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### Emerald ash borer intensifies harvest regimes on private land

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### Abstract

Invasive forest insects have significant direct impacts on forest ecosystems, and they are also generating new risks, uncertainties, and opportunities for forest landowners. The growing prevalence and inexorable spread of invasive insects across the United States, combined with the fact that the majority of the nation's forests are controlled by thousands of autonomous private landowners, raises an important question: To what extent will private landowners alter their harvest practices in response to insect invasions? Using a quasi-experimental design, we conducted a causal analysis to investigate the influence of the highly impactful emerald ash borer (EAB) on (1) annual probability of harvest; (2) intensity of harvest; and (3) diameter of harvested trees, for both ash and non-ash species on private land throughout the mid-western and mid-Atlantic regions of the United States. We found that EAB detection had a negative impact on annual harvest probability, and a positive impact on harvest intensity, resulting in a net increase in harvested biomass. Furthermore, our estimates suggest that EAB detection will influence private landowners to harvest greater quantities of ash, relative to non-ash species. We also found that harvested trees in EAB-infested areas had smaller diameters, on average, compared to those unaffected by EAB. These results can help policymakers, forest managers, and extension programs to anticipate and better advise landowners and managers about their options and the associated outcomes for forests.

**Keywords:** forest management, harvest regimes, invasive insects, emerald ash borer, *Fraxinus*, causal inference, zero-inflated beta regression, covariate matching, coupled human and natural systems, disturbance ecology, Forest Inventory and Analysis

### 1. Introduction

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Non-native plants, animals, and microorganisms are fundamentally altering the composition and function of ecosystems, particularly forests, whose slow growth and remoteness often hinder the timely detection of invasive species (Liebhold, Brockerhoff, & Nuñez, 2017). While most non-native organisms have negligible impacts on their host environments, a selection of woodboring beetles have established themselves as a major source of disruption to forests. Over the past two centuries, woodboring beetles have been unintentionally moved between continents in wood and wood packaging material (Brockerhoff, Bain, Kimberley, & Kníñek, 2006), with dramatic consequences in their new habitats. For instance, tree-killing bark beetles can convert coniferdominated stands into broad-leaf forests, effectively replacing entire swaths of trees with other, often functionally different, plant species (Edburg et al., 2012). In addition to modifying forest structure and function, bark and woodboring insects in the United States cost hundreds of millions of dollars per year in lost timber revenue (Liebhold et al., 2017).

Invasive insects and timber harvesting represent the primary disturbance agents in eastern North American forests, and through selective mortality they substantially alter the composition and structure of the forested landscape (Canham, Rogers, & Buchholz, 2013; Fei, Morin, Oswalt, & Liebhold, 2019; Liebhold et al., 2017). Synergies between invasive insects and timber harvesting pose risks and uncertainties for the future of forest management. Anticipating how landowners will respond to the presence or threat of insects is challenging and not well understood, though salvage cutting (or pre-emptive salvage cutting) has long been the default management choice when faced with an exogenous disturbance (Lindenmayer et al. 2010). Specific management

decisions are strongly influenced by attributes of the insect (e.g., rate of spread, lethality, and host specificity), the landowner type, and the social context (Markowski-Lindsay et al., 2020). Past outbreaks in the region have been accompanied by accelerated harvesting, and there are distinct ecological legacies of the interactions between these two classes of biotic disturbance. From 1972 – 1986, for example, industrial timberland owners in Maine dramatically increased clear-cut salvage harvesting during an extensive spruce budworm (*Choristoneura fumiferana*) outbreak, resulting in the widespread conversion of spruce-fir forests to deciduous ones (Irland et al. 1988). Similarly, following reports that hemlock woolly adelgid (*Adelges tsugae*) had reached Connecticut in the 1980s and 1990s, many landowners harvested hemlock trees, despite their low commercial value (Orwig, Foster, & Mausel, 2002). In 2008, when Asian longhorned beetles (*Anoplophora glabripennis*) were discovered in Worcester, MA, the USDA responded by felling and chipping >35,000 trees along city streets and in urban woodlots (Dodds & Orwig, 2011). Understanding the connections and feedbacks among these drivers of change is critical for anticipating ecological impacts and developing sustainable policies.

In recent years, the phloem-feeding buprestid beetle emerald ash borer (EAB; *Agrilus planipennis*) has become the most destructive and costly forest insect to ever invade North America (Aukema et al., 2011; Lovett et al., 2016; Morin, Liebhold, Pugh, & Crocker, 2017). The impact of EAB is so widespread and severe that American ash species (*Fraxinus* spp.) could be functionally extinct within decades (Herms & McCullough, 2014). Forest landowners and managers have been forced to adapt their decision-making to account for the presence and threat of EAB throughout range of ash in North America.

EAB, native to Asia, was first identified in the US in 2002 near Detroit, Michigan, although it is now understood that the initial invasion occurred in the mid 1990s. Since its arrival in North America, the insect has spread to dozens of US states and has killed millions of ash trees. The lack of resistance in North American ash hosts (Anulewicz, Mccullough, Cappaert, & Poland, 2008) results in rapid spread of EAB, threatening the persistence of North American species in the genus *Fraxinus*. EAB dispersal is primarily a function of time (i.e., the invasion spreads across the host range until saturation occurs), although other significant correlates of EAB dispersal include human population density (+) , ash and non-ash tree densities (+) , and temperature (-) (Ward, Fei, & Liebhold, 2020). Once EAB is established, ash species experience an increased mortality rate and corresponding decreases in volume until most live ash are killed (Klooster et al., 2018; Morin et al., 2017; Pugh, Liebhold, & Morin, 2011).

