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ABSTRACT

Substance Abuse Treatment Centers and Local Crime*

In this paper we estimate the effects of expanding access to substance-abuse treatment on local crime. We do so using an identification strategy that leverages variation driven by substance-abuse-treatment facility openings and closings measured at the county level. The results indicate that substance-abuse-treatment facilities reduce both violent and financially motivated crimes in an area, and that the effects are particularly pronounced for relatively serious crimes. The effects on homicides are documented across three sources of homicide data.

JEL Classification: I12, K14, K42

Keywords: substance abuse treatment, crime, homicides

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1 Introduction

Drug-induced deaths in the United States have increased 280 percent since 1999 and now represent the largest major category of external causes of death by a wide margin: there were 47,055 deaths due to drug overdoses in 2014 compared to 32,675 due to motor vehicle accidents.[1] These facts underscore a growing need to understand how to reduce drug-related harms. Towards this end, a large body of work has shown that policies targeting the supply of drugs are rarely effective.[2] In contrast, recent work indicates that expanding access to substance-abuse treatment (SAT) facilities significantly reduces severe drug abuse, as measured by drug-induced mortality (Swensen, 2015). While this evidence highlights that investments in SAT can improve outcomes for some individuals, it does not necessarily reflect a broad-based benefit for communities that might be considering making such investments. In this paper we fill this important gap in the literature by estimating the effects of SAT facilities on local crime.

There are several mechanisms through which SAT facilities may affect local crime. As outlined in Goldstein's (1985) influential tripartite conceptual framework for the drugs-violence nexus, drugs may affect violence through psychopharmacological effects, economically compulsive effects, and systemic effects. In these terms, SAT could be expected to reduce violence by: (i) reducing the use of drugs that lead to aggressive behavior (though there may be some offsetting effects caused by withdrawal), (ii) by reducing conflicts associated with financially motivated crimes committed by addicts seeking funds to buy drugs, and (iii) by reducing violence among and against those associated with the drug trade.[3] Moreover, drug-abuse treatment may reduce gun carrying through all three of these mechanisms, which could serve to reduce the amount—and intensity—of violence in communities. It is also important to keep in mind that a relatively large share of drug users have mental health problems that contribute to their addiction and to violent behaviors (Lavine, 1997; Hoaken and Stewart, 2003). As such, we could expect SAT to reduce violence because it can itself include—or can direct patients towards—treatment for underlying mental health problems that contribute to violence (Lavine, 1997; Marcotte and Markowitz, 2011). Finally, SAT treatment may reduce criminal activity through positive spillover effects on friends and family members of those receiving treatment.

[1] See Rudd et al. (2016) and NCSA (2015).

[2] See for instance Dinardo (1993), Yuan and Caulkins (1998), Miron (2003), Cunningham and Liu (2003), Kuziemko and Levitt (2004), Dobkin and Nicosia (2009), Cunningham and Finlay (2013), and Dobkin, Nicosia, Weinberg (2014).

[3] Prior studies have documented causal effects of drug activity on community violence by exploiting variation in drug use induced by price shocks (Markowitz, 2001, 2005) and by exploiting variation in the timing with which specific drugs became available across different cities (Evans, et al., 2012; Fryer et al., 2013).

Although these mechanisms highlight how SAT facilities can reduce crime through their effect on drug abuse, there are other mechanisms through which we might expect SAT facilities to *increase* local crime. Featuring prominently in not-in-my-backyard arguments against SAT facilities is the notion that such facilities pose risks by drawing into the area individuals who have relatively high rates of crime perpetration (drug users). Going beyond the idea of shifting crime perpetration from one place to another, SAT facilities could increase crime by altering the social and environmental context faced by drug users. That is, by altering the types of people and places that they encounter and with which they interact.

In this study we contribute to this policy debate by quantifying the effects of SAT facilities on crime. Specifically, we use annual county-level data on the number of SAT facilities to evaluate the degree to which crime rates change when SAT facilities open and close. We consider various crime outcomes measured over time at the county and law-enforcement agency level, based on data from the National Center for Health Statistics and the FBI's Uniform Crime Reporting Program. These panel data allow us to include a rich set of fixed effects (county/agency and state-by-year) and control variables (demographics, various measures of economic conditions, and law enforcement presence) in our models, so the estimates are identified based on plausibly exogenous variation. Several ancillary analyses support the validity of this research design, including analyses that demonstrate that outcomes in an area change after but not before the number of facilities change.

Our approach shifts the focus from the effects of SAT on those who receive treatment to the effects of SAT facilities on the communities they serve. This allows us to make several contributions. First, we consider outcomes that tend to be beyond the scope of randomized control trials (RCTs), which are limited by small samples, short follow-up periods, and the potential for false reporting. In particular, our approach allows us to consider severe-but-infrequent outcomes (e.g., homicide) and behaviors that individuals are likely to conceal (e.g., sexual assault). Second, our estimates reflect the effects of SAT on patients and the spillover effects onto the broader community, inclusive of any spillover effects on nearby friends and family and on the market for illegal drugs. In so doing, our estimates will allow for more comprehensive cost-benefit considerations. Third, whereas the nature of RCTs tends to require the use of small localized samples, which may have limited external validity, our use of administrative data allows us to obtain estimates that reflect the effects of SAT facilities across the United States.

Our analysis reveals significant and robust evidence that expanding access to SAT through additional treatment facilities reduces local crime. The effects appear to be particularly pronounced for relatively serious violent and financially motivated crimes: homicides, aggravated assaults, robbery, and motor vehicle theft. We do not find significant effects on more frequent but less serious crimes (simple assault, burglary, and larceny), nor do we find a significant effect on sexual assault. Overall, we find that an additional treatment facility reduces felony-type crimes by 0.10 percent annually. We show that the estimated effect on homicides is present across three different sources of homicide data.

Despite the various contributions of our research described above, there are some limitations that bear noting. First, our empirical approach, which focuses on county- and law-enforcement-agency-level aggregates, implies that we cannot separate the effects of SAT facilities on those who receive treatment from the effects of SAT facilities on the broader community. That said, we view this as a reasonable tradeoff in order to be able to speak to the effects on the community as a whole. Second, while there is significant variation across SAT facilities in the types of treatment that they offer, our estimates will reflect an average of the effects of these facilities. Finally, openings and closings of SAT facilities are not random. While this has the potential to compromise our ability to identify causal effects, our ancillary analyses, which are discussed in detail in subsequent sections, demonstrate that it is unlikely in light of our empirical strategy.

The remainder of the paper is structured as follows. Section 2 discusses relevant background on drug abuse and treatment in the United States, in addition to related studies that have considered the effects of SAT on crime. Sections 3 and 4 describe the data and our empirical approach in detail. Section 5 begins with a replication and extension of Swensen (2015) to show the effects of SAT facilities on severe drug abuse and then presents the results of our analyses that focus on crime. We offer concluding remarks in Section 6.

2 Background

2.1 Substance Abuse and Treatment

According to the National Survey of Drug Use and Health over 21.5 million people in the U.S. are classified as having a substance-use disorder (CBHSQ, 2015).[4] A high incidence of substance abuse is also apparent in crime perpetration, with 40 percent of convicted violent criminals being under the influence of alcohol and nearly 60 percent of all arrestees testing positive for some illicit substance

[4]Based on criteria specified in the Diagnostic and Statistical Manual of Mental Disorders, 4th edition (DSM-IV)

at the time of arrest.[5] The annual societal costs of drug abuse solely in terms of drug-related crime are estimated at over 56 billion dollars.[6]

Though substance-abuse treatment is a promising avenue to reduce these costs, treatment rates for those in need remain very low. In 2014, 85 percent of those abusing or dependent on an illicit substance did not receive treatment and despite the prevalence of alcohol and drugs among arrestees, 70 percent of arrestees have never been in any form of drug or alcohol treatment (ONDCP, 2014). Notably, recent changes brought about by the Affordable Care Act are expected to increase coverage and take-up of treatment (Buck, 2011; Beronio, Glied, and Frank 2014).

In this context, the number of substance-abuse treatment facilities may be a particularly relevant policy parameter. In the United States, over 14,500 stand-alone treatment facilities are the primary setting for delivery of substance-abuse treatment, offering a wide range of drug-treatment programs and related services (SAMHSA, 2014). Local treatment centers most commonly offer outpatient care to deliver treatment programs such as detoxification, methadone maintenance, regular outpatient, adolescent outpatient, and drug-court programs (SAMHSA, 2014). For more serious substance-abuse problems, facilities provide residential treatment in which clients temporarily live at the treatment site (e.g. inpatient detoxification, chemical dependency programs, therapeutic communities). While treatment programs vary substantially and often target particular demographic groups or specific drug addictions, all treatment approaches share similar goals to mitigate the consequences of drug abuse and encourage healthier lifestyles.

