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Original Article

Exploring the relationship between drug and alcohol treatment facilities and violent and property crime: A socioeconomic contingent relationship

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Abstract Siting of drug and alcohol treatment facilities is often met with negative reactions because of the assumption that these facilities increase crime by attracting drug users (and possibly dealers) to an area. This assumption, however, rests on weak empirical footings that have not been subjected to strong empirical analyses. Using census block groups from Philadelphia, PA, it was found that the criminogenic impact of treatment facilities in and near a neighborhood on its violent and property crime rates may be contingent on the socioeconomic status (SES) of the neighborhood. Paying attention to both the density and proximity of facilities in and around neighborhoods, results showed that the criminogenic impact of treatment facilities depended largely on neighborhood SES. Under some conditions more treatment facilities nearby was associated with lower crime. Reasons why the presumed criminogenic impact of treatment facilities appears only under some conditions were suggested.

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Keywords: drug treatment facilities; place management; environmental criminology; land use; negative binomial regression

Introduction

Drug use and its potential link with other criminal activities is a social problem occurring with increasing frequency in impoverished inner-city neighborhoods (Wilson, 1996; Simon and Burns, 1997; Anderson, 1999). Many have argued that drug treatment is essential for addressing the drug problem facing the United States (Belenko, 1998; Belenko and Dembo, 2003). Treatment center locations are largely restricted to socially disorganized inner-city communities, resulting in a network of facilities located in areas that have low levels of territorial control and high levels of drug use and crime;¹ a reality that has been shown to have a strong negative influence on treatment attrition and relapse (Boardman *et al.*, 2001).

The importance of drug treatment to reduce the prevalence of drug crime is generally acknowledged, but communities are often resistant to hosting these facilities (Hornblower *et al.*, 1988; Substance Abuse and Mental Health Services Administration, 1995; Ericson,



2009). In other words, the general public acknowledges the value of drug treatment services, but wants these services located 'somewhere else'. Given this rather strong public sentiment it is unfortunate that the empirical relationship between drug treatment centers and crime remains, at best, tentative.

Two competing perspectives derived from routine activity theory (Cohen and Felson, 1979; Clarke and Felson, 1993) were used to frame the theoretical relationship between treatment facilities and crime undertaken in this analysis. First, treatment facilities can be conceptualized as nodes of routine activities for people frequently involved with the criminal justice system, both as offenders and as victims. Facilities designed for populations that have high rates of criminality and drug usage have been found to attract drug markets and other criminal activity (Rengert *et al*, 2005). This leads to the prediction that crime will be higher in locals with higher treatment intensity. Second, and alternatively, facilities may have staff members and employees that act in such a way that they provide capable guardianship thereby reducing crime in the immediate surrounding areas. The central questions being addressed in this analysis: Does the number and proximity of drug and alcohol treatment centers impact violent and property crime?

Treatment Facilities and Crime

Scholars have argued that treatment centers have at least the potential to create environments favorable to crime and disorder. Businesses that service drug using clientele such as drug treatment centers may function as 'crime attractors' within a routine activities framework. If treatment centers act as crime attractors they may attract both drug users and drug sellers to a particular area and surrounding location potentially increasing the customer base for local drug markets. Existing research on drug markets has established their tendency to cluster in areas with higher levels of social disorganization that are often low income, inner-city communities (Rengert *et al*, 2005). More organized communities may be resistant to drug markets and crime in general because of their increased ability to restrict the placement of potential crime attractors or because of their increased levels of territorial control. We discuss these two issues beginning with crime attractors, and then examining the role of territorial functioning and place management.

Ecological theories explaining the relationship between geographic location and crime have a rich history (Park *et al*, 1925; Shaw and McKay, 1942). One of the dominant place-based theories is routine activities theory, which originally sought to explain crime trends in the United States over time but has since been expanded to explain crime in micro-space (Cohen and Felson, 1979). Routine activities theory argues that crime occurs when: (1) a motivated offender comes into contact with (2) a suitable target (3) in the absence of capable guardianship. The foundation of the theory is that daily patterns of people explain crime and victimization. As a result the most effective way to control crime is to manage how people utilize space, so that motivated offenders and potential targets do not congregate in the absence of a capable guardian (Felson, 1987). Routine activities theory, however, provides two alternative perspectives on how treatment facility intensity should impact crime levels. The intuitive position would be that facilities increase the number of motivated offenders and/or suitable targets within an area that ultimately leads to higher levels of crime. In this sense, treatment facilities may act like traditional crime attractors.



Using the notion of treatment facilities as crime generators, it would be expected that an increase in such businesses would increase crime in the surrounding areas. However, there is a lack of consistent evidence to suggest that treatment facilities increase community-based drug crime (Lasnier *et al*, 2010). McCord *et al* (2007) and Taylor *et al* (1995) found that areas with higher levels of non-residential land use (including treatment facilities) had greater levels of incivilities including litter, vandalism and desiccated structures. Other studies, however, have come to different conclusions. For example, McCord and Ratcliffe (2007) conducted a micro-spatial analysis of the demographic and environmental correlates of drug markets. Their results suggested that after controlling for socioeconomic characteristics, treatment facilities were not significant predictors of drug distribution activity. Taken together, these studies suggest that the role of drug treatment centers as crime attractors is unclear and would benefit from further investigation.

Alternatively, theory provides a mechanism whereby the presence of treatment facilities may reduce crime in the surrounding area by increasing place management. Territorial functioning is the system of people or groups that create bonds that focus on providing control in an area (Taylor *et al*, 1984). Territorial functioning is a key feature to effective place management. Territorial function is concerned with both who has access to an area and what activities are being conducted in that space. Areas with stronger territorial control make it easier to determine who does, and who does not, belong to an area. This ultimately facilitates access to, and regulation of, activities in the area.