As with forest insects, timber harvest regimes are critical drivers of meso-scale ecological dynamics (Thompson, Canham, Morreale, Kittredge, & Butler, 2017). Harvest regimes are driven by physical, social, and economic factors (Thompson et al., 2017). Aboveground tree biomass, species, and diameter are correlated with the probability and intensity of harvest (Canham et al., 2013; Silver, Leahy, Weiskittel, Noblet, & Kittredge, 2015). The demographic attributes population density and median household income are negatively correlated with harvest intensity (Kittredge, Thompson, Morreale, Short Gianotti, & Hutyra, 2017). Ownership type has also been shown to affect harvest regimes, with private woodland owners generally removing more trees than public entities (Thompson et al., 2017). Although timber market prices are intuitively tied to harvest patterns, Kittredge & Thompson (2016) found that fluctuations in

stumpage are an unreliable predictor of aggregate harvest activity for non-industrial private landowners.

An open question is the degree to which EAB detection influences harvest regimes, an interaction that could potentially compound and modify the disturbance impact on the forested ecosystem by either broadening its impact (e.g., accelerated harvesting, transportation of infested firewood) or by limiting its spread (e.g., removal of host trees). Of particular interest is the impact of EAB detection on logging by private landowners, who autonomously make decisions that collectively affect the majority of US forestland. A 2017 mail survey of private landowners in New England found that 84% of respondents (n = 688) intended to harvest, in some capacity, in response to a hypothetical tree insect invasion (Markowski-Lindsay et al., 2020). Empirical evidence of a synergy between EAB detection and harvesting regimes, however, is lacking.

Here we determine whether EAB detection (henceforth, 'EAB') affects harvest regimes on privately owned forestland. Disturbances such as forest insect pests often prompt 'salvage' harvesting, which serves to recover monetary value in affected timber or meet certain silvicultural goals (Lindenmayer, Burton, & Franklin, 2008). While salvage harvests typically occur after a disturbance such as wind or fire, 'sanitation' harvests can also occur preemptively in an attempt to mitigate future damage or value loss, particularly in the case of forest insects (Waring & O'Hara, 2005). The effects of salvage and/or sanitation harvesting can extend beyond the host species alone; for example, the spruce budworm and the hemlock woolly adelgid prompted landowners to harvest a mix of host and non-host tree species (Irland, Dimon, Baum, Falk, & Stone, 1988; Kizlinski, Orwig, Cobb, & Foster Harvard, 2002). The removal of non-host tree species with the host species serves to increase the commercial value of the harvest and/or to promote a desired regeneration of species (MacLean et al., 2020). In our analysis, we examine the effects of EAB on both host (ash) and non-host (co-occurring with ash) tree species.

Using publicly available datasets, our analysis addressed the following three research questions: (1) How is the annual probability and intensity of ash-species harvested impacted by EAB? (2) How is the annual probability and intensity of non-ash-species harvested influenced by EAB? (3) Does the presence of EAB impact the mean diameter of harvested trees?

2. Materials and Methods

### 2.1. Summary of Methodology

Using data from the US Forest Service's Forest Inventory and Analysis (FIA), the US Department of Agriculture's Animal and Plant Health Inspection Service (APHIS), and the American Community Survey (ACS), we quantified the influence of EAB on harvest frequency, harvest intensity, and mean diameter of removed trees. We analyzed these data using a quasiexperimental statistical design to test for a causal relationship between the presence of EAB and altered harvest behavior *sensu* Larsen et al (2019). Borrowing language from randomized control trials, we use 'treatment' to denote EAB presence; 'control' refers to no EAB; and our 'response' is tree-harvesting. We first implemented a matching algorithm to ensure that 'treatment' (EAB) and 'control' (no EAB) observations had similar variable distributions with respect to the covariates shown by Ward et al. (2020) to impact EAB dispersal (e.g., human population density, tree density, temperature). Then, to quantify the effect of EAB on harvesting, we performed regression analysis using covariates shown by Thompson et al. (2017) to impact harvesting (e.g., volume of living trees, human population density, median household income). Finally, we compared the diameters of harvested trees on plots with and without EAB using a Student's t-test, with separate comparisons for ash and non-ash species.

### 2.2. Data Description

We obtained annual county-level EAB invasion status from the USDA APHIS for nine US states, including parts of the mid-west and mid-Atlantic regions (Figure 1). At the county level, measurable impacts on forests generally begin to appear about five years after establishment and are widespread at ten years (Morin et al., 2017). As a compromise between EAB tenure, which began in 2002 in the APHIS dataset, and number of treatment (EAB) observations, we conducted our analysis for the years 2007-2012, mirroring the second EAB "invasion cohort" described in Ward et al. (2021). Any plot in a county in which EAB was detected prior to 2007 was in the treatment group; all plots in counties that were infected after 2012 were in the control group (Figure 1). Response (harvest) data were extracted for the years 2007-2012. By omitting from our analysis counties that detected EAB between 2007-2012, we temporally separated the treatment effect from the response, which leads to a more straightforward matching routine (Section 2.3).

Plot characteristics and tree data were extracted from the US Forest Service FIA program using the rFIA package (Stanke & Finley, 2020; Stanke, Finley, Weed, Walters, & Domke, 2020) for

the statistical software R (Core Team, 2020). We used data from plots for which there were two censuses conducted using the contemporary plot design (1999 onwards) to allow determination of prior and subsequent plot characteristics (e.g., which trees were removed). Specifically, all prior observations were conducted between 1999 and 2006; all subsequent observations were conducted between 2007-2012. By comparing the initial and follow-up observations of each plot, we determined which trees were harvested as well as the species and diameter of each harvested tree. In accordance with FIA protocol, we considered harvested trees to be those that were "cut or removed by direct human activity related to harvesting, silviculture or land clearing" (Woudenberg et al., 2010). Trees with diameter < 12.7 cm (5 inches) were omitted from our analysis (including plot-level statistics) in order to be consistent with FIA demographic estimates.

Plots that did not contain any ash trees were removed from the data since these plots were not subject to the treatment effect. In the context of this study, 'ash species' includes white ash (*Fraxinus americana*), green ash (*Fraxinus pennsylvanica*), and black ash (*Fraxinus nigra*). We considered privately-owned plots only (omitting federal and state plots) in order to contextualize our findings within the discussion of private landowner behavior (e.g., Holt et al., 2020; Markowski-Lindsay et al., 2020).