More broadly, the substance-abuse treatment industry includes profit, non-profit, and public providers, the bulk of which (87 percent) are privately-owned facilities.[7] Though the objective functions of facilities may differ somewhat by ownership status and treatment focus, the decision to open or close a treatment facility likely depends crucially on (i) a perceived need for treatment providers or opportunities to improve upon currently offered treatment services and (ii) the ability to secure funding for treatment services from either public or private third-party payers (SAMHSA 2011). Given the high need for addiction treatment and existing evidence of binding treatment capacity constraints and long wait lists, the availability of funds is particularly relevant when considering the predictors of facility openings and closings.[8]

[5] See https://ncadd.org/about-addiction/alcohol-drugs-and-crime.

[6] Estimates based on the 2011 National Drug Threat Assessment counducted by the National Drug Intelligence Center.

[7] According to the 2013 National Survey of Substance Abuse Treatment Services, 60 percent of facilities are nonprofit, 30 percent are for profit, and 10 percent are public.

[8] Evidence suggests that capacity concerns and being put on a wait list are important barriers to treatment enrollment (Appel et al., 2004; Friedmann et al., 2003; Pollini et al., 2006). Relatedly, Dave and Mukerjee (2011)

Unlike general health care, which relies on funding through insurance mechanisms, substance-abuse treatment relies primarily on public funding in the form of federal block grants and state subsidies. That said, recent mental health parity legislation and the rise of managed-care contracts have increased the importance of public and private insurance revenue to providers (Horgan and Merrick, 2001; Olmstead and Sindelar, 2004). Assuming these sources of financing generally increase with drug abuse and related problems, analyses of the effect of treatment provision on drug-related outcomes may understate the actual effect of treatment.

2.2 Related Literature on SAT and Crime

An extensive literature has evaluated the relationship between substance-abuse treatment programs and criminal activities, including some that use "the gold standard" for empirical research, randomized control trials (RCTs). In a widely-cited meta analysis, Pendergast et al. (2002) reviewed 78 studies of SAT, 60 percent of which used random or quasi-random assignment to treatment and 25 of which examined crime outcomes. The authors found an average 13 percent decline in criminal involvement as a result of treatment.[9] More recent reviews of specific treatment approaches provide consistent evidence that criminal involvement declines during treatment and mixed evidence when considering longer-run crime outcomes (Amato et al., 2005; Holloway et al., 2006; Egli et al., 2009; Mattick et al., 2014).

The existing literature also adds insight into the efficacy of specific treatment settings in reducing drug-related crime. Some of the more convincing and consistent evidence comes from studies evaluating prison-based drug treatment. This is partly due to the relative ease of employing a randomized treatment design and the ability to consider recidivism rates rather than relying on self-reported criminal activity.[10] Summarizing the literature, Mitchell et. al (2012) review 74 studies of prison-based treatment programs and conclude that substance-abuse treatment for inmates reduces recidivism by 15 percent. Existing evidence also suggests that court-mandated treatment programs, which account for a third of all treatment admissions, can be effective in reducing crime.[11] For instance, Wilson, Mitchell, and Mackenzie (2006) identify and review 55 quasi-experimental and

analyze the effect of state legislation that reduces out-of pocket costs for mental health and substance-abuse treatment and find a relatively small effect on treatment admissions. They argue that the effect on admissions is muted, in part, because of treatment capacity constraints suggested by limited growth in the number of treatment facilities and increasing treatment waiting periods.

[9] Crime outcomes included self-reported crimes and official records on arrest, conviction and incarceration. As such, this review includes evidence from crime outcomes during and after treatment.

[10] Treatment rates increased by 34 percent among state inmates and 90 percent among federal inmates from 1997-2004.

[11] See SAMHSA (2014) for a breakdown of admissions by treatment referral source.

experimental evaluations of drug courts. They concluded that court-referred treatment does lower re-arrest rates though the estimated effects were notably smaller and less precise among evaluations that employed randomization. They also find consistent evidence of declines in re-offending both during and following court-referred treatment programs, however the estimated effects do decay over time.

Together, this literature provides consistent evidence that treatment programs can reduce crime. While these studies have made significant contributions to our knowledge, the merit of our study is predicated on the notion that some of the most important questions about the effects of SAT are only likely to be answered using alternative methods applied to observational data. In particular, our study shifts the focus from the effects of SAT on those who receive treatment to the effects of SAT facilities on the communities they serve and uses data that allows us to obtain estimates that reflect the effects of SAT facilities on local-area crime across the United States.

To our knowledge only one other recent working paper attempts to consider the effects of SAT on crime in such a comprehensive fashion. Wen, Hockenberry, and Cummings (2014) consider the effects of changes in SAT rates on property and violent crimes using data collected by the FBI that span the United States. Their instrumental variables approach relies on the assumption that state health insurance expansions (made possible through Health Insurance Flexibility and Accountability waivers) only relate to changes in crime through their impacts on SAT.[12] This assumption could be violated if, for example, expanding access to health insurance affects crime through its impact on treatment for mental health problems or through its impacts on overall health and well being. As all observational studies rely on fundamentally untestable assumptions, and as any body of evidence is more compelling when similar results are documented using approaches that rely on different assumptions, we view our work as an important contribution that complements this prior study, which reports that increases in substance-use-disorder treatment significantly reduces robbery, aggravated assault, and larceny.

3 Data

Following Swensen (2015), we identify county-level changes in the number of substance-abuse treatment facilities using data from the U.S. Census Bureau's County Business Patterns (CBP). The

[12] They also use as an instrumental variable state-level mandates requiring private group health plans to provide benefits for substance-use disorder treatment that are no more restrictive than the benefits for medical insurance parity mandates; however, it is always used in conjunction with the waiver expansion instrument, presumably due to a lack of independent power.

CBP data reports the annual number of substance-abuse treatment clinics (a single physical location) in each U.S. county for both outpatient and residential facilities from 1999-2012.[13] Although classified separately in the CBP data, residential and outpatient establishments often offer both residential and outpatient treatment services with 90 percent of all admissions occurring in an outpatient setting (SAMHSA, 2014). Therefore, estimating the effects separately for outpatient and residential facilities would not be informative as residential and outpatient services are not distinctly identified. As such, we combine outpatient and residential classifications using the total count of establishments as an indicator for county-level provision of substance-abuse treatment.

We merge CBP data with several independent data sources for drug abuse and criminal activity. We first revisit the effect of SAT on drug abuse, as measured by drug-related deaths, using annual county-level mortality data from the National Center for Health Statistics (NCHS) Multiple Cause of Death Data. Drug-induced mortality is measured using causes of death with specific reference to drug-induced poisoning, identified by International Classification of Diseases (ICD) codes.[14] To calculate mortality rates and to create county-by-year controls for demographic characteristics, we use population data from the National Cancer Institutes's Surveillance Epidemiology and End Results (Cancer-SEER) program.[15]

To estimate the effect of treatment facilities on local-area crime we use the NCHS mortality data, which provide a measure of homicides, and the Uniform Crime Reports (UCR) which are compilation of annual crime statistics reported by local law-enforcement agencies across the United States to the FBI.[16] Specifically, we use the offenses known data from the Offenses Known and Cleared by Arrests UCR segment. These data, which we will refer to as UCR Offenses Known, include the most commonly reported violent and property crimes including criminal homicide, sexual assault, robbery, assault, burglary, larceny theft, and motor vehicle theft. We focus on known offenses in order to capture crimes that come to the attention of law enforcement, as opposed to alternative data sets that are available but are restricted to crimes that have been cleared by arrest. In addition, we use the UCR Supplementary Homicide Reports (SHR) to consider additional details of the victims, offenders, and circumstances associated with homicides. The SHR is an incident-

[13]The following six-digit NAICS codes identify treatment establishments: 621420 —"Outpatient mental health and substance abuse centers" and 623220—"Residential mental health and substance abuse facilities."

[14]In particular, we use the following ICD-10 codes to measure drug-induced mortality: X40-X45, X60-X65, X85, Y10-Y15.

[15]As reported by Stevens et al. (2015), the Cancer-SEER population data are more accurate than data interpolated from the Census because they "are based on an algorithm that incorporates information from Vital statistics, IRS migration files, and the Social Security database."

