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# HEALTH OUTCOMES AND OPTIMAL CHOICES IN URBAN AREAS IN RESPONSE TO ENVIRONMENTAL SHOCKS AND CHANGES IN FOREST AMENITIES

Benjamin Jones

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**HEALTH OUTCOMES AND OPTIMAL CHOICES IN URBAN  
AREAS IN RESPONSE TO ENVIRONMENTAL SHOCKS AND  
CHANGES IN FOREST AMENITIES**

**BY**

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M.A., Economics, University of New Mexico, 2013

DISSERTATION

Submitted in Partial Fulfillment of the  
Requirements for the Degree of

**Doctor of Philosophy  
Economics**

The University of New Mexico  
Albuquerque, New Mexico

**December, 2015**

## **DEDICATION**

To Kristopher, who always pushes me to work harder and never give up.

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## **ABSTRACT**

Forests and trees may play important roles in human health outcomes and choices made by individuals in urban areas. Disruptions to forest amenities and tree canopy coverage caused by shocks to the natural environment may affect urban air quality, behavioral decisions, time use habits, and environmental management. This work exploits two distinct and unrelated shocks to forests in the United States to investigate the environmental and health economic links in urban areas between people and trees, and a proposed deeply ingrained role for environmental health in how people live, interact, optimize in their communities.

The first chapter argues that environmental quality and forest amenities are important determinants of health and behavioral patterns in urban areas. The conclusion is that further investigations into the indirect market and nonmarket effects of forests and trees on the urban economy are necessary to better guide self-investments in health and management of natural resources. Chapter 2 examines one mechanism through which shocks to the natural environment caused by forest fires in the Mountain West affect health in high-density communities distant from the flame zone. Using a case study

wildfire event in eastern Arizona that brought smoke over Albuquerque, New Mexico in 2011, this chapter advances the methodology by which wildfire smoke damages are assessed by modifying a relatively new US EPA benefit transfer computer program, coupling it with original household survey data, and demonstrating how it can be applied to wildfire smoke events. This chapter concludes that not only are wildfire smoke events costly in urban areas, but that perhaps wildfire smoke is more toxic to health than conventional urban air pollution, necessitating more deliberate and nuanced choices by analysts tasked with estimating the damages of wildfire events.

Chapter 3 exploits a different shock to forest cover, caused by the emerald ash borer (EAB), to investigate heterogeneity in urban invasive species management when health is directly accounted for by environmental managers and policymakers. Simulation results show that accounting for health impacts associated with lost tree cover increases net benefits of management by more than 1100% in a combined management model and leads to mortality reductions of 21 persons over 50 years and 5,500 cases of reduced morbidity over the same time period for a representative EAB infested county in the US. Additionally, results indicate that a “one size fits all” management approach may be inappropriate for responding to large-scale invasive species infestations due to heterogeneity in county demographics, underlying health incidence, and tree coverage.

Chapter 4 further exploits the shock to forest and tree cover caused by EAB to examine behavioral changes in infested areas. Specifically, this chapter investigates how a shock to environmental quality caused by detection of EAB influences labor-leisure tradeoffs made by residents of infested areas using data from the nationally-representative American Time Use Survey. Econometric results from a variety of models

indicate a negative relationship between EAB detection and daily outdoor leisure time in addition to a contemporaneous positive relationship between EAB detection and daily time spent on labor supply activities. These findings exist primarily along the extensive margin and persist after controlling for year and area fixed effects and daily weather conditions. Changes are persistent; lasting for 2 years and longer.

The overall conclusion presented in chapter 5 is that forests and trees have economically meaningful impacts on health outcomes and individual behavioral patterns in urban areas as a result of shocks to environmental quality. It may be useful for policymakers and environmental managers to consider forest amenities, and disruption to forest quality in particular, when setting environmental and labor market policy. Accounting for the links between nature, health, and optimal choices, may lead to better informed policy, particularly in high-density populated areas where impacts of trees are perhaps the greatest.



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## **Chapter 1**

### **Introduction: Thinking about shocks to urban forest cover and impacts on human health and behavior**

Environmental quality in US urban areas is periodically affected by unexpected disturbances or shock events. Shocks may be anthropogenic (e.g., wildfires caused by unattended campfires, accidental oil spills, or transporting invasive species along global trade routes, etc.) or natural (e.g., wildfires caused by lightning, hurricanes, floods, or extreme temperatures, etc.). Climate change is expected to increase the number and magnitude of shocks to environmental quality in the coming years, creating reverberations throughout the economy (Rahmstorf & Coumou, 2011). Urban forests and forest amenities in particular are often disrupted by environmental shocks, with associated market and non-market effects. However, reverberations of secondary and tertiary market and non-market effects (so-called indirect effects) of forest shocks through a regional economy are poorly understood.

One way to study indirect effects of forest amenities is vis-à-vis the ties between trees and people. People may be connected to trees in a wide variety of ways. Trees provide aesthetic value and are a source of recreational opportunities for communities. People often hike, camp, or walk through forests and urban parks in order to (re-)connect with nature and “recharge.” Research has connected trees to physical and mental health and well-being (Tyrväinen et al., 2005). Additionally, trees are a significant source of air pollution removal and particle deposition (Nowak et al., 2013), which can be especially



important in urban areas where there are significant concentrations of air pollutants and substantial pollutant-related cardiorespiratory health effects. Economists have measured many *direct* market and non-market benefits of urban trees, from harvesting and stumpage values (both market) to aesthetic and cultural values (both nonmarket). Given the nuanced relationship between people and trees, a more complete picture of the *indirect* economic benefits of trees is required to fully comprehend the economic reverberations created by environmental shocks.

A starting point would be to look at how forests and trees influence human health and behaviors. Consider the following scenario. Imagine for a moment that you live a block away from an urban park filled with large shade trees and walking trails. You often take strolls or runs through the park in the evening, perhaps with a friend, partner, or a pet. Maybe you occasionally bike along the trails too. Now, imagine there is some environmental shock, say an invasive pest or disease, which first stresses and then begins to kill some of the park trees. The park is now less shaded and less “green” than it was previously. How might you react or respond? Maybe you would go to the park fewer times per week or spend less time during each visit. Might your health or well-being be affected by this change? Perhaps in ways that you are not even aware of? What about the physical environment around you? If the lost tree canopy is not replaced, we might expect localized pollution levels to marginally increase. Alternatively, perhaps you are not impacted at all and continue to live and function the same as before the shock. Ultimately, the interesting question for the economist is whether or not such a disruption (and others like it) induce measurable economic impacts and how inclusion of such impacts in environmental management and policymaking more generally influences

optimal choices and the benefit-cost calculus used to respond to environmental shocks. In other words, is inclusion of the nuanced link between trees and people a potentially important economic factor that should be admissible evidence in debates regarding environmental quality?

The contribution of this work is to investigate the indirect economic links between trees, health, and behavior in high-density US urban areas, moving beyond the direct benefits that have previously been analyzed.<sup>1</sup> In particular, this work demonstrates that shocks to forests and forest amenities can be highly disruptive to human health and certain behavioral outcomes, creating both market and non-market costs that reverberate through the economy.

Nature can be linked back to health using the concept of the health production function. This is based on the idea of endogenous health in which increments and decrements in health are influenced by behavior and self-made investments (engaging in preventative care, having a balanced diet, or washing your hands, for example). Shocks to environmental quality act as exogenous determinants, affecting how health is produced. For example, worsening air quality due to wildfire smoke often affects cardiorespiratory health and can lead to spikes in mortality rates. A shock to environmental quality may be unavoidable in the very short run, but in the days, weeks, and months following an event an individual could seek out a physician, move out of a community, purchase goods or services to better defend themselves against future shocks (e.g., a home air purifier), petition their elected officials to take action, or could become involved themselves (e.g., volunteer to spread the word on the dangers of unattended campfires). These types of

investments might improve health instantaneously or minimize health impacts of future shocks.

However, before an investment can even be considered in response to an environmental shock it must be the case that the shock is viewed or perceived as potentially health altering. If a shock is believed to be completely *unrelated* to health, then endogenous choices regarding behavioral changes and potential investments are unlikely to be made – why take action if no reward is perceived? On the other hand, if people do perceive a shock as health altering, action is more likely– such as when people stay indoors more during wildfire smoke events. The key is in knowing when a shock may affect health. This is challenging in practice, as there is often an information gap between the science of health and the health of communities. For example, many people might not realize that trees promote health by scrubbing the air or that forest and watershed restoration and maintenance of distant forest land can reduce the likelihood of a wildfire event, keeping rivers, lakes, and airsheds free of certain toxins. Better understanding and dissemination of information on how health is connected with nature can aid people in making more informed decisions on self-investments in health in response to environmental shocks.

The main argument advanced in this dissertation is that environmental quality and health are connected in complex and indirect ways, which are just now beginning to be understood. Ignoring these connections when setting economic policy, engaging in environmental management, or even determining how to pass the hours in a day, can harm health and produce economic consequences. Closing the information gap on how shocks reverberate through an economy can lead to increased investments in health and

changes in behavior to mitigate decrements in well-being created by disruptions to forests and trees.

From a policy perspective, and from the perspective of an environmental economist, this is not to say that we have no understanding of the impacts of shock events on welfare. Decades of economic research exists on environmental shocks. The focus has primarily been on direct, immediate, and localized impacts; with some notable exceptions (e.g., the Exxon Valdez spill, the BP Deepwater Horizon blowout). Studying direct impacts, however, may not fully capture the extent and nuances to which a shock disrupts society. More importantly, persistent and long-term impacts of environmental shocks are likely to be indirect (e.g., lost trees due to an invasive species has an immediate impact on children's health, perhaps influencing long-term levels of educational attainment). This is keeping with the *biophilia hypothesis* introduced and popularized by biologist E.O. Wilson, which suggests an intimate and complex relationship between humans and nature (Wilson, 1984). Meaningful interactions between humans and nature (e.g., visits to the lake cabin as a child, staring at the stars under a pitch black sky, caring for a pet, etc.) can leave lasting impressions on people that deeply guide their worldview and decision making processes. Likewise, according to *biophilia*, changes to nature or the quality of the interactions between humans and nature can also have lasting impacts. For the environmental economist, it is our task to expand notions of environmental value and benefit to include such broader definitions of "impact" in order to guide the efficient use of limited natural resources.

## **1.1 Research methods and empirical tools**

The goal of the following chapters is to examine the links between nature, health, and behavior beyond the obvious direct and localized relationships. Specifically, this examination will focus on densely populated urban areas where environmental shocks often have the greatest aggregate impact on health and behavior given high levels of pollution, limited amount of greenspace, and large populations in urban areas. Methods and tools from environmental and ecological economics, health economics, and mathematical economics are brought to bear to address the issue. A challenge faced when investigating causal mechanisms is to not fall into the correlation trap; correlation does not imply causation. This can be particularly problematic when looking at human dimensions of environmental quality given selection bias and residential sorting. For instance, outdoor enthusiasts may self-select to live in communities with abundant forest and tree cover. Even within such a community, residential sorting may result in nonrandom placements of households according to access to forest amenities and ecosystem services they provide. These actions muddle the direction of causation, potentially leading to biased study results unless careful design and planning are utilized to tease out the causal mechanisms.

To address these concerns, the following chapters exploit natural experiments, so-named because they can approximate “as good as random” controlled trial experiments, but in a nonlaboratory or “natural” setting. In a classic natural experiment, some exogenous and random shift, change, or shock occurs, affecting experimental and control populations in some known and measurable way. Importantly, the process governing exposures is both natural and quasi-random, meaning that researchers have no control over the assignment of participants to “treatment” and “control” groups. Rather,

divergences in environmental quality, for example, can offer the opportunity to analyze groups of people as if they had been part of an experiment; some are exposed and some are not. Given the sudden and unpredictable nature of environmental shocks, it is practically impossible for people to self-select and sort in nonrandom ways that would influence the probability of being impacted once a shock occurs. Therefore, natural experiments provide stronger evidence of causal links than correlational studies, though of course can never unequivocally determine causation.<sup>2</sup>

Chapter 2 exploits a natural experiment created by a shock to air quality levels in a high-density urban area precipitated by a wildfire smoke event in the Southwestern US. The shock increased counts of fine particulate matter (PM<sub>2.5</sub>) in the Albuquerque, New Mexico airshed, resulting in cardiorespiratory morbidity impacts. The crux of this chapter is to investigate the ongoing debate regarding how to capture morbidity impacts and associated economic costs of smoke from wildfires in densely populated areas when original data collection is not possible, yet where aggregate population impacts are the largest. Particularly, the nonmarket costs associated with behavioral changes during a smoke event. Estimates of such indirect impacts and costs may differ by key assumptions made by the researcher in their damage assessment. A comparative analysis of “choices of the analyst” will indicate to what degree estimates of economic impacts associated with a shock event vary across behavioral and health assumptions, while along the way also providing some important lessons for how to empirically link nature, health, and behavior.

Chapter 3 takes the next step by developing an original model of environmental management inclusive of indirect health impacts, using some of the key qualitative

findings from chapter 2 about how environmental shocks are linked to health in urban areas. The application in chapter 3 is to an invasive species, the emerald ash borer (EAB). Another natural experiment, EAB quasi-randomly infests North American native ash trees, leading to their death within 1-2 years. The sudden shock to environmental quality created by lost ash affects air quality levels in urban areas, where ash is often highly prevalent. Dynamic simulations are used to explore how EAB management differs (if at all) when indirect health impacts are included in the decision making process.

The results of chapter 3 also begin to shed light on the economic reverberations created by environmental shocks. A small beetle (EAB) infests and kills a tree, which degrades environmental quality, causing health and behavioral impacts, likely with long-term implications on regional economic health and community well-being. In urban areas, where ash are a popular yard and street tree, degradations to environmental quality can be quite significant. Taken in this light, EAB is no longer “just” a beetle, but is actually an important determinant of societal welfare with the power to affect people’s lives and economic livelihoods.

A shortcoming of the empirical approach in chapter 3 is that the relationship between nature, health, and behavior is assumed, based on extant literature linking EAB to excess mortality and morbidity. In chapter 4, an original empirical analysis is conducted to determine how shocks to urban forest and tree cover relate to behavioral changes. If meaningful changes are observed, this chapter would contribute a new dimension of indirect impacts associated with environmental shocks in urban settings. The behavioral impacts focused on in this chapter are how people allocate their time in a day between leisure activities and labor market activities. The labor-leisure decisions of

working adults prior to EAB infestation are compared to the labor-leisure decisions of working adults after an EAB infestation. Given the natural experiment setting, observed labor-leisure differences across the two groups would be consistent with a casual story; the shock to environmental quality created by EAB is associated with changes in daily time allocations. Moreover, the direction and magnitude of labor-leisure changes would provide insight into how people live and interact with trees.

Finally, a general set of conclusions and broad implications of each individual chapter will be provided in chapter 5. The chapters are logically ordered, beginning with the fundamental methodological issues surrounding links between nature, health, and behavior (chapter 2), advancing to a model of nature, health, and behavior and what such a model tells us about optimal environmental management (chapter 3), and finishing with a novel empirical estimate of indirect impacts of environmental shocks on behavior (chapter 4), in order to come full circle to address the original question on how shocks indirectly reverberate through an economy. Taken together, the results from each chapter are scrutinized in order to articulate whether forest and trees have a deeply ingrained role in human health and how people live, interact, and optimize in their communities.



## Notes

<sup>1</sup>Direct benefits of forests and trees that have been previously studied include their timber and stumpage values (Thompson et al., 1997), market impact on property values (Donovan & Butry, 2010), energy and CO<sub>2</sub> reductions because of tree shade (McPherson et al., 2005), stormwater interception (*ibid*), ability to reduce air pollution (Escobedo & Nowak, 2009), and nonmarket aesthetic, cultural, or psychological values (Majumdar et al., 2011; Dwyer et al., 1989).

<sup>2</sup>But for the social scientist who takes society as their laboratory, natural experiments are currently as close as it gets to the ideal randomized controlled trial (RCT) experiments used by laboratory scientists. Unequivocal causation will always prove elusive for the economist unless an RCT is carried out, which is impossible (and unethical) in many circumstances, including the study of environmental shocks.

## **Chapter 2**

### **Wildfire smoke health costs: A methods case study for a Southwestern US “mega-fire”**

#### **2.1 Introduction**

Due to prolonged drought, climate change, and fuels build-up on forested lands, the frequency and severity of wildfire events is expected to increase across much of the western United States (US) (Liu et al., 2010; US Global Change Research Program, 2014). In assessing the damage from such events, there is increasing realization of the need to incorporate wildfire impacts outside of the flame zone such as downstream water quality, regional ecosystem health, and adverse health effects associated with exposure to smoke into wildfire management policy. Economists are interested in measuring the economic benefits and costs associated with wildfire impacts to inform efficient use of limited control resources (Milne et al., 2014). Original estimation of the economic costs of wildfire smoke-related health effects is time consuming and costly, requiring extensive micro-level data collection in affected areas (e.g., Richardson et al., 2012). However, there is an urgent need to better understand the environmental-health costs of wildfire events, including effects on both nearby and regional urban populations.

Benefits transfer – using existing data to inform decisions in a different setting or context (Rosenberger & Loomis, 2003) – is a more accessible way to estimate smoke-exposure health costs and has been used in several wildfire studies (e.g., Martin et al.,

2008; Rittmaster et al., 2006; Hon, 1999). Previous research often transfers results from non-“wildfire-specific” studies, which may be inappropriate for estimating costs of severe, short-duration smoke events (Kochi et al., 2010). The objective of this chapter is to provide a case study illustration of a wildfire benefits transfer using the US Environmental Protection Agency’s (EPA) benefits mapping and analysis program – community edition (BenMAP-CE), and investigate the resulting impact on estimated health costs of transferring functions and values from wildfire-specific studies instead of ones from the “urban air” literature. BenMAP-CE is an open-source Windows-based application that estimates the economic benefits associated with changes in air quality over a geographic area (Davidson et al. 2007). This chapter configures and modifies BenMAP-CE (version 1.0.8)<sup>3</sup> for application to an urban wildfire smoke event in the Albuquerque, New Mexico (NM) metropolitan area caused by the 2011 Wallow Fire (Wallow “mega-fire,” hereafter) that burned 535,000 acres in Arizona and New Mexico (US Forest Service, 2011).

This chapter addresses several open issues in the literature, including: (i) the appropriateness of valuing smoke-induced health impacts through wildfire-specific willingness to pay (WTP) measures; and (ii) selection of transferred air quality concentration-response (CR) functions. On (i), we contrast mega-fire event health costs using an originally constructed wildfire-specific WTP measure with WTP and cost-of-illness (COI) values estimated using BenMAP-CE’s built-in valuation functionality. On (ii), comparisons are made between estimated health incidence calculated using wildfire-specific CR functions and BenMAP-CE’s built-in urban air quality CR functions, transferred by the EPA from non-wildfire event studies. Again, the objectives are not

only to provide a “proof-of-concept” application of BenMAP-CE to a mega-fire caused smoke event, but to also explore differences in estimated health impacts and costs across types of transferred CR and WTP functions (wildfire-specific or not). Transferred study selection in a wildfire smoke benefit transfer is an unsettled methodological issue, which is likely to be confronted by researchers estimating the costs of a wildfire event.

The contributions of this chapter are threefold. First, following only one previous study (unpublished), we provide the second case study application and configuration of BenMAP-CE for a wildfire smoke event. Second, we provide preliminary empirical evidence of smoke-related health incidence and valuation sensitivity to choice of transferred air quality CR functions and WTP values (wildfire-specific or not). Finally, using original survey data to complement the case study, we add to the small set of available wildfire smoke WTP valuation estimates.

Results indicate that the economic costs of a wildfire smoke event are substantial. Smoke event morbidity and health costs vary considerably according to whether or not a wildfire CR function is used in place of an urban air CR function. Additionally, use of an originally constructed WTP measure from a wildfire smoke experience questionnaire produces substantially larger health costs than those found by using an urban air quality WTP value. Differences are consistent with the nascent literature on divergences between conventional and wildfire-specific air quality studies (Kochi et al., 2010; Vedal & Dutton, 2006).

## 2.2 Background

A combination of natural and human caused factors (e.g., prolonged drought, history of fire suppression policy and concomitant fuels build-up in forests, rapid expansion of the wildland urban interface) have increased the risk of wildfires in the US west and elsewhere (Ryan & Opperman, 2013). Damages from high severity wildfires have followed an increasing trend, and can be economically significant (US Global Change Research Program, 2014). Further, with climate change, recent assessments conclude that wildfire risk and associated damages are expected to increase (Liu et al., 2010).

Damages from a wildfire event can occur both within the burn area and outside of it (e.g., due to smoke plumes, and subsequent floods and debris flows, etc.). Resource managers must account for effects of fire on ecosystem health, water quality, and soil composition both in and immediately surrounding the flame zone (Dale, 2006). Wildfire impacts on environmental and behavioral regimes can extend well beyond the flame zone, to include downstream surface water quality (Smith et al., 2011), ash fallout (Earl & Blinn, 2003), and air quality within the smoke plume (Henderson & Johnston, 2012; Fowler, 2003). Wildfire smoke plumes may contain particulates that are especially harmful to health (Naeher et al., 2007). These plumes have immediate localized effects on communities in and around the flame zone, but can travel great distances (e.g., hundreds of miles) according to their atmosphere injection height, which strongly influences dispersion.

The site for our case study, Albuquerque, is located in Bernalillo County in north-central New Mexico (NM). With a city population of 545,852 and a metropolitan population of 662,564, Albuquerque is the largest urban center in NM (US Census Bureau, 2010). While not situated in forested lands itself, Albuquerque has forest and wildland urban interface (WUI) areas to the east (i.e., the eastern slopes of Sandia Mountains and parts of the Cibola National Forest) and hundreds of miles to the southwest (Gila and Apache National Forests). Predominant winds out of the southwest (Ryan & Opperman, 2013) can bring smoke plumes from wildfires into Albuquerque. Wildfire smoke over Albuquerque is not uncommon, with smoke from the 2011 Wallow mega-fire in southeastern Arizona being the most recent prolonged event. The Wallow mega-fire significantly impacted air quality levels across central and northern NM, some 300 miles away from the burn site, including Albuquerque.<sup>4</sup> Health effects associated with smoke from the fire have been investigated and include respiratory and cardiovascular illnesses (Resnick et al., 2015), though to-date no smoke damage assessment has been performed.

### **2.2.1 Wildfire smoke health impacts**

Recognition that wildfire smoke affects human health is not new (Henderson & Johnston, 2012; Fowler, 2003; Duclos et al., 1990). Despite decades of “awareness,” it is still unclear what many of the short- and long-term health impacts of wildfire smoke are in an exposed population. Many studies focus on estimating changes in emergency room visits (Rittmaster et al., 2006; Hon, 1999; Duclos et al., 1990), hospital admissions (Crabbe, 2012; Delfino et al., 2009; Mott et al., 2005; Shahwahid & Othman, 1999), or mortality (Johnston et al., 2011; Hänninen et al., 2009; Vedal & Dutton, 2006).

Generally, wildfire smoke events are associated with increased cardio-respiratory related physician and hospital visits. However, the link between increased daily mortality and smoke exposure is unclear (Vedal & Dutton, 2006).

Health impacts of exposure to air pollutants may vary depending on their source. Research has investigated whether wildfire smoke or wood smoke exposure produces the same health impacts as exposure to urban air pollution (Kochi et al., 2010; Hänninen et al., 2009; Naeher et al., 2007; Seagrave et al., 2006). Results have been mixed. Seagrave et al. (2006) find little evidence to suggest increased toxicity of wood smoke compared to urban pollutants, though only smoke from fireplaces and prescribed forest burns was examined. Naeher et al. (2007) argued that insufficient evidence exists to make any general conclusions regarding relative pollutant source toxicity. Hänninen et al. (2009) observed wildfire-specific mortality increases that were consistent with expected estimates from urban air pollutant models. By contrast, Kochi et al. (2010) concluded that wildfire smoke is “consistently” more detrimental to cardio-respiratory health than urban air pollutants, though less of a threat to mortality. Kochi et al. (2010) only examined studies that directly investigated smoke known to be from forest or brush fires, which may explain differences in their results compared to earlier studies.

Several causes have been proposed to explain why wildfire smoke may be more toxic than urban air pollution. These include chemical composition differences between smoke plumes and urban air, differences in perceived health risks (people may perceive wildfire smoke as more health damaging), and behavioral response patterns (i.e., averting behaviors) (Hänninen et al., 2009; Kunzli et al., 2006; Vedal & Dutton, 2006). If wildfire health impacts substantively differ from urban air health impacts, then CR functions

estimated for one class, say urban air, are inappropriate for use in a benefit transfer estimation of health impacts in the other class, wildfire, for example. In the extreme, use of an urban air CR function may lead to incorrectly ascribing mortality or morbidity incidence to a wildfire smoke event. For this reason, Kochi et al. (2010) recommend using wildfire-specific study results whenever possible in a benefit transfer. It remains an open empirical question as to how much bias may be introduced by using urban air study results in a wildfire smoke damage assessment. Comparing smoke exposure health impacts between wildfire-specific and urban air pollutant transferred studies for a specific benefit transfer case study, like the one carried out in this chapter, may shed additional light on this open debate.

### **2.2.2 Evaluating health impacts and costs of wildfire smoke events**

Wildfire damage assessments often use benefit transfers to capture the economic costs of smoke exposure (e.g., Martin et al., 2008; Rittmaster et al., 2006; Cardoso de Mendonça et al., 2004; Butry et al., 2001), though not in all cases (e.g., Richardson et al., 2012; Hon, 1999; Shahwahid & Othman, 1999). One advantage of benefit transfer is that it can be used in circumstances where original data are unavailable. Existing data and information originally collected for use at one site are transferred to a different context or “policy site” (Rosenberger & Loomis, 2003). Ideally, the context and site to which the original research is being adapted to is similar in many respects so that the transferred values are as close to the “true” value as possible.

In a wildfire smoke benefit transfer, two types of transfers are made from prior studies: (i) transfers of CR air quality functions to estimate changes in health incidence,



and (ii) transfers of cost-of-illness (COI) and WTP values to estimate the economic costs of health incidence changes. In (i), CR functions from either the urban air quality or wildfire smoke literature are used to relate changes in pollutant concentrations to changes in health incidence. The economic costs of these changes are valued in (ii) using estimates from previous studies (e.g., cost of an emergency room visit, WTP to avoid a smoke related health impact, etc.). For example, in a simple benefit transfer, an existing CR function for PM<sub>2.5</sub> (particulate matter up to 2.5 micrometers in size) from the urban air literature might be used to estimate changes in mortality due to a wildfire smoke event. WTP results from the value of a statistical life literature might then be used to determine the economic costs of the event in terms of increased mortality.

Mixed-transfer or “hybrid” wildfire smoke benefit transfers have also been used. In a hybrid transfer, the researcher(s) transfers either CR functions or economic cost values, but not both (e.g., Kochi et al., 2012; Cardoso de Mendonça et al., 2004). The non-transferred results are then estimated using original data specific to the wildfire event. In this chapter, we perform both a benefit transfer and a hybrid benefit transfer, where in the latter we estimate WTP to avoid a wildfire smoke health impact using original data from a smoke health impact questionnaire.

### **2.2.3 Using WTP and COI to estimate costs**

Economic costs of a wildfire smoke event can be estimated either using COI or WTP approaches. In a COI approach, the direct and indirect resource costs of a smoke-related illness are identified and measured. These costs include expenditures on medical care and medications, opportunity costs of time spent acquiring medical treatment, and

the value of lost wages due to time spent sick (Richardson et al., 2013). COI is an imperfect measure of the total burden of wildfire smoke on society because it does not fully capture the disutility of illness (Richardson et al., 2013; Richardson et al., 2012; Kochi et al., 2010; Freeman, 2003). WTP to avoid a wildfire smoke health impact is the preferred utility-theoretic alternative and has been used in a handful of studies (e.g., Martin et al., 2008; Rittmaster et al., 2006; Hon, 1999). However, *all* these previous studies (except for Richardson et al., 2012) use a WTP measure derived from the urban air literature. In the only published WTP value to avoid health damages estimated for wildfire smoke specifically, Richardson et al. (2012) found a WTP of \$93.15 (2014\$) per exposed person per day for a large wildfire in southern California. The authors suggest that their result is consistent with the health literature, but do not make a direct comparison with urban air study results. Is WTP to avoid a smoke health impact meaningfully different than WTP to avoid an illness caused by urban air pollutants? If yes, then a wildfire benefit transfer utilizing urban air economic valuation measures may over- or under-value smoke-related health costs. Kochi et al. (2010) posited that such value differences might exist, but to-date no comparison has been made. Using survey data for Albuquerque, NM, we contribute the second estimate of WTP to avoid illnesses from wildfire smoke specifically, and compare our value to a commonly used urban air WTP value from Dickie and Messman (2004).

#### **2.2.4 Benefit transfer using BenMAP-CE**

The US EPA's BenMAP-CE is a benefit transfer tool that utilizes transferred CR functions and economic values to estimate benefits (for an improvement) or costs (for a decrement) associated with changes in air quality for non-overlapping health endpoints

(Davidson et al., 2007). First, the user inputs modeled or monitored air quality data such as particulate matter (PM) into an air quality grid over a defined geographic space. After specifying the analysis timeframe, health endpoints of interest, and population-grid size, the user defines an air quality policy change (called a control). For example, this could be a hypothetical reduction in PM<sub>2.5</sub> of  $1 \mu\text{g}/\text{m}^3$  annually over a decade in Albuquerque. Using the supplied data and selection of health endpoints, BenMAP-CE calculates point estimates of changes in incidence for each endpoint associated with the air quality change within each grid-cell. Finally, COI and WTP values are transferred from air quality and health endpoint literatures or transferred from original estimates by the researcher to value estimated incidence changes at the grid-cell level. At the discretion of the user, incidence and economic valuations can be spatially aggregated.

BenMAP-CE has been applied to analyze health impacts of changes in air quality standards in the US (Fann et al., 2012; US EPA, 2010; 2013), and internationally (Voorhees et al., 2014). In an unpublished thesis, Douglass (2008) provides the only prior application to wildfire smoke. Given the open-source nature and peer-reviewed development of BenMAP-CE, it's a robust benefit transfer tool for estimating and valuing wildfire smoke health impacts. The potential of using BenMAP-CE for wildfire events is tremendous because it provides a way to quickly estimate health impacts of a wildfire event using hourly and daily pollutant measures. Until recently, this was not easy to do in a systematic and controlled way.

This chapter will configure BenMAP-CE for a wildfire smoke event and apply it in a case study of a Southwestern US mega-fire caused smoke event in Albuquerque, NM. To evaluate differences between transfers of wildfire-specific and urban air study results,

two benefit transfers will be performed in BenMAP-CE. In the first, built-in urban air study CR functions, COI, and WTP values will be employed to estimate smoke exposure incidence and associated health costs. In the second, wildfire-specific CR functions, COI, and an originally estimated wildfire WTP will be utilized. Comparisons will be made between estimated incidence and health costs across transfers. This is the first case study illustration of results sensitivity to choice of transferred study results (wildfire or urban air) and only the second case study application of BenMAP-CE to a wildfire smoke event. The value-added of our analysis over the previous BenMAP-CE application (Douglas, 2008) is that we investigate sensitivity to transferred study type and use originally estimated economic valuation results.

