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A game-theoretic approach to incentivize landowners to mitigate an emerald ash borer outbreak

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ABSTRACT

This article addresses the challenge posed by the Emerald Ash Borer (EAB), a wood–boring insect that threatens to kill ash trees, one of the North America's most vital tree genera. Current strategies include monitoring, treatment, and removal. However, the absence of a private-public partnership hinders progress on private ash trees. We propose two cost-sharing programs where local governments reimburse landowners for their management costs. This approach considers the EAB's dynamic growth over two periods based on different treatment decisions. Two mathematical models are developed for designing reimbursements: one based on the number of infested trees and another on the number of treated trees. We derive analytical solutions for the optimal treatment decisions and reimbursements in the first period. Our study reveals that treatment effectiveness and the likelihood of new infestations in the second period influence the optimal decisions. Comparing the reimbursement models, the treatment-based program proves more effective, encouraging landowners to treat more trees with higher reimbursements and overall benefits. Further, we show that continuing EAB treatment beyond the 2-year cost-sharing program is expected to yield superior long-term benefits. The approach seeks to foster private-public partnerships in addressing environmental challenges through resource sharing, such as managing water, land, and wildfires.

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1. Introduction

Invasive species are non-native plants, animals, or pests that cause significant economic and environmental damage by harming biodiversity and degrading the environment (Wilcove *et al.*, 1998; Levine *et al.*, 2003). The cost of invasive species to the United States' economy is estimated to be more than 20 billion dollars each year, and the associated costs continue to increase (Fantle-Lepczyk *et al.*, 2022). As invasive species threaten biodiversity, controlling the growing spread of invasive alien species has been one of the United Nations (U.N.) Sustainable Development Goals (Mohieldin and Caballero, 2015; United Nations, 2021). Furthermore, various national and international communities, such as the United Nations' Global Invasive Species Program (GISP) and National Invasive Species Council (NISC), have called for rapid management and control of invaders to minimize their harmful impacts on sustainability and human well-being (Büyüktahtakın and Haight, 2018).

One prime example of an invasive species is the Emerald Ash Borer (EAB) (*Agrilus planipennis*), a non-native forest insect that attacks and kills North American ash trees (*Fraxinus* spp.) (see Herms and McCullough (2014) for review). Ash trees are one of North America's most widely distributed tree genera (Atha and Boom, 2017), comprising more than 25 forest community types in the eastern U.S. (MacFarlane and Meyer, 2005) and providing food and habitat for numerous organisms from birds and mammals to insects and microorganisms (Atha and Boom, 2017). Among ash species, white ash (*Fraxinus americana*) is the most abundant, and white ash wood is known for its strength and resiliency and is used for products such as tool handles, flooring, and furniture (MacFarlane and Meyer, 2005). Following the EAB invasion of a forest stand, mature ash dies within 10 years (Klooster *et al.*, 2014). If ash seedlings and saplings become infested and die prior to reaching reproductive maturity, then ash will be extirpated from the stand, with cascading direct and indirect effects on forest community composition and ecosystem processes (Gandhi and Herms, 2010).

Ash trees are also an important part of urban forests. Landscape ash trees have been planted along streets, in parks, and in people's yards for decades, due to their tolerance to ecological stresses such as drought and soil compaction (MacFarlane and Meyer, 2005). As part of urban forests, ash trees provide ecological benefits such as habitat for wildlife, stormwater absorption, and local cooling, social benefits such as pleasant environments for people to live and work, and human health benefits such as reduced stress (Dwyer *et al.*, 1992; Pataki *et al.*, 2021). Since EAB was discovered near Detroit, Michigan, and Windsor, Ontario, in

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2002, the insect has spread to 36 states in the U.S. and five Canadian provinces (Emerald Ash Borer Information Network, 2022), killed millions of ash trees (Herms and McCullough, 2014), and cost homeowners and cities hundreds of millions of dollars in losses of property value and damage mitigation (Kovacs *et al.,* 2010).

In response to the threat of EAB, cities and communities have developed EAB management plans with the goal of slowing ash mortality. The management plans include surveillance of ash tree health, application of systemic insecticides to protect trees by killing any EAB adults or larvae, and preemptive removal of highly infested trees before larvae can complete development (Herms and McCullough, 2014). An obstacle to implementing a city-wide EAB management plan arises where ash trees are owned by both public and private entities. The city forester usually does not have the authority to manage ash trees growing on private land, where landowners manage their trees using their own preferences and budgets without consideration of city-wide objectives. Because many landowners do not have knowledge or budgets for tree care activities, levels of management, tree survival, and net benefits across ownerships may be much less than those attainable with a centralized cross-ownership management plan and actions (Kovacs *et al.,* 2014).

To overcome this obstacle, local governments may use cost-share programs to induce landowners to undertake management actions. To design such programs, we present a principal-agent framework where a city forester (i.e., the principal) offers to reimburse a landowner (i.e., the agent) for a portion of its costs of EAB management. Within this framework, we use a two-period horizon to capture the dynamics of tree management, infestation, and survival. If the landowner does not accept the city forester's offer, then they do not inspect or treat any ash trees in the first period and bear the costs of removing and foregoing benefits of any infested trees that perish in the second period. If the landowner accepts the offer, they identify infested ash trees through surveillance and determine how many trees to treat and/or remove in the first period to maximize their expected net benefits of surviving trees in the second period. The city forester sets its reimbursement offer to ensure that the landowner participates and to maximize the expected benefits of surviving trees net a penalty for trees that perish and the cost of reimbursement.

We develop and analyze two program designs: one in which reimbursement is based on the number of infested trees and another in which reimbursement is based on the number of treated trees. In the Infestation-Based Reimbursement (IBR) design, the city forester offers a payment based on the landowner's reported infestation level, and if accepted, the landowner decides how many trees to treat to maximize their net benefits. We find three possible treatment decisions that can be optimal for the landowner - treating all (infested and healthy) trees, treating only the infested trees, and treating none of them - depending on treatment effectiveness and the likelihood of new infestations. We provide the analytical solution for optimal reimbursement and characterize the conditions under which each of the treatment decisions can be optimal.

In the Treatment-Based Reimbursement (TBR) design, the city forester announces a reimbursement schedule in which the level of reimbursement increases with the number of trees that are treated. Following surveillance of the infestation, the landowner decides how many trees to treat to maximize their net benefit, accounting for the level of reimbursement. We find eight optimal reimbursement schedules and identify the conditions under which each can be optimal.

We compare the efficacy of the two cost-sharing models through a numerical analysis over some infestation and treatment effectiveness scenarios and conclude that the TBR program is superior. Despite the higher reimbursement required, the TBR program induces the landowner to treat more trees, and as a result, the city forester achieves higher expected net benefits.

2. Literature review

2.1. Management of invasive species and the EAB

Several optimization models have been presented to study the surveillance (Epanchin-Niell *et al.*, 2012; Horie *et al.*, 2013; Onal *et al.*, 2020; Bushaj *et al.*, 2021; Kibs *et al.*, 2021) and control (Büyüktahtakın *et al.,* 2011; Kovacs *et al*,. 2014; Büyüktahtakın *et al.,* 2015; Kıbış and Büyüktahtakın, 2017) of invasive species. Büyüktahtakın and Haight (2018) provides a review of optimization models to detect and control biological invasions.

Some of the optimization models have focused on the surveillance and control of the EAB (Kovacs *et al.,* 2014; Bushaj *et al.,* 2021; Kıbış *et al.,* 2021; Bushaj *et al.,* 2022). These models assume a central planner maximizes public benefits over time and space, without considering ownership boundaries. For example, Kıbış *et al.* (2021) present a multi-stage stochastic mixed-integer programming model for optimizing surveillance, treatment, and removal of ash trees across neighborhoods of a city. However, bio-invasions often take place in landscapes encompassing multiple landowners, where each decision maker's control choices affect invasion spread and damages across ownership boundaries (Wilen, 2007; Epanchin-Niell *et al.,* 2012). When landowners make a decision based on their preferences, costs, and expected damages, it may lead to increased invasion of the landscape (Wilen, 2007). A central planner, optimizing bio-invasion control measures, can mitigate this externality and increase net benefits across ownerships (e.g., Feder and Regev (1975); Bhat and Huffaker (2007); Richards *et al.* (2010); Sims-Chilton *et al.* (2010)). However, practical obstacles hinder implementing centralized plans. For example, the central planner may lack authority over private land infestations or municipal planners' concurrence for funding activities outside municipal limits (Kovacs *et al.,* 2014). As a result, potential welfare gains from centralized planning in a landscape with multiple stakeholders may not be attainable.

