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The association between urban trees and crime: Evidence from the spread of the emerald ash borer in Cincinnati

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HIGHLIGHTS

- The emerald ash borer (EAB) began killing ash trees in Cincinnati in 2007.
- We used a natural experiment approach to assess impact of tree loss on crime.
- We compared crimes in EAB-infested blockgroups to those in non-infested blockgroups.
- Multiple crime types had significant and positive associations with EAB infestation.
- Urban trees may reduce crime.

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ABSTRACT

The ecological impact of invasive tree pests is increasing worldwide. However, invasive tree pests may also have significant social costs. We investigated the association between the emerald ash borer (EAB)—an invasive tree pest first discovered in the US in 2002—and crime in Cincinnati, Ohio. We used a natural experimental approach, and compared crime (in 11 classes) on census block groups infested with EAB with crime on block groups not infested with EAB between 2005 and 2014. We accounted for demographic and biological differences between infested and un-infested block groups using propensity-score weighting. EAB infestation was significantly and positively associated with relative increases in crime in all but four crime categories. Our results suggest that invasive tree pests may be associated with social costs worth considering when managing invasive species. By extension, healthy trees may provide significant social benefits.

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 on a variety of social outcomes including health (Donovan, Michael, Butry, Sullivan, & Chase, 2011; Hystad et al., 2014) and 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 safety (Frumkin, 2013).

In North America, one of the most virulent invasive tree pests is the emerald ash borer (EAB), which was estimated in 2008 to have killed over 100 million trees since it was first discovered in Detroit, Michigan in 2002 (Smitley, Davis, & Rebek, 2008) (Fig. 1). We took 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. This study's objective was to use the spread of EAB in Cincinnati as a natural experiment to test for the association between tree loss and crime. We estimated logistic regression

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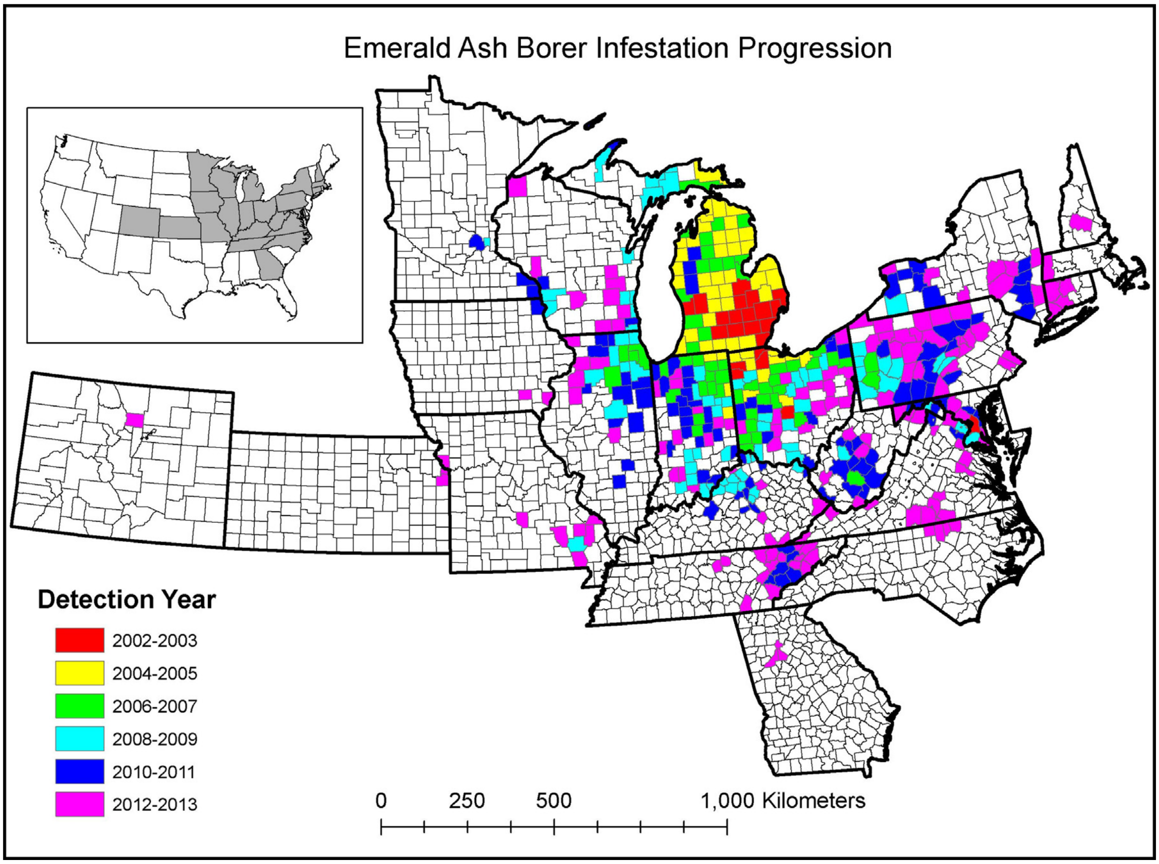

