

Department of Criminology

Working Paper No. 2015-12.0

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The Effect of Trees on Urban Crime: Evidence from the Spread of the Emerald Ash Borer in Cincinnati

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1. Introduction

Invasive tree pests are an increasing worldwide problem that often have devastating ecological consequences (Boyd, Freer-Smith, Gilligan, & Godfray, 2013). At the same time, their spread provides a unique opportunity to study the social benefits of trees such as improved public-health outcomes (Donovan, Michael, Butry, Sullivan, & Chase, 2011; Hystad et al., 2014) and reduced crime (Kuo & Sullivan, 2001). The chance to study tree loss over time is invaluable, as the spread pattern of invasive tree pests are often uncorrelated with other drivers of social benefits. In contrast, measuring and isolating the social effects of trees at one point in time can be problematic, because people with higher socio-economic status are more likely to live in areas with more trees (Jesdale, Morello-Frosch, & Cushing, 2013) and socio-economic status is an important driver of social benefits such as health and crime (Frumkin, 2013).

In North America, one of the most virulent invasive tree pests is the emerald ash borer (EAB), which has killed over 100 million trees since it was first discovered in Detroit, Michigan in 2002 (Smitley, Davis, & Rebek, 2008) (Fig.1). We take advantage of the spread of EAB to study the relationship between trees and crime in Cincinnati, Ohio. We chose Cincinnati, because the city kept detailed records of where and when they removed a diseased ash tree.

Studies have identified varying, and sometimes contradictory, associations between presence of trees or vegetation and crime. For example, dense vegetation has been shown to promote crime by providing criminals a place to hide themselves or illegal goods

(Fisher & Nasar, 1992; Michael, Hull, & Zahm, 2001; Nasar, Fisher, & Grannis, 1993). In contrast, emerging evidence suggests that urban green space, measured in various ways, may be associated with lower rates of crime and violence. As a broad measure of urban green space, vegetation abundance has been linked to reductions in violent crimes, property crimes (Kuo & Sullivan, 2001), assault, robbery and burglary (Wolfe & Mennis, 2012). Other studies have used more specific measures. For example, street trees and large residential-lot trees have been associated with fewer total crimes, property crimes, and vandalism (Donovan & Prestemon, 2012; Troy, Morgan Grove, & O'Neil-Dunne, 2012).

However, with few exceptions, most green space and crime studies have been crosssectional, so they provide limited evidence of causal effects and are prone to confounding by unmeasured drivers of crime (Lee & Maheswaran, 2011). Some exceptions include a natural experiment in a large public-housing development, which found vegetation was associated with lower violent and property crime (Kuo, 2001). A quasi-experimental study in Philadelphia found that greening of vacant lots was associated with reduced gun assaults and vandalism (Branas et al., 2011). Similarly, another quasi-experimental study found that construction of green stormwater infrastructure projects in Philadelphia was associated with reduced narcotics possession arrests (Kondo, Low, Henning, & Branas, 2015).

1.1 Possible mechanisms linking trees and crime

Several criminology theories provide insight into how trees might influence crime. For example, broken windows theory hypothesizes that signs of blight and disorder in the built environment signal that an area is uncared for, which may encourage crime signaling that an area is "fair game" for "fun or plunder" (Wilson & Kelling, 1982). A number of studies have found an association between measures of disorder and crime, but they are mostly cross sectional (Perkins & Taylor, 2002; Sampson & Raudenbush, 1999; Taylor, Shumaker, & Gottfredson, 1985). Only one series of small-scale field experiments in the Netherlands have found strong evidence that physical disorder encourages other forms of disorder and minor offending (Keizer, Lindenberg, & Steg, 2008).

Situational crime prevention theory characterizes crime as an opportunistic process: motivated offenders recognize criminal opportunities during daily routine activities (Clarke, 1995). Trees and other green space may signal change in perceived access, or suggest that a target is guarded, even if it is not. Crime prevention through environmental design (CPTED) and defensible space theories are related to situational crime prevention theory. These theories suggests that features of the built environment, including trees, make areas more or less attractive to would-be offenders by affecting natural surveillance, access control, target hardening, and signs of territoriality (Cozens, Saville, & Hillier, 2005).