[16]NCHS homicides include deaths by another person with the intent to injure or kill. They do not include homicides due to legal intervention, operations of war, or homicides from the Sept. 11, 2001 attacks.

level dataset that includes detailed information on each homicide as voluntarily reported by agencies participating in the UCR program. For agencies that do report homicides in the SHR, we impute zeros by expanding the SHR to the same agency-years as our UCR Offenses Known sample. We link the UCR agency-level data with county-level CBP data using the primary county in which each municipality resides and calculate crime rates using the annual reported population covered by each municipal agency.

We restrict our analysis to U.S. counties with at least one treatment facility over the 1999-2012 time period and counties with available identifiers in the 48 contiguous states.[17] The resulting data include treatment facility, mortality, and crime data in 48 states, spanning 14 years.[18] In Table 1 we present summary statistics for our sample, weighted by the relevant populations. CBP data indicate that counties have a population-weighted average of 49.5 SAT facilities. Importantly, there is substantial variation in the number of facilities with the average county experiencing 5.8 net facility openings and 3.7 net closings from 1999 to 2012, where a net opening is an observed increase in the number of facilities from one year to the next and a net closing is defined similarly. For reference, Table 1 also shows summary statistics for each mortality and crime outcome used in our analysis.

4 Empirical Approach

We identify the effects of SAT facilities using year-to-year variation within counties driven by facility openings and closings, controlling for state-by-year shocks common to areas within a state in addition to time-varying county characteristics. As we analyze both county and agency-level outcomes, we operationalize this strategy using a regression model that includes either county or agency fixed effects in addition to state-by-year fixed effects and county-year covariates:

$$y_{ast} = \theta Facilities_{cs,t-1} + \alpha_{as} + \alpha_{st} + \beta X_{cst} + \epsilon_{ast},$$

[17] Specifically, we drop all counties in HI and AK and combine counties that experience boundary changes over time. This involves combining Adams, Broomfield, Boulder, Jefferson, and Weld in Colorado; Prince George's and Montgomery in Maryland; Gallatin and Yellowstone National Park in Montana; Craven and Carteret in North Carolina; Alleghany and Clifton Forge in Virginia; Augusta and Waynesboro in Virginia; Bedford and Bedfort City in Virginia; Halifax and South Boston City in Virginia; Prince William and Manassas Park in Virginia; Southampton and Franklin in Virginia; and York and Newport News in Virginia.

[18] Over the same time-frame, the aggregate number of facilities increases from 12,428 to 16,959.

where y_{ast} represents outcomes in area a (either county or agency) in state s in year t. We use log rates to measure drug abuse and crime outcomes. We add one to all counts before constructing log rates to avoid dropping area-year observations for which the outcome would otherwise be undefined, but we show that results of all of our analyses are similar if we instead simply focus on areas that always have a positive count, with the sample being defined separately for each outcome considered. In support of using the log transformation, we have verified that Poisson models (where computationally feasible) yield very similar estimates. $Facilities_{cs,t-1}$ represents the number of SAT facilities in county c in state s in year t-1, α_{as} are area fixed effects, α_{st} are state-by-year fixed effects, and X_{cst} includes county unemployment rates, the number of firm births, number of law enforcement officers per 100,000, and the fraction of the county population that is: white, black, male, less than 10 years old, 10-19 years old, ... , 60-69 years old.[19] Finally, ϵ_{ast} is a random error term that we allow to be correlated across time within a county and across all counties in any given year by estimating two-way standard errors following Cameron et al. (2011).[20] To be clear, our measure of facilities is a county-level measure even when we are considering crimes at the agency level. We also note that our main results are based on regressions that weight by the relevant population size in order to improve efficiency.

Our focus on within-area variation accounts for fixed characteristics of areas (both observable and unobservable) that may be correlated with the number of SAT facilities in the county and our outcomes of interest. For example, this approach will address the fact that there are inherent differences between urban and rural counties. The inclusion of state-by-year fixed effects account for aggregate time-varying shocks, such as aggregate economic conditions or changes in the national drug-control strategy. They also control for state-specific shocks such as changes in state funding for law enforcement services. The controls for unemployment rates and firm births account for the possibility that our outcomes of interest and treatment facilities may both be related to local economic conditions. The controls for demographics account for the possibility that compositional changes in a county's population may affect outcomes and investments in SAT facilities.

Our empirical approach closely follows Swensen (2015), who also conducts several ancillary analyses in support the validity of the research design. In particular, Swensen demonstrates that

[19] County unemployment rates are from the BLS Local Area Unemployment Statistics. Firm births include all county-level firm births reported by the U.S. Census Statistics of U.S. Businesses. The number of law-enforcement officers per 100,000 residents are calculated using the UCR agency-specific employment reports available in the Law Enforcement Officers Killed and Assaulted (LEOKA) database.

[20] That is, we estimate two-way standard errors clustered on counties and years. This approach yields more conservative estimates than estimates that solely cluster on counties, reflecting that there are unobserved shocks to outcomes that span counties.

additional facilities lead to increases in treatment admissions and that the effects of additional facilities are greatest for causes of death that are most closely related to drug abuse.[21] Importantly, a third of all treatment admission are court-ordered, often as an alternative to incarceration. As such, increases in admissions due to an additional SAT facility may correspond with more drug offenders in public, leading to estimates that understate any decreases in drug-related criminal activity.

To address concerns regarding reverse causality, Swensen plots drug-induced mortality rates leading up to and following changes in the number of facilities and finds no evidence of systematic deviations of drug-related mortality from expected levels prior to changes in the number of facilities. Furthermore, his estimates from models that consider additional lags and leads of treatment facilities show that the that previous- and current-year changes in the number of facilities is significantly related to drug-induced mortality, but that drug-induced mortality is not related to the number of facilities in future periods.[22] In a similar fashion, we estimate a version of Eq. (1) that also considers the effect of the number of facilities in the current, previous and subsequent years on the outcomes that are the focus of this paper. The results of this analysis, discussed in more detail below, indicate that changes in the number of treatment facilities are also not driven by recent changes in drug abuse or crime. That said, we note that our estimates would understate the benefits of SAT facilities if they opened in response to recent increases in drug abuse and related crimes.

5 Results

5.1 Revisiting the Effects of SAT Facilities on Drug-Induced Mortality

We begin our analysis of the effects of SAT facilities by documenting their effects on serious drug abuse measured by drug-induced mortality rates at the county level. Specifically, we expand on Swensen's (2015) analysis by adding four additional years of restricted-use NCHS mortality data to bring it in line with the years of data used in our analysis of crime, which run through 2012.

[21]Swensen uses data on admissions into facilities receiving public funding to offer "proof of concept" that increases in treatment facilities leads to a change in an underlying factor associated with treatment. Notably, other mechanisms—including perceptions toward treatment or factors influencing the quality and accessibility treatment—may also contribute to declines in substance abuse as treatment services expand.

[22]Swensen also estimates models using demand-side characteristics to predict treatment facility openings in order to offer insight into the degree to which treatment provision responds to changes in the demand for addictive substances. His results suggest that the number of treatment facilities varies directly with measures that proxy for the demand for addictive substances, he argues that not adequately accounting for these correlations would understate the effect of an additional treatment facility on drug-related mortality.

In Table 2, we show the results of this analysis, using logged drug-induced mortality rates as the outcome. Columns 1–5 report the estimates from increasingly flexible specifications: Column 1 shows estimates based on a model that only includes county and year fixed effects; Column 2 shows estimates that additionally control for state-by-year fixed effects; and Columns 3–5 show estimates that additionally control for county-level time-varying measures of demographics, economic conditions, and the size of the police force.[23] With the exception of the Column 1 estimate, which omits controls for state-by-year fixed effects, the estimates are precise and similar in magnitude across specifications. They indicate a 0.50 percent decline in drug-induced mortality rates associated with an additional SAT facility in a county.[24] This estimate is very similar to the estimated effect of 0.42 percent reported in Swensen (2015).

5.2 Estimated Effects on Crime

5.2.1 Homicides

Before turning to estimates that are based on Uniform Crime Reports data, we begin our analysis of crime by analyzing homicide deaths recorded in NCHS mortality data. Though these also include justified homicides, 94 percent are unjustified criminal homicides and, as such, they can shed light on the degree to which treatment interventions affect the most serious and costly form of criminal activity.[25] The results of this analysis, shown in the first panel of Table 3, provide causal evidence that county-level homicide rates are reduced by SAT facilities. Specifically, the estimates indicate a 0.24 percent decline in intentional homicide death rates associated with an additional SAT facility.