Fig. 1. Spread of the emerald ash borer by county 2002–2013.

models using propensity score weighting to test whether Cincinnati census block groups experienced a change in crime levels after being infected by EAB compared to block groups uninfected by EAB.

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 cross-sectional, 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 fewer reports of narcotics possession (Kondo, Low, Henning, & Branas, 2015).

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) (Also see Demotto and Davies (2006) for an example of empirical evidence related to vegetation). The loss of trees on a block may provide a sign of blight, as dead or decaying trees may make an area look unkempt. Studies have found an association between measures of blight and physical 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). But these studies have not examined tree loss as a potential sign of blight and disorder. It is also possible that if a tree dies and is removed, the atmosphere and impression of environment may decline relative to the demographic background or density level.

Routine activity theory characterizes crime as an opportunistic process: motivated offenders recognize criminal opportunities during daily routine activities (Cohen & Felson, 1979). Based on routine activity theory, situational crime prevention (Clarke, 1980) and crime prevention through environmental design (CPTED) (Newman, 1972; Jeffrey, 1971) suggest that trees and other green space may prevent crime by altering crime-promoting environment components. 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). For example, according to Donovan and Prestemon's (2012) empirical study, trees could be a source of target hardening

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

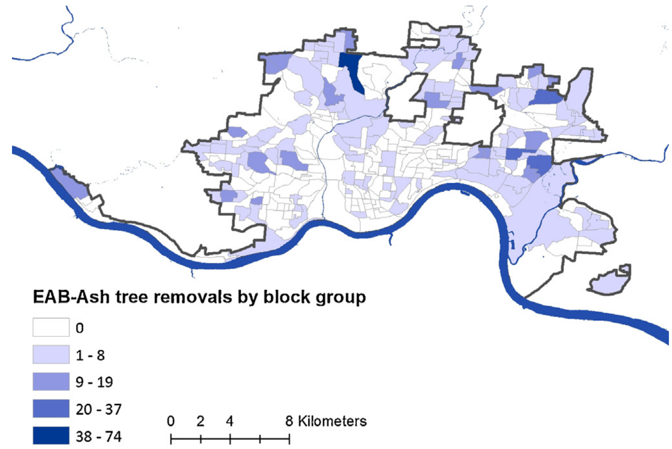

Fig. 3. Map of ash tree removals in Cincinnati by Census block group, April 2007–September 2014.

in a neighborhood if the trees block sight lines, making it unclear if individuals in homes are watching the street or not. In contrast, trees that are lower and overgrown could also increase crime in an area if they sufficiently obscure views in a way that provides cover for criminals to hide and commit burglaries, thefts, and robberies.

While there is a rich literature of case studies, quasi-experiments, and actual experiments examining how manipulations of the physical environment make areas less attractive to criminal opportunities (MacDonald, 2015), the relationship between tree loss and crime is ambiguous. In the present study we seek to fill a gap in the literature by examining the effect that the loss of trees caused by the EAB had on crime in Cincinnati, Ohio. The tree loss caused by the EAB provided a unique opportunity to examine how crime changes in blockgroups before and after trees are removed. The EAB's spread provides a natural experiment as the infestation in the local ash tree canopy is uncorrelated with underlying crime conditions in neighborhoods.