Socioeconomic variables shown to be correlated with the treatment and/or response were downloaded from the ACS using the tidycensus package (Walker, Herman, & Eberwein, 2020). We obtained human population density at the county level in order to match EAB and non-EAB counties (Ward et al., 2020). Human population density and median household income were also obtained at the census tract level to be incorporated into the finer-resolution harvest models.

Meteorological variables known to be predictive of the treatment effect were downloaded from PRISM (PRISM, 2019). We obtained climate normals (three-decade averages) for precipitation (mm), minimum temperature (°C) and maximum temperature (°C) for the period 1981-2010 at a 4 km x 4 km resolution raster. We then conducted a principal components analysis (PCA) and aggregated the rotated principal component scores to the county level by averaging values for all grid cells whose centroids occurred within a given county boundary. Minimum and maximum temperatures had high loadings on the first principal component ('PC1') whereas precipitation had high loadings on the second ('PC2'). Ward et al. (2020) identified PC1 as being correlated with the treatment effect; as such, we included PC1 as a covariate in our matching routine.

### 2.3. Covariate Matching

When using observational data to consider a causal relationship, such as the effect of EAB on harvest regimes, one must address confoundedness, or the possibility that differences in the response variable between treatment and control groups are caused by factors that predict treatment rather than the treatment itself (Cochran & Rubin, 1973). As an example of confoundedness, ash tree density may be a causal mechanism for both EAB invasions and ash harvesting; in this scenario, it would be impossible to identify the relationship between EAB and ash harvesting without controlling for ash tree density. Therefore, before assessing the relationship between EAB and harvest regimes, we (1) identified variables known to be correlated with the treatment effect and (2) ensured that the joint distributions of these variables were similar between treatment and control groups.

We matched covariates using the Genetic Matching algorithm (Diamond & Sekhon, 2013), which is a generalization of propensity score and Mahalanobis distance matching (Rosenbaum & Rubin, 1985). The algorithm is a multivariate matching method that uses an evolutionary search routine developed by Sekhon and Mebane (Sekhon & Mebane, 1998) to maximize the balance of observed covariates (i.e., the joint distribution) across treatment and control units. Human population density, ash tree density, non-ash tree density, and temperature are variables shown to be correlated with EAB invasion (Ward et al., 2020), and thus were used as covariates for the matching algorithm. EAB spread has also been shown to be spatially and temporally autocorrelated (e.g., EAB in a county is influenced by EAB in neighboring counties). We removed spatiotemporal interactions between the treatment and response by utilizing the following framework: All sites that first detected EAB from 2002-2006 were treatment units; sites that first detected EAB from 2013 onwards were control units; and we collected response data between 2007-2012, effectively separating the treatment effect from the response. The tradeoff of this approach is that we introduce variability in the time since EAB was detected; since EAB was first detected at treatment sites anywhere between 2002-2012, the duration human knowledge of EAB in the county varied from 1-10 years (Figure 1, histogram).

The Genetic Matching algorithm assigns weights to control observations such that the weighted controls are similar to the unweighted treatment units. For matching numeric covariates, as in our case, the standardized difference in means can be used to diagnose balance. While there is no

universally agreed upon threshold of the standardized difference in means, a difference that is near or below 0.1 has generally been taken to indicate a negligible difference in the mean covariate between treatment and control groups (Normand et al., 2001). We used the MatchIt package (Ho et al., 2020) to implement the Genetic Matching algorithm.

### 2.4. Regression Modeling

Using the matched data, our statistical model estimated two components of the harvest regime: (1) probability of being logged; and (2) percentage basal area removed if logged. Both components were modeled simultaneously, similar to Canham et al. (2013). We used a zero-inflated beta distribution for the likelihood function, since the harvest data include many zeros (unlogged plots), and the distribution of percentage basal area removed (if logged) must fall between zero and one. The zero-inflation term was modeled as a logistic regression. Both the logistic and beta components of the model varied as a function of the same four harvest covariates: aboveground biomass (*AGB*) at the previous observation, human population density (*popden*), median household income (*MHHI*), and *EAB*.

We followed a Bayesian model-fitting procedure to estimate our piecewise regression. The zeroinflation term (harvest probability) is modeled as follows, where *N* is the number of years between plot observations and *w* is the probability of not harvesting. By raising the inverse of harvest probability to the power *N*, we return estimates for annualized harvest probability. The regression coefficients  $\beta$  have uninformative priors  $\beta \sim Normal(0, 10^2)$ .

$$\mu_i = \beta_0 + \beta_1 AGB_i + \beta_2 popden_i + \beta_3 MHHI_i + \beta_4 EAB_i$$
(1)

$$p_i = invLogit(\mu_i) \tag{2}$$

$$w_i = (1 - p_i)^N (3)$$

The beta-distributed component of the model (harvest intensity) is expressed as follows, where  $\gamma$  is a regression coefficient drawn from an uninformative prior  $\gamma \sim Normal(0, 10^2)$ ; *y* is the percent basal area harvested; and *r* is the concentration parameter of the beta distribution, which we treat as a random variable with prior  $r \sim Gamma(0.1, 0.1)$ . For readability, we define the log of the beta distribution explicitly.

$$\eta_i = \gamma_0 + \gamma_1 AGB_i + \gamma_2 popden_i + \gamma_3 MHHI_i + \gamma_4 EAB_i$$
(4)

$$s_i = invLogit(\eta_i) \tag{5}$$

$$logBeta_i = log(beta(y_i, rs_i, r(1 - s_i)))$$
(6)

Next, we define an indicator variable z to denote harvested and non-harvested observations:

$$z_{i} = \begin{cases} 1 \ if \ y > 0 \\ 0 \ if \ y = 0 \end{cases}$$
(7)

Combining the zero-inflation and continuous model components, we arrive at the likelihood function. Observe that in the absence of harvest (z = 0), the logistic term dominates the likelihood, whereas both the logistic and beta terms are influential when harvest is non-zero.

$$logLikelihood_{i} = (1 - z_{i}) * log(w_{i}) + z_{i} * (log(1 - w_{i}) + logBeta_{i})$$

$$(8)$$

The model was implemented using JAGS via the R2jags package (Su & Yajima, 2012). A total of three separate models were estimated in order to characterize the influence of EAB on ash and non-ash harvest regimes: Model 1 (ash species only); Model 2 (non-ash species); and Model 3 (ash expressed as a fraction of total harvest).