## **2.3 Methods**

### **2.3.1 Modifications to BenMAP-CE**

BenMAP-CE (v.1.0.8) has more than forty built-in “health impact” functions covering twenty-two health endpoints from acute bronchitis to hospital admissions to work loss days. In BenMAP-CE, a health impact function refers to the relationship between a change in pollutant concentration ( $\Delta p$ ) and a change in health incidence ( $\Delta y$ ). It’s numerically derived from an air quality CR function, which relates pollutant concentration ( $p$ ) to health incidence ( $y$ ). Each health impact function comes from a unique CR function.<sup>5</sup> Importantly, none of the built-in health impact functions were transferred from wildfire-specific studies.

The open-source nature of the program means that practically any health impact function can be input by the user as long as it has a specific CR function that relates

incremental changes in pollutant levels to changes in incidence, such as those from regression estimation of relative risk or odds ratios. Focusing our search of the wildfire smoke literature to studies where a CR function was estimated produces a handful of results (see Appendix A). Higher morbidity rates during wildfire smoke events are consistently observed, with increases in cardio-respiratory emergency room visits and hospital admissions being common (Resnick et al., 2015; Crabbe, 2012; Henderson et al., 2011; Delfino et al., 2009; Hannigan et al., 2008; Moore et al., 2006). Other CR functions estimated in the literature include pharmaceutical dispensations for salbutamol (Elliot et al., 2013) and non-hospital physical visits (Henderson et al., 2011). A previously mentioned, evidence linking wildfire smoke to mortality is mixed (see Kochi et al., 2010).

For the wildfire-specific benefit transfer explored as part of our case study, CR functions estimated by Delfino et al. (2009) and Resnick et al. (2015) are used. These two studies are selected because they are recent and are specific to western US wildfires, where our study area is located. Only statistically significant results are utilized from each study and only functions covering individuals aged 0-99 or “all ages” are included. We coded into BenMAP-CE four health impact functions for the following endpoints: (i) *emergency room visits asthma*; (ii) *hospital admission all respiratory*; (iii) *hospital admission asthma*; and (iv) *hospital admission pneumonia*. Relative risks of each health endpoint were converted to coefficients for use in a log-linear health impact function, following the BenMAP User’s Manual (Abt Associates, 2012).

In our benefit transfer utilizing built-in urban air quality transfers, we select CR functions from Mar et al. (2010), Zanobetti et al. (2009), Slaughter et al. (2005), Ito

(2003), and Sheppard (2003) for the same set of health endpoints as in the wildfire-specific analysis. Additionally, CR function results from Ostro and Rothschild (1989) are used to estimate incidence of minor restricted activity days (MRAD).<sup>6</sup> MRADs capture most symptoms and illnesses associated with smoke exposure, including those requiring physician or hospital treatment. Thus, it is a broad-based measure of health effects. Incidence of MRAD closely matches our originally constructed WTP measure to avoid any wildfire smoke-related health impact. This allows us to compare health costs estimated using the built-in WTP measure with a wildfire-specific one.

The next step was to define the relevant air quality grid. PM<sub>2.5</sub> was chosen for the geographic grid-area of Bernalillo County, NM, which completely contains Albuquerque and a majority of the metropolitan population. A Community Multi-scale Air Quality Model (CMAQ) 12x12km grid was used in BenMAP-CE. This is the finest grid size available in the program and is commonly used in the literature (US EPA, 2010). A 50km radius around each air quality monitoring station was used to define the extent of the CMAQ grid. Figure 2.1 illustrates the final CMAQ grid used in BenMAP-CE. Incidence and valuation results were calculated for each grid-cell and aggregated to the county level (Bernalillo).

BenMAP-CE calculates incidence based on differences in air quality between a baseline and a treatment. Our treatment is the air quality level in Albuquerque, NM during the Wallow mega-fire. The fire started in southeastern Arizona on May 29, 2011, but due to atmospheric conditions, quickly developed a smoke plume that affected the Albuquerque area (some 200 miles away) by the next day. Sporadically for several weeks in June, smoke from the mega-fire significantly impacted PM levels in Albuquerque and

across much of northern and western New Mexico, with measured daily PM<sub>2.5</sub> levels spiking to  $70.5 \mu\text{g}/\text{m}^3$  at one monitoring site in Albuquerque on June 4<sup>th</sup>; an increase of 675% above the three-year site average for that day.

A Wallow mega-fire smoke event day was identified as monitored daily-average PM<sub>2.5</sub> levels in excess of the 99<sup>th</sup> percentile of daily average readings per monitor site over the previous five years (2008-2012). Only smoke event days occurring during the wildfire event period (May 29-July 8) were considered. The 99<sup>th</sup> percentile threshold for an event day is consistent with recent literature in this area (Johnston et al., 2011). If PM<sub>2.5</sub> levels did not exceed the 99<sup>th</sup> percentile for the site, then that day was not considered a smoke event day for that monitoring station and baseline PM<sub>2.5</sub> readings were used. Monitoring stations were excluded from this part of the analysis if they did not report PM levels for the entire month of June or had at least three missing observations during the Wallow mega-fire event.

### **2.3.2 WTP estimation using the defensive behavior method**

We employ the defensive behavior method to estimate wildfire-specific WTP. This method captures individual WTP for changes in health status caused by a pollutant, incorporating costly averting and mitigating behaviors. Examples of averting behavior include staying indoors, wearing a mask, or avoiding work during a wildfire smoke event, while examples of mitigating behavior would be buying medicine or being admitted to the hospital. The model applied here is from Freeman (2003) and Dickie (2003).

The basis of the model is the individual's health production function,  $h(\cdot)$ , which relates exogenous environmental exposure to a pollutant ( $p$ ), averting actions ( $a$ ), and

mitigating actions ( $m$ ) to changes in health status ( $s$ ). An individual produces a health output according to a health production function,

$$s = h(p, a, m, \mathbf{x}) \quad (2.1)$$

where  $\mathbf{x}$  is a vector of socioeconomic and demographic variables affecting health.

Exposure to the pollutant decreases health ( $h_p < 0$ ) and averting and mitigating actions are assumed to be non-harmful ( $h_a, h_m \geq 0$ ). Effects of socioeconomic variables are not *a priori* clear. For this application,  $p$  captures exposure to wildfire smoke and  $s$  reflects whether or not an individual experienced a wildfire smoke-related health effect.

Using equation (1) within a utility maximization framework, Freeman (2003) derives the marginal WTP for an exogenous reduction in illness from an averting action as,

$$WTP = - \frac{p_a}{\frac{\partial s}{\partial a}} \quad (2.2)$$

That is, the WTP for a reduction in illness is the negative ratio of the price of the averting action to the marginal effect of that action on health status. Use of equation (2.2) relies on an empirical estimate of  $\partial s / \partial a$ , obtained from equation (2.1) as a post-estimation marginal effect.

For estimation of equation (2.1), a linear-in-the-parameters probit model is applied,

$$\Pr(s = 1 \mid p, a, m, \mathbf{x}) = \Phi(\beta_0 + \beta_1 p + \beta_2 a + \beta_3 m + \mathbf{x}'\boldsymbol{\gamma}) \quad (2.3)$$

where  $\Phi(\cdot)$  is the standard normal cumulative distribution function. The binary dependent variable ( $s$ ) is whether the respondent experienced a wildfire smoke health effect



(Yes/No). The coefficient of interest for an averting action is  $\beta_2$  - the marginal effect of averting actions ( $a$ ) on health status ( $s$ ). A probit model is employed because the data indicates whether or not an individual experienced a smoke-related health effect, but not the duration or symptom days of health effects. This data limitation precludes using a symptom count model as done by Richardson et al. (2012) for wildfire smoke. Fitting a count data model without a clear picture of the temporal symptom profile would necessitate potentially strong assumptions on average symptom days and their intensity as experienced by individuals, potentially biasing estimated WTP. A probit specification of the type employed here does not require assumptions on symptom profiles and is more consistent with available data, though is arguably not as informative as count models in determining the relationship between averting actions and health status because it only captures a discrete change instead of intensity of symptoms.

Endogeneity is often a concern in estimation of equation (2.3) as an individual might take an averting action to prevent an illness (averting behavior causing health status) or an ill individual might take an averting action to limit future symptoms (health status causing averting behavior). The direction of causation is unclear. To prevent biased coefficient estimates (Wooldridge, 2011), endogeneity will be purged using a two-stage maximum likelihood instrumental variables approach (Freedman & Sekhon, 2010).

To econometrically estimate (2.3), we follow Richardson et al. (2012) and investigate the relationship between health status and the averting behavior *used air filter/cleaner*. This is because *used air filter/cleaner* is endogenous to the model<sup>7</sup> and is the only averting action whose coefficient is negative, both as theoretically predicted. Furthermore, prices of air filters, cleaners, and purifiers ( $p_a$ ) are readily available from

many sources.<sup>8</sup> Equation (2.3) is estimated as a two-stage bivariate probit model with *used air filter/cleaner* as the primary independent variable of interest. Other covariates include smelling smoke at home, a control for chronic respiratory disease, controls for symptoms (headaches, coughs, shortness of breath, asthma, allergies, and other symptoms), education, years in NM, Latino, and number of children under age five in the home. We use *income* as an instrument in a second-stage equation prediction of *used air filter/cleaner*. This is consistent with Richardson et al. (2012). *Income* is found to be a relevant, but not particularly strong instrument. The post-estimation marginal effect of *used air filter/cleaner* will be used in conjunction with the average price of an air filter/cleaner, \$29.71, to determine WTP for a reduction in wildfire smoke health effects.

## **2.4 Data**

### **2.4.1 Air quality data**

Daily monitored PM2.5 air quality data from stations in the Albuquerque metropolitan comes from US EPA AirData<sup>9</sup> for the years 2008-2012, inclusive. The raw data contain daily 24-hour average PM2.5 levels in units of  $\mu g/m^3$  per air monitoring site. There are six sites in Albuquerque and one site in Valencia County located in the town of Los Lunas (immediately south and adjacent to Albuquerque). Figure 2.2 shows the locations of the seven monitoring sites.

For creation of the baseline air quality grid, an average for each site was calculated using five years (2008-2012) of site-specific daily mean PM2.5 concentrations. This yields 365 (366 for a leap year) observations per site. PM2.5 deviations from the five-

year daily average during a wildfire event is the source of variation BenMAP-CE uses to identify health impacts.

#### **2.4.2 Wildfire experience survey**

Researchers at the University of New Mexico developed and administered a survey questionnaire on wildfire risk and surface water supply to a sample of households in Albuquerque, in September-December, 2013. The focus of the survey was on household support for implementation of a payment for ecosystem services model to reduce wildfire risk in the larger forested watershed approximately 100 miles or more from Albuquerque. The survey was part of a larger New Mexico EPSCOR/NSF-funded grant to study wildfire and water in New Mexico. Focus groups, individual interviews, and pre-tests were used to aid development of the survey instrument. Up to five contacts were mailed to 2,596 households in Albuquerque selected from a sampling frame of 190,000 Bernalillo County homeowners, consisting of (i) an initial cover letter; (ii) a survey packet; (iii) a reminder postcard; (iv) a second survey packet; and (v) a final letter with an additional survey packet. Contacts were mailed until a returned survey packet was obtained, the respondent notified us they did not want to participate, or a contact came back as undeliverable. Respondents could choose to complete the questionnaire online or via mail. Out of the 2,596 questionnaires mailed, 133 were undeliverable. 911 were returned (751 by mail and 160 online) for a response rate of 37%.

A section of the questionnaire asked about past wildfire smoke experience, health effects of past exposure, and averting or mitigating actions taken to avoid exposure. Respondents were asked if they had ever smelled smoke from a wildfire at their home

and if exposure to smoke had ever affected their health. If they had smelled smoke, they were asked to indicate symptoms experienced (e.g., headache, cough, etc.), averting actions taken (e.g., stayed indoors, used an air purifier), and if they took a mitigating action (e.g., went to the hospital/physician). Wildfire-specific survey questions fielded to Albuquerque, NM homeowners are listed in Appendix A.

The survey results on health effects and demographics are used to econometrically estimate WTP to avoid a wildfire smoke-related illness. Variable definitions on health and demographic questions and their summary statistics are presented in Table 2.1. Results indicate that 71% of respondents took at least one averting action during previous wildfire smoke events, compared to 1% of respondents who took a mitigating action.

Survey results also indicate that a significant percentage of respondents have smelled wildfire smoke at their home (88%), with 26% reporting that wildfire smoke has impacted their health at some point. The most commonly reported symptom associated with wildfire smoke is a cough (25%) followed closely by allergies (21%). Fifty-five percent of respondents reported staying indoors more than usual during a smoke event, with 42% reporting avoiding normal outdoor recreation and exercise. Overall, survey results demonstrate considerable health and behavioral impacts of wildfire smoke in the Albuquerque metropolitan area.

## **2.5 Results**

### **2.5.1 Wildfire smoke health incidence**

Increases in incidence associated with smoke exposure from the Wallow mega-fire event are substantial (Table 2.2). Health endpoints are listed separately, by column, and

incidence results are categorized by source of transferred CR function. Reported incidences are the number of additional visits per Albuquerque resident estimated by BenMAP-CE over the 5-week smoke event.<sup>10</sup> For MRADs, the reported incidence is in units of person-days. Across all endpoints, MRADs are the largest health effect associated with wildfire smoke. Over 14,700 person-days of minor health impacts are created, which corresponds to an average of 0.03 days or about 44 minutes per Albuquerque resident over the event. *Emergency room asthma* visits are the second largest health impact in the wildfire-specific benefit transfer, with 16 additional cases over the 5-week event. Less than one additional emergency room visits is estimated by BenMAP-CE when an urban air CR function is used. *Hospital admissions for any respiratory illness* increase between 3 and 5 cases, depending on type of CR function. Increases in admissions due to pneumonia (2.7 cases) are the largest component of overall respiratory admissions based on urban air CR functions, though when wildfire functions are used, increases in asthma admissions (2.2) drive overall respiratory admissions.<sup>11</sup>

Incidence estimates based on wildfire-specific CR functions are between 43% (*hospital admission all respiratory*) and 2,617% (*emergency room asthma*) larger than incidences estimated using urban air study results. This is consistent with the literature on greater morbidity impacts of wildfire smoke compared to urban air pollutants (Kochi et al., 2010). However, *hospital admission pneumonia* incidence is 30% lower across the two sources, suggesting that perhaps wildfire smoke has less of an impact on pneumonia morbidity than typical urban air pollutants in this case study. MRAD incidence is

identical across CR function sources because no wildfire-specific health impact function exists for this broad endpoint.

### **2.5.2 Health costs (COI and WTP) of smoke exposure**

Built-in BenMAP-CE COI valuation functions are used to value changes in incidence associated with endpoints *emergency room asthma* and *hospital admission respiratory*. Inclusion of endpoints *hospital admission asthma* and *hospital admission pneumonia* would overestimate event COI because endpoint *hospital admission all respiratory* already includes all respiratory-related illnesses. Costs are estimated separately for urban air and wildfire-specific incidence results and are inflation-adjusted to 2014 US dollars (USD). Total COI health costs of Wallow mega-fire smoke exposure in the Albuquerque metropolitan area are estimated by BenMAP-CE at \$74,000 in the urban air function analysis and \$111,000 in the wildfire function analysis (Table 2.3). These are the medical costs associated with diagnosis and treatment plus lost wages due to illness, estimated by BenMAP-CE and aggregated by the software for Bernalillo County. *Emergency room asthma* costs are 2,535% higher and *hospital admission all respiratory* costs are 44% higher in the wildfire benefit transfer, reflective of greater estimated morbidity when wildfire-specific CR functions are used.

To estimate WTP to avoid a wildfire smoke health effect, the survey data is used, and a bivariate probit version of equation (2.3) is estimated. For brevity, individual results from estimation of that model are reported in Appendix A. The marginal effect associated with *used air filter/cleaner* is estimated at -0.227 with a 95% confidence interval of (-0.400, -0.054). Dividing the negative of the average price of an air cleaner,

\$29.71, by -0.277 and adjusting for inflation, produces \$130.79 (range: \$74.19-\$551.33), which is the marginal WTP for a reduction in wildfire smoke health effects. This is larger than a comparable urban air WTP value of \$98 (range: \$68-\$146) from Dickie and Messman (2004) and also larger than the only other wildfire-specific WTP of \$93.15 (no bounds provided) estimated by Richardson et al. (2012).

To arrive at an estimate of WTP health costs using wildfire-specific study results, MRAD results from Table 2.2 were put into per capita terms and multiplied by the previously estimated marginal WTP of \$130.79. Table 2.4 reports the results from these wildfire-specific calculations, performed in BenMAP-CE, and the results from a separate urban air specific estimation in BenMAP-CE using the Dickie and Messman (2004) urban air WTP value. Estimated health costs utilizing WTP to avoid an air pollutant-related symptom range from \$338,000 (urban air value) to \$429,000 (wildfire smoke value); an increase of 27%. Additionally, WTP health costs are between 3.9 and 4.6 times larger than comparable COI health costs. This is suggestive evidence of differences in estimated wildfire smoke health costs depending on the source of transferred economic value (urban air vs. wildfire-specific) and economic value utilized (WTP vs. COI). Although, had we instead transferred the Richardson et al. (2012) WTP value estimated for Southern California, the resulting WTP health costs would be similar to the urban air costs. While our estimated WTP value is arguably more appropriate – it's specific to wildfire and study site (Albuquerque) – in other settings (e.g., California) perhaps urban air and wildfire WTP values are not meaningfully different. That said, there is clearly room for additional original valuation studies for health effects associated with wildfire

events and comparisons of WTP values in other contexts, accounting for differences in study design, estimation methods, and sampled populations.

## **2.6 Conclusions**

This chapter illustrates how a robust benefit transfer tool, BenMAP-CE, can be applied to wildfire smoke damage assessments in an urban area. Application results demonstrate sensitivity to choice of transferred CR function and economic values. Use of transferred results from urban air quality studies undervalues the health impacts of wildfire smoke compared to use of wildfire-specific study results. We find higher incidences of emergency room asthma visits, all respiratory, and asthma hospital admissions when CR functions from the wildfire smoke literature are utilized. Increases range from 43% to 2,617%. Health costs in the wildfire benefit transfer are 27% (WTP) to 50% (COI) larger than costs in the urban air benefit transfer.

These findings provide the first empirical support (albeit from a case study) of Kochi et al.'s (2010) recommendation to use wildfire-specific study results when possible in wildfire damage assessments. Short-duration, extreme shocks to air quality created by wildfire smoke plumes appear to have more significant impacts on human health than the same pollutant concentration change to levels of urban air quality. This may be because a concentration,  $X$ , of wildfire smoke is more toxic than the same concentration,  $X$ , of urban air (Vedal & Dutton, 2006). For these reasons, it's our recommendation that analysts performing wildfire smoke benefit transfers carefully consider the source of transferred functions so as not to over- or under-value morbidity changes and associated health costs of wildfire smoke.



The urgency to better understand how wildfire affects health, across many dimensions, especially in the western US, is underscored by climate change, possible connections to carbon sequestration capacity of standing forests (see Koirala & Mysami, 2015), increased depletion of water in the west, continued growth of western cities, and recent increases in the number and severity of wildfires associated with prolonged drought in many western US states. BenMAP-CE is a useful tool for studying wildfire health impacts that researchers should be aware of and we hope this empirical demonstration spurs additional applications of the program to wildfire damage events. While this chapter shows where some of the important choices are, it also illustrates where additional data collection may be needed, including wildfire-specific CR functions for health impacts (mortality, especially) and wildfire-specific WTP measures.

There are several limitations of this analysis. First, the only air quality impact considered was PM<sub>2.5</sub> and not other pollutants created by wildfires such as ozone, NO<sub>2</sub>, etc. Including these in the analysis would raise both incidence and health costs of a wildfire smoke event. Second, only monitored air quality data were used. A more sophisticated approach would incorporate modeled air quality data to interpolate PM in areas where sites are not located. It is unclear how this would alter results, but given the significant number of monitoring sites in Bernalillo County and close proximity to one another, the advantages of modeling are diminished. However, modeled data might be appropriate in areas with fewer proximal sites. Third, statistical differences in study design, sampled populations, or estimation methods across the urban air and wildfire-specific CR functions used in this analysis were not investigated. Previous research (e.g., Kochi et al., 2010; Vedal & Dutton, 2006) has examined this issue and offered various

explanations on how and why wildfire smoke may be more damaging to health. The focus of the present chapter is on the meaningful application of a benefit transfer tool to wildfire smoke, inclusive of previous literature demonstrating differences between urban air and wildfire smoke. A formal statistical analysis exploring how or why wildfire smoke may be more damaging to health is outside this scope. Thus, an important caveat is that while a comparison of BenMAP-CE calculated point estimates is informative and illustrative of how differences in CR functions and WTP values manifest into overall damage assessment heterogeneity, it is not sufficient evidence to draw general conclusions regarding the relationship between smoke and urban air.

Fourth, a formal statistical analysis to assess the consistency of BenMAP-CE with previously estimated costs of wildfire smoke events was not performed. This chapter is only a proof-of-concept that BenMAP-CE can be adapted to study wildfire smoke effects in urban areas. While an important first step, future work should use BenMAP-CE to replicate wildfire smoke economic assessments carried out using other means (e.g., questionnaires, hospital admissions, emergency room visits, etc.). Results from BenMAP-CE, after being modified to assess wildfire smoke events, could be statistically compared. Such an approach would provide more conclusive evidence on the viability of the program for wildfire smoke analyses. We hope that this chapter spurs such further investigations.

## Notes

<sup>3</sup>BenMAP-CE is accessible at: <http://www.epa.gov/airquality/BenMAP-CE/ce.html>

<sup>4</sup>As an example of the increasingly common mega-fires seen in recent years in the western US, the Wallow Fire burned more than 538,000 acres (841 square miles), and is the largest fire on record in Arizona (Ryan & Opperman, 2013). The fire covered parts of four counties in eastern Arizona and one in southwestern New Mexico. The fire started near the Bear-Wallow Wilderness Area in the Apache National Forest, and the ignition source was from an unattended campfire. More than 6,000 people were evacuated and physical property damages have been estimated to be over \$109 million (Ryan & Opperman, 2013). While not the source of any known fatalities, the smoke plume extended across New Mexico and into Texas and Oklahoma.

<sup>5</sup>Appendix C of the BenMAP User's Manual (Abt Associates, 2012) describes the health impact function derivation process, though we note that it's easily performed by-hand.

<sup>6</sup>A minor restricted activity day (MRAD) is defined as any day on which an individual was forced to alter his or her normal activities due to minor illnesses, including both respiratory and nonrespiratory conditions (Ostro & Rothchild, 1989). One shortcoming is that the single MRAD CR function that exists (Ostro & Rothchild, 1989) is estimated for urban air quality.

<sup>7</sup>Endogeneity was tested for using a Wu-Hausman F-test ( $p < 0.01$ ) and a Durbin-Wu-Hausman  $\chi^2$ -test ( $p < 0.01$ ).

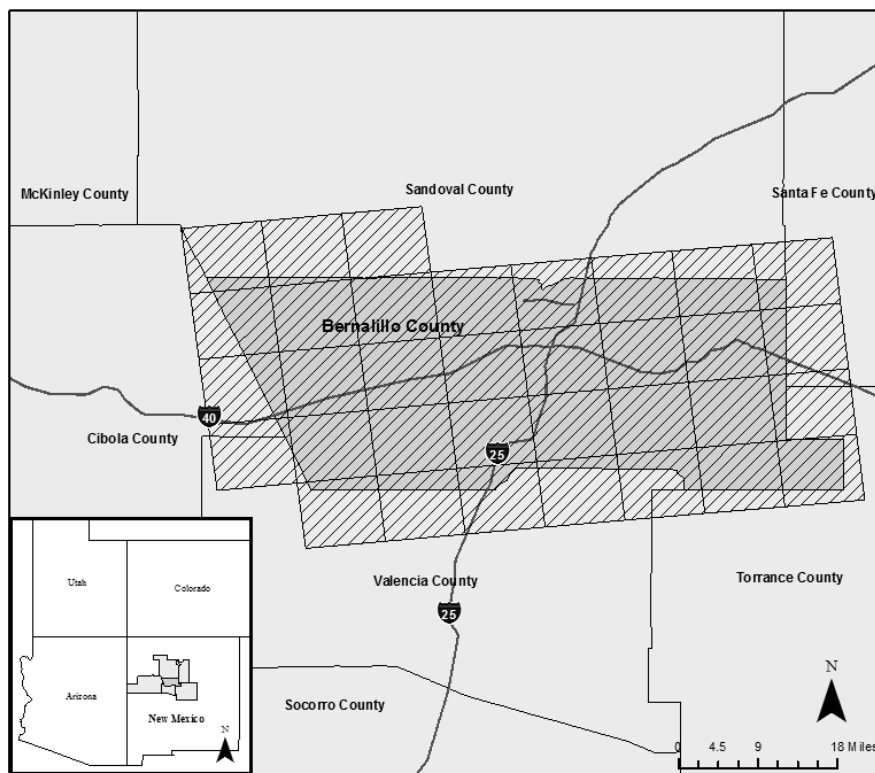
<sup>8</sup>The inflation-adjusted price reported in Richardson et al. (2012) of \$29.71 (2014\$) is used. This result is an average of self-reported prices (including \$0). Prices from other sources (e.g., Home Depot, Amazon.com) were investigated and results are available upon request.

<sup>9</sup>[http://www.epa.gov/airdata/ad\\_data\\_daily.html](http://www.epa.gov/airdata/ad_data_daily.html)

<sup>10</sup>Results presented in the Table 2.2 row labeled “urban air quality literature” are estimated by BenMAP-CE using urban air quality CR functions selected by us in the programs’ graphical user interface, which had already been coded into the software by US EPA programmers for the five health endpoints listed. Similarly, results in the row labeled “wildfire smoke literature” are estimated by BenMAP-CE using wildfire-specific CR functions that we manually and individually coded into the program for four of the five incidence endpoints. All individual results in Table 2.2 are produced by BenMAP-CE calculations.

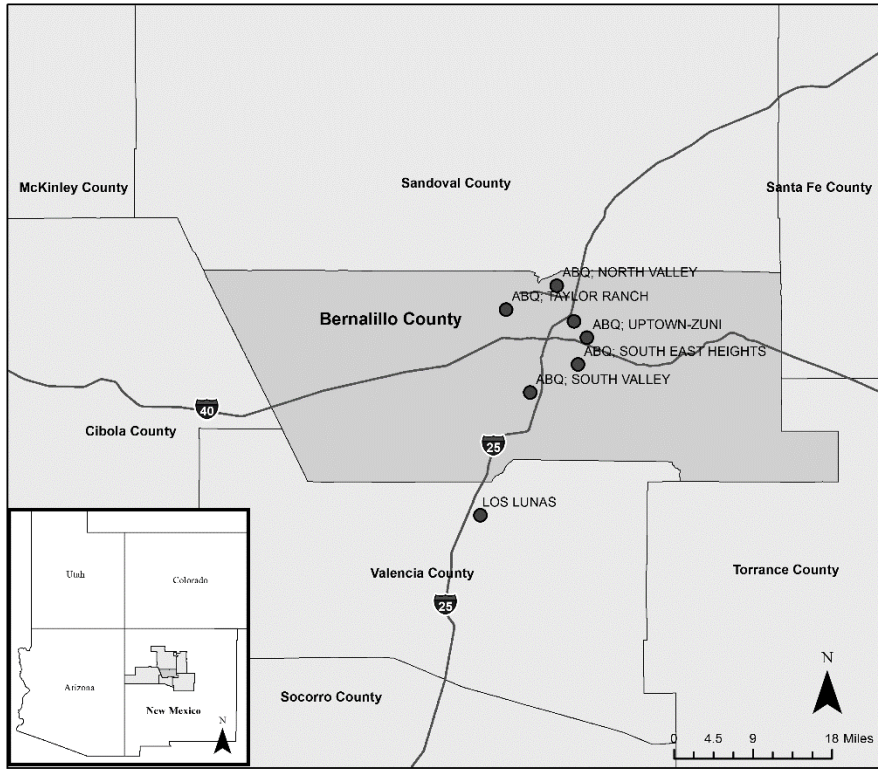
<sup>11</sup>The health endpoint “hospital admission: all respiratory” is comprised of both asthma and pneumonia admissions, in addition to any other respiratory illnesses (not estimated in this analysis). The two endpoints separately illustrate specific drivers of overall respiratory admissions using endpoint-specific CR functions.

Figure 2.1: CMAQ-12km Air Quality Grid for Bernalillo County, NM (Albuquerque Metro Area)



Source: constructed by the author in ESRI ArcMap 10.1

Figure 2.2: US EPA Air Quality Monitoring Sites for Bernalillo and Valencia Counties, NM (Albuquerque Metro Area)



Source: constructed by the author in ESRI ArcMap 10.1

Table 2.1: Wildfire Survey Variable Definitions and Summary Statistics ( $n=911$ )

Variable	Coding	Mean	Std. Dev.	Min	Max
<i>Wildfire Smoke Exposure</i>					
Smelled smoke at home	1= yes, 0= no	0.88	0.33	0	1
Own a home north of Albuquerque	1= yes, 0= no	0.10	0.29	0	1
Smoke has affected health	1= yes, 0= no	0.26	0.44	0	1
Changed routine because smelled smoke	1= yes, 0= no	0.47	0.50	0	1
<i>Averting Actions</i>					
Evacuated	1= yes, 0= no	0.05	0.22	0	1
Covered face with mask	1= yes, 0= no	0.07	0.25	0	1
Used air filter/cleaner	1= yes, 0= no	0.16	0.37	0	1
Avoided work	1= yes, 0= no	0.01	0.11	0	1
Removed ashes from property	1= yes, 0= no	0.04	0.20	0	1
Stayed indoors	1= yes, 0= no	0.55	0.50	0	1
Avoided outdoor recreation/exercise	1= yes, 0= no	0.42	0.49	0	1
Took no averting action	1= yes, 0= no	0.29	0.45	0	1
<i>Mitigating Actions</i>					
Visited physician or admitted to hospital related to smoke exposure	1= yes, 0= no	0.01	0.12	0	1
<i>Symptoms</i>					
Headaches	1= yes, 0= no	0.14	0.35	0	1
Coughs	1= yes, 0= no	0.25	0.43	0	1
Dizziness	1= yes, 0= no	0.02	0.13	0	1
Blurred vision	1= yes, 0= no	0.03	0.17	0	1
Shortness of breath	1= yes, 0= no	0.11	0.31	0	1
Asthma	1= yes, 0= no	0.11	0.31	0	1
Allergies	1= yes, 0= no	0.21	0.41	0	1
Experienced none of the above symptoms	1= yes, 0= no	0.49	0.50	0	1
<i>Health History</i>					
Chronic respiratory disease	1= yes, 0= no	0.33	0.47	0	1
Heart disease	1= yes, 0= no	0.14	0.35	0	1
<i>Demographics</i>					
Female	1= yes, 0= no	0.37	0.48	0	1
White	1= yes, 0= no	0.80	0.40	0	1
Hispanic/Latino	1= yes, 0= no	0.28	0.45	0	1
College graduate	1= yes, 0= no	0.62	0.49	0	1
Income	1= <14,999; 2=15,000-24,999; 3=25,000-34,999; 4=35,000-49,999; 5=50,000-74,999; 6=75,000-99,999; 7=100,000-149,999; 8=150,000-199,999	5.30	1.74	1	8
Years lived in New Mexico	continuous	35.26	19.32	1	85
Number of children under 5 in house	continuous	0.12	0.39	0	3
<i>Beliefs</i>					
Effectiveness of averting actions	1= "Not at all effective;" 2= "Slightly effective;" 3= "Somewhat effective;" 4= "Moderately effective;" 5= "Highly effective"	3.19	0.97	1	5

Table 2.2: Smoke Exposure Health Incidences by CR Function Source for Wallow Mega-Fire

Source of CR Function	Incidence Endpoint (Number of Cases)				
	Emergency Room: Asthma	Hospital Admission: All Respiratory	Hospital Admission: Asthma	Hospital Admission: Pneumonia	Minor Restricted Activity Days (MRAD)
Urban air quality literature	0.6	3.5	1.2	2.7	14,786.4
Wildfire smoke literature	16.3	5.0	2.2	1.9	14,786.4
<i>Percentage change:</i>	(+) 2616.7%	(+) 42.9%	(+) 83.3%	(-) 29.6%	(+) 0.0%

*Notes:* Emergency room asthma incidence for urban air quality results is average of incidences from Mar et al. (2010) and Slaughter et al. (2005) transferred functions. Percentage change in incidence from urban air to wildfire smoke is reported in the final row. *Source:* BenMAP-CE calculations (v.1.0.8). Urban air quality literature results come from BenMAP-CE calculations using CR functions from the urban air literature that were selected from the existing BenMAP-CE database. Wildfire smoke literature results come from BenMAP-CE calculations using CR functions from the wildfire smoke literature that were manually and individually added by the authors to the BenMAP-CE database. Incidence of minor restricted activity days is identical across CR function sources because only one literature estimate exists for this incidence endpoint.