In addition, economic opportunity theory argues that crime occurrence is influenced by the supply of available targets (Cook, 1986). If trees and other green space in the built

environment influence the supply of would-be targets, this too could impact crime. For example, trees may encourage more pedestrians on a street, which makes it more likely that a potential offender is seen.

2. Methods

2.1 Data

In the US, EAB was first confirmed in Detroit, Michigan in 2002. It has since spread to 23 states. It kills virtually all ash trees within 2-5 years (Poland & McCullough, 2006)(Figs. 2a and 2b). EAB was first detected in Cincinnati (area: 205.9 square kilometers) in 2007. Prior to EAB invasion, ash trees represented approximately 7.5% of all street trees, and 10% of total forest canopy (Cincinnati Parks, 2010). Between April 2007 and September 2014 the city removed 646 mature ash trees in the public right-of-way (Fig. 3). The city removed all dead or dying ash trees, to prevent hazards, and kept detailed records for each tree removal, including location, date removed, and diameter of the tree. We assumed that this data represented removal of all mature ash street trees affected by EAB. We geocoded the location of each removed tree using the ESRI 2014 US address locator. We then used these geo-coded data to calculate tree removals for each of the 307 census block groups (statistical divisions of census tracts, containing between 600 to 3,000 people) in Cincinnati. We used the date that the first tree was removed in a block group as the removal date for an entire block group.

Cincinnati Police Department provided incident-level crime data (with date, location and class) from 2005 through 2014. We geo-coded these data using the same 2014 US

address locator. We then aggregated the 103 available crimes types in to eight classes: 1) simple assault, 2) felony assault, 3) rape, 4) theft, 5) burglary, 6) robbery, 7) breaking and entering, and 8) criminal damage or endangerment. In addition, we created two index crimes: 9) violent crimes (representing all incidences of Part I crimes (Federal Bureau of Investigation, 2004) including murder, rape, simple and felony assault, and robbery), and 10) property crimes (representing incidences of Part II crimes that involved properties, including burglary, theft, in addition to criminal damage and endangerment, and breaking and entering). Average yearly counts of crimes on block groups ranged from 50.2 to 104.7 (simple assault), 12.6 to 29.7 (felony assault), 4.1 to 8.0 (rape), 186.9 to 284.0 (theft), 39.6 to 63.0 (burglary), 25.1 to 57.5 (robbery), 25.1 to 46.2 (breaking and entering), 66.5 to 99.9 (damage/endangerment), 93.1 to 199.9 (violent crimes), and 293.0 to 481.5 (property crimes).

To convert the crime data from points to a continuous surface, we used a kernel density method, which uses a quadratic function to form a smooth surface from a set of points. Therefore, a crime has influence beyond a single point or block group boundary.

We obtained seven demographic variables that have been found to be associated with crime (Cook, 2009; Land, McCall, & Cohen, 1990; Sampson, Raudenbush, & Earls, 1997) from the American Community Survey 2008-2012 at the block group level. We gathered block group level estimates of demographic variables shown in Table 1. We also calculated the percent total tree cover for each block group from an Urban Tree Copy Assessment (2000 and 2010) (Cincinnati Parks, 2010). The study period is 2005 through

2014, in yearly time intervals for a total of 10 time periods. The average pre-period (time between 2005 and the first onset of EAB in a block group) was 5.1 years and post-period (time between the last onset of EAB in a block group and 2014) was 3.9 years.

2.2 Statistical Methods

The spread of EAB is a natural experiment: block groups with ash tree removals are the treatment group (N=130) and block groups without ash removals are the control group (N=177). In contrast to a true experiment, the treatment is not randomly assigned, so there may be systematic differences between the treatment and control groups. To address this issue we used propensity-score weighting so that the two groups joint distributions would be statistically similar on demographic confounders of crime and tree canopy cover. We employed a non–parametric logistic regression model using the "twang" code in R to estimate the propensity score regression weights, which allows for nonlinear relationships and maximizes the comparability between treatment and control block groups (McCaffrey, Ridgeway, & Morral, 2004; Ridgeway, McCaffrey, Morral, Burgette, & Griffin, 2014).

We weighted control block groups using the propensity scores: block groups that were demographically similar to block groups in the treatment group were given a higher weight, whereas block groups that were different in terms of demographics and percent tree canopy received a lower weight (Table 2).