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) (Fig. 2a and b). EAB was first detected in Cincinnati (area: 205.9 km^2) 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 tree removed 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 3000 people, boundaries determined based on roads, railroad tracks, streams, and property lines) 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 crime descriptions 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). Existing studies suggest that the relationship between trees and different types of crime may not be universal. For example, depending on the study, a negative relationship between vegetation abundance or presence of trees have been linked to reductions in total crimes, violent crimes, property crimes, assault, shooting, robbery, burglary, theft, and vandalism (Donovan & Prestemon, 2012; Troy et al., 2012; Wolfe & Mennis, 2012). We therefore included all available crime classes in our analyses.

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).

Instead of using counts of crimes at the block-group level, we represented crimes using a kernel density method. This method converts the crime data from points to a continuous surface using a quadratic function to form a smooth surface from a set of points (Silverman, 1986). This approach gives greater weight to crimes

Table 1
Census[a] 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

[a] American Community Survey 2008–2012.

occurring near trees that were killed by the EAB, and avoids artificially assuming all crime changes within a block group equally across space.

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 2005–2009 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) (Cincinnati Parks, 2010). The study period is 2005 through 2014, in yearly time intervals for a total of 10 time points. 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 to reduce bias in our regression equations relating to observed demographic confounders of crime and tree canopy cover. We used tree canopy cover data from 2000 and demographic data from the US Census American Community Survey (2005–2009) to represent the pre-onset condition in propensity score methods. Applying propensity-score weights to each control block group would ensure that the treatment and control groups' joint distributions would be statistically similar in terms of sociodemographics 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 the control group.

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:

$$Y_{it} = \beta_1 Post_{it} * Trees_{it} + \beta_2(\text{pre-EABtrend}) + \gamma_i + \delta_t \quad (1)$$

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 ($Trees_{it}$). The β_1 parameter is the effect of EAB tree removals on crime outcomes. We used a Poisson regression with robust standard errors rather than Negative Binomial model to avoid a potential omitted variable bias (Gould, 2011; Wooldridge, 2010). In this model the propensity score weights are used as a standard-error correction.

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 & Wooldridge, 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 already balanced on these variables with the propensity score weights.

The block group fixed effects, γ_i, control 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.

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 Eq. (1) without the linear trend and saved coefficient β_1. We repeated this process 1000 times—randomly re-assigning EAB timing before each iteration. If EAB does affect crime, then its random assignment should matter: the $_{\beta1}$ coefficient from the randomized models (over the 1000 iterations) should be significantly different from the non-randomized models. The p-values generated from these permutation tests are also not sensitive to the distributional assumptions of the Poisson regression model we estimated.

3. Results

Table 3 shows the effect (β_1 in Eq. (1)) of EAB on the 10 classes of crime. We found that EAB infestation was significantly associated with higher crime in EAB-infected block groups compared to control block groups 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 block groups compared to in non-EAB infected block groups. Crime incidents saw a relative increase between 1 and 2 percent by block group. Marginal effects at the 10th through 90th percentiles in the distribution of quantities of trees removed are shown in Fig. 4. The charts show, for example, that block groups at the 90th percentile in the trees removal distribution experienced less than 1 more felony assault, and up to 2 more violent crimes, thefts, and breaking and enterings compared to non-EAB block groups. Property crimes experienced the largest difference; over 6 more crimes occurred in EAB-block groups at the 90th percentile compared to non-EAB block groups.

Fig. 5 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

Table 2
Census[a] demographic mean values and (sd) for treatment and control groups, and propensity-score-adjusted values for control groups.

