Essays on Environmental Economics with a Focus on Non-Market Valuation

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ABSTRACT

This dissertation consists of two research projects in the area of Environmental Economics: water-recycling technology adoption and its cost-effectiveness in the U.S. horticulture industry (in Chapter 2), and urban tree cover's impact on residential location decision making in Milwaukee, WI (in Chapter 3).

Chapter 2 evaluates the economic effects of labeling plants grown with water-recycling technology (WRT) practices in selected nursery operations in the Mid-Atlantic region of Virginia, Maryland and Pennsylvania. Partial budgeting, whole enterprise-level budgeting, sensitivity and break-even analyses are conducted to determine whether consumer premiums for plants grown with recycled water are sufficient to make WRT economically feasible combined with plant eco-labeling, and how such a labeling program would affect greenhouse/nursery production costs, gross revenues and net revenues. It is concluded that consumer premiums for plants grown with recycled water could offer nursery growers a method to improve their net returns while reducing pollution runoff and improving irrigation water usage efficiency.

Chapter 3 focuses on non-market valuation of environmental (dis)amenities. Specifically, this chapter investigates the impact of urban tree cover on residential property location decision in the housing market of Milwaukee, WI. Residential sorting model embedded with "horizontal preference structure" is established to estimate the heterogeneous preferences for tree cover and other land cover attributes that vary by household socio-economic characteristics and then to identify the housing property owners' demand for these land cover attributes. The first part of this chapter mainly recovers the demand for "community trees" at the census block group level combined with 10 years property transaction data and neighborhood characteristics where the median income is aggregated to represent the household annual income. It is found that "community trees" are positively valued by the housing property owners and have a positive impact on housing price due to its positive externalities. Furthermore, income is found to be a strong exogenous demand shifter, leading to heterogeneous preference for the tree cover.

The second part of Chapter 3 further investigates the impacts of both nearby trees and distant trees on residential property location decision using different spatial scales of land covers measurements. Instead of aggregating block group level median income, this study matches and merges disaggregated individual household annual incomes from the Home Mortgage Disclosure Act (HMDA) dataset to mitigate the potential aggregation bias. It is found that different spatial scales of land cover measurement result in varying willingness to pay estimates, implying that housing property owners have heterogeneous demands for nearby trees and distant trees. In other words, preferences for urban tree cover not only vary by household annual income, but also differ across spatial scales of the tree cover measurement.

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GENERAL AUDIENCE ABSTRACT

This dissertation contains two research projects related to researches on environmental economics. Chapter 2 talks about how adoption of water-recycling technology affects nursery growers' finance (i.e., production cost, gross revenue, profit) and operation management in Mid-Atlantic region of Virginia, Maryland and Pennsylvania. It is found that consumers are willing to pay more money for horticultural plants produced with recycled water and these additional moneys would be sufficient for the growers to compensate the extra costs after adopting the water-recycling technology in the production. This study helps nursery growers and policy makers assess WRT adoption to improve crop water productivity and to reduce pollution of off-site surface waters.

Chapter 3 discusses the impact of urban tree cover on housing price in the area of Milwaukee, WI. It is assumed that households with different socio-economic characteristics (e.g., household annual income) would have varying preferences for tree cover and other key characteristics when they make decisions on choosing their residential property locations. The first part of this chapter mainly focuses on "community trees", namely the trees and forest within given census block groups. The second part of this chapter further takes nearby trees into consideration besides the distant trees so as to determine how trees on/near the residential properties affect the housing prices and whether the housing property owners prefer more trees on/near their properties. It is found that urban tree cover is valued by housing property owners and households with different income levels have diverse preferences for both nearby and distant trees. The research presented in this chapter not only makes academic contributions to the literatures of residential sorting model related to landscape (dis)amenities, but also facilitates the policy making of local governments and practitioners when it comes to urban and community trees and forestry programs.

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TABLE OF CONTENTS

page

LIST OF TABLES

LIST OF FIGURES

Figure page

CHAPTER 1
Introduction

This dissertation consists of two research projects in the area of Environmental Economics. Despite different topics and methods, the two studies in Chapters 2 and 3 aim to understand and explore human behavior in some specific circumstances related to environment. Specifically, Chapter 2 evaluates the financial feasibility and cost-effectiveness of labeling plants grown with water-recycling technology (WRT) practices in selected nursery operations in the Mid-Atlantic region of Virginia, Maryland and Pennsylvania. Chapter 3 has two parts: 1) examines the demand of housing property owners in the Milwaukee area for "community trees" at the census block group level with consideration of heterogeneous preference based on household demographic characteristics; 2) further recovers the demand for nearby trees and distant trees measured at different special scales rather than "community trees" at census block group level.

Chapter 2 analyzes the economic effects of labeling plants grown with water-recycling technology (WRT) in selected nursery operations in the Mid-Atlantic region of Virginia (VA), Maryland (MD) and Pennsylvania (PA). The U.S. nursery and greenhouse industry are facing twin challenges of reduced water availability and increased pressure to mitigate pollution from horticultural production. WRT has been adopted by some nursery producers to improve crop water productivity and to enhance water supply security. The economic feasibility of WRT adoption if producers received some portion of retail price premiums for eco-labeled products is evaluated in this study. Three annual bedding plants, Geraniums (*Pelargonium spp.*), Petunias (*Petunia spp.*), and Chrysanthemums (*Chrysanthemum spp.*) and three broadleaf evergreen plants, Azaleas (*Rhododendron spp.*), Holly (*Ilex spp.*) and Boxwood (*Buxus spp.*) are analyzed based on their sales in the study region of Virginia, Maryland and Pennsylvania. Of the eight case study nurseries and two synthesized nurseries examined, five showed increased net costs with recycling. However, in almost all cases for which at least a portion of a retail consumer premium was returned to growers, the premium was adequate to compensate for recycling investment costs. This study helps nursery growers and policy makers assess WRT adoption to improve crop water productivity and to reduce pollution of off-site surface waters.

Chapter 3 first establishes a horizontal residential sorting model to analyze how tree cover and other land cover attributes affect residential property value and to estimate households' heterogeneous preferences for tree cover that vary by their observable demographic characteristics. The spatial scale of tree cover measurement in this study is at the census block group level, representing the "community trees". A comprehensive micro-level dataset is formed including 10 years property transaction data with structural attributes, census block group level land cover attributes and neighborhood characteristics. In addition, median income from the 2010 Census is aggregated to represent the household annual income. The results show that "community trees" are valued by the housing property owners and have positive impact on housing price due to its positive externality. Furthermore, income is found to be a strong exogenous demand shifter, leading to heterogeneous preferences for tree cover.

In addition, the second part of Chapter 3 presents an extended research on the basis of the residential sorting model established in first part to further investigate the demand for both nearby trees and distant trees through incorporating different spatial scales of land cover measurements. Instead of using block group level land cover attributes, this study recalculates the tree cover within three buffer rings in order to capture the effects of tree cover at varying spatial scales. Besides, this study also incorporates disaggregated individual household annual income matched and merged from the Home Mortgage Disclosure Act (HMDA) dataset to mitigate the potential aggregation bias resulted from block group level median income data. It is found that housing property owners have varying preferences and willingness to pay for tree cover in response to different spatial scales, indicating that the demands for nearby trees and distant trees are heterogeneous after controlling household annual income.

Traditional hedonic price model has identification and endogeneity issues to recover the demand curve and the demand analysis on tree cover is limited. Chapter 3 establishes the residential sorting model to successfully elicit the demand for tree cover, offering new evidence in the regime of demand analysis on environmental (dis)amenities and adding new empirical literatures on residential sorting model in terms of landscape (dis)amenity. Through providing comprehensive information of the demand for land cover characteristics with a focus on tree cover, Chapter 3 offers suggestions on land use management and land cover policy (e.g., urban and community forestry program) in its design and implementation. In terms of methodology, Chapter

3 provides an opportunity to compare residential sorting model and second-stage hedonic demand analysis in respect of underlying theory, MWTP estimates and performance of policy evaluation.

CHAPTER 2

Recycling Irrigation Water on Ornamental Nursery Operations: Could Consumer Premiums Compensate for Grower Adoption Costs?

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2.1 Introduction

Productivity of irrigation water use and contaminant runoff control are becoming increasingly important to nursery and greenhouse growers as well as to policy makers and the public. Increased attention to minimizing total applications of water to obtain a healthy plant (water use productivity) is prompted by water scarcity in U.S. regions such as the West as well as by environmental concerns about agricultural runoff. Concern for water quality in the Chesapeake Bay and its tributaries led the U.S. Environmental Protection Agency (U.S. Environmental Protection Agency, 2010) to issue a Total Maximum Daily Load (TMDL) plan for reducing nitrogen, phosphorus and sediment runoff in the Chesapeake Bay watershed. Under increasing pressure to adopt solutions to address regulatory and drought concerns, some nurseries have adopted water-recycling technology (WRT), which involves capturing and recycling irrigation water to improve crop water productivity and to enhance water supply security while reducing contaminants lost from nursery and greenhouse production sites. It is estimated that a 0.4 ha (one-acre) greenhouse producing ornamental crops requires approximately 83,270 liters (22,000 gallons) daily for irrigation, and container nursery operations may require up to 102,195 liters (27,000 gallons) daily (Bailey, Bilderback, & Bir, 1999; Robbins, 2010). With WRT, it is estimated that 40-50% of water applied could be conserved through recapture and re-use of both irrigation water and any storm water run-off (Wilson & von Broembsen, 2015), thus increasing security of water supplies and reducing pollutant loads to nearby surface waters. Ferraro, Bosch, Pease, and Owen (2017) provided detailed analysis of recycling requirements and costs for Virginia, Maryland and Pennsylvania nurseries.

Long term access to secure irrigation water supply is of critical importance to nursery growers. WRT also can potentially provide social benefits by reducing discharge to streams and rivers of polluted water from horticultural operations. In some cases, the increased risk of water-borne plant pathogens spreading through recycled water has impeded WRT adoption and associated social benefits from reduced water pollution (Hong & Moorman, 2005; von Broembsen, 1998). In addition, the concern about production cost increases associated with WRT and the uncertainty of revenue enhancement discourage many growers from implementing the new technology (Cultice, Bosch, Pease, Boyle, & Xu, 2016).

Many retail customers of horticultural products are concerned about environmental degradation and are now more aware of environmental aspects of production. Previous research has indicated that consumers are willing to pay premiums for plants produced and labeled as "environmentally friendly" or "eco-friendly" (Behe et al., 2014; Gardner, Eastwood, Brooker, Riley, & Klingeman, 2002; Michaud, Llerena, & Joly, 2012; Yue et al., 2010). Plants grown with WRT qualify for such a designation because WRT reduces discharge of polluted water. For example, consumers are willing to pay more for "eco-labelled" roses certifying eco-friendly cultivation practices (Michaud et al., 2012). Eco-labeling of environmentally friendly or "green" products has gained interest because environmental practices are highlighted (e.g., utilizing recycled water). Consumers receive more information about the product, and new market opportunities and potential higher profits may be generated. In addition, contract farming has become more common in the U.S. horticulture industry (MacDonald, 2015). Contracting producers and wholesale purchasers such as landscapers or retailers such as "big-box" stores should share price premiums obtained from consumers with contracting producers as financial incentives to promote adoption of conservation practices like WRT. Little research has been conducted as to how such price premiums might be transmitted through stages of the distribution system from consumers back to growers, or how such premiums relate to costs incurred by growers to produce such eco-labeled attributes. In this case, nursery growers find it hard to obtain useful economic information about the profit potential of WRT and its anticipated effect on their business' long-term bottom line.

Will consumer premiums for plants grown with recycled water be sufficient to make WRT economically practical? This analysis evaluates the economic effects of labeling plants grown with WRT in selected nursery operations in the Mid-Atlantic region of Virginia (VA), Maryland (MD) and Pennsylvania (PA). The goal is to estimate the economic feasibility of WRT production practices, which include capturing and recycling rainfall and irrigation runoff, combined with plant eco-labeling, and to determine how such a program would affect greenhouse/nursery production costs, gross revenues and net revenues. Research results can help nursery growers and policy makers assess WRT adoption to improve crop water productivity and to reduce pollution of off-site surface waters.

2.2 Literature Review

Driven by increased awareness of the need for environmental protection, green products have become more popular among consumers in both food and non-food marketing systems. A so-called "green" product usually refers to a product produced with methods that improve environmental quality or reduce environmental pollution compared to an equivalent product produced with conventional practices (Durif, Boivin, & Julien, 2010). For example, plants grown with WRT could be considered "green" because recycling water may reduce discharge of polluted water to rivers and streams. Schlegelmilch, Bohlen, and Diamantopoulos (1996) illustrated that consumer environmental consciousness has positive effects on their purchasing decisions for green products. Laroche, Bergeron, and Barbaro-Forleo (2001) investigated the profile of consumers willing to pay more for green products generally including their demographics, attitudes toward environmentally friendly programs, daily behavior and personal values. They found this segment of consumers was more likely to be female, married and with at least one child living at home.

Horticultural products provide both private and public benefits for consumers. Private product benefits are limited to the buyer, while public benefits are available to the buyer as well as others. For example, if a horticultural product is produced in a manner that reduces or eliminates pollutants, the product presents a public benefit. Consumers cannot readily evaluate some public benefits such as reduced pollution unless these attributes are communicated via product labeling. Research has found that consumers prefer and are willing to pay a price premium for horticultural products that promise environmental benefits (Behe et al., 2013; Behe et al., 2014; Gardner et al., 2002; Hartter, 2012; Khachatryan et al., 2014; Michaud et al., 2012; Yue et al., 2016; Yue et al., 2010). Gardner et al. (2002) used the contingent valuation method to estimate that consumers were willing to pay a retail premium of as much as $13.35 for a flowering dogwood tree labeled as "resistant to powdery mildew". Using hypothetical conjoint analysis and non-hypothetical experimental auctions, Yue et al. (2010) found that consumers were willing to pay premiums for plants grown in biodegradable versus plastic containers. Michaud et al. (2012) found that consumers were willing to pay an average premium of €1.91 ($2.56) per stem for roses with an eco-label and an average premium of €2.51 ($3.36) per stem for roses claiming a carbon footprint reduction. Hartter (2012) conducted a choice experiment to estimate the premiums that consumers would be willing to pay for ornamental plants produced with water recycling technology and labeled as "water conservation". The author found that, on average, retail consumers were willing to pay 9%-36% more than the average retail price for Geranium, Petunia, Chrysanthemum, Azalea, Holly and Boxwood. Behe et al. (2013) profiled nine consumer segments in terms of their preferences for local and sustainably grown plant products.

More recently, a subsequent paper by Behe et al. (2014) used eye-tracking technology to categorize three plant consumer groups as plant-oriented, production method-oriented and price-oriented. The authors found that regardless of their groups, all consumers preferred ornamental plants labeled "grown using water-saving practices" over other production labels such as "grown using energy-saving practices", "grown using sustainable practices" and "grown using conventional practices". The results also indicated that 11% of the respondents were production method oriented among which water-saving label increased their Likert willingness to pay (WTP) scale by approximately 6.5%. Khachatryan et al. (2014) performed a mixed-logit model to estimate consumers' premiums for environmental attributes of horticulture plants, finding that individuals were willing to pay a premium for energy-saving production practices ($0.13), non-plastic containers such as compostable ($0.23), plantable ($0.12), and recyclable ($0.16), and locally grown plants ($0.22). Yue et al. (2016) investigated the U.S. consumers' WTP for sustainable attributes in plants via experimental auctions. The results showed that consumers were willing to pay a price premium for energy and water savings in plant production of $0.15 and $0.12 per unit, respectively, and the WTP for products labeled "sustainable" was estimated at $0.08 per unit. These previous studies indicate that consumers are willing to pay premiums for the underlying environmental attributes of a product that promises societal benefits.