Table 2.3: COI Health Costs (2014\$) by CR Function Source for Wallow Mega-Fire

Source of CR Function	<i>Incidence Endpoint Costs</i>		<b>TOTAL:</b>
	<b>Emergency Room: Asthma</b>	<b>Hospital Admission: All Respiratory</b>	
Urban air quality literature	\$177	\$73,760	\$73,937
Wildfire smoke literature	\$4,664	\$106,405	\$111,069
<i>Percentage change:</i>	<i>(+) 2535.0%</i>	<i>(+) 44.3%</i>	<i>(+) 50.2%</i>

*Notes:* Cost-of-illness (COI) event costs reported. Emergency room asthma costs for urban air quality results is average of costs based on estimated incidence from Mar et al. (2010) and Slaughter et al. (2005) transferred functions. Percentage change in COI from urban air to wildfire smoke is reported in the final row. *Source:* BenMAP-CE calculations (v.1.0.8). COI calculated by BenMAP-CE separately by source of CR functions. Urban air quality literature results come from BenMAP-CE calculations of the COI associated with health incidence estimated using CR functions from the urban air literature. Wildfire smoke literature results come from BenMAP-CE calculations of the COI associated with health incidence estimated using CR functions from the wildfire smoke literature.

Table 2.4: WTP Health Costs (2014\$) by CR Function Source for Wallow Mega-Fire

Source of WTP metric	Minor Restricted Activity Days (MRAD)	WTP-COI Ratio
Urban air quality literature	\$337,623	4.6
Wildfire smoke (originally estimated)	\$429,156	3.9
<i>Percentage change:</i>	<i>(+) 27.1%</i>	NA

*Notes:* Willingness to pay (WTP) event costs reported. NA = not applicable. Percentage change in WTP from urban air to wildfire smoke is reported in the final row. WTP-COI ratio is the ratio of WTP and COI (Table 2.3) health costs per economic value transfer. *Source:* BenMAP-CE calculations (v.1.0.8). Urban air quality literature results come from BenMAP-CE calculations of the WTP health costs associated with minor restricted activity days when an urban air WTP value (\$98) is used from the existing BenMAP-CE valuation database. Wildfire smoke results come from BenMAP-CE calculations of the WTP health costs associated with minor restricted activity days using an originally estimated wildfire-specific WTP value (\$130.79) that was manually coded into the software's valuation database.

## Chapter 3

### **Optimal management of invasive species inclusive of human health impacts: application to the emerald ash borer and North American ash trees**

#### **3.1 Introduction**

Invasive pests are disruptive to native ecosystems and may have substantial effects on human health. Management of invasive species needs to consider health impacts in policy decisions. A number of invasive pests cause damage and loss of native vegetation, reducing environmental quality and posing an environmental health hazard. Disruption to land-use patterns (Hobbs, 2000), impairment of food yields (McMichael & Bouma, 2000), changes in disease vectors (Juliano & Lounibos, 2005), and deterioration of ecosystem services (Pyšek & Richardson, 2010) that result after invasion are hazards to human health. Health impacts span the spectrum from the benign – pollen allergies caused by invasive pampas grass – to the severe – poisoning and potential death from consuming shellfish tainted with invasive *Alexandrium catenella*; the cause of red tide. Environmental management may be suboptimal when health effects are not fully included in planning decisions (e.g., Chay and Greenstone, 2003; Currie et al., 2009; Currie and Walker, 2011). This may lead to larger invasive pest populations and greater harm to health. As such, it is important that environmental policy be guided by a fuller understanding of the consequences posed by invasive species so as to facilitate the efficient use of limited pest control resources.

Economic theory tells us that adding health to the management decision will raise the marginal benefit of action, resulting in the use of more management at the optimum where marginal benefits and costs are equated; a point that has been theoretically demonstrated by Jones and McDermott (2015). However, to call it a day there would be premature for two reasons. First, the relationship between environmental quality and health is spatially heterogeneous. Areas highly susceptible to invasion vary from neighborhood-to-neighborhood, city-to-city, county-to-county, *et cetera*. For example, loss of tree cover in a downtown urban park due to an invasive pest will have a very different impact on people living downtown (e.g., on their outdoor physical activity, on localized concentrations of air pollutants) than on somebody living in a distant suburban area where trees are resistant to invasion. Management inclusive of health should be spatially distributed to match the vector of invasive species health impacts. In this case, a blanket policy of “more management everywhere” is clearly suboptimal.

Second, management practices used when health is omitted from consideration may be Pareto dominated by alternative health-centric management techniques. For many invasive pests, eradication is the first choice of management, and then managed control when eradication proves infeasible (as is often the case). However, managed control only results in managed ecological disruption, with associated, though arguably diminished health impacts. An alternative management policy might jointly use managed control with preemptive planting of replacement invasive-resistant vegetation (e.g., planting comparable trees in areas threatened by a forest-attacking pest). A joint management approach may yield greater net social benefits than managed control alone if the value of native species is sufficiently high (Vannatta et al., 2012). In other words, compositional

changes to management might be more appropriate instead of “more” management when health is accounted for. This chapter sheds light on the spatial and dynamic nature of management for environmental health and examines how health-centric management potentially differs from ecological-focused management often used in response to invasive pests.

Health impacts associated with invasive pests are worth considering and may be substantial. The increasingly interconnectedness of the world and the explosion of global trade have made it easier for invasive species to jump political boundaries and across continents. Invasive species serve as novel hosts for disease vectors (Juliano & Lounibos, 2005; Leak, 1998), have been linked to increased mortality rates (Donovan et al., 2013), and produce reductions in water quality and availability (Richardson & van Wilgen, 2004; Zavaleta, 2000). Complex interactions between climate change, ecological dynamics, land-use patterns, and human transportation networks are likely to increase the spread of invasive pests in the future (Crown et al., 2008), leading to further reductions in environmental quality and human health. In some areas, invasive species and climate change may work in tandem by increasing the intensity or frequency of fires and floods, putting communities at increased health risk (Pejchar & Mooney, 2009). Examining integrated environmental management inclusive of a broader array of social health impacts provides an opportunity to deepen our understanding of the mechanisms through which invasive species create economic disruption and how environmental policy can be used when invasion occurs to improve societal well-being.

In this chapter, I develop a bioeconomic model of invasive pest management and comparable replacement of lost native vegetation with invasive-resistant specimens.

Optimal time-dependent management trajectories are determined in the presence of health impacts and compared to the case where health is ignored in the policy decision. An important feature of this model is that health status is a function of environmental quality. As such, the optimal management decision will depend on the relative magnitudes of invasive species' impacts on environmental quality and health. The dynamic nature of this relationship means that intertemporal tradeoffs are likely between short-term preservation of native plants and long-term improvements to health. The timeframe over which these tradeoffs occur will be largely influenced by the infection pattern of the pest and the growth rates of replacement vegetation. I investigate these tradeoffs by applying the model to the emerald ash borer (EAB), an invasive phloem-feeding arthropod that targets and destroys all species of North American ash trees.

Two key features of invasive pests are critical for this type of bioeconomic analysis. First, a clear causal connection or at least a strong association exists between the pest and human health, whether directly (e.g., pollen allergies of invasive plants) or indirectly (e.g., destruction of health-improving vegetation). Second, management responses are available that can mitigate or preempt health-damaging impacts, so that there is room to investigate the net benefits of alternative management profiles. Both of these features apply to EAB as described in the Application to EAB section.

Results of this chapter suggest that consideration of health does in fact alter the economically efficient invasive species management profile by influencing the benefits of native vegetation. In particular, policy decisions inclusive of health substitute away from biological and chemical treatments of invasive species and toward investments in vegetation replacement, which in effect is an act of “ecological consumption smoothing,”

or an attempt to minimize the impacts of lost vegetation until a comparable replacement can be planted. Net benefits of ecological consumption smoothing primarily depend on the length of the planning horizon. In a constrained environment, preemptive investments in vegetation replacement mean fewer resources available for managed control, raising short-term mortality and morbidity rates in favor of long-term health benefits. In contrast, ignoring health impacts results in less overall management and more reliance on biological and chemical treatments instead of vegetation replacement, so as to preserve more valuable native vegetation longer over less valuable discounted future vegetation. Without any value to health, the impetus to engage in ecological consumption smoothing is reduced given the large costs of preemptive vegetation replacement. Additionally, I find that demographic and ecological characteristics of the study area, such as percent vegetation cover, baseline health incidence, and population are key determinants of invasive species management levels. Results are robust to a range of sensitivity analyses and specifications of the environmental health relationship. These findings suggest that social well-being can be improved by taking health into consideration when managing invasive species. This has direct implications for environmental policy, particularly where a strong association between the natural environment and human health exists.

### **3.2 Application to EAB**

EAB (*Agrilus planipennis*) is a small phloem-feeding beetle native to Asia and eastern Russia that was first detected in the state of Michigan, USA in 2002, where it was introduced through imported ash and ash by-products. EAB larvae feed on the inner layers of bark (phloem), disrupting the transfer of nutrients and water through the tree. Ash typically die within 1-3 of infestation (Poland & McCullough, 2006). EAB are quick

and effective killers, attacking all North American ash species, even healthy adults. As of September 2014, EAB have been found in 564 counties across 24 US states and the District of Columbia and in two Canadian provinces and is considered to be the most destructive forest pest ever introduced in the US (Herms & McCullough, 2014; P. Chaloux, personal communication, September 22, 2014). Between 2002 and 2006, EAB killed some 20 million ash trees in Michigan alone, with at least 5-7 million deaths occurring in the first year of detection (Anulewicz et al., 2007). A lower bound estimate for ash tree mortality between 2009-2019 is 17 million (Kovacs et al., 2010), though dendrologists believe that the entire stock of 8 billion ash trees in the US are at high risk of destruction (Anulewicz et al., 2007; Kovacs et al., 2010; Sydnor et al., 2011; Herms & McCullough, 2014). Unfortunately, the spread of EAB continues to progress with newly infected areas discovered on a weekly to monthly basis.

Ash trees provide flows of ecosystem services including the provision of shade, interception of rainfall, reductions in storm runoff, and the capturing of air pollutants. Tree cover increases property values (Sander et al., 2010) with positive externalities on neighborhood aesthetics and community identity (Sydnor and Subburaylu, 2011). Trees are also a source of recreation opportunities with associated impacts on physical and mental health and overall well-being (Tyrväinen et al., 2005). Ellaway et al. (2005) found a 40% lower obesity rate and significantly higher frequency of physical activity in residential environments containing high levels of green space, including trees. Among children, Roemmich et al. (2006) estimated that a 1% increase in forested park area was associated with a 1.4% increase in average physical activity in upstate New York. It is unclear, however, whether or not such associations are causal or merely correlational. A



stronger causal connection may exist between trees, air pollutants, and cardiorespiratory health (Nowak et al., 2006; McDonald et al., 2007; Nowak et al., 2013). Ash trees in particular are highly effective at capturing airborne pollutants (Freer-Smith et al., 2004) such as ozone (O<sub>3</sub>), sulfur dioxide (SO<sub>2</sub>), nitrogen dioxide (NO<sub>2</sub>), and particulate matter (PM). By removing harmful pollutants from the air, trees can substantially reduce mortality and morbidity rates, especially in heavily polluted urban areas. For ten US cities, Nowak et al. (2013) estimated annual improvements in air quality ranging from 0.05% in San Francisco, CA to 0.24% in Atlanta, GA because of tree cover, leading to mortality reductions of 0.6 person/yr. in San Francisco and 1.2 persons/yr. in Atlanta. It is likely that a sudden loss of ash trees in a community due to invasive EAB would increase air pollutant concentrations, putting the population at increased risk of cardiorespiratory illnesses.

While perhaps the clearest causal links have been found between trees and air pollution, other health-altering mechanisms may also be at work, such as behavioral and mental health changes. In the only study of EAB and health, Donovan et al. (2013) investigated the causal relationship between trees and health across all pathways and discovered that between 1990 and 2007, EAB was associated with an additional 6113 lower respiratory deaths and 15,080 cardiovascular-related deaths across 15 US states.

The economic value of trees, including ash, have been determined in several ways. Implicit private values of trees have been estimated using hedonic pricing models (Dombrow et al., 2000; Tyrväinen & Miettinen, 2000; Price, 2003; Donovan & Butry, 2010; Netusil et al., 2010; Pandit et al., 2013). On average, presence of a landscape tree increases residential homes values by 0.5%-1%, though size and distance from the home

are all key predictors of value. Larger trees are more valuable than smaller trees and trees closer to the home increase property values more than distant ones. The ability of trees to capture air pollutants has also been valued in terms of avoided health impacts. Nowak et al. (2013) estimated average US health benefits per hectare of tree cover at \$1,600/yr., largely driven by reductions in cardiorespiratory mortality incidence.

Trees also produce value by reducing stormwater runoff and reducing indoor electricity demand (thanks to the shade they create), which creates measurable reductions in CO<sub>2</sub> emissions. Combining these other benefits of trees with the value of improved air quality, results in tree benefits ranging from \$31/tree/yr. to \$89/tree/yr. (2005\$) in the US (McPherson et al., 2005). Finally, aesthetic, cultural, and historical nonmarket values (i.e., public goods value) of trees may be substantial (Dwyer et al., 1989; Tyrväinen & Väänänen, 1998; Majumdar et al., 2011). For example, Majumdar et al. (2011) applied the contingent valuation method to estimate willingness-to-pay (WTP) for urban forest preservation in Savannah, GA, USA. The annual value of Savannah's urban forest ranged from \$81 million to \$167 million. Of course, economic value estimates of trees are site and species specific. Urban trees are more valuable than rural or timberland trees and ash are among the most popular urban trees in many US communities, meaning that the economic costs of their loss are substantial (Kovacs et al., 2010).

Early management of EAB focused on containment and eradication. Quarantines of ash and ash by-products were imposed in infected areas in an effort to limit EAB spread while infested ash were removed and destroyed. These efforts were unsuccessful as outlier populations beyond the containment zone were regularly detected. Soon after EAB was discovered in the US, managers began searching for and releasing natural

enemies. North American woodpeckers may represent the single greatest threat to EAB larvae, but certain parasitoids have also proven effective at killing the beetle (e.g., *Oobius agrili* and *Tetrastichus planipennisi*). It remains unclear how effective natural enemy releases have been at slowing EAB dispersion (Herms & McCullough, 2014).

Integrated management via the “SLOW Ash Mortality” or SLAM project represent, perhaps, the most effective EAB control option available at the moment. Initiated in 2008, SLAM seeks to slow EAB population growth and subsequently slow ash mortality. This is achieved through the integrated use of insecticides, girdling, and phloem reduction (i.e., harvesting ash prior to death). The insecticide emamectin benzoate or TREE-age® has proven highly effective in trials and spatial simulations at slowing overall rates of ash decline (McCullough & Mercader, 2012; Herms et al., 2014).

Other management options including preemptive removal of ash, removal and replacement, and a “do-nothing” approach have been investigated and dismissed as welfare inferior compared to SLAM (Vannatta et al., 2012), but no published analysis has evaluated a preemptive planting *without* removal strategy. Preemptively planting of comparable-in-benefits saplings such as EAB-resistant Asian ash, while native ash trees are still living, mitigates disruptions to environmental quality by smoothing the stream of tree benefits. Figure 3.1 illustrates this idea through a comparison of hypothetical ash tree or comparable EAB-resistant tree instantaneous benefits over time for an infested area. Without preemptive planting of comparable tree saplings, ash tree benefits approach zero due to mortality. This represents a complete ash tree extinction event in an area. By preemptively planting comparable resistant saplings prior to and during the invasion, the loss of tree benefits is mitigated as the saplings grow and mature, eventually offsetting

the lost benefits from the now dead native ash. This is perhaps easiest to conceptualize in an absurd example where as soon as a native ash dies because of EAB, a comparable-in-benefits tree “switches” on such that the stream of tree benefits remains unaltered. While this is not physically possible for large, mature trees, the next best alternative is to plant a sapling that grows over time to replace the lost stream of ash benefits. The idea is to minimize the vertical distance between the “with preemptive planting” benefit path and ash tree benefits prior to EAB in Figure 3.1, or what I had previously defined as ecological consumption smoothing. The timing of planting and the ecological properties of the replacement species will both determine the precise benefit path, but the theoretical principle remains the same. Of course, it should be noted that tree benefits and not *net* tree benefits of management are illustrated in Figure 3.1. The net benefits time path may look substantively different depending on the relative benefits and costs associated with ash trees and EAB management.

This chapter makes three contributions to the EAB management literature. First, it demonstrates the importance of including health in the EAB manager’s objective function through a comparison of net social benefits and health incidence across optimal control model simulations inclusive and exclusive of health. Second, it illustrates why a spatially homogeneous or “one size fits all” management approach is suboptimal in the presence of demographic and tree cover geographic variability. Finally, it will be shown that over certain planning horizons ecological consumption smoothing using a combination of biological or chemical treatments and preemptive tree planting creates positive net social benefits when health is included in the policy decision process.

### 3.3 Methods

Consider two types of trees, those that are native to an area and highly susceptible to invasive pests,  $a_n$ , and those that are non-native and pest resistant,  $a_r$ .<sup>12</sup> There are two sub-types of resistant trees, adults (mature),  $a_{ra}$ , and juveniles (saplings),  $a_{rj}$ . Juveniles grow logistically according to an intrinsic rate,  $r$ , bounded by a maximum carrying capacity,  $K$ , and transition into adults at rate  $\theta$ . Additions to the stock of juvenile trees,  $m$ , are determined endogenously as a management decision. The per period change in the stock of pest resistant juvenile trees is given by,

$$\dot{a}_{rj}(t) = (1 - \theta) \left[ r a_{rj}(t) \left( 1 - \frac{a_{rj}(t)}{K} \right) \right] + m(t) \quad (3.1)$$

where  $\dot{a}_{rj}(t) \equiv da_{rj}(t)/dt$  for time period,  $t$ .

The stock of adult resistant trees depends on the transition of juveniles to adults,  $\theta a_{rj}(t)$ , minus adult mortality,  $\varphi a_{ra}(t)$ , where  $\varphi$  is the natural mortality rate of adult trees. Thus, the per period change in the stock of invasive arthropod resistant adult trees is given by,

$$\dot{a}_{ra}(t) = \theta a_{rj}(t) - \varphi a_{ra}(t) \quad (3.2)$$

where  $\dot{a}_{ra}(t) \equiv da_{ra}(t)/dt$  for time period,  $t$ . It is assumed throughout that adult trees are fully grown though have a non-zero mortality rate.

Native invasive-prone trees,  $a_n$ , grow logistically at rate  $g$  ( $g \neq r$ , necessarily), also up to a maximum allowable carrying capacity,  $K$ .<sup>13</sup> Following previous literature, invasive pests affect trees through the carrying capacity,  $K(e)$  (Barbier, 2007), where

$K_e < 0$ . Biological and chemical treatment management of the pests,  $z(t)$ , reduces their population,  $e(z(t))$ , such that  $e_z < 0$ . The change in native tree stock is thus,

$$\dot{a}_n(t) = (1 - \varphi)ga_n(t) \left( 1 - \frac{a_n(t)}{K(e(z(t)))} \right) \quad (3.3)$$

where  $\dot{a}_n(t) \equiv da_n(t)/dt$  for time period,  $t$ . Pest management,  $z(t)$ , is bounded below by zero and can be no larger than the number of native trees in any given time period;  $0 \leq z(t) \leq a_n(t)$ .<sup>14</sup> Increases in the invasive species population reduce the maximum allowable trees in an area, which will reduce native tree growth in equation (3.3). An alternative way to conceptualize  $K(e(z(t)))$  is that management reduces the impact or effectiveness that pests have on the carrying capacity. That is, the effect of a given invader on  $K$  can be controlled through  $z(t)$ .

This chapter focuses on the health benefits of trees in terms of improved air quality because of consistent causal mechanisms linking the two (Willis & Crabtree, 2011). Air quality is modeled as a function of native invasive-prone trees and resistant adult trees,  $w(a_n(t), a_{ra}(t))$ , where trees improve air quality, i.e.,  $w_{a_n}, w_{a_{ra}} > 0$ . Current health status,  $h(c, w(a_n(t), a_{ra}(t)))$ , is a function of air quality and an exogenous composite health good,  $c$ , representing all other health goods that an agent could consume (Grossman, 1972), where  $h_w > 0, h_{ww} < 0, h_c > 0, h_{cc} < 0$ .

Trees provide many benefits to society along multiple environmental quality and health dimensions. For the purposes of this analysis, I focus on dual benefits of trees as creators of environmental aesthetic value and reducers of air pollution. To this end, I include health status as a function of air pollution in the benefits function following the

health-pollution framework presented in Aloï and Tournemaine (2011). Aesthetic environmental quality is modeled as a function of the stock of ash and is directly introduced as a societal benefit in line with Maupertuis and Sauveur (2005). Accounting for the dual environmental and health benefits of trees produces the following implicit social benefit function:  $B(v(a_n(t), a_{rj}(t), a_{ra}(t)), h(c, w(a_n(t), a_{ra}(t))), y)$ . Social benefits are a function of environmental quality and aesthetic benefits,  $v(\cdot)$ , human health impacts via air quality,  $h(\cdot)$ , and a composite of other ecosystem service flows provided by trees,  $y$ . Social benefits are increasing in environmental quality and health status ( $B_v, B_h > 0$ ). For simplicity, other ecosystem service flows are assumed constant throughout the model ( $B_y = 0$ ).

A basic model for the problem of choosing management of invasive species over a management horizon  $T$  when human health impacts of trees are included can be formulated as,

$$\max_{m,z} \int_0^T e^{-\delta t} \left[ B(v(a_n(t), a_{rj}(t), a_{ra}(t)), h(c, w(a_n(t), a_{ra}(t))), y) - c(m(t)) - d(z(t)) \right] dt \quad (3.4a)$$

subject to:

$$\dot{a}_{rj}(t) = (1 - \theta) \left[ r a_{rj}(t) \left( 1 - \frac{a_{rj}(t)}{K} \right) \right] + m(t) \quad (3.4b)$$

$$\dot{a}_{ra}(t) = \theta a_{rj}(t) - \varphi a_{ra}(t) \quad (3.4c)$$

$$\dot{a}_n(t) = (1 - \varphi) g a_n(t) \left( 1 - \frac{a_n(t)}{K(e(z(t)))} \right) \quad (3.4d)$$

$$a_{rj}(t=0) = a_{rj}(0); \quad a_{ra}(t=0) = a_{ra}(0); \quad a_n(t=0) = a_n(0) \quad (3.4e)$$

$$a_{rj}(T) = free; a_{ra}(T) = free; a_n(T) = free \quad (3.4f)$$

where  $\delta$  is the discount factor and  $c(m(t)), d(z(t))$  are the management costs associated with planting replacement trees and treating invasive pests, respectively.

The two solutions to this problem are functions,  $m(t)$  and  $z(t)$ , describing for each time period, the optimal level of replacement tree planting ( $m$ ) and use of biological or chemical invasive pest treatments ( $z$ ) that maximizes net social benefits. Combining the first order conditions that define an interior maximum and taking their derivative with respect to time (see Appendix B), allows for examination of the two relationships of interest:

$$\lambda_2 = \frac{1}{(\delta + \varphi)} (\dot{\lambda}_2 + B_v v_{a_{ra}} + h_w w_{a_{ra}}) \quad (3.5)$$

$$\frac{B_v v_{a_n} + h_w w_{a_n}}{\left( \frac{K(e(z))^2}{(1-\varphi)g a_n^2 K' e'} \right) \left( \delta - g(1-\varphi) + \frac{2g(1-\varphi)a_n}{K(e(z))} \right)} = d'(z) \quad (3.6)$$

As one would expect, the shadow value for adult EAB-resistant trees (equation (3.5)) is increasing in both marginal environmental quality ( $B_v v_{a_{ra}}$ ) and marginal health ( $h_w w_{a_{ra}}$ ). This demonstrates an important point, which is that omission of health impacts associated with trees will produce an undervaluation of the future stream of adult resistant tree benefits. Additionally, it can be seen in equation (3.5) that heterogeneity in adult tree marginal effects, perhaps spatially or geographically driven, will lead to shadow value heterogeneity. If, for example, air quality and environmental quality impacts of trees vary by location (e.g., urban vs. rural), then we might expect spatial differences in adult tree shadow values,  $\lambda_2^{urban} \neq \lambda_2^{rural}$  because of spatial differences in



marginal impacts,  $w_{ara}^{urban} \neq w_{ara}^{rural}$  and  $v_{ara}^{urban} \neq v_{ara}^{rural}$ . This will create differences in optimal management time-paths, meaning that a “one size fits all” management is inconsistent with the theory if tree marginal impacts differ along some measurable level.

Equation (3.6) provides some insight into how management indirectly impacts human health through native tree stock. The left-hand side of (3.6) is the marginal benefit (MB) of an additional unit of chemical or biological treatment, which along the optimal trajectory equals marginal cost (MC) of treatment (right-hand side term). One key insight of this expression lies in the determination of what the optimal MB/MC tradeoff looks like when health is added to the model. For positive marginal health effects,  $h_w w_{a_n} > 0$ , the LHS numerator is larger than it would otherwise be if health were omitted. However, it is unclear whether a positive or negative change in treatment ( $z$ ) is necessary to maintain the equality because of ambiguity in the relative magnitudes of LHS terms. Assume for the moment that health is omitted from equation (3.6). If EAB treatment effectiveness ( $K'e'$ ) is sufficiently small relative to the carrying capacity,  $K(e(z))$ , meaning chemical treatments are ineffective at protecting native trees, then the LHS denominator is increasing in absolute value in  $z$ , lowering MB of treatment. For sufficiently large health impacts it is possible that adding  $h_w w_{a_n} > 0$  to the LHS numerator would sufficiently raise MBs to offset the decline from the increase in management, thereby equating MB inclusive of health and MC. This means that adding health to the model could lead to increased use of chemical treatments. Conversely, if treatment is highly effective or health impacts of trees are minor, then considering health could lead to fewer treatments. Thus, it is ambiguous whether treatment management of

native trees increases or decreases when health is included, consistent with our earlier argument that “more” management is not guaranteed.

Ambiguity surrounding the marginal impacts involved in the model limit the insights that can be gained from a purely theoretical discussion. Therefore, functional forms for the model in equations (3.4a)-(3.4d) are defined to numerically determine the optimal management time paths. The model is then parameterized for the case of the emerald ash borer (hereafter EAB).

### 3.3.1 Functional forms of the EAB bioeconomic model

I first define a functional form for native ash carrying capacity as influenced by EAB management:  $K(e(z))$ . I focus on “SLoW Ash Mortality” or SLAM, the dominant management strategy used against EAB, and specify a management effectiveness function in terms of the ash carrying capacity:

$$K(e(z)) = \frac{K}{\alpha e(1/1 + z) + 1} \quad (3.7)$$

where  $K$  is the maximum allowable carrying capacity per acre ( $m^2$  ba/ac),  $\alpha$  is the emergent density threshold of ash dieback ( $m^2$ /EAB),  $e$  is the exogenously determined stock of EAB (EAB/acre),<sup>15</sup> and  $z$  is the endogenously determined level of SLAM management ( $m^2$  ba/ac). As EAB stock increases,  $K(e(z))$  falls, but as SLAM management increases, the effect of a given level of EAB on  $K(e(z))$  is diminished. This contrasts with an eradication management tool in that EAB are not killed; SLAM slows population growth, but does not reverse it. If EAB have minimal or no effect on ash trees (e.g., the case of Asian ash),  $\alpha \rightarrow 0$  and  $\lim_{\alpha \rightarrow 0} K(e(z)) = K$ .

My approach to modeling the relationship between EAB, ash trees, and health is a modified air pollution model from Nowak (1994) and Nowak et al. (2006). The daily change in concentration for the  $j^{th}$  air pollutant per  $i^{th}$  ash tree,  $PO_{ij}$ , is equal to the product of ash tree pollutant flux,  $F_{ij}$ , the inverse boundary layer height,  $BL^{-1}$ , and the inverse site study area,  $SA^{-1}$ :

$$PO_{ij} = F_{ij} \times BL^{-1} \times SA^{-1} \quad (3.8)$$

where  $PO_{ij}$  is in units of concentration; micrograms per meter cubed per day ( $\mu g m^{-3} d^{-1}$ ) for  $i = 1, \dots, N$  ash trees and  $j = 1, \dots, 4$  pollutants – ozone (O3), PM2.5, SO2, and NO2.  $F_{ij}$  describes the rate of ash tree pollutant removal over a given surface (in units of mass). Boundary layer height,  $BL$ , is the height of the atmospheric level where mixing is well-developed. Equation (3.8) gives the change in concentration for the  $j^{th}$  pollutant produced by a single ash tree over a geographic space (e.g., neighborhood, city, county, etc.) over time and is similar to equation (2) in Nowak et al. (2013).<sup>16</sup>

When a new ash tree is planted or an existing one dies, the total amount of pollutant concentration changes by some measureable amount. This effects current health status,  $h(c, w(a_n, a_{ra}))$ , and can be modeled using a concentration response function. Following the US EPA (Abt Associates, 2012), the impact of changes to ash tree stock on health endpoint  $k$  in time period  $t$  is given by the log-linear concentration response function for pollutant  $j$ :

$$h_{kj}(c, w_j(a_n, a_{ra})) = B_k e^{\beta_{kj}(PO_{ij}(a_n + a_{ra}))} \quad (3.9)$$

where  $B_k$  is the incidence rate of  $h_{kj}$  when  $(PO_{ij}(a_n + a_{ra}))$  is zero (i.e., the underlying incidence rate),  $\beta_{kj}$  relates pollutant concentration  $j$  to the incidence rate of endpoint  $k$ , and  $(PO_{ij}(a_n + a_{ra}))$  is the concentration of pollutant  $j$  removed from the air by the stock of adult and native ash per unit time.<sup>17</sup> I examine  $k = 1, \dots, 4$  health endpoints: mortality (long-term and short-term), hospital admissions, emergency room (ER) visits, and minor restricted activity days (MRAD). Equation (3.9) is in units of incidence per time for a given pollutant (e.g., number of daily ER visits associated with ozone emissions). Thus, for any level of ash stock it is possible to calculate avoided mortality and morbidity associated with tree cover.