Treatment facilities may alter the prevailing territorial functioning of the areas where they are located. Treatment facilities have staff and employees that may be functioning as place managers that can provide effective territorial control, an idea originally introduced by Eck (1994; see also Felson, 1995). Place managers can include security guards, apartment managers, store staff and homeowners, who deter crime and reduce opportunities through their presence during daily activities (Eck, 1994). Place managers are mainly concerned with activities that occur at places where they have direct control although, in practice, place managers are often interested in controlling behavior beyond their area of interest and take on crime control duties for the street block where their business or residence is located (Mazerolle *et al*, 1998). Relevant to the current study, treatment counselors and staff may function as strong place managers. Given their goal of reducing drug and alcohol use in their clients, they may take active roles as more traditional place managers in deterring drug and alcohol use and crime both within their facility and in the surrounding locale. Thus, it is possible that increased presence of treatment facilities may reduce crime.²

The preceding discussion says nothing about why drug users, as a group, may be more inclined to commit crimes. Although a routine activity perspective may explain why we would expect to see higher crime around treatment facilities, it does not explain why drug users (or recovering drug users as it may be) would be more inclined to engage in criminal activity. Goldstein (1985) created a typology that helps to frame the connection between drug use and criminal behavior. This typology provides a useful bridge between location-focused crime trends (such as those under study here) and the individual crime event. The psychopharmacological model that posits that because of drug use, the user becomes volatile, often exhibiting violent criminal behavior. Common substances that precipitate this result include alcohol and methamphetamines (Zhang *et al*, 2002; Baskin-Sommers and Sommers, 2006; Sommers *et al*, 2006; Stretesky, 2009). The economic compulsive model argues that drug users participate in economically focused crime such as robbery to support

the financial cost of their addiction. Cocaine and heroin are commonly associated with violent crime because of their high cost (Inciardi, 1979; Collins *et al.*, 1985). The systemic model refers to the historically aggressive relationship between the system of drug distribution and usage. Gang rivalries over territory, assault and robberies that are the result of enforcing normative codes, retribution for selling fake drugs, and punishment for failure to pay one's debts are all possible side effects of unregulated drug market.

Goldstein's typology provides a useful framework for understanding how drug and alcohol treatment may work to reduce crime. For example, the psychopharmacological model relies on specific effects of drug use to precipitate crime. Those who are in drug treatment may not be using drugs, be using at a significantly reduced rate, or taking licit prescribed medications (for example, buprenorphine, methadone), all of which reduces the potential for psychopharmacological interactions. The economic compulsive model has comparable implications, namely individuals in treatment may use drugs less, or not at all. These individuals would, therefore, be less compelled to commit crimes strictly for obtaining money needed to purchase illicit drugs. The systemic model would be similarly changed by reduced drug use: less drug use may result in less competition, or reduced drug distribution activity, thereby reducing systemic violence. Goldstein's framework provides a useful bridge between the environmental approach adopted here and the intervening individual-level criminal activity. Ultimately, this intervening relationship is an empirical question that must be left to future studies.

The effect of treatment center-based place management may be contingent upon the socioeconomic status (SES) of the neighborhood in which it is located. Low SES areas may have lower levels of resident-based territorial control (Taylor, 1988). These areas may more heavily rely upon formal avenues of territorial control to establish order. It is possible then that the impact of treatment centers will be at least partially contingent upon the prevailing levels of territorial control in an area. Insofar as socioeconomic or other demographic characteristics structure the level of territorial control treatment centers may have a differential impact depending on the characteristics of the neighborhoods where they are located.

If higher SES areas are more likely to have stronger territorial controls and increased levels of place management, why not simply locate treatment facilities in these 'better' communities in order to reduce the likelihood of treatment facilities acting as crime attractors? One answer is the Not in My Backyard or 'NIMBY' perspective taken by many communities. NIMBY is rooted in the conflict between wealthy communities that have the social and political capital to resist hosting unwanted (but necessary facilities) and lower income areas that lack the social and political capital to resist having such facilities located in their communities (Bullard, 1994).

Locating treatment centers in economically and socially disadvantaged areas may also be explained by another urban process that is largely non-economic and rooted in the stigmatization of those who require certain human services such as drug treatment. Dear and Taylor (1982) noted that traditional theories regarding the location of public service facilities focused on locating the facilities where they could provide maximum access to clients and minimize the cost of providing services. As a result, human service facilities are frequently located in lower income, inner-city neighborhoods; leading to the evolution of what Dear and Wolch (1987) refer to as the 'service dependent ghetto'. The dynamics that drive where treatment locations establish themselves, like those of crime, are strongly influenced by SES.



SES has a long established empirical relationship with neighborhood crime levels (Shaw and McKay, 1942; Sampson and Groves, 1989; Sampson *et al*, 1997). Speaking generally, and with due deference to the ecological fallacy, areas of low SES tend to have a greater level of crime than their higher status counterparts. This can be problematic because, as discussed previously treatment facilities are often relegated to the most disadvantaged neighborhoods, and as a result, we may expect to find a more complicated relationship between neighborhood SES, crime and treatment provider locations. Research suggests that community dynamics, such as the wealth of an area, can influence where offenders choose to commit crime (Taylor and Gottfredson, 1986). Higher income areas may provide high target attractiveness because of the superior quality items available (for example, top quality electronics, jewelry) in the area. Locating drug treatment facilities in higher income areas may, therefore, provide a legitimate reason for a potential offender to explore areas that are 'target rich', and which could lead to an expanded awareness space and higher levels of criminality. The converse may be true of low SES areas. Potential offenders may become aware of the relative presence of unappealing targets suggesting that crime may actually be lower in these areas.

Treatment facilities are not the only characteristics of the built environment that may spatially structure crime. Just as the presence or absence of treatment centers may increase or decrease crime, the presence of other commercial land uses may impact localized crime levels. Commercial land use may impact territorial control and also has the capacity to concentrate crime attractors and crime generators (Taylor *et al*, 1995; Kurtz *et al*, 1998; Kinney *et al*, 2008). Therefore, any attempt to quantify the impact of treatment facilities must also control the prevailing levels of other commercial land use.

Data and Methods

The unit of analysis for these analyses was the census block group; the smallest unit of aggregation for which the relevant socio-demographic variables were available. Crime counts were aggregated to census geographies to provide a count of violent and property crime per unit.