### 2.5 Harvest Diameter

Using the matched dataset, we conducted a weighted Student's t-test to compare the diameters of harvested trees (diameter  $\geq$  12.7 cm) in EAB and non-EAB counties. Ash and non-ash species were analyzed separately.

3. Results

### 3.1. Matching

Before we matched the data, the treatment and control groups exhibited significant mean differences in covariates that are known to impact the probability of EAB invasion, thereby

confounding causal interpretation of the results. Ash density and non-ash density both had standardized mean differences of 0.36. Population density was the most similar covariate between the two groups (0.15), whereas PC1 had the greatest contrast (0.90). The large difference in PC1, which represents temperature, can be explained by the fact that most treatment observations are located in the northern state of Michigan, whereas many of the control observations are in warmer areas of West Virginia, Indiana, and Illinois (Figure 1).

The Genetic Matching algorithm achieved negligible mean differences between treatment and control groups in ash density (0.07), non-ash density (0.01), population density (0.002) and PC1 (0.06) (Appendix S1). This balance was achieved by selecting 310 of the control observations most similar to the 691 treatment observations (2033 control observations were discarded). The 310 control units were assigned weights such that all units sum to one.

3.2. EAB impacts on harvest probability and intensity

Ash and non-ash harvests were detected in 6% and 9% of the FIA plots, respectively. When ash was harvested, 63% of the plot's basal area ash was removed, and ash species amounted to about half of the total harvest, on average. Non-ash removals averaged 32% of the plot's basal area. The average time interval between subsequent measurements (N in Eq. 3) was 5.08 years (SD = 0.65).

Harvest probability was modelled in tandem with harvest intensity (Equation 8), wherein both the probability and intensity terms varied as functions of aboveground biomass (AGB), EAB

presence, human population density, and median household income (MHHI). Each model converged after 2000 iterations with a burn-in period of 200. Based on the deviance information criterion (DIC) (Spiegelhalter, Best, Carlin, & van der Linde, 2002), Model 1 (ash species only) had the best fit, followed by Models 3 (ash species expressed as a fraction of total harvest) and 2 (non-ash species; Table 1).

Tree biomass was the strongest predictor of harvest and was a significant variable in all three models. AGB had a statistically significant positive effect on harvest probability in Model 1 (ash) and Model 2 (non-ash). AGB was also positively correlated with the intensity component of Model 3 (fraction of harvest composed of ash) (Table 1). On the contrary, AGB had a negative impact on non-ash harvest intensity.

The two demographic variables, human population density and median household income, displayed limited effects in our models. MHHI was negatively correlated with the probability of non-ash harvest but had a positive influence on the intensity component of Model 3. Human population density was not estimated to be significant in any of the regressions.

EAB, our main variable of interest, had a statistically significant and negative impact on non-ash harvest probability. Our model predicts that a plot with 50 Mg/ha of non-ash biomass will experience a 0.13 reduction in annual probability of harvest due to EAB (Figure 2A). Ash harvest probability, on the other hand, was not sensitive to the presence of EAB within the 95% credible interval.

Harvest intensity was positively influenced by EAB, but this effect was statistically significant for ash species only (Model 1). Figure 2B illustrates the predicted effects of EAB on harvest intensity. The percentage of basal area removed decreases as a function of AGB, and, in the case of ash species, EAB induces approximately 25% more basal area removal (Figure 2B).

Finally, EAB had a positive impact on the ash fraction of harvest (Model 3, intensity component), although this estimate is statistically significant only at the 90% credible interval. Figure 3 portrays the predicted probabilities of harvesting ash (Figure 3A) and, if ash is harvested, the fraction of the total harvest comprised of ash (Figure 3B), as a function of the ash fraction of available aboveground biomass. For an FIA plot with 50% aboveground ash biomass, EAB is estimated to increase the ash composition of harvest by about 15% (Figure 3B).

### 3.3. Harvest Diameter

A weighted Student's t-test indicated that trees harvested in EAB counties were smaller than those in non-EAB counties, for both ash and non-ash species. The mean diameter of harvested ash trees in EAB counties was 25.1 cm, compared to 31.9 cm in counties without EAB (p =0.06). Harvested trees of non-ash species had a mean diameter of 27.2 cm in EAB counties, compared to 36.7 cm in non-EAB counties (p=0.007) (Figure 4).

4. Discussion

The inevitable spread of EAB throughout much of the United States poses an interesting question: To what degree will EAB influence harvest regimes? And, if harvest regimes are altered by EAB, what is the significance of those shifts? Using publicly available data, we combined covariate matching and regression analysis to uncover causal relationships between EAB and several aspects of private forest owner harvest regimes. Our results demonstrate that EAB increased the amount of harvested biomass, and that EAB-induced harvests contained greater quantities of ash, relative to non-ash species. We also find that harvested trees in EAB-infested areas had smaller diameters, on average, compared to those unaffected by EAB.

The positive effects of EAB on (1) ash harvest intensity and (2) the fraction of the overall harvest composed of ash suggest that a wave of ash removals will follow the spread of EAB across the landscape. This synchronized harvest behavior by private woodland owners is in contrast with the general characterization of private landowners as exhibiting unpredictable harvest behavior. Kittredge (2004) presented a decision cycle for private woodland owners, whereby the individual does not engage in harvesting until an exogenous personal event (e.g., medical expenses, college tuition, etc.) occurs that incentivizes a timber sell-off. However, the detection (or impending detection) of EAB could serve to upend this variability and harmonize harvest patterns of private forest owners. This opportunistic harmonization of logging has the potential to alter forest development trajectories and change structural legacies, with consequences for ecosystem services and biodiversity (Leverkus et al., 2018). Species that co-occur with ash, and particularly those that are preferred species for harvest, are most likely to be removed and are most vulnerable to EAB-induced harvests (MacLean et al., 2020).