Benefits of ash trees are assumed to be additively separable in types of ash and health impacts. A simplifying assumption is that all ash of a given maturity have the same aesthetic value. Native and EAB-resistant ash have a per unit value of  $P_A$  (\$/m<sup>2</sup> of bark area).<sup>18</sup> Juvenile EAB-resistant ash have a per unit value of  $P_J$  (\$/m<sup>2</sup> of bark area). The value of avoided health impacts is calculated as the product of equation (9) and the economic value of health endpoint  $k$ ,  $P_k$ . To arrive at an aggregate value for a given study area, this calculation is repeated for all pollutant-endpoint combinations, summed, and multiplied by the study area population size, ( $POP$ ). Benefits of trees are thus,

$$B(v(a_n, a_{rj}, a_{ra}), h(c, w(a_n, a_{ra})), y) \\ = A[P_A(a_n + a_{ra}) + P_J a_{rj}] + \left( \sum_{k=1}^4 \sum_{j=1}^4 P_k B_k e^{\beta_{kj} PO_{ij}(a_n + a_{ra})} \right) \times POP \quad (3.10)$$

where  $A$  (acres) is the size of the study area under investigation such that equation (3.10) is in units of dollars (\$).

The cost function for management is defined as,

$$c(m) + d(z) = A[(c/2)m^2 + (d/2)z^2] \quad (3.11)$$

where  $c$  (\$/m<sup>2</sup> of bark area) is the marginal cost of planting a new EAB-resistant tree and  $d$  (\$/m<sup>2</sup> of bark area) is the marginal cost of SLAM. Costs are increasing at an increasing rate in management, consistent with a non-linear density-impact curve (Yokomizo et al., 2009). Total costs are multiplied by the size of the area of interest to put (11) in units of dollars (\$).

### 3.3.2 Overview of dynamic simulations

The functions in equations (3.7), (3.10), and (3.11) are used to make explicit the bioeconomic model in equations (3.4a)-(3.4f) as applied to EAB. Since there is no closed-form solution to the explicit bioeconomic problem, numerical simulation techniques are used to find the optimal trajectories. The simulation scenarios may be conceptualized as follows.

A manager of invasive EAB in a representative county chooses her optimal levels of SLAM management ( $z$ ) and planting of replacement trees (PLAN hereafter) management ( $m$ ) that maximize net benefits of ash trees.<sup>19</sup> There are no EAB present in the county at the initial time period ( $e(0) = 0$ ), but they are introduced in the subsequent period. Initially, the county contains  $a_n(0) = 2700$  square meters of ash bark area per acre ( $m^2$  ba/ac) of native EAB-susceptible ash and  $a_{ra}(0) = a_{rj}(0) = 0$  ( $m^2$  ba/ac) resistant ash trees, both of which are varied in the sensitivity analysis. The optimal management time paths for this county are simulated over a 50 year planning horizon to capture the main stages of EAB invasion: introduction, detection, colonization, and

naturalization. Additionally, it is assumed that EAB managers update their management policy on an annual basis, which is the level at which the timestep is set at. Optimal starting values for choice and costate variables are determined by a grid-search algorithm. A 3% discount rate is assumed in the base case, but is varied in the sensitivity analysis. Numerical simulations were performed in Powersim® Studio 9 Academic.

To investigate the appropriateness of a “one size fits all” invasive management strategy, a four county scenario analysis is also performed. If simulated management is consistent across the four areas, then this is suggestive that a uniform management approach is appropriate for EAB. By contrast, meaningful differences in optimal management profiles across counties would indicate that a nuanced or spatially-target approach would lead to greater improvements in net benefits. Four geographically-disparate EAB counties were selected at random by US region (e.g., West, South, Midwest, and Northeast) from 564 infested counties (as of September 2014). Using county-specific demographic, health incidence, and tree canopy data, optimal time trajectories of PLAN and SLAM management are simulated for each county.

Finally, impacts of parameter uncertainties on results were investigated through a sensitivity analyses, which was performed by changing parameter values one-by-one and re-simulating the model for each new value.

### **3.4 Data**

Data were gathered for ecological, pollutant flux, health, and economic model parameters. Table 3.1 presents the ecological and pollutant flux parameters. Health and economic model parameters are presented in Table 3.2. The parameter base values are

used in the main effects analysis and minimum and maximum values are used in the sensitivity analysis.<sup>20</sup> Sources of data are listed below each table.

Additional nonparametric data were also collected, as described in the following paragraphs.

EAB detection data from date of first US detection (July 2002) through September 2014 was provided by the US Department of Agriculture (USDA) Animal and Plant Health Inspection Service (APHIS). Data are at the county-level and include county name, state name, FIPS, year of detection, and date that detection was confirmed. Land area and population data for each infested county were collected from the US Census Bureau State and County QuickFacts database for the year 2010. Area data were converted to  $m^2$  or acres as needed.

Tree cover data comes from two sources. First, Nowak et al. (2013) report estimates of the percentage tree cover in 10 US cities over various years from 1996-2009. Tree cover ranges from 16.0% of total land area in San Francisco, CA to 52.1% in Atlanta, GA, with an average estimate of 26.5%. The base model utilizes the 26.5% average. Second, tree cover was independently estimated using the US Forest Service *i-Tree Canopy* application for EAB counties as part of the scenario analysis. *i-Tree Canopy* allows users to estimate tree cover within a defined geographic area using remotely-sensed aerial photography data. To enhance the precision of our estimates, 700 randomly selected points were investigated per county, resulting in standard errors less than 2%.

Ash trees typically comprise 5-10% of forest cover (Wisconsin Department of Natural Resources, 2014). Using mean estimates, I assume a 7.5% ash composition of

total forest cover in EAB infested counties in our base model. A minimum of 5% and a maximum of 10% are considered in the sensitivity analysis. In the four county scenario analysis, estimates of ash cover were obtained from county- or state-specific sources (Colorado Department of Agriculture, 2013; Connecticut Department of Energy & Environmental Protection, 2013; Georgia Invasive Species Task Force, 2013).

Additional data on pollution concentrations for NO<sub>2</sub>, O<sub>3</sub>, SO<sub>2</sub>, and PM<sub>2.5</sub> were collected for EAB infested counties. County-level concentration data for 2014 comes from US EPA AirData<sup>21</sup> and was averaged daily across counties to arrive at an annual per pollutant arithmetic mean. Data from counties with an air quality monitoring station not reporting to the EPA or without any monitoring station were excluded. Using all available data produced annual mean concentrations for NO<sub>2</sub> (55 counties), SO<sub>2</sub> (127 counties), O<sub>3</sub> (134 counties), and PM<sub>2.5</sub> (542 counties).

Baseline health incidence for the four county scenario analysis was obtained from *BenMAP-CE* (v.1.0.8) using 2010 data compiled by the US EPA (Abt Associates, 2012). The EPA used individual-level mortality incidence from the Centers for Disease Control National Center for Health Statistics, hospitalization and emergency room rates from the Healthcare Cost and Utilization Project, and minor restricted activity day (MRAD) incidence from Ostro and Rothschild (1989). Individual-level incidence is aggregated in *BenMAP-CE* and population- and age-adjusted to the year of interest. Data are from 2010 and aggregated to the county-level. If multiple incidence measures were available, the most recent one that captured the largest age range was selected.

Summary statistics for EAB-detected counties are presented in Table 3.3. Statistics are reported for detection year, county area (square miles), population,



population density (per square mile), tree cover (%), and air pollutant concentrations. The average EAB detection year is early 2010 and the average county has an area of 524 square miles; roughly the size of Phoenix, AZ. Mean county density is low to moderate at 348 persons per square mile with an average population of 147,000. Concentrations of NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub>, and PM<sub>2.5</sub> for 2014 are within acceptable levels of current US EPA National Ambient Air Quality Standards.

### **3.5 Results**

Dynamic simulation results are presented beginning with the “base case” model (SLAM, not inclusive of health). Next, health impacts associated with ash cover are added in the “base case with health” simulation (SLAM, inclusive of health). Finally, PLAN management is added in the “combined management with health” simulation (SLAM & PLAN, inclusive of health) and compared to a simulation where health impacts are excluded; “combined management” (SLAM & PLAN, not inclusive of health). Figure 3.2 summarizes the presentation of simulation results.

#### **3.5.1 “Base case” and “base case with health” results**

In the base case (Figure 3.3), EAB managers have SLAM ( $z$ ) at their disposal and do not include ash tree health impacts in their planning decision. As EAB begin to infest ash trees, SLAM management grows exponentially through years 2-4. SLAM peaks in year 5 at 880  $m^2$  ba/ac, corresponding to the year when stock of EAB approaches its carry capacity. At peak SLAM in year 5, managers are treating roughly every ash tree remaining in the county. After simulation year 5, the stock of ash quickly falls, sharply reducing the optimal level of SLAM to low-levels that persist through year 25. The long

tail on SLAM management is being economically driven by the relatively large marginal benefit of the few remaining ash. Managers continue to SLAM the ever-shrinking ash population in an attempt to preserve the stock of trees for as long as possible. Net present value (NPV) of ash tree benefits over the 50 year planning horizon are \$3.2 billion.

Inclusive of ash tree health effects (base case with health), EAB managers increase the level of SLAM in all simulation years compared to the base case model (Figure 3.3). The SLAM with health time path is an upward-shifted version of the base case time path. This is not a surprising result as the marginal benefit of a unit of SLAM is greater than before because of its indirect effects on mortality and morbidity. Net benefits of ash are roughly \$1 billion greater when health impacts are included in the model, approaching \$4.1 billion over 50 years.

Reductions in health incidences due to tree pollutant removal are presented in Table 3.4 for the base case (column 2) and the base case with health (column 3). Results are cumulative over the 50 year planning horizon. The effect of including health in the management model is captured by the difference in health incidences, presented in column 4 of the table. Changes in incidence are heterogeneous across the health endpoints investigated. EAB management inclusive of health reduces mortality by an additional 0.3 persons over 50 years (a 1.5% improvement) compared to the simulation where health impacts are excluded. 61 minor restricted activity days are avoided (a 1.2% improvement) and visits to the ER are reduced by 0.1 events (a 0.8% improvement) when health is included in EAB management. Results suggest that the greatest impact of incorporating ash tree health impacts in the management decision is on mortality.

### 3.5.2 “Combined management with health” and “combined management” results

Figure 3.4 presents the optimal management time paths for combined management with health and combined management simulations. PLAN time paths are on the left panel and SLAM are on the right. I first focus on the combined management with health time paths, which are the solid black paths in each panel. In the combined management with health optimal time paths, the manager preemptively plants 1236  $m^2$  ba/ac resistant saplings in the initial period (PLAN, health), filling 95% of available forest space in the county. This is despite the fact that no native ash have actually died in the initial period. Maximum PLAN occurs in the initial period so that saplings have the greatest amount of time to grow prior to the death of the native ash they are intended to replace. Plantings rapidly decline in each year after the initial period, bottoming out in year 10 after enough saplings have been planted to replace the stock of lost native ash. Managers complement their plantings with chemical and biological treatments (SLAM, health), which peaks in year 5 at 180  $m^2$  ba/ac, corresponding to the height of the EAB infestation. Native ash trees are virtually extinct by simulation year 15, when SLAM management converges to zero. This is ecological consumption smoothing at work; preserve the current native stock of ash while simultaneously planting resistant tree saplings in order to minimize the loss of tree benefits. Present value net benefits of the combined management with health simulation are \$39.1 billion over 50 years; an increase of 1112% over the base case and an 18% increase over combined management net benefits. This is evidence that over this planning period, ecological consumption smoothing is welfare improving.

By comparison, excluding ash tree health impacts from the management decision (the dashed time paths in Figure 3.4) leads managers to plant 88% fewer resistant ash saplings in the initial period (PLAN, no health) compared to combined management with health simulation. However, the decay in PLAN management over time when health impacts are ignored is slower than in the combined management with health simulation. This is indicative of decreased ecological consumption smoothing. Fewer saplings are planted and they are planted over a longer period of time compared to the simulation where health is considered. The mechanism driving this change is the sharply reduced marginal benefits of PLAN when health is omitted. Now, a planted sapling that grows into an adult provides marginal benefits of  $P_A$  from Equation (10) instead of  $P_A + \sum_{k=1}^4 \sum_{j=1}^4 \beta_{kj} PO_{ij} P_k B_k e^{\beta_{kj} PO_{ij} (a_{ra})} > P_A$  when health is included. As panel (a) of Figure 3.4 demonstrates, this change in ash benefits substantially alters the optimal management trajectory. SLAM management is similarly affected (Figure 3.4; panel (b)). The optimal trajectory of SLAM management is shifted upward when health effects are excluded (SLAM; no health) and is larger in every simulation year. SLAM (no health) peaks in year 5 at  $589 \text{ m}^2 \text{ ba/ac}$ ; a 227% increase over the peak of SLAM (health). The optimal EAB management profile favors more SLAM and less PLAN when ash tree health impacts are ignored. This demonstrates that adding health to the EAB manager's problem does not necessarily lead to "more" of a given type of management, but in this case, engagement in ecological consumption smoothing, which is a diversification of management.

Mortality and morbidity incidence are compared across combined management simulations in Table 3.5. Including ash tree health effects in the combined management

decision reduces mortality by 21 persons over 50 years (a 13.5% improvement), prevents 13 emergency room visits (a 13.5% improvement) and 0.3 hospital admissions (a 10.7% improvement), and eliminates 5,443 minor restricted activity days (a 13.5% improvement) in the representative county. To contextualize the mortality improvement, I look to Donovan et al. (2013) who estimated actual EAB-related mortality at 0.96 excess deaths/county/yr. or 48 excess deaths/county/50 yrs., on average. Assuming for the moment that the Donovan et al. (2013) result is a reliable estimate of average EAB-related county-level mortality, then my simulation results suggest that adding health impacts to the EAB manager's problem when SLAM and PLAN are available could almost halve the number of excess EAB-related deaths from 48 to 27, a 21 person or 44% decrease over 50 years. While only a first approximation of the potential consequences of ignoring health impacts in an invasive species management model, the comparison is nonetheless contextually enlightening.

### **3.5.3 Planning horizon impacts net benefits of ecological consumption smoothing**

Two comparisons are made between base case and combined management profiles: (i) base case *vs.* combined management with health; (ii) base case *vs.* base case with health. I use these comparisons to illustrate the dynamic relationship between the planning horizon and the net benefits of ecological consumption smoothing (Table 3.6).

Across both comparisons, inclusion of health impacts results in larger net present benefits and higher reductions in mortality and morbidity at the end of the 50 year planning horizon, consistent with our earlier results (Table 3.6, column 3). The difference is most pronounced in comparison (i) where a combined management with health profile reduces incidence by 40,700 MRADs, 157 incidences of mortality, 97 emergency room

visits, and 3 hospital admissions over 50 years compared to the base case (Table 3.6, column 3). This is suggestive that ecological consumption smoothing may produce substantial welfare gains over the long-term if PLAN and health impacts are added to an EAB management toolbox relying exclusively on SLAM.

However, if the management horizon is shorter then consumption smoothing is not necessarily welfare improving (Table 3.6, column 2, comparison (i)). Between simulation years 0 and 9, including PLAN and health impacts of ash in the management decision results in lower net present benefits and higher incidences of mortality and morbidity compared to the base case simulation. This difference is greatest in year 5, where net benefits are \$4.5 billion lower, MRADs are 1,100 higher, there are 3 additional emergency room visits, and 4 excess deaths. This short-term effect is transpiring because optimal SLAM levels are substantially higher in the base case model, resulting in slower decay of native ash trees and hence higher pollutant flux. By contrast, the combined management with health simulation engages in ecological consumption smoothing, substituting away from SLAM and toward PLAN, which means a quicker loss of native ash. This illustrates the implicit tradeoff discussed earlier between short-term native ash preservation and long-term improvements to health. Along the economically efficient combined management trajectory, ecological consumption smoothing results in increased short-term health consequences, but long-term health gains. This is a key result of this study. Observe that this phenomena does not occur in comparison (ii). This is because there is no possibility of ecological consumption smoothing since PLAN is not available in the base case simulation. In comparison (ii), including health impacts results in higher net benefits regardless of the simulation year. These results demonstrate that the decision

to engage in ecological consumption smoothing by using health-centric invasive species management such as PLAN must be properly informed of the management horizon being considered so as not to be harmful to health.

Figure 3.5 summarizes net benefits across the four simulations presented thus far. Net benefits associated with a “no action” or do nothing management profile are also presented for comparison purposes. Both the combined management and the combined management with health simulations produce 50 year net present benefits substantially higher than the base case and no action simulations. Inclusion of health impacts in the management decision raises net benefits for both the combined management and base case simulations, though a larger increase is observed for combined management. No action results in the lowest net benefits compared to utilizing SLAM, PLAN, or some combination of the two.

#### **3.5.4 Four county scenario analysis**

The results of the four county analysis are now presented. Recall that four geographically disparate EAB infested counties were randomly selected in order to investigate management spatial heterogeneity. These counties are Boulder County, CO; Clare County, MI; Hartford County, CT; and Rockdale County, GA. Demographic, health incidence, and tree canopy data were gathered for each county (Table 3.7). There is considerable heterogeneity along these measures. Boulder, CO is the wealthiest county (\$68,000 median household income) with the lowest poverty rate (14.2%) and largest land area (726 sq. miles). Hartford, CT has the highest population (898,000) and density rate (1216 persons per sq. mile), with the greatest baseline hospital admissions (215 persons per 100,000) and ER visits (691 per 100,000) out of the four counties. Baseline

mortality is greatest in Clare, MI (1782 per 100,000), which is also the poorest (\$33,000) and least populated (31,000) county investigated. Rockdale, GA has the highest percentage of forest cover (65.9%), though the smallest ash tree cover (1%). The highest percentage of ash cover is found in Boulder County (15%).<sup>22</sup>

For the scenario analysis, the combined management model was re-simulated utilizing county-specific parameter values. Two simulations were completed per county. One includes ash tree pollutant-related health impacts in the analysis while the other excludes them. Comparisons of the “health” and “no health” simulations are made as before (Figure 3.6). For the first few simulation years, PLAN management inclusive of health impacts is substantially larger than PLAN management without health impacts, across all counties. SLAM is used more in all counties when health effects are omitted. These are similar results to what was observed in the combined management simulation of the representative county. However, there is considerable cross-county management heterogeneity.

Initial levels of PLAN (health) vary from  $1087 \text{ m}^2 \text{ ba/ac}$  (Rockdale) to  $1802 \text{ m}^2 \text{ ba/ac}$  (Hartford). PLAN (no health) varies considerably less in the initial period, ranging from  $179 \text{ m}^2 \text{ ba/ac}$  (Hartford) to  $191 \text{ m}^2 \text{ ba/ac}$  (Boulder and Clare). There is no clear relationship between initial PLAN and SLAM. For example, Clare managers use relatively little PLAN in the initial period ( $m(0) = 1123 \text{ m}^2 \text{ ba/ac}$ ), but utilize the same amount of SLAM in the initial period as Boulder ( $z(0) = 24 \text{ m}^2 \text{ ba/ac}$ ), even though Boulder managers PLAN substantially more ( $m(0) = 1357 \text{ m}^2 \text{ ba/ac}$ ). Similarly, managers in Hartford PLAN the most out of the four counties in the initial period ( $m(0) = 1802 \text{ m}^2 \text{ ba/ac}$ ), though only SLAM by two more  $\text{m}^2 \text{ ba/ac}$  than Boulder and



Clare at  $t=0$  and by one more unit than Rockdale (which has the lowest initial level of PLAN).

Benefits of management are greatest in Boulder where ash tree cover is highest and lowest in Rockdale where ash cover is the smallest. Even though Clare County is sparsely populated and highly rural, net benefits of EAB management are substantial relative to other counties given its sizeable forest cover (62.4%) and ash tree cover (7.5% of forest cover). In this case, benefits are being driven largely by aesthetic environmental values of ash and not through their impacts on health. By contrast, a mixture of urban and suburban land use in Hartford County (which fully contains the city of Hartford, CT) has lower forest cover (51.3%), though the 2<sup>nd</sup> largest net benefits. In Hartford, health benefits of ash are substantial because of its greater population (900,000) compared to Clare County (31,000). This suggests that in areas with relatively modest populations, benefits of management are predominantly due to aesthetic environmental values of ash, whereas in higher population centers, the health benefits of ash are an important component of aggregate net benefits. However, this does not necessarily mean that net benefits are always larger in high population areas. Clare County has a 97% lower population than Hartford, but only 35% lower net benefits. Other factors such as land area, forest cover, and ash cover are also important determinants of net benefits aside from population. Though, these results suggest that population is a strong driver of health incidence and thusly health benefits of ash.

Mortality and morbidity incidence reductions vary across counties (Table 3.8). Ash trees and EAB management reduce health incidences the most in Hartford County and the least in Rockdale County. For the case of Hartford, a combination of high

population and a large land area mean that more people benefit from greater air quality improvements. Over 50 years, Hartford ash trees reduce mortality incidence by 1105 cases in the health inclusive simulation and by 1033 cases in the simulation excluding health impacts. This is 21-22 cases annually. For other counties, mortality reductions range from 11 cases (Rockdale) to 311 cases (Boulder) in the health simulations and from 11 (Rockdale) to 280 cases (Boulder) for the no health simulations. Emergency room visits are reduced anywhere from 18 (Rockdale) to 2107 cases (Hartford) over 50 years because of improved air quality. Reductions in hospital admissions are negligible for Clare County, but upwards of 70 for Hartford. Minor restricted activity day (MRAD) incidence reductions range from 8187 days (Rockdale) to 667,746 days (Hartford) over 50 years, which corresponds to 0.002 days per person per year in Rockdale County and 0.01 days per person per year in Hartford County. Across all counties and all health endpoints, incorporating ash tree health impacts into the EAB management decision results in greater reductions in mortality and morbidity, but non-uniformly so.

There is clearly substantial heterogeneity in management, especially PLAN, and associated tree health impacts across these four counties. Deviations from the idiosyncratic optimal county management trajectories would lower net benefits and increase mortality and morbidity incidence. Thus, a uniform or one size fits all management approach where the same level or percentage of management were applied to all areas would be suboptimal and could be Pareto improved upon by using spatially-tailored management considerate of influential factors such as population and ash tree coverage. Additionally, these results serve as a further demonstration that naively managing “more” when health is considered in the planning decision is also suboptimal.

Across all four counties, SLAM management is actually lower when health is included, a result of ecological consumption smoothing. The takeaway here is that invasive species management should not only consider health, but the dynamic spatial relationship between demographics, underlying ecology, and health.

### **3.5.5 Sensitivity analysis**

Sensitivity analyses were performed on all simulations by changing each parameter to its minimum or maximum and re-simulating. Given that the EAB manager's problem contains over 35 parameter values, this resulted in over 200 sensitivity simulations for the representative county analysis and over 140 simulations for the four county scenario analysis. In lieu of reporting this many individual results, I limit the discussion to the combined management with health sensitivity analysis because it is the most complex of the models simulated and I find that it has the greatest sensitivity. This still leaves 81 sensitivity simulation results to discuss! Of these, 66 produced net benefits changes of 10% or less from the baseline combined management with health simulation. Results are insensitive to changes in these parameters. Therefore, attention is focused on the 15 simulations (for nine different parameters) that results are sensitive to, meaning that a re-specification resulted in >10% change in net benefits. I discuss each parameter in-turn.<sup>23</sup>

Changing the size of an average ash, *BA*, impacts both the amount of pollutants captured per tree and the effective number of trees that can exist on an acre of land. For example, smaller ash trees mean fewer captured pollutants per tree, but a higher quantity of individual free-standing ash on a parcel of land. It is possible in the aggregate that more pollutants are actually captured with smaller trees, if the increase in the number of

individual trees is sufficiently large. Indeed, this is what is found. A small decrease in ash surface bark area from its base of  $15.43 \text{ m}^2$  to its minimum of  $13.89 \text{ m}^2$  increases net benefits by 12.1% over 50 years thanks to an overall increase in the quantity of pollutants captured. A similar increase in the bark area of an individual tree from  $15.43 \text{ m}^2$  to its maximum of  $16.97 \text{ m}^2$  subsequently decreases net benefits by 10.3% for the opposite reason; fewer pollutants are captured. Additions of ash are preferred to increasing the size of existing ash in this model.

Increasing the carrying capacity of ash trees on each acre of land,  $K$ , substantially increases net benefits of combined management. For example, an increase in  $K$  from its base of  $4000 \text{ m}^2 \text{ ba/ac}$  to its maximum of  $6156 \text{ m}^2 \text{ ba/ac}$  increases ash tree net benefits by 55% over 50 years. This is not surprising because all ash have value in the model, such that increasing the ability of the land to hold more of them will produce more management value.

With greater natural adult ash mortality,  $\phi$ , a larger number of juvenile EAB-resistant ash are maintained to buffer the increased rate of adult tree losses. With more juvenile ash and fewer adult ash, pollutant flux is reduced, which reduces net benefits. For example, an increase in the mortality rate from its base of 4.4% per year to its maximum of 6.8% per year reduces benefits by 13% over the management horizon. Simulations are also sensitive to the rate of transition between juvenile EAB-resistant ash and adult resistant ash,  $\theta$ . Increasing the rate at which one juvenile ash transitions to an adult from a base of 9 years to a maximum of 50 years, reduces net benefits by 65%. As modeled in the EAB manager's problem, net benefits will always be lower the longer the transition period since adult ash provide higher aesthetic, environmental, and pollutant-

capturing benefits. In fact, net benefits are maximized when  $\theta$  equals zero because then all juvenile ash have equal benefits as adults.

Raising the initial number of native ash,  $a_n(0)$ , from its base of  $2700 \text{ m}^2 \text{ ba/ac}$  to the carrying capacity of  $4000 \text{ m}^2 \text{ ba/ac}$ , lowers net benefits by 13% over 50 years. The ability of the manager to engage in ecological consumption smoothing is reduced the closer the initial stock of ash is to the carrying capacity. Preemptive plantings of EAB-resistant saplings are limited by the availability of the system to support them. If the initial ash stock is at the carrying capacity, then a manager must wait until a native ash dies in order to replace it, which limits the effectiveness of consumption smoothing by reducing it to a simple “remove and replace” strategy. This produces greater health impacts, subsequently reducing benefits of ash trees

Percentage of land area that is covered by trees (forest cover) and ash trees specifically (ash cover) are additional influential variables in the manager’s problem. Net benefits are increasing in both variables. For example, an increase in the forest cover of the representative county from its base of 26% to its maximum of 52% increases net benefits by 96%; almost doubling net benefits over the baseline. Percent ash tree cover is not quite as influential. An increase in ash cover from a base of 7.5% of forest cover to a maximum of 10% of forest cover raises net benefits of EAB management by 33%.<sup>24</sup> With larger tree canopies come larger benefits of action, or, equivalently, greater costs of inaction, inducing more ecological consumption smoothing and creating greater returns to management.

The larger the population (*POP*), the greater the health benefits associated with EAB management. Moving from the base population of 147,182 to the maximum of 5.2

million raises benefits by a whopping 125% due to mortality and morbidity improvements. This large change in net benefits is attributable to the multiplicative relationship between population and health incidence inherent in the log-linear specification of the concentration response function (see Equation (12)). Finally, the discount rate lowers net benefits of ash trees. Higher discount rates of 6% and 12% reduce benefits by 12% and 14%, respectively, because the future is now less valuable. Since investments in EAB-resistant ash are immediate, whereas the benefits accrue over time, a greater discounting of the future will thusly lower present value net benefits.

Based on this sensitivity analysis, I find that results are most sensitive to the population of the study area and the size of the tree canopy. Both parameters influence the magnitude of ash tree health impacts, and are easily measurable for areas of interest in the US. I find little sensitivity to changes in any health parameters or pollutant flux values. This gives some confidence in the modeling approach adopted in this chapter for the EAB-ash-health relationship.

### **3.6 Conclusions**

This research links invasive species management and health through a bioeconomic model of EAB, a North American ash tree attacking pest. The impact of including health in the management decision operates through two distinct channels by influencing the type of management used and the quantity applied. Chemical and biological treatments of EAB are heavily used by managers when health is omitted from their planning decision. Health benefits of ash trees, when accounted for by management, induce ecological consumption smoothing, lowering use of chemical treatments while increasing preemptive replacement plantings of EAB-resistant tree saplings. An

unexpected result of this chapter is that including health in the management decision may actually produce harmful short-run increases in mortality and morbidity due to a reallocation of resources away from slowing native tree infestation toward replacement plantings. For short-term planning horizons (10 years or less in our simulations) a single management policy of chemical and biological treatments may yield higher welfare than a combined treatment-replacement policy.

Heterogeneity across infested areas along demographic, ecological, and underlying health dimensions necessitates a more spatially-nuanced management approach. Management should be particularly sensitive to infested areas that are urban, highly populated, and have large ash tree canopies. It is in these areas that marginal benefits of including health in management are perhaps the greatest because of the substantial health benefits provided by ash. Any uniform or “one size fits all” management strategy consisting of similar management intensity from infested area to infested area and not tailored to an area’s unique attributes will be suboptimal, as was demonstrated in the scenario analysis.

Though my model provides the first rigorous insight into the importance of health in invasive species management, there are some limitations to the approach taken. First, it is assumed that SLAM is only able to slow ash mortality, but not prevent it. Recent computer simulations suggest that randomly using SLAM can protect 99% of an urban forest from EAB (McCullough & Mercader, 2012). If this technique proves to be viable in the field, then PLAN becomes unnecessary, raising net benefits of management. Second, averting or mitigating behaviors are not incorporated (e.g., proactively planting resistant trees, spending less time outdoors, etc.). Agents might make behavioral changes

in response to EAB and loss of ash cover that would change their mortality or morbidity risk profile. In this case, avoided health incidences of management would be overstated, as would net benefits. However, it is unknown how much, if at all, this is occurring. Third, the ability of the ecological system to naturally regenerate flora after an ash fall is not accounted for. In areas rich with vegetation, a lost ash tree will naturally be replaced with some other type of plant life. Incorporating regeneration into the model would raise net benefits by lowering the required amount of managed replacement planting. Future work might consider what species are replacing fallen ash and how their pollutant capturing properties compare to native ash. Additionally, ecological effects of EAB resistant plantings should be investigated with an eye toward induced health effects.

These findings have important policy implications. Government funding of EAB management has begun to wane as the possibility of eradicating and preventing its spread becomes ever less likely (Miller, 2014). The inevitable loss of all North American ash trees seems imminent to some, reducing the sense of urgency among political leaders and agency heads and their willingness to commit resources. Linking EAB to health and human well-being, both physically and mentally, may rekindle interest in this salient issue. At the same time, scarce resources should be used to minimize health impacts over the long-term by committing Federal and state EAB management to large-scale *preemptive* planting of replacement trees, instead of more commonly used “remove and replace” initiatives. Setting well-defined and achievable preemptive planting goals may take away the “lost cause” stigma, while at the same time improving environmental quality, community health and individual well-being.