Drug and alcohol treatment facilities

Data on the location and type of drug and alcohol treatment facilities were obtained from the Pennsylvania Department of Public Health's Quality Assurance Database (Pennsylvania Department of Health, 2009). Treatment centers within the State of Pennsylvania must be licensed by the Division of Drug and Alcohol Program Licensure. These licenses provided specific details on the type of treatment undertaken at each facility. All treatment facility locations located within the City of Philadelphia were successfully geocoded ($n = 110$).³

Quantifying drug and alcohol treatment facilities

Quantifying facility locations has proven to be a difficult task which has been approached from a number of directions. Perhaps, the simplest approach would be to simply count the

number of facilities falling within the boundary of the areal unit. This method, although easy to understand and computationally simple, has substantial limitations. These simple point-in-polygon techniques (Gombosi and Zalik, 2005) are highly sensitive to small changes in zoning (a subset of the modifiable areal unit problem), where small changes in the border of the areal unit produces substantially different results (Yule and Kendall, 1950; Openshaw and Taylor, 1979; Chainey and Ratcliffe, 2005). This method is also problematic from a more conceptual perspective. We would not, for example, expect a facility to impact crime up to the edge of a block group and then stop abruptly. Instead, we would expect the influence of a facility to decay over a distance with no clearly demarcated boundary.

A better measure of land use would be sensitive to both the density *and* proximity of the facilities to the area of interest. This can be achieved through an intensity measure such as that utilized by McCord *et al* (2007). We adopted a similar approach and used a program to calculate the intensity measure of treatment facilities (Ratcliffe, 2007). This program counts all events falling within a pre-specified distance (bandwidth) and weighs events such that events further away count less than events nearby. A 0.33 negative exponential weighting function was employed.⁴ Under this regime, an event happening at the centroid to the block group would be assigned a value of 1 whereas events occurring at half the distance of the bandwidth would receive a value of 0.33.

Although bandwidth selection is less critical because of the inverse distance weighting there is still a need to select an appropriate distance. A geographic information system (ArcGIS 10.0) was used to calculate the minimum distance necessary for all census block group centroids to have at least one facility. In other words, this program calculated the largest distance between a census block group centroid and the closest facility to that centroid. This census block group would then receive a value of 0 on the intensity measure for that facility whereas all other census block groups would receive positive values. The bandwidth was set to 16182 ft. While these distances may seem large, it is important to remember the strong distance decay function applied to the weighting algorithm. The 0.33 weighting function would allocate a score of 0.33 to facilities occurring at half the bandwidth distance. The treatment intensity measure was calculated from the centroid of the census block group. This procedure was sensitive to both the density of the facilities, as well as their proximity while reducing the impact of artificial borders and arbitrary methodological decisions. Figure 1 displays facility intensity.

Facility intensity is strongest in the North Philadelphia region, an area that has a long-standing high concentration of poverty.

Recorded crime

Crime data from 2008 were sourced directly from the Philadelphia Police Department's (PPD) records management system. This data set contained point-level information on the type of crime and the location of the event. The locations of the crimes were geocoded (with a hit-rate in excess of 97 per cent) by the PPD and were stored as *X–Y* coordinates. Crimes were separated into two dependent variables. The first was constructed from Uniform Crime Report (UCR) Part 1 violent crimes: homicide, rape, robbery and aggravated assault (hereafter referred to as violent crime; $n=19491$). The second dependent

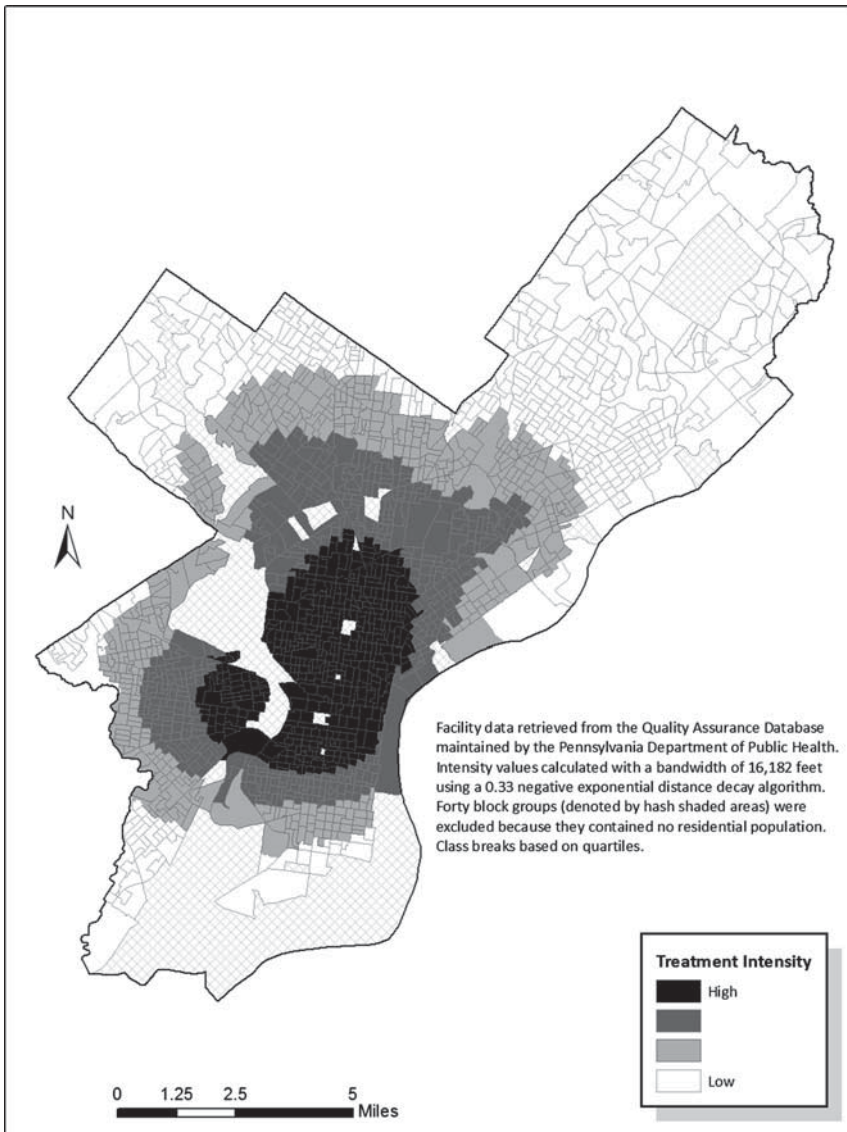


Figure 1: Treatment facility intensity.

variable was constructed from UCR Part 1 property crimes: burglary, theft, auto theft and arson (hereafter referred to as property crime; $n=65\,152$). Serious crimes were selected because they leave the responding officers less discretionary powers in recording and reporting the event (Klinger, 1997) and, therefore, it is possible to rely on these crime measures to be a more accurate indicator of criminal activity and less of an indicator of discretionary police actions.