After the weighting process, we conducted descriptive analyses of compiled data. Summary statistics for the seven demographic variables and percent tree canopy (shown in Table 2) were almost identical and no statistically significant differences existed. For example, before weighting, the mean number of households headed by a female in the control group was 0.21 compared to 0.17 in the control group. After weighting, the mean number of households headed by a female was 0.17 in both the control and treatment groups.

Using the propensity score regression weights generated for each block group, we estimated a difference-in-differences Poisson regression model for each of the 10 classes of crime:

$$Y_{it} = \beta_1 \text{Post*Trees}_{it} + \beta_2 (\text{pre-EAB trend}) + \gamma_i + \delta_t$$
(1)

where Y_{it} is the crime outcome for block group *i* in year *t*. Post_{it} is an indicator variable denoting when block group *i* is infested with EAB in year t multiplied by the number of trees removed. The β_1 parameter is the effect of EAB tree removals on crime outcomes. In some cases, different trends in the data existed as a result of what occurred before EAB-onset. To control for that form of endogeneity, or a violation of the parallel slope assumption (Imbens, 2009), we added a covariate for the pre-EAB linear trend in any block with EAB and the overall trend in all other control blocks. We did not include any demographic variables in our models because we used demographic variables to weight the data.

The block group fixed effects, γ_i , controls for unobserved time-stable differences in block groups. Similarly, the year fixed effects, δ_t , account for trends in crime over time that are common to all blocks groups. We specified a Poisson model with robust standard errors clustered on block group to control for unobserved serial dependence within blocks, and adjust for heteroskedasticity in the data.

To test the robustness of our estimates of tree removal from EAB on crime, we used Monte Carlo permutation tests (Bertrand, Duflo, & Mullainathan, 2004). We randomly assigned the time of the EAB infection to 130 block groups. We then estimated equation 1 without the linear trend and saved coefficient β_1 . We repeated this process 1,000 times—randomly re-assigning EAB timing before each iteration. If EAB does affect crime, then its random assignment should matter: the β_1 coefficient from the randomized models (over the 1,000 iterations) should be significantly different from the nonrandomized models.

3. Results

Table 3 shows the effect (β_1 in equation 1) of EAB on the 10 classes of crime. We found that EAB infestation was significantly associated with higher crime in EAB-infected blockgroups compared to control blockgroups with no EAB in all categories of crime except damage/endangerment, burglary, robbery and rape. Based on the quantity of trees removed at each site, we calculated that the loss of each additional tree was associated with a significant increase in theft, breaking and entering and property crime incidents (p<0.001) and in simple assaults, felony assaults and violent crimes (p<0.01) at EAB-

infected blockgroups compared to in non-EAB infected blockgroups. Crime incidents saw a relative increase between 1 and 2 percent by blockgroup. Using the Monte Carlo permutation tests, we found that our randomized (pseudo β_1) only exceeds the nonrandomized EAB coefficients (β_1) in three of the crime outcomes of rape, robbery, and damage to property that were not significantly associated with EAB tree removals (see Table 3).

Fig. 4 compares both violent and property crimes over time in block groups with and without EAB. Before EAB reached Cincinnati in 2007, treatment block groups that would become infested with EAB had significantly lower rates of violent and property crimes. However, by 2012, violent- and property-crime rates in EAB-infested block groups were comparable to rates in un-infested block groups.

4. Discussion and Conclusions

There are an estimated 7.5 billion ash trees in the US. Ash are one of the most widely distributed tree genera in North America and are a popular urban tree even outside its native range (MacFarlane & Meyer, 2005; Poland & McCullough, 2006). In addition, to the ecological cost of ash loss—altered nutrient cycles, understory environment and succession (Gandhi & Herms, 2010)—EAB will have significant social and economic costs. However, research on the economic cost of EAB has been primarily focused on tree maintenance and removal costs (Kovacs et al., 2010). Our results suggest that the loss of ash trees due to EAB infestation, in urban areas such as Cincinnati, may also be associated with a relative increase in crime.

Our study did not provide any insights into the mechanisms linking tree loss to shifts in crime. However, our results are consistent with criminology theories suggesting that trees may reduce crime by making the built environment less attractive to potential offenders. On the other hand, tree loss may be a sign of neighborhood blight, which signal to a potential offender that a neighborhood is not well cared for. If trees indeed encourage more pedestrians on a street, which deters potential offenders, the loss of trees could serve the opposite purpose.