## Notes

<sup>12</sup>In reality, resistance or susceptibility to invasive pests for any given tree depends on a multitude of factors including stress, health, age, size, etc. While some species are generally more naturally resistant to invaders than others, it's still possible for a resistant tree to be invaded if it's dying or unhealthy. I generalize to these two cases for the sake of exposition, but recognize that inter- and intra-species heterogeneity exists.

<sup>13</sup>Total stock of trees cannot exceed the carrying capacity of the system:  $a_{rj}(t) + a_{ra}(t) + a_n(t) \leq K$ .

<sup>14</sup>Similarly, in equation (3.1) new plantings cannot push the total stock of trees above the carrying capacity. In other words,  $a_{rj}(t) + m(t) + a_{ra}(t) + a_n(t) \leq K$  must hold at every time period.

<sup>15</sup>See Appendix B for a detailed presentation of the exogenous EAB population growth model.

<sup>16</sup>The chief difference between equation (3.8) and the one presented in Nowak et al. (2013) is that I make explicit the pollutant capturing effects of an individual tree.

<sup>17</sup>Other functional forms for concentration response functions exist (e.g., linear, logistic, hazard models, etc.). However, the log-linear specification is the most widely reported in the literature.

<sup>18</sup>As presently defined,  $a_n$  contains both juvenile and adult native ash trees. This differs from  $a_{ra}$ , which is defined as only adult trees. Environmental (and health) benefits of adult trees differ from saplings and juveniles due primarily to differences in size (Anderson & Cordell, 1988). One possible correction for this would be to include a

differential term,  $0 < \pi < 1$ , that represents the proportion of adult  $a_n$  trees. This is omitted here and in equation (3.13) because I find that the results are insensitive to reasonable specifications of  $\pi$ .

<sup>19</sup>The representative county is constructed to have average demographic, ecological, and baseline health incidence characteristics based on all 564 EAB infested US counties (as of September 2014). Using a representative county for my analysis allows me to talk about “average” effects, but since it is not an actual county, it serves only to demonstrate important features and implications of the model. Management results may differ for actual EAB infested counties from those presented here.

<sup>20</sup>If a minimum or maximum does not exist in the literature for a given parameter, a +/- 10% sensitivity on the base value is reported.

<sup>21</sup><http://www.epa.gov/airdata/>

<sup>22</sup>Boulder County contains the city of Boulder, CO and is situated northwest of Denver. Clare County is a rural county in central Michigan containing no major urban centers. Hartford County contains the city of Hartford, CT along with several suburban and rural towns. Rockdale County is southeast of and adjacent to Atlanta and part of the Atlanta-Sandy Springs-Roswell, GA MSA. Rockdale contains the small city of Conyers, GA.

<sup>23</sup>Full sensitivity analysis results for all 81 parameter changes are available upon request.

<sup>24</sup>Of course, this analysis does not consider where the increase in ash cover comes from. If the growth in ash stock comes at the expense of other hardwood trees, then the realized benefits may be different depending on the relative values of trees.

Figure 3.1: Principle of Ecological Consumption Smoothing for a Hypothetical EAB Infested Area

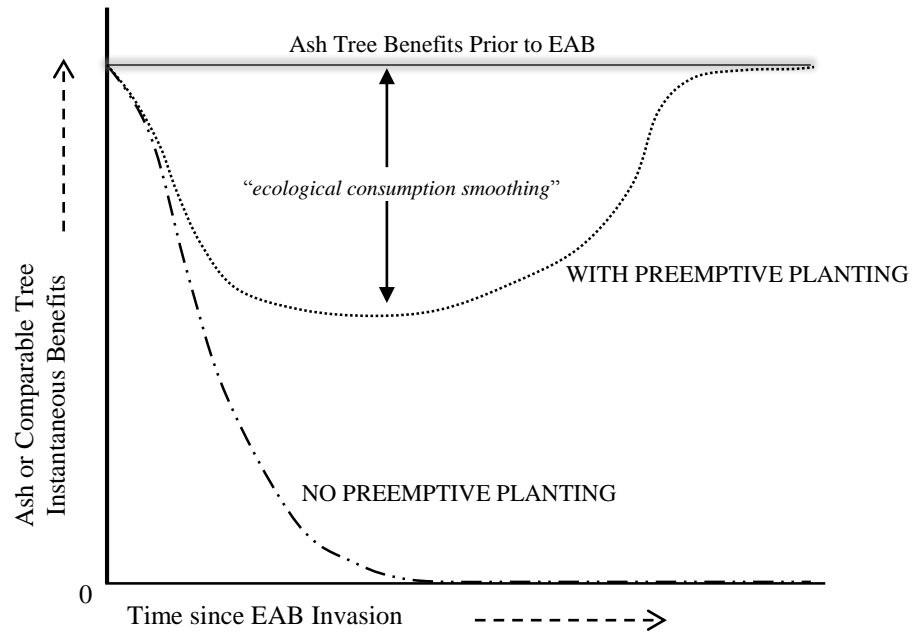


Figure 3.2: Simulation Names by Management Type and Health Inclusion

		MANAGEMENT TYPE			
OBJECTIVE FUNCTION		SLAM	PLAN	Both	Neither
	Not Health Inclusive	<i>"base case"</i>		<i>"combined management"</i>	<i>"no action"</i>
	Health Inclusive	<i>"base case with health"</i>		<i>"combined management with health"</i>	

Note: cells shaded in gray indicate that no simulation was performed for that management-health combination.

Figure 3.3: “Base Case” and “Base Case with Health” Optimal Time Paths

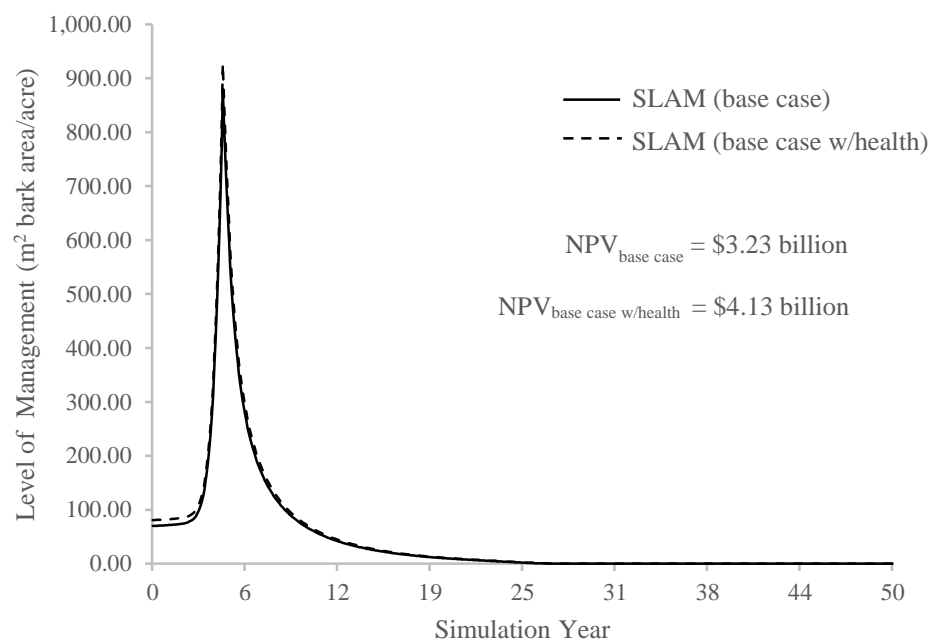
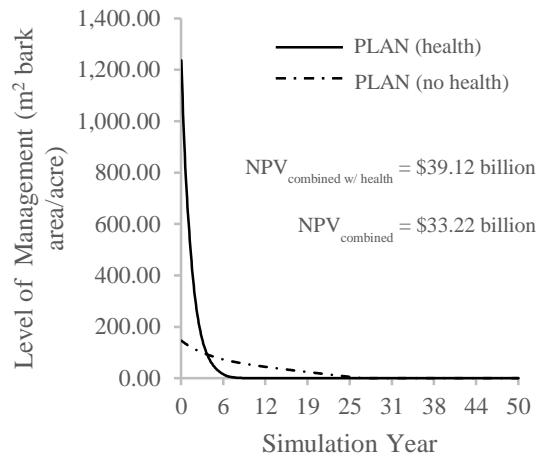


Figure 3.4: “Combined Management with Health” vs. “Combined Management” Optimal Time Paths

Panel (a): PLAN management ( $m$ )



Panel (b): SLAM management ( $z$ )

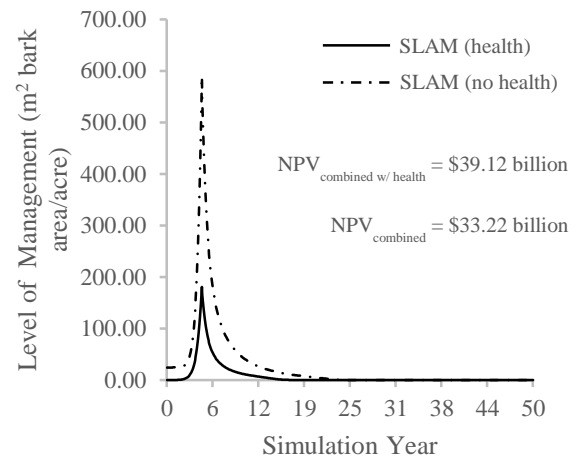
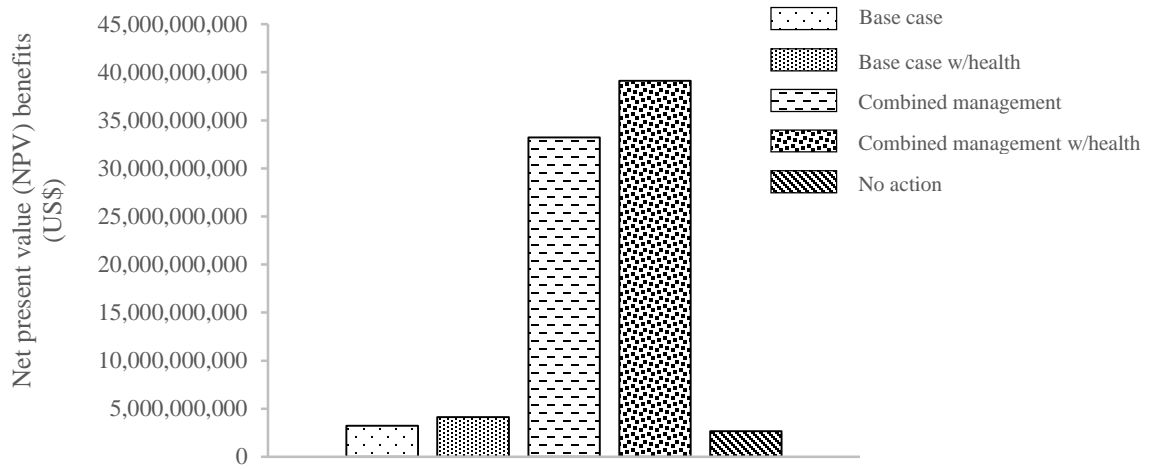


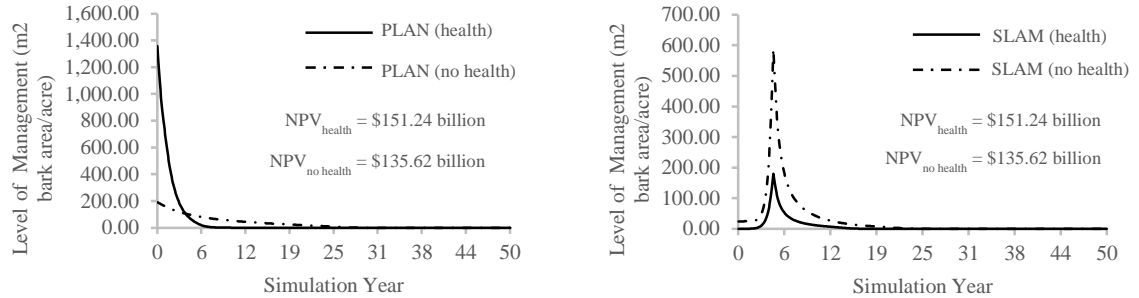
Figure 3.5: Summary of Net Present Value Benefits across Simulations (US\$)



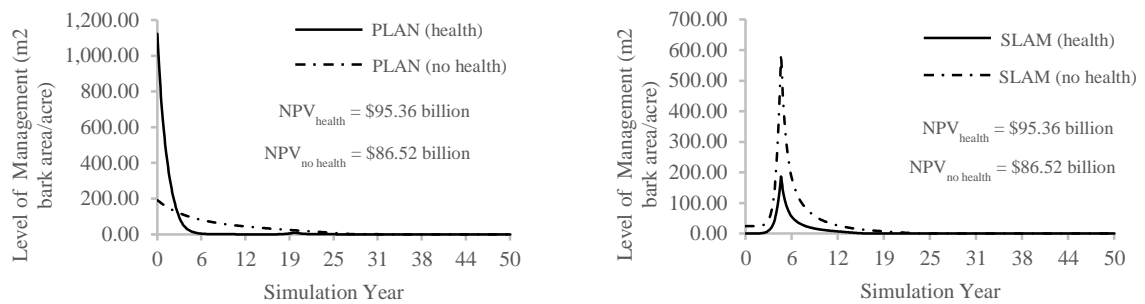
*Note:* benefits are in inflation-adjusted 2014 dollars over a 50 year planning horizon for a representative county with EAB. Net benefits are calculated for the “base case” (SLAM not inclusive of health), “base case with health,” “combined management” (SLAM & PLAN not inclusive of health), “combined management with health,” and “no action” (neither SLAM nor PLAN; do nothing to manage EAB).

Figure 3.6: Scenario Analysis Time Paths (“Combined management” vs. “Combined management with health”)

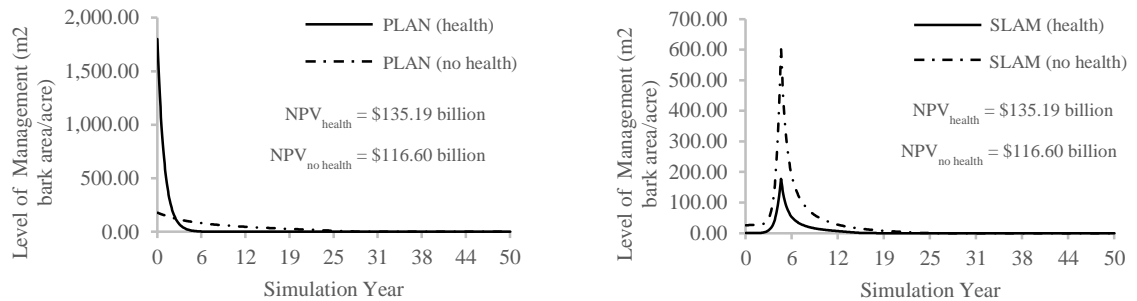
Panel (a): Boulder County, Colorado



Panel (b): Clare County, Michigan



Panel (c): Hartford County, Connecticut



Panel (d): Rockdale County, Georgia

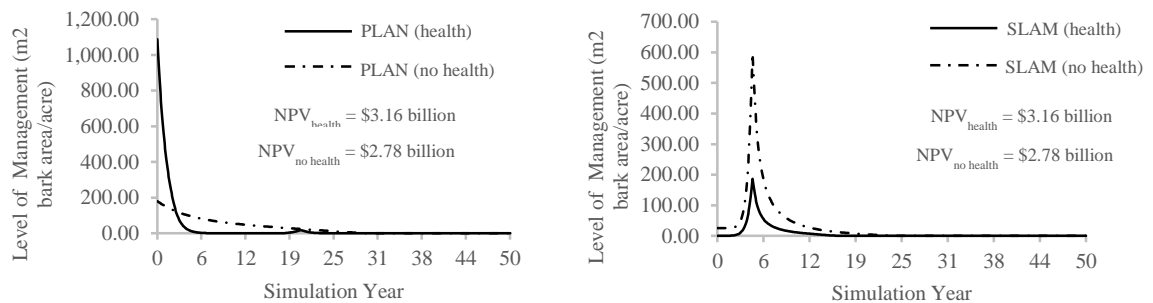




Table 3.1: Ecological and Pollutant Flux Model Parameters

Parameter	Description	Base value	Minimum	Maximum	Units
<i>Ecological Parameters</i>					
$T$	Ash canopy coverage area <sup>a</sup>	27.34	26.67	28.00	$m^2$
$BA$	Ash surface bark area <sup>b</sup>	15.43	13.89	16.97	$m^2$
$K$	Ash carrying capacity <sup>c</sup>	4000	1543	6156	$m^2$ bark area/acre
$r = g$	Intrinsic growth rate of ash <sup>d</sup>	0.20	0.18	0.22	/yr
$\phi$	Ash mortality rate <sup>e</sup>	0.044	0.02	0.068	/yr
$\theta$	Ash transition parameter <sup>f</sup>	0.11	0.11	0.02	/yr
$\alpha$	EAB emergent density for apparent ash dieback <sup>g</sup>	30	25	35	EAB/ $m^2$ bark area
<i>Pollutant Flux Parameters</i>					
$BL$	Boundary layer height <sup>h</sup>	550	300	1050	$m$
$V_{d,NO_2}$	Deposition velocity for NO <sub>2</sub> <sup>i</sup>	0.00225	0.00075	0.00375	$ms^{-1}$
$V_{d,SO_2}$	Deposition velocity for SO <sub>2</sub> <sup>i</sup>	0.0045	0.0015	0.0075	$ms^{-1}$
$V_{d,O_3}$	Deposition velocity for O <sub>3</sub> <sup>i</sup>	0.00338	0.00075	0.006	$ms^{-1}$
$V_{d,PM_{2.5}}$	Deposition velocity for PM <sub>2.5</sub> (inclusive of resuspension) <sup>j</sup>	0.00261	0.00128	0.00481	$ms^{-1}$

<sup>a</sup>Average of values reported in Anderson et al. (2000) and Remphrey et al. (1987). <sup>b</sup>Calculated for an average ash of 60 ft. in height and 2.77 ft. in circumference. <sup>c</sup>The carrying capacity for ash is calculated as  $K = BA * ash\_ac$ , where  $ash\_ac$  is the number of ash trees per acre, ranging from 100-399 with a mean of 259.2 (Soloman & Zhang, 2000; Kennedy, 1990). <sup>d</sup>Inferred from Ludwig et al. (1978). <sup>e</sup>Nowak et al. (2004). <sup>f</sup>Average time to ash maturity is assumed to be 9 years; annual rate of 1/9. However, some ash species can take 40-50 years to mature, depending on soil quality and sunlight availability. <sup>g</sup>Emergent density of EAB when ash dieback becomes apparent calculated from Anulewicz et al. (2007). <sup>h</sup>Average of day and night heights reported in Nowak et al. (2013) and Nowak (1994). <sup>i</sup>Lovett (1994). <sup>j</sup>Day and night average from Freer-Smith et al. (2004) for various wind speeds and estimated resuspension rates.

Table 3.2: Health and Economic Model Parameters

Parameter	Description	Base value	Minimum	Maximum	Units
<i>Health Parameters</i>					
$B_{LTM}$	Baseline incidence rate for long-term mortality <sup>a</sup>	3,287.08	2,958.37	3,615.79	rate/100,000/yr
$B_{STM}$	Baseline incidence rate for short-term mortality <sup>a</sup>	2,335.62	2,102.06	2,569.18	rate/100,000/yr
$B_{HA}$	Baseline incidence rate for hospital admissions <sup>a</sup>	140.14	126.13	154.16	rate/100,000/yr
$B_{ER}$	Baseline incidence rate for emergency room (ER) visits <sup>a</sup>	522.40	470.16	574.64	rate/100,000/yr
$B_{MRAD}$	Baseline incidence rate for minor restricted activity days (MRAD) <sup>a</sup>	780,000	702,000	858,000	rate/100,000/yr
$\beta_{ER,NO_2}$	Coefficient on NO <sub>2</sub> concentration for ER visits <sup>b</sup>	0.00546	0.00363	0.00729	ppb
$\beta_{ER,SO_2}$	Coefficient on SO <sub>2</sub> concentration for ER visits <sup>b</sup>	0.00437	0.00104	0.00771	ppb
$\beta_{LTM,O_3}$	Coefficient on O <sub>3</sub> concentration for long-term mortality <sup>c</sup>	0.00392	0.00133	0.00652	ppb
$\beta_{STM,O_3}$	Coefficient on O <sub>3</sub> concentration for short-term mortality <sup>d</sup>	0.00052	0.00027	0.00077	ppb
$\beta_{ER,O_3}$	Coefficient on O <sub>3</sub> concentration for ER visits <sup>e</sup>	0.003	0.00104	0.00496	ppb
$\beta_{MRAD,O_3}$	Coefficient on O <sub>3</sub> for MRAD <sup>f</sup>	0.00260	0.00108	0.00412	ppb
$\beta_{LTM,PM_{2.5}}$	Coefficient on PM <sub>2.5</sub> for long-term mortality <sup>g</sup>	0.00583	0.00394	0.00771	ppb
$\beta_{HA,PM_{2.5}}$	Coefficient on PM <sub>2.5</sub> for hospital admission <sup>h</sup>	0.00332	0.00128	0.00537	$\mu g m^{-3}$
$\beta_{ER,PM_{2.5}}$	Coefficient on PM <sub>2.5</sub> for ER visits <sup>i</sup>	0.0056	0.00148	0.00972	$\mu g m^{-3}$
$\beta_{MRAD,PM_{2.5}}$	Coefficient on PM <sub>2.5</sub> for MRAD <sup>f</sup>	0.00741	0.00604	0.00878	$\mu g m^{-3}$
<i>Economic Parameters</i>					
$P_A$	Per unit value of adult ash <sup>j</sup>	848.96	771.46	926.45	\$/tree
$P_J$	Per unit value of juvenile ash <sup>k</sup>	0	0	0	\$/tree
$P_M$	Per unit economic value of forgone mortality <sup>l</sup>	8.70	1.00	23.36	millions of \$/event
$P_{HA}$	Per unit economic value of forgone hospital admission <sup>a</sup>	15,523.38	13,971.04	17,075.72	\$/event
$P_{ER}$	Per unit economic value of forgone ER visits <sup>m</sup>	360.51	346.38	374.64	\$/event
$P_{MRAD}$	Per unit economic value of forgone MRAD <sup>n</sup>	135.36	121.82	148.90	\$/event
$c$	Marginal cost of PLAN management ( $m$ ) <sup>j</sup>	352.86	317.57	388.15	\$/m <sup>2</sup> bark area
$d$	Marginal cost of SLAM management ( $z$ ) <sup>o</sup>	94.41	57.65	131.59	\$/m <sup>2</sup> bark area

Note: all economic values are in 2014 real dollars. <sup>a</sup>US averages estimated by the US EPA for use in national air quality assessments (Abt Associates, 2012). <sup>b</sup>Ito et al. (2007). <sup>c</sup>Jerrett et al. (2009). <sup>d</sup>Bell et al. (2004). <sup>e</sup>Wilson et al. (2005). <sup>f</sup>Ostro and Rothschild (1989). <sup>g</sup>Krewski et al. (2009). <sup>h</sup>Sheppard (2003). <sup>i</sup>Mar et al. (2010). <sup>j</sup>Sydnor et al. (2007). <sup>k</sup>Anderson and Cordell (1988) report no appreciable effect on property value for “small” trees. Furthermore, in their analysis of EAB economic impacts, Sydnor et al. (2007) only include ash  $\geq 30$ cm diameter above breast height (dbh). <sup>l</sup>US Environmental Protection Agency [EPA] (2014). <sup>m</sup>Stanford et al. (1999). <sup>n</sup>Dickie and Messman (2004). <sup>o</sup>Sowers et al. (2009).

Table 3.3: EAB-detected County Summary Statistics

Item	Mean	Std. Dev.	Minimum	Maximum
Detection year	2010.22	3.31	2002	2014
Land area (sq. mile)	524.16	230.81	58.15	1558.42
Population	147,182	308,600	2,156	5,194,675
Density (sq. mile)	348.35	896.16	4.0	12,415.6
Forest cover (%)	0.26	0.11	0.16	0.52
NO2 concentration (ppb)	12.89	6.20	3.10	27.06
SO2 concentration (ppb)	2.43	1.25	0.19	7.20
O3 concentration (ppm)	0.05	0.00	0.03	0.05
PM2.5 concentration ( $\mu\text{gm}^{-3}$ )	10.86	2.27	3.86	19.37

*Source:* detection data from USDA APHIS database. Demographic data from the US Census Bureau, 2009-2013. Forest cover obtained from Nowak et al. (2013). Concentration data are the mean of 2014 observed values from US EPA AirData.

Table 3.4: Reduction in Health Incidences due to Pollutant Removal by Ash Trees in “Base Case” and “Base Case with Health” Simulations

Health effect	Incidence reduction (base case)	Incidence reduction (base case w/health)	Difference in incidence (%)	Units
Emergency room visits	12.3	12.4	0.8%	events/50 yrs.
Hospital admissions	0.4	0.4	<i>nil</i>	events/50 yrs.
Minor restricted activity days (MRAD)	5,135.8	5,196.7	1.2%	days/50 yrs.
Mortality	19.8	20.1	1.5%	persons/50 yrs.

Incidence reduction is cumulative over 50 years. Difference is the percentage change in health incidence from “base case” and “base case with health.” *Source:* results of simulations performed by the authors in Powersim Studio 9.

Table 3.5: Reduction in Health Incidences due to Pollutant Removal by Ash Trees in “Combined Management” and “Combined Management with Health” Simulations

Health effect	Incidence reduction (combined mngmt.)	Incidence reduction (combined mngmt. w/health)	Difference in incidence (%)	Units
Emergency room visits	96.4	109.4	13.5%	events/50 yrs.
Hospital admissions	2.8	3.1	10.7%	events/50 yrs.
Minor restricted activity days (MRAD)	40,393.9	45,836.6	13.5%	days/50 yrs.
Mortality	156.0	177.0	13.5%	persons/50 yrs.

Incidence difference is the cumulative difference in incidences between the “combined management” simulation and the “combined management with health” simulation *Source:* results of simulations performed by the authors in Powersim Studio 9.

Table 3.6: Incidence Differences Between Simulations: (i) “Base Case” vs. “Combined Management with Health” & (ii) “Base Case” vs. “Base Case with Health”

Health effect	Incidence difference (t=5)	Incidence difference (t=50)
<i>Comparison (i)</i>		
Emergency room visits	-2.7	97.0
Hospital admissions	-0.1	2.8
Minor restricted activity days (MRAD)	-1,132.4	40,652.9
Mortality	-4.4	157.0
NPV (\$)	-4,534,341,316.11	35,891,524,138.35
<i>Comparison (ii)</i>		
Emergency room visits	0.1	0.2
Hospital admissions	0.0	0.0
Minor restricted activity days (MRAD)	46.4	61.0
Mortality	0.2	0.2
NPV (\$)	156,137,912.10	125,728,730.10

Comparison (i) contrasts “combined management with health” to the “base case.” Comparison (ii) contrasts management profiles “base case” and “base case with health.” Incidence difference is from simulation inclusive of health impacts. Incidence differences may vary slightly from results in Tables 3.5-3.7 due to rounding. *Source:* results of simulations performed by the authors in Powersim Studio 9.

Table 3.7: Overview of EAB Counties Used in Scenario Analysis

Item	Boulder County, CO	Clare County, MI	Hartford County, CT	Rockdale County, GA
Population	310,048	30,569	898,272	86,919
HS graduates (%)	0.939	0.839	0.881	0.862
Median household income (\$)	67,956	32,668	64,967	52,579
Poverty rate (%)	0.142	0.265	0.116	0.147
Land area (sq. mile)	726.29	564.32	735.10	129.79
Pop. Density (sq. mile)	405.6	54.8	1216.2	656.5
Mortality incidence (per 100,000)	934.6	1781.5	1394.6	1104.2
Hospital admission incidence (per 100,000)	65.2	72.4	214.7	128.0
Emergency room incidence (per 100,000)	389.8	544.2	690.8	490.4
MRAD incidence (per 100,000)	780,000	780,000	780,000	780,000
Tree cover (%)	38.0	62.4	51.3	65.9
Ash tree cover (% of tree cover)	15.0	7.5	9.5	1.0

*Source:* Demographic data is the 2009-2013 average from US Census Bureau. Baseline incidence data for 2010 from the US EPA. Tree cover data for 2014 from the US Forest Service *i-Tree Canopy* and ash tree cover for 2013 from various sources described in the text.

Table 3.8: Health Incidence Reductions in Four County Scenario Analysis

<b>Incidence</b>	<b>Boulder County</b>	<b>Clare County</b>	<b>Hartford County</b>	<b>Rockdale County</b>
Emergency room visits (health)	499.1	54.6	2107.0	19.5
Emergency room visits (no health)	450.2	50.9	1970.3	18.3
Hospital admissions (health)	8.9	0.8	70.1	0.6
Hospital admissions (no health)	8.1	0.7	65.5	0.5
MRAD (health)	280,315.6	21,943.7	667,746.1	8714.3
MRAD (no health)	252,860.2	20,469.3	624,425.1	8186.9
Mortality (health)	310.8	46.4	1104.5	11.4
Mortality (no health)	280.3	43.3	1032.8	10.7

Incidence reduction is cumulative over 50 years. (health) indicates that the simulation includes ash tree human health impacts and (no health) indicates that health impacts were omitted from the model. *Source:* results of simulations performed by the authors in Powersim Studio 9.



## **Chapter 4**

### **Work more and play less? Time use impacts of changing ecosystem services: the case of the invasive emerald ash borer**

#### **4.1 Introduction**

Invasive alien species may have indirect impacts on human activities and well-being through disruptions to ecosystem services. According to the World Health Organization (2015), ecological impacts of invasive species on biodiversity represent an existential ongoing threat to how people live and interact in their communities. Investigations of direct impacts of invasive species on human well-being have been made (e.g., Mazza et al., 2014; Vilá et al., 2011; Crowl et al., 2008), including cases of economic benefits (e.g., Pienkowski et al., 2015). However, there is a growing acknowledgement that invasive species may have nuanced and complex indirect anthropogenic impacts through ecosystem change, such as impacts on behavior and time use patterns (Pyšek & Richardson, 2010; Pejchar & Mooney, 2009). The European Environment Agency (2012) cautions that ecological disruption caused by alien species will likely precipitate “complex, unpredictable cascades of effects” on human behavior, due to factors such as global climate change and increasing international movements of people and goods. However, there is a gap in the literature on quantitative measures indirectly linking invasive species to human behavior vis-à-vis ecosystem change. This absence of empirical assessment on indirect effects hinders our ability to holistically

evaluate and predict when and where invasive species might produce “cascades of effects” and hence be most deleterious.

The objective of this chapter is to assess indirect human behavior changes associated with detection of an invasive species. A natural experiment is exploited that caused a sharp degradation of ecosystem services, and hence a sharp decline in environmental quality, within a relatively short period of time across the Midwest and Northeast US. Tens of millions of ash trees (*Fraxinus* spp.) have died in the US over the past decade due to the introduction of invasive emerald ash borer (*Agrilus planipennis*), EAB hereafter, sharply reducing the size and diversity of forest canopies (Herms & McCullough, 2014). This chapter explores behaviorally-induced effects of EAB, and thus reductions in environmental quality, on allocation of time among individuals living in EAB infested US counties. Specifically, I investigate the so-called “labor-leisure decision” of how an individual allocates time between labor market and leisure activities. Labor and leisure activities are selected because they represent the second and third largest use of daily time, respectively, among US adults, behind sleeping (Tudor-Locke, 2011), and are important determinants of overall human well-being (Krueger, 2009).