Demographic variables

Demographic variables were drawn from the 2000 US Census. Variables were selected based on their well-established links to crime. Factorial ecology has, over several decades and numerous community settings, found three demographic dimensions that consistently link to crime: status, race/ethnicity and stability/familism (Hunter, 1971, 1972; Janson, 1980; Taylor and Covington, 1988). A recent meta-analysis by Pratt and Cullen (2005) identified socioeconomics and race to be the most consistent predictors of crime levels. Indicators for both of these dimensions were included. Factor analysis (results omitted) was used to inform the creation of theoretically relevant and statistically acceptable demographic scales. A scale representing SES was created from the following variables: median home value, median income and percent of people with less than a high school education (Cronbach's $\alpha=0.79$). Race/ethnicity was measured with one scale (comprised of the percent of households linguistically isolated, the percent of the population foreign born and the percent of the population that was Hispanic; Cronbach's $\alpha=0.66$) and one stand-alone variable, the percent of the population that was African American. Measures of residential stability, as a precursor to the formation of local supervisory control, were also included. This was measured through a scale constructed from the percent of people living in the same home 5 years prior, the percent of homes owner occupied and the percent of people aged 20–24 years (Cronbach's $\alpha=0.88$).

Demographic variables were obtained at the census block group level of aggregation. Not all of Philadelphia's 1812 census block groups contain the variables necessary to construct the measures of socio-demographic indicators. Forty block groups either contained no residential population or had a population count too low to provide the necessary demographic data. These areas mainly comprised Fairmount Park, Philadelphia International Airport and Philadelphia Northeast Airport. For this reason, we restrict our analysis to the 1772 census block groups with the relevant variables. Restricting analyses to block groups with useable census data excluded 332 violent crimes (1.7 per cent) and 3107 (4.6 per cent) property crimes.

Interaction between drug treatment intensity and socioeconomics

The preceding section established that the relationship between treatment facilities and crime may be contingent upon the prevailing levels of SES in the surrounding areas. To explore the possible interaction between SES and drug treatment facilities two interaction terms were created. A dummy variable was created to represent cases that scored in the top quartile (20 per cent of cases) on both the socioeconomic scale, as well as the treatment provider intensity. This was repeated for cases in the lowest quartile of socioeconomics and the highest quartile of treatment provider intensity creating two dummy variables: (1) high socioeconomics*high treatment intensity, (2) low socioeconomics*high treatment intensity. For example, on the first dummy variable a case would score a value of 1, if it was in the highest quartile of socioeconomics *and* the highest quartile treatment intensity. These dummy variables allow for contrast between those cases which score in the top (or bottom) quartile on both SES and treatment intensity with cases that do not score as high (or low) on both of these measures.⁵



Land use and spatial effects

This analysis controls for the level of commercial land use within the census block group. Zoning data for the City of Philadelphia were obtained from the Pennsylvania Spatial Data Access website (www.pasda.psu.edu/). This data set provided zoning information for every parcel of land within the city. Parcels that were zoned as mixed-use commercial areas, commercial areas, commercial centers, commercial entertainment district, neighborhood shopping centers, area shopping center and office commercial were selected for inclusion in this analysis. Commercial land use was quantified as the percentage of land within each block group zoned as one of these commercial land use categories. This variable could range from 0 per cent if no commercial land use was contained within the boundaries of the census block group to 100 per cent if the entire block group was zoned as commercial.

Crime frequently demonstrates spatial patterns and spatial clustering (Braga *et al*, 1999; Eck *et al*, 2005) that if not accounted for can lead to biased parameter estimates and misleading indicators of model fit (Messner *et al*, 1999). Spatial effects were controlled through the inclusion of a second-order queen contiguity spatial lag variable created with GeoDa 0.9.5-i5 (Anselin, 2004; Franzese and Hyas, 2007). Variance inflation factor (VIF), a diagnostic test for collinearity, and tolerance values when including all demographic, facility, land use and interaction variables were within acceptable levels (VIF < 2.5; tolerance > 0.40). Table 1 presents

Table 1: Descriptive statistics for crimes, facility intensities, demographic variables and spatial lags

	Mean	Median	Minimum	Maximum	SD
Count of violent crimes	11.00	9.00	0.00	64.00	9.00
Count of property crimes	36.77	29.00	1.00	677.00	37.00
Population	853.30	772.50	6.00	4012.00	510.13
Spatial lag (violent) ^a	11.45	11.07	1.58	30.58	5.00
Spatial lag (property) ^a	38.79	35.33	13.63	170.75	17.83
Treatment intensity ^b	8.39	7.79	0.11	21.27	5.17
High treatment * high SES ^c	0.05	0.00	0	1	0.23
High treatment * low SES ^c	0.12	0.00	0	1	0.32
% Commercial	8.99	4.81	0.00	72.00	11.78
SES ^d	0.02	-0.05	-2.33	8.47	0.83
Stability ^e	0.01	0.15	-6.36	1.66	0.78
Race/ethnicity ^f	0.00	-0.29	-0.65	5.70	0.77
% Af. Am.	0.47	0.40	0.00	1.00	0.40

^aSpatial lag constructed with a second-order queen contiguity weights matrix.

^bFacility intensity was calculated with a 0.33 negative exponential weighting function. Bandwidth for the treatment facilities was set to 16 182 ft.

^cInteraction terms created by identifying block groups with top quartile (or bottom quartile) of SES scale and top quartile of treatment provider intensity score.

^dThe socioeconomic scale was comprised z-scored and averaged median home value, median income and percent of people with less than a high school education (Cronbach's $\alpha=0.79$).

^eThe stability scale was comprised z-scored and averaged percent of people living in the same home 5 years prior, percent of homes owner occupied and percent of people aged 20–24 years (Cronbach's $\alpha=0.88$).

^fThe race scale was comprised z-scored and averaged percent of households linguistically isolated, percent of the population foreign born, and percent of the population that was Hispanic (Cronbach's $\alpha=0.66$).

Unit of analysis: block groups' ($n=1772$), crime data from 1 January 2008 to 31 December 2008.



the mean, median, minimum, maximum and standard deviation of the variables utilized in these analyses.