However, product labels do not completely define a product, especially in terms of environmental attributes. Usually, certifications conveyed to consumers by product labeling confirm environmental attributes. Previous research has found that consumers prefer to pay more for certified versus uncertified products, and that they generally prefer third party certification to first party or "self-certification" (Aguilar & Vlosky, 2007; Curtis & Cowee, 2010; Hartter, 2012; Michaud et al., 2012). Hartter (2012) assumed three categories of third-party certification authorities for water conservation including governmental organizations, industry organizations and non-governmental organizations (NGO). Specifically, the USDA represented the governmental organization; the American Nursery Association (ANA) (a fictitious certifying authority) represented an industry-backed agency; and Water for Tomorrow and Plant Society of America represented a fictitious NGO for water conservation certification. The estimation results indicate that consumers have varying preferences and WTPs for plants certified by different authorities.

On the producer side of markets, studies of WRT adoption by horticultural growers are limited. Cultice (2013) conducted a mail survey of Mid-Atlantic irrigated nursery producers to determine irrigation practices and used a conditional logit model to estimate the impacts of disease probability, drought probability and water-recycling cost on producers' WTP to adopt water-recycling techniques and practices. Of 260 irrigated nurseries, 55% reported that they did not capture any irrigation runoff, and only 14% captured all irrigation runoff (Cultice et al., 2016). Only 6 irrigated nurseries (2.3%) sourced all their irrigation water from captured runoff. Recycling cost was the most important deterrent factor to grower adoption of water recycling (Cultice et al., 2016). Dennis et al. (2010) surveyed greenhouse and nursery crop growers nationally regarding their sustainable practices including water recycling and other water conservation measures. The authors found that 26% of their respondents had already adopted water recycling practices, with only 4% considering future implementation of WRT. DeVincentis, Brumfield, Gottlieb, and Johnson (2015) conducted cost and benefit partial budgeting analysis of various disinfection techniques for recycled irrigation water in southern New Jersey. Disinfection methods included ultraviolet-lights, chlorinators, flooders and drippers. The study calculated the net present value (NPV) of each disinfection technique based on site visits to five nurseries. The results indicated there was a positive correlation between system costs and the complexity of the water disinfection method. All the case nurseries had positive NPVs indicating profitable investments. Most recently, Ferraro et al. (2017) used partial budgets to estimate and compare the annual costs of recapturing and recycling irrigation water versus extraction costs from wells or municipal water supply sources. They found that six of eight case nurseries (all of whom had already adopted some WRT practices) had lower production costs from capturing and recycling on 75% of their production areas compared to using well or municipal water.

2.3 Materials and Methods

In this study, budgets from Ferraro et al. (2017) provide the basis for assessing producer costs of capturing and recycling. Calibrated consumer premium results are taken from Hartter (2012) as the prices that consumers would be willing to pay for plants grown with WRT. These premiums allow us to compare non-water-recycling practices (e.g. grower net returns sourcing irrigation water from municipal or private well sources) versus returns from WRT. With adoption of WRT, changes in production costs including water-supply cost, labeling cost and certification cost are compared with benefits from price premiums for plants labeled as "irrigation water recycled", and varying proportions are assumed to be returned to growers as compensation for the WRT investment. Hinson, Paudel, and Velástegui (2012) studied market channels of ornamental plant industry and concluded that mass merchandisers have sufficient market power to affect grower prices and profitability. Retailers (e.g., "big-box" stores) could use their market power to mandate grower WRT practices while retaining some of or the entire premium for themselves. We reflect this uncertainty by varying the proportion of the premium returned to the grower (R) as was done by White, Brady, Capper, and Johnson (2014) in a study of consumer premiums for sustainable beef production practices.

We conducted the study with eight case nurseries varying in terms of size, location, and water supply method. The eight case nurseries include three in Virginia (VA-1, VA-2, and VA-3), three in Maryland (MD-1, MD-2, and MD-3) and two in Pennsylvania (PA-1 and PA-2), as shown in Figure 2.1. All eight operations are adopters of WRT since they capture rainfall and irrigation runoff in collection basins and then recycle the water to supplement water supply in addition to using municipal city water or well water. Nurseries VA-2, VA-3, MD-2, MD-3 and PA-2 obtain 100% of their irrigation water from recycling, and VA-1, MD-1 and PA-1 obtain 34%, 50% and 20%, respectively, from recycling. In addition, two simulated nurseries (SynSmall and SynLarge) representing mean characteristics and practices in terms of water source, grower size and water usage are constructed based on survey responses of irrigated Mid-Atlantic ornamental nurseries by Cultice et al. (2016). SynSmall represents small nurseries with gross revenues of $500,000 or less, while SynLarge represents large nurseries with gross revenues greater than $500,000. Most surveyed nurseries did not capture irrigation runoff or rainfall from any portion of their production area (Cultice, 2013), therefore the most common alternative to WRT (well water) is assumed as the main irrigation water source for the simulated nurseries. Furthermore, we assumed the two simulated nurseries to be located in Maryland, where regulations for well drilling are the most restrictive and expensive. This provides the most favorable case for adoption of WRT (Maryland Department of the Environment, 2015). Table 2.1 indicates the general characteristics of case study nurseries with regard to size, location and current water supply method.

According to the 2014 Census of Horticultural Specialties (Table 2.2), Geraniums (*Pelargonium* spp.), Petunias (*Petunia* spp.) and Chrysanthemums (*Chrysanthemum* spp.) rank among the top 5 annual plants sold in Virginia, Maryland and Pennsylvania. Azaleas (*Rhododendron* spp.), Holly (*Ilex* spp.) and Boxwood (*Buxus* spp.) are among the top 5 broadleaf evergreen plants sold in the three states. Due to their popularity and to be consistent with premiums estimated by Hartter (2012), this analysis uses these six plants for investigating impacts of WRT adoption and consumer premiums on sales.

This study estimates enterprise level costs and returns from WRT for each of the six plants assuming that the ten case nurseries produce only these plants. Similar to Hartter (2012), we assume that Geraniums are sold in 10.2 centimeter (4-inch) or .47 liter (0.125 gallon) pots, that Petunias are sold in 6-packs, and that Chrysanthemums are sold in 3.8 liter (1-gallon) pots. Azaleas and Boxwoods are sold in 3.8-liter pots with plant heights ranging from 30.5 to 38.1 centimeters (12 to 15 inches), and Hollies are sold in 7.6 liter (2 gallon) pots with plant heights ranging from 38.1 to 45.7 centimeters (15 to 18 inches).

Because of varying container sizes, the normal production per hectare (without disease losses) differs by plant species. Approximately 49,421-54,363 containers 3.8 liter (1-gallon) in size will cover one hectare of production area (Halcomb & Fare, 2009). For Geraniums planted in 10.2-centimeter (4-inch) pots, potential production is about 415,136 pots per hectare. For Petunias planted in a 6-pack, potential production per hectare is 69,189 six-packs. For Chrysanthemum, Azalea and Boxwood planted in 3.8-liter pots, one hectare can produce approximately 51,892 pots. For Holly planted in 7.6-liter pots, one hectare can produce nearly 25,946 pots. In the Mid-Atlantic region, commercial nurseries generally produce only one cycle of these plants per year.

The possibility of increased plant death rates with WRT must be considered. Hong and Moorman (2005) found that risk is increased as water-borne pathogens such as *Pythium* and *Phytophthora* will re-inoculate with recycled irrigation water and runoff collected from nursery production areas. To mitigate such risks, growers typically treat recycled irrigation water with sterilizers such as liquid or gas chlorination systems. In the survey conducted by Cultice (2013), the average proportion of nursery revenue loss in sales from all types of plant disease (i.e., plant death rate) for both non-water recyclers and water recyclers was reported. On average, plant death rates for non-adopters and adopters of WRT were estimated at 2% and 3%, respectively. Based on the mean survey responses, this analysis assumes that plant death rate will increase to 3% due to diseases caused by water-borne pathogens after adoption of WRT compared to 2% for non-adoption of WRT. Thus, for the case nurseries and the two hypothetical nurseries, the reduced production per hectare resulting from converting to recycling for each of the six plants is assumed the same, which can be expressed as:

$$\Delta Y_i = Y_i \cdot (-1\%) \tag{2.1}$$

where Y_i is normal production cost per hectare of the six plants without disease losses as stated above and -1% indicates the reduction in yield resulting from a switch to WRT. Because the yield losses lead to growers' sales losses, the opportunity cost of yield loss resulting from adoption of WRT for plant type i can be expressed as:

$$OP_i = -\Delta Y_i \cdot P_i^w \tag{2.2}$$

where P_i^w is the wholesale price accepted by growers of plant i.

The change in production cost resulting from water recycling for plant i, ΔPC_i, is

$$\Delta PC_i = \Delta WSC_i + \Delta LC_i + \Delta CC_i \tag{2.3}$$

where ΔWSC_i is water supply cost change, ΔLC_i is labeling cost change and ΔCC_i is certification cost change. Water supply cost change results from the change in cost of delivering irrigation water to the crop as a result of switching to WRT. Labeling cost change accounts for a change in cost of labeling individual pots resulting from yield changes. Certification cost change accounts for the cost of hiring a third-party contractor to certify that advertised plants receive water from WRT practices. These costs are described below.

Ferraro et al. (2017) used partial budgets to evaluate water supply cost changes from adoption of recycling for the case nurseries. They analyzed differences in practices and associated costs for recycling in comparison with the next best option (well water or municipal water). Capital costs for both conventional water supply (well or municipal source) and WRT were amortized on an annual basis; thus ΔWSC_i refers to annual water-supply cost change. Partial budget results in 2014 dollars from Ferraro et al. (2017) are presented in Table 2.3. ΔWSC_i is the difference between WRT cost and the cost of the next best alternative; thus, a negative ΔWSC_i refers to a cost advantage with WRT and vice versa. WRT costs vary among nurseries depending on physical layout, distance to water source, and other factors. Nurseries VA-1, VA-2, VA-3, MD-1, MD-2 and PA-1 have cost advantages with WRT of -$1,624/ha, -$29,910/ha, -$6,339/ha, -$813/ha, -$2,851/ha and -$343/ha, respectively. As discussed in Ferraro et al. (2017), the major factors determining cost advantage per hectare from WRT are the availability and cost of the alternative well or municipal water source and the costs of WRT investment. For example, VA-2 saves more costs with WRT than VA-1 due to much higher costs of obtaining municipal water. WRT costs are also highly variable among nurseries due to differences in the cost of digging recapture ponds, opportunity cost (forgone income) of land used for ponds, and regrading cost.

Nurseries MD-3 and PA-2 incur increased costs with WRT, estimated at $7,516/ha and $2,199/ha, respectively (Table 2.3). For the two simulated nurseries SynSmall and SynLarge, that are assumed to use well water as the main irrigation water supply, WRT increased water supply costs by an estimated $3,810/ha and $7,651/ha, respectively.

Certification is necessary to assure consumers of the attribute associated with paying a premium. However, there are no industry-wide certification systems to define production with recycled irrigation water. It is assumed that producers who wish to increase net returns with recycling would contract a qualified and respected third party to certify that their operation practices and nursery products accord with specific standards of WRT. Such standards would specify minimum requirements as to how water is recycled to ensure that the environmental benefits of recycling are achieved. After certification, producers are authorized to label plants as "produced with recycled water," whereby consumers can acquire environmental information that may influence their preferences and WTP for horticultural products.

Labeling cost and certification costs also relate to the documentation of cost changes in water-supply practices resulting from recycling. Based on information provided by the owners and managers of the case nurseries during on-site interviews, the unit labeling cost is approximately \$0.10/pot. Thus, a labeling cost change is:

$$\Delta LC_i = 0.1 \cdot \Delta Y_i \tag{2.4}$$

where ΔLC_i is the labeling cost change, and ΔY_i is the net negative change of normal production per hectare for recyclers specified in equation 2.1 above. The labeling cost associated with WRT in 2.4 is negative due to the yield loss from increased plant death rate.

The example cost data for certification is developed from the "Sustainability Standard for Nursery and Greenhouse Operations" operated by Food Alliance, a nonprofit organization that has certified over 330 farms, ranches, and food processors in Canada, Mexico, and 23 U.S. states for good environmental stewardship. Although the organization does not have an independent certification program focusing on water recycling for the nursery industry, the sustainability standard does contain specific criteria for water conservation and recycled water quality in nursery operations. The Food Alliance publishes detailed certification costs on its website that are used in this analysis. The certification costs consist of an inspection fee and a license fee. The inspection fee includes a non-refundable \$350 document processing charge and a \$400 deposit towards the actual cost of inspection. According to Food Alliance, in most cases, the average inspection fee is between \$900 to \$1,500. Since Food Alliance certification is valid for 3 years, the average annual inspection fee ranges from \$300 to \$500 per year. In addition, nursery operations pay a variable annual license fee based on a percentage of gross annual sales (\$100 flat fee under \$100,000, 0.10% from \$100,000 to \$1,000,000 and 0.05% above \$1,000,000), with a licensing fee cap of \$5,000. For example, gross revenue for nursery MD-2 reported in the survey is \$7,000,000, thus the annual license fee would be \$3,500. After adding the maximum average annual inspection fee of \$500, the average annual certification cost would be approximately \$94/ha ($\$94/\text{ha} = [\$3{,}500 + \$500]/42.5\ \text{ha}$). Errors in estimating certification costs are unlikely to affect final results, because in three fourths of the cases (Table 2.4, Table 2.5, Table 2.6 and Table 2.7), the certification cost is three percent or less of the total production cost change.

For this analysis, it is assumed that in a typical wholesale nursery production contract, retailers offer price premiums to encourage contract growers to produce plants with WRT.

Following Cultice (2013), approximately 52% of growers are wholesalers. Thus, a conservative assumption in this analysis is that the case nurseries are wholesalers who sell all plants directly to retailers, who in turn sell to consumers and return a portion of the premium to growers. If growers were retailers, they would retain all of the premium. Equation 2.5 below clarifies how price premiums tied to WRT plants could be returned proportionally to growers and increase gross revenue.

$$\begin{aligned}\Delta GR_i &= GR_i^{WRT} - GR_i^{Non-WRT} \\ &= Y_i(100\% - 3\%)P_i^{w\prime} - Y_i(100\% - 2\%)P_i^w \\ &= .97Y_i \cdot (P_i^w + WTP \cdot R) - .98Y_iP_i^w \\ &= \Delta Y_i \cdot P_i^w + .97 \cdot Y_i \cdot WTP \cdot R \end{aligned} \tag{2.5}$$

where $P_i^{w\prime} = P_i^w + WTP \cdot R$ is the new wholesale price after adding a proportional premium (denoted as WTP), in which R is a conveyance rate indicating the fraction of the consumer premium being returned to the water-recycling nursery. After readjusting, $\Delta Y_i \cdot P_i^w$ refers to the gross revenue loss from WRT due to yield loss while $.97 \cdot Y_i \cdot WTP \cdot R$ is the increased gross revenue resulting from consumer premiums for plants grown with WRT.

Premium estimates obtained from growers by Hartter (2012) are based on survey responses to a hypothetical choice experiment. However, hypothetical responses may suffer from "hypothetical bias", i.e., overstating consumer willingness to pay compared to revealed choices of consumers with actual purchases in non-hypothetical situations (Blumenschein, Blomquist, Johannesson, Horn, & Freeman, 2007; Cummings, Harrison, & Rutström, 1995; Harrison, 2006; Harrison & Rutström, 2008; List & Gallet, 2001; Silva, Nayga Jr, Campbell, & Park, 2007; Yue et al., 2010). For example, List and Gallet (2001) summarized 29 experimental studies and concluded that respondents on average overestimated their preferences by a factor of 3 in hypothetical settings compared with actual purchases. Silva et al. (2007) found that on average, the non-hypothetical estimates of WTP estimates for different groups of novel products were from 8% to 29% lower than the hypothetical WTP estimates in two elicitation mechanisms including experimental auction and conjoint analysis. Blumenschein et al. (2007) concluded that the average WTP for a pharmacist-provided diabetes program in a real purchasing group was 50% lower than that obtained in hypothetical surveys. Yue et al. (2010) found that the mean WTP for plant containers made from rice hulls (straw) obtained from an experimental auction was 29% (39%)

lower than that obtained from a hypothetical conjoint analysis. Although Hartter (2012) applied a "cheap talk" method as suggested by Cummings and Taylor (1999) to reduce hypothetical bias and the potential for artificially high WTP estimates, premium estimates are calibrated (divided by 3) as suggested by List and Gallet (2001).