Disruptions to forest ecosystems caused by alien species may affect labor and leisure time use either positively or negatively depending on underlying relationships between people and trees. Leisure time may be higher and labor time lower in areas abundant with trees because of increased recreational opportunities. People living proximal to forests and greenspace often spend more time outdoors and engage in more exercise than their peers (Coombes et al., 2010), perhaps at the expense of time spent working. Alternatively, ecosystems sustained by forests promote neighborhood cohesion

and meaningful social interactions (Maas et al., 2009; Kuo, 2003), which might result in increased economic opportunities and partnerships, increasing time devoted to labor. It is unclear from a qualitative perspective which, if any, of these factors might dominate. This has precipitated calls for additional quantitative research on indirect anthropogenic impacts of invasive species (Katsanevakis et al., 2014; McLaughlan et al., 2014) using stronger identification strategies to address issues of ecological confounding (Frumkin, 2013). Such research can inform ongoing debates on management prioritization guided by a more complete understanding of ecological and economic “impact” of invasion, and provide information on determinants of time allocation in response to ecological shocks.

This chapter exploits a natural experiment that created large and exogenous reductions in environmental quality through the sudden loss of ash trees due to the invasive EAB. Natural experiments are useful when randomized controlled trials are unavailable, as they provide an exogenous source of variation in exposure independent of outcome, strengthening the identification strategy (Meyer, 1995). Natural experiments have previously been used to study EAB and health risks (Donovan et al., 2015; Donovan et al., 2013), though this is the first application of this method to EAB and time use allocation. A fixed effects cross-county comparison design is used to explore individual labor and leisure time allocations before and after EAB detection, for a nationally representative, repeated cross-section sample of US adults in the American Time Use Survey.

Results suggest that EAB has a significant impact on labor-leisure time allocation. Along the extensive margin, adults are less likely to engage in outdoor leisure recreation after detection of EAB in their county of residence and more likely to work after

detection compared to individuals in non-detected counties. Impacts persist for 2+ years after detection, indicative of long-term effects. I find no evidence of a lead effect of EAB detection, consistent with a causal story, and observe that the results are robust to alternative control specifications and inclusion of potential weather and macroeconomic confounding variables.

## **4.2 Background**

### **4.2.1 Invasive species and their impacts**

There are many ecological economic dimensions of invasive species, including market and nonmarket benefits and costs (Pienkowski et al., 2015; McDermott et al., 2013; Pimentel, 2011), the public goods nature of biological exclusion and control (Ricciardi et al., 2011; Perrings et al., 2002), invasives as a threat to public health and well-being (World Health Organization, 2015; Jones & McDermott, 2015; Donovan et al., 2013), global economic drivers of biological invasion (Dalmazzone & Giaccaria, 2014), and models of ecosystem changes (Gallien et al., 2010; Cook et al., 2007). A focus has been on the direct economic costs associated with biological invasion (e.g., Aukema et al., 2011; Kovacs et al., 2010) and the use of invasive species management to mitigate direct impacts (e.g., Vannatta et al., 2012; Settle & Shogren, 2002). Less attention has been given to indirect impacts, such as human behavioral patterns and interference with day-to-day activities, where impacts may be particularly significant (Cardinale et al., 2012; Perrings et al., 2002).

Presence of an invasive pest may have direct and indirect effects on behavior. We might expect to observe changes related to protection of native habitats and management

of invasive pests through control and eradication, directly caused by detection. For example, farmers or homeowners may spend more time outdoors removing invasive weeds or spraying them with herbicides. Management of a biological invader may also create employment opportunities or shift time use patterns for certain types of workers. Indirect behavioral effects of alien species induced by changes in environmental quality are also possible. For example, reductions in biodiversity or loss of environmental aesthetics due to an invasive pest may attenuate time spent outdoors and time engaged in outdoor recreation activities, for example, walking, hiking, sports, or camping (Nilsson et al., 2011). Tuomainen et al. (2011) report that not only are behavioral changes in response to ecosystem degradation common both today and throughout history, but are often rapid and immediate, as individuals search for more favorable day-to-day living arrangements and social outcomes. Therefore, a case can be made that by impacting environmental quality, invasive species may have immediate and meaningful effects on behavior and time use patterns, especially in cases where ecosystem change is significant.

Additionally, behavioral changes induced by invasive species may persist through time. Disruptions to ecosystems due to invasive pests are often long-term and can even be permanent in some cases (Pejchar & Mooney, 2009). For example, in the case of EAB, degradation of the forest ecosystem may persist for many years until non-ash replacements are introduced and grow to maturity (Hermes & McCullough, 2014). The duration of time between ash fall and when a replacement is planted (or the forest naturally repopulates) and grows to maturity could be a decade or longer, depending on a variety of factors such as replacement species, weather, soil quality, management

intensity, financial budgets, etc. It is therefore likely that time use impacts of an invasive pest could last for several years, if not decades.

#### **4.2.2 Natural experiments as a source of ecological variation**

Confounding factors make it difficult to establish independent impacts of environmental quality on time use allocations, and labor-leisure decisions in particular. Correlational studies analyzing cross-sectional data cannot demonstrate a causal relationship. Wealthier households (who often work more hours) can afford to live in places with better environmental quality (Hobden et al., 2004) and are also more likely to exercise than less well-off households (Popham & Mitchell, 2007). Wealth or income might be a strong determinant of both labor and leisure time use as well as a strong determinant of environmental quality in the area where a person lives. This makes it challenging to estimate the independent causal role of quality on time use.<sup>25</sup> More sophisticated identification strategies are required to tease out such nuanced mechanisms.

Natural experiments are often used to provide more suggestive evidence of correlational relationship when randomized trials are unavailable. While natural experiments cannot fully demonstrate causality, they exploit degrees of randomness over which treatments are applied, which is an important missing component from correlational studies. The randomness exploited in such studies may strengthen the identification strategy and has the potential to greatly increase our understanding of important economic relationships (Angrist & Krueger, 2001).

In a recent natural experiment specific to invasive species, Donovan et al. (2013) exploited exogenous detections of EAB in US counties to investigate the relationship

between human health and ecosystem services provided by forests. Since spread of EAB is quasi-random by flight and economic activity there is a certain degree of randomness present in treatment assignment; an important tenant of natural experiments. Donovan et al. (2013) found that EAB detection was associated with 21,193 excess cardiorespiratory deaths over 1990-2007, which was posited to be a consequence of changes to forest ecology. Similar and more recent work, again using EAB detection as a natural experiment, suggests that woman are at greater risk of cardiorespiratory disease after detection of EAB in their county of residence, perhaps due in part to behavioral shifts in time allocation (Donovan et al., 2015). Whether or not, and to what degree, shifts in time allocation are occurring in response to EAB detection is an open question that if answered would provide evidence of a new dimension of invasive species impacts.

To address this gap, this chapter exploits a natural experiment created by quasi-random county-level detections of EAB from 2003-2013. I investigate two research questions: (i) does EAB affect the decision to participate in labor or outdoor leisure activities?; and (ii) what is the magnitude of the labor-leisure EAB effect and for how long does it persist? This chapter contributes to the literature on social impacts of invasive species by providing the first quantitative estimates of time use externalities associated with ecological disruption caused by an invasive pest, EAB.

### **4.3 EAB and its impacts**

EAB is a small phloem-feeding beetle native to Asia and eastern Russia that was introduced into the US through transportation of ash and ash by-products, likely through international trade. First detected in Michigan in 2002, adult EAB lay eggs in the conductive tissue of ash trees. Larvae feed on the inner layers of bark, disrupting the

transfer of nutrients and water throughout the tree. EAB appear to attack all species of North American ash, including both stressed and healthy specimens. Infested ash typically die within 1-3 years (Poland & McCullough, 2006). As of July 2015, EAB have been detected in 677 US counties across 25 states and in the District of Columbia and is regarded as the most destructive invasive species ever introduced in the US (Herms & McCullough, 2014). Eradication and containment efforts have proven largely ineffective at controlling spread, through research continues on new chemical and biological treatments (McCullough & Mercader, 2012). Experts believe that the entire stock of some 8 billion North American ash are at risk of extinction (Sydnor et al., 2011). Even the current extent of ash loss (estimated to be well over 100 million trees) has proven damaging to environmental quality and native ecosystem regimes, for example, by decreasing plant and insect biodiversity (Gandhi et al., 2014). Sudden changes to the forest canopy, especially in urban areas where ash can comprise 30% or more of total tree cover, could have significant impacts on behavior and time use decisions.

The sudden loss of ash in a neighborhood, in city parks, or along walking paths and streets might reduce the amount of time individuals spend outdoors. This could be because of reduced shade cover, increased temperatures, reduced aesthetics or natural beauty, or changes in perceptions of “greenness.” For example, Ellaway et al. (2005) found that residents living in areas with high levels of greenery, including trees, were three times more likely to be physically active than residents living in less green areas. Similarly, Roemmich et al. (2006) estimated that a 1% increase in park area was associated with a 1.4% increase in average physical activity among children in New York. Thus, one story is that loss of ash due to EAB will reduce time spent outdoors. An



alternative story could be that EAB may have no impact on outdoor recreation or perhaps have even a positive impact. A strain of literature suggests that tree cover encourages social interaction and enhances community and civic engagement and trust among community members (Elmendorf, 2008; Kuo, 2003). More meaningful interpersonal interactions and relationships may provide additional economic and labor market opportunities, increasing time spent working, perhaps at the expense of recreation and leisure time. Which effect may dominate is not *a priori* clear. More sophisticated empirical approaches are required.

## **4.4 Methods**

### **4.4.1 Overall empirical approach**

To investigate time use effects of EAB, I focus on county-level EAB detections over 2003-2013 as officially reported by the USDA Animal and Plant Health Inspection Service (USDA APHIS). My research design exploits the fact that EAB are detected at different times in different counties. I compare time use allocations of individuals in detected counties to like individuals in contemporaneously non-detected counties, but where detection occurs within the timeframe of analysis. Fixed effects are used to control for unobservable county heterogeneity and underlying time trends in labor-leisure patterns. Differences in labor or leisure time between individuals in detected counties and individuals in contemporaneously non-detected counties, after controlling for demographic, environmental, and economic confounders, in addition to county and time fixed effects, can be taken as suggestive evidence of an EAB effect. Importantly, such evidence has stronger identification than a correlational analysis, because detection is

determined by an exogenous, quasi-random process, providing an “as if” random source of ecological variation.

The possibility cannot be ruled out of some unobserved variable closely trending with both detections and time use patterns, which might bias results, falsely giving the appearance that EAB is related to time use. The speed and pattern of EAB’s spread (25 states over 13 years; or just under two states annually, on average), in addition to its rapidly changing quasi-random detection process make it unlikely that tree loss is confounded by such an unmeasured factor. This viewpoint is consistent with recent research in this area (e.g., Donovan et al., 2015; Donovan et al., 2013). However, given that potential confounding may still be a concern, I also perform a lead-lag analysis where the effect of detection several years prior to actual detection is investigated. Lead-lag analyses cannot demonstrate causation, but provide strong evidence in support of a causal story (Angrist & Pischke, 2009). If EAB is actually related to time use, then we should expect detection to have no impact prior to when it actually occurred. Additionally, I seek to eliminate several potential sources of confounding through use of controls of known determinants of labor and outdoor leisure time use in the preferred models, including controls for demography, weather, air quality, tree cover, macroeconomic conditions, and socioeconomics.

#### **4.4.2 Empirical model**

A key feature of time use data is that they tend to contain a large number of zero observations. This could be because the respondent never participates in a given activity or because the respondent spent zero time on a given activity on the specific diary day, but engages in the activity in general. For example, employed people tend to work during

the week, but if interviewed on the weekend might report zero work time. The empirical challenge is in deciding whether an observed zero is a true zero or simply represents a disconnect between the period of a diary day (a single 24h period) and the period of interest over which decisions are made (e.g., weeks, months, or longer). Stewart (2009) demonstrates via data simulations that if an observed zero is due to mismatch (i.e., the respondent engages in the activity though not on the diary day) ordinary least squares (OLS) generates unbiased estimates compared to a Tobit (censored regression) or a two-part model. However, Stewart (2009) also points out that if it is not possible to identify those who never engage (“non-doers”) from those who do (“doers”), then OLS along with the Tobit and two-part models produce biased estimates. In practice, it is often the case that non-doers cannot be separated from doers, especially for the ATUS which only provides a single 24h window of observation. There does not appear to be a convincing way to identify a doer from a non-doer in this setting without making some potentially strong assumptions. Therefore, two-part, OLS, and Tobit results will all be biased to a given degree.

Since theory is an imperfect guide of model selection and since there are ongoing debates in the literature as to how time use diary data should be modeled (e.g., Foster & Kalenkoski, 2013; Frazis & Stewart, 2012; Stewart, 2009), the labor-leisure decision is modeled using the three most appropriate and commonly applied techniques. First, a two-part model (Jones, 2000; Cragg, 1971) is used. In a two-part model, the first stage decision to participate in an activity (extensive margin) is modelled separately from the second stage decision of how much time to devote to the activity given any participation (intensive margin). As it is commonly applied (e.g., Bäck et al., 2014; Vaara & Matero,

2011) the first stage is estimated using a discrete choice regression model (e.g., logit, probit), while conditional OLS is used in the second stage on the subset of individuals participating in the activity. The second model used is a Tobit, which is a censored regression model with flexibility to account for large numbers of zeros. The Tobit is also often applied to time use data (Kimmel & Connelly, 2007; Kalenkoski et al., 2005). An assumption made when using a Tobit is of identical latent processes for participation and time use. If observed zero time use for an activity is assumed to be from actual non-doers, then the Tobit may be an appropriate choice (Foster & Kalenkoski, 2013) and will produce consistent estimates (Amemiya, 1973). Finally, an unconditional OLS is used on the full respondent sample following Cawley and Liu (2012). As previously mentioned, this will produce unbiased estimates if all respondents are assumed to be doers, though perhaps not on their diary day. Estimates are compared and contrasted across the three models.

The basic econometric model is:

$$TIME_{atc} = \beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c + \varepsilon_{atc} \quad (4.1)$$

where the outcome of interest is the time spent in either outdoor leisure recreation or work (*TIME*) by individual *a* during the diary day at time *t* residing in county *c*, the regressor of interest is an indicator variable of EAB detection *DET* at time *t* in county *c*, and we jointly control for air quality and weather *WEATH* at time *t* in county *c*, the percentage of county land area covered by trees *TREE* at time *t* in county *c*, a vector of county-level macroeconomic characteristics *CMAC* at time *t* in county *c*, and a vector of characteristics *X* of individual *a* at time *t* in county *c*.  $\mu_t$  is a time fixed effect and  $\pi_c$  is a county fixed effect. Fixed effects are important components for allowing control of

unobservable time trends in leisure and work patterns and unobservable county heterogeneity that may drive labor-leisure time allocations.

Specific variables included in equation (4.1) are age (and its square), gender, log annual household income, whether there is a child under the age of 18 in the household, whether the residence is owned by the respondent or another household member, race, if the respondent is married, student status, employment status, if the interview day was a holiday, day of week of interview, month of interview, county median income, percentage of county population in poverty, county unemployment rate, percentage of county with a high school diploma, air quality index (AQI), snowfall, precipitation, maximum temperature, minimum temperature, and percent tree cover. For the labor time use equations, a control for business cycles is also included since labor market conditions can vary considerably across business cycles, and a control for self-reported health status (=1 if “fair” or “poor” health; =0 otherwise) is used to control for sick days.

Equation (4.1) is estimated in a variety of ways. For the two-part model, separate estimations are made of a logit version of the extensive margin decision for whether to spend time in leisure or work and a conditional OLS version of the intensive margin decision of minutes spent in leisure or work:

*First-stage Logit (two-part model)*

$$\begin{aligned}
 \Pr(BIN\_TIME_{atc} = 1) &= F(\beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c) \\
 &= \frac{1}{1 + e^{-(\beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c)}}
 \end{aligned} \tag{4.2a}$$

where  $BIN\_TIME$  is a binary variable that equals 1 if the respondent engaged in any leisure or labor on the diary day and zero otherwise, and  $F(.)$  is the cumulative standard logistic distribution function. The second-stage equation is presented as,

*Second-stage Conditional OLS (two-part model)*

$$TIME_{atc} > 0 = \beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c + \varepsilon_{atc} \quad (4.2b)$$

which uses respondents reporting  $>0$  time spent on labor or leisure on the diary day.

A Tobit version of equation (4.1) is estimated employing a lower bound at zero.

Let  $TIME^*$  be the latent variable and  $TIME$  the observed variable. The general Tobit formulation is then:

$$\begin{cases} TIME_{atc}^* = \beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c + \varepsilon_{atc} \\ TIME_{atc} = 0 & \text{if } TIME_{atc}^* \leq 0, \\ TIME_{atc} = TIME_{atc}^* & \text{if } TIME_{atc}^* > 0. \end{cases} \quad (4.3a)$$

with associated log likelihood function (Greene, 2008):

$$\ln L = \sum_{TIME_{atc} > 0} -\frac{1}{2} [\log(2\pi) + \ln \sigma^2 + \frac{(TIME_{atc} - x'_{atc} \alpha)^2}{\sigma^2}] + \sum_{TIME_{atc} = 0} \ln [1 - \Phi \left( \frac{x'_{atc} \alpha}{\sigma} \right)] \quad (4.3b)$$

where  $x'_{atc} \alpha$  is a condensed form vector version of the regressors in equation (4.1),  $\sigma^2$  is the error variance, and  $\Phi$  is the standard normal cumulative density function. I focus on the Tobit marginal effects for uncensored observations,

$\partial E[TIME_{atc} | x_{atc}, TIME_{atc} > 0] / \partial x_{atc}$ , since the main interest is on the average effect of EAB on positive time use.

Finally, an unconditional OLS version of equation (4.1) is estimated on the full respondent sample, including those with zero and non-zero labor-leisure time use:

$$TIME_{atc} \geq 0 = \beta DET_{tc} + \gamma WEATH_{tc} + \theta CMAC_{tc} + \sigma TREE_{tc} + \delta X_{atc} + \mu_t + \pi_c + \varepsilon_{atc} \quad (4.4)$$

Equations (4.2)-(4.4) are estimated separately for labor and leisure time use. Only working age adults (>15 years of age) are included in the analysis. All specifications use cluster-robust standard errors at the county level.

## 4.5 Data

Time use data comes from the American Time Use Survey (ATUS). This is a nationally-representative, repeated cross-sectional diary survey completed annually since 2003. A subset of adults on their outgoing Current Population Survey (CPS) rotation are selected to participate in the ATUS. The respondent is asked to detail all activities they engaged in and the duration of time spent in each activity over a single 24-hour period (4am on the previous day to 4am on the interview day). Each activity and its duration are appropriately coded to fully account for every minute of the respondent's day. For more information on the ATUS, see the ATUS User's Guide (BLS, 2014).

The ATUS-X extract builder ([www.atusdata.org](http://www.atusdata.org)) was used to construct the dataset for this chapter. All years for which ATUS data are available were selected (2003-2013). This produced 148,345 initial observations. Time use variables were constructed for minutes engaged in outdoor recreation (*OUT\_REC*) and minutes engaged in work or work-related activities (*WORK*). Some 24 sport, exercise, and recreation activities are included in *OUT\_REC*, from football and baseball to walking and biking to lawn care and outdoor home repair. Activities not performed outdoors were excluded as

were minutes where the respondent was engaged in a relevant activity, but were not outdoors (e.g., driving to a baseball game). Activities included in *WORK* are time spent working in a job, time spent in work-related activities (e.g., a business lunch, driving to work, etc.), and other income-generating activities (e.g., side jobs).

To obtain respondent county of residence, ATUS data were merged with monthly CPS datasets from the National Bureau of Economic Research (NBER). Respondents living in counties with populations less than 100,000 are not identified in the CPS for privacy reasons. County of residence was successfully identified for 65,629 unique respondents (44% match rate).

A listing of all US EAB county-level initial detections from 2002 through 2014 was obtained from the USDA APHIS. This includes date (mm/dd/yy) of detection and county and state name. EAB has been detected in 564 counties as of September 2014. Once EAB has been detected in a county, it is considered to be permanently infested. By county and date, initial EAB detections were merged with the combined ATUS-CPS dataset. This allows identification of county infestation status on each respondent's ATUS interview date. Merging produced 16,600 ATUS-CPS respondents living in a county where EAB was detected between 2003 and 2013.

Weather has been identified as a potential confounder of time spent outdoors (Bäck et al., 2014). To control for this, daily county-level temperature (minimum and maximum), precipitation, and snowfall data were obtained from the National Climatic Data Center (NCDC) for 2003-2013. Data reported by the NCDC are for individual monitoring stations and most counties have multiple stations. To get county-level results, median weather values were calculated across stations within each county. Using the



median value reduces the effect of extreme values, which may not represent weather experienced by most of the population.<sup>26</sup> For a few counties on a few days, weather data could not be obtained due to all stations being offline or not reporting on that day. County-level data were obtained on a respondent's interview date for maximum temperature (95% match rate), minimum temperature (95% match rate), precipitation (99% match rate), and snowfall (96% match rate).

To control for other environmental influences on time use, air quality data was extracted from the US EPA's AirData System and tree canopy data was obtained from the USGS National Land Cover Database (NLCD). Air quality is determined by the Air Quality Index (AQI), a 0 to 500 scaling of observed air pollutants regulated under the Clean Air Act: particulate matter (PM), ozone (O<sub>3</sub>), carbon monoxide (CO), sulfur dioxide (SO<sub>2</sub>) and nitrogen dioxide (NO<sub>2</sub>). The highest pollutant AQI value observed within the county determines the overall AQI score for a given day. Higher scores indicate greater health risks of exposure. Daily AQI data were obtained for each EAB infested county from 1/1/03 to 12/31/13. To determine tree canopy extent, NLCD "Percent Tree Canopy" conterminous US raster files were downloaded for 2001, 2006, and 2011. GIS spatial analysis tools were used to calculate the annual percent of forested land cover in each county. For years between data releases, percent tree cover was linearly interpolated, and for years outside releases (2012 and 2013) a linear extrapolation was used.

Macroeconomic conditions may also be important determinants of labor and leisure time use allocations. Therefore, data on county-level macroeconomic measures were obtained from the US Census Bureau Small Area Income and Poverty Estimates

(SAIPE), the decennial US Census, and the Bureau of Labor Statistics Local Area Unemployment Statistics (BLS LAUS). Specifically, annual data over 2003-2013 were collected on percentage of the county population with a high school diploma or college degree (decennial census), percentage of households below the Federal poverty level (SAIPE), median income of the county (SAIPE), and county unemployment rate (BLS LAUS). Educational attainment data is decennial, so a linear interpolation was used for years between censuses.<sup>27</sup>

Summary statistics for the final constructed dataset are presented in Table 4.1. After dropping missing or “not in universe” ATUS (8215 obs.) and weather (847 obs.) values,  $n=6936$  useable observations remain across 102 counties, representing 21.7% of EAB infested counties between 2003 and 2013 and 22.0% of the US population. ATUS respondents spend an average of 16 minutes on outdoor leisure recreation on interview days and an average of 189 minutes (3 hours) working. The proportion of respondents reporting any ( $>0$ ) outdoor recreation time is 13% and the proportion reporting any ( $>0$ ) work time is 45%. Mean family income of \$64,500 is lower than the national average of \$72,600 as reported by the US Census Bureau in 2014, though the fact that ATUS censors income at \$150,000 may explain this difference.

## **4.6 Results**

### **4.6.1 Two-part model results**

Two-part model results are presented in Table 4.2 for the extensive margin decision of engaging in outdoor leisure or work (logit) and for the intensive margin decision of how many minutes to engage in labor or leisure given participation (OLS).

Time use is divided into panels A (outdoor leisure recreation) and B (labor time).

Controls used in each regression are described at the bottom of each panel along with goodness-of-fit measures. The coefficients on the detection variables measure the independent effects of a positive EAB detection in the county by time since detection; within the first year, 1-2 years, and 2+ years after detection. Z- or t-statistics are reported below each coefficient value. Pairs of equations for each two-part model (one logit and one OLS) are numbered (1) to (4) in each panel and will be referred to as “columns” in what follows.

For outdoor leisure recreation (panel A), column 1 illustrates a negative relationship between EAB detection and probability of spending any amount of time recreating outdoors when no controls are included. The effect is only present within the first year of detection (1% significance). There is no statistical evidence of intensive margin effects on time use in column 1. Adding demographic and county economic controls in column 2 increases the magnitude and significance of detection (1-2 years). Detection of EAB has both an immediate ( $\leq 1$  year) and medium-term (1-2 years) negative impact on the probability that an adult engages in outdoor leisure recreation. There is also weak evidence (at the 10% level) of EAB effects on the intensive margin decision within the first year of detection.

In column 3 controls are added for weather, AQI, and forest cover and a stronger negative effect of detection after 1-2 years is observed, while the immediate effect of detection remains negative and significant at the 1% level. Including year and county fixed effects (column 4) makes the coefficient on detection (2+ years) negative and marginally significant (10% level). Initial EAB detection now has an immediate and

persistent effect on leisure time, though the effect appears to diminish over time. Column 4 is the preferred model because it has the most controls for potential confounding variables known to influence labor and leisure. Computing marginal effects of column 4, I find that within the first year of EAB detection, there is a 6.2% ( $p < 0.001$ ) drop in the probability that an adult recreates outdoors for leisure purposes, a 5.6% ( $p < 0.01$ ) drop between years 1 and 2, and a 4.2% ( $p < 0.1$ ) drop for years 2 and higher. No significant impact of EAB detection on the minutes spent outdoors (intensive margin) is observed in the preferred model.

Time devoted to labor (panel B) is impacted in the opposite direction to leisure time. In the preferred model in column 4, EAB detection has a positive and immediate impact on the probability of engaging in labor activities within the first year of detection and has a positive persistent and significant impact on the probability of labor time 2+ years after detection. Specifically, marginal effects suggest an 8.8% ( $p < 0.01$ ) increase in the probability spending anytime at work within the first year of detection and a 7% ( $p < 0.05$ ) increase for 2+ years after detection.

Similar to the leisure time results, no intensive margin impact of detection on the number of minutes spent on labor time is observed. Interestingly, there is also no significant relationship observed between detections and labor time use in columns 1-3. Only when all control variables and fixed effects are included does a positive association become significant. There is no immediate explanation for this finding. Based on the results of the preferred model, there is evidence of immediate and persistent impacts of EAB detection on the labor time use decision. If we assume that the increase in labor time is at least partially a result of re-allocation away from outdoor leisure time, then

these results along with those for outdoor leisure recreation in panel A suggest that EAB detection is associated with substitution of leisure with labor time.

#### 4.6.2 Tobit model results

Tobit estimation results are presented in Table 4.3, again divided into panels A (leisure) and B (labor) with the controls used in each regression described at the bottom of each panel. In the basic outdoor leisure recreation model with no control variables (column 1), EAB detection has a negative and significant (1% level) impact on minutes spent in leisure activities within the first year of detection and a negative and marginally significant (10% level) impact after 1-2 years of detection. Controlling for demographic, weather, and county economic characteristics in columns 2 and 3 has little impact on the detection coefficients though improves model fit. Including year and county fixed effects in column 4 causes the coefficients on detection ( $\leq 1$  year) and detection (1-2 years) to become more negative and significant (1% and 5% levels, respectively), while also causing the coefficient on detection (2+ years) to flip in sign and become marginally significant (10% level).

The uncensored marginal effects of detection on outdoor leisure time,  $\partial E[OUT\_REC|x, OUT\_REC > 0]/\partial x$ , were calculated for the preferred model in column 4. They suggest that EAB detection is associated with a 14.23 minute ( $p < 0.001$ ) decline in leisure time in the first year after detection, an 11.10 minute ( $p < 0.05$ ) decline in years 1-2, and an 8.13 minute ( $p < 0.1$ ) decline 2 years or more after initial EAB detection. Note that the effects of detection diminish and become less significant as we move further away in time from the point of initial detection. Additionally, Tobit results are consistent

with those from the two-part model insofar as detection has an immediate (first year) and persistent (2+ years) impact on leisure time use.

The preferred labor time use model results in panel B, column 4 suggest a positive relationship between detection and minutes spent on work or work-related activities. The 5% significance on coefficients for both detection ( $\leq 1$  year) and detection (2+ years) indicates an immediate and persistent effect of EAB detection on labor time. Similar to two-part model results, I find no relationship between detection and labor time use in the models with fewer controls (columns 1-3). For the preferred model in column 4, EAB detection is associated with a 34.83 minute ( $p < 0.05$ ) increase in labor time within the first year of detection and a 29.84 minute ( $p < 0.05$ ) increase for years 2 and higher after detection. Note that effects are diminishing as time since detection increases. Consistent with the two-part model results, detection has an almost zero and highly insignificant effect on labor time 1-2 years after detection. Why EAB effects labor time immediately after detection and again 2 years after detection, but not for years 1-2 is puzzling. Overall, the narrative from the Tobit results is consistent with the two-part model; initial county detections of EAB are associated with fewer minutes spent on outdoor leisure activities and more minutes spent on work and work-related activities. Effects appear immediately after detection and persist for 2 years and longer past detection, indicative that perhaps changes to time use patterns are permanent.

#### **4.6.3 Unconditional OLS model results**

Finally, unconditional OLS results on the full respondent sample are considered, including those not engaging in any outdoor leisure or labor activities on the diary day. Results of these regressions are presented in Table 4.4 by activity panel. There is a

negative relationship between detection and leisure time use for the first year after EAB detection and 1-2 years after detection across all four specifications in columns 1-4. Adding controls increases the magnitude and significance of the negative association. The preferred model in column 4 indicates that EAB detection is associated with a 9.01 minute ( $p < 0.001$ ) decline in time spent on leisure recreation activities in the first year after detection and an 8.32 minute ( $p < 0.05$ ) decline in years 1-2 after initial detection. This contrasts with two-part model and Tobit results where evidence of a persistent effect of detection on leisure time use more than 2 years after initial detection was observed. OLS results indicate no persistent impacts on leisure time use.

Work and work-related OLS time use results (panel B) for the majority of models estimated show no meaningful relationship between labor and detection. In the preferred model in column 4, a weak positive association between EAB detection and minutes spent working within the first year of detection is observed, consistent with two-part model and Tobit results. However, there is no persistent impact 2+ years after detection in contrast to two-part and Tobit model results. Differences in assumptions surrounding the data generating process (i.e., doers vs. non-doers) may explain why a persistent labor market effect is not observed. Nevertheless, there is nothing in the unconditional OLS results that are inconsistent with findings from the other two econometric models estimated. In fact, there is weak confirmatory evidence for the first year of detection.

Overall, results across the three econometric models investigated consistently demonstrate that detection is negatively related with time spent on leisure recreation and positively associated with time spent on work and work-related activities. Furthermore, as time since initial detection increases, impacts diminish in magnitude as one might

expect. The consistency of results across models demonstrates that results are robust to various assumptions on the data generating process.