The increased intensity of ash removals in response to EAB supports the survey results of Markowski-Lindsay et al. (2020), which found that that private landowners in the northeastern United States overwhelmingly intended to harvest in response to invasive insects (including EAB, hemlock woolly adelgid, and/or Asian longhorn beetle). In fact, ash removal was encouraged in the early years of EAB detection as a means to contain the invasion (McCullough & Siegert, 2007). Somewhat surprising, however, is the estimated negative effect of EAB on harvest probability – a reduction that was statistically significant for non-ash species but not for ash. This negative effect could be due to sanitation logging that occurred prior to the timeframe of our analysis. In other words, while we estimated the effects of EAB within the first ten years of detection, it is likely that EAB-induced harvesting occurred prior to this time, either due to undocumented EAB cases or to the foresight of proactive landowners. Savvy forest owners in the control group might also have pre-emptively harvested trees prior to the official EAB detection date, which would weaken the observed effect of EAB on harvest probability. The lower annual probability of harvest on EAB plots could also be due to the fact that more of these plots are located in colder regions where trees experience slower growth rates, compared to non-EAB plots. It is important to note that, despite the negative effect of EAB on harvest *probability*, the positive effect of EAB on harvest *intensity* dominated our statistical model and yields a predicted net increase in harvested basal area.

In addition to changes in the probability and intensity of tree removals due to EAB, we detected differences in the average plot harvest diameter for both ash (p = 0.06) and non-ash (p = 0.007) species when comparing treatment and control groups. On one hand, this is surprising since early efforts in Michigan originally focused on removing only the largest ash trees to reduce the

available phloem for EAB development in order to slow its spread (McCullough & Siegert, 2007). However, McCullough & Siegert (2007) also mention locations in MI and OH where all ash stems surrounding a focal tree in infested areas were removed. Our results are more indicative of the latter and suggest that EAB may reduce the choosiness of foresters, who, faced with either infected timber or the impending threat of EAB, decide to harvest more ash from a site, resulting in harvest smaller average trees than would normally be cut. Given that non-ash species also exhibited a difference in harvest diameter, this reduced choosiness appears to extend to the entire harvest. It is unclear from the data whether the increased removal of smaller non-ash trees due to EAB serves a silvicultural purpose, economic goal, or both.

Regression analysis of the matched dataset supports previous estimates of the influence of aboveground biomass on harvest probability. Similar to Canham et al. (2013) and Thompson et al. (2017), we estimated AGB to have a positive effect on harvest probability for both ash and non-ash species (Figure 2). The relationship between AGB and harvest intensity has been found to vary greatly by state and forest type, but northern hardwood forests and the Great Lakes states are known to exhibit a negative trend (Canham et al., 2013; Thompson et al., 2017), which we also observed in our estimated effect of AGB in the non-ash model (Model 2). This may be because most harvests on land owned by private owners are frequent, low intensity harvests that remove less than 20% of overstory basal area (Thompson et al. 2017).

Socioeconomic variables did not play a large role in our statistical models. We estimated no significant effect of human population density; moreover, median household income influenced only the probability of harvest for non-ash species and the intensity of ash composition of the

harvest. The positive relationship between affluence and the ash composition of harvest could suggest that private landowners of lower affluence capitalize on the opportunity to harvest more tree species (in addition to ash) due to higher financial need. In general, lower-income forest owners are thought to harvest at greater intensities than their wealthier counterparts (Thompson et al., 2017).

Causal interpretation of our regression analysis was enabled by a Genetic Matching algorithm that achieved covariate balance between treatment and control units. However, this balance came at the expense of statistical power; in order to achieve such balance, 1723 out of 2033 control observations were discarded. This 'imbalance-n' tradeoff typically observed in matching routines is analogous to the well-known 'bias-variance' tradeoff encountered in statistics and machine learning (Geman, Bienenstock, & Doursat, 1992). Furthermore, in matching the joint distributions between treatment and control groups, we assume that we have identified the key sources of confoundedness. Indeed, our four matching covariates (ash density, non-ash density, PC1, and human population density) are well-founded correlates of EAB invasion in the literature; however, other potential influences of EAB spread exist. For instance, urban forests, which are absent from the FIA dataset, are known to play an important role in the spread of EAB by serving as the first point of contact for the pest (Colunga-Garcia, Haack, Magarey, & Margosian, 2010; Paap, Burgess, & Wingfield, 2017). Urban trees often exist as single species plantings (Donaldson et al., 2014), and may be predisposed to infestation due to anthropogenic stress, increasing the likelihood of exotic forest pests becoming established and proliferating (Pautasso, Schlegel, & Holdenrieder, 2015). Nevertheless, spatiotemporal dynamics are the primary driver of EAB invasion (Ward et al., 2020) and, in our experimental design, we remove

spatiotemporal pressure as a potential confounder by separating the treatment and response in time and space (Figure 1).

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Despite controlling for many potentially confounding influences, several potential sources of bias remain within our quasi-experimental design . As indicated previously, EAB detection methods were more refined for the control group compared to the treatment group. Similarly, the control group had higher levels of knowledge of, and familiarity with, EAB. These disparities could mean that (1) the treatment group experienced a wider range of damage due to EAB; and (2) the control group had a better opportunity to preemptively harvest healthy trees, both of which could dampen the observed effect of EAB on harvest regimes (i.e., our estimated effect may be underestimated). The evolving understanding of EAB, and the ever-changing protocols associated with its spread, make it difficult to generalize causal effects observed during any particular period of time. Another potential confounder is the implementation of quarantines (efforts to curb the transportation of infested wood), which were typically established at the county level once EAB was detected. Since quarantines roughly coincide with EAB arrival, the effect of quarantines on harvest activity is a potential source of noise.

