,037
Mean	64	43	21
Panel B: Female Sample			
Total Facilities$_{t-1}$	0.0023	-0.0007	0.0030
	(0.0085)	(0.0068)	(0.0022)
Observations	1,037	1,037	1,037
Mean	29	21	8
State fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
State controls	Yes	Yes	Yes
State-specific linear trends	Yes	Yes	Yes

Notes: This table uses state-year level admissions data from Treatment Episode Dataset (TEDS), 1998-2019. The dependent variable in column (1) is total admissions to alcohol or drug treatment in facilities that report to state administrative data systems, normalized by 10,000 population. The outcomes in columns 2 and 3 are drug-related admissions and alcohol-related admissions per 10,000 population. All regressions include state and year fixed effects, and state-specific linear trends. Controls include state controls (police per capita, whether a state has a medical marijuana law, and whether a state has a prescription monitoring program (PDMP) of any form). Outcome means are for the sample period and are listed in rows under standard errors. Standard errors are clustered at the state level. ***, **, and * denote significance at the 1, 5, and 10 percent levels.