Analytical approach

A typical approach to understanding crime patterns would be to use a crime rate (the number of events observed divided by the population of interest) as a dependent variable (Harries, 1991). The use of crime rates, however, presents some difficulties especially areas of low population (Osgood, 2000). A more statistically appropriate analytic method is to use count regression models. These statistical techniques disentangle the numerator from the denominator and allow for a more robust analysis (Long and Freese, 2006).

Negative binomial regression models were conducted because of overdispersion found in both violent ($G^2=6174.03$; $P<0.001$) and property crime ($G^2=26000$; $P<0.001$) counts (StataCorp, 2006). Two sets of analyses were conducted on violent crime and property crime counts, modeling each crime type independently. Model 1 included two control variables: population and the spatial lag term. Model 2 built upon Model 1 by adding the intensity value of treatment centers. Model 3 omitted the treatment intensity variable and only included demographic and land use characteristics. This model provided a gross estimate of community socio-demographic factors and land use on crime. Model 4 included the measure of treatment intensity, community social structures and land use. This model estimated the net impact of treatment intensity after partialling out the impact of socio-demographics and land use. Finally, Model 5 introduced two interaction terms to fully explore the relationship between treatment intensity and SES.

Results

Parameters are discussed as incident rate ratios (IRR) because of their simple interpretation. An IRR of 2.0 suggests that a one unit change in the independent variable would be expected to increase the average predicted count on the outcome variable by a factor of 2.0, while holding all other variables constant. Put another way, with an IRR of 2.0 we would expect a 1 unit increase in the independent variable to correspond to a 100 per cent increase in the average predicted count of the outcome variable, while holding all other variables constant. An IRR of 0.5, on the other hand, would indicate that a one unit change in the independent variable would be expected to decrease the average predicted count of the dependent variable by a factor of 0.50 (50 per cent), while holding all other variables constant.

Violent crime

Treatment center impacts

Treatment provider intensity, when not accounting for demographics and land use, linked positively to violent crime. A one unit increase in treatment intensity was associated with



Table 2: Negative binomial regression models of violent crime counts and treatment facility intensity

	Model 1			Model 2			Model 3			Model 4			Model 5		
	B (SE)	IRR	IRR	B (SE)	IRR	IRR	B (SE)	IRR	IRR	B (SE)	IRR	IRR	B (SE)	IRR	IRR
Population	0.0003*** (0.00003)	1.0003	1.0004	0.0004*** (0.00003)	1.0004	1.0005	0.0005*** (0.00003)	1.0005	1.0005	0.0005*** (0.00003)	1.0005	1.0005	0.0005*** (0.00003)	1.0005	1.0005
Spatial lag ^a	0.090*** (0.003)	1.09	1.09	0.086*** (0.003)	1.09	1.064	0.062*** (0.003)	1.064	1.064	0.062*** (0.003)	1.064	1.064	0.060*** (0.003)	1.062	1.062
Treatment intensity ^b	—	—	1.02	0.020*** (0.003)	1.02	—	—	—	0.992	—	—	—	—	0.992	0.992
High treatment*high SES ^c	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
High treatment*low SES ^d	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
% Commercial	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
SES ^e	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Stability ^f	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Race/ethnicity ^f	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
% Af. Am.	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
AIC ^g	11 223.68***	—	—	11 189.76***	—	—	10 891.92***	—	—	10 889.16***	—	—	10 874.97***	—	—

^aSpatial lag constructed with a second-order queen contiguity weights matrix.
^bFacility intensity was calculated with a 0.33 negative exponential weighting function. Bandwidth for the treatment facilities was set to 16 182 ft.
^cInteraction terms created by identifying block groups with top quartile (or bottom quartile) of SES scale and top quartile of treatment provider intensity score.
^dThe socioeconomic scale was comprised z-scored and averaged median home value, median income and percent of people with less than a high school education (Cronbach's $\alpha=0.79$).
^eThe stability scale was comprised z-scored and averaged percent of people living in the same home 5 years prior, percent of homes owner occupied and percent of people aged 20–24 years (Cronbach's $\alpha=0.88$).
^fThe race scale was comprised z-scored and averaged percent of households linguistically isolated, percent of the population foreign born, and percent of the population that was Hispanic (Cronbach's $\alpha=0.66$).
^gThe Akaike Information Criterion (AIC) is based on the log-likelihood function and is a measure of model fit. Models with the smallest value are considered to have the best fit (Hilbe, 2008).
 Unit of analysis: block groups^h ($n=1772$), negative binomial regression of the count of violent crimes.
 * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

a 2 per cent increase in violent crime (Table 2, Model 2). After controlling for demographics and land use, however, these effects are substantially altered. The relationship between treatment intensity and crime becomes negative with a one unit increase in treatment intensity associated with a modest 0.08 per cent decrease in violent crime (Table 2, Model 4).⁶ After including the treatment intensity/socioeconomic interaction the main effect of treatment intensity was not significant (Table 2, Model 5).⁷

Demographic and land use impacts

Commercial land use was consistently positively linked to violent crime. A 1 per cent increase in the percentage of land within a block group zoned as commercial was associated with a 1.7 per cent increase in the count of property crime after controlling for treatment intensity, demographic characteristics and spatial effects (Table 2, Model 3, 4 or 5).

SES was also consistently related to property crime. Areas of higher SES were associated with lower violent crime, on average, after controlling for land use, other demographic characteristics, and treatment facility intensity (Table 2, Model 3, 4 or 5). The only other demographic characteristic that linked to violent crime was the percent of the block group population that was African American. A block group that was comprised of 100 per cent African American residential population would, on average, have a violent crime count 35 per cent to 40 per cent higher than a block group that had 0 per cent African American residential population. Neither stability nor the race/ethnicity scales attain statistical significance in these of the models (Table 2, Model 3, 4 or 5).

Spatial lag and population

Population was significantly related to violent crime. On average, a 1000 person increase in the residential population was associated with a 0.5 per cent increase in violent crime count after controlling for demographic characteristics, land use, spatial effects and treatment facility intensity (Table 2, Model 5). The spatial lag variable was also positive and significant. A one unit increase in the lagged crime variable was associated with a 6 per cent increase in violent crime in the target block group.