In the second and third panels of Table 3 we investigate the effects on homicide rates using law-enforcement-agency-level data from the UCR's Offenses Known and Supplemental Homicide Reports databases, respectively. We continue to estimate the same models when using these data, but use agency fixed effects instead of county fixed effects and use agency covered population as the denominator to construct homicide rates. Analyses of these data continue to indicate that SAT facilities significantly reduce homicides in areas covered by municipal law-enforcement agencies, though the estimates are somewhat smaller, indicating a 0.18 percent decline in intentional homicide death rates associated with an additional SAT facility.

[23] Controls for county economic conditions are the unemployment rate and firm births; controls for demographics are the fraction of the population that is white, fraction black, fraction male, fraction 0–9 years old, fraction 10–19 years old, ... , fraction 60–69 years old.

[24] Percent effects are calculated as $(e^{\beta} - 1) \times 100\%$.

[25] For a breakdown of justified and unjustified homicides in 2013, see https://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2013/crime-in-the-u.s.-2013/offenses-known-to-law-enforcement/expanded-homicide

As described in Section 4, in all of our analyses we add one to outcome counts before constructing log rates to avoid dropping area-year observations for which the outcome would otherwise be undefined. We acknowledge that this transformation could introduce bias, especially for an outcome like the homicide rate which tends to be relatively low. Out of concern for this possibility, in Section 5.4 we will present estimates for each outcome based on an alternative approach in which we do not add one to outcome counts and we instead focus on areas for which outcome counts are positive in every year. These estimates are almost identical to our main results for nearly all of the outcomes we consider, including the overall homicide rate.

5.2.2 Homicides by Relationship

In Table 4, we report the results of analyses that exploit the details available in the SHR data to separately consider homicides involving different victim-offender relationships. In particular, we explore the degree to which the reduction in homicides associated with SAT facilities (reported in Table 3) are driven by reductions in homicides committed by individuals who were friends or acquaintances of the victim, homicides committed by strangers, homicides committed by family members, and/or homicides in which the victim-offender relationship was not established by law enforcement. Victim-offender relationships can provide useful information regarding the nature of homicide incidents. For instance, investigators were unable to establish victim-offender relationships in 43 percent of homicides in our sample. These "uncleared" incidents are more likely to be gang, drug-related, and stranger homicides.[26] When the victim-offender relationship is known, friend groups account for 44 percent, strangers for 29 percent, and family for 27 percent of homicides.

The results shown in Table 4 suggest that the effects of SAT facilities on homicides are concentrated among homicide incidents in which the relationship to the offender was unknown or in which the offender was a friend. Specifically, these estimates indicate that an additional treatment facility leads to a 0.14 percent decline in "uncleared" homicides and a 0.26 percent decline in homicides where the offender was a friend of the victim. There is no evidence of effects on homicides committed by family members.

[26] The fraction of homicides with an "unknown" victim-offender relationship has steadily increased over the past several decades which has been attributed to the changing nature of homicides. Drug-related homicides in particular are less likely to be cleared (Riedel, 2008; Quinet and Nunn, 2014).

5.2.3 Violent Crimes More Broadly

Having established that SAT facilities reduce severe drug abuse and reduce the most costly of crimes (homicides), we next consider the degree to which treatment facilities affect other types of violent crimes. In Table 5 we show a detailed breakdown of the effects of SAT facilities on violent crimes based on analyses of the UCR Offenses Known data. While we focus our discussion below on the point estimates from models with the richest set of controls (Column 5), we note that the estimated effects are similar across specifications once state-by-year fixed effects and demographic controls are included as covariates. The estimates are not sensitive to the inclusion of other county-year control variables.

Across the first four panels of Table 5, we sequentially report the estimated effects on violent crimes of decreasing severity according to social cost estimates reported in McCollister, French and Fang (2010): homicides ($9,881,198 per incident), sexual assault ($264,854), aggravated assault ($117,722), and simple assault.[27] We defer our consideration of robbery until the next section where we focus on financially motivated crimes. As mentioned above, the estimated effect on homicides indicates a significant reduction caused by SAT facilities. While the point estimate for the effect on sexual assault is also negative, suggesting that SAT facilities reduce sexual assault as well, it is not close to being statistically significant at conventional levels. The estimated effect on aggravated assaults also suggests a reduction in crime associated with SAT facilities, though this estimate is only marginally statistically significant. Finally, the estimates suggest no effect on simple assaults.

The mixed findings described above naturally raise the question of whether there is a "general effect" of SAT facilities on violent crime, or whether the significant effects we document are a result of random chance which becomes increasingly likely as one considers a larger set of outcomes. As described in Anderson (2008), this issue can be addressed through the analysis of summary indices that are invariant to the number of outcomes considered. We take this approach across the final three panels of Table 5 as we consider violent crimes in the aggregate. First, we estimate the effect on all violent crimes and do not find a significant effect. This is not surprising because we did not find evidence of effects on simple assaults, which represent 77 percent of the crimes considered. Second, we estimate the effect on all violent crimes that are typically considered felonies. This approach amounts to excluding simple assaults from the analysis, which encompass any attempted

[27] Note that we have adjusted the cost estimates for inflation to put the amounts in 2016 dollars. McCollister, French and Fang (2010) do not include estimates for simple assault.

or completed physical contact with malicious intent that does not rise to the level of severity to constitute an aggravated assault. The results of this analysis indicate a statistically significant effect of SAT facilities on felony-type violent crimes.

Finally, we estimate the effects on overall violent crime weighted by the social cost estimates associated with each of the violent crimes considered. Specifically, we use the log of the inflation-adjusted cost estimates put into 2016 dollars from McCollister, French, and Fang (2010). As McCollister, French, and Fang (2010) do not estimate the social cost of simple assault, we calculate the cost of simple assaults as 20 percent of the cost of aggravated assaults, which is consistent with Cohen and Piquero (2009).[28] The estimates indicate a 0.15 percent decline in the social costs associated with violent crime (excluding robbery). A back-of the envelope calculation based on this estimate suggests that an additional treatment facility decreases social costs associated with these crimes by approximately $615,000 annually.[29]

5.2.4 Financially Motivated Crimes

Table 6 shows the estimated effects on financially motivated crimes. We again sequentially report the estimated effects on crimes of decreasing severity according to social cost estimates: robbery ($46,541), motor vehicle theft ($11,849), burglary ($7,108), and larceny ($3,885). As with the estimated effects on violent crimes, these estimates suggest more pronounced effects of SAT facilities on relatively serious crimes. The point estimates indicate that a SAT facility reduces robbery by 0.11 percent, motor vehicle theft by 0.12 percent, burglary by 0.05 percent, and larceny by 0.04 percent. The estimated effects on burglary and larceny are not statistically significant at conventional levels.

Our estimates of financially motivated crimes in the aggregate provide further evidence that SAT facilities reduce crime. The estimated effect on financially motivated crimes overall is almost the same as the estimated effect on larceny, which is not surprising since these crimes represent 65 percent of the crimes considered, and yields a p-value of 0.0720. Excluding larceny theft, which is often considered a misdemeanor offense, our estimates indicate that a SAT facility reduces financially motivated crimes by 0.08 percent (p-value = 0.0214). Finally and similar to our approach to violent crimes, we consider the log of the social costs of financially motivated crimes as a dependent variable. These estimates indicate that an additional SAT facility reduces social costs attributed

[28] In Appendix Table A2, we show results that use a social cost of simple assault set at varying fractions of the social cost of aggravated assault. Appendix Table A1 shows the corresponding summary statistics.

[29] This calculation is based on average annual social costs of violent crime totaling $1,273,156 per 1,000 people each year in the average agency jurisdiction and an average population covered of 321,685.

to financially motivated crime by 0.07 percent annually. In dollar terms, this estimate suggests an approximate annual $60,000 decline in the social costs of financially motivate crimes.[30]

5.2.5 Analysis of All Crimes Combined

The estimates in Tables 5 and 6 provide evidence that county-level expansions in treatment facilities significantly reduce both violent and financially motivated crimes and that the effects are concentrated among more serious types of these crimes. In Table 7 we present estimates that pool violent and financially motivated crimes together so that the estimates reflect the effects on overall crime. The first panel shows the effect of SAT facilities on all crime including the less serious crimes of simple assault and larceny, which account for 68 percent of all crimes considered. The estimates suggest a marginally significant 0.004 percent decline in crime associated with an additional SAT facility. Considering all felony-type crimes in the second panel, which excludes simple assault and larceny, the estimates indicate an effect of 0.010 percent. In the third panel, we report the estimated effects on the log of the social costs of crime, which weights each crime by its estimated social cost estimate as before. These estimates indicate that an additional SAT facility reduces social costs attributed to all crime by 0.14 percent annually, which corresponds to approximately $700,000.[31]

5.3 Assessing Endogeneity and Lag Structure

As discussed in Section 4, the main threat to the validity of our empirical strategy is the possibility that changes in the number of facilities in an area might be driven by trends in the outcomes we consider (or the correlates thereof) and/or recent shocks to the outcomes we consider (or the correlates thereof). To the degree to which such trends and/or shocks occur at the state level or relate to changing demographics, economic conditions, or the size of police forces, they should be captured by state-year fixed effects and the control variables included in our analysis. As this is fundamentally untestable, we propose a test of the validity of our identification strategy based on examining the lead and lag structure of the estimated effects. Specifically, we estimate versions of Eq. (1) that consider the link between our outcome variables and the number of SAT facilities in a county *in a future year*.