#### **4.7 Leads and lags analysis**

Additional support for a causal story of EAB detection impacts on the labor-leisure decision comes from an investigation of detection leads and lags. If the underlying cause of the labor-leisure time use changes is detection of EAB, then we expect to observe significant lag effects (i.e., post-detection impacts), but insignificant lead effects (i.e., pre-detection impacts). In other words, the detection variable should have no impact prior to when actual detection occurred, but should have a meaningful impact on or after actual detection. This pattern, if demonstrated, would be consistent with a causal interpretation of results, as discussed by Angrist and Pischke (2009). Such an analysis can also provide a concise visual representation of the impacts associated with an ecological shock.

A lead and lag analysis on the labor-leisure decision was performed by respecifying the preferred econometric models to include one, two, and three year lead effects of EAB detection. These were constructed as indicator variables just as the previously reported lagged detection ( $\leq 1$  year), (1-2 years), and (2+ years) variables were. The same set of confounding variables were controlled for as in the preferred model (4) in Tables 4.2-4.4, in addition to year and county fixed effects. The lead effects capture any effect of detection one to three years prior to when actual detection occurred. For the main effect results to be consistent with a causal story, the lead effects should all be insignificant, indicative that we have identified an actual driver of the labor-leisure time use decision instead of some other non-detection related confounder.



Results of the lag-lead analysis for the two-part model are in Figure 4.1. Tobit and unconditional OLS lag-lead results are in Figure 4.2. Average marginal effects or estimated coefficient values and their 95% confidence intervals are plotted for each of the three leads (3 years before, 2 years before, or 1 year before) and three lags (0-1 years after, 1-2 years after, 2+ years after) relative to EAB detection. Figure 4.1 is divided vertically into outdoor leisure recreation and labor time, and activities are divided horizontally into (i) logit (extensive margin) and (ii) conditional OLS (intensive margin) plots. As expected, across all plots in Figure 4.1 lead detection variables are statistically insignificant and generally close to zero. Along the extensive margin plots in (i), leads 1, 2, or 3 years prior EAB detection have insignificant effects on leisure time use. Consistent with the previously reported numerical results, there is a significant drop in the probability of engaging in leisure recreation and a significant increase in the probability of engaging in any labor activity immediately after detection. Changes in marginal effects generally persistent for 2+ years after detection, though are diminished in magnitude and significance compared to the initial effect. Neither the leads nor the lags of detection are significant along the extensive margin (plots labeled (i)), mirroring earlier findings of no impact of EAB detection on the conditional decision of how much time to devote to a given activity. Importantly, however, is that the lead effects on the conditional decisions are all insignificant, consistent with a causal story.

Tobit and unconditional OLS results (Figure 4.2) are separated by panels, which are further divided into time use activities. In panel A, uncensored Tobit marginal effects are plotted along with 95% confidence intervals. Lead effects 1, 2 and 3 years prior to detection for outdoor leisure and labor time use are all highly insignificant and generally

close to zero. Immediately after detection, we see significant declines in leisure time use and significant increases in time devoted to labor, consistent with earlier findings. Lagged detection variables diminish in magnitude and significance as we move further away from the point of initial detection, though there is evidence of persistent effects 2+ years after detection for both leisure (10% level) and labor (5% level) time use. Coefficients and associated 95% confidence intervals for unconditional OLS results are presented in panel B. Leads 1, 2, and 3 years before EAB detection are all insignificant at conventional levels. Post-detection lags are negative and generally significant for outdoor leisure recreation, though not persistent for 2+ years after detection. Detection lags for labor time are positive for 0-1 years and 2+ years after detection though not significant at the 5% level, consistent with our earlier results.

Across all models, detection has insignificant lead effects on the labor-leisure time use, consistent with a causal EAB story. Given the cross-sectional nature of the data, definitive evidence of a causal link between EAB detections and time use decisions remains elusive. However, use of a natural experiment along with causally-consistent results from a lag-lead analysis provides a stronger identification strategy than conventional cross-sectional approaches, and subsequently, stronger suggestive evidence of the impact of invasive species on time use habits.

## **4.7 Conclusions**

Shocks to ecological systems brought about by invasive species may have impacts on human behavior along multiple dimensions. In this chapter, the relationship between environmental quality and the labor-leisure time use decision in highly populated areas was investigated. By exploiting a natural experiment created by detections of the invasive

emerald ash borer (EAB) in the Midwest and Northeast US (2003-2013), I examined how shocks to ash tree coverage and quality impacted individual's minutes allocated to labor market activities and outdoor leisure recreation. Results indicate an immediate impact of detection on labor-leisure time use, persisting for 2+ years. Specifically, adults spend fewer minutes on outdoor leisure activities and more minutes on labor activities post-detection. Effects are especially pronounced along the extensive margin decision of whether to participate in any nonzero amount of labor or leisure time. This is perhaps more troubling than an effect along the intensive margin because it indicates a complete shift away from any level of participation, which might be detrimental to health, consistent with recent evidence on EAB (Donovan et al., 2015; Donovan et al., 2013).

Findings illustrate yet another social externality of invasive EAB, further underscoring the importance of managing its spread away from currently non-infested areas. Additionally, public awareness campaigns might be warranted, in light of these results, encouraging people in infested areas to go outdoors and reaffirming that EAB poses no direct threat to health or safety. Future research might investigate the role that publically-available information on EAB has on behavior both in the short- and long-term. It is perhaps surprising that detections have an immediate effect on time use habits when tree mortality is generally delayed by 1-3 years after initial infestation. While this is consistent with previous findings of immediate impacts of EAB from Donovan et al. (2013), a mechanistic explanation is still lacking. It is possible that immediate impacts are informationally-induced, creating some type of environmental "fear factor" that shifts behavioral patterns and keeps people indoors. I leave this to future research.

## Notes

<sup>25</sup>Simply controlling for wealth or income in an empirical model is not sufficient to address this concern. Wealth correlates with environmental quality (through residential sorting), while additionally correlating with labor-leisure time use allocations. To isolate the independent effect of environmental quality on time use, residential sorting has to be dealt with, otherwise the effects of environmental quality will be overstated. So-called “equilibrium sorting” models can be used to capture such wealth effects, though the development and application of such models is still in its infancy (Kuminoff, Smith & Timmins, 2013).

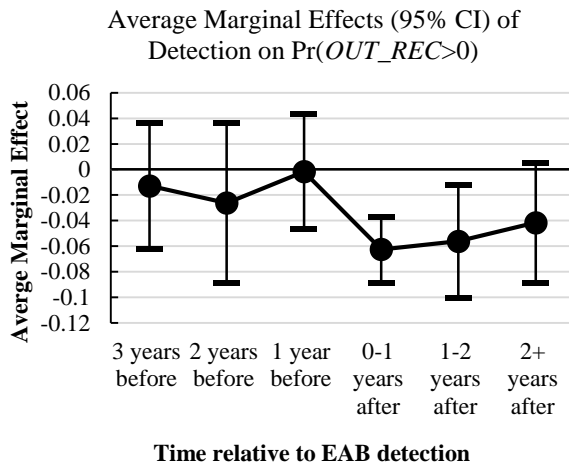
<sup>26</sup>This will matter most for counties with large intra-county weather heterogeneity due to large differences in elevation, for example, Boulder County, CO.

<sup>27</sup>See Appendix C for additional information on the data collection process.

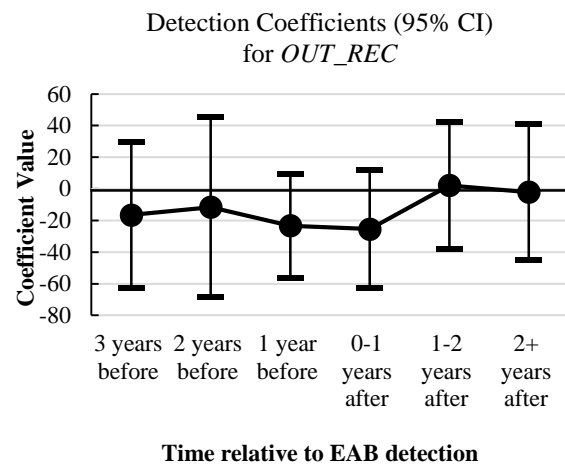
Figure 4.1: Two-Part Model Leads and Lags Marginal Effects of EAB Detection on Labor and Leisure Time Use

### OUTDOOR LEISURE RECREATION

(i) *Logit (extensive margin)*

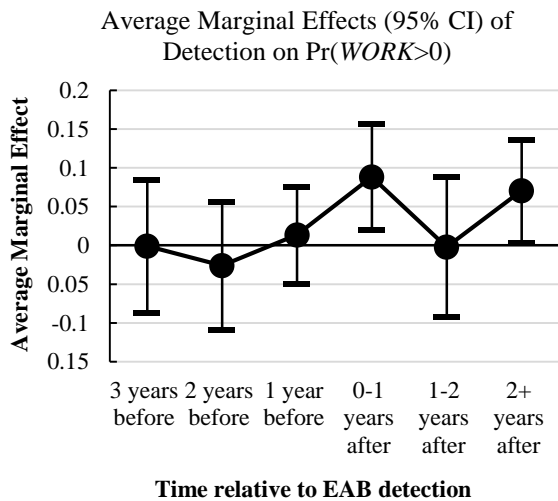


(ii) *Conditional OLS (intensive margin)*



### LABOR TIME

(i) *Logit (extensive margin)*



(ii) *Conditional OLS (intensive margin)*

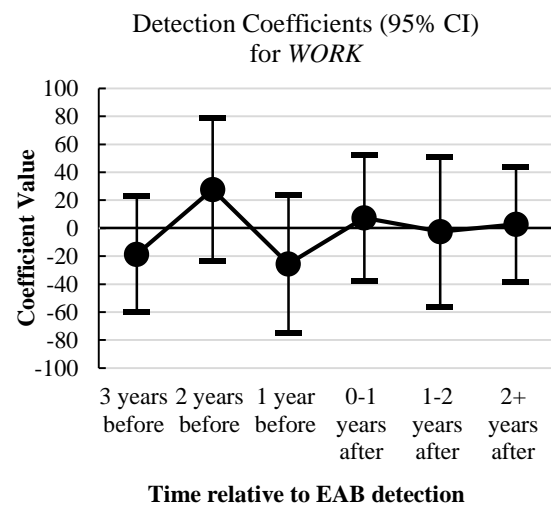
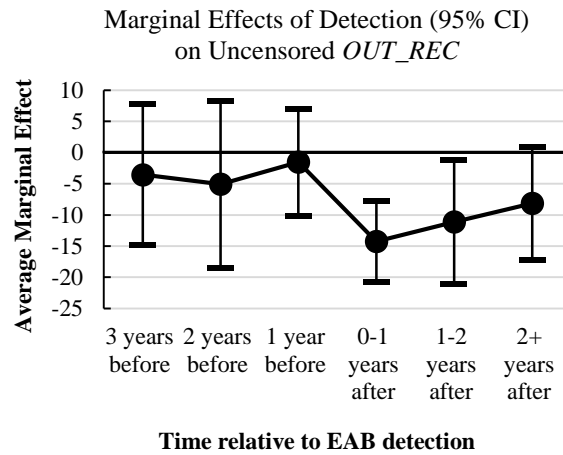


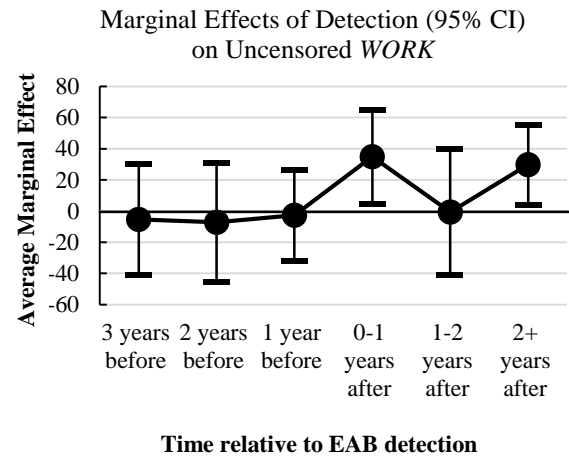
Figure 4.2: Tobit and Unconditional OLS Leads and Lags Marginal Effects of EAB Detection of Labor and Leisure Time Use

### A. Tobit Model

#### OUTDOOR LEISURE RECREATION

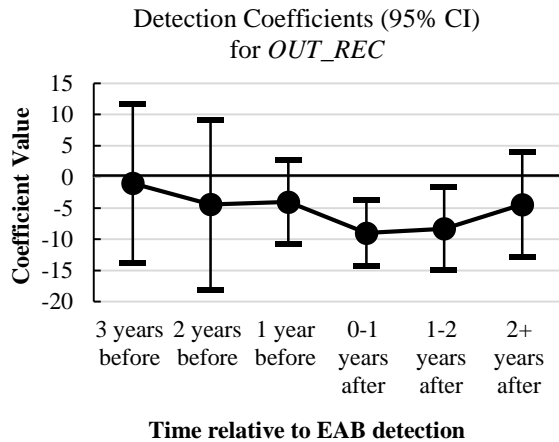


#### LABOR TIME



### B. Unconditional OLS

#### OUTDOOR LEISURE RECREATION



#### LABOR TIME

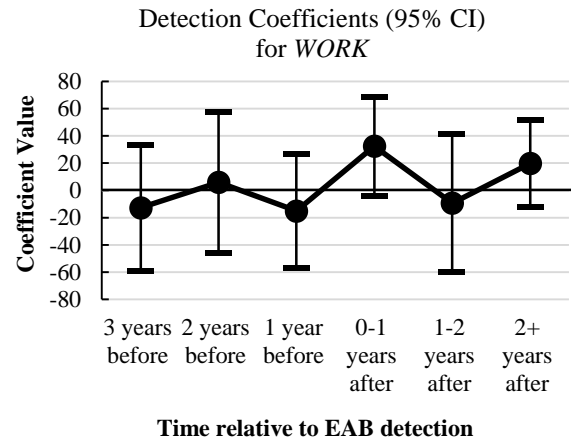


Table 4.1: Summary Statistics of Combined ATUS-CPS and EAB Detection Dataset  
( $n=6936$ )

	Mean	St. Dev.	Min	Max
<b>Time Use</b>				
<i>OUT_REC</i>	16.25	59.40	0	890
$\text{Pr}(\text{OUT\_REC} > 0)$	0.13	0.34	0	1
<i>WORK</i>	189.12	249.68	0	1380
$\text{Pr}(\text{WORK} > 0)$	0.45	0.50	0	1
<b>Daily Weather</b>				
Minimum temperature (°F)	41.16	50.00	-12.46	81.05
Maximum temperature (°F)	60.31	52.20	1.58	102.47
Precipitation (in.)	0.11	0.30	0	5.34
Snowfall (in.)	0.11	0.65	0	16.56
<b>EAB Detected Counties</b>				
Year of detection	2008.59	3.96	2003	2013
High school diploma	0.89	0.03	0.80	0.97
Four year college degree	0.32	0.12	0.11	0.62
Household income	55875.31	16115.65	33958	119525
Poverty rate	0.12	0.05	0.03	0.28
Unemployment rate	0.07	0.03	0.02	0.18
AQI	45.57	24.27	0	203
Percent tree canopy	0.23	0.16	0.02	0.75
<b>Individual Characteristics</b>				
Age	33.94	9.84	15	85
Female	0.55	0.50	0	1
Bachelor's degree	0.30	0.46	0	1
Student	0.19	0.39	0	1
Hispanic	0.07	0.26	0	1
Black	0.15	0.36	0	1
Married	0.49	0.50	0	1
Homeowner	0.72	0.45	0	1
Unemployed	0.08	0.27	0	1
Family income	64501.39	41155.68	5000	150000

Note: family income censored between \$5000 and \$150,000 in the ATUS.

Table 4.2: Results of Two-Part Model for Labor and Outdoor Leisure Time Use

<b>A. Outdoor Leisure Recreation</b>								
	(1)		(2)		(3)		(4)	
	Logit	OLS (y>0)	Logit	OLS (y>0)	Logit	OLS (y>0)	Logit	OLS (y>0)
Detection ( $\leq 1$ year)	-0.59*** (-2.61)	-3.75 (-0.27)	-0.57*** (-2.85)	-25.79* (-1.78)	-0.56*** (-2.79)	-26.98* (-1.91)	-0.82*** (-3.69)	-25.43 (-1.35)
Detection (1-2 years)	-0.40 (-1.63)	-3.66 (-0.25)	-0.50* (-1.95)	-14.53 (-1.01)	-0.51** (-2.01)	-12.32 (-0.85)	-0.71** (-2.06)	2.24 (0.11)
Detection (2+ years)	0.02 (0.14)	10.47 (1.09)	0.06 (0.47)	3.00 (0.30)	0.10 (0.74)	4.80 (0.45)	-0.45* (-1.73)	-2.05 (-0.09)
Demographic and day controls			x	x	x	x	x	x
Weather, AQI, and forest cover controls					x	x	x	x
County economic controls			x	x	x	x	x	x
Year fixed effect							x	x
County fixed effect							x	x
Pseudo R <sup>2</sup> (or R <sup>2</sup> )	0.00	0.00	0.11	0.16	0.12	0.17	0.16	0.29
Log likelihood	-1.85e10	-	-1.66e10	-	-1.64e10	-	-1.57e10	-
Observations	6913	936	6913	936	6913	936	6913	936
<b>B. Labor Time</b>								
	(1)		(2)		(3)		(4)	
	Logit	OLS (y>0)	Logit	OLS (y>0)	Logit	OLS (y>0)	Logit	OLS (y>0)
Detection ( $\leq 1$ year)	0.24 (1.12)	-11.14 (-0.62)	0.35 (1.43)	-1.79 (-0.11)	0.35 (1.49)	-3.37 (-0.20)	0.50** (2.45)	7.34 (0.32)
Detection (1-2 years)	-0.27 (-1.40)	-32.01 (-1.20)	-0.06 (-0.29)	-8.89 (-0.40)	-0.05 (-0.22)	-10.10 (-0.47)	-0.01 (-0.05)	-2.48 (-0.09)
Detection (2+ years)	-0.09 (-0.85)	-9.21 (-0.83)	0.12 (1.01)	-1.83 (-0.19)	0.13 (1.09)	-3.42 (-0.38)	0.39** (2.08)	2.80 (0.14)
Demographic and day controls			x	x	x	x	x	x
Weather, AQI, and forest cover controls					x	x	x	x
County economic controls			x	x	x	x	x	x
Year fixed effect							x	x
County fixed effect							x	x
Pseudo R <sup>2</sup> (or R <sup>2</sup> )	0.00	0.00	0.18	0.24	0.18	0.24	0.22	0.29
Log likelihood	-2.07e10	-	-1.71e10	-	-1.71e10	-	-1.62e10	-
Observations	3951	1835	3951	1835	3951	1835	3951	1835

*Note:* Results of county-level EAB detection for the first year, second year, and 2+ years are reported. Logit results are for the extensive margin participation decision and OLS results are for the intensive margin time use decision conditional on participation. Demographic and day control variables include age (its square), gender, log annual household income, presence of child in household, whether residence is owned by respondent or other household member, married, student, employment, day of week, month of interview, and whether interview day was a holiday. For labor time results, additional demographic controls added for economic recession and self-reported health. Weather, AQI, and forest cover controls include maximum temperature, minimum temperature, snowfall, precipitation, AQI, and percent forest cover. County economic controls include county median income, county poverty rate, county unemployment rate, and percentage of county population with a HS diploma. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. t- or z-statistics in parenthesis.



Table 4.3: Results of Tobit Model for Labor and Outdoor Leisure Time Use

<b>A. Outdoor Leisure Recreation</b>				
	(1)	(2)	(3)	(4)
Detection ( $\leq 1$ year)	-69.16*** (-2.65)	-66.82*** (-3.07)	-64.71*** (-2.99)	-91.29*** (-3.86)
Detection (1-2 years)	-47.82* (-1.66)	-51.14* (-1.92)	-51.07* (-1.93)	-69.55** (-2.00)
Detection (2+ years)	5.91 (0.45)	8.81 (0.62)	13.41 (0.93)	-47.42* (-1.75)
Demographic and day controls		x	x	x
Weather, AQI, and forest cover controls			x	x
County economic controls		x	x	x
Year fixed effect				x
County fixed effect				x
Pseudo R <sup>2</sup>	0.00	0.04	0.04	0.06
Log likelihood	-5.42e10	-5.23e10	-5.20e10	-5.13e10
Observations	6936	6936	6936	6936
<b>B. Labor Time</b>				
	(1)	(2)	(3)	(4)
Detection ( $\leq 1$ year)	43.24 (0.96)	49.40 (1.47)	47.76 (1.44)	73.14** (2.34)
Detection (1-2 years)	-81.43* (-1.74)	-18.25 (-0.48)	-17.81 (-0.47)	-1.23 (-0.03)
Detection (2+ years)	-27.04 (-1.03)	18.96 (1.00)	18.42 (0.98)	65.44** (2.26)
Demographic and day controls		x	x	x
Weather, AQI, and forest cover controls			x	x
County economic controls		x	x	x
Year fixed effect				x
County fixed effect				x
Pseudo R <sup>2</sup>	0.00	0.04	0.04	0.05
Log likelihood	-1.31e11	-1.26e11	-1.26e11	-1.25e11
Observations	3951	3951	3951	3951

*Note:* Results of county-level EAB detection for the first year, second year, and 2+ years are reported. Coefficients from Tobit estimation with censoring at zero are reported. Demographic and day control variables include age (its square), gender, log annual household income, presence of child in household, whether residence is owned by respondent or other household member, married, student, employment, day of week, month of interview, and whether interview day was a holiday. For labor time results, additional demographic controls added for economic recession and self-reported health. Weather, AQI, and forest cover controls include maximum temperature, minimum temperature, snowfall, precipitation, AQI, and percent forest cover. County economic controls include county median income, county poverty rate, county unemployment rate, and percentage of county population with a HS diploma. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. t-statistics in parenthesis.

Table 4.4: Results of Unconditional OLS Model for Labor and Outdoor Leisure Time Use

<b>A. Outdoor Leisure Recreation</b>				
	(1)	(2)	(3)	(4)
Detection ( $\leq 1$ year)	-6.21*** (-2.81)	-5.12*** (-2.75)	-4.85** (-2.53)	-9.01*** (-3.39)
Detection (1-2 years)	-4.65* (-1.76)	-5.50** (-2.14)	-5.63** (-2.17)	-8.32** (-2.48)
Detection (2+ years)	1.66 (0.92)	2.13 (1.15)	2.59 (1.29)	-4.45 (-1.05)
Demographic and day controls		x	x	x
Weather, AQI, and forest cover controls			x	x
County economic controls		x	x	x
Year fixed effect				x
County fixed effect				x
R <sup>2</sup>	0.00	0.06	0.06	0.09
Observations	6936	6936	6936	6936
<b>B. Labor Time</b>				
	(1)	(2)	(3)	(4)
Detection ( $\leq 1$ year)	19.60 (0.78)	21.94 (1.18)	20.19 (1.08)	32.51* (1.78)
Detection (1-2 years)	-45.83* (-1.92)	-15.08 (-0.73)	-15.92 (-0.76)	-9.32 (-0.37)
Detection (2+ years)	-15.44 (-1.10)	6.28 (0.59)	4.91 (0.46)	19.74 (1.24)
Demographic and day controls		x	x	x
Weather, AQI, and forest cover controls			x	x
County economic controls		x	x	x
Year fixed effect				x
County fixed effect				x
R <sup>2</sup>	0.00	0.29	0.29	0.32
Observations	3951	3951	3951	3951

*Note:* Results of county-level EAB detection for the first year, second year, and 2+ years are reported. Coefficients from unconditional OLS estimation on the full respondent sample are reported. Demographic and day control variables include age (its square), gender, log annual household income, presence of child in household, whether residence is owned by respondent or other household member, married, student, employment, day of week, month of interview, and whether interview day was a holiday. For labor time results, additional demographic controls added for economic recession and self-reported health. Weather, AQI, and forest cover controls include maximum temperature, minimum temperature, snowfall, precipitation, AQI, and percent forest cover. County economic controls include county median income, county poverty rate, county unemployment rate, and percentage of county population with a HS diploma. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1. t-statistics in parenthesis.

## **Chapter 5**

### **Conclusions: Evaluating the role of environmental shocks on health and behavior**

The relationship between the natural environment and human well-being is undeniable. Changes to environmental quality can meaningfully alter community interactions with nature, consistent with E.O. Wilson's biophilia hypothesis presented in chapter 1. How this deeply ingrained relationship between nature and humans fits within economics was the central question raised at the beginning of this work. Connections between the environment and society abound; nature provides us with food and water, air to breathe, the means to build shelter and power a consumptive economy. Disruptions or shock events that affect environmental quality have impacts on society through direct and indirect channels. Throughout the preceding chapters, several indirect impacts associated with environmental shocks were demonstrated and their implications explored. This is part of a larger narrative intended to argue for the consequentiality of including links between nature, health, and behavior in environmental policy and management.

The indirect role of nature in human well-being is often ignored by economists. Put another way, the health and behavioral dimensions of value created by ecosystem services are severely underweighted. The focus of this dissertation has been on forests and trees and their value to society. The central hypothesis advanced at the outset in chapter 1 is that environmental shocks to forests and trees create meaningfully complex reverberations throughout a regional economy. The perspective taken has been subtle and

nuanced; the preceding chapters did not investigate forests *per se*, but instead analyzed how shocks to forest quality and coverage have economically consequential impacts on communities. This study of induced effects or indirect impacts of trees enables us to capture the unique causal relationships between forests, health, and behavior in novel ways.

Some might balk at the notion that forests have consequential health and behavioral impacts. A few economists might even reject this hypothesis outright as absurd. Whether or not the links between forests, health, and behavior are relevant dimensions to consider or not is ultimately an empirical question. Furthermore, it is possible that if these relevant dimensions of value are omitted from consideration when setting economic and environmental policy, then the resulting outcomes will be suboptimal at best and harmful at worst. Given these stakes, a thorough investigation of the economic consequentiality of forests is surely warranted.

The results of the previous chapters support the consequentiality hypothesis on several levels. The second chapter showed that smoke produced by forest fires has significant economic and health consequences, hundreds of miles distant from the flame zone. Economic impacts of smoke events were found to vary considerably depending on the choices of the analyst in selecting concentration response and economic valuation functions from either the urban air literature or the wildfire literature. Consistent with a growing body of epidemiology and economic literature, the results in chapter 2 suggest that wildfire smoke is more toxic than urban air pollution. Furthermore, the estimate made of WTP to avoid a smoke-related health impact was significantly higher than a commonly used estimate coming out of the urban air literature. Combined, these findings

suggest an intimate link between wildfire smoke and health, which should be considered unique from the link between urban air pollution and health.

This nuanced finding supports the original hypothesis in that a distant shock (wildfire in this case) creates indirect economic reverberations through changes in health outcomes and behavioral patterns. Given that many (and recent) benefit-cost analyses of wildfires rely on literature estimates transferred from the urban air literature and not the wildfire literature, there is the potential that past damage assessments undervalue the impact of forest fire smoke. Again, this is consistent with a narrative in which the health and behavioral dimensions of value created by forest amenities (indirect effects) are underweighted compared to direct impacts within the flame zone – e.g., lost structures, evacuations, suppression costs, etc., which are the primary considerations given in many wildfire damage assessments. More complete and holistic damage assessments are required, which consider an expanded view of “impact” and “environmental value,” inclusive of secondary and tertiary smoke impacts such as distant health effects and induced behavioral changes among exposed populations. This has the real potential to affect forest management and wildfire suppression decisions by changing the benefit-cost calculus commonly used in guiding policy.

The lesson for the researcher and the academician from chapter 2 is that empirically estimating the links between forests, health, and behavior requires careful attention to the nuances implicit in how forests are situated in an environment and how people live and interact with their environment. In the case of Albuquerque, NM, a southwestern city rich in outdoor amenities and recreational opportunities, wildfire smoke is impactful because it causes people to stay indoors and avoid outdoor activities.

In another city, region, or country the way in which people live and interact with their environment may be very different (e.g., less outdoors time), such that wildfire smoke has less of an effect on health and behavior, with correspondingly attenuated economic damages. Perhaps in these areas damage assessments can rely on urban air literature estimates instead of looking to the wildfire literature. The takeaway point is that effects of environmental shocks vary over time and space, such that a relationship observed between forests, health, and behavior in one locale may be completely inappropriate in another setting or different context. To that end, a further implication of this work is that it demonstrates that the beneficiaries of wildfire risk reduction can be very distant from the flame zone and broader in geographic scope. This has implications not just for benefit-cost analyses but also for how we design funding mechanisms public payment schemes for payment for ecosystem services.

This conclusion and way of thinking about environmental shocks provided the original impetus for the environmental health model constructed and simulated in chapter 3, relating to the invasive emerald ash borer (EAB). Instead of assuming a stationary and static relationship between forests and health, an original dynamic model was created and then calibrated based on extant research. This is an important contribution because idiosyncrasies in how forests are situated in an environment and how people live and interact with nature are not assumed at the onset, but given the flexibility to vary through time and space. The results in chapter 3 demonstrate that such flexibility is warranted when considering environmental health impacts of invasive species, as optimal management varies dynamically and heterogeneously across infested counties.

The heterogeneous management result highlights the deeply ingrained role of forests and the hypothesized meaningfully complex reverberations in an economy created by environmental shocks. Impacts of EAB on health and behavior vary according to the ecology of an area and the demographics of the infested community. Why? Simply because people live, interact, and optimize within a natural environment differently from place to place. This may not come as a surprise, but is actually often overlooked by environmental management and policy, which frequently creates blanket regional or nationwide guidelines and regulations that are insensitive to spatial heterogeneity. Invasive species managers working out of a blanket or “one size fits all” playbook will manage EAB suboptimally, as was found in chapter 3. Improvements to societal welfare and community health could be made if nuanced contextual and site-specific forest and environmental health pathways were included in the EAB management decision.

This discussion surrounding heterogeneous EAB management is of course contingent upon the finding in chapter 3 that forests matter both to an individual’s health and to the health of regional economy. Ignoring health and behavioral dimensions of forest amenity value when managing EAB creates costly reverberations and impacts rates of mortality and morbidity in infested communities. Naïve assessments of EAB economic damages omitting indirect and induced effects associated with changes in ash tree quality and coverage, provide an incomplete picture of the far reaching reverberations of this invasive species. This is problematic because the narrative surrounding EAB is that lost ash trees primarily effect a single individual or single household through property values, loss of shade, and recreational opportunities.<sup>28</sup> Rather, the results from chapter 3

demonstrate that the largest impacts of lost ash are on public health and the community-at-large and not necessarily on the tree owner alone.

Bringing into the management fold the public goods nature of ash trees recasts the EAB epidemic as a social welfare problem, requiring a rethinking of management approaches. In this light, the focus of management should be to minimize harm to society – the idea of ecological consumption smoothing. Given that eradication and containment of EAB is practically impossible, the third chapter proposes and then demonstrates the usefulness of engaging in preemptive/concurrent planting of EAB-resistant trees (PLAN). Including health and behavioral impacts in the EAB manager's problem pushes optimal management towards PLAN, thus solving the externality problem.<sup>29</sup> This ties back to the original hypothesis in that it supports the idea of nature as consequential to well-being and more importantly, that accounting for links between forests, health, and behavior in policy creates opportunities for investments (e.g., PLAN) that can minimize the effects of environmental shocks.