### 5. Conclusion

Our study suggests that private forest owners alter their management decisions based on the presence of invasive forest insects. In the case of the EAB in the central U.S., we show that landowners harvested more intensely and across a wider range of tree sizes when the insect was present in the county. This finding is significant because the abundance and severity of wood-

boring insects in North America is projected to increase three-to-four-fold by 2050 as a result of climate change and global trade (Ayres & Lombardero, 2000; Leung, Springborn, Turner, & Brockerhoff, 2014). It is particularly valuable to understand private landowner dynamics vis-à-vis wood-boring insects, as this owner group controls a large majority of forestland in the United States and its decision-making is largely uncoordinated. Our analysis suggests that these insects will influence timber harvest regimes in novel ways with potentially significant impacts on forest and the services they provide. By understanding the relationship between insects and harvest regimes, policymakers, forest managers, and extension programs will be better equipped to advise landowners and managers about their options and the associated outcomes for forests.

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### 7. References

Anulewicz, A. C., Mccullough, D. G., Cappaert, D. L., & Poland, T. M. (2008). Host range of the emerald ash borer (Agrilus planipennis Fairmaire) (Coleoptera: Buprestidae) in North

America: Results of multiple-choice field experiments. *Environmental Entomology*, *37*(1), 230–241. https://doi.org/10.1603/0046-225X(2008)37[230:HROTEA]2.0.CO;2

- Aukema, J. E., Leung, B., Kovacs, K., Chivers, C., Britton, K. O., Englin, J., ... Von Holle, B.
  (2011). Economic Impacts of Non-Native Forest Insects in the Continental United States. *PLoS ONE*, 6(9), e24587. https://doi.org/10.1371/journal.pone.0024587
- Ayres, M. P., & Lombardero, M. J. (2000). Assessing the consequences of global change for forest disturbance from herbivores and pathogens. *Science of the Total Environment*, 262(3), 263–286. https://doi.org/10.1016/S0048-9697(00)00528-3
- Brockerhoff, E. G., Bain, J., Kimberley, M., & Kníñek, M. (2006). Interception frequency of exotic bark and ambrosia beetles (Coleoptera: Scolytinae) and relationship with establishment in New Zealand and worldwide. *Canadian Journal of Forest Research*, 36, 289–298. https://doi.org/10.1139/X05-250
- Canham, C. D., Rogers, N., & Buchholz, T. (2013). Regional variation in forest harvest regimes in the northeastern United States. *Ecological Applications*, 23(3), 515–522. https://doi.org/10.1890/12-0180.1
- Cochran, W. G., & Rubin, D. B. (1973). Controlling Bias in Observational Studies: A Review. Sankhyā: The Indian Journal of Statistics, Series A (1961-2002), 35(4), 417–446. Retrieved from http://www.jstor.org/stable/25049893
- Colunga-Garcia, M., Haack, R. A., Magarey, R. A., & Margosian, M. L. (2010). Modeling spatial establishment patterns of exotic forest insects in Urban areas in relation to tree cover and propagule pressure. *Journal of Economic Entomology*, *103*(1), 108–118. https://doi.org/10.1603/EC09203

Core Team, R. (2020). R: a language and environment for statistical computing. Vienna, Austria:

R Foundation for Statistical Computing.

- Diamond, A., & Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, 95(3), 932–945. https://doi.org/10.1162/REST\_a\_00318
- Dodds, K. J., & Orwig, D. A. (2011). An invasive urban forest pest invades natural environments
   Asian longhorned beetle in northeastern US hardwood forests. *Canadian Journal of Forest Research*, 41(9), 1729–1742. https://doi.org/10.1139/X11-097
- Donaldson, J. E., Hui, C., Richardson, D. M., Robertson, M. P., Webber, B. L., & Wilson, J. R.
  U. (2014). Invasion trajectory of alien trees: the role of introduction pathway and planting history. *Global Change Biology*, 20(5), 1527–1537. https://doi.org/10.1111/gcb.12486
- Edburg, S. L., Hicke, J. A., Brooks, P. D., Pendall, E. G., Ewers, B. E., Norton, U., ... Meddens, A. J. H. (2012, October 1). Cascading impacts of bark beetle-caused tree mortality on coupled biogeophysical and biogeochemical processes. *Frontiers in Ecology and the Environment*. John Wiley & Sons, Ltd. https://doi.org/10.1890/110173
- Fei, S., Morin, R. S., Oswalt, C. M., & Liebhold, A. M. (2019). Biomass losses resulting from insect and disease invasions in US forests. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(35), 17371–17376. https://doi.org/10.1073/pnas.1820601116
- Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. *Neural Computation*, *4*(1), 1–58.
- Herms, D. A., & McCullough, D. G. (2014). Emerald ash borer invasion of north america:
  History, biology, ecology, impacts, and management. *Annual Review of Entomology*, *59*, 13–30. https://doi.org/10.1146/annurev-ento-011613-162051