The horticultural plant price data P_i^w (wholesale) and P_i^r (retail) is obtained from the Census of Horticultural Specialties (U.S. Department of Agriculture, 2014). The calibrated (divided by 3) mean values of estimated premiums by Hartter (2012) are shown with 2014 census prices in Table 2.8 and Table 2.9 after adjustment to 2014 dollars using the Consumer Price Index (CPI) of indoor plants and flowers (U.S. Bureau of Labor Statistics, 2015).

Finally, the net revenue change from recycling (ΔNR_{i}) is the difference between gross revenue change and production cost change:

$$\Delta NR_i = \Delta GR_i - \Delta PC_i \tag{2.6}$$

where ΔGR_i is the gross revenue change calculated with equation 2.5 and ΔPC_i is the production cost change calculated with equation 2.3.

The sensitivity of gross and net revenue changes to the conveyance rate (R) is evaluated with the premium estimate fixed at its mean value. Three possible R values are selected: 0%, $\frac{P_i^w}{P_i^r}$, and 100%. Zero percent is a pessimistic value at which the grower receives nothing from the consumer premiums; $\frac{P_i^w}{P_i^r}$ is the census price ratio of wholesale price and retail price of each plant in Table 2.8 and Table 2.9; and 100% is an optimistic value at which the grower receives the complete premium. Where price ratios $\frac{P_i^w}{P_i^r}$ exceed 100%, such as Azalea in PA, Holly in MD and Boxwood in VA and MD, 100% is used. In addition, break-even analyses to balance production cost and gross revenue change associated with WRT (i.e., $\Delta NR_i = 0$) are conducted in terms of conveyance rate R, premium estimate and plant death rate.

2.4 Results

2.4.1 Production Cost Changes

Labeling cost changes, certification cost changes and production cost changes resulting from WRT are presented in Table 2.4, Table 2.5, Table 2.6 and Table 2.7. For each of the six plants, nurseries VA-1, VA-2, VA-3, MD-1, and MD-2 have lower production costs with WRT compared to well water or municipal water, as the reduced labeling cost and water supply cost more than offset the certification cost in each case. For nurseries MD-3, PA-1, and PA-2 and for the two simulated nurseries SynSmall and SynLarge, the production costs of WRT are higher than using well water or municipal water. Production costs increase for MD-3, PA-2, SynSmall, and SynLarge due to large water supply cost increases ranging from \$2,199 to \$7,651 per hectare. WRT reduces water supply costs for PA-1; however, production costs increase modestly due to the certification cost (\$988/ha/year). The high certification cost for PA-1 is mainly due to its reported high per hectare gross revenue (approximately \$241,915/ha), much higher than other nurseries.

2.4.2 Gross Revenue Changes with WRT

Table 2.10 shows the estimated changes in gross revenues by plant species with alternative conveyance rates. Y_i and ΔY_i are held constant for all nurseries, therefore changes of gross revenues resulting from different wholesale prices garnered by each nursery operation are based on its geographic location. SynSmall and SynLarge are assumed located in Maryland, so their gross revenue changes match those of Maryland case nurseries. When no premiums go back to growers (conveyance rate $R = 0\%$), all nurseries have negative gross revenue changes for each of the six plants due to the assumed increased plant death rate with WRT. When the conveyance rate is 100% (growers obtain all the premium) and when $R = \frac{P_i^w}{P_i^r}$, all ten nurseries have positive changes in gross revenue for five plants with Holly as an exception. For Holly, the nurseries in Virginia have decreased gross revenues at -\$1,098/ha when $R = \frac{P_i^w}{P_i^r}$; the nurseries in Maryland as well as the synthetic nurseries have negative gross revenue changes estimated at -\$219/ha when $R = \frac{P_i^w}{P_i^r}$ or $R = 100\%$.

2.4.3 Net Revenue Changes with WRT

After deducting production cost changes from the gross revenue changes, the net revenue changes for alternative conveyance rates are shown in Table 2.11 and Table 2.12. In the cases of Azalea in Pennsylvania, Holly in Maryland, and Boxwood in Virginia and Maryland, the wholesale price (P_i^w) is greater than the retail price (P_i^r) reported in the Census as shown in Table 2.8 and Table 2.9. In those cases, P_i^w is assumed equal to P_i^r resulting in the same gross revenue change as obtained for $R = 100\%$.

When the conveyance rate R is 0%, only nursery VA-2 has increased net revenue for all plants due to its large production cost saving from WRT that fully offsets the opportunity cost of yield loss. For nursery VA-1, only Petunia generates a positive net revenue change of $291/ha. Nursery VA-3 has increased net revenues for all plants except Geranium (-$1,034/ha) and Boxwood (-$6,561/ha), since its production cost savings for these two plants fail to cover the opportunity cost of yield loss. MD-2 has relatively small positive net revenue changes for Petunia ($1,899/ha) and Chrysanthemum ($157/ha). The remaining nurseries (MD1, MD3, PA1, PA2, SynSmall and SynLarge) have negative net revenue changes for all six plants when R is 0%.

When $R = \frac{P_i^w}{P_i^r}$, MD-3 and SynLarge have decreased net revenue for Azalea, estimated at -$1,315/ha and -$1,436/ha, respectively. VA-1, MD-3, PA-1, PA-2, SynSmall and SynLarge have negative changes for Holly, estimated at -$41/ha, -$7,765/ha, -$406/ha, -$2,021/ha, -$4,112/ha, -$7,886/ha, respectively.

Except for three cases (Holly on MD-3, SynSmall and SynLarge), all ten nurseries gain more net revenues for all plants from WRT when the conveyance rate $R = 100\%$ than well water or municipal water. Net revenues increase because the returned premiums generate larger gross revenues to offset the opportunity costs of yield losses as well as the increased production costs with WRT.

2.4.4 Break-Even Conveyance Rate R

For those nurseries that suffer from decreased net revenues associated with WRT for different plants as shown in Table 2.11 and Table 2.12, the corresponding break-even conveyance rates to balance gross revenue and production cost changes ($\Delta NR_i = 0$) are shown in Table 2.13. For example, for nursery VA-1, a small break-even conveyance rate $R = 3.0\%$ will balance the -$6,275/ha net revenue change associated with WRT for Geranium; while for nursery PA-2, a large break-even $R = 98.3\%$ offsets the -$8,327 /ha net revenue change related to WRT for Holly. With only three exceptions (Holly on nursery MD-3, SynSmall, and SynLarge), break-even conveyance rates are below 100% as shown in Table 2.13, indicating that growers could cover WRT costs with a sufficient share of consumer premiums.

2.4.5 Break-Even Premium Results

Table 2.14 shows the break-even premiums corresponding to the breakeven R shown in Table 2.13 that should be returned to growers in order to balance net revenue. Overall, with only two exceptions (Holly in nursery MD-3 and SynLarge), the break-even premiums are $0.50/pot or less for all plants and all nurseries. Specifically, the break-even premiums for the three annual bedding plants are well below $0.20/pot on average, and are more consistent with previous finding such as Yue et al. (2016), while the break-even premiums for the three broad leaf evergreen are slightly higher than previous findings.

2.4.6 Break-Even Death Rate Results

The death rate after adoption of WRT is assumed to be non-decreasing based on survey responses reported in Cultice (2013). However, pathogen mitigation practices (Hong & Moorman, 2005) might reduce plant disease incidence below the level obtained without WRT. Reducing plant disease incidence might provide another way to offset additional costs associated with WRT even without returned premiums. Table 2.15 shows the break-even death rates required to offset the added WRT production costs of nurseries MD-3, PA-1, PA-2, SynSmall and SynLarge if no premiums are assumed to be returned to producers ($R = 0\%$). These five nurseries are highlighted because they show an increase in production cost with recycling (Table 2.4, Table 2.5, Table 2.6 and Table 2.7). The results illustrate that for most cases, reducing death rates below 2%, the assumed average rate for non-recycling nurseries, can offset the additional cost incurred from conversion to WRT even without returned premiums. However, there are six exceptions (e.g., Petunia for MD-3) where the death rate would need to be reduced by more than 2% to offset increased production cost with recycling. A greater than 2% reduction leads to a physically impossible negative death rate. For these exceptions, reducing plant disease incidence fails to completely offset the added WRT production costs.

2.5 Concluding Remarks and Policy Implications

Public desire to improve water quality poses environmental challenges for the horticulture industry as demonstrated by policies that require conservation measures. The nursery industry continues to face challenges of reduced product sales resulting from the downturn in the housing market in 2009, although it has partly recovered in recent years. At the same time, the industry faces increasing competition for scarce water supplies in some regions. This study concludes that consumer premiums for plants grown with recycled water could offer nursery growers a method to improve their net returns while addressing environmental challenges and improving irrigation crop water productivity.

Adoption of WRT offers some nurseries the opportunity to reduce water supply costs relative to well water or municipal water. In addition, consumer premiums that could be obtained from plants grown with WRT could outweigh increased production costs of WRT as well as possible economic losses associated with increased plant disease risk. Additional production costs of WRT could also be lowered by reducing plant death rate below levels that occur without WRT (Table 2.15). Therefore, treatment of recycled water with effective pathogen mitigation procedures should always be considered as suggested by Hong and Moorman (2005).

Nursery growers have diverse production operations and management practices, which depend on location, state and federal policies, market channel, and other considerations. For some nurseries, physical layout restricts the adoption of WRT. For example, limited land or shallow water tables will deter some nurseries from regrading or digging ponds for recycled water, making it impossible to implement WRT regardless of public or private incentives.

While consumer premiums have potential to make WRT economically feasible for many growers, the logistical resources needed to establish a labelling program for WRT may be beyond the capability of a single horticultural firm. A centralized government or industry organization may be best suited to lead the implementation of certification and labeling of plants grown with WRT. In this case, the “green washing” for WRT practices imposed by sellers, i.e., the act of misleading consumers via promising more environmental benefits of the product than they actually deliver, can be effectively mitigated through well-established industry standards and certification programs.

The results of this analysis are specific to only eight case nurseries and two simulated nurseries in Mid-Atlantic states. These results should be replicated with a larger set of nurseries and in alternate climate zones. Further analysis could also focus on the upfront costs facing growers who wish to transition to WRT and the length of time required to pay back these costs with alternative recycling premiums. Investments in water saving technology (e.g., precision watering) provide an alternate way of reducing water use and should be evaluated as well. Researchers should consider the potential for scale economies when evaluating such investments. The premiums estimated by Hartter (2012) were based on hypothetical questions instead of actual marketing experiments. Better estimation of consumer premiums should be possible through experiments involving actual consumer purchases (Chang, Lusk, & Norwood, 2009; Hudson, Gallardo, & Hanson, 2012). Additional research should focus on how consumer premiums would be allocated at each distribution stage under different market channels, locations, and plant types. Such research could shed additional light on how consumer premiums for horticultural plants produced with WRT can assist the industry to address environmental challenges.

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Figure 2.1: Geographic Location of the Eight Case Nurseries in the Study Area.

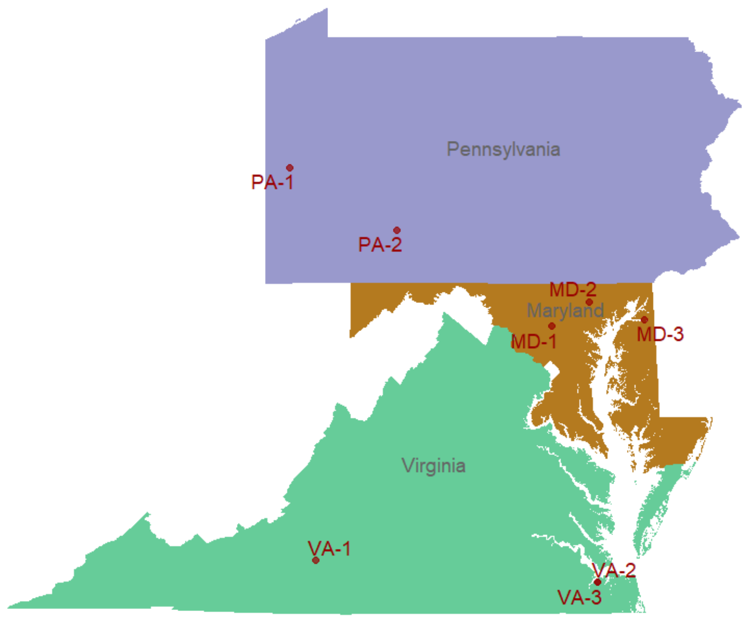

Table 2.1: Size and Water Source of the Eight Case Study Nursery Operations and Two Simulated Nurseries.

Nursery	Hectares	Current water supply method
VA-1	1.0	34% Recycling, 66% Well
VA-2	40.5	100% Recycling
VA-3	80.9	100% Recycling
MD-1	6.7	50% Recycling, 50% Well
MD-2	42.5	100% Recycling
MD-3	22.3	100% Recycling
PA-1	2.0	20% Recycling, 80% Well
PA-2	10.9	100% Recycling
SynSmall	5.5	100% Well Water
SynLarge	36.0	100% Well Water

Data source: Ferraro, Bosch, Pease, and Owen (2017).

Table 2.2: Sales and Percent of Total U.S. Sales of Six Horticultural Plants by State In 2014.

	Geranium			Petunia			Chrysanthemum		
	VA	MD	PA	VA	MD	PA	VA	MD	PA
Wholesale ($1000)	6,773	1,112	5,585	6,253	1,594	1,077	7,204	N/A	2,485
	6.0%	1.0%	4.9%	9.8%	2.5%	1.7%	15.2%	N/A	5.3%
Retail ($1000)	854	326	3,185	260	200	857	47	N/A	207
	1.7%	0.6%	6.2%	1.6%	1.2%	5.4%	1.3%	N/A	5.7%
Total ($1000)	7,627	1,438	8,770	6,513	1,794	1,934	7,251	25	2,692
	4.6%	0.9%	5.3%	8.2%	2.2%	2.4%	14.2%	0.05%	5.3%

	Azalea			Holly			Boxwood		
	VA	MD	PA	VA	MD	PA	VA	MD	PA
Wholesale ($1000)	3,323	1,615	359	8,528	12,651	759	5,611	8,852	1,775
	3.8%	1.8%	0.4%	7.3%	10.8%	0.6%	4.8%	7.5%	1.5%
Retail ($1000)	36	75	105	91	256	248	36	14	429
	0.8%	1.6%	2.3%	1.6%	4.4%	4.2%	0.4%	0.2%	5.2%
Total ($1000)	3,359	1,690	464	8,619	12,907	1,007	5,647	8,866	2,204
	3.6%	1.8%	0.5%	7.0%	10.5%	0.8%	4.5%	7.0%	1.7%

Note: The percentage number placed under each sale volume represents each state's share of US Retail/Wholesale/Total sales for each type of the six plants.
Data source: U.S. Department of Agriculture (2014).

Table 2.3: Net Water Supply Cost Changes for Eight Nursery Operations (VA-1 To PA-2) and Two Simulated Nurseries (Synsmall And Synlarge) with Alternative Water Sources.

Nursery	Alternative	More profitable option	WRT cost ($/ha)	Alternative cost ($/ha)	Water supply cost change with WRT ($/ha)
VA-1	Municipal Water	WRT	4,400	6,024	-1,624
VA-2	Municipal Water	WRT	4,817	34,728	-29,910
VA-3	Municipal Water	WRT	5,874	12,213	-6,339
MD-1	Well Water	WRT	650	1,463	-813
MD-2	Municipal Water	WRT	3,770	6,621	-2,851
MD-3	Well Water	Well Water	7,923	406	7,516
PA-1	Well Water	WRT	26,967	27,310	-343
PA-2	Municipal Water	Municipal Water	4,242	2,044	2,199
SynSmall	Well Water	Well Water	5,956	2,146	3,810
SynLarge	Well Water	Well Water	9,035	1,384	7,651

Data source: Ferraro, Bosch, Pease, and Owen (2017).

Table 2.4: Labeling Cost Change (ΔLC_i), Certification Cost Change (ΔCC_i), and Production Cost Change (ΔPC_i) with Water Recycling Technology for Geranium.