This research would be incomplete without an original investigation of the linkages between trees and people. Whereas chapters 1-3 take for granted, in a sense, the relationship between forests, health, and behavior, chapter 4 provides an original analysis of behavioral impacts associated with EAB.<sup>30</sup> There is an endogeneity problem inherent in any investigation of forest impacts on behavior; do trees in a community cause people to behave in a certain way or is it that people with similar behavioral patterns (e.g., hikers, outdoor enthusiasts, etc.) move to forested communities? In the former, trees drive behavior (causation), while in the latter, trees have little to no effect on behavior (correlation). To tease out causation from correlation, the natural experiment created by



quasi-random introductions of EAB was exploited. If forests influence behavior, then a shock to forest quality and canopy coverage will have anthropogenic consequences.

The key finding in chapter 4 was that detection of EAB in a county was associated with both an immediate and persistent impact on the probability that an individual spent time recreating outdoors (leisure time) and the probability that an individual spent time engaged in a labor market activity (labor time). Specifically, people are less likely to recreate and more likely to work in response to detection of EAB in their county of residence. There is also evidence to suggest that the labor-leisure change is structural, meaning that a long-term shift in the fundamental structure of the labor market has occurred in response to the environmental quality shock created by EAB.

Consistent with the original hypothesis, EAB induces economic reverberations vis-à-vis changes to the structure of the labor market, and time use allocation more generally. It is not entirely clear what the causal pathways are that bring about this observed change. One plausible explanation is that as forests and trees become infested and die, people spend less time outdoors because of reduced shade, increased temperatures, and deteriorating outdoor aesthetics. Less time spent outdoors means more time available for indoor activities. It is interesting that the observed substitution is away from outdoor leisure and toward labor, instead of toward indoor leisure. In fact, no statistical change was observed for time spent on indoor leisure activities after detection of EAB. Instead, there is an almost a perfect one-to-one substitution of a minute of outdoor leisure with a minute of indoor labor. Future research might further explore the causal mechanisms behind the decision to work more in response to a shock to forest quality.

The behavioral impacts of EAB observed in chapter 4 are consistent with a causal story because (1) they come from a natural experiment, and (2) there were no lagged effects of detection in the leads and lags analysis performed at the end of the chapter. These results add yet another dimension to the ecosystem services story of trees. Forests are providing a myriad of services to society, such that the loss of a tree or a decline in the health of the forest will impact people in direct and indirect ways; conversely, the planting of a new tree or addition of a new species will also be impactful. Effects may be immediate or occur over the long-term as has been demonstrated throughout this research.

One could imagine incorporating this behavioral relationship into the dynamic model in chapter 3 and then simulating out how it affects EAB management over time and space. This would be challenging to do because it is not clear what the benefits and costs to society are from the observed labor-leisure change. In other words, a way to quantify (in dollars) the observed movement away from outdoor leisure towards indoor labor would be required. How to do this and what constitutes a benefit or a cost in this setting is left to future research. However, the difficulty associated with quantifying the labor-leisure effect of EAB is in no way meant to be dismissive or suggestive that it is irrelevant to the discussion. On the contrary, this is a fascinating line of research on the deeply ingrained role of forests and trees in the economy.

## **5.1 Limitations and future research**

The goal of this research has been to investigate the health and behavioral dimensions of shocks to urban forests and trees as they reverberate through the economy across time and space. Trees play important ecological roles in urban areas and have a

meaningful role in determining health outcomes. It has been argued throughout that there is heterogeneity in impacts across urban communities, contingent upon the role of trees in a community and the interactions that people have with them. Pinning down the relationship between forests, behavior, and health is challenging, and this research has tried to contribute to this important area.

The most pressing issue for future research is in determining when health and behavioral dimensions should be considered in environmental management and economic policy more generally. One might say that it should be included “when and where it matters,” but far too little research has been done to-date to know when and where it makes a difference. To that end, further research on the complex and nuanced links between societal well-being and the natural environment is needed. A starting point for this type of research would be a continued exploitation of natural experiments where some random disruption to environmental quality has occurred. Hypothesized connections between the environmental amenity disrupted and human well-being can be tested and explored, such as long-term labor market outcomes, educational attainment, and disease incidence.

Addressing this issue will require the construction of original micro-level time series datasets linking individual behavior and outcomes to well-identified environmental shock events. This type of data can be very challenging to acquire given the sensitive nature of information on health status and labor earnings, though has proven possible in practice.<sup>31</sup> Where stated preference data are not available, it is possible that revealed preference approaches could be successfully utilized as was done in chapter 2 for wildfire smoke health damages. With this approach, the effects of a shock are “revealed” to the

researcher as derivatives of utility-theoretic models of simple behavioral patterns and expenditures on goods and services. Economists often prefer revealed preference approaches because of the biases and measurement errors sometimes associated with stated preference survey designs. Though, each method has its advantages and disadvantages.<sup>32</sup>

An added complication to constructing micro-level data sets on environmental shocks is that impacts can vary greatly from place to place. What is true in one area may not be true in another area. Socioeconomics, preexisting environmental quality and access to nature, and even differences in cultural heritages and community identity may create heterogeneous health and behavioral impacts associated with a shock, as was demonstrated for the case of EAB in chapter 3. One limitation of the approach taken in chapter 3 was that the modeled relationship between trees and health was at the county level. There is likely significant spatial heterogeneity within any given county due to micro-level differences in land use patterns and socioeconomic levels, among other things. Using a geographic information system (GIS) would enable higher resolution estimates of impacts to be ascertained. US Census data could be used to narrow down demographic and socioeconomic data to Census tracts or neighborhood blocks. Then, this information could be merged with high resolution remotely-sensed data on land use and environmental quality. Doing this annually would produce a time series GIS that could be used to investigate more sophisticated relationships between forests, health, and behavior.

This is the idea of linking “one tree to one person” or more accurately, a small set of trees in public places and open spaces to a small set of people. Least squares or maximum likelihood spatial regression techniques could be used, enabling researchers to

better understand the micro-level influences that trees (and nature more generally) have on health and behavior. One could imagine this information being visually compiled into a sort of environmental shock “heat map,” illustrating the ripple-effects on neighborhoods and communities associated with some disruption to environmental quality. This would provide insight into how variations in neighborhood characteristics correlate with shock event intensity, providing environmental managers with critical information on where disruptions are the most impactful and hence where limited control resources might be targeted; ultimately addressing the question of when and where health and behavior effects should be included in planning decisions.

Future research should also address non-forest amenities and other shocks to the natural environment unrelated to trees and forests. Another limitation of this research was that it focused only on forests and trees, when, for example, appreciable shocks to environmental quality are also created by nighttime outdoor lighting, extreme weather events, the construction or expansion of highways, droughts, and fires. What are the health and behavioral impacts associated changes in the provision of these amenities? How do impacts vary across time and space? As more and more of these analyses are performed, it is also important to begin comparing impacts across different types of shocks (i.e., meta-analyses) to develop a better understanding of underlying causal pathways. Investigations across regions and states would also be useful, especially comparisons across areas dominated by public lands (the western US) to areas dominated by private lands (the Northeast).

## **5.2 Environmental health policy perspectives**

Finally, it has been stated in several of the previous chapters that environmental policy often ignores the link between nature and health. The crux of this research has been to demonstrate the economic significance of this link through investigations of environmental shocks. But from an environmental health policy perspective, or a health policy perspective, the relevant question becomes, then, how should the information presented here be used in the policy process?

At a general level, one conclusion from this research is that forests and trees are determinants of health. People not only coexist with trees, but appear to have their health and behavioral patterns influenced by them along several dimensions. This coupled human-natural system means that the quality of interactions people have with nature can affect their physical and mental health status. By this logic, disruptions to nature, either anthropogenic or natural in origin, have important and indirect effects. A reasonable question for the health-conscience policymaker tasked with responding to an environmental shock (e.g., floods, hurricanes, invasive species, wildfires, etc.) is how can my actions or inactions both today and in the future mitigate the harm to health and minimize behavioral disruptions created by this event? The focus here is not so much on the obvious actions such as providing basic needs, rebuilding structures, and providing financial compensation. Rather, the focus is on repairing the ties between people and nature that were damaged or possibly cut when the shock occurred.

The notion of forests as a determinant of health means that health policy should broaden to include forest health and access to forests and trees in communities. At the simplest of levels, one could imagine a physician writing a prescription for “walks

through the park” as a treatment option. That is not exactly what is meant by broadening health policy to include forests, but gives the idea. A structural and top-down health policy approach that promotes interactions with trees, plantings of tree saplings in public areas and along roads, and maintenance of forest health in the face of diseases, fires, and invasive species is more consistent with the findings of this research. For example, a public campaign centered on increasing urban tree coverage and diversity of tree species, similar to the ongoing MillionTreesNYC (MTNYC) initiative in New York City, but with a more health-centered focus, would be a way to integrate this research into the policy process.<sup>33</sup>

Yet, it remains unclear whether it is cost effective to promote environmental health as a way to improve overall health status. Resources might be better used in more conventional schemes such as expanding insurance coverage or access to medical care. This does not deny the role that nature has in determining health nor does it preclude considerations of environmental health when setting policy. Additionally, sometimes it is not a question of diverting resources away from other health programs, but using existing resources more efficiently. For the case of EAB, using existing management resources from the US Department of Agriculture and various state agencies and universities to plant new trees may provide more benefits to society than continuing along the current path of controlling spread, in hopes that EAB can one day be eradicated.

Managers of EAB may not see what they do as health policy work, but it is in the sense that public health in part depends on whether or not EAB ever makes it to a given community. As soon as EAB is discovered in an area, the health of that community will forever be changed unless actions are taken to mitigate the impacts of lost ash. Whether

or not adding health policy to an environmental manager's list of responsibilities passes economic muster will depend on as of yet unperformed benefit-cost analyses. The argument advanced in this research is that health and behavioral impacts are relevant considerations in such policy analyses. To the degree that health dimensions of value created by forests are not reflected in health policy, and the degree to which society would benefit from a broader consideration of health, will largely determine the setting of future forest policy in ways that are consistent with managing forests for the benefit of society.



## Notes

<sup>28</sup>Ash trees in parks, along streets, or in public areas are generally assumed to be less valuable (Sydnor et al., 2007). Much of the responsibility for EAB detection and treatment rests with the individual homeowner who has ash on their property. The argument being advanced here is that the public goods nature of ash trees requires a rethinking of the obligations associated with the private property right in this setting. Actions or inactions of the property owner may be more consequential for the community, in terms of public health, than for the homeowner alone.

<sup>29</sup>In this case, the under provision of a good (trees) creates positive externalities.

<sup>30</sup>In chapters 1-3, extant literature was primarily called upon to inform the discussion of wildfire smoke health impacts (chapter 2) and was used to build a pollutant deposition model for forests (chapter 3). An original investigation into the empirical relationship between trees, health, and behavior was not performed. Given that many such studies exist for wildfire smoke and air pollutant models, the marginal contribution of an original analysis would be nil. However, little research has been performed on the time use behavioral impacts of an environmental shock: the focus of chapter 4.

<sup>31</sup>One example of where this data challenge was overcome is Isen et al. (2013). There, the authors were able to obtain access to restricted US administrative earnings data through the US Department of Treasury to study the long-term labor market effects of the Clean Air Act, which provided a shock to air quality levels in US urban areas. It is likely that future research will similarly need to rely on restricted data sets from government agencies to ensure adequate representation and a high degree of data quality.

<sup>32</sup>Stated preference surveys can suffer from biases associated with asking hypothetical questions, interviewer bias, or bias from the warm glow effect (i.e., supporting a proposal because of the moral satisfaction it gives). Revealed preference is no panacea, however, because it relies on the accuracy of the theoretical model and the explicit and implicit assumptions associated with it. If the relationship of interest is modeled incorrectly or under unrealistic assumptions, the information “revealed” to the researcher may be an inaccurate representation of preferences. Additionally, revealed preference data itself often is taken from survey samples (e.g., US Census, Current Population Survey, etc.), which are subject to the same set of biases as stated preference data.

<sup>33</sup>The MillionTreesNYC (MTNYC) initiative, started in 2007, set a goal of adding 1 million trees to New York City by 2017. As of 2015, over 800,000 new trees have been planted in NYC, and other cities across the world from London to Shanghai have started similar “million tree” projects. However, the focus of the initiative is to plant trees “in and around” city parks. A more health-centered approach would be to identify areas of the city where the marginal *health* benefit of trees is highest (e.g., areas of high traffic congestion, areas with little to no existing trees, areas with poor health outcome, etc.) and focus plantings in those areas. In terms of health policy, planting new trees in these areas would yield the greatest return on investment.

## **Appendix A**

### **Additional data descriptions and results for Chapter 2**

#### **A.1 Recent wildfire smoke epidemiology studies**

Careful review of the wildfire epidemiology literature produced a handful of concentration response (CR) function results. Table A.1 presents selected wildfire epidemiology studies with information on the study location, the health endpoints investigated and main significant results. Studies are categorized by type of particulate matter (PM) studied, either PM<sub>2.5</sub> or PM<sub>10</sub>.

While there is limited evidence linking PM<sub>2.5</sub> wildfire smoke to mortality, PM<sub>10</sub> wildfire smoke has been consistently linked to increased short-term mortality in Australia. Most studies consistently find higher morbidity rates during wildfire smoke events, with respiratory illnesses being the most common. There is a geographical bias in the literature, where North American studies focus mainly on PM<sub>2.5</sub>, while international studies use PM<sub>10</sub>.

Omitted from Table A.1 are studies that investigated the relationship between wildfire smoke and health, but did so without using direct measures of PM air quality or did not statistically estimate the relationship between PM and incidence. BenMAP-CE cannot use these non-statistical types of results, and therefore, they are not presented.

Table A.1: Selected Wildfire Smoke Epidemiology Study Results by PM Type

<i>PM<sub>2.5</sub> Studies</i>			
Study	Study Location	Health Endpoints	Main Findings
Elliott et al. (2013)	British Columbia, Canada	Pharmaceutical dispensations for salbutamol.	Increased salbutamol dispensations in fire-affected areas.
Resnick et al. (2015)	Albuquerque, New Mexico	Cardio-respiratory emergency room (ER) visits.	Increased ER visits for asthma (age 65+), cardiovascular (all ages), pulmonary disease (age 20-64), cerebrovascular disease (age 20-64) and circulatory diseases (age 65+).
Delfino et al. (2009)	Southern, California	Cardio-respiratory hospital admissions.	Increased admissions for asthma and heart failure.
Moore et al. (2006)	British Columbia, Canada	Physician visits for respiratory, cardiovascular and mental illnesses.	Increased visits for respiratory illnesses in smoke exposed areas.
<i>PM<sub>10</sub> Studies</i>			
Study	Study Location	Health Endpoints	Main Findings
Crabbe (2012)	Darwin, Australia	Respiratory and cardiovascular hospital admissions.	Increased admissions for respiratory and cardiovascular illnesses during fire season.
Henderson et al. (2011)	British Columbia, Canada	Respiratory and cardiovascular physician visits and hospital admissions.	Increased respiratory physician visits and hospital admissions.
Johnston et al. (2011)	Sydney, Australia	Mortality.	Increased short-term mortality during wildfire smoke events.
Hanigan et al. (2008)	Darwin, Australia	Cardio-respiratory hospital admissions.	Increased respiratory admissions. Higher for indigenous populations.

## A.2 Instrumental variables regression coefficient results

Full econometric results of estimating the instrumental variables model in 2.5.2 are presented in Table A.2. Robust standard errors are reported. Since *used air filter/cleaner* is endogenous in the model of health (as checked using a Hausman F-test and a Hausman chi-squared test), a two-stage probit (called a bivariate probit) is used to purge the endogeneity. *Income* is used as the relevant, yet exogenous instrument, as discussed in 2.3.2.

In Table A.2, equation 1, the first-stage equation, the probability that a respondent used an air filter or air cleaner is predicted using a multitude of independent variables, including the instrument *income*. All else equal, respondents with higher incomes are more likely to use an air filter/cleaner during a smoke event ( $p < 0.01$ ) as are respondents who smell smoke in their home ( $p < 0.1$ ). Respondents with chronic respiratory diseases ( $p < 0.01$ ) and those with symptoms of coughs ( $p < 0.01$ ) and shortness of breath ( $p < 0.05$ ) are also more likely to use an air filter/cleaner during a smoke event. Additionally, homeowners with small children under 5 years of age are more likely to use an air filter ( $p < 0.05$ ). Those respondents who are Hispanic/Latino ( $p < 0.05$ ) or have a college degree ( $p < 0.1$ ) are less likely to use an air filter/cleaner on a smoky day.

In Table A.2, equation 2, the second-stage equation, using an air filter/cleaner reduces the probability that a respondent reported having a smoke-related health effect ( $p < 0.01$ ), consistent with the theory on averting behaviors. Not surprisingly, respondents who smelled smoke at home ( $p < 0.01$ ) or have chronic respiratory disease ( $p < 0.01$ ) are more likely to have their health affected by wildfire smoke. Respondents reporting symptoms of headaches ( $p < 0.01$ ), coughs ( $p < 0.01$ ), shortness of breath ( $p < 0.01$ ),

asthma ( $p < 0.01$ ), allergies ( $p < 0.01$ ), or other symptoms ( $p < 0.05$ ) were also more likely to report having a health impact. As the number of years that a respondent lives in New Mexico increases, the likelihood of them experiencing a smoke-related health impact also increases ( $p < 0.01$ ), consistent with expectations. Finally, Hispanic/Latino respondents report fewer health impacts ( $p < 0.05$ ), all else equal. Unlike in equation 1, having a small child in the house or having a college degree has no statistical impact on the probability of reporting a smoke health effect.

Since  $\rho = 0.80$  is statistically greater than zero ( $p = 0.04$ ), the econometric model is more efficient by estimating it as a simultaneous system of two-equations than estimating two separate equations. That is, allowing cross-equation error correlation produces a more efficient model; further evidence that *used air filter/cleaner* is endogenous to the model.

Table A.2: Bivariate Probit Model Results ( $n=911$ )

Variable	Equation 1 Coefficients Pr( <i>used air filter/cleaner</i> = 1)	Equation 2 Coefficients Pr( <i>health effect</i> = 1)
Used air filter/cleaner	-	-1.16*** (0.35)
Income	0.42*** (0.13)	-
Smelled smoke in home	0.48* (0.28)	1.01*** (0.21)
Existing chronic respiratory disease	0.69*** (0.15)	1.11*** (0.14)
Headaches	0.15 (0.16)	0.44*** (0.17)
Coughs	0.41*** (0.15)	0.73*** (0.14)
Shortness of breath	0.46** (0.18)	0.51*** (0.19)
Asthma	-0.03 (0.19)	0.74*** (0.22)
Allergies	0.15 (0.15)	0.45*** (0.14)
Other symptoms	-0.07 (0.24)	0.55** (0.26)
Female	-0.04 (0.13)	0.16 (0.13)
Hispanic/Latino	-0.28** (0.14)	-0.28** (0.14)
College degree	-0.24* (0.14)	-0.10 (0.12)
Child under 5 in home	0.30** (0.12)	-0.01 (0.16)
Years in New Mexico	0.00 (0.00)	0.01*** (0.00)
Constant	-2.23*** (0.37)	-2.71*** (0.39)
<i>rho</i>	0.80	0.80
Prob <i>rho</i> > 0 (Wald test)	0.04	0.04
Log likelihood	-498.65	-498.65
Wald chi2 (28)	334.71	334.71
Prob > chi2	0.00001	0.00001
<i>N</i>	911	911

Notes: Income is the excluded instrument in equation 2. Used air filter/cleaner in equation 2 is the predicted value from equation 1. Robust standard errors in parenthesis. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

### **A.3 Wildfire smoke experience survey questions**

Researchers at the University of New Mexico developed and administered a survey questionnaire on wildfire risk and surface water supply to a sample of households in Albuquerque, NM, in September-December, 2014, as described in 2.4.2. Fielded survey questions specific to wildfire smoke are presented below. Respondents were asked to respond to questions on smelling smoke at home, behavioral changes in response to smelling smoke, and health effects of smoke exposure.



## Wildfire Smoke Experience Survey Questions

Now we'd like to ask you a little bit about your experience with wildfire and its impacts.

15. Have you ever smelled smoke and/or ash from a wildfire at your place of residence? *Check one.*

1	Yes
2	No ----> Go to Question 17

16. **If you answered Yes to Question 15**, did you change your normal routine based on smelling the smoke and/or ash? *Check one.*

1	Yes
2	No

17. Has exposure to smoke and/or ash from wildfires affected the health of anyone in your household (including you)? *Check one.*

1	Yes
2	No

18. Does anyone in your household have a chronic respiratory disease (e.g. asthma, respiratory allergies, emphysema, chronic bronchitis, chronic obstructive pulmonary disease, etc.)? *Check one.*

1	Yes
2	No

19. Does anyone in your household have a heart disease (e.g., coronary artery disease, congestive heart failure, ischemic heart disease, etc.)? *Check one.*

1	Yes
2	No

20. Which of the following actions, if any has your household taken to reduce the possibility of health effects from exposure to smoke and/or ash from previous wildfires ? *Check all that apply.*

1	Evacuated / left area affected by smoke
2	Covered face with a mask (dust, surgical, etc.)
3	Used an air filter, air cleaner, or humidifier
4	Avoided going to work
5	Removed ashes from property (yard, car, pool, etc.)
6	Stayed indoors more than usual
7	Avoided normal outdoor recreation activities / exercise
8	Other activity (please explain) _____
9	My household did not take any of the above actions --> Go to <b>Question 22</b>

21. **If you identified an action in Question 20**, how effective overall do you think the actions you identified were at reducing or eliminating the health effects from exposure to wildfire smoke and/or ash? *Circle one.*

Not at all effective	Slightly effective	Somewhat effective	Moderately effective	Highly effective
1	2	3	4	5

22. Has anyone in your household ever been admitted to a hospital or visited a doctor's office because of smoke and/or ash exposure from previous wildfires? *Check one.*

1	Yes
2	No ----> <b>Go to Question 22</b>

23. **If you answered No to Question 22**, which of the following symptoms, if any, has your household experienced due to smoke and/or ash from previous wildfires? *Check all that apply.*

1	Headaches
2	Coughs
3	Dizziness
4	Blurred vision
5	Shortness of breath
6	Asthma
7	Allergies
8	Other symptom (please explain) _____
9	My household has not experienced any of the above symptoms

## Appendix B

### Additional derivations and models for Chapter 3

#### B.1 Analytical solution to the EAB manager's problem

Equations (3.5) and (3.6) in section 3.3 are derived as follows. First, the dynamic optimization problem in equations (3.4a)-(3.4f) is solved using the current-valued Hamiltonian:

$$H^{cv} = B(v(a_n, a_{rj}, a_{ra}), h(c, w(a_n, a_{ra})), y) - c(m) - d(z) + \lambda_1 \left( (1 - \theta) \left[ r a_{rj} \left( 1 - \frac{a_{rj}}{K} \right) \right] + m \right) + \lambda_2 (\theta a_{rj} - \varphi a_{ra}) + \lambda_3 \left( (1 - \varphi) g a_n \left( 1 - \frac{a_n}{K(e(z))} \right) \right) \quad (B1.1)$$

where  $\lambda_1, \lambda_2$  and  $\lambda_3$  are costate variables. For ease of exposition, explicit time notation has been suppressed. Given unique and interior optimal trajectories for choice variables  $m$  and  $z$ , the first order conditions are characterized by the maximum principle (Pontryagin, 1987):

$$\frac{\partial H^{cv}}{\partial m} = 0 \rightarrow \lambda_1 = c'(m) \quad (B1.2)$$

$$\frac{\partial H^{cv}}{\partial z} = 0 \rightarrow \lambda_3 = \frac{d'(z) K(e(z))^2}{(1 - \varphi) g a_n^2 K' e'} \quad (B1.3)$$

$$\frac{\partial H^{cv}}{\partial a_{rj}} = -\dot{\lambda}_1 + \delta \lambda_1 \rightarrow \dot{\lambda}_1 = \lambda_1 \left( \delta - r(1 - \theta) + \frac{2r(1 - \theta)a_{rj}}{K} \right) - B_v v_{a_{rj}} - \lambda_2 \theta \quad (B1.4)$$

$$\frac{\partial H^{cv}}{\partial a_{ra}} = -\dot{\lambda}_2 + \delta \lambda_2 \rightarrow \dot{\lambda}_2 = \lambda_2 (\delta + \varphi) - B_v v_{a_{ra}} - h_w w_{a_{ra}} \quad (B1.5)$$

$$\frac{\partial H^{cv}}{\partial a_n} = -\dot{\lambda}_3 + \delta \lambda_3 \rightarrow \dot{\lambda}_3 = \lambda_3 \left( \delta - g(1 - \varphi) + \frac{2g(1 - \varphi)a_n}{K(e(z))} \right) - B_v v_{a_n} - h_w w_{a_n} \quad (B1.6)$$

$$\frac{\partial H^{cv}}{\partial \lambda_1} = 0 \rightarrow \dot{a}_{rj} = (1 - \theta) \left[ r a_{rj} \left( 1 - \frac{a_{rj}}{K} \right) \right] + m \quad (B1.7)$$

$$\frac{\partial H^{cv}}{\partial \lambda_2} = 0 \rightarrow \dot{a}_{ra} = \theta a_{rj} - \varphi a_{ra} \quad (B1.8) \quad ; \quad \frac{\partial H^{cv}}{\partial \lambda_3} = 0 \rightarrow \dot{a}_n = (1 - \varphi) g a_n \left( 1 - \frac{a_n}{K(e(z))} \right) \quad (B1.9)$$

Solving Equation (B1.5) for  $\lambda_2$  yields the following expression:

$$\lambda_2 = \frac{1}{(\delta + \varphi)} (\dot{\lambda}_2 + B_v v_{a_{ra}} + h_w w_{a_{ra}}) \quad (B1.10)$$

which is the same as equation (3.5) in the main text. Equation (B1.10) describes the value of the costate variable or “shadow value” at any given time for adult invasive-resistant trees.

Evaluating Equation (B1.6) at steady state and substituting in Equation (B1.3) yields the following expression:

$$0 = \frac{d'(z) K(e(z))^2}{(1 - \varphi) g a_n^2 K' e'} \left( \delta - g(1 - \varphi) + \frac{2g(1 - \varphi) a_n}{K(e(z))} \right) - B_v v_{a_n} - h_w w_{a_n} \quad (B1.11)$$

Algebraic manipulation yields the following:

$$\frac{B_v v_{a_n} + h_w w_{a_n}}{\left( \frac{K(e(z))^2}{(1 - \varphi) g a_n^2 K' e'} \right) \left( \delta - g(1 - \varphi) + \frac{2g(1 - \varphi) a_n}{K(e(z))} \right)} = d'(z) \quad (B1.12)$$

which is equivalent to equation (3.6) in the main text. The RHS term in Equation (B1.12) is the marginal cost of chemical and biological treatments, which equals the marginal benefit of treatment (the LHS term) at steady state.

## B.2 Exogenous model of EAB growth

The exogenous model of EAB growth used in 3.3.1 is described here. EAB,  $e$ , grow at rate  $r_e$  according to a logistic growth function with carrying capacity  $K_e$ :

$$\dot{e} = r_e e \left(1 - \frac{e}{K_e}\right) \quad (B2.1)$$

In the numerical simulations,  $r_e$  is calculated based on a female EAB being able to produce 60-90 eggs annually (Poland & McCullough, 2006). Conservatively, 60 eggs with an 89% survival rate means that an adult EAB can reproduce about 26.7 larvae annually (BenDor et al., 2006), yielding a growth rate of 3.28.

EAB carrying capacity is calculated as  $K_e = 300K$  based on BenDor et al. (2006) who reported a bark area carrying capacity of 300 EAB/ $m^2$  ba and  $K$  is the ash carrying capacity ( $m^2$  ba/ac). In the base simulations,  $K = 4000 m^2$  ba/ac, or  $K_e = 1,200,000$  EAB/acre.

One EAB is introduced into the system in the second time period;  $e(1) = 1$ . In subsequent periods, stock of EAB is governed by the growth function in equation (B2.1).

A +/- 10% sensitivity analysis was performed on all parameters in the EAB growth model. Results were insensitive to this analysis, changing by 10% or less.

## **Appendix C**

### **Additional data descriptions for Chapter 4**

#### **C.1 Construction of original dataset**

Annual ATUS data for 2003 through 2013 were assembled using the ATUS-X extract builder at [www.atusdata.org](http://www.atusdata.org). To ascertain respondent county of residence, we merged ATUS data with CPS basic monthly files from NBER at [http://www.nber.org/data/cps\\_basic.html](http://www.nber.org/data/cps_basic.html). The respondent's county of residence for month-in-sample 8 (MIS-8) was merged with ATUS data using individual and household identifying keys. Links were checked using sex, race, and age to verify accurate merging. County FIPS codes were reported for individuals residing in counties with populations greater than 100,000. Date of initial county EAB detections that we obtained from the USDA APHIS over 2003 to 2013 was then merged. Finally, using county FIPS, we merged data on daily weather, annual forest cover, daily air quality (AQI), and annual macroeconomic conditions. Table C.1 summarizes how observations were lost during the data merging process.

In Table C.1, we started with 148,345 individual observations on time use patterns over a single 24h period. After merging observations with county of residence, 65,629 observations remain (44.2% match rate). Observations were lost because the respondent lived in a county with less than 100,000 residents. Of these respondents, 16,600 live in a county where EAB was detected at some point between 2003 and 2013 (25.3% match rate). Observed daily weather data was unavailable for 870 respondents on their diary day. In all cases, this was due to downed or not reporting weather stations in

the respondent's county. This leaves us with 15,730 observations where daily weather could be ascertained (94.8% match rate). County forest cover, AQI, and macroeconomic conditions were merged for 15,730 observations (100% match rate). Finally, we dropped respondents who had missing or "not in universe" (NIU) ATUS observations for any of the confounding variables investigated. NIU observations reflect errors in the original data (e.g., a respondent answer a question they were not supposed to answer). The bulk of the missing or NIU observations (83.7%) were for family income and school enrollment status. Since both these variables are arguably strong determinants of time use habits, we felt that their inclusion in the final models was important to avoid omitted variable bias. We considered using other income measures (e.g., weekly earnings, hourly wage rate), but found even more of these observations were NIU compared to family income. After dropping missing and NIU ATUS observations, 6,913 useable observations remained in the final dataset.



Table C.1: Total Observations after Data Merging

Year	ATUS Obs.	Matched to County	Matched to EAB Detection	Matched to Weather	Matched to forest cover, AQI, macroeconomic conditions	After Dropping Missing or NIU ATUS Obs.
2003	20,720	8446	1979	1914	1914	800
2004	13,973	5771	1469	1434	1434	571
2005	13,038	5434	1429	1380	1380	635
2006	12,943	5889	1519	1408	1408	622
2007	12,248	5583	1416	1325	1325	613
2008	12,723	5789	1458	1365	1365	576
2009	13,133	6016	1591	1499	1499	637
2010	13,260	6050	1543	1460	1460	664
2011	12,479	5749	1473	1391	1391	638
2012	12,443	5660	1390	1307	1307	599
2013	11,385	5242	1333	1247	1247	558
<b>Total</b>	148,345	65,629	16,600	15,730	15,730	6,913

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