- Accepted Articl
- Ho, D., Imai, K., King, G., Stuart, E., Whitworth, A., & Greifer, N. (2020). MatchIt: Nonparametric Preprocessing for Parametric Causal Inference.
- Holt, J. 2021. jon-holt/EAB-harvest-regimes: EAB Harvest Regimes (v1.0). Zenodo. https://doi.org/10.5281/zenodo.5173143
- Holt, J. R., Borsuk, M. E., Butler, B. J., Kittredge, D. B., Laflower, D., MacLean, M. G., ...
  Thompson, J. R. (2020). Landowner functional types to characterize response to invasive forest insects. *People and Nature*, 2(1), 204–216. https://doi.org/10.1002/pan3.10065
- Irland, L. C., Dimon, J. B., Baum, E., Falk, J., & Stone, J. L. (1988). *The Spruce Budworm Outbreak in Maine in The 1970's*—*Assessment and Directions for the Future*. Orono, ME.
- Kittredge, D. B. (2004). Extension/outreach implications for America's family forest owners. *Journal of Forestry*, 102(7), 15–18. https://doi.org/10.1093/jof/102.7.15
- Kittredge, D. B., & Thompson, J. R. (2016). Timber Harvesting Behaviour in Massachusetts,
  USA: Does Price Matter to Private Landowners? *Small-Scale Forestry*, *15*(1), 93–108.
  https://doi.org/10.1007/s11842-015-9310-1
- Kittredge, D. B., Thompson, J. R., Morreale, L. L., Short Gianotti, A. G., & Hutyra, L. R.
  (2017). Three decades of forest harvesting along a suburban-rural continuum. *Ecosphere*, 8(7), e01882. https://doi.org/10.1002/ecs2.1882
- Kizlinski, M. L., Orwig, D. A., Cobb, R. C., & Foster Harvard, D. R. (2002). Direct and indirect ecosystem consequences of an invasive pest on forests dominated by eastern hemlock. *Journal of Biogeography*, 29, 1489–1503.
- Klooster, W., Gandhi, K., Long, L., Perry, K., Rice, K., & Herms, D. (2018). Ecological Impacts of Emerald Ash Borer in Forests at the Epicenter of the Invasion in North America. *Forests*, 9(5), 250. https://doi.org/10.3390/f9050250

- Larsen, A. E., Meng, K., & Kendall, B. E. (2019). Causal analysis in control–impact ecological studies with observational data. *Methods in Ecology and Evolution*, 10(7), 924–934. https://doi.org/10.1111/2041-210X.13190
- Leung, B., Springborn, M. R., Turner, J. A., & Brockerhoff, E. G. (2014). Pathway-level risk analysis: the net present value of an invasive species policy in the US. *Frontiers in Ecology and the Environment*, *12*(5), 273–279. https://doi.org/10.1890/130311
- Leverkus, A. B., Rey Benayas, J. M., Castro, J., Boucher, D., Brewer, S., Collins, B. M., ... Gustafsson, L. (2018). Salvage logging effects on regulating and supporting ecosystem services — A systematic map. *Canadian Journal of Forest Research*. Canadian Science Publishing. https://doi.org/10.1139/cjfr-2018-0114
- Liebhold, A. M., Brockerhoff, E. G., & Nuñez, M. A. (2017). Biological invasions in forest ecosystems: a global problem requiring international and multidisciplinary integration.
   *Biological Invasions*, 19(11), 3073–3077. https://doi.org/10.1007/s10530-017-1547-5
- Lindenmayer, D., Burton, P., & Franklin, J. (2008). Salvage Logging and Its Ecological Consequences. Washington, DC: Island Press. Retrieved from https://books.google.com/books?hl=en&lr=&id=9HX56iaZuncC&oi=fnd&pg=PR9&dq=Sa lvage+logging+and+its+ecological+consequences&ots=5sK-DlfCwi&sig=mVVF0IGlZFmbxbZYuGU-JM2HsfA#v=onepage&q=Salvage logging and its ecological consequences&f=false
- Lovett, G. M., Weiss, M., Liebhold, A. M., Holmes, T. P., Leung, B., Lambert, K. F., ... Weldy, T. (2016). Nonnative forest insects and pathogens in the United States: Impacts and policy options. *Ecological Applications*, 26(5), 1437–1455. https://doi.org/10.1890/15-1176

MacLean, M. G., Holt, J., Borsuk, M., Markowski-Lindsay, M., Butler, B. J., Kittredge, D.

B., ... Thompson, J. R. (2020). Potential Impacts of Insect-Induced Harvests in the Mixed Forests of New England. *Forests*, *11*(5), 498. https://doi.org/10.3390/f11050498

Markowski-Lindsay, M., Borsuk, M. E., Butler, B. J., Duveneck, M. J., Holt, J., Kittredge, D.

- B., ... Thompson, J. R. (2020). Compounding the Disturbance: Family Forest Owner
  Reactions to Invasive Forest Insects. *Ecological Economics*, *167*.
  https://doi.org/10.1016/j.ecolecon.2019.106461
- McCullough, D. G., & Siegert, N. W. (2007). Estimating potential emerald ash borer
  (Coleoptera: Buprestidae) populations using ash inventory data. *Journal of Economic Entomology*, *100*(5), 1577–1586. https://doi.org/10.1603/0022-0493(2007)100[1577:EPEABC]2.0.CO;2
- Morin, R. S., Liebhold, A. M., Pugh, S. A., & Crocker, S. J. (2017). Regional assessment of emerald ash borer, Agrilus planipennis, impacts in forests of the Eastern United States. *Biological Invasions*, 19(2), 703–711. https://doi.org/10.1007/s10530-016-1296-x
- Normand, S. L. T., Landrum, M. B., Guadagnoli, E., Ayanian, J. Z., Ryan, T. J., Cleary, P. D., & McNeil, B. J. (2001). Validating recommendations for coronary angiography following acute myocardial infarction in the elderly: A matched analysis using propensity scores. *Journal of Clinical Epidemiology*, 54(4), 387–398. https://doi.org/10.1016/S0895-4356(00)00321-8
- Orwig, D. A., Foster, D. R., & Mausel, D. L. (2002). Landscape patterns of hemlock decline in New England due to the introduced hemlock woolly adelgid. *Journal of Biogeography*, 29(10–11), 1475–1487. https://doi.org/10.1046/j.1365-2699.2002.00765.x
- Paap, T., Burgess, T. I., & Wingfield, M. J. (2017). Urban trees: bridge-heads for forest pest invasions and sentinels for early detection. *Biological Invasions*, 19(12), 3515–3526.