Game-theoretic approaches are increasingly used to tackle challenges in Invasive Species Management (ISM). For example, Bhat and Huffaker (2007) develop a dynamic contract through a two-person differential game for landowners. This model allows renegotiation and variable transfer payments, enabling control of a cross-boundary mammal population. Liu and Sims (2016) develop an optimization model for spatially-connected landowners to determine side-payment timing and levels. These payments involve un-invaded landowners compensating neighbors to curb bio-invasion spread. Cobourn *et al.* (2019) employ a dynamic, cooperative Nash bargaining model to determine the sequence of transfer payments from an uninfested city to an infested city. This strategy is designed to facilitate control measures that effectively impede the invader's expansion. Further, Siriwardena *et al.* (2018) extend the cooperative Nash bargaining model to examine how the distribution of land ownership within each municipality affects the path of a negotiated transfer payment. Although these examples demonstrate a growing interest in game theory for transfer or subsidy determination in ISM, the design of incentive programs to strengthen public-private partnerships in ISM has not been addressed.

2.2. Incentive design using the principal-agent framework

The principal-agent framework was developed to better align conflicting interests between two parties and enhance outcomes through incentive structuring, particularly when there is information asymmetry. Its widespread application lies in the coordination of decentralized players in supply chain management (Taylor and Xiao, 2009; Yang *et al.*, 2009; Yang *et al.*, 2012; Kim and Netessine, 2013; Chen *et al.*, 2016) and production (Iyer *et al.*, 2005; Chick *et al.*, 2017). Additionally, a growing body of literature explores public–private partnerships and authority-led initiatives, such as non-profit organizations funding and auditing (Privett and Erhun, 2011), farmer information sharing (Xiao *et al.*, 2020), emissions mitigation via carbon-capturing (Cai and Singham, 2018), infrastructure development (Paez-Perez and Sanchez-Silva, 2016), container-inspection policy (Bakshi and Gans, 2010), and performance-based health service contracts (Fuloria and Zenios, 2001; Jiang *et al*,. 2012; Andritsos and Tang, 2014; Aswani *et al.*, 2019). Despite this diverse range of applications, we are unaware of any principal-agent framework that tackles spatio-temporally growing environmental issues.

Principal-agent models may be categorized into moral hazard (hidden actions) and adverse selection (hidden information). We adapt both types to design incentive programs for public–private partnerships in ISM. In the first case, the city forester (principal) offers reimbursement based on observed infestation levels, a scenario of moral hazard where the landowner (agent) decides tree treatment and removal post-reimbursement. The city forester aligns the reimbursement with infestation levels to guide the landowner's actions towards the city forester's objective. In the second case, the city forester offers a reimbursement schedule according to the number of treated trees, an adverse selection situation where the landowner is privy to infested tree counts, whereas the city forester is not. Consequently, the city forester must design the reimbursement schedule to prompt optimal tree treatment without any knowledge on the initial infestation.

2.3. Key contributions

To the best of our knowledge, we are the first to adopt a principal-agent framework to design incentive programs for local governments, aiming to induce private landowners to manage dynamically evolving environmental problems. Specifically, we focus on mitigating the harmful impacts of the invasive EAB, a beetle inflicting damage on forests. We hypothesize that government subsidies can effectively motivate landowner participation, and consequently, lead to improved outcomes in combating the detrimental effects of this invasive species. Moreover, our game-theoretic models hold potential for adaptation to various public–private partnerships that necessitate collaborative resource contributions across time and space, such as water, land, and wildfire management. Thus, our study could motivate partnerships among local governments and private owners, fostering resource sharing to address important social and environmental challenges.

A distinguishing feature of our principal-agent models is their incorporation of the population dynamics associated with environmentally detrimental species. In both the IBR and TBR models, we embrace a two-period framework that captures the progression of ash tree infestation caused by the EAB. Our models are designed with this dynamic aspect in mind, tracking infestation growth over two consecutive periods based on different treatment decisions in the initial period. The initial period spans 1 year, whereas the second can extend up to 2 years, due to the 2-3 year protection period offered by pesticide treatment. Additionally, we assume the city forester only offers the reimbursement program in the initial period, aligning with their intention to assess the program every 2-3 years.

Further, our models differ from the classic principal-agent framework in that the agent's utility function does not satisfy the single-crossing property. Specifically, when the initial infestation level is high, it may be desirable not to treat any trees, especially when the treatment is ineffective, as it leads to fewer trees being successfully treated. Conversely, when the initial infestation level is low, it may be beneficial to treat only infested trees (excluding healthy ones), due to limited treatment efficacy. Alternatively, treating all trees (infested and healthy) trees could be preferred to prevent new infestations. Consequently, the optimal treatment decision in our models differs from the seminal result of Maskin and Riley (1984), where the quantity offered to the agent is non-decreasing in their type. In the context of ISM, this means that a landowner with a higher infestation level would be encouraged to treat more trees. However, we show that the optimal number of trees to treat exhibits a non-monotonic relationship with the infestation level.

The rest of this article is organized as follows. In Section 3, we introduce the IBR model, where the infestation level is verifiable by the city forester. The optimal solutions are presented analytically. In Section 4, we present the TBR model where the number of trees treated is verifiable instead and several sets of optimal treatment decisions. The two cost-sharing models are compared against the case where no programs are offered in Section 5. We summarize the key takeaways in Section 6 and conclude the article in Section 7.

3. The IBR model

We set up a two-period model of the decisions made by a city forester (she henceforth) and a private landowner (he henceforth). Table 1 summarizes the notation used in the model. At the beginning of the first period, the city forester verifies the initial infestation level (number of infested trees) of a private landowner. This can be achieved by requiring the landowner to submit a surveillance report issued by a professional tree service. Based on the reported infestation level, she selects a reimbursement level to maximize her expected utility. The reimbursement helps the landowner pay for insecticide treatments to protect his ash trees from EAB infestation and death. The city forester's utility depends on the number of surviving trees at the end of the second period, where s is the marginal value the city forester has for a healthy ash tree. Because treatments protect trees for up to 3 years (Herms and McCullough, 2014), the length of the management horizon is 3 years. The city forester selects the reimbursement based on what she expects the landowner to do after receiving the payment. The landowner is assumed to be rational, i.e., his treatment decisions maximize his utility, which depends on the number of surviving trees at the end of the horizon, where θ is the marginal value the landowner has for a surviving ash tree. The landowner's treatment decisions also depend on the reimbursement, the evolution of the number of infested trees in the two periods, and the consequences of each possible treatment decision.

Characterization of the initial infestation level of a private property. Let n denote the number of ash trees a landowner has on his private land at the beginning of the first period. This information is considered common knowledge because trees can be counted along the curb without accessing the landowner's property. Let π denote the likelihood of an ash tree being infested by EAB in the first period. We refer to π as the initial (or first-period) attack rate. It can be computed based on the proportion of infested trees on the neighboring properties or other infestation information provided by local agencies. We characterize the landowner's ash trees as either healthy-looking or infested-looking, based on the ash canopy condition rating scale described by Knight *et al.* (2014). Healthy-looking trees have no visible canopy damage, whereas infested trees have visible canopy damage. Professional tree services easily identify these canopy condition classes and corresponding degree of EAB infestation (Flower *et al.*, 2013). A more detailed description of our ash tree classification is provided in the E-Companion. The initial infestation level of a private property is denoted by i, the number of trees in the infested tree class. Since each tree can be attacked independently by EAB, we assume that the infestation level i follows a binomial distribution with the rate π, i.e., $i \sim B(n, \pi)$. Let α denote the visual surveillance cost per tree. Its value depends on the hourly cost of tree-care professionals and the amount of time spent inspecting each tree.

The landowner's available options. In addition to estimates of the numbers of healthy-looking and infested trees, the landowner has information about the effectiveness of insecticide treatments, such as soil or trunk injections. With treatment, infested trees with visible canopy damage may recover depending on the extent of the EAB damage and

Table 1. Notation.

Input parameters:	
n	The number of ash trees owned by a landowner has
π	The initial (or first-period) attack rate. $\bar{\pi} = 1 - \pi$
i	The initial infestation level, which follows a binomial distribution with rate π
c	Cost of removing a dead tree due to the EAB infestation
α	Cost of inspecting an ash tree
β	Cost of treating an ash tree
γ	Penalty cost for a dying tree
ρ	The treatment success rate. $\rho < 1$ and $\bar{\rho} = 1 - \rho$
θ	The marginal value of a landowner having a surviving ash tree
s	The marginal value the city forester has for a healthy ash tree
π^l	The low second-period attack rate. $\bar{\pi}^l = 1 - \pi^l$. $\pi^l < \pi$
π^h	The high second-period attack rate. $\bar{\pi}^h = 1 - \pi^h$. $\pi < \pi^h$
Value function:	
$v(w, d)$	The value function of the city forester of having w surviving ash trees while losing d trees. $v(w, d) = s \cdot w - \gamma \cdot d$
$V(w)$	The value function of the landowner having w surviving ash trees at the end of the second period. $V(w) = \theta \cdot w$
Decision variables only applicable to the IBR model:	
$q(i)$	The number of trees a landowner will treat given i out of n ash trees are infested
$r(i)$	Reimbursement offered to the landowner for having i infested ash trees
Decision variables only applicable to the TBR model:	
$\mathbf{q}$	$\mathbf{q} = [q(0), q(1), \ldots, q(n)]$ is a $(n+1)$-tuple that prescribes the number of trees to be treated based on infestation level i, where $q(i) \in [0, n]$
$\mathbf{r}$	$\mathbf{r} = [r(0), r(1), \ldots, r(n)]$ is a $(n+1)$-tuple that prescribes the reimbursement scheme based on the treatment decision $q(i)$

which insecticide treatment is used (Herms *et al.*, 2019). For example, while treated trees with less than 50% canopy dieback will likely survive and recover after 2-3 years, treated trees with greater than 50% dieback may not recover (Herms *et al.*, 2019). Therefore, we assume the treatment's success rate represents the likelihood that an infested tree with visible canopy damage that is treated in the first period survives to the end of the second period. Without treatment, infested trees with visible canopy damage die in 2-4 years (Herms and McCullough, 2014). Healthy-looking trees (without visible canopy damage) that are treated in the first period survive until the end of the two-period horizon, which is consistent with the management guidance described by Herms *et al.* (2019). Dead trees at the end of the horizon are assumed to be hazardous and must be removed with cost c. The cost of treatment is per tree, where β is much lower than c.