Treatment facility intensity and socioeconomic interactions

Comparing Model 2 to Model 4 suggests that treatment intensity–crime link is altered by the inclusion of socio-demographic characteristics (Table 2; Model 2 versus Model 4). This relationship was further explored through the use of interaction terms. On average, areas of high treatment intensity and high SES (top 25 per cent on each variable) had 26 per cent more violent crime than areas of more moderate treatment intensity or SES. These results were opposite when considering the interaction between high levels of treatment intensity and low SES. This interaction term indicated that areas of high treatment facility (highest 20 per cent of block groups) and low SES (lowest 20 per cent of block groups) actually had about 16 per cent less crime (Table 2, Model 5).

Property crime

Treatment center impacts

When not accounting for demographic characteristics and land use, the intensity of outpatient treatment facilities was associated with higher levels of property crime (Table 3,



Table 3: Negative binomial regression models of property crime counts and treatment facility intensity

	Model 1			Model 2			Model 3			Model 4			Model 5		
	B (SE)	IRR	B (SE)	IRR	B (SE)	IRR	B (SE)	IRR	B (SE)	IRR	B (SE)	IRR	B (SE)	IRR	
Population	0.003*** (0.00003)	1.0003	0.0004*** (0.00003)	1.0004	0.0004*** (0.00002)	1.0004	0.0004*** (0.00003)	1.0004	0.0004*** (0.00003)	1.0004	0.0004*** (0.00003)	1.0004	0.0004*** (0.00003)	1.0004	
Spatial lag ^a	0.016*** (0.001)	1.016	0.015*** (0.001)	1.015	0.009*** (0.001)	1.009	0.009*** (0.001)	1.009	0.009*** (0.001)	1.009	0.009*** (0.001)	1.009	0.008*** (0.001)	1.008	
Treatment intensity ^b	—	—	0.014*** (0.003)	1.014	—	—	—	—	—	—	—	—	0.008* (0.004)	1.008	
High treatment*high SES ^c	—	—	—	—	—	—	—	—	—	—	—	—	0.019 (0.076)	1.019	
High treatment*low SES ^c	—	—	—	—	—	—	—	—	—	—	—	—	-0.256*** (0.048)	0.774	
% Commercial	—	—	—	—	0.018*** (0.001)	1.018	0.017*** (0.001)	1.018	0.017*** (0.001)	1.018	0.018*** (0.001)	1.018	0.018*** (0.001)	1.018	
SES ^d	—	—	—	—	-0.126*** (0.017)	0.882	0.124*** (0.017)	0.883	0.124*** (0.017)	0.883	0.124*** (0.017)	0.883	-0.155*** (0.020)	0.856	
Stability ^e	—	—	—	—	-0.090*** (0.017)	0.914	0.087*** (0.017)	0.914	0.087*** (0.019)	0.917	0.087*** (0.019)	0.917	-0.079*** (0.019)	0.924	
Race/ethnicity ^f	—	—	—	—	-0.030 (0.020)	0.970	0.031 (0.020)	0.970	0.031 (0.020)	0.970	0.031 (0.020)	0.970	-0.026 (0.019)	0.974	
% Af. Am.	—	—	—	—	-0.182*** (0.040)	0.833	0.188*** (0.041)	0.833	0.188*** (0.041)	0.829	0.188*** (0.041)	0.829	-0.197*** (0.042)	0.821	
AIC ^g	15 131.38***		15 109.50***		14 791.93***		14 793.72***		14 793.72***		14 768.32***		14 768.32***		

^aSpatial lag constructed with a second-order queen contiguity weights matrix.

^bFacility intensity was calculated with a 0.33 negative exponential weighting function. Bandwidth for the treatment facilities was set to 16 182 ft.

^cInteraction terms created by identifying block groups with top quartile (or bottom quartile) of SES scale and top quartile of treatment provider intensity score.

^dThe socioeconomic scale was comprised z-scored and averaged median home value, median income and percent of people with less than a high school education (Cronbach's $\alpha=0.79$).

^eThe stability scale was comprised z-scored and averaged percent of people living in the same home 5 years prior, percent of homes owner occupied and percent of people aged 20–24 years (Cronbach's $\alpha=0.88$).

^fThe race scale was comprised z-scored and averaged percent of households linguistically isolated, percent of the population foreign born and percent of the population that was Hispanic (Cronbach's $\alpha=0.66$).

^gThe Akaike Information Criterion (AIC) is based on the log-likelihood function and is a measure of model fit. Models with the smallest value are considered to have the best fit (Hilbe, 2008).

Unit of analysis: block groups^h ($n=1772$), negative binomial regression of the count of violent crimes.

^h* $P < 0.05$; *** $P < 0.001$.

Model 2). After controlling for demographic characteristics and land use, the strength of the relationship between drug treatment intensity and crime was reduced but was still significant (Table 3, Model 4).⁸

Demographic and land use impacts

Commercial land use was associated with higher levels of property crime regardless of model specification. A 1 per cent increase in the level of land zoned commercial within a block group was associated with a 1.8 per cent increase in property crime, net of demographics, spatial effects and treatment intensity (Table 3, Models 3, 4 or 5). SES also consistently linked to property crimes. A one unit increase in the SES scale was associated with about 14 per cent less property crime after controlling for other relevant variables (Table 3, Model 5). Unlike violent crime, the stability scale was also significantly associated with property crimes. A one unit increase in the stability scale was associated with an 8 per cent reduction in property crime after controlling for other environmental and demographic characteristics (Table 3, Model 5). Finally, the percent African American linked differently to property crime than violent crime. When looking at property crime, a block group that was 100 per cent African American would have an expected property crime count about 18 per cent lower than a block group with 0 per cent African American residential population (Table 3, Model 5).

Spatial lag and population

Higher levels of residential population were associated with higher levels of property crime. On average, a 1000 person increase in the residential population was associated with a 0.3 per cent to 0.4 per cent increase in property crime with only small variations across model specification (Table 3). The spatial lag variable was also positive and significant. A one unit increase in the lagged crime variable was associated with an increase in property crime between 0.8 and 1.6 per cent depending on model specification.

Treatment facility intensity and socioeconomic interactions

Interaction terms between the areas of highest SES and the highest drug treatment facility intensity showed some differences than what was found with violent crimes. The variable representing areas of high treatment intensity and high SES, while in the same direction as found for violent crime, was not significant. Areas of high treatment intensity and low SES were associated with 23 per cent less property crime than areas that scored more moderately on these variables. These relationships persisted net of other demographics, land use, spatial effects and the main treatment variable (Table 3, Model 5).