Selection Variables	Treatment (n = 130)	Control (n = 177)		Effect	
		unweighted	weighted	size	p-value[b]
% Youth	0.14 (0.11)	0.16 (0.15)	0.14 (0.12)	0.006	0.961
% Female head of household	0.16 (0.13)	0.19 (0.16)	0.16 (0.12)	0.008	0.944
% Less than HS education	0.15 (0.12)	0.22 (0.17)	0.16 (0.12)	−0.075	0.535
% Unemployed	0.40 (0.15)	0.44 (0.19)	0.41 (0.17)	−0.054	0.688
% Poverty	0.14 (0.14)	0.24 (0.24)	0.15 (0.16)	−0.037	0.760
% Black	0.37 (0.32)	0.47 (0.32)	0.36 (0.31)	0.027	0.828
% Hispanic	0.02 (0.03)	0.02 (0.04)	0.02 (0.04)	−0.063	0.657
% Tree Canopy	9022818 (9228089)	6794548 (10239191)	8939760 (10436836)	0.009	0.948

[a] American Community Survey 2008–2012.
[b] We used the absolute standardized mean difference of the effect size for the *t*-test. We did not find any difference in the results between *t*-test and the Kolmogorov-Smirnov test.

Table 3
Effects of EAB on classes of crime.

Crime	Coef.	SE	95% CI	p-value[a]	Percent pseudo $\beta_1 > \beta_1$[b]
Simple assault	0.007	0.003	(0.002, 0.013)	**	0%
Felony assault	0.013	0.005	(0.004, 0.022)	**	0%
Rape	0.005	0.003	(−0.002, 0.011)		1%
Violent crimes	0.008	0.003	(0.003, 0.013)	**	0%
Theft	0.008	0.002	(0.004, 0.012)	***	0%
Burglary	0.005	0.003	(−0.002, 0.011)		0%
Robbery	0.005	0.003	(−0.000, 0.011)		0%
Breaking & entering	0.014	0.003	(0.008, 0.020)	***	0%
Damage/endangerment	0.002	0.001	(−0.001, 0.004)		2%
Property crimes	0.007	0.002	(0.003, 0.010)	***	0%

n = 3070 (307 block groups X 10 years).
[a] *p < 0.05; **p<0.01; ***p < 0.001.
[b] Percent of permutation test coefficients greater than regression coefficients for each crime.