Plant type	Nursery	Labeling cost change ($/ha)	Certification cost change ($/ha)	Water-supply cost change ($/ha)	Production cost change ($/ha)
Geranium (10.2 cm pot)	VA-1	-415	593	-1,624	-1,446
	VA-2	-415	136	-29,910	-30,189
	VA-3	-415	67	-6,339	-6,687
	MD-1	-415	300	-813	-929
	MD-2	-415	94	-2,851	-3,172
	MD-3	-415	56	7,516	7,157
	PA-1	-415	988	-343	230
	PA-2	-415	62	2,199	1,845
	SynSmall	-415	110	3,810	3,504
	SynLarge	-415	42	7,651	7,278

Table 2.5: Labeling Cost Changes (ΔLC_i), Certification Cost Change (ΔCC_i), and Production Cost Changes (ΔPC_i) with Water Recycling Technology for Petunia.

Plant type	Nursery	Labeling cost change ($/ha)	Certification cost change ($/ha)	Water-supply cost change ($/ha)	Production cost change ($/ha)
Petunia (6 packs)	VA-1	-69	593	-1,624	-1,100
	VA-2	-69	136	-29,910	-29,843
	VA-3	-69	67	-6,339	-6,341
	MD-1	-69	300	-813	-583
	MD-2	-69	94	-2,851	-2,826
	MD-3	-69	56	7,516	7,503
	PA-1	-69	988	-343	576
	PA-2	-69	62	2,199	2,191
	SynSmall	-69	110	3,810	3,850
	SynLarge	-69	42	7,651	7,624

Table 2.6: Labeling Cost Changes (ΔLC_i), Certification Cost Change (ΔCC_i), and Production Cost Changes (ΔPC_i) with Water Recycling Technology for Chrysanthemum, Azalea and Boxwood.

Plant type	Nursery	Labeling cost change ($/ha)	Certification cost change ($/ha)	Water-supply cost change ($/ha)	Production cost change ($/ha)
Chrysanthemum; Azalea; Boxwood (3.8 liter pot)	VA-1	-52	593	-1,624	-1,083
	VA-2	-52	136	-29,910	-29,826
	VA-3	-52	67	-6,339	-6,324
	MD-1	-52	300	-813	-566
	MD-2	-52	94	-2,851	-2,809
	MD-3	-52	56	7,516	7,521
	PA-1	-52	988	-343	594
	PA-2	-52	62	2,199	2,208
	SynSmall	-52	110	3,810	3,868
	SynLarge	-52	42	7,651	7,641

Table 2.7: Labeling Cost Change (ΔLC_i), Certification Cost Change (ΔCC_i), and Production Cost Change (ΔPC_i) with Water Recycling Technology for Holly.

Plant type	Nursery	Labeling cost change ($/ha)	Certification cost change ($/ha)	Water-supply cost change ($/ha)	Production cost change ($/ha)
Holly (7.6 liter pot)	VA-1	-26	593	-1,624	-1,057
	VA-2	-26	136	-29,910	-29,800
	VA-3	-26	67	-6,339	-6,298
	MD-1	-26	300	-813	-540
	MD-2	-26	94	-2,851	-2,783
	MD-3	-26	56	7,516	7,546
	PA-1	-26	988	-343	619
	PA-2	-26	62	2,199	2,234
	SynSmall	-26	110	3,810	3,894
	SynLarge	-26	42	7,651	7,667

Table 2.8: Calibrated Premiums and Wholesale and Retail Prices of Three Annual Bedding Plants by States, Adjusted to 2014 Dollars.

Plant Type i	Premiums Mean	Prices by State			
		State	P_i^w	P_i^r	$\frac{P_i^w}{P_i^r}$
Geranium ($/10.2 cm pot)	0.52	VA	1.86	2.69	0.69
		MD	2.06	3.46	0.59
		PA	1.79	2.93	0.61
Petunia ($/6-pack)	0.33	VA	1.17	3.12	0.38
		MD	1.34	2.67	0.50
		PA	1.20	2.76	0.44
Chrysanthemum ($/3.8 liter pot)	0.46	VA	3.59	5.88	0.61
		MD	5.11	5.11	1.00
		PA	3.72	5.77	0.64

Note: Wholesale and retail prices for Chrysanthemum in Maryland are not available, so the wholesale and retail prices are both equal to total sale value divided by total number sold.
Data sources: Hartter (2012); U.S. Department of Agriculture (2014).

Table 2.9: Calibrated Premiums and Wholesale and Retail Prices of Broadleaf Evergreen Plants by States, Adjusted to 2014 Dollars.

Plant Type i	Premiums Mean	Prices by State			
		State	P_i^w	P_i^r	$\frac{P_i^w}{P_i^r}$
Azalea ($/1 3.8 liter pot)	0.43	VA	8.95	12.44	0.72
		MD	10.99	20.13	0.55
		PA	18.91	13.04	1.45
Holly ($/3.8 liter pot)	0.34	VA	13.50	47.57	0.28
		MD	33.50	21.83	1.53
		PA	23.48	31.55	0.74
Boxwood ($/3.8 liter pot)	0.60	VA	24.83	24.42	1.02
		MD	25.65	16.00	1.60
		PA	16.65	23.20	0.72

Data sources: Hartter (2012); U.S. Department of Agriculture (2014).

Table 2.10: Gross Revenue Sensitivity (ΔGR_i) to Conveyance Rates (R).

	Gross revenue changes under alternative R values ($/ha)					
	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$
	Annual bedding plants			Broadleaf evergreen plants		
Nursery Type	Geranium			Azalea		
VA (1,2,3)	-7,722	136,136	200,331	-4,644	11,048	17,168
MD (1,2,3)	-8,552	115,318	199,501	-5,703	6,205	16,109
PA (1,2)	-7,431	119,673	200,622	-9,813	11,999	11,999
Syn (Small, Large)	-8,552	115,318	199,501	-5,703	6,205	16,109
	Petunia			Holly		
VA (1,2,3)	-810	7,580	21,562	-3,503	-1,098	4,970
MD (1,2,3)	-927	10,300	21,444	-8,692	-219	-219
PA (1,2)	-830	8,896	21,541	-6,092	214	2,381
Syn (Small, Large)	-927	10,300	21,444	-8,692	-219	-219
	Chrysanthemum			Boxwood		
VA (1,2,3)	-1,863	12,274	21,291	-12,885	17,484	17,484
MD (1,2,3)	-2,652	20,503	20,503	-13,310	17,059	17,059
PA (1,2)	-1,930	12,997	21,224	-8,640	13,155	21,729
Syn (Small, Large)	-2,652	20,503	20,503	-13,310	17,059	17,059

Note: The two simulated nurseries are assumed located in Maryland, thus the results for Syn (Small, Large) and MD (1, 2, 3) are always equal in this table.

Table 2.11: Net Revenue Sensitivity (ΔNR_i) to Conveyance Rates (R) for Three Annual Bedding Plants.

	Net Revenue changes under different R values (\$/ha)								
	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$
Nursery	Geranium			Petunia			Chrysanthemum		
VA-1	-6,275	137,582	201,777	291	8,680	22,662	-780	13,357	22,374
VA-2	22,468	166,326	230,520	29,034	37,423	51,405	27,963	42,100	51,117
VA-3	-1,034	142,824	207,018	5,532	13,921	27,903	4,461	18,598	27,615
MD-1	-7,623	116,247	200,430	-344	10,883	22,027	-2,086	21,068	21,068
MD-2	-5,380	118,490	202,673	1,899	13,127	24,270	157	23,312	23,312
MD-3	-15,709	108,160	192,343	-8,430	2,797	13,941	-10,172	12,982	12,982
PA-1	-7,661	119,443	200,391	-1,407	8,320	20,965	-2,524	12,404	20,630
PA-2	-9,276	117,828	198,776	-3,021	6,705	19,350	-4,139	10,789	19,015
SynSmall	-12,056	111,813	195,996	-4,778	6,450	17,594	-6,519	16,635	16,635
SynLarge	-15,830	108,040	192,223	-8,551	2,676	13,820	-10,293	12,861	12,861

Table 2.12: Net Revenue Sensitivity (ΔNR_i) to Conveyance Rates (R) for Three Broadleaf Evergreen Plants.

	Net revenue changes under different R values (\$/ha)								
	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$	$R = 0\%$	$R = \frac{P_i^w}{P_i^r}$	$R = 100\%$
Nursery	Azalea			Holly			Boxwood		
VA-1	-3,562	12,131	18,250	-2,446	-41	6,027	-11,802	18,567	18,567
VA-2	25,182	40,875	46,994	26,298	28,702	34,771	16,941	47,310	47,310
VA-3	1,680	17,372	23,492	2,795	5,200	11,269	-6,561	23,808	23,808
MD-1	-5,137	6,771	16,675	-8,152	321	321	-12,745	17,624	17,624
MD-2	-2,894	9,014	18,918	-5,909	2,564	2,564	-10,501	19,868	19,868
MD-3	-13,223	-1,315	8,588	-16,238	-7,765	-7,765	-20,831	9,538	9,538
PA-1	-10,406	11,406	11,406	-6,712	-406	1,761	-9,234	12,561	21,135
PA-2	-12,021	9,791	9,791	-8,327	-2,021	147	-10,849	10,946	19,520
SynSmall	-9,571	2,338	12,241	-12,586	-4,112	-4,112	-17,178	13,191	13,191
SynLarge	-13,344	-1,436	8,468	-16,359	-7,886	-7,886	-20,951	9,417	9,417

Table 2.13: Break-Even Conveyance Rate R Required to Balance Gross Revenue and Production Cost Changes ($\Delta NR = 0$).

	Break-even R					
Nursery	Geranium	Petunia	Chrysanthemum	Azalea	Holly	Boxwood
VA-1	3.0%	N/A	3.4%	16.3%	28.9%	38.9%
VA-2	N/A	N/A	N/A	N/A	N/A	N/A
VA-3	0.5%	N/A	N/A	N/A	N/A	21.6%
MD-1	3.7%	1.5%	9.0%	23.6%	96.2%	42.0%
MD-2	2.6%	N/A	N/A	13.3%	69.7%	34.6%
MD-3	7.6%	37.7%	43.9%	60.6%	191.6%	68.6%
PA-1	3.7%	6.3%	10.9%	47.7%	79.2%	30.4%
PA-2	4.5%	13.5%	17.9%	55.1%	98.3%	35.7%
SynSmall	5.8%	21.4%	28.2%	43.9%	148.5%	56.6%
SynLarge	7.6%	38.2%	44.5%	61.2%	193.1%	69.0%

Note: N/A refers to the case where break-even analysis is not applicable because the net revenue change is already positive without any premium returned as show in Tables 2.11 and 2.12. Break-even rates greater than 100% indicate that the estimated consumer premium is not adequate to cover production cost changes.

Table 2.14: Break-Even Premiums Corresponding to the Break-Even R Required to Balance Gross Revenue and Production Cost Changes ($\Delta NR = 0$).

	Break-even premium ($/pot)					
Nursery	Geranium	Petunia	Chrysanthemum	Azalea	Holly	Boxwood
VA-1	0.02	N/A	0.02	0.07	0.10	0.23
VA-2	N/A	N/A	N/A	N/A	N/A	N/A
VA-3	0.003	N/A	N/A	N/A	N/A	0.13
MD-1	0.02	0.01	0.04	0.10	0.32	0.25
MD-2	0.01	N/A	N/A	0.06	0.23	0.21
MD-3	0.04	0.13	0.20	0.26	0.65	0.41
PA-1	0.02	0.02	0.05	0.21	0.27	0.18
PA-2	0.02	0.05	0.08	0.24	0.33	0.22
Syn-S	0.03	0.07	0.13	0.19	0.50	0.34
Syn-L	0.04	0.13	0.20	0.27	0.65	0.42

Note: N/A refers to the case where break-even analysis is not applicable because the net revenue change is already positive without any premium returned as show in Tables 2.11 and 2.12.

Table 2.15: Break-Even Death Rate to Offset Added Water Recycling Technology Production Costs of Nurseries MD-3, PA-1, PA-2, Synsmall And Synlarge When Conveyance Rate $R = 0\%$.

	Break-even death rate					
Nursery	Geranium	Petunia	Chrysanthemum	Azalea	Holly	Boxwood
MD-3	1.2%	N/A	N/A	0.7%	1.1%	1.4%
PA-1	2.0%	1.3%	1.7%	1.9%	1.9%	1.9%
PA-2	1.8%	N/A	0.9%	1.8%	1.6%	1.7%
SynSmall	1.6%	N/A	0.5%	1.3%	1.6%	1.7%
SynLarge	1.1%	N/A	N/A	0.7%	1.1%	1.4%

Note: For some plants, death rates would have to be negative in order for breakeven between recycling and not recycling without any premiums returned. Because negative death rates are impossible, such cases are labeled N/A.

CHAPTER 3

Estimating the Demand for Urban Tree Cover Using a Residential Sorting Model: The Case of Milwaukee, Wisconsin

3.1 Introduction

Trees in residential neighborhood provide wide ecological benefits to homeowners and communities. Scientific research has found that trees can protect against soil erosion, reduce runoff and flooding, improve air quality and supply habitat for wildlife (Nowak et al., 2010). Tree cover (the land area covered by tree canopy) on or within buffers of residential properties is an important environmental attribute which provides shade and privacy to homeowners, enhances life quality via improving landscape aesthetics and sheltering residents from negative effects from undesirable land use (e.g., noise and congestion from road nearby) (Sander, Polasky, & Haight, 2010).

The economic benefits generated by tree cover can be capitalized into the values of residential property through first-stage hedonic property price model, referring to the implicit price or the amenity value of tree cover. Multiple hedonic studies have found positive impacts of tree cover on property values, concluding tree cover is an important environmental amenity for residential properties with positive externalities (Mansfield, Pattanayak, McDow, McDonald, & Halpin, 2005; Netusil, Chattopadhyay, & Kovacs, 2010; Paterson & Boyle, 2002; Sander & Haight, 2012; Sander et al., 2010). For example, Mansfield et al. (2005) used percentage of residential single family parcel that was forested as measurement of tree cover in hedonic model and they found that 10% more tree cover on a parcel can increase home sale price by $800 in Orange and Durham counties, North Carolina. In addition, a Minnesota, USA study indicated that house value increases by $1371 ($836) with additional 10% tree cover within 100m (200m) buffer around the house (Sander et al., 2010).

Researchers also attempted to estimate the household's demand for tree cover and other land cover characteristics with consideration of exogenous demand shifters such as income and individual household socio-economic characteristics, usually referring to second-stage hedonic demand analysis as suggested by Rosen (1974). However, the second-stage hedonic demand analysis suffers from identification and endogeneity problem which requires either multiple-market approach or restrictions on the structure of preferences (Kuminoff, Smith, & Timmins, 2013). The multiple-market approach is data intensive, thus very few empirical studies have implemented Rosen's second-stage model to estimate the demand for amenities, with no exception for tree cover. Indeed, the analyses on demand for tree cover is limited. Netusil et al. (2010) estimated the demand for tree canopy using a second-stage hedonic price model in Portland, Oregon. The authors conducted an individual-level survey to collect additional data on household's preferences and socio-economic characteristics in order to help identify the demand curve. The results indicated that the average benefit estimates for the mean tree canopy within 0.25 mile of residential property in the study area ranged from 0.75% to 2.52% of the mean sale price. Mei, Hite, and Sohngen (2017) estimated the demand for tree cover in California using a two-stage hedonic price model. The authors accounted for spatial autocorrelation in the first-stage estimation, then adopted a market segmentation strategy (i.e., dividing study area into five different counties in California) and instrumented the implicit price estimates using "the percent of population change" so as to identify the demand curve for tree cover. They concluded that the own price elasticity of demand for tree cover in California is -0.075, indicating that tree cover is an inelastic public good.