Our study had several limitations. We aggregated crime to the block-group level, so our results may be subject to ecological bias or limited generalizability: results may not apply to different levels of aggregation than a block group due to potential ecological fallacy (Robinson, 2009). In addition, we assigned a single tree-removal date (date of first removal) to a block group; however, trees in a block group were often removed over several years. Our results are, therefore, conservative in assigning the earliest date as the time of infection. Another limitation is that our data set included only street tree removals, and not removals of trees on personal property. However, the loss of street trees may be a proxy for the loss of yard trees, as areas with more ash street trees may also have more ash yard trees. However, even if this is the case, it would serve to increase, though not change the direction, of coefficients. Nonetheless, we believe that our results suggest that tree loss was associated with a relative increase in crime rates in Cincinnati between the years 2007 and 2014. By extension, our results suggest that healthy trees may significantly deter crime. Finally, the management of invasive tree

pests has focused almost exclusively on ecological costs. Our results suggest that in cities such as Cincinnati, social costs might also be considered.

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Table 1Census1 demographic variables

Demographic	Census indicators
Income	% of the population below federal poverty status
Employment	% unemployed
Household characteristics	% female-head of household
Race and ethnicity	% white, black, Asian, Hispanic
Education	% of the population older than 18 without a high school diploma
Age	% of the population between the ages 8 and 18

¹ American Community Survey 2008-2012

Table 2

Census	^l demographic	mean values ar	d (sd) for tre	atment and o	control group	s, and
propens	sity-score-adjus	sted values for	control group	os		

	Treatment	Control (n=177)		Effect		
Selection Variables	(n=130)	unweighted	weighted	size	p-value	
% Youth	0.21	0.24	0.21	-0.0006	0.965	
	(0.01)	(0.01)	(0.01)			
% Female head of	0.17	0.21	0.17	0.005	0.970	
household	(0.01)	(0.01)	(0.01)			
% Less than HS	0.14	0.20	0.15	-0.010	0.424	
education	(0.01)	(0.01)	(0.10)			
% Unemployed	0.11	0.16	0.12	-0.005	0.635	
	(0.01)	(0.01)	(0.01)			
% Poverty	0.18	0.31	0.19	-0.006	0.727	
	(0.01)	(0.02)	(0.12)			
% Black	0.40	0.47	0.40	-0.008	0.827	
	(0.03)	(0.02)	(0.03)			
% Hispanic	0.02	0.03	0.02	-0.002	0.635	
	(0.00)	(0.00)	(0.00)			
% Tree Canopy	9022818	6794549	8768628	254190	0.834	
	(809357)	(769625)	(9022818)			

¹ American Community Survey 2008-2012

Table 3

Effects of EAB or	classes of crime
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					Percent
					pseudo $\beta_1 >$
Crime	Coef.	SE	95% CI	p-value ^a	$\beta_1{}^b$
Simple assault	0.007	0.003	(0.001, 0.012)	**	0%
Felony assault	0.012	0.005	(0.003, 0.020)	**	0%
Rape	0.004	0.003	(-0.002, 0.011)		1%
Violent crimes	0.007	0.003	(0.002, 0.012)	**	0%
Theft	0.008	0.002	(0.004, 0.012)	***	0%
Burglary	0.004	0.003	(-0.002, 0.013)		0%
Robbery	0.005	0.003	(-0.001, 0.010)		17%
Breaking & entering	0.014	0.003	(0.007, 0.020)	***	0%
Damage/endangerment	0.001	0.001	(-0.001, 0.004)		8%
Property crimes	0.006	0.002	(0.003, 0.010)	***	0%

n=3,070 (307 block groups X 10 years)

a. *p<.05; ***p<.001

b. Percent of permutation test coefficients greater than regression coefficients for each crime

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Fig. 4. Violent and property crime fitted values in treatment and control block groups



Fig. 1. Spread of the emerald ash borer by county 2002-2013

Figs. 2a and 2b. A street lined with ash trees in Toledo, OH in 2006 and 2009 (photo credit: Dan Herms Ohio State University)





Fig. 3. Map of ash tree removals in Cincinnati by Census block group, April 2007 to



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