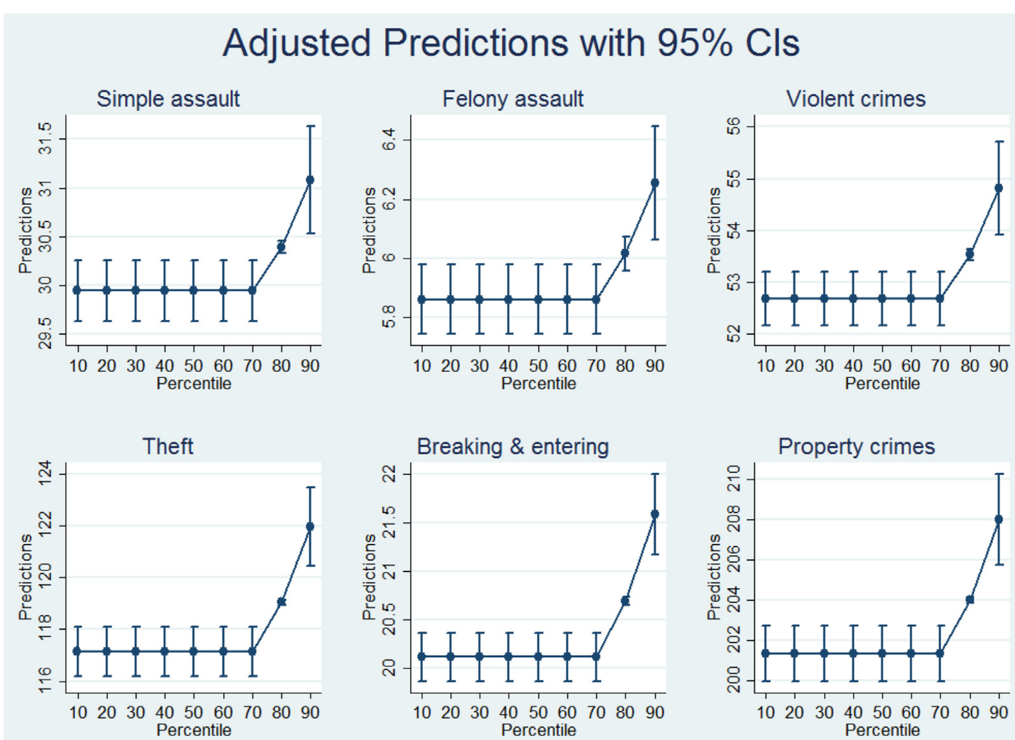

Fig. 4. Adjusted predictions with 95% confidence intervals (CIs) for crime outcomes found to have significant effects in Poisson regression models.

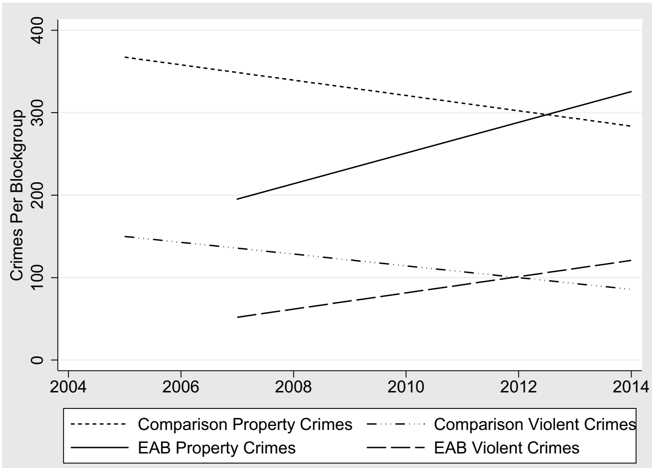

Fig. 5. Violent and property crime fitted values in treatment and control block groups.

EAB-infested block groups were comparable to rates in un-infested block groups. This rate comparison is adjusted for sociodemographic factors occurring within block groups over time that might influence a change in crime levels.

In addition, using the Monte Carlo permutation tests to evaluate the robustness of our estimates, we found that our randomized EAB coefficients (pseudo β_1) only exceeded the non-randomized EAB coefficients (β_1) in two of the crime outcomes (rape and damage to property) that were not significantly associated with EAB tree removals (see Table 3). These permutation tests show that with the exception of two crime outcomes our estimates from the timing of EAB are not sensitive to the distributional assumptions of the Poisson regression model estimated or serial dependence in the timing of when EAB trees removals occurred.

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. Land managers and planners might consider targeting areas that lose trees with extra crime-prevention measures. Tree planting in high-crime areas may also be worth exploring as a potential complement to traditional crime-prevention activities, like improving street lighting, neighborhood watch groups, and providing routine police patrol of neighborhoods.

However, our study did not provide any insights into the mechanisms linking tree loss to shifts in crime. For example, one remaining question is whether the loss of ash street trees lead to an increase in the overall level of crime in Cincinnati, or whether an "infill" effect occurred where crime moved from other parts of the city to areas particularly affected by tree loss. A large-scale randomized controlled trial and careful observation of areas would be required to establish any specific causal mechanisms whereby trees influence crime in neighborhoods. Nevertheless, our results are consistent with criminology theories, including broken windows and routine activity theories, suggesting that the loss of trees may increase crime by making the built environment more attractive to potential offenders by sending a signal that a neighborhood is not being cared for, or by decreasing the natural surveillance of blocks. If trees indeed encourage more pedestrians on a street, which deters potential offenders, the loss of trees could have the opposite effect.

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). Therefore, urban-form, or building-level policy implications cannot be drawn from this study. An experimental (randomized and controlled) trial study design would be required to establish such mechanisms. Nevertheless, quasi-experimental studies such as this can indicate patterns of association occurring across a landscape.

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. Even if this is the case, separately accounting for the loss of yard trees could change the magnitude of coefficients of interest, but not their sign. 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 the presence of or increase in healthy trees may deter crime.

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