Unlike previous studies, this study establishes a residential sorting model instead of a traditional hedonic price model to analyze how urban tree cover affect residential property values, and to estimate household's demand for tree cover. Unlike traditional hedonic price model which assumes households are free to choose continuous amenity level, the residential sorting model allows households to make discrete choices from various housing types in a given housing market. Compared to traditional hedonic price model which requires identical households from various markets with homogeneous preferences for certain characteristics related to the housing property to help identify the demand curve, a residential sorting model allows households to have heterogeneous preferences for the characteristics including housing structural attributes, neighborhood attribute as well as the environmental (dis)amenities. In addition, since the residential sorting model focuses on the process of how the market equilibrium is formed, it facilitates policy evaluation via simulating how households and market react to non-marginal changes of environmental (dis)amenities and measuring welfare changes. In contrast, average marginal willingness-to-pay (MWTP) obtained from traditional hedonic price model, as argued by previous studies (Klaiber & Kuminoff, 2013; Kuminoff, Smith, & Timmins, 2010), provides weak and insufficient basis for policy evaluation.

Specifically, this chapter first presents a residential sorting model which is an aggregation analysis to recover heterogeneous demands for "community trees" at census block group level which vary by aggregated household demographic characteristics. Furthermore, another residential sorting model is established at disaggregated level in which the heterogeneity in spatial scales of tree cover measurement is incorporated to elicit households' demands for nearby trees and distant trees which also vary by individual household demographic characteristics.

This study provides additional evidence on demand for tree cover and adds a new empirical literature on residential sorting model considering landscape amenity. In addition, the findings from this research offer suggestions on land use management and land cover policy (e.g., forest conservation programs) in its design and implementation. In terms of methodology, this analysis generates a potential opportunity to compare residential sorting model and second-stage hedonic demand analysis in respect of underlying theory, MWTP estimates and welfare analysis in the future.

This chapter is organized as follows: Section 3.2 describes the conceptual framework of residential sorting model, Section 3.3 elaborates the econometric implementation of residential sorting model, Section 3.4 talks about the data used in analysis, Section 3.5 explains how choice set is constructed, Section 3.6 presents the empirical results including price index estimation results, first-stage estimation results, second-stage estimation results and marginal willingness to pay estimates. In addition, Section 3.7 is the extended analysis which focuses on nearby trees and distant trees. Section 3.8 concludes key findings and discusses policy implications.

3.2 Conceptual Framework

The basic premise in a residential sorting model is that the amount and character of housing and amenities vary across an urban landscape and each household chooses its mostly preferred bundle of public goods and private goods based on its wealth and relative prices involved. Three assumptions are embedded in residential sorting model in order to remove market frictions, including *full information, free mobility* and *no discrimination*. In a sorting equilibrium, the prices, housing structural attributes, neighborhood attributes, amenities and location choices are all defined such that no household could improve its utility by moving (i.e., utility maximization) and each household should occupy exactly one house. Single crossing condition helps characterize the sorting equilibrium, under which, any sorting equilibrium must satisfy three properties: *increasing bundles, stratification* and *boundary indifference. Increasing bundles* property requires that household must pay for higher level amenity provided by a housing property or a neighborhood through paying higher housing price. *Stratification* property argues that conditional on preferences (income), households with higher income (stronger preferences) will always choose to live in the houses or communities with more amenities. *Boundary indifference* property says that the households located on the boundary between two adjacent communities must be indifferent to choose which one to live in.

This study applies a horizontal residential sorting model within the framework of Random Utility Model (RUM) proposed by McFadden (1973) and McFadden (1978). Our conceptual framework follows Bayer, McMillan, and Rueben (2004), Bayer, Ferreira, and McMillan (2007) and Klaiber and Phaneuf (2010). The utility specification for household i ($i = 1, 2, \dots, I$) to choose a housing type h ($h = 1, 2, \dots, H$) in a given housing market is:

$$U_h^i = V\left(S_h, g_h, N_h, Z^i, p_h, \xi_h\right) + \varepsilon_h^i \tag{3.1}$$

where the indirect utility V is determined by housing structural attributes S_h, environmental (dis)amenities g_h, neighborhood attributes N_h, observed household demographic characteristics Z^i, house prices p_h, and unobserved attributes of house ξ_h. An idiosyncratic error ε_h^i is added to account for any unobserved household-specific taste on housing type h, which could not be observed by researchers.

The explicit specification of the utility function shown in equation 3.1 can be written as:

$$U_h^i = \alpha_S^i S_h + \alpha_g^i g_h + \alpha_N^i N_h + \alpha_p p_h + \xi_h + \varepsilon_h^i \tag{3.2}$$

where $\alpha_X^i, X \in \{S, g, N\}$ are the parameters for S_h, g_h, N_h which take the "horizontal preference structure" as suggested by Bayer et al. (2004) as follows:

$$\alpha_X^i = \alpha_{0X} + \sum_{q=1}^{Q} \alpha_{qX} Z_q^i \;\; \forall\, X \in \{S, g, N\} \tag{3.3}$$

where Q is the number of household demographic characteristics Z^i. This horizontal preference structure decomposes preference parameters into a mean parameter (α_{0X}) which is the average taste that is common to all households and a set of household-specific parameters (interaction terms $\sum_{q=1}^{Q} \alpha_{qX} Z_q^i$) which allow households to have heterogeneous preferences based on their own demographic characteristics. It should be noted that household demographic characteristics Z^i could also be interacted with house prices, but in order to mitigate multicollinearity and simplify counterfactual simulation and welfare computation in the future, this study assumes a homogeneous price parameter as suggested by Klaiber and Phaneuf (2010).

In the sorting equilibrium, household i chooses housing type h^* to maximize its utility such that:

$$U_{h^*}^i \geq U_h^i \; \forall \; h^* \neq h \tag{3.4}$$

In order to define the sorting equilibrium, it should be noted that each household's choice of housing type depends on all available housing types in the market. Therefore, the probability for household i to choose housing type h can be derived as:

$$\mathrm{Pr}_\mathrm{h}^\mathrm{i} = f_h(\boldsymbol{S}, \mathbf{g}, \boldsymbol{N}, \boldsymbol{p}, Z^i, \boldsymbol{\xi}) \tag{3.5}$$

where the probability depends on all possible characteristics across the market $\boldsymbol{S}, \boldsymbol{g}, \boldsymbol{N}, \boldsymbol{p}, \boldsymbol{\xi}$ and the specific demographic characteristics of household i, Z^i. The functional form $f_h(\cdot)$ is determined by the distributional assumption imposed on the idiosyncratic error term ε_h^i. With the specification of a distribution for ε_h^i, estimation is based on observing households' actual choices of housing types and deriving the probability for household i to choose utility maximizing housing type h^*.

Market clearing condition must be satisfied in the sorting equilibrium such that for each housing type h, its expected aggregated demand must be equal to its exogenous aggregated supply. Mathematically,

$$D_h = \sum_i^I Pr_h^i = S_h \tag{3.6}$$

where $D_h = \sum_i^I Pr_h^i$ is the expected (predicted) demand for choosing housing type h through aggregating the probabilities in equation 3.5 over all observed households and S_h is the exogenous (observed) supply of housing type h.

3.3 Econometric Implementation

The estimation aims to recover the parameters shown in equation 3.2. Similar to previous studies such as Bayer et al. (2004) and Klaiber and Phaneuf (2010), this study adopts a two-stage estimation strategy discussed by Berry, Levinsohn, and Pakes (1995). Specifically, first-stage estimation is to recover all the heterogeneous preferences parameters shown as the interaction terms along with mean indirect utilities for all housing types. Then, second-stage estimation is to recover a set of average taste parameters regardless of household demographic characteristics.

The utility function in equation 3.2 can be rewritten as follows:

$$U_h^i = \Theta_\mathrm{h} + \Gamma_h^i + \varepsilon_h^i \tag{3.7}$$

where:

$$\Theta_\mathrm{h} = \alpha_{0S} S_h + \alpha_{0g} g_h + \alpha_{0N} N_h + \alpha_p p_h + \xi_h \tag{3.8}$$

$$\Gamma_h^i = \left(\sum_{q=1}^{Q} \alpha_{qS} Z_h^i\right) S_h + \left(\sum_{q=1}^{Q} \alpha_{qg} Z_h^i\right) g_h + \left(\sum_{q=1}^{Q} \alpha_{qN} Z_h^i\right) N_h \tag{3.9}$$

Explicitly, first-stage estimation is to recover all the $\alpha_{qX}, X \in \{S, g, N\}$ (heterogeneous preferences parameters) along with all Θ_h (the mean indirect utilities) via Maximum Likelihood Estimation (MLE) on equations 3.7 and 3.9. Second-stage estimation is to recover all the $\alpha_{0X}, X \in \{S, g, N\}$ and α_p in 3.8 based on estimates of Θ_h from the first-stage estimation. The estimation strategy is illustrated in Figure 3.1 and further explained in the following sections.

3.3.1 First-Stage Estimation

If ε_h^i is assumed to be independent and identically distributed Type I extreme value, then the conditional logit probability for household i to choose housing type h is expressed as:

$$Pr_h^i = \frac{\exp\left(\Theta_h + \Gamma_h^i\right)}{\sum_{h=1}^{H} \exp\left(\Theta_h + \Gamma_h^i\right)} \tag{3.10}$$

The log-likelihood function is derived as:

$$ll = \sum_{i=1}^{I} \sum_{h=1}^{H} Y_h^i \ln(Pr_h^i) \tag{3.11}$$

where $Y_h^i = 1$ if household i actually chooses housing type h in the data and $Y_h^i = 0$ otherwise. The gradient of above log-likelihood function in regard to $\boldsymbol{\beta} = (\sum_{q=1}^{Q} \alpha_{qS}, \sum_{q=1}^{Q} \alpha_{qg}, \sum_{q=1}^{Q} \alpha_{qN})$ is derived as follows:

$$\frac{\partial ll}{\partial \boldsymbol{\beta}} = \sum_i \sum_h Y_h^i [X_h^i - \sum_{h'}^{H} (Pr_{h'}^i \cdot X_{h'}^i)] \tag{3.12}$$

More implicitly, the first-order condition of the above log-likelihood function in regard to mean indirect utility Θ_h is derived as follows:

$$\begin{aligned} \frac{\partial ll}{\partial \Theta_h} &= \sum_{i \in h} \frac{\partial \ln(Pr_h^i)}{\partial \Theta_h} + \sum_{i \notin h} \frac{\partial \ln(Pr_h^i)}{\partial \Theta_h} \\ &= \sum_{i \in h} (1 - Pr_h^i) + \sum_{i \notin h} Pr_h^i \\ &= S_h - \sum_i^I Pr_h^i = 0 \end{aligned} \tag{3.13}$$

It is obvious that the first-order condition 3.13 reflects the market clearing condition in sorting equilibrium such that the aggregation of expected probability of each household to choose housing type h should be equal to the supply of this housing type. Thus the first-stage estimation recovers the interaction parameters which best match each household with its chosen housing type, while also ensuring that total expected demand always equals supply for each housing type.

For many applications of residential sorting model, the number of housing types is relatively large, making the gradient-based computation of mean indirect utility parameters Θ_h burdensome. Berry et al. (1995) demonstrated a contraction mapping which enables recovery of estimates $\widehat{\Theta}_h$ instead of gradient-based searches. Following Bayer et al. (2004) and Klaiber and Phaneuf (2010), the contraction mapping is expressed as:

$$\Theta_h^{k+1} = \Theta_h^k - \ln\left(\frac{\sum_i^I Pr_h^i}{S_h}\right) \tag{3.14}$$

where k indexes iteration for the contraction mapping. For any set of heterogeneous preferences parameters in Γ_h^i, equation 3.14 can be used to calculate the vector of Θ_h which satisfies the first-order condition shown in equation 3.13. Specifically, an initial guess at Θ_h is made and then the equation 3.14 is evaluated repeatedly until convergence is (approximately) achieved. In equation 3.14, $k = 0, \dots, K$ where the K is the smallest integer such that $||\Theta_h^K - \Theta_h^{K-1}||$ is smaller than a specified tolerance level so that Θ_h^K is the approximation of Θ_h. This contract mapping has been proved to have a unique fixed point which acts as both local and global solutions to the maximization of the log-likelihood function 3.11 (Berry et al., 1995). Also, this contraction mapping speeds model convergence significantly (Klaiber & Kuminoff, 2013).

In general, the first-stage estimation can be summarized as follows:

Step 1: Set an initial guess for $\mathbf{\Theta}$**;**

Step 2 (outer loop): Given $\mathbf{\Theta}$, maximize log-likelihood function 3.11 with respect to all interaction terms $\boldsymbol{\beta}$ via derived gradient shown in 3.12;

Step 3 (inner loop): Given the coefficients of $\boldsymbol{\beta}$ estimated from step 2, update new $\mathbf{\Theta}$ via the contraction mapping in 3.14;

Step 4: Repeat steps 2 and 3 until all estimates converge.

3.3.2 Second-Stage Estimation

The second-stage estimation decomposes the estimated mean indirect utilities $\widehat{\Theta}_h$ into observed and unobserved components in equation 3.8, denoted as $\alpha_{0X}, X \in \{S, g, N\}$, α_p and ξ_h, respectively. However, it raises several econometric issues. First, since the dependent variable in second-step estimation is the estimates of mean indirect utilities, $\hat{\Theta}_h$, additional criteria should be imposed in order to establish consistency and asymptotic normality (Bayer et al., 2004; Klaiber & Kuminoff, 2013). Consistency requires that the number of households must grow relatively faster than the number of housing types, i.e., $\frac{H\log H}{I} \to 0$; Asymptotic normality requires that $\frac{H^2}{I}$ must be bounded (Berry, Linton, & Pakes, 2004).

Another issue is endogeneity, i.e., house prices p_h are likely to be correlated with unobserved attributes of the housing type ξ_h. Endogeneity arises because better locations, which are characterized partly by the unobserved house attributes, usually have higher prices, leading to a potential correlation between prices and unobserved factors. Thus the prices must be instrumented. The spatial structure of housing market provides a strategy of instruments on price since observed house prices are the results of a sorting equilibrium which depends on all housing type attributes across a given housing market (Klaiber & Phaneuf, 2010). Previous studies such as Bayer et al. (2004), Bayer and Timmins (2007), Klaiber and Phaneuf (2010) used exogenous attributes of distant housing types in the same housing market as instruments on house prices since they affect the sorting process jointly with attributes of a local housing type to achieve equilibrium, while it is unlikely that unobserved attributes of a local housing type are correlated with exogenous attributes of distant housing types.

Some practical techniques in second-step estimation should be clarified. The construction of instruments on prices depends on the "true" values of the coefficients of parameters from equation 3.7. However, the values of $\alpha_{0X}, X \in \{S, g, N\}$ and α_p are unknown thus an iterative procedure is suggested. Consider an auxiliary regression based on equation 3.8 as follows:

$$\Theta_h - \alpha_p^* p_h = \alpha_{0\mathrm{S}} S_h + \alpha_{0g} g_h + \alpha_{0N} N_h + \sum_{m=1}^{M} \delta_m C_m + \widetilde{\xi_h} \tag{3.15}$$

where the price term is moved to the left-hand side with a plausible guess of the value for the price coefficient, labeled as α_p^*. Additional control terms, i.e., the exogenous attributes of distant housing types, are added into the right-hand side, denoted as $C_m \forall\, m \in \{1, 2, \dots, M\}$ where M is the number of the control terms. $\tilde{\xi}_h$ is the new error term in this auxiliary regression.

The coefficients of S_h, g_h, N_h and C_m $\forall\, m \in \{1, 2, \dots, M\}$, denoted as $\widetilde{\alpha_{0\mathrm{S}}}$, $\widetilde{\alpha_{0\mathrm{g}}}$, $\widetilde{\alpha_{0\mathrm{N}}}$ and $\widetilde{\delta_m}$ $\forall\, m \in \{1, 2, \dots, M\}$, can be obtained using Ordinary Least Square (OLS) in the above auxiliary regression. Then set residual $\widetilde{\xi_h} = 0$ and solve for the instrumented price set, p_h^{IV} that satisfies the market clearing condition as shown in equation 3.6:

$$D_h = \sum_i^I \frac{\exp\left(\widetilde{\Theta_h} + \widehat{\Gamma_h^\iota}\right)}{\sum_{h=1}^{H} \exp\left(\widetilde{\Theta_h} + \widehat{\Gamma_h^\iota}\right)} = S_h \tag{3.16}$$

where $\widetilde{\Theta_h} = \alpha_p^* p_h^{IV} + \widetilde{\alpha_{0\mathrm{S}}} S_h + \widetilde{\alpha_{0g}} g_h + \widetilde{\alpha_{0N}} N_h + \sum_{m=1}^{M} \widetilde{\delta_m} C_m$ are the new predicted mean utilities and $\widehat{\Gamma_h^\iota}$ are the estimates of heterogeneous preferences parameters from the first-stage estimation. In this case, p_h^{IV} can absorb the exogenous residual variation in 3.15, reflecting the landscape features of distant neighborhoods which is assumed to be exogenous.