Progression of the infestation level. Let $q(i)$ denote the number of treated trees in the first period. If no trees are infested $(i = 0)$ or if all of the infested trees are treated $(q(i) = i)$ in the first period, the chance of a healthy, untreated tree becoming newly infested in the next period is assumed to decrease from π to π^l. On the other hand, if any of the infested trees are left untreated $(q(i) < i)$, the attack rate in the second period increases from π to π^h. Further, any healthy tree that is treated in period 1 becomes EAB-resistant for both periods; that is, it will not be infested in period 2. If all trees are infested $(i = n)$, there will be no new infestation in the second period.

Landowner's expected utility if he does *not* participate in the cost-sharing program. The landowner is assumed to neither inspect nor treat any trees in either period. Otherwise, the landowner should participate to offset the cost with the reimbursement. Let θ denote the landowner's marginal value of a healthy ash tree; his value of having w surviving trees at the end of the planning horizon, denoted by $V(w)$, is thus $\theta \cdot w$. Let a_0 denote the decision of not participating in the cost-sharing program, then his expected utility given the initial infestation level (i) is

$$\phi(a_0|n, i) = \begin{cases} \theta\bar{\pi}^l n - c\pi^l n & \text{if } i = 0 \\ \theta\bar{\pi}^h(n-i) - c(i + \pi^h(n-i)) & \text{if } 1 \le i \le n. \end{cases} \tag{1}$$

If there are no infested trees $(i = 0)$ initially, the attack rate in the second period is π^l. Therefore, $\pi^l n$ trees are expected to be infested in the second period and die without treatment. The term $\theta\bar{\pi}^l n$ in (1) is the landowner's value of having $\bar{\pi}^l n$ surviving trees, whereas $c\pi^l n$ is the cost of removing $\pi^l n$ dead trees. If at least one tree is infested $(i \ge 1)$ initially, inaction in the first period would lead to a higher attack rate (π^h) in the second period. The expected number of trees to be infested in the next period is thus $\pi^h(n - i)$. The landowner's expected utility is the difference between the value of healthy trees, $\theta \cdot \bar{\pi}^h(n - i)$, and the removal cost, $c \cdot (i + \pi^h(n - i))$.

Landowner's expected utility if he participates in the cost-sharing program. Here, the landowner will first pay for an inspection to identify the infested trees. The inspection cost of all trees is αn, where α is the unit cost. Upon learning the infestation level i, the landowner decides on how many trees to treat, denoted by $q(i)$, by considering the progression of the infestation level. Figures 1 and 2 depict the two possible outcomes, which depend on the relationship of $q(i)$ and i. In both figures, I_t denotes the number of newly infested trees in period t, where $t = 1, 2$. H_t represents the number of healthy trees in period t, T_t the number of treated trees in period t, IST_t the number of infested trees that are successfully treated in period t, IUT_t the number of infested trees that are unsuccessfully treated in period t, NT_t the number of trees that are not treated in period t, and D_t the number of dead trees in period t.

The consequence of not treating all infested trees in the first period, i.e., $q(i) < i$ is illustrated in Figure 1. When $q(i)$ out of the i infested trees are treated, the $i - q(i)$ untreated ones will die and must be removed. Further, the $\bar{\rho}q(i)$ unsuccessfully-treated trees will also not survive, whereas the $\rho q(i)$ successfully-treated ones will recover and stay healthy in the second period. As not all infested trees are treated, the attack rate among the $n - i$ healthy trees increases to π^h in the second period. As a result, $\pi^h(n - i)$ trees may become infested in period 2 while $\bar{\pi}^h(n - i)$ ones remain healthy. For simplicity, we assume that all newly infested trees will be treated, then $\rho\pi^h(n - i)$ trees will become healthy, but $\bar{\rho}\pi^h(n - i)$ trees may die, because the treatment is unsuccessful. Therefore, the overall number of treated trees is $t_1 = q(i) + \pi^h(n - i)$, the total number of trees survived by the end of period 2 is $w_1 = \rho q(i) + \bar{\pi}^h(n - i) + \rho\pi^h(n - i)$, and the aggregated number of dead trees is $d_1 = i - q(i) + \bar{\rho}q(i) + \bar{\rho}\pi^h(n - i)$. The landowner's expected utility when $q(i) < i$ is

$$\phi(q(i), r(i)|n, i, q(i) < i) = \theta \cdot w_1 + r(i) - \alpha \cdot n - \beta \cdot t_1 - c \cdot d_1. \tag{2}$$

The first two terms in (2) are the landowner's value of having w surviving trees and the reimbursement received from the city forester. The next three terms represent the inspection cost, the treatment cost, and the removal cost, respectively.

Similarly, Figure 2 shows the outcome of treating not only infested trees, but also some healthy trees in the first period, i.e., $q(i) \ge i$. Because all infested trees (i) are treated, the successfully-treated trees (ρi) will survive and stay healthy in the second period, whereas the unsuccessfully-treated ones $(\bar{\rho}i)$ would die. The healthy trees that are treated $(q(i) - i)$ in the first period become resistant to EAB. Further, the attack rate among the healthy, untreated trees $(n - q(i))$ decreases to π^l in the second period. Therefore, $\pi^l(n - q(i))$ trees are expected to be infested in period 2, while $\bar{\pi}^l(n - q(i))$ trees are expected to remain healthy. Since all newly infested trees in the second period are assumed to be treated, $\rho\pi^l(n - q(i))$ of them are expected to be successfully treated and survive, while the rest are expected to die. The landowner's expected utility when $q(i) \ge i$ is

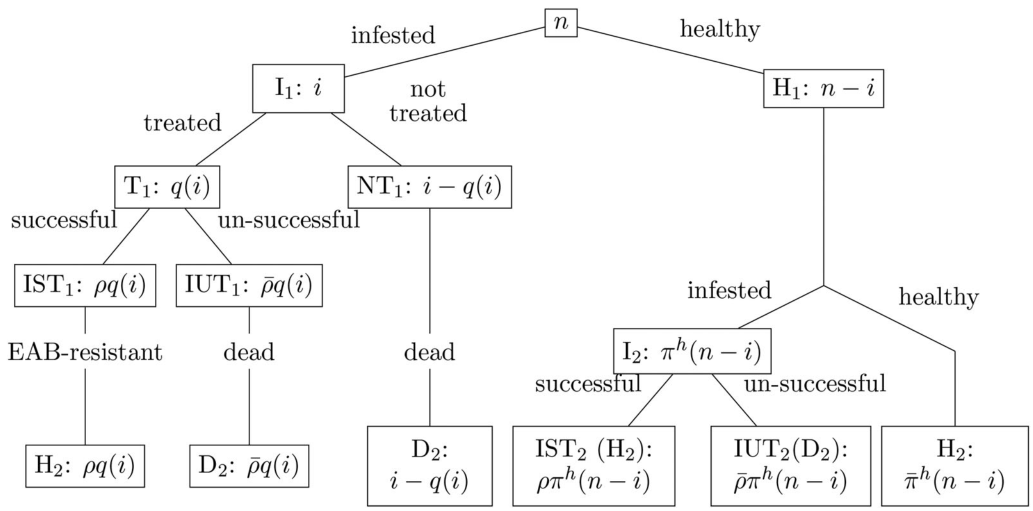

Figure 1. Progression of infestation in two consecutive periods when some infested trees are *not* treated in the first period ($q(i) < i$).