We also expand on Eq. (1) to consider contemporaneous versus lagged measures of SAT fa-

[30]This calculation is based on average annual social costs of financially-motivated crime totaling $278,382 per 1,000 people each year in the average agency jurisdiction and an average population covered of 321,685.

[31]This calculation is based on average annual social costs of crime totaling $1,551,538 per 1,000 people each year in the average agency jurisdiction and an average population covered of 321,685.

cilities. We do so in order to evaluate our choice to focus on the number of facilities in the prior year as our main variable of interest, a choice we made to avoid attenuation bias that would likely be caused by the fact that newly opened (or closed) facilities would only affect counties for some fraction of the year.

Table 8 shows estimates of this type for all of the outcomes considered across Tables 2 through 7. Specifically, it shows estimates based on our richest model while additionally considering the number of facilities in the current year and in the future year. Across the 24 outcomes we consider, the estimated effects of the number of facilities one year in the future is *never* statistically significant. We interpret these results as evidence that reverse causality, or the possibility that changes in the number of SAT facilities may be driven by recent changes in drug abuse and related outcomes, is not a major concern. As such, these results provide support for a causal interpretation of our main results.

These results also provide support for our focus on the lagged measure of facilities. In particular, where we see significant effects on outcomes, it is always the case that the number of treatment facilities in the prior year has a stronger effect than the number of treatment facilities in a given year. Moreover, the estimated effects of the number of treatment facilities in the current year is usually not statistically significant.

Further results along these lines are presented in Appendix Tables A3 through A8. In these tables, we reproduce our main estimates in Column 1 for ease of comparison; in Column 2 we simultaneously consider the estimated effects of the number of SAT facilities in the preceding two years on current year outcomes; in Column 3 we simultaneously consider the estimated effects of the number of SAT facilities in the current year and the prior year on current year outcomes; and in Column 4, we simultaneously consider the estimated effects of the number of SAT facilities in the prior year, current year, and one year in the future, on current year outcomes (as in Table 8). The results of these analyses lead to the same conclusions as before. We also note that they sometimes indicate that the number of facilities two years prior is more strongly related to current year outcomes than the number of facilities on year prior, which suggests an important avenue for future work in exploring the effects of SAT facilities over time through alternative methodologies.

5.4 Alternative Empirical Approach

As an additional test of the robustness of our estimates, in Table 9 we show the estimated effects for each outcome based on the subset of areas for which the log outcome rate can be defined in each year without adding one.[32] For nearly all of the outcomes we consider, these estimates are virtually the same in both statistical and economic significance. The one exception is the homicide rate estimates by victim-offender relationship. For these outcomes, this approach produces estimated effects that are larger in magnitude for homicides in which the relationship is unknown and homicides committed by friends. As before, these are statistically significant while the estimated effects on homicides committed by strangers and family members are not.

6 Discussion and Conclusion

In the preceding sections, we document statistically and economically significant effects of SAT facilities on drug-related mortality and on several categories of crime. The updated estimates we provide for the effects on county-level drug-related mortality suggest that an additional SAT facility reduces drug-related mortality by 0.50 percent annually. Based on a value of 7 to 8 million dollars per expected life saved, the estimate implies a decline in a county's annual drug-related mortality costs by 4.2 to 4.8 million dollars.[33,34] Our estimates of the effects on agency-level crime indicate that an additional facility in a county reduces municipal felony-type crimes by 0.10 percent annually. In conjunction with social-cost-of-crime estimates from McCollister, French, and Fang (2010), our estimates indicate that an additional SAT facility in a county reduces municipal crime costs by 0.14 percent annually, which corresponds to approximately $700,000 per municipality. Given an average of 6 municipal governments in each county, this suggests a decline in annual costs of county-level crime by approximately 4.2 million dollars for each additional facility. In total, these cost calculations suggest that the county-level benefits of an additional facility—in terms of drug-related mortality and criminal activity—are between 8.4 and 9 million dollars.

To compare these benefits to the annual costs of treatment at each facility, we can consider the average number of annual treatment admissions (255) from the National Survey of Substance Abuse Treatment Services (N-SSATS), and treatment modality-specific cost estimates from French, Popovici, and Tapsell (2008).[35] A back-of-the-envelope calculation indicates that the annual costs

[32] As such, the set of areas contributing to the estimates varies across outcomes, with fewer areas contributing to the estimates focusing on rarer outcomes such as homicides.

[33] This estimate is based on 10.9 drug-related deaths per 100,000 and an an average weighted county population of 1.09 million.

[34] Kniesner et al. (2010) suggest a 7 to 8 million dollar value of a statistical life (VSL) for health and safety regulation cost-benefit analyses, which is consistent with median VSL estimates from meta analysis of existing VSL research (Viscusi and Aldy, 2003).

[35] Estimates from French, Popovici, and Tapsell (2008) include all treatment delivery costs related to personnel, supplies and materials, contracted services, buildings and facilities, equipment, and miscellaneous items.

of treatment for a SAT facility are approximately 1.1 million dollars.[36] These calculations suggest that the benefits of expanding treatment facilities far outweigh the associated treatment costs.

While our data do not allow us to establish a direct link between substance-abuse treatment and incidents, the results of our analyses provide support for the idea that there are broad-based benefits of SAT facilities in terms of public safety. This evidence is in contrast to not-in-my-backyard arguments that have been used to hinder attempts to expand access to SAT through additional facilities. That said, an important limitation of our research design is that it identifies effects of having an additional SAT facility *in the county*, which could mask heterogeneous effects for areas in a county that are nearer versus farther from such a facility. Assessing whether such heterogeneity exists would seem to be an important avenue for future research.

[36] We use the annual number of treatment admissions reported in Swensen (2015) based on the 2002-2008 N-SSATS data. More recent N-SSATS data do not include treatment admissions information. To calculate the total cost of treatment at a SAT facility, we use the median of the cost bands reported for each modality in French Popovici, and Tapsell weighted by the proportion of total admissions accounted for by each modality as reported in the 2013 N-SSATS reports.

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Table 1
Summary Statistics

	Mean	Std Dev
Substance Abuse Treatment Facilities (2,454 counties)		
Total	49.5	90.0
Net Openings	5.8	10.1
Net Closings	3.7	4.4
Facilities per 100,000	5.0	3.6
NCHS Mortality Files (2,454 counties)		
Drug Deaths per 100,000	10.9	6.7
Homicides per 100,000	5.9	5.2
UCR Offenses Known Database (2,156 counties, 9,139 agencies)		
Violent Crimes per 100,000	1461.8	1074.5
Felony-Type Violent Crimes per 100,000	343.3	301.0
Financially-Motivated Crimes per 100,000	3867.8	21.96.3
Felony-Type Financially-Motivated Crimes per 100,000	1343.1	992.4
Homicides per 100,000	5.7	8.3
Sexual Assaults per 100,000	31.9	26.6
Aggravated Assaults per 100,000	232.5	421.8
Robbery per 100,000	164.5	178.3
Simple Assaults per 100,000	1118.6	872.9
Burglary per 100,000	757.7	517.5
Larceny per 100,000	2524.7	1450.7
Motor Vehicle Theft per 100,000	420.9	456.4
UCR Supplementary Homicide Reports (1,764 counties, 5,202 agencies)		
Homicides per 100,000	6.2	8.7
Homicides with unknown victim-perpetrator relationship per 100,000	2.6	5.3
Homicides committed by friend groups per 100,000	1.5	2.8
Homicides committed by strangers per 100,000	1.0	1.8
Homicides committed by family members per 100,000	0.9	2.0

Notes: These data span 1999-2012. The means and standard deviations for the substance-abuse treatment facilities are derived from the NCHS Mortality sample. The reported facility statistics are similar when using the UCR Known Offenses sample and the UCR Supplementary Homicide Reports sample. The means and standard deviations from the NCHS Restricted Mortality Files represent rates per 100,000 residents in each county and are weighted by county population. The means and standard deviations for the UCR Offenses Known Database and UCR Supplementary Homicide Reports represent rates per 100,000 residents covered by the municipal law enforcement agency and are weighted by agency population coverage.