Next step is to perform the instrumental variables (IV) estimation of equation 3.8 using instrumented price set p_h^{IV} derived from equation 3.16. After obtaining the new estimate of price coefficient α_p^1, where the superscript indexes the number of iterations, the process described above from equations 3.15 to 3.16 is re-run again using α_p^1 instead of initial guess α_p^*. Repeating this iterative process several times ensures the stability of the price coefficient α_p so as to remove the dependence on the initial guess α_p^*.

3.4 Data

Generally, the residential sorting model requires comprehensive micro-level datasets including housing property values, structural characteristics, environmental (dis)amenities, neighborhood/community characteristics and household demographic characteristics. Because this research focuses on analyzing tree cover across urban landscape, the spatial land cover data is significantly important. In recent years, with the development of Geographic Information System (GIS) and Remote Sensing techniques, the growing number of spatially explicitly landscape datasets can be measured and calculated accurately and precisely, providing researchers with opportunities for great data validation and consistency for scientific research. Census data has been widely used to measure the neighborhood/community characteristics at a certain spatial level such as tract, block group and block. However, when it comes to household demographic characteristics, census data on individual household characteristics are usually publicly unavailable at a consistent level of spatial resolution due to confidentiality reason and only limited set of characteristics at block group or block level are available for the public. Thus, aggregation is necessary to build up the approximate information for each individual household in a given housing market using census data. This section first introduces the study area and then describes the data used in the residential sorting model.

3.4.1 Study Area

The Milwaukee metropolitan area ("Metro Milwaukee") in Southeastern Wisconsin is selected as the study area for research, in which the boundaries are determined using the 2010 Census definition of an Urban Statistical Area (U.S. Census Bureau, 2010). Geographically, it contains the city of Milwaukee, plus portions of Waukesha, Washington as well as Ozaukee counties. The Metro Milwaukee is the largest metropolitan area in Wisconsin and its population reached 1.57 million in 2014 according to the U.S. Census Bureau (U.S. Census Bureau, 2014b).

The Metro Milwaukee area is self-contained and independent since it is far from other large metropolitan areas. In this case, it could be assumed that the individual is not likely to commute from outside area to work or live within the study area. Thus, the real estate market in the Metro Milwaukee area is assumed to be localized. In addition, given the large spatial extent of the area, the high diversity of landscape patterns can facilitate the horizontal residential sorting model to better capture household's preference heterogeneity for local land cover attributes such as tree cover.

3.4.2 Property Transaction Data

Arm-length single-family housing property transactions from year 2005 to 2014 for the Metro Milwaukee area are extracted from the Multiple Listing Service (MLS) dataset. Each residential property's location is identified by its street address, Federal Information Processing Standard Publication (FIPS) code and coordinate information (latitude and longitude). The MLS dataset contains sale price of the property, sale date, housing structural attributes (e.g., size of living area in square feet, lot size in acres, age of the property, numbers of bedrooms and bathrooms), sale year as well as both house buyer's and seller's information such as sale (purchasing) price, loan amount and loan lender's name. All property sales are categorized into sale types of new sales, regular resales, real estate owned (REO) sales and foreclosures. Furthermore, property sales are also classified into single-parcel or multi-parcel transactions.

The data is cleaned for incorrect geographical location, duplicated records, missing values and incongruous observations in regard to housing attributes. All single-parcel property transactions (both new and repeated sales) are selected for research while other sale types are excluded (multi-parcel, REO sales and foreclosures). Sale prices are converted into $2010 using seasonally adjusted housing price index provided by U.S. Federal Housing Finance Agency at the state level. In addition, the properties falling into either the upper or lower 5% of price per unit living area ($/sq^2) are trimmed out of the dataset. After cleaning, there are 40,666 single family detached housing property transactions obtained with a set of key housing structural attributes. Figure 3.2 maps these property transactions located within 746 census block groups in the Metro Milwaukee area.

3.4.3 Land Cover Data

The EnviroAtlas Milwaukee, WI Meter Urban Land Cover (MULC) data (map) is used to measure the land cover attributes. Specifically, the MULC data was generated from the four-band aerial photography from Late Summer 2010 at 1-meter high-resolution spatial scale from the National Agricultural Imagery Program (U.S. Environmental Protection Agency, 2010). The area mapped in MULC is defined by the 2010 Census definition of Urban Statistical Area for Milwaukee. Figure 3.3 illustrates the raster map provided by EnviroAtlas.

The Metro Milwaukee area is located within the Southeastern Wisconsin Till Plain ecoregion, which has severe, humid continental climate with warm summers and harsh winters (U.S. Environmental Protection Agency, 2015). Given these climatic characteristics, the main vegetation in the study area includes hardwood forests and oak savannahs, accounting for over 50% of the total land cover. Although urban growth has continued in the Metro Milwaukee area during the past decades, there are some portions of the area that have been transformed to agricultural use. The Metro Milwaukee area has eight types of land cover attributes defined by the EPA including water, impervious surface, soil & barren, trees & forest, grass & herbaceous, agriculture, woody wetlands and emergent wetlands (See Table A1 in the Appendix for detailed land cover definitions). Figure 3.4 maps the land cover composition of the study area with the census block group outlined for Milwaukee and Waukesha Counties. It is found that the dominant land cover in the Milwaukee area is trees & forest (28.71%), followed by grass & herbaceous (25.31%), impervious surface (19.53%), agriculture (8.79%), water (7.84%), woody wetlands (6.50%), emergent wetlands (2.64%) and soil & barren (0.67%). Further, the percent of each type of land cover attributes is calculated using the 2010 census block group boundaries, representing the "community" land cover attributes.

3.4.4 Neighborhood Characteristics Data

The GIS information on census block group boundaries within the Metro Milwaukee area is merged with the property transactions data so that neighborhood characteristics can be assigned to each property. The neighborhood characteristics are at census block group level and acquired from the 2010 Census, including but not limited to median household income, median age, percent of people above 25-year-old with bachelor's degree or higher, average household size, population density, vacancy rate and percent of population by racial characteristics.

3.4.5 Household Demographic Characteristics

Census data on individual demographic characteristics is not available for public use, thus this study collects and aggregates the block group level demographic characteristics for the estimation of heterogeneous preferences. Income measure is an important exogeneous demand shifter and it is assumed that households with different annual incomes would have different preferences for land cover attributes as well as other characteristics related to the housing properties. Here data of median income at the block group level is obtained from the 2014 American Community Survey (U.S. Census Bureau, 2014a) and used in the estimation of the heterogeneous preferences. Specifically, each household in the transaction dataset is assigned to the corresponding median income group based on its location within block group boundaries.

3.5 Choice Set

Since the residential sorting model is based on the discrete-choice model, the definition of the choice set is essential for the estimation. Similar to Klaiber and Phaneuf (2010) and Tra (2010), the residential locations are characterized in term of housing type rather than individual housing units. These housing types make up the choice set for the households. Using housing type as choice set reduces the computation burden of the estimation and it is also a key to the identification and asymptotic properties of the estimates (Bayer et al., 2007). Mathematically, the following condition must be satisfied:

$$I > H + k - 1 \tag{3.17}$$

where I is the number of households, H is the number of housing types and k is the number of all interaction terms in the first-stage estimation. If this condition is violated, then the identification might fail since there are insufficient observations to explain all the parameters in the first-stage estimation.

Specifically, housing types are defined in terms of three components including location, house size and time of purchase. Location refers to the block groups defined in the 2010 Census, each of which consists of approximate 300 - 500 households. Geographically, census block group is small enough to be distinguished from one another in terms of neighborhood characteristics and landscape patterns. House size is an important element since it may limit the range of alternative housing types a household will consider. Census block groups are geographically broad enough to contain houses of different sizes, so the house size is the second component to further define the housing types. Thus, the 33rd and 66th percentiles of living square footage as given by the property transaction data are used to assign a housing property into three house size ranges including "Small" (<1,162 ft^2), "Medium" (1,162-1,587 ft^2) and "Large" (>1,587 ft^2). Through aggregating houses based on location and house size, the defined choice set actually represents a bundle of housing types that are geographically relevant and economically feasible to households. The third component of a choice alternative is the time when a household made purchase on the housing property. Since the time range of property sales is from 2005-2014, the existing housing types already defined by the location and house size are further grouped by year of purchasing.

In summary, there are $H = 11{,}609$ housing types defined from $I = 40{,}666$ housing property transactions in terms of unique location, house size and year of purchasing. The observed transaction for each household refers to the choice outcome resulting from purchasing decision made by the household. In addition, the medians of structural attributes of all the houses belonging to a particular housing type are used to construct variables to describe the aggregated structural attributes of this housing type. Table 3.1 provides summary statistics for the aggregated housing structural attributes across the defined housing types for the study area.

3.6 Empirical Results

3.6.1 Price Index Estimation

The price of a certain housing type h reflects various characteristics in terms of spatial location, house size and time dimension in which the property transaction occurred, plus any unobserved attributes that are unique to the housing type. Following Bayer, Keohane, and Timmins (2009) and Klaiber and Phaneuf (2010), the following Ordinary Least Squares (OLS) regression is performed in order to eliminate effects of those unobserved attributes attached to a particular housing type on price:

$$P_h^i = p_h e^{\eta_h^i} \tag{3.18}$$

where P_h^i is the actual sale price paid by the household i on housing type h, p_h is a constant term representing the price index of housing type h and η_h^i is the error term of equation 3.18, representing any unobserved attributes affecting the house price P_h^i. Taking natural logarithm on equation 3.18 results in:

$$\ln P_h^i = \ln p_h + \eta_h^i \tag{3.19}$$

Running OLS estimation on equation 3.19 returns a set of constant terms ($\widetilde{\ln p_h}$) for all housing types. Taking natural exponential of $\widetilde{\ln p_h}$ gives the price index of a particular housing type h as p_h. The summary statistics of p_h are incorporated into Table 3.1.

3.6.2 First-Stage Estimation Results

The first-stage estimation recovers interaction parameters and the mean indirect utilities for the 11,609 defined housing types. However, there is a computation issue to address in first-stage estimation. Since the sample sizes (I and H) are usually large for a housing market, it is infeasible to estimate the conditional logit model if including all non-chosen alternative housing types in a household's choice bundle due to the limitation of physical memory. Nevertheless, since the conditional logit specification maintains the Independence of Irrelevant Alternatives (IIA) assumption, then the model can be estimated using a subset of non-chosen alternatives for each household along with the chosen housing type. McFadden (1978) has demonstrated that this estimation scheme can still recover consistent estimates but at the cost of reduction of estimates precision. In the current case, household's choice set includes the observed chosen housing type plus 1,000 random samples from the remaining non-chosen alternative housing types.

Income is a crucial determinant of housing property location for households, thus median household annual income at the census block group level is interacting with structural attributes (lot size in acres, house age, number of bedrooms) and “community” land cover attributes at the block group level (i.e., water, impervious surface, soil & barren, trees & forest, grass & herbaceous, agriculture, woody and emergent wetlands) in this study. Here number of bathrooms is excluded since it is highly correlated with living square footage with a correlation coefficient at 0.85. Due to the correlation, the information provided by number of bathrooms can be reflected by the choice set since living square footage is used to divide the housing properties into “Small”, “Medium” and “Large” categories.

The estimation results are shown in Table 3.2. When interpreting the first-stage estimation results, the signs of the coefficients are of greater importance than their magnitudes because the interactions terms in the first-stage estimation are mainly used to divide the overall average marginal values of the given attributes into parts among all the defined housing types, which further affect the interpretation of the coefficients from the second-stage estimation (Klaiber & Phaneuf, 2010).

As for the structural attributes, the interaction between house age and household annual income has a negative and significant sign reflecting that the households with higher incomes would prefer to choose newly built housing properties. Similarly, it is also found that higher-income households would prefer to choose the housing properties with large lot size in acres and more bedrooms.

When it comes to the interactions between land cover attributes and household income, the results reveal that higher-income households would prefer to choose the housing properties located in the communities with more coverage of water, trees & forest, grass & herbaceous and wetlands. This finding is reasonable as expected because these four land cover attributes, especially the trees and forests, are usually regarded and perceived as environmental amenities which offer positive externalities to the public. Furthermore, the interaction between impervious surface covering percentage and household income is negative and statistically significant. Impervious surface is generally anthropogenic including roads, concrete buildings and any other surfaces to prevent rainwater infiltrating into the ground and seeping into streams, leading to negative externalities such as increasing runoff of pollutants, producing urban "heat island" and reducing ecological productivity (Arnold Jr & Gibbons, 1996; Barnes, Morgan, & Roberge, 2001; Wilby, 2007). Given these facts, the negative correlation between impervious surface covering and household income obtained from the first-stage estimation is supported.

Agricultural land, usually treated as a negative externality, is found to be negatively correlated with household income. This finding indicates that higher-income households have a lower preference to live in a housing property located within the community highly covered by agricultural lands, given the fact that it usually causes adverse effects on environment such as soil degradation and water pollution from the fertilizer and pesticide usage.

In general, the first-stage estimates have expected signs and are consistent with previous findings such as Klaiber and Phaneuf (2010) where the authors found household income is positively related to open space but negatively related to agricultural land. These first-stage estimates support the hypothesis that there exists the preference heterogeneity in tree cover and other land cover attributes in response to varying household annual income, which plays an important role in residential housing property purchasing decision.

3.6.3 Second-Stage Estimation Results

The second-stage estimation needs to deal with endogeneity on price as suggested by (Bayer et al., 2007). The auxiliary regression 3.15 is conducted with additional control variables C_m added including the land cover percentage for the cumulative 1, 2, 3, 4, 5-mile buffer rings around each centroid of the census block group boundary and several key neighborhood characteristics including percent of white population, median income, percent of owner-occupied houses and vacancy rate for the 1, 2, 3, 4, 5-mile buffer rings around each centroid of the census block group boundary. Land cover attributes in percentage within varying buffer rings are directly calculated from the at 1-meter high-resolution map from EnviroAtlas described in Subsection 3.4.3. When it comes to the neighborhood characteristics from a distant community, since each buffer ring starting from the centroid of a given census block group covers varying proportional areas of its adjacent or distant block groups, weighted-averaging is necessary to calculate the representative neighborhood characteristics based on the portions assigned to the buffer ring.

Table 3.3 shows the second-stage estimation results after the IV method described in Subsection 3.3.2. The coefficient of the price is negative which makes sense because higher housing price leads to lower utility from purchasing the housing property. As for the housing structural attributes, it is found that households generally prefer to choose the housing property with larger lot size and more bedrooms regardless of their socio-economic characteristics such as income. In addition, they also prefer newly built rather than orderly built properties since the coefficient of house age is negative and statistically significant.

Concentrating on the land cover attributes, most coefficients are in line with prior expectations. For example, as public goods providing positive externalities, trees & forest, grass & herbaceous, and wetlands have positive and statistically significant signs, indicating that they are preferred by the households when compared to soil & barren, the omitted land cover category. In addition, impervious surface is found to be statistically insignificant at the 0.1 level, indicating it has no direct impact on household's preference if compared to the soil & barren. Agriculture is found to be positive and significant at the 0.05 level, which means housing property owners may prefer more agricultural lands than soil & barren.

Several important neighborhood characteristics which don't interact with household income in the first-stage estimation are added into the second-stage estimation and all present expected signs and significances. Households prefer to live in the community with higher white population ratio and higher educated ratio. However, they would not like to live in the community with low owner-occupied ratio as well as high vacancy rate. These finding confirms previous studies such as (Bayer et al., 2004; Klaiber & Phaneuf, 2010) where the authors concluded that higher percent of owner-occupied houses and lower vacancy rate would contribute to increased utility.