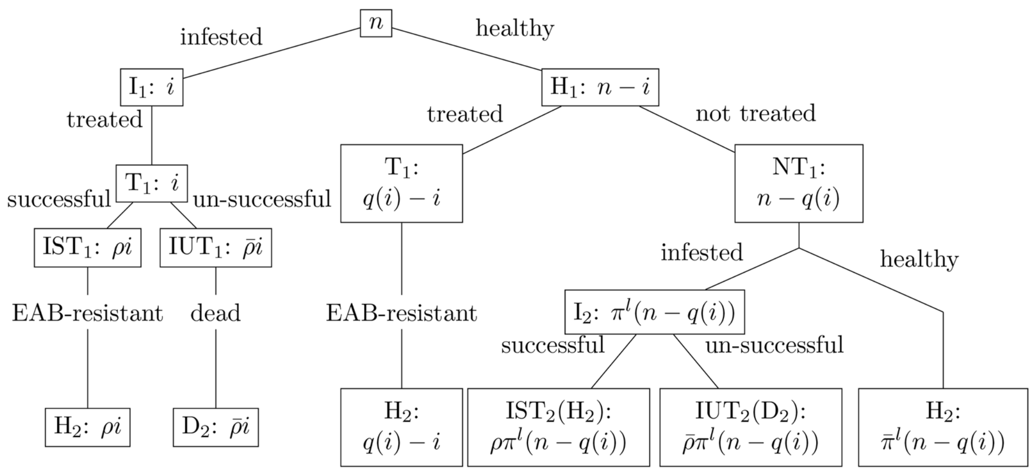

Figure 2. Progression of infestation in two consecutive periods when *all* of the infested trees are treated in the first period ($q(i) \geq i$).

$$\phi(q(i), r(i)|n, i, q(i) \geq i) = \theta \cdot w_0 + r(i) - \alpha \cdot n - \beta \cdot t_0 - c \cdot d_0. \quad (3)$$

The terms in (3) are similar to those in (2), except that the total number of treated trees is $t_0 = i + (q(i) - i) + \pi^l(n - q(i))$, the aggregated number of trees surviving by the end of the second period is $w_0 = (q(i) - i) + \rho i + \bar{\pi}^l(n - q(i)) + \rho\pi^l(n - q(i))$, and the overall number of dead trees is $d_0 = \bar{\rho} i + \bar{\rho}\pi^l(n - q(i))$. Let μ_i be an indicator such that $\mu_i = 1$ when $q(i) < i$ and $\mu_i = 0$ otherwise. $\bar{\mu}_i = 1 - \mu_i$. The landowner's expected utility from participating in the cost-sharing program is

$$\phi(q(i), r(i)|n, i) = \mu_i \cdot \phi(q(i), r(i)|n, i, q(i) < i) + \bar{\mu}_i \cdot \phi(q(i), r(i)|n, i, q(i) \geq i). \quad (4)$$

Sequence of events. Figure 3 illustrates the interactions between the city forester and the landowner over two consecutive periods if he participates in the cost-sharing program. At the beginning of the first period, both parties have the same knowledge about the ash trees on the landowner's property: there are n ash trees, and the attack rate is π. The landowner pays for a tree care professional to inspect ash trees and finds out the number of trees (i) that are already infested. He reports the information to the city forester, who then offers a financial assistance ($r(i)$) that depends on the infestation level (i). Upon receiving the reimbursement $r(i)$, the landowner decides how many trees ($q(i)$) to treat. If he does not treat all of the infested trees ($q(i) < i$) in the first period, then the outcome of his decision over the next two periods is depicted in Figure 1. Otherwise, the outcome follows Figure 2.

City forester's optimization problem. We assume that both the city forester and the landowner are rational decision makers who maximize their utilities over a two-period planning horizon. Let $v(w, d) = s \cdot w - \gamma \cdot d$ denote the city forester's value function. The first term is the city forester's value of having w surviving trees, where s is the marginal value of a tree. The second term, $\gamma \cdot d$, is the city forester's penalty of having d infested trees either untreated or unsuccessfully-treated. This penalty is included because if an infested tree on the landowner's parcel is not treated or not successfully treated, then ash trees in nearby parcels would be more likely to be infested in the following period. The penalty also represents the cost of enforcing a city ordinance to remove dead trees. The city forester's goal is to maximize her utility function, which is the difference between her

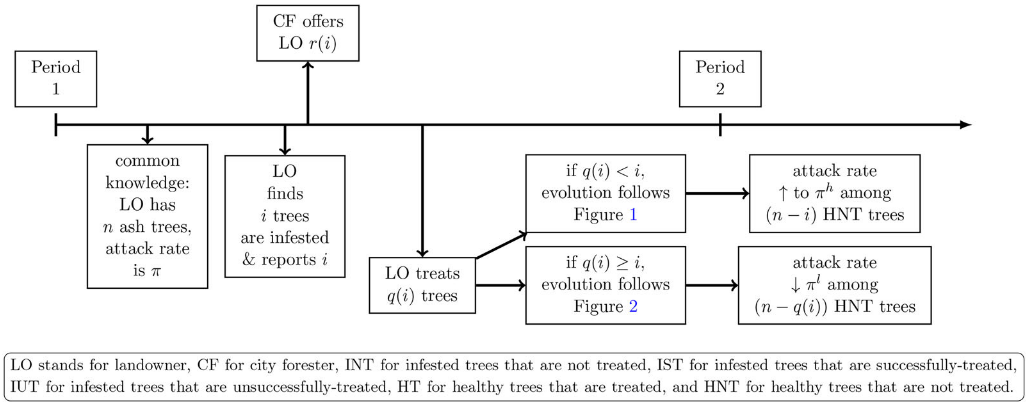

Figure 3. Sequence of events for the IBR model.

value function and the reimbursement. In the case where $q(i) < i$, as shown in Figure 1, the number of surviving trees at the end of the period is $w_1 = \rho q(i) + \bar{\pi}^h(n-i) + \rho\pi^h(n-i)$, with the number of untreated or unsuccessfully-treated trees being $d_1 = i - \rho q(i) + \bar{\rho}\pi^h(n-i)$. Similarly, in the case where $q(i) \geq i$, $w_0 = q(i) - \bar{\rho} i + \bar{\pi}^l(n-q(i)) + \rho\pi^l(n-q(i))$ and $d_0 = \bar{\rho} i + \bar{\rho}\pi^l(n-q(i))$, as illustrated in Figure 2. The city forester's problem is as follows:

$$
\begin{array}{lll}
\max_{q(i),r(i)} \Psi(q(i), r(i)|n,i) = & \mu_i \cdot (s \cdot w_1 - \gamma \cdot d_1) + \bar{\mu}_i(s \cdot w_0 - \gamma \cdot d_0) - r(i) & \\
\text{s.t.} & \phi(q(i), r(i)|n,i) \geq \phi(a_0|n,i) & (\text{IR}) \\
 & \phi(q(i), r(i)|n,i) \geq \phi(j, r(i)|n,i) \quad \forall 0 \leq j \leq n & (\text{IC}_{ij}) \\
\text{and} & q(i), r(i) \geq 0 \qquad (\text{NN}_i) &
\end{array}
\tag{5}
$$

The objective function in (5) is the net expected utility of the city forester, considering two scenarios: (i) when $q(i) < i$ (or $\mu_i = 1$) and (ii) when $q(i) \geq i$ (or $\mu_i = 0$). The first term is the value of having w_1 surviving trees at the end of the second period minus the penalty for losing d_1 trees when $q(i) < i$. Similarly, the second term is the difference between the value of having w_0 surviving trees and the penalty for losing d_0 trees when $q(i) \geq i$. The last term is the cost of providing the financial award to the landowner. The Individual Rationality (IR) constraint ensures the landowner is incentivized to participate in the cost-sharing program. The Incentive Compatibility (IC $_j$) constraints guarantee that the landowner will prefer to treat the number of trees desired by the city forester $q(i)$ based on the infestation level (i) rather than another treatment decision (j). The non-negativity constraints (NN_i) ensure that neither $q(i)$ nor $r(i)$ is negative.

3.1. Analytical solutions and optimal solution characteristics for the IBR model

In this section, we first present the Optimal Treatment Decision (OTD) in the first period visually and then discuss the optimal solution characteristics based on the initial infestation level. There are three types of OTD: treating no trees (N as an abbreviated notation), treating only infested trees (I), and treating all trees (A). As shown in the tree diagram of Figure 4, the OTD depends on the infestation level (i) in the first period, the treatment effectiveness (ρ), and the second-period attack rates (π^l and π^h). In this figure, LE, SE, and VE stand for less effective, somewhat effective, and very effective, respectively. Similarly, L (resp. M and H) stand for low (resp. medium and high) levels of π^l and π^h. The categorizations of ρ, π^l, and π^h are defined in the E-Companion.

At the top level, the tree diagram is split into three branches based on the initial infestation level (i). The left branch corresponds to when there are no infested trees ($i = 0$). The OTD is governed by the value of the low second-period attack rate (π^l). Recall that if a healthy tree is not treated in the first period, it may become infested in the second period with the probability π^l. When π^l is high, treating all trees (A) in the first period will prevent all healthy trees from becoming infested in the second period. On the other hand, when π^l is low or medium, healthy trees are unlikely to be infested in the second period, and thus, there is no need to treat any of them (N) in the first period. Similarly, the right branch represents when all trees are infested ($i = n$), the OTD is solely driven by whether or not the treatment is very effective. If yes, then the landowner prefers to treat all trees (A). Otherwise, the landowner is better off not treating them (N) and simply removing all in the first period.