Table 2
Estimated Effects of SAT Facilities on Log Drug-Related Mortality Rates

	(1)	(2)	(3)	(4)	(5)
Facilities Last Year	-0.0029*	-0.0051***	-0.0051***	-0.0050***	-0.0050***
	(0.0013)	(0.0010)	(0.0011)	(0.0010)	(0.0010)
County and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: Estimates are based on 31,882 county-year observations. Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by county population. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 3
Estimated Effects of SAT Facilities on Log Homicide Rates

	(1)	(2)	(3)	(4)	(5)
Homicide Data: NCHS Restricted Mortality Files					
Facilities Last Year	-0.0025***	-0.0031***	-0.0026***	-0.0024***	-0.0024***
	(0.0007)	(0.0005)	(0.0005)	(0.0004)	(0.0004)
Homicide Data: UCR Offenses Known Database					
Facilities Last Year	-0.0023***	-0.0024***	-0.0018***	-0.0018***	-0.0018***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Homicide Data: UCR Supplementary Homicide Reports					
Facilities Last Year	-0.0023***	-0.0024***	-0.0018***	-0.0017***	-0.0018***
	(0.0005)	(0.0003)	(0.0004)	(0.0004)	(0.0004)
County/Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: Estimates are based on 31,882 county-year observations for the NCHS Restricted Mortality Files, 92,145 agency-year observations for the UCR Offenses Known Database, and 57,609 agency-year observations for the UCR Supplementary Homicide Reports. Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by county population when using the NCHS Mortality data and are weighted by agency population coverage when using the UCR Offenses Known data and the UCR Supplementary Homicide Reports.
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 4
Estimated Effects of SAT Facilities on Log Homicide Rates by Relationship

	(1)	(2)	(3)	(4)	(5)
Unknown victim-perpetrator relationship					
Facilities Last Year	-0.0018***	-0.0022***	-0.0015**	-0.0014**	-0.0014**
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Homicides committed by friend groups					
Facilities Last Year	-0.0028***	-0.0031***	-0.0024***	-0.0025***	-0.0026***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Homicides committed by strangers					
Facilities Last Year	-0.0019***	-0.0014**	-0.0009	-0.0008	-0.0009
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Homicides committed by family members					
Facilities Last Year	-0.0007	-0.0004	-0.0001	-0.0000	-0.0001
	(0.0011)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: Estimates are based on 57,609 agency-year observations. Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 5
Estimated Effects of SAT Facilities on Log Violent Crime Rates

	(1)	(2)	(3)	(4)	(5)
Homicides					
Facilities Last Year	-0.0023***	-0.0024***	-0.0018***	-0.0018***	-0.0018***
	(0.0005)	(0.0005)	(0.0004)	(0.0004)	(0.0004)
Sexual Assaults					
Facilities Last Year	-0.0011**	-0.0005	-0.0005	-0.0005	-0.0006
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Aggravated Assaults					
Facilities Last Year	-0.0034***	-0.0023***	-0.0013*	-0.0013*	-0.0014*
	(0.0009)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Simple Assaults					
Facilities Last Year	-0.0004	0.0005	0.0001	0.0001	0.0000
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
All Violent Crimes					
Facilities Last Year	-0.0015***	-0.0006	-0.0004	-0.0004	-0.0005
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Felony-type Violent Crimes					
Facilities Last Year	-0.0032***	-0.0022***	-0.0013**	-0.0013**	-0.0014**
	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0006)
Estimated Social Costs Associated with All Violent Crimes					
Facilities Last Year	-0.0025***	-0.0020***	-0.0015***	-0.0015***	-0.0015***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: Estimates are based on 92,145 agency-year observations. Social costs for homicides, sexual assault, and aggravated assault come from McCollister, French, and Fang (2010). We set the cost of simple assaults equivalent to 20% of the cost of aggravated assaults consistent with Cohen and Piquero (2009). Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 6
Estimated Effects of SAT Facilities on Log Financially-Motivated Crime Rates

	(1)	(2)	(3)	(4)	(5)
Robbery Total					
Facilities Last Year	-0.0015***	-0.0019***	-0.0012***	-0.0011***	-0.0011***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Motor Vehicle Theft					
Facilities Last Year	-0.0007	-0.0020***	-0.0013**	-0.0012**	-0.0012**
	(0.0009)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Burglary Total					
Facilities Last Year	-0.0012***	-0.0010***	-0.0006*	-0.0005	-0.0005
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Larceny Theft					
Facilities Last Year	-0.0004	0.0001	-0.0004	-0.0004	-0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
All Financially-Motivated Crimes					
Facilities Last Year	-0.0006*	-0.0007**	-0.0004*	-0.0004*	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Felony-type Financially-Motivated Crimes					
Facilities Last Year	-0.0013*	-0.0015***	-0.0009**	-0.0008**	-0.0008**
	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Estimated Social Costs Associated with All Financially-Motivated Crimes					
Facilities Last Year	-0.0009**	-0.0012***	-0.0007***	-0.0007***	-0.0007***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: Estimates are based on 92,145 agency-year observations. We use social costs from McCollister, French, and Fang (2010). Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 7
Estimated Effects of SAT Facilities on Log of Combined Crime Rates

	(1)	(2)	(3)	(4)	(5)
All Crimes					
Facilities Last Year	-0.0008**	-0.0006**	-0.0004	-0.0003	-0.0004*
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Felony-Type Crimes					
Facilities Last Year	-0.0017***	-0.0017***	-0.0010***	-0.0010***	-0.0010***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Estimated Social Costs Associated with All Crimes					
Facilities Last Year	-0.0022***	-0.0019***	-0.0014***	-0.0014***	-0.0014***
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: All crimes consists of homicide, sexual assaults, aggravated assaults, simple assaults, robbery, larceny, burglary, motor vehicle theft and attempts to commit said crimes. Felony-type crimes consists of homicide, sexual assaults, aggravated assaults, robbery, burglary, motor vehicle theft and attempts. We use social costs from McCollister, French, and Fang (2010). We set the social cost of simple assault equivalent to 20% the cost of aggravated assaults consistent with Cohen and Piquero (2009). Estimates are based on 92,145 agency-year observations. Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 8

Expanding Model To Additionally Consider Contemporaneous and Future Facility Counts

	Drug-Related Mortality	Homicide (NCHS Data)	Homicide (UCR Data)	Homicide (SHR Data)	Homicide Unknown Offender	Homicide Friend Offender	Homicide Stranger Offender	Homicide Family Offender	Sexual Assault	Aggravated Assault	Simple Assault	All Violent Crimes
Facilities Last Year	-0.0030**	-0.0014*	-0.0018**	-0.0021***	-0.0014	-0.0032***	-0.0011	-0.0001	-0.0008	-0.0020**	-0.0000	-0.0007*
	(0.0010)	(0.0007)	(0.0007)	(0.0005)	(0.0012)	(0.0008)	(0.0010)	(0.0011)	(0.0006)	(0.0007)	(0.0004)	(0.0004)
Facilities This Year	-0.0024	-0.0006	0.0004	0.0005	-0.0003	0.0017	-0.0000	-0.0001	-0.0001	0.0014	-0.0003	0.0004
	(0.0013)	(0.0010)	(0.0008)	(0.0007)	(0.0011)	(0.0016)	(0.0011)	(0.0013)	(0.0006)	(0.0008)	(0.0004)	(0.0004)
Facilities Next Year	-0.0007	-0.0010	-0.0006	-0.0001	-0.0005	-0.0016	-0.0004	0.0002	0.0005	-0.0011	0.0004	-0.0003
	(0.0014)	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0017)	(0.0011)	(0.0013)	(0.0006)	(0.0007)	(0.0004)	(0.0003)