Discussion

The relationship between treatment intensity and crime demonstrated minor differences between violent and property crime. Recall that treatment facility intensity was positively associated with violent crime when failing to control for other relevant environmental characteristics (Table 2, Model 2). After controlling for demographics, land use and spatial effects, however, this same variable was negatively associated with violent crime (Table 2, Model 4). In the violent crime models, the interaction terms indicated that areas of high SES



and high treatment provider intensity tended to have significantly higher levels of violent crime, net of controls for land use, demographics and spatial effects (Table 2, Model 5). This interaction term in property crime models was in the same direction but did not attain significance (Table 3, Model 5). Conversely, for both violent and property crimes, areas of low SES and high treatment provider intensity tended to have significantly less violent and property crime, net of land use, demographics and spatial effects (Tables 2 and 3, Model 5). These interaction terms indicated that the relationship between treatment intensity and crime was different at different levels of SES.

Three explanations may help to explain this seemingly counterintuitive finding. First, it may be that drug treatment facilities are acting as nodes of routine activity that facilitate the expansion of both awareness space and opportunity space. In other words, the person in treatment becomes familiar with the neighborhood in which the facility is located. If the facility is located in a high socioeconomic neighborhood the individual may become aware of many attractive targets such as residential homes and businesses that are of high monetary value (Brantingham and Brantingham, 1995; Lopez and Van Nes, 2007). Put more succinctly, locating treatment facilities within high socioeconomic neighborhoods may increase a potential offender's awareness space and provide familiarity with the area that could lead to new avenues for criminal activity (Rengert and Wasilchick, 2000). This new-found understanding of the high socioeconomic area could help to explain why crime would be higher in these locals. The same dynamic applies to the other side of this finding. Offenders attending treatment in low socioeconomic neighborhoods may be dissuaded from committing crime, if conditions in the surrounding local are sufficiently unappealing.

Alternatively, treatment centers may be having a differential impact on the level of territorial control in the surrounding area. In low socioeconomic areas, treatment facilities may be increasing territorial control because treatment center staff acts as capable guardians. In the absence of resident-based territorial control, these treatment facilities may be acting as the default territorial control mechanism. By contrast, high socioeconomic areas may not suffer from the same lack of resident-based territorial control. Under these conditions, treatment facilities may be acting to disrupt the territorial control of the residential population in the area. This disruption may lead to higher levels of crime in higher SES areas.

Finally, the relationship between treatment intensity and socio economics may be because of differences in 'other' land uses displaced by the treatment facility. It may be that in low socioeconomic areas, treatment centers are displacing other businesses that are even more criminogenic. For example, treatment centers may be 'better' neighbors than other facilities traditionally considered crime generators (for example, bars and pubs). This would create lower levels of crime in areas of high treatment intensity and low SES. However, treatment centers may not be displacing 'bad' neighbors in high socioeconomic neighborhoods. In higher socioeconomic neighborhoods, drug treatment centers may be the 'bad' neighbor. By this way, we would expect to see higher crime around treatment facilities in areas of high SES. These theoretical models help to explain the potentially counterintuitive finding demonstrated by these interaction terms. The exact process whereby community and environmental characteristics interact with treatment centers and crime remains an important avenue for future research.

Given that we can only speculate as to the intervening process linking treatment providers to crime levels any policy recommendations must be undertaken with caution. It appears that, at least at this level of spatial aggregation in this urban setting, treatment facilities are

not unilaterally bad neighbors and may not deserve the negative reputation that they carry. Nevertheless, these findings suggest that treatment providers must be careful in selecting locations for their facilities. For example, the location of a treatment facility should be considered in light of pre-existing crime problems, as well as environmental characteristics such as commercial land use. Future studies may be well advised to seek out community protective factors that have the potential to reduce the criminogenic impact of these facilities.

Commercial land use linked positively to both violent and property crimes regardless of model specification. Higher levels of land zoned as commercial was related to higher counts of both violent and property crimes. Previous research has found that commercial land use concentrates crime generators and crime attractors (Kinney *et al*, 2008). These facilities either draw in people that are crime prone or create situations that are conducive to criminal activity.

SES was also consistently related to both violent and property crimes. Locations with higher levels of socioeconomic status had lower levels of violent and property crime after controlling for other environmental and demographic characteristics. Consistent with Pratt and Cullen (2005) these results indicated that SES was a stronger predictor of violent and property crime than residential stability. Differences in the impact of residential stability appeared between the two crime categories. Stability linked negatively to property crime but had a non-significant association with violent crime. Residential stability may be a necessary precursor to the formation of effective neighborhood social control mechanisms (Sampson and Groves, 1989). People's willingness to intervene may be more sensitive to these mechanisms when considering property crime over violent crimes. Given residential stability's empirical link to a wide variety of criminal activities, including drug use (Freisthler *et al*, 2005), homicide (Kubrin, 2003) and juvenile violence (Osgood and Chambers, 2000), it is somewhat surprising to find that this link does not maintain with violent crime in this study. Whether this is a difference because of the study setting or a finding that is driven by differences of areal aggregation will be an important avenue for future research. The race/ethnicity scale did not attain significance in any model for either violent or property crimes outcomes. In contrast, the percent of the population responding as African American linked with greater levels of violent crime but lower levels of property crime.

These analyses revealed significant effects of the spatial lag variable; crime in one area was influenced by crimes in nearby areas. This has a number of plausible interpretations. This could be indicative of a crime spill over, or spatial diffusion, effect of crime. Alternatively, the lag variable could be measuring processes that were not captured in the model. In other words, although these analyses controlled for the most well-established environmental correlates of crime there may be other unidentified processes at play. The exact nature of this underlying spatial process represents an important avenue for future research.

A few limitations of the current study are worth discussing. Underreporting of crime events is, of course, a limitation of any study using any official crime data sources. Within the context of the current study underreporting may be especially problematic, if the spatial pattern is such that underreporting occurs more frequently in lower socioeconomic areas (see Anderson, 1999). If this were true, it would make it especially difficult to use officially reported crime data to disentangle the relationship between treatment provider intensity and SES. Using victimization data may ameliorate this problem, but underreporting has also been an issue owing to how individuals perceive victimization. Future studies may want to incorporate official crime data sources, as well as victimization data to get a more robust view of criminal activity.