The middle branch shows when some (but not all) trees are infested, the OTD is jointly determined by ρ, π^l, and π^h. This branch is thus further split into multiple sub-branches. Rather than discussing each branch separately, we summarize the results based on the OTD. First, the

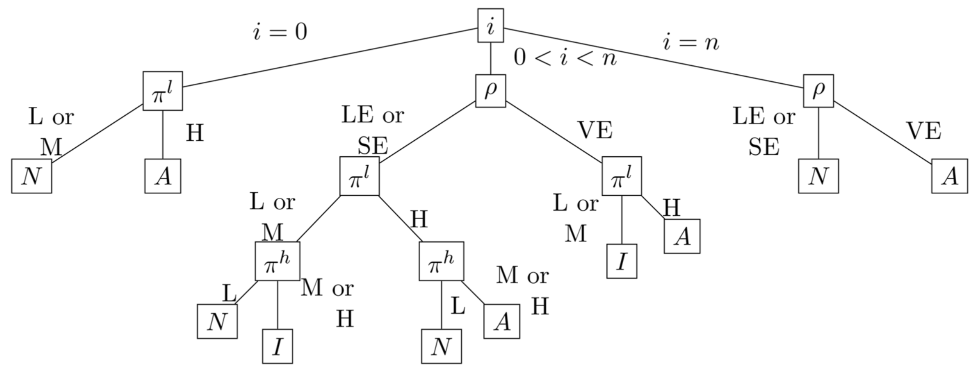

Figure 4. The OTD vs. key parameters.

landowner is induced to treat all trees (A) if π^l is high. Treating all trees will not only improve the chance of survival for the infested trees, but also make the healthy trees EAB-resistant. The only exception is when π^h is low. Because the risk of having new infestations is low, treating all trees is unnecessary. Second, treating only infested trees (I) is optimal if π^l is low or medium, and either the treatment is very effective, or π^h is medium or high. Because healthy trees in the first period are less likely to get infested in the second period when the infested trees are treated, they do not require preventative treatment. In the first case, where the treatment is very effective, infested trees that are treated would likely survive. In the second case, where π^h is medium or high, treating infested trees would prevent the infestation level from increasing significantly in the second period.

Last, it is optimal not to treat any trees (N) if π^h is low and the treatment is less or somewhat effective. Because π^h is low, the infestation level will not increase significantly in the second period. Further, since the benefit of treating infested trees does not justify the cost of treatment, the landowner is better off removing the infested trees.

In the next sections, we present both the OTD and the optimal reimbursement under three settings: when no trees are infested, when all trees are infested, and when some trees are infested. The proofs for the presented propositions can be found in the E-Companion.

3.1.1. Optimal solution characteristics when no trees are infested

Because there are no infested trees ($i = 0$) in the first period, the second-period attack rate is π^l no matter what the landowner chooses to do in the previous period. Let $q^*(i)$ and $r^*(i)$ denote the optimal treatment option selected by the landowner and the reimbursement from the city forester, respectively. The characteristics of the optimal solution when no trees are infested are summarized in Proposition 1.

Proposition 1. *When no trees are infested in the first period, both the OTD and the optimal reimbursement depend on the low second-period attack rate (π^l), as shown in Table 2. If π^l is low or medium, the landowner is induced not to treat any trees (N) in the first period. The reimbursement decreases in the treatment effectiveness (ρ). Further, it is less (resp. greater) than or equal to the inspection cost, αn, if the treatment is very effective (resp. less effective or somewhat effective). If π^l is high, the city forester encourages the landowner to treat all trees (A). The reimbursement decreases in π^l. Further, it is less than the inspection cost when π^l is very high $\left(\pi^l > \max\{\frac{\beta}{\theta+c}, \ddot{\pi}^l\}\right)$. Otherwise, the reimbursement is greater than the inspection cost.*

Table 2. The optimal solution when $i = 0$.

Conditions	*Opt. Treatment*	*Opt. Reimbursement*
$\pi^l \in [0, \ddot{\pi}^l)$	$q^*(0) = 0$ *(N)*	$r^*(0) = \max\{0, \alpha n + a_1 \pi^l n\}$
$\pi^l \in [\ddot{\pi}^l, 1]$	$q^*(0) = n$ *(A)*	$r^*(0) = \max\{0, \alpha n + (\beta - (\theta + c)\pi^l)n\}$

Insights from Proposition 1. There are two interesting results. First, even though the city forester does not want the landowner to treat any trees (N) in the first period when π^l is low or medium, the reimbursement must include the future cost of (or benefit from) treating newly infested trees in the second period. If the treatment is not very effective ($\rho \in [0, \ddot{\rho})$), the net loss for the landowner is $a_1 = \beta - \rho(\theta + c)$ per infested tree. Anticipating $\pi^l n$ trees to be infested in the second period, the city forester reimburses the landowner the net expected loss from unsuccessful treatment, $a_1 \pi^l n$, to induce the landowner's participation. Therefore, the reimbursement is greater than the inspection cost ($r^*(0) > \alpha n$). As the treatment effectiveness (ρ) increases, a_1 decreases. When ρ becomes very effective, a_1 turns negative, and its absolute value represents the landowner's net gain per infested tree. Consequently, the reimbursement becomes less than or equal to the inspection cost ($r^*(0) \leq \alpha n$) and thus the $\max\{0, \cdot\}$ operator ensures a non-negative reimbursement. Second, the treatment strategy must change when the likelihood of new infestation in the second period is high ($\pi^l \in [\ddot{\pi}^l, 1]$). The city forester prefers the landowner to treat all trees (A) in the first period so that all healthy trees are resistant to EAB in the second period. The reimbursement is smaller than the inspection cost because $\beta - (\theta + c)\pi^l$ is negative when π^l is greater than $\frac{\beta}{\theta+c}$.

3.1.2. Optimal solution characteristics when all trees are infested

In the case where all trees are already infested in the first period, any untreated trees will die, whereas the successfully-treated ones will be EAB-resistant in the next period. We summarize the results in Proposition 2.

Proposition 2. *When all trees are infested in the first period, both the OTD and the optimal reimbursement are determined by the treatment effectiveness (ρ), as presented in Table 3. If the treatment is less or somewhat effective, the city forester reimburses the landowner's inspection cost, and consequently, the landowner does not treat any trees (N). If, on the other hand, the treatment is very effective, the city forester induces the landowner to treat all trees (A) with a reimbursement less than the inspection cost.*

Insights from Proposition 2. The reimbursement is always less than or equal to the inspection cost. When the treatment is less effective or somewhat effective, all trees will die because of the absence of treatment. Since the landowner is responsible for removing the dead ash trees, the city forester only needs to compensate the landowner with the inspection cost. On the other hand, when the treatment is very effective, the landowner treats all trees. Therefore, the cost of the inspection is offset by the landowner's gain in utility from successfully-treated trees. Consequently, the city forester only needs to cover a portion of the inspection cost to induce the landowner to participate. The reimbursement monotonically decreases as ρ increases, and it can be reduced to zero when ρ is really high (or $\rho \geq \frac{\alpha+\beta}{\theta+c}$).

3.1.3. Optimal solution characteristics when some trees are infested

We discuss two scenarios based on the effectiveness of the treatment. First, we examine the case where the treatment is very effective, and the key results are summarized in Proposition 3.

Proposition 3. *If the treatment is very effective, the OTD depends on the low second-period attack rate (π^l), while the reimbursement depends on both second-period attack rates (π^l & π^h), as shown in Table 4. The landowner is induced to treat all infested trees (I) when π^l is low or medium and to treat all trees (A) when π^l is high. The reimbursement is only positive when π^h is low or medium.*

Insights from Proposition 3. Because the landowner will, at a minimum, treat the infested trees in the first period, π^h would not be realized in the second period. However, the reimbursement decreases as π^h increases. When π^h is high, the reimbursement is zero. This is because as the risk of healthy trees getting infested in the second period increases, the landowner would have to treat the trees anyhow. Therefore, the city forester only needs to offer a small award to induce the landowner to participate.

Next, we present the optimal solution when the treatment is not very effective in Proposition 4.

Proposition 4. *If the treatment is not very effective, the OTD and the optimal reimbursement are determined by both of the second-period attack rates (π^l and π^h), as illustrated in Table 5. When π^h is low, the landowner is induced not to treat any trees (N). The city forester offers a reimbursement that is higher than the inspection cost. When π^h is medium, the value of π^l determines the optimal solution. For a low or medium π^l, the landowner is induced to treat all infested trees (I) with a positive reimbursement. For a high π^l, the city forester prefers the landowner to treat all trees (A) and offers a positive reimbursement. When π^h is high, the reimbursement is always zero. The landowner will treat all trees when π^l is high and treat only the infested trees (I) otherwise.*

Insights from Proposition 4. When the treatment is not very effective, the benefit from treatment does not justify the cost of inducing the landowner to treat any of the infested trees, especially when π^h is low. Therefore, N is optimal in this case. However, the city forester still needs to offer a reimbursement that covers not only the inspection cost, but also, part of the treatment cost in the second period, as there will be newly infested trees, and the landowner is assumed to treat them.