	Felony Violent Crimes	Social Costs of Violent Crimes	Robbery	Motor Vehicle Theft	Burglary	Larceny Theft	All Financial Crimes	Felony Financial Crimes	Social Costs of Financial Crimes	All Crimes	All Felony Crimes	Social Costs of All Crimes
Facilities Last Year	-0.0020**	-0.0017***	-0.0011***	-0.0009	-0.0007*	-0.0011	-0.0004*	-0.0009*	-0.0007**	-0.0005**	-0.0012**	-0.0015***
	(0.0007)	(0.0005)	(0.0003)	(0.0007)	(0.0004)	(0.0014)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0004)	(0.0004)
Facilities This Year	0.0012	0.0006	0.0003	-0.0002	0.0004	0.0000	-0.0000	0.0002	0.0001	0.0000	0.0004	0.0005
	(0.0008)	(0.0005)	(0.0004)	(0.0009)	(0.0004)	(0.0016)	(0.0003)	(0.0006)	(0.0004)	(0.0003)	(0.0006)	(0.0005)
Facilities Next Year	-0.0010	-0.0007	-0.0004	-0.0007	-0.0003	0.0011	0.0001	-0.0004	-0.0002	-0.0000	-0.0005	-0.0006
	(0.0006)	(0.0006)	(0.0004)	(0.0006)	(0.0003)	(0.0016)	(0.0003)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	0.0005

Notes: Outcomes are in log rates. All estimates control for county fixed effects, year fixed effects, state-by-year fixed effects, demographic controls, economic controls, and the size of the police force in the area. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by the population represented by each cell.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 9

Estimates Restricting Sample to Areas Reporting Positive Counts in All Years

	Drug-Related Mortality	Homicide (NCHS Data)	Homicide (UCR Data)	Homicide (SHR Data)	Homicide Unknown Offender	Homicide Friend Offender	Homicide Stranger Offender	Homicide Family Offender	Sexual Assault	Aggravated Assault	Simple Assault	All Violent Crimes
Facilities Last Year	-0.0055***	-0.0023***	-0.0019***	-0.0017*	-0.0032**	-0.0040**	0.0022	-0.0008	-0.0007	-0.0014**	0.0002	-0.0005
	(0.0012)	(0.0004)	(0.0006)	(0.0008)	(0.0011)	(0.0018)	(0.0034)	(0.0035)	(0.0006)	(0.0006)	(0.0004)	(0.0004)

	Felony Violent Crimes	Social Costs of Violent Crimes	Robbery	Motor Vehicle Theft	Burglary	Larceny Theft	All Financial Crimes	Felony Financial Crimes	Social Costs of Financial Crimes	All Crimes	All Felony Crimes	Social Costs of All Crimes
Facilities Last Year	-0.0013**	-0.0015***	-0.0010***	-0.0012**	-0.0005	-0.0001	-0.0004*	-0.0008**	-0.0007**	-0.0004	-0.0010**	-0.0014***
	(0.0006)	(0.0004)	(0.0002)	(0.0005)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0003)

Notes: Outcomes are in log rates. All estimates control for county fixed effects, year fixed effects, state-by-year fixed effects, demographic controls, economic controls, and the size of the police force in the area. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by the population represented by each cell.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Appendix

Table A1
Summary Statistics for the Social Costs of Crimes

	Mean	St Dev	Cost per Crime (2016 dollars)
UCR Offenses Known Database (2,156 counties, 9,139 agencies)			
Homicides	565,481	822,074	9,881,197
Sexual Assaults	84,523	70,433	264,853
Aggravated Assaults	359,777	331,942	117,722
Robbery	76,557	82,994	46,541
Simple Assaults	263,375	205,508	$117{,}722 \times 0.2$
Burglary	53,862	36,788	7,108
Larceny	98,090	56,363	3,885
Motor Vehicle Theft	49,873	54,081	11,849
All Crimes	1,551,538	1,349,029	
Violent Crimes	1,273,156	1,195,357	
Felony-Type Violent Crimes	1,009,781	1,082,884	
Financially-Motivated Crimes	278,382	188,874	
Felony-Type Financially-Motivated Crimes	180,292	153,461	

Notes: We use social costs from McCollister, French, and Fang (2010). We set the social cost of simple assault equivalent to 20% the cost of aggravated assaults consistent with Cohen and Piquero (2009). The means and standard deviations represent rates per 1,000 agency population coverage-year and are weighted by agency population coverage.

Table A2

Estimated Effects on the Log of Violent Crime Costs Using Alternative Costs for Simple Assaults

	(1)	(2)	(3)	(4)	(5)
Simple Assault Social Cost = 40% of Aggravated Assaults Social Cost					
Facilities Last Year	-0.0023***	-0.0017***	-0.0013***	-0.0013***	-0.0014***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Simple Assault Social Cost = 20% of Aggravated Assaults Social Cost					
Facilities Last Year	-0.0025***	-0.0020***	-0.0015***	-0.0015***	-0.0015***
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Simple Assault Social Cost = 0% of Aggravated Assaults Social Cost					
Facilities Last Year	-0.0026***	-0.0023***	-0.0016***	-0.0016***	-0.0017***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Agency and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
State-by-year Fixed Effects	No	Yes	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes	Yes
Economic Controls	No	No	No	Yes	Yes
Officer Rate per 1,000	No	No	No	No	Yes

Notes: McCollister, French, and Fang (2010) do not estimate a social cost estimate for simple assaults. This table considers alternative measures for costs of simple assaults. Cohen and Piquero (2009) estimated simple assaults to have a social cost of 20% of aggravated assaults. Estimates are based on 92,145 agency-year observations. Demographic control variables include the fraction of the population that are: white, black, male, ages 0–9, ages 10–19, ages 20–29, ages 30–39, ages 40–49, ages 50–59, and ages 60–69. Controls for economic conditions include the county unemployment rate and number of firm births. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A3

Estimated Effects on Log of Drug-Related Mortality Rates, Lags and Lead

	(1)	(2)	(3)	(4)
Facilities 2 Years Ago		-0.0008		
		(0.0011)		
Facilities Last Year	-0.0050***	-0.0046**	-0.0032***	-0.0030**
	(0.0010)	(0.0016)	(0.0009)	(0.0010)
Facilities This Year			-0.0024**	-0.0024
			(0.0011)	(0.0013)
Facilities Next Year				-0.0007
				(0.0014)
N	31882	29424	31882	29423

Notes: Column 1 reproduces the estimate shown in Column 5 of Table 2. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by county population.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A4
Estimated Effects on Log Homicide Rates, Lags and Lead

	(1)	(2)	(3)	(4)
NCHS Restricted Mortality Files				
Facilities 2 Years Ago		-0.0008		
		(0.0006)		
Facilities Last Year	-0.0024***	-0.0017**	-0.0016**	-0.0014*
	(0.0004)	(0.0007)	(0.0005)	(0.0007)
Facilities This Year			-0.0011**	-0.0006
			(0.0004)	(0.0010)
Facilities Next Year				-0.0010
				(0.0009)
N	31882	29424	31882	29423
UCR Offenses Known Database				
Facilities 2 Years Ago		-0.0003		
		(0.0005)		
Facilities Last Year	-0.0018***	-0.0017***	-0.0019***	-0.0018**
	(0.0004)	(0.0005)	(0.0006)	(0.0007)
Facilities This Year			0.0001	0.0004
			(0.0005)	(0.0008)
Facilities Next Year				-0.0006
				(0.0008)
N	92145	80050	92145	80118
UCR Supplementary Homicide Report				
Facilities 2 Years Ago		-0.0001		
		(0.0005)		
Facilities Last Year	-0.0018***	-0.0017***	-0.0020***	-0.0021***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)
Facilities This Year			0.0004	0.0005
			(0.0004)	(0.0007)
Facilities Next Year				-0.0001
				(0.0008)
N	57609	53777	57609	52846

Notes: Column 1 reproduces the estimate shown in Column 5 of Table 3. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by county population for the NCHS Mortality Files and are weighted by agency population coverage for the UCR Offenses Known Database and the UCR Supplementary Homicide Report.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A5

Estimated Effects on Log Homicide Rates by Relationship, Lags and Lead

	(1)	(2)	(3)	(4)
Unknown victim-perpetrator relationship				
Facilities 2 Years Ago		0.0004		
		(0.0010)		
Facilities Last Year	-0.0014**	-0.0018	-0.0014	-0.0014
	(0.0006)	(0.0012)	(0.0010)	(0.0012)
Facilities This Year			0.0001	-0.0003
			(0.0008)	(0.0011)
Facilities Next Year				0.0005
				(0.0010)
Homicides committed by friend groups				
Facilities 2 Years Ago		-0.0013		
		(0.0012)		
Facilities Last Year	-0.0026***	-0.0015	-0.0034***	-0.0032***
	(0.0005)	(0.0011)	(0.0008)	(0.0008)
Facilities This Year			0.0012	0.0017
			(0.0008)	(0.0016)
Facilities Next Year				-0.0016
				(0.0017)
Homicides committed by strangers				
Facilities 2 Years Ago		-0.0008		
		(0.0015)		
Facilities Last Year	-0.0009	-0.0002	-0.0011	-0.0011
	(0.0006)	(0.0016)	(0.0008)	(0.0010)
Facilities This Year			0.0003	-0.0000
			(0.0007)	(0.0011)
Facilities Next Year				0.0004
				(0.0011)
Homicides committed by family members				
Facilities 2 Years Ago		-0.0001		
		(0.0009)		
Facilities Last Year	-0.0001	0.0001	0.0002	-0.0001
	(0.0006)	(0.0010)	(0.0010)	(0.0011)
Facilities This Year			-0.0004	-0.0001
			(0.0008)	(0.0013)
Facilities Next Year				0.0002
				(0.0013)
N	57609	53777	57609	52846