Accepted Articl

https://doi.org/10.1007/s10530-017-1595-x

- Pautasso, M., Schlegel, M., & Holdenrieder, O. (2015). Forest Health in a Changing World. *Microbial Ecology*, 69(4), 826–842. https://doi.org/10.1007/s00248-014-0545-8
- PRISM. (2019). PRISM Climate Group, Oregon State University. Retrieved from http://prism.oregonstate.edu
- Pugh, S. A., Liebhold, A. M., & Morin, R. S. (2011). Changes in ash tree demography associated with emerald ash borer invasion, indicated by regional forest inventory data from the Great Lakes States. *Canadian Journal of Forest Research*, 41(11), 2165–2175. https://doi.org/10.1139/x11-138
- Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician*, 39(1), 33. https://doi.org/10.2307/2683903
- Sekhon, J. S., & Mebane, W. R. (1998). Genetic Optimization Using Derivatives: Theory and Application to Nonlinear Models. *Political Analysis*, *7*, 189–203.
- Silver, E. J., Leahy, J. E., Weiskittel, A. R., Noblet, C. L., & Kittredge, D. B. (2015). An Evidence-Based Review of Timber Harvesting Behavior among Private Woodland Owners. *Journal of Forestry*, 113(5), 490–499. https://doi.org/10.5849/jof.14-089
- Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & van der Linde, A. (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 64(4), 583–639. https://doi.org/10.1111/1467-9868.00353
- Stanke, H., & Finley, A. (2020). rFIA: Space-Time Estimation of Forest Variables using the FIA Database. Retrieved from https://cran.r-project.org/package=rFIA

Stanke, H., Finley, A. O., Weed, A. S., Walters, B. F., & Domke, G. M. (2020). rFIA: An R

package for estimation of forest attributes with the US Forest Inventory and Analysis database. *Environmental Modelling and Software*, *127*, 104664. https://doi.org/10.1016/j.envsoft.2020.104664

- Su, Y.-S., & Yajima, M. (2012). R2jags: A Package for Running jags from R. *R Package Version 0.03-08, URL Http://CRAN. R-Project. Org/Packages= R2jags.*
- Thompson, J. R., Canham, C. D., Morreale, L., Kittredge, D. B., & Butler, B. (2017). Social and biophysical variation in regional timber harvest regimes. *Ecological Applications*, 27(3), 942–955. https://doi.org/10.1002/eap.1497
- Walker, K., Herman, M., & Eberwein, K. (2020). tidycensus: Load US Census Boundary and Attribute Data as "tidyverse" and 'sf'-Ready Data Frames.
- Ward, S. F., Fei, S., & Liebhold, A. M. (2020). Temporal dynamics and drivers of landscapelevel spread by emerald ash borer. *Journal of Applied Ecology*, 57(6), 1020–1030. https://doi.org/10.1111/1365-2664.13613
- Ward, S. F., Liebhold, A. M., Morin, R. S., & Fei, S. (2021). Population dynamics of ash across the eastern USA following invasion by emerald ash borer. *Forest Ecology and Management*, 479, 118574. https://doi.org/10.1016/j.foreco.2020.118574
- Waring, K. M., & O'Hara, K. L. (2005). Silvicultural strategies in forest ecosystems affected by introduced pests. In *Forest Ecology and Management* (Vol. 209, pp. 27–41). Elsevier. https://doi.org/10.1016/j.foreco.2005.01.008
- Woudenberg, S. W., Conkling, B. L., O'Connell, B. M., LaPoint, E. B., Turner, J. A., &
  Waddell, K. L. (2010). The forest inventory and analysis database: Database description and users manual version 4.0 for phase 2. USDA Forest Service General Technical Report RMRS-GTR, 245(245). https://doi.org/10.2737/RMRS-GTR-245

Table 1: Model estimates. Both the zero-inflation (harvest probability) and continuous (harvest intensity) components of each model vary as a function of aboveground biomass (AGB), EAB, human population density, and median household income (MHHI). Mean estimates with a non-zero 95% credible interval are in bold. Deviance information criterion (DIC) is an estimate of model error.

M. J.I	Harvest		сD	EAD				MIIII		DIC
Niodel	component	AGB		EAB		pop. den.		MHHI		DIC
			Std.		Std.		Std.		Std.	
<ol> <li>1: Ash species</li> <li>2: Non-ash species</li> </ol>		Mean	Dev.	Mean	Dev.	Mean	Dev.	Mean	Dev.	
	Probability	0.04	0.01	-0.27	0.27	-0.39	0.29	-0.24	0.17	187137
	Intensity	-0.01	0.01	0.91	0.35	-0.18	0.51	-0.14	0.22	
	Probability	0.02	0	-0.54	0.22	-0.28	0.2	-0.33	0.14	188703
	Intensity	-0.01	0	0.25	0.25	0.49	0.27	-0.21	0.16	
3: Ash as a fraction of total harvest	Probability	0.01	0.01	-0.28	0.28	-0.38	0.29	-0.22	0.17	187212
	Intensity	0.02	0.01	0.55	0.33	0.24	0.47	0.75	0.22	

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Figure 1: Study area. FIA plots in counties where EAB was detected before 2007 are in the treatment group; observations from counties where EAB was detected after 2012 are in the control group. Tree characteristics and harvest data were extracted from 2007-2012. Treatment observations (orange) had a range of EAB infestation from between 1-10 years. Negative values in the histogram indicate time-to-arrival for EAB.

Figure 2: Model predictions for Model 1 (ash species) and Model 2 (non-ash species). Annual probability of harvest follows a logistic distribution (a); intensity of harvest (percent basal area removed) follows a beta distribution (b). Grey shading indicates the 95% credible interval for the estimated effect of EAB.

Figure 3: Model predictions for the probability (a) and intensity (b) components of Model 3 (ash as a fraction of total harvest). The grey shading indicates the 95% credible interval for the effect of EAB on the probability of harvesting ash (a) and, if ash is harvested, the fraction of the total harvest comprised of ash (b).

Figure 4: Boxplots comparing the mean plot diameters of harvested trees in counties with and without EAB. P-values of the weighted Student's t-test are printed in the center of each panel.

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