3.6.4 Marginal Willingness to Pay Heterogeneity

In order to better interpret the results from both stages together and comprehensively, marginal willingness to pay (MWTP) measures at the data averages and along with household income (minimum, mean and maximum) are reported in Table 3.4. These MWTP values are calculated through taking ratio of the coefficients of key variables and the negative coefficient of the housing price index. The MWTPs change in response to different household income on the basis of the heterogeneous preference parameters acquired from the first-stage estimation.

Focusing on hosing structural attributes, it is found that household would like to pay \$17,373 for 0.1 acre increase in lot size when the income is at its mean value, \$59,740. In addition, average-income households are willing to pay extra \$57,017 for one additional bedroom and \$2,860 for one-year younger house.

When it comes to the land cover attributes, average-income households are willing to pay \$4,912, \$4,375, \$1,990 and \$5,268 for one percent increase of water, trees & forest, grass & herbaceous, and wetlands within the census block group, respectively, since these public goods generate positive externalities. For impervious surface and agricultural land, their MWTPs are estimated at -\$2,232 and -\$179 for one percent increase since they don't prefer these land cover attributes which have adverse impacts on environment and other negative spillover effects.

Furthermore, average-income households would like to pay \$639, \$1,440 and \$515 for one percent increase in percent of white population, percent of people of age older than 25 years with bachelor's degree and owner-occupancy, respectively. The MWTP of vacancy rate is estimated at -\$1,222 for households with average income.

3.7 A Further Look on Nearby Trees vs. Distant Trees

In previous sections, a horizontal residential sorting model is established to elicit the heterogeneous preferences and general demand for "community tree" at the level of census block group in the Metro Milwaukee area, combined with median income provided by the 2010 Census. The estimation results show that the tree cover measured within the block group boundaries is valued by the housing property owners, implying that the community tree cover is an important determinant of their residential location decisions.

However, due to the geographic scale of census block group, the "community trees" defined previously contains all the trees and forests regardless of the distance from the property to the trees within the boundaries. In this case, nearby trees (e.g., trees on/near to properties) and distant trees (e.g., trees from 1km away) are mixed in the census block group, indicating that the effects of nearby and distant trees on residential location decisions cannot be distinguished separately.

In order to better understand the heterogeneous preferences for both nearby and distant trees varied by geographic distance, this section considers tree cover within neighborhoods measured using three different spatial scales. It is assumed that the trees on/near the property (nearby trees) are more bonded to the housing property itself, while the trees in vicinity or distant location (distant trees) provide external benefits to property owners. In this section, the nearby trees are represented by the tree cover measured within a buffer area of 0-100m around the centroid of each property, and the distant trees are represented by the tree covers measured within 100-500m and 501-1000m from the property. Inclusion of all these tree covers measured at varying spatial scales in the model estimation allows researchers to evaluate differential effects of trees in both private housing properties and public lands, facilitating policy making in terms of urban and community trees and forestry program. It should be noted that the measurement of nearby and distant trees does not involve ownerships of trees, i.e., the nearby trees within 0-100m buffer may contain private trees owned by the property owners as well as the public forests. Similarly, the distant trees within 101-500m and 501-1000m buffer rings may contain private trees owned by distant property owners as well as the trees on public lands such as local parks and public forests.

As argued by Klaiber and Phaneuf (2010), due to the data unavailability of confidential household demographic characteristics from the U.S. census bureau, aggregating block group level census data to represent the individual observable demographic characteristics may have measurement errors so as to have effects on efficiency and consistency of estimates. Following the procedures proposed by Bishop and Timmins (2016) and Bayer, McMillan, Murphy, and Timmins (2016), this section matches and merges disaggregated individual household annual income from the Home Mortgage Disclosure Act (HMDA) dataset to mitigate the potential aggregation bias from using block group level median income data. In this case, the observable individual income data is consistent with property price, structural attributes and land cover attributes in terms of spatial scale.

In summary, this section investigates the impacts of both nearby trees and distant trees on housing property location decision using different spatial scales of land cover measurements, combined with individual household income data. Besides identifying the heterogeneous preferences for tree cover that vary by household income, this section also describes the preference heterogeneity for nearby and distant trees in terms of spatial scales after controlling for household income.

3.7.1 Land Cover Measurement at Varying Spatial Scales

The property transaction dataset including sale price and structural attributes as well as neighborhood characteristics data are the same as described in Section 3.4. This subsection mainly describes how tree covers at difference spatial scales are measured and how individual household annual income data from the HMDA is incorporated into the dataset.

The EnviroAtlas Milwaukee, WI Meter Urban Land Cover (MULC) data (map) is used to measure land cover percentage based on three different spatial scales (buffer rings). The buffer zones are defined as the circle rings originating from the centroid of the property, which could be visualized as "donuts". Trees within 0-100m buffer represents nearby trees and trees within 101-500m and 501-1000m buffer rings refer to distant trees. Besides tree cover, other land cover attributes including water, impervious surface, grass & herbaceous, agriculture, woody wetlands and emergent wetlands are also measured within each buffer ring. Soil & barren is found to be out of the 0-1000m range for all properties in the dataset thus its ratio within all three buffer rings is 0%.

3.7.2 Disaggregated Individual Household Demographics

As stated above, individual level household demographic information is usually absent in the Census dataset. The Census has three levels of geographic units including census blocks, block groups and census tracts. Census block is the most disaggregated geographic unit which typically contains less than 50 households. Census blocks are grouped into block groups, which are further grouped into census tracts. However, the 2010 Census provided very limited set of characteristics at the block level for the public. Thus one drawback of using the block level data is the lack of important demographic characteristics such as race and household income. More information on demographic composition is available at a larger unit, i.e., block group, in the Census.

There is a tradeoff between high spatial resolution data in price, structural attributes, land cover attributes and the capability to acquire disaggregated household demographic characteristics. Although Bayer et al. (2004) and Tra (2010) used public use census micro-data (PUMS) which provides detailed household information, the authors suffer from the limitation of location observations. Klaiber and Phaneuf (2010) conducted an aggregation-level analysis since they assigned census block group level demographic characteristics on census block (approximately 30 household/block) in which four household demographic characteristics are contained at the block level (average number of children per household, average number of working adults per household, average number of retirees per household, and average household size) plus one at the block group level (median income).

Instead of census block group level median income, a unique dataset of individual household demographic characteristics is merged and matched from the Home Mortgage Disclosure Act (HMDA), which was enacted by Congress in 1975 and is now implemented by the Federal Reserve Board's Regulation C (Bayer et al., 2016). The HMDA dataset provides annual income, race and gender of the mortgage applicants, as well as the mortgage loan amount, mortgage lender's name and the census tract of property location. Bayer et al. (2016) and Bishop and Timmins (2016) successfully merged HMDA dataset with 55% and 66% of their property sales based on four common variables: loan amount, sale date, lender's name and census tract. Their matching procedure is applied here. After eliminating duplicated matches, a unique dataset of matched sales is obtained for the Metro Milwaukee area. In detail, 12,788 sales are merged with the HMDA dataset from 2007 to 2014.[1]

In order to ensure the representativeness of the matched dataset, descriptive statistics of both original sales dataset and the merged sales dataset are performed and compared in Table 3.5. The comparison suggests that the set of houses which have a unique loan record from the HMDA is representative of the universe of houses. Thus, the matching procedure described above is proved to be valid and the merged data is able to represent the housing market for the Metro

[1] Note: The HMDA datasets for year 2005 and 2006 is not available. The cash transactions are excluded in the merging process.

Milwaukee area. The visualization of merge property sales with the HMDA is presented in Figure 3.5.

3.7.3 Choice Sets

The choice set is defined following the same strategy in Section 3.5 based on property's location (census block group), house size (33^{rd} and 66^{th} percentiles of living square footage) as well as sale year. In summary, there are $H = 5{,}978$ housing types defined from $I = 12{,}788$ housing property transaction. The observed transaction for each household refers to the choice outcome resulting from purchasing decision made by themselves. In addition, the medians of structural attributes and the land cover attributes of all the houses belonging to a particular housing type are used to construct variables to describe the aggregated structural attributes of this housing type. Table 3.6 provides summary statistics for the aggregated structural attributes and land cover attributes measures with three buffer rings across the defined housing types for the study area.

3.7.4 First-Stage Estimation Results

Estimation strategy follows the same implementation discussed in Section 3.3 including price index estimation, first-stage heterogeneous preferences estimation as well as second-stage mean indirect utility decomposition. IIA assumption is applied here so each household's choice set includes the observed chosen housing type plus 1,000 random samples from the remaining non-chosen alternative housing types. Individual household annual income is interacting with structural attributes and land cover attributes. Number of bathrooms is excluded from the interactions due to its high correlation with number of bedrooms. It should be noted that the three buffer rings are adjacent to each other spatially, thus there exists potential correlations for land cover attributes within the buffer ring and between the buffer rings. In this case, impervious surface percentage within 0-100m, 101-500m and 501-1000m buffer rings are excluded from the first-stage estimation in order to mitigate problems caused by multicollinearity.

The first-stage estimation results are presented in Table 3.7. Heterogeneous preferences for structural attributes that vary by household income are detected. For example, higher income households prefer to live in a newer house with larger lot size and number of bedrooms. This finding is consistent with the estimation results in Subsection 3.6.4. More importantly, the results reveal that preferences for tree cover not only vary by household annual income, but also differ in terms of spatial scales of the land cover measurement. Several key findings are summarized here. All coefficients for land cover attributes within 0-100m buffer are negative, indicating that households with higher income would prefer less quantity of environmental (dis)amenities on/near their housing properties than impervious surface, the omitted land cover attribute. Instead, they may spend more budget on impervious surface on their properties such as building a new patio or constructing a swimming pool. When the spatial scale increases, it is found that households with higher income would prefer to choose the housing properties with more environmental amenities such as trees, water, grass and wetlands within the 101-500m and 501-1000m buffer rings. When income is controlled, it is found that households would have greater preferences for distant trees (101-500m and 501-1000 buffer rings) rather than nearby trees (0-100m buffer).

3.7.5 Second-Stage Estimation Results

The second-stage estimation decomposes the mean indirect utilities estimated from the first-stage estimation into average taste, i.e., homogeneous preference regardless of household demographic characteristics. Same as Subsection 3.6.3, instrument variable is constructed to deal with the endogeneity. The second-stage estimation results are reported in Table 3.8 where the omitted land cover attribute is impervious surface measured at each spatial scale. Preference heterogeneity for varying land cover attributes measured at different spatial scales are identified without considering individual household annual income. Especially, it is found that nearby trees are negatively valued by households. Although trees usually have positive externalities, trees on/near the properties may have some negative externalities such as preventing sunshine entering into the house, blocking views from home, and suffering from tree-borne disease and insects (e.g., Mountain Pine Beetle). In contrast, households prefer to live with higher percent of distant trees. These findings conclude that spatial scales have significant effects on recovering the demand curve for tree cover. In addition to tree cover, other land cover attributes such as water, grass & herbaceous, agriculture and wetlands also present diverse impacts on residential location decision across various spatial scales.

The coefficient signs and magnitudes of structural attributes and neighborhood characteristics are expected and consistent with the results shown in Subsection 3.6.3. For example, households generally prefer to choose the newer housing properties with larger lot size and more bedrooms. And they prefer to live in the community with higher white population ratio, higher education ratio, higher owner-occupancy rate and lower vacancy rate.

3.7.6 Marginal Willingness to Pay Heterogeneity

Table 3.9 displays the marginal willingness to pay for one unit change of all attributes considered in the estimation at the data averages. When household annual income is fixed at its mean, \$71,706, it is found that household would like to pay \$7,255 for 0.1 acre increase in lot size, \$67,524 for an additional bedroom and \$1,059 for one-year younger housing property.

When it comes to tree cover, average-income households are willing to pay -\$454 for one percent increase in nearby trees within 0-100m buffer, \$748 for one percent increase in distant trees within 101-500m buffer rings and \$2,072 for one percent increase in distant trees within 501-1000m. There are also discrepancies in the MWTPs for other land cover attributes resulted from spatial scale difference.

Also, average-income households would like to pay \$544, \$1,398 and \$593 for one percent increase in percent of white population, percent of people of age older than 25 years with bachelor's degree and owner-occupancy, respectively. The MWTP of vacancy rate is estimated at -\$622 for households with average income. These values are consistent with previous MWTP results showed in Subsection 3.6.4.

3.8 Conclusions and Discussion

Most previous studies used the first-stage hedonic model to estimate the "implicit price" of tree cover, but failed to move forward to the second-stage demand analysis due to the identification and endogeneity issues. Instead of traditional hedonic model, this chapter presents a demand analysis for environmental (dis)amenities with a focus on tree cover through establishing a residential sorting model under the framework of random utility theory. Based on the "horizontal preference structure" imposed in the sorting model, heterogeneous preferences for land cover attributes based on household demographic characteristics are incorporated into the estimation. The first part of this chapter suggests that tree cover at census block group level is valued by the housing property owners and higher-income households would prefer to live in higher tree covered community. In fact, household preferences for the different land cover attributes vary with income, implying that the benefits brought from the positive externalities (e.g., water, trees & forests, grass & herbaceous and wetlands) and the adverse outcomes generated from the negative externalities (e.g., impervious surface and agriculture) will be diversely conveyed to housing property owners based on household income.

The above findings contribute to several policy implications, especially for urban landscape planners who are now facing challenges from climate change and urbanization. Community tree loss due to climate change or other unexpected events such as flooding or drought should be replaced, because the sorting model results suggest that people will re-sort themselves in the housing market in response to a non-marginal change of tree cover, i.e., leaving the community with dead trees and moving to a new one with more trees. In addition, any urban and community forestry programs need to be refined to be more localized instead of spatially homogeneous across the whole urban area to account for the effects caused by the discrepancy in demographic socio-economic characteristics.

Furthermore, the second part of this chapter examines the effects of both nearby and distant trees on residential location decision through incorporating different measurements of land cover attributes based on varying spatial scales. The results reveal that households have heterogeneous preferences for nearby and distant trees across the landscape spatially. Distant trees (i.e., tree within 101-500m and 501-1000m buffer rings) are positively valued by the housing property owners, but nearby trees (i.e., trees on/near the properties within 0-100m buffer ring) are not. Higher income households would prefer more impervious surface on/near their properties rather than private trees or other environmental amenities. These key findings suggest policy makers and urban landscape planners setting up community tree and forest programs (e.g., construct local parks, forested open space and street trees), zoning policy as well as tax incentives to reduce the trees on/near residential properties but to increase the tree cover at a further distance.

Moreover, the second part of this chapter uses individual household annual income matched from the HMDA dataset to reduce the aggregation bias resulted from assigning the census block group median income to households. However, there is a tradeoff between using the HMDA demographic characteristics and the census data because sample size is decreasing during the matching process since the HMDA only records information of home buyers who had mortgages rather than those paid by cash. Besides the risk of losing sample size, there is another uncertainty about the validation of income in the HMDA dataset because a home buyer may only report the income which is just qualified for the mortgage requirement instead of his/her actual household annual income.

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Figure 3.1: Structure and Estimation Strategy of Horizontal Residential Sorting Model.