One limitation to the methodology used to quantify the facilities is the inability to account for differences in the size of the treatment providers. This difference, both across and within treatment centers, may impact these results. Future research should seek to disentangle the effects of treatment provider client size and the relationship on crime.

Given the cross-sectional nature of this investigation, we are unable to ascertain a causal ordering between treatment centers and crime. Future research using longitudinal models may be able to clarify this relationship. One difficulty to conducting such a study is the relative stability of the treatment facility locations. Numerous treatment facilities have been licensed at the same location for over 30 years. Collecting data, especially spatially referenced crime and environmental data, over such a long period of time presents substantial difficulties. Nevertheless, truly clarifying the relationship between treatment centers and crime would be best accomplished by longitudinal models.

Conclusion

Drug and alcohol treatment facilities are widely thought to have negative impacts on the community in which they are located. That is, it is assumed that these facilities bring crime to the areas surrounding their location. The empirical basis for this assertion is tenuous at best. This analysis has not found a definitive relationship between treatment centers and crime. The relationship between treatment provider intensity and crime was found to be conditional upon the level of SES of the area. Areas of high SES and high treatment provider intensity had higher levels of violent and property crime. Conversely, areas of low SES and high treatment provider intensity had lower levels of violent and property crime. These models also suggest that socio-demographic characteristics, as well as land use may impact the effects of treatment centers on violent and property crimes. These findings may not sit well with people looking for clear cut answers regarding the criminogenic impact of treatment facilities. At best, it is possible to say that treatment providers are not unilaterally bad neighbors and that in the certain areas these facilities may be associated with lower crime in the surrounding areas. This must be balanced with the fact that these same facilities may, under certain circumstances, also be criminogenic. Further research would be wise to further investigate the dynamics that are underlying these results.

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Notes

1 Davidson (1981) stated that there were three types of neighborhoods that did not resist having community-based treatment centers: those who tolerate deviant behavior, those who were members of the community who do



not value the community enough to consider it worth protecting and those who lack the capital needed to mount effective opposition.

- 2 Treatment facilities are, of course, not equal and can be broken down into two broad categories: inpatient facilities and outpatient facilities. Differences between these typologies may be expected because of the increased level of contextual overlap in the treatment ecology of outpatient facilities. Outpatient facilities require people to travel to and from the facility on a regular and frequent basis. This has the potential to increase a patient's awareness space of the areas surrounding a treatment facility (Brantingham and Brantingham, 1995). Also treatment providers at inpatient facilities may be able to act more effectively as place managers because they would be required to staff the facility on a near constant basis whereas outpatient treatment facilities may be closed during evening or other non-business hours. Both factors lead to the possibility that treatment provider typology may have differential impacts on crime outcomes. As facilities need separate licenses for these programs, it was possible that a single facility could be listed as both an inpatient and outpatient treatment provider. In a few cases ($n=6$) the license type did not definitively identify the type of treatment facility. In these cases, the researchers consulted the program's webpage for further clarification. It was then possible to classify all treatment facilities as inpatient or outpatient. All locations (outpatient $n=73$; inpatient $n=37$) were successfully geocoded.
- 3 Twelve of these locations (six pairs) were located at the same physical address. Even though two treatment centers occupied the same address they were counted as two separate facilities. Counting each treatment center, rather than each address, is most consistent with the density and proximity approach adopted here to quantify facility intensity.
- 4 Although a number of different weighting functions are possible, their impact in actual practice is minimal (Bailey and Gatrell, 1995).
- 5 To explore the effects of treatment typology, interaction terms were also created for individual treatment facility type (outpatient and inpatient). A dummy variable was created to represent cases that scored in the top quartile (20 per cent of cases) on both the socioeconomic scale, as well as the outpatient treatment provider intensity. This was repeated for cases in the lowest quartile of socioeconomics and the highest quartile of inpatient treatment provider intensity. The same process was employed for outpatient treatment facilities and resulted in four dummy variables: (1) high socioeconomics*high outpatient; (2) low socioeconomics*high outpatient; (3) high socioeconomics*high inpatient; and (4) low socioeconomics*high inpatient.
- 6 Substantial changes in the magnitude of a coefficient or changes to the directionality of the coefficient are often referred to as a 'bouncing beta' issue and can be indicative of issues regarding multicollinearity (Gordon, 1968). To assess this possibility a number of additional analyses were conducted. Scatter plots and histograms of the independent variables were checked for outliers and discontinuous variables. No evidence of these problems was found. Correlations between treatment intensity variables and other independent variables were also checked. Under this combination of variables (treatment intensity, land use, spatial effects and demographics) VIF values were less than 2.1 and tolerance values were greater than 0.49. These models demonstrated the same pattern of results: treatment intensity was related to higher violent crime when entered alone, entered with population and/or entered with spatial effects. Treatment intensity switches directions and becomes negative after controlling for demographics and land use. Re-specifying these models, this time omitting the percent African American (the next strongest correlate with inpatient treatment intensity), produced the same negative relationship between inpatient intensity and violent crime. Given the robust nature of these results it is unlikely this change in coefficient directionality was simply a result of multicollinearity.
- 7 Violent crime models were re-specified to look at the effects of outpatient and inpatient treatment facilities independently (results omitted). No noteworthy differences were found between models specified with outpatient versus inpatient treatment intensity. Consistent with the effect of overall treatment intensity the main effect of both inpatient and outpatient treatment was negative and significant after including the interaction terms. Interaction terms were also consistent with the primary models presented in Table 2. High levels of outpatient or inpatient treatment in high socioeconomic areas was associated with significantly higher levels of crime. High outpatient or inpatient treatment in low SES areas was associated with lower levels of crime. This was consistent with the main models presented in Table 2 (Model 5).
- 8 Property crime models were re-specified to investigate the impact by treatment typology (results omitted). Models were consistent whether they were specified with outpatient or inpatient treatment intensity. Consistent with the overall treatment intensity models, the primary effect of both outpatient and inpatient treatment variables were positive and significant. Interaction variables between specific treatment typologies and SES were also consistent with the primary models presented in Table 3. Although non-significant, high levels of



outpatient or inpatient treatment in high socioeconomic areas was associated with higher levels of crime. High outpatient or inpatient treatment in low SES areas was associated with lower levels of crime. This was consistent with the main models presented in Table 3 (Model 5).

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