Notes: Column 1 reproduces the estimate shown in Column 5 of Table 4. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A6
Estimated Effects on Log Violent Crime Rates, Lags and Lead

	(1)	(2)	(3)	(4)
Homicides				
Facilities 2 Years Ago		-0.0003		
		(0.0005)		
Facilities Last Year	-0.0018***	-0.0017***	-0.0019***	-0.0018**
	(0.0004)	(0.0005)	(0.0006)	(0.0007)
Facilities This Year			0.0001	0.0004
			(0.0005)	(0.0008)
Facilities Next Year				-0.0006
				(0.0008)
Sexual Assaults				
Facilities 2 Years Ago		-0.0001		
		(0.0007)		
Facilities Last Year	-0.0006	-0.0003	-0.0006	-0.0008
	(0.0005)	(0.0008)	(0.0006)	(0.0006)
Facilities This Year			0.0001	-0.0001
			(0.0005)	(0.0006)
Facilities Next Year				0.0005
				(0.0006)
Aggravated Assaults				
Facilities 2 Years Ago		-0.0017**		
		(0.0007)		
Facilities Last Year	-0.0014*	0.0001	-0.0013	-0.0020**
	(0.0006)	(0.0004)	(0.0007)	(0.0007)
Facilities This Year			-0.0001	0.0014
			(0.0006)	(0.0008)
Facilities Next Year				-0.0011
				(0.0007)
Simple Assaults				
Facilities 2 Years Ago		0.0002		
		(0.0004)		
Facilities Last Year	0.0000	0.0001	0.0002	-0.0000
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Facilities This Year			-0.0002	-0.0003
			(0.0004)	(0.0004)
Facilities Next Year				0.0004
				(0.0004)
All Violent Crimes				
Facilities 2 Years Ago		-0.0006**		
		(0.0002)		
Facilities Last Year	-0.0005	0.0002	-0.0003	-0.0007*
	(0.0004)	(0.0005)	(0.0004)	(0.0004)
Facilities This Year			-0.0002	0.0004
			(0.0004)	(0.0004)
Facilities Next Year				-0.0003
				(0.0003)
Felony-Type Violent Crimes				
Facilities 2 Years Ago		-0.0017**		
		(0.0006)		
Facilities Last Year	-0.0014**	0.0001	-0.0013*	-0.0020**
	(0.0006)	(0.0004)	(0.0007)	(0.0007)
Facilities This Year			-0.0001	0.0012
			(0.0005)	(0.0008)
Facilities Next Year				-0.0010
				(0.0006)
Estimated Social Costs Associated with All Violent Crimes				
Facilities 2 Years Ago		-0.0008**		
		(0.0003)		
Facilities Last Year	-0.0015***	-0.0009**	-0.0015**	-0.0017***
	(0.0004)	(0.0003)	(0.0005)	(0.0005)
Facilities This Year			-0.0000	0.0006
			(0.0003)	(0.0005)
Facilities Next Year				-0.0007
				(0.0006)
N	92145	80050	92145	80118

Notes: Column 1 reproduces the estimate shown in Column 5 of Table 5. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. We use social costs from McCollister, French, and Fang (2010). We set the social cost of simple assault equivalent to 20% the cost of aggravated assaults consistent with Cohen and Piquero (2009). Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.
*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A7

Estimated Effects on Log Financially-Motivated Crime Rates, Lags and Lead

	(1)	(2)	(3)	(4)
Robbery Total				
Facilities 2 Years Ago		-0.0016***		
		(0.0003)		
Facilities Last Year	-0.0011***	0.0003	-0.0011***	-0.0011***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)
Facilities This Year			-0.0001	0.0003
			(0.0003)	(0.0004)
Facilities Next Year				-0.0004
				(0.0004)
Motor Vehicle Theft				
Facilities 2 Years Ago		-0.0003		
		(0.0005)		
Facilities Last Year	-0.0012**	-0.0009	-0.0006	-0.0009
	(0.0005)	(0.0005)	(0.0007)	(0.0007)
Facilities This Year			-0.0009	-0.0002
			(0.0008)	(0.0009)
Facilities Next Year				-0.0007
				(0.0006)
Burglary Total				
Facilities 2 Years Ago		-0.0004		
		(0.0004)		
Facilities Last Year	-0.0005	-0.0001	-0.0005	-0.0007*
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Facilities This Year			-0.0000	0.0004
			(0.0003)	(0.0004)
Facilities Next Year				-0.0003
				(0.0003)
Larceny Theft (no MVT)				
Facilities 2 Years Ago		-0.0008		
		(0.0010)		
Facilities Last Year	-0.0004	0.0004	-0.0010	-0.0011
	(0.0005)	(0.0012)	(0.0014)	(0.0014)
Facilities This Year			0.0008	0.0000
			(0.0016)	(0.0016)
Facilities Next Year				0.0011
				(0.0016)
All Financially-Motivated Crimes				
Facilities 2 Years Ago		-0.0004*		
		(0.0002)		
Facilities Last Year	-0.0004*	0.0001	-0.0003	-0.0004*
	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Facilities This Year			-0.0001	-0.0000
			(0.0003)	(0.0003)
Facilities Next Year				0.0001
				(0.0003)
Felony-Type Financially-Motivated Crimes				
Facilities 2 Years Ago		-0.0006*		
		(0.0003)		
Facilities Last Year	-0.0008**	-0.0003	-0.0007	-0.0009*
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Facilities This Year			-0.0002	0.0002
			(0.0005)	(0.0006)
Facilities Next Year				-0.0004
				(0.0004)
Estimated Social Costs for All Financially-Motivated Crimes				
Facilities 2 Years Ago		-0.0006**		
		(0.0002)		
Facilities Last Year	-0.0007***	-0.0001	-0.0005*	-0.0007**
	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Facilities This Year			-0.0002	0.0001
			(0.0003)	(0.0004)
Facilities Next Year				-0.0002
				(0.0003)
N	92145	80050	92145	80118

Notes: Column 1 reproduces the estimate shown in Column 5 of Table 6. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. We use social costs from McCollister, French, and Fang (2010). Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table A8
Estimated Effects on Log of Combined Crime Rates, Lags and Lead

	(1)	(2)	(3)	(4)
All Crimes				
Facilities 2 Years Ago		-0.0004**		
		(0.0001)		
Facilities Last Year	-0.0004*	0.0001	-0.0002	-0.0005**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Facilities This Year			-0.0002	0.0000
			(0.0002)	(0.0003)
Facilities Next Year				-0.0000
				(0.0002)
Felony-Type Crimes				
Facilities 2 Years Ago		-0.0008**		
		(0.0003)		
Facilities Last Year	-0.0010***	-0.0002	-0.0009**	-0.0012**
	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Facilities This Year			-0.0002	0.0004
			(0.0004)	(0.0006)
Facilities Next Year				-0.0005
				(0.0003)
Estimated Social Costs Associated with All Crimes				
Facilities 2 Years Ago		-0.0008**		
		(0.0003)		
Facilities Last Year	-0.0014***	-0.0007**	-0.0013***	-0.0015***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Facilities This Year			-0.0001	0.0005
			(0.0003)	(0.0005)
Facilities Next Year				-0.0006
				(0.0005)
N	92145	80050	92145	80118

Notes: All crimes consists of homicide, sexual assaults, aggravated assaults, simple assaults, robbery, larceny, burglary, and motor vehicle theft. Felony-type crimes consists of homicide, sexual assaults, aggravated assaults, robbery, burglary, and motor vehicle theft. We use social costs from McCollister, French, and Fang (2010). We set the social cost of simple assault equivalent to 20% the cost of aggravated assaults consistent with Cohen and Piquero (2009). Column 1 reproduces the estimate shown in Column 5 of **Table 7**. Columns 2–4 are based on the same model with the inclusion of the additional variables highlighted in the table. Robust standard errors two-way clustered at the county and year levels are shown in parentheses. The regressions are weighted by agency population coverage.

*, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.