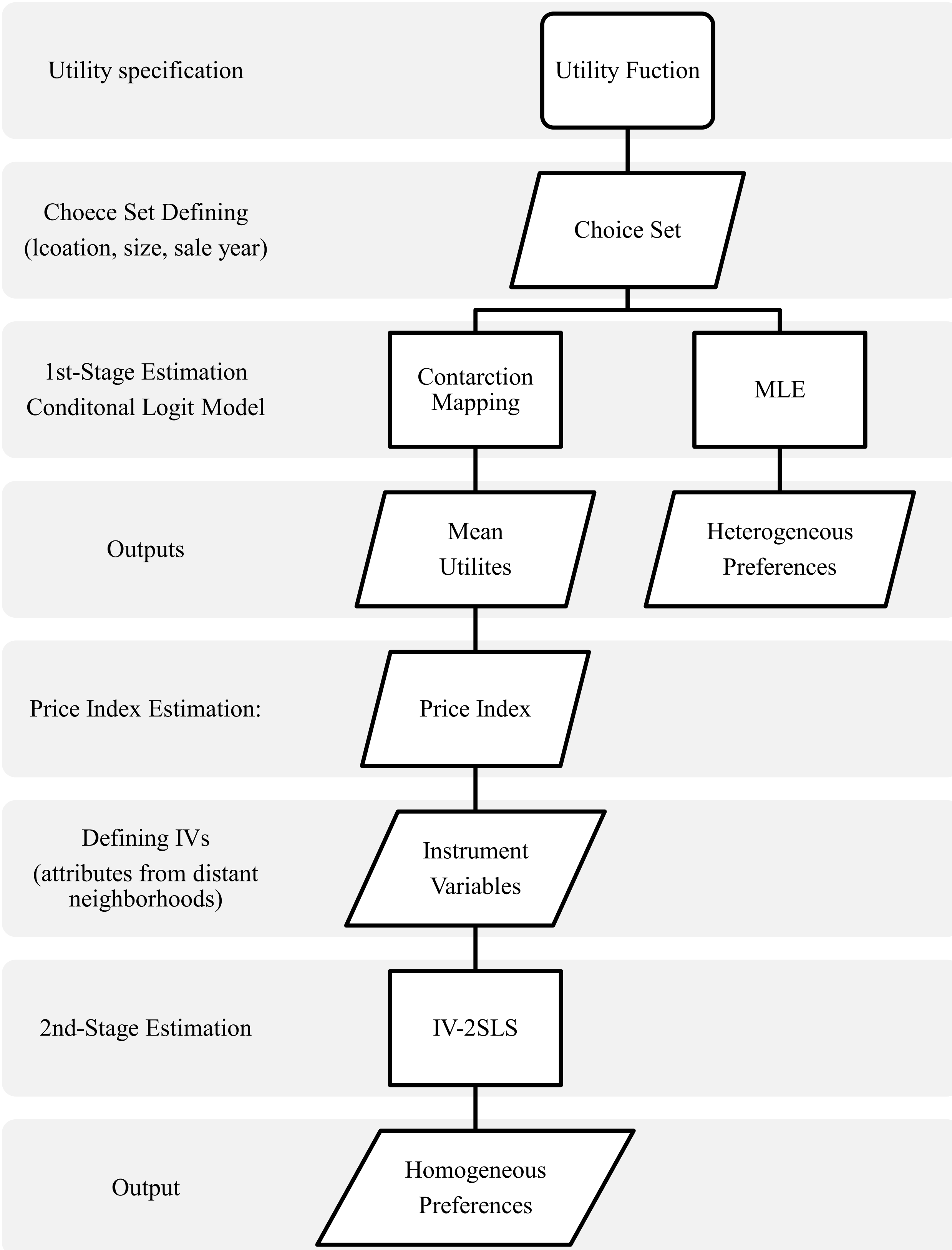
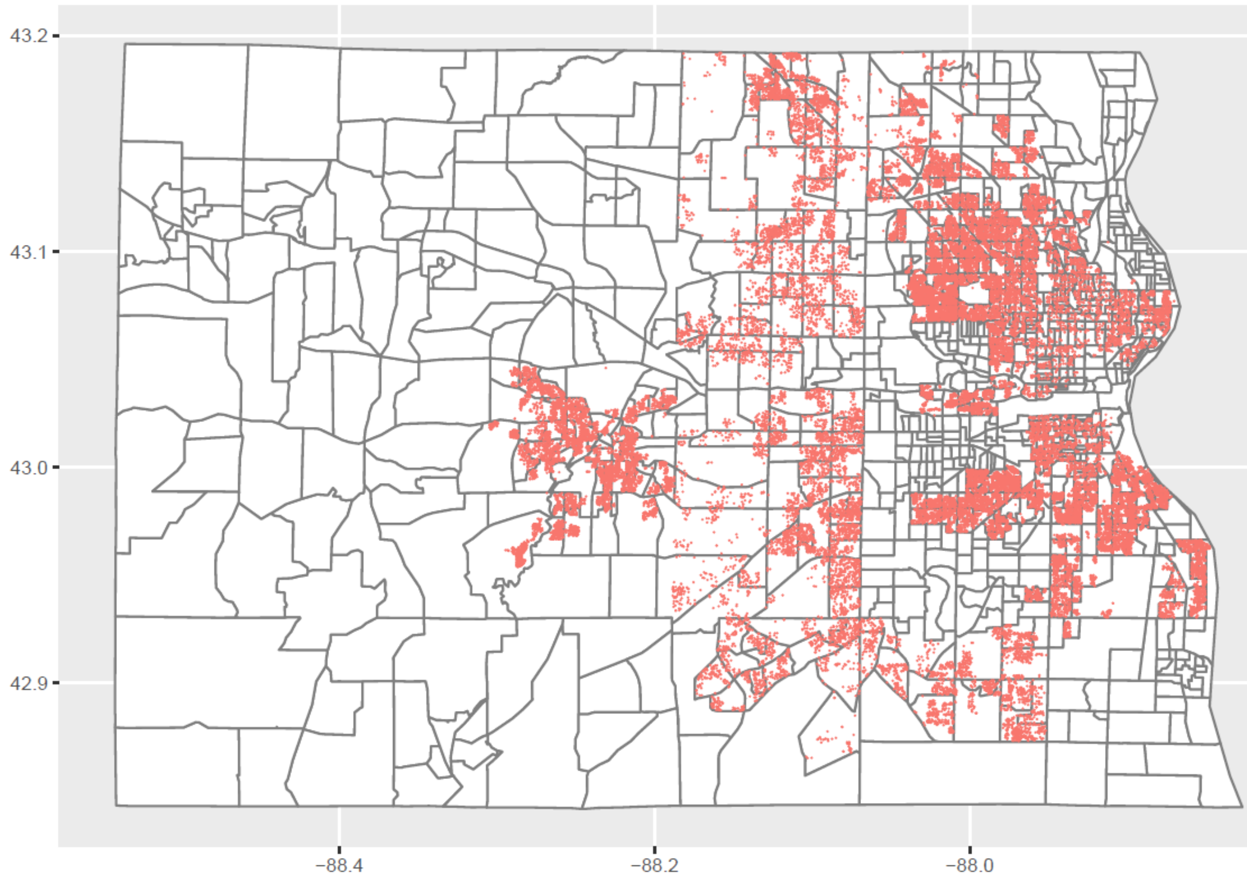


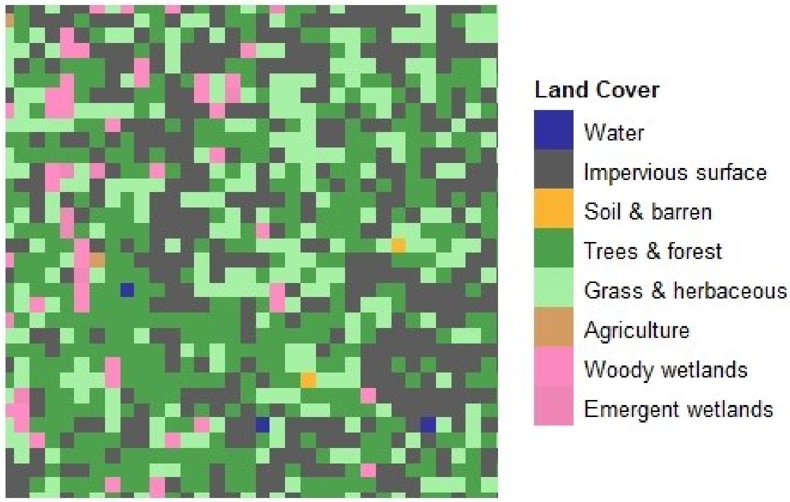
Figure 3.2: Property Transactions Mapping within the Boundaries of the 2010 Census Block Groups in the Metro Milwaukee Area.



Source: MLS Dataset and the 2010 Census.

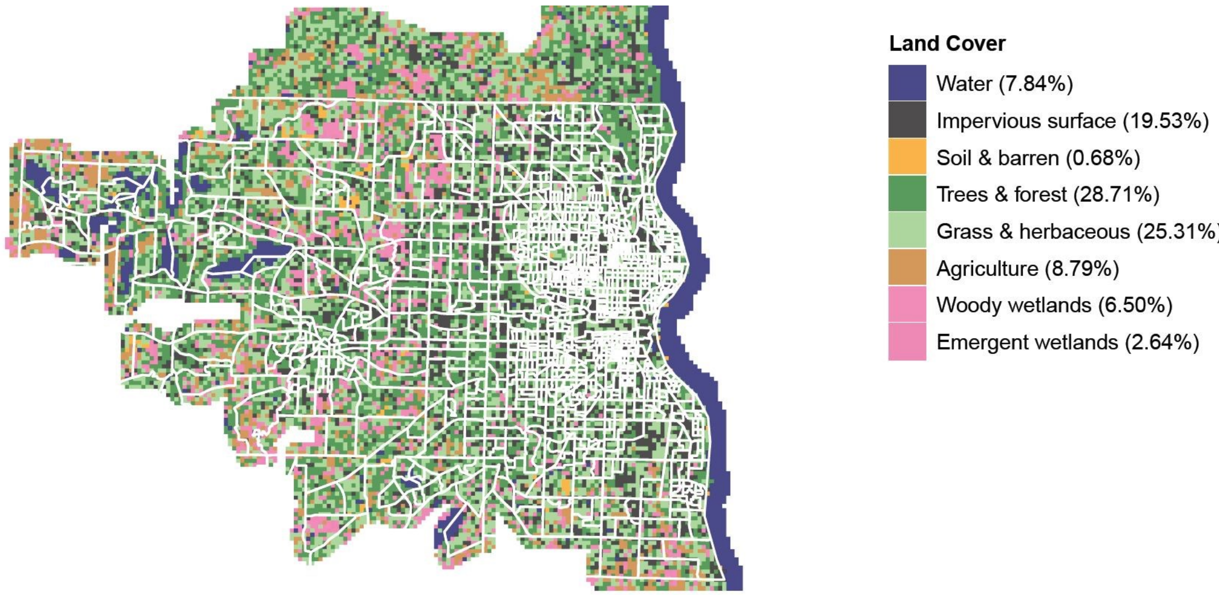
Note: Each red dot represents a housing property transaction.

Figure 3.3: Example of Raster Map provided by EnviroAtlas.



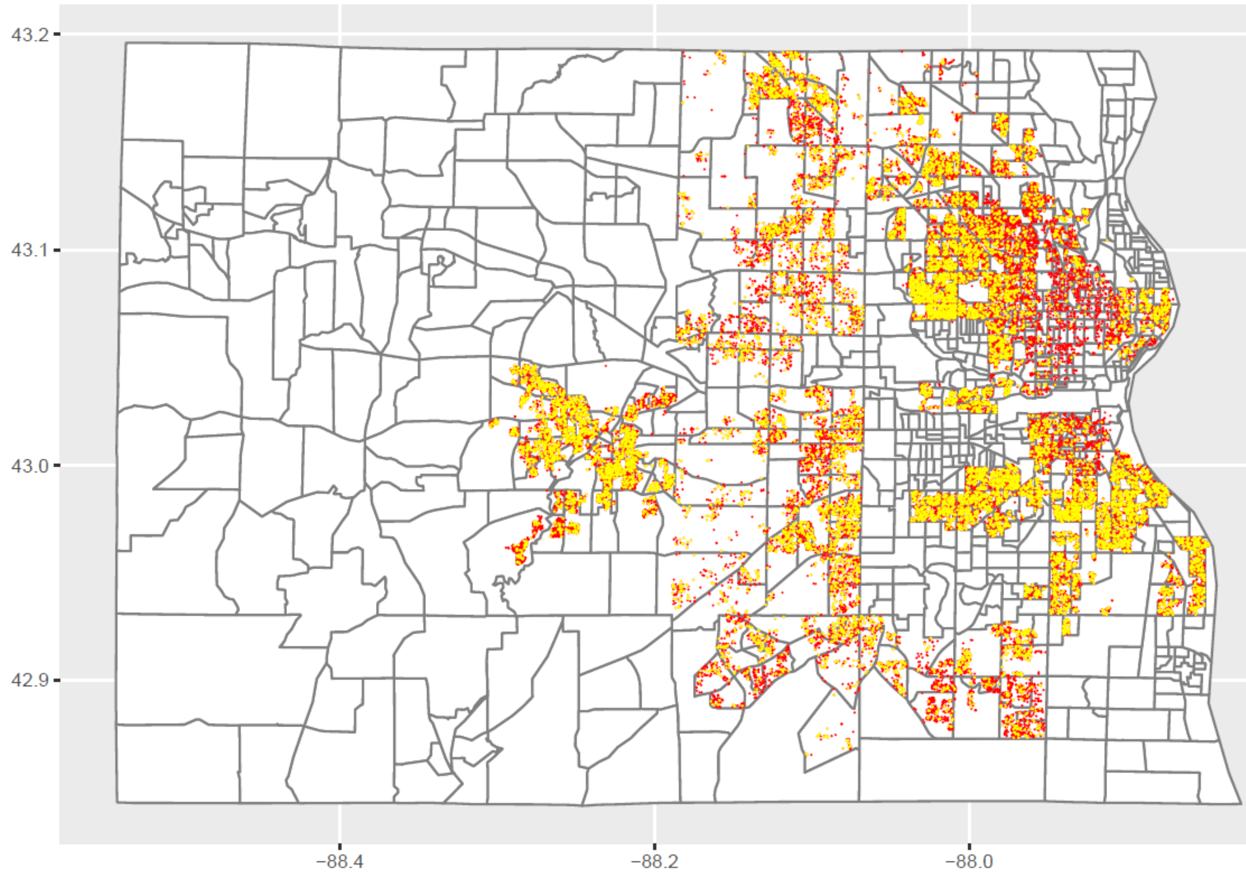
Source: EnviroAtlas, EPA.

Figure 3.4: Land Cover Composition within the 2010 Census Block Group Boundaries of the Metro Milwaukee Area.



Source: EnviroAtlas, EPA.

Figure 3.5: Visualization of Merged Property Sales with the HMDA for the Metro Milwaukee Area.



Source: MLS Dataset and the 2010 Census.

Note: Red dots represent all property transaction sales in dataset and yellow dots represent merged sales with the HMDA dataset.

Table 3.1: Descriptive Statistics for the Key Variables.

	Mean	Std. Dev.	Min	Max
Household Demographics ($I = 40{,}666$)				
Income ($10k)	5.9740	2.5230	0.9030	18.4250
Housing Types ($H = 11{,}609$)				
Structural attributes				
Lot size (acre)	0.2306	0.2543	0.0200	9.7300
Living square footage	1443.0000	482.1503	540.0000	8482.0000
House age	62.0300	26.8191	1.0000	165.0000
Number of bedrooms	3.0860	0.6429	1.0000	9.0000
Number of bathrooms	1.5290	0.5157	1.0000	5.0000
Land cover (block group level)				
% Water	0.0056	0.0293	0.0000	0.4317
% Impervious surface	0.3908	0.1413	0.0690	0.8176
% Soil & barren	0.0021	0.0114	0.0000	0.1539
% Trees & forest	0.3448	0.1195	0.0261	0.8270
% Grass & herbaceous	0.2226	0.0829	0.0110	0.7556
% Agriculture	0.0067	0.0240	0.0000	0.2287
% Wetlands (Woody or Emergent)	0.0274	0.0600	0.0000	0.4531
Neighborhood characteristics (block group)				
% White population	0.6588	0.3234	0.0026	0.9838
% Education	0.2835	0.1781	0.0032	0.8603
% Owner-occupied houses	0.6325	0.2288	0.0072	0.9941
% Vacant houses	0.0678	0.0476	0.0000	0.3467
Price Index ($10k)	14.9610	7.0190	1.9530	87.6870

Note: % Education refer to the percent of people of age older than 25 years with bachelor's degree. Land cover percentage is shown as decimal fractions.

Table 3.2: First-Stage Heterogeneous