4. The TBR model

In the TBR model, we assume that the number of treated trees (q) is verifiable. This can be achieved if the city forester requires the submission of a service receipt issued by a professional tree care service who provided the EAB treatment. Differently from the previous model, the infestation level (i) is assumed to be not verifiable. Moreover, the

Table 3. The optimal solution when $i = n$.

Condition	*Opt. Treatment*	*Opt. Reimbursement*
$\rho \in [0, \ddot{\rho})$	$q^*(n) = 0$ (N)	$r^*(n) = \alpha n$
$\rho \in [\ddot{\rho}, 1]$	$q^*(n) = n$ (A)	$r^*(n) = \max\{0, \alpha n + a_1 n\} < \alpha n$

Table 4. The optimal solution when $0 < i < n$ and the treatment is very effective ($\rho \geq \ddot{\rho}$).

Condition	*Opt. Treatment*	*Opt. Reimbursement*
π^l is low or medium: $\pi^l \in [0, \ddot{\pi}^l)$		
$\pi^h \in [0, \ddot{\pi}^h(i))$	$q^*(i) = i$ (I)	$r^*(i) = \alpha n + a_1 n - [a_1 \bar{\pi}^l + (\theta + c)(\pi^h - \pi^l)](n - i) > 0$
$\pi^h \in [\ddot{\pi}^h(i), 1]$	$q^*(i) = i$ (I)	$r^*(i) = 0$
π^l is high: $\pi^l \in [\ddot{\pi}^l, 1]$		
$\pi^h \in [0, \ddot{\pi}^h(i))$	$q^*(i) = n$ (A)	$r^*(i) = \alpha n + a_1 n - [a_1 - \beta + (\theta + c)\pi^h](n - i) > 0$
$\pi^h \in [\ddot{\pi}^h(i), 1]$	$q^*(i) = n$ (A)	$r^*(i) = 0$

Table 5. The optimal solution when $0 < i < n$, and the treatment is not very effective ($\rho < \ddot{\rho}$).

	π^h is low: $\pi^h \in [0, \dot{\pi}^h(i))$	
Condition	*Opt. Treatment*	*Opt. Reimbursement*
$\pi^l \in [0, 1]$	$q^*(i) = 0$ (N)	$r^*(i) = \alpha n + a_1 \pi^h (n - i) > \alpha n$
	π^h is medium: $\pi^h \in [\dot{\pi}^h(i), \ddot{\pi}^h(i))$	
Condition	*Opt. Treatment*	*Opt. Reimbursement*
$\pi^l \in [0, \ddot{\pi}^l)$	$q^*(i) = i$ (I)	$r^*(i) = \alpha n + a_1 n - [a_1 \bar{\pi}^l + (\theta + c)(\pi^h - \pi^l)](n - i) > 0$
$\pi^l \in [\ddot{\pi}^l, 1]$	$q^*(i) = n$ (A)	$r^*(i) = \alpha n + a_1 n - [a_1 - \beta + (\theta + c)\pi^h](n - i) > 0$
	π^h is high: $\pi^h \in [\ddot{\pi}^h(i), 1]$	
Condition	*Opt. Treatment*	*Opt. Reimbursement*
$\pi^l \in [0, \ddot{\pi}^l)$	$q^*(i) = i$ (I)	$r^*(i) = 0$
$\pi^l \in [\ddot{\pi}^l, 1]$	$q^*(i) = n$ (A)	$r^*(i) = 0$

reimbursement is given to the landowner after treatment, not prior to it.

Sequence of events. The interactions between the city forester and the landowner over two consecutive periods can be summarized as follows. At the start of the first period, both parties have the same knowledge about the ash trees: the landowner has n ash trees, and the attack rate is π. The city forester announces a reimbursement schedule, $\mathbf{r} = [r(0), r(1), ..., r(n)]$, that prescribes the reimbursement corresponding to the number of treated trees (q). As an example, $r(0)$ is the reimbursement if no trees are treated ($q = 0$). After inspection, the landowner realizes the infestation level (i), but does not report this information to the city forester. Instead, he decides the number of trees to be treated ($q(i)$) based on the infestation level (i) and the reimbursement schedule ($\mathbf{r}$). After treatment, the landowner submits the service receipt to the city forester and receives the reimbursement according to the schedule. The progression of the infestation level follows the depiction in Figure 1 if some infested trees are not treated and in Figure 2 otherwise. Similar to the IBR model, reimbursement is only available in the first period. Therefore, a landowner who wishes to participate must sign up before the infestation level is revealed. See the E-Companion for a graphical illustration of this interaction.

Landowner's expected utility when he does *not* participate in the program. Because the first-period attack rate is π, the chance of having i infested trees is

$$\binom{n}{i} \cdot \pi^i \bar{\pi}^{n-i}.$$

If no trees are infested ($i = 0$) in the first period, the attack rate in the second period decreases to π^l. The expected number of trees infested in period 2 is $\pi^l n$, whereas the expected number of surviving trees is $\bar{\pi}^l n$. The landowner's utility is the difference between the value of surviving trees and the cost of removal: $\theta \bar{\pi}^l n - c\pi^l n$. Conversely, if the initial infestation level is at least one, the second-period attack rate is increased to π^h in the absence of any treatment in the first period. The death toll is the sum of the infested trees (i) in the first period and the expected number of trees that will be infested ($\pi^h(n - i)$) in the second period. The number of surviving trees at the end of period 2 is $\bar{\pi}^h(n - i)$. The landowner's expected utility is, therefore

$$\binom{n}{i} \pi^i \bar{\pi}^{n-i} \cdot (\theta \bar{\pi}^h (n - i) - c(\pi^h (n - i) + i)).$$

His expected utility over all possible infestation levels, $\Phi(a_0|n)$, can be computed as follows:

$$\Phi(a_0|n) = \bar{\pi}^n \cdot (\theta \bar{\pi}^l n - c\pi^l n) + \sum_{i=1}^{n} \binom{n}{i} \pi^i \bar{\pi}^{n-i} \cdot (\theta \bar{\pi}^h (n - i) - c(\pi^h (n - i) + i)). \tag{6}$$

Landowner's expected utility when he participates in the program. If the landowner does not treat all infested trees ($q(i) < i$), his expected utility would be

$$\begin{aligned} \phi(q(i), r(q(i))|n, i, q(i) < i) = \\ \theta \cdot \left[\rho q(i) + \bar{\pi}^h (n - i) + \rho \pi^h (n - i)\right] + r(q(i)) - \alpha \cdot n \\ -\beta \cdot \left[q(i) + \pi^h (n - i)\right] - c \cdot \left[i - \rho q(i) + \bar{\rho} \pi^h (n - i)\right]. \end{aligned} \tag{7}$$

The terms in (7) are similar to those in (2), except that $r(i)$ has been replaced by $r(q(i))$. Similarly, the landowner's expected utility is

$$\begin{aligned} \phi(q(i), r(q(i))|n, i, q(i) \geq i) = \\ \theta \cdot \left[q(i) - \bar{\rho} i + \bar{\pi}^l (n - q(i)) + \rho \pi^l (n - q(i))\right] + r(q(i)) \\ -\alpha \cdot n - \beta \cdot \left[q(i) + \pi^l (n - q(i))\right] - c \cdot \left[\bar{\rho} i + \bar{\rho} \pi^l (n - q(i))\right] \end{aligned} \tag{8}$$

if he treats not only all infested trees, but also, some healthy trees ($q(i) \geq i$). Recall that μ_i is defined as an indicator such that $\mu_i = 1$ when $q(i) < i$ and $\mu_i = 0$ otherwise. $\bar{\mu}_i = 1 - \mu_i$. The landowner's expected utility from participating in the cost-sharing program is thus

$$\Phi(\mathbf{q}, \mathbf{r}|n) = \sum_{0}^{n} \binom{n}{i} \pi^i \bar{\pi}^{n-i} \cdot \phi(q(i), r(q(i))|n, i), \tag{9}$$

where

$$\begin{aligned} \phi(q(i), r(q(i))|n, i) = \mu_i \cdot \phi(q(i), r(q(i))|n, i, q(i) < i) + \bar{\mu}_i \\ \cdot \phi(q(i), r(q(i))|n, i, q(i) \geq i). \end{aligned} \tag{10}$$

City forester's optimization problem. The city forester's objective is to maximize her net expected utility, which is the difference between her value from the surviving trees and the reimbursement provided to the landowner. We can write the problem of the city forester as follows:

The objective function in (11) is the city forester's net expected utility given a set of treatment decisions ($\mathbf{q}$) and a reimbursement schedule ($\mathbf{r}$). The individual rationality (IR)

$$
\begin{array}{lll}
\max_{\mathbf{q},\mathbf{r}} \Psi(\mathbf{q},\mathbf{r}|n) = & \displaystyle\sum_{i=0}^{n} \binom{n}{i} \pi^i \bar{\pi}^{n-i} \cdot \left[\mu_i \cdot (s \cdot w_1 - \gamma \cdot d_1) + \bar{\mu}_i \cdot (s \cdot w_0 - \gamma \cdot d_0) - r(q(i))\right] & \\
\text{s.t.} & \begin{array}{lll} \Phi(\mathbf{q},\mathbf{r}|n) \geq \Phi(a_0|n) & & (\text{IR}) \\ \phi(q(i)|n,i) \geq \phi(j|n,i) & \forall 0 \leq i \leq n, \quad 0 \leq j \leq n & (\text{IC}_{ij}) \\ r(q(i)) \geq r(q(i)-1) & \forall 1 \leq q(i) \leq n & (\text{MON}_i) \\ q(i), r(q(i)) \geq 0 & \forall 0 \leq i \leq n & (\text{NN}_i), \end{array} & \\
\text{where} & \begin{array}{ll} w_1 = \rho q(i) + (\bar{\pi}^h + \rho \pi^h)(n-i), & d_1 = i - \rho q(i) + \bar{\rho}\pi^h(n-i), \\ w_0 = q(i) - \bar{\rho} i + (\bar{\pi}^l + \rho \pi^l)(n - q(i)), & d_0 = \bar{\rho} i + \bar{\rho}\pi^l(n - q(i)). \end{array} &
\end{array}
\tag{11}
$$

constraint encourages the landowner to participate in the cost-sharing program by ensuring the landowner's expected utility is higher if he participates. The incentive compatibility (IC_{ij}) constraints induce the landowner to pick the treatment decision ($q(i)$) desired by the city forester. The monotonic (MON_i) constraints ensure the reimbursement is non-decreasing in the number of treated trees. This set of constraints is unnecessary in the IBR model because the landowner must first report the infestation level and select the reimbursement accordingly. In fact, the optimal reimbursement is non-monotonic in the infestation level. Finally, both the number of treated trees and the reimbursement are restricted to be non-negative (NN_i).

4.1. Optimal solution characteristics for the TBR model

We classify the OTDs into eight sets, which are identified through an extensive numerical analysis. Each set contains $n+1$ treatment decisions, with each decision corresponding to the initial infestation level (i). A graphical illustration is provided in the E-Companion. Different from the IBR model, there are four types of OTD: treating none (N), treating only infested trees (I), treating all trees (A), and treating some trees (S). To simplify the representation, we use a subscript and a superscript that follow an OTD to represent the starting and ending infestation levels, respectively, where the same OTD applies. As an example, $N_0^0 I_1^{n-1} A_n^n$ denotes the set of OTDs where it is optimal for the landowner to not treat any trees when no trees are infested initially ($i=0$), treat only infested trees when the initial infestation level (i) is between 1 and $n-1$, and treat all trees when all are infested ($i=n$).

The OTDs are determined by the treatment effectiveness (ρ) and the second-period attack rates (π^l and π^h). We use the tree diagram in Figure 5 to facilitate our discussion. Similar to the IBR model, we categorize the treatment effectiveness (ρ) into three regions: less effective (LE), somewhat effective (SE), and very effective (VE). Further, we classify π^l to low (L), medium-low (ML), medium-high (MH), and high (H) levels and π^h to low (L), medium (M) and high (H) levels. See the E-Companion for detailed definitions.

Next, we examine the OTDs when π^l is high. As shown by the right branch of the tree diagram in Figure 5, either one of the following sets can be optimal: A_0^n, $A_0^{n-1}S_n^n$, $A_0^j N_{j+1}^n$. All three sets of decisions agree to treat all trees in the first period, so long as the infestation level is at or below a cutoff value (j) and j can be $n-1$, to avoid the realization of a high π^l in the second period. When most of the trees are already infested in the first period ($i > j$), however, the decision depends on the effectiveness of the treatment. If the treatment is very effective, then treating all trees is optimal because the chance of survival is high. On the contrary, if the treatment is not effective, then all trees should be removed. Interestingly, when the treatment is somewhat effective, it can be optimal to treat some (but not all) infested trees.

Last, the OTDs when π^l is medium-low or medium-high are driven by the effectiveness of the treatment, as shown in the middle branch of the tree diagram in Figure 5. If the

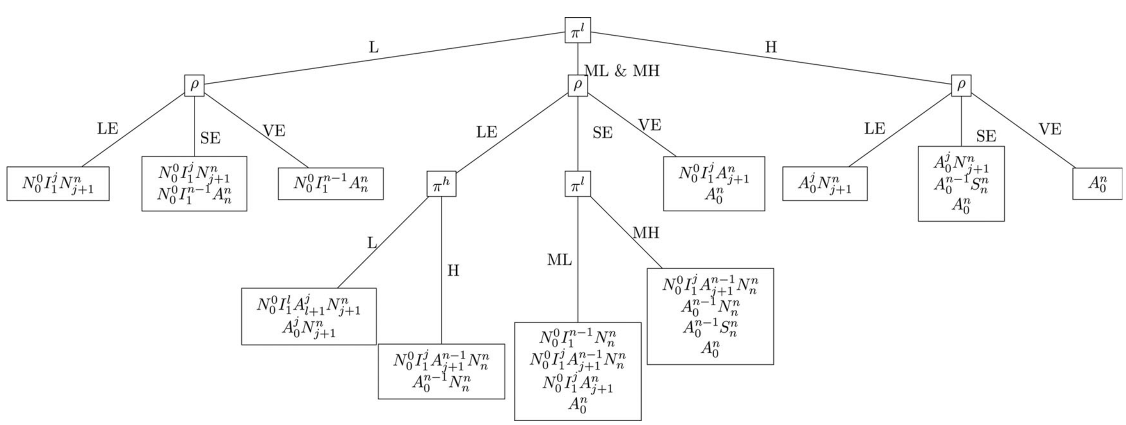

Figure 5. OTDs vs. key parameters.

treatment is very effective (VE), either A_0^n or $N_0^0 I_1^j A_{j+1}^n$ can be optimal. Both sets of OTDs agree to treat all trees if the infestation level is beyond some threshold j. Below that value, the landowner may either treat only infested trees or treat all. If, on the other hand, the treatment is less effective (LE), the value of the high second-period attack rate (π^h) determines the optimal treatment decisions. Specifically, when π^h is low, either $N_0^0 I_1^l A_{l+1}^j N_{j+1}^n$ or $A_0^j N_{j+1}^n$ is optimal. The landowner would treat either the infested trees or all trees if the infestation level is low, whereas not treating any trees if the infestation is high. This result is driven by the fact that the treatment is less effective, and therefore it should be used mainly for the prevention of trees becoming infested in the next period. When π^h is high, both OTDs ($N_0^0 I_1^j A_{j+1}^{n-1} N_n^n$ and $A_0^{n-1} N_n^n$) agree with treating all trees if the infestation level is sufficiently high ($j \le i < n$) to prevent healthy trees in the first period from becoming infested in the second. If the treatment is somewhat effective (SE) and π^l is medium-low (ML), then $N_0^0 I_1^{n-1} N_n^n$, $N_0^0 I_1^j A_{j+1}^{n-1} N_n^n$, $N_0^0 I_1^j A_{j+1}^n$ or A_0^n can be optimal. Although the four sets of OTDs appear to be quite different, they all settle on treating at least the infested trees so long as not all trees are already infested. On the other hand, if the treatment is somewhat effective (SE) and π^l is medium-high (MH), then the set of optimal decisions includes $N_0^0 I_1^{n-1} N_n^n$, $A_0^{n-1} N_n^n$, $A_0^{n-1} S_n^n$, and A_0^n. Here, the common optimal decisions among the OTDs are to treat all trees when the infestation level is high, save for the case where all trees are already infested.

5. Model comparisons

In this section, we compare the efficacy of the two cost-sharing models in several metrics. In addition to the IBR and TBR models, we also consider a third model in which the city forester does not offer a cost-sharing (or NCS) program. Four scenarios are analyzed by varying the treatment effectiveness (between very effective and not very effective) and the low second-period attack rate (between low/medium and high). Due to the page limit, the most interesting scenario is presented here, with the remaining scenarios being relegated to the E-Companion. Managerial insights from all scenarios are summarized in Section 6.

5.1. Scenario 1: The treatment is not very effective, and the low second-period attack rate is low or medium

Scenario 1 represents a situation where infested trees have relatively high levels of canopy damage, causing low treatment efficacy. Further, EAB population pressure in the neighborhood is relatively low, causing the low second-period attack rate to be medium or low. Table 6 presents the expected number of surviving trees (E_{trees}), the expected reimbursement (E_r), the expected objective function value (E_{obj}) of the city forester, and the OTDs of the three models. Under NCS, the city forester does not offer any financial assistance, and thus, E_r is zero. E_{trees} is computed as the expected number of surviving trees, assuming that the landowner would not take any actions in mitigating the negative impact of EAB, i.e., the landowner's OTDs are N_0^5. The E_{obj} is computed as the expected value of $\Psi(q(i), r(i)|n, i)$, the objective function value in (5) where both $q(i)$ and $r(i)$ are set to zero, over i. Similarly, E_r in IBR (resp. TBR) is the expected value of $r^*(i)$ (resp. $r^*(q(i))$) over i, while E_{obj} is the expected value of $\Psi(q^*(i), r^*(i)|n, i)$ (resp. $\Psi(\mathbf{q}^*, \mathbf{r}^*|n)$) in (5) (resp. (11)) over i.

In this scenario, π^l is low ($\pi^l < \dot{\pi}^l$), ρ is less effective ($\rho < \dot{\rho}$), and π^h varies from low ($\pi^h = 0.35$ or 0.50, $\pi^h < \hat{\pi}^h$) to high ($\pi^h = 0.70 > \hat{\pi}^h$). Under both IBR and TBR, the OTDs all follow the same structure: $N_0^0 I_1^j N_{j+1}^n$, which is non-monotonic in the initial infestation level. As π^h increases, the index j increases. This suggests that the landowner prefers to treat more infested trees as the likelihood of new infestation increases. As the value of π^h increases, the required expected reimbursement is lower under TBR, and consequently, a higher expected objective function value than that under IBR. Further, though the OTDs are different under TBR and IBR, neither is monotonic in the initial infestation level. Interestingly, not offering a cost-sharing program may be desirable to the city forester, even though it always leads to the lowest number of surviving trees. Case in point: when π^h is 0.35, the expected objective function value is the highest under NCS, even though the expected number of surviving trees is lower. This is due to the high expected reimbursement required to run either of the cost-sharing programs. Another intriguing result is that the expected number of surviving trees increases as π^h increases from 0.35 to 0.5 or 0.7 under both IBR and TBR. This is due to the landowner's higher treatment effort, which is incentivized by those two cost-sharing programs.

6. Managerial insights

In this section, we present three key managerial insights for city foresters concerning EAB management practices. First, our results suggest that the TBR model is superior to the

Table 6. Comparisons under Scenario 1 ($\pi^l < \ddot{\pi}^l$ and $\rho < \ddot{\rho}$). Other parameters used: $n = 5$, $\alpha = 40$, $\beta = 294$, $c = 738$, $\theta = 50$, $s = 100$, $\gamma = 100$, $\rho = 0.20$, $\pi = 0.30$, $\pi^l = 0.25$. Calculated cutoffs: $\dot{\rho} = 0.30$, $\ddot{\rho} = 0.37$, $\dot{\pi}^l = 0.27$, $\ddot{\pi}^l = 0.32$, $\hat{\pi}^l(\rho) = 0.27$, $\hat{\pi}^h = 0.57$.

	$\pi^h = 0.35$				$\pi^h = 0.50$				$\pi^h = 0.70$			
	E_{trees}	E_r	E_{obj}	OTDs	E_{trees}	E_r	E_{obj}	OTDs	E_{trees}	E_r	E_{obj}	OTDs
IBR	2.97	270	−176	$N_0^0 I_1^2 N_3^5$	3.07	108	6	$N_0^0 I_1^3 N_4^5$	3.06	71	42	$N_0^0 I_1^3 N_4^5$
TBR	2.97	270	−176	$N_0^0 I_1^2 N_3^5$	3.07	0	114	$N_0^0 I_1^3 N_4^5$	3.06	0	113	$N_0^0 I_1^3 N_4^5$
NCS	2.59	0	17	N_0^5	2.27	0	−46	N_0^5	1.84	0	−131	N_0^5

IBR model. The TBR model encourages the landowner to treat more trees, resulting in higher expected reimbursement and a greater net benefit in that more ash trees survive at the end of the planning period. Second, the optimal treatment decision in the first period depends on the number of infested trees and the second-period attack rate for the TBR model. When the number of infested trees is low, the city forester can create a subsidy to induce the landowner to treat all infested trees. Further, the optimal number of treated trees increases with the likelihood of second-period attack rate, and reimbursement encourages the landowner to treat all (infested and healthy) trees in the first period. Third, the effectiveness of insecticide treatment plays a crucial role in the optimal treatment decision. When treatment is very effective (i.e., when trees are either healthy or have less than 50% canopy decline), treating all trees is optimal regardless of the number of trees infested. The reimbursement required to induce the landowner to treat all trees is likely to be small. On the other hand, when the treatment is not very effective (i.e., when infested trees have greater than 50% canopy damage) and a high number of infested trees are present in the first period, not treating any trees and removing them within 1-3 years is optimal.

These three insights align with EAB management practice and research results. In practice, incentive programs are not common. Instead, landowners are required to remove their ash trees when they die. Communities that do have incentive programs roughly follow the TBR model, where the city forester subsidizes the cost of insecticide treatment in proportion to the number of trees the landowner treats. For example, Burnsville, Minnesota, offers a cost-sharing program where the cost of insecticide treatment per tree is discounted by a fixed amount. Our TBR model can help promote such programs where they do not exist or refine existing programs to increase net benefits.

Our results also concur with broad EAB management guidelines (Herms *et al.*, 2019), recommending insecticide treatments for healthy ash trees when there is a moderate to high risk of EAB attack. Trees with over 50% canopy decline are not recommended for treatment, as studies have shown that ash trees in the later stages of infestation are unlikely to be saved by insecticide treatment (Herms *et al.*, 2019). The optimal treatment decisions, considering the number of infested trees, treatment effectiveness, and second-period attack rates, add valuable refinement to the existing management guidance in the literature.

Additionally, our results are consistent with the results of simulation and optimization studies of urban ash populations, which show that EAB management strategies emphasizing insecticide treatment have higher net benefits than strategies that focus on tree removal (McCullough and Mercader, 2012; Kovacs *et al.*, 2014; Bushaj *et al.*, 2021; Kıbış *et al.*, 2021). For example, Kıbış *et al.* (2021) show that it is critical to detect and locate EAB immediately and then prioritize the treatment of minimally-infested trees followed by the removal of highly infested and dead trees. Although previous studies provide guidance for a city forester managing a large urban ash population in public ownership, our results are particularly relevant to a private landowner who must decide how to manage the small number of ash trees on their property. For a city forester, our findings aid in designing incentive programs to encourage landowners to manage their ash trees.

However, the practicality of our models may be limited in two ways. First, the assumption of perfectly rational landowners may not hold in reality, as they may not have the accurate information, such as the second-period attack rates, to select the best course of action. Further, they may not have the budget to treat trees even with the reimbursement from the city forester. Second, some parameter values, such as the marginal valuation of surviving ash trees, can vary drastically among landowners, making it challenging to design a cost-sharing program for heterogeneous landowners.

Lastly, in order to assess the strengths and weaknesses of the two-period framework as a representation of a multi-period decision problem, we conduct a comparative analysis focusing on two actions following the conclusion of the cost-sharing program. The actions examined are: (i) The landowner continues inspecting and treating EAB-infested ash trees over multiple periods and (ii) The landowner discontinues the treatment of EAB infestations. Our findings indicate that, in most instances, the ongoing treatment of EAB infestations is expected to provide superior long-term benefits. The details of the study is relegated to the E-Companion.

7. Conclusions

In this work, we develop two cost-sharing models for a city forester to induce a private landowner in mitigating the impact of EAB on ash trees, considering different types of information asymmetry. The IBR model deals with a moral hazard problem, where the city forester must incentivize the landowner to treat the desired number of trees based on the infestation level post-reimbursement. In contrast, the TBR model faces an adverse selection problem, aiming to prevent landowners the landowner from overtaking to claim a higher reimbursement.

We identify optimal treatment decisions and the conditions under which each treatment decision can be optimal for each model. Specifically, we analytically characterize the optimal treatment decisions and the reimbursement schedule for the IBR model. Further, we compare the efficacy of the cost-sharing programs among the IBR, TBR, and no cost-sharing models. In all scenarios but one, the TBR model leads to the highest number of surviving trees while maximizing the city forester's net benefit, despite requiring higher reimbursement. The only exception is when the treatment is ineffective and both second-period attack rates are low.

Our future work will focus on two tasks. First, we aim to develop a heuristic for finding the optimal solution in the TBR model, reducing search time by using structures of optimal treatment decisions, using the structures of the optimal treatment decisions already identified. Second, we plan to integrate game-theoretic models with an optimization model to maximize the number of surviving ash trees in both public and private lands under a limited budget through a public–private partnership. This integrated framework will provide optimal budget allocations for managing public trees and running cost-sharing programs with landowners that are heterogeneous in the number of ash trees and attack rates.

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Data and code availability statement

All input data used is presented either in the manuscript or in the E-Companion. The codes generated and data used are accessible for reference at https://zenodo.org/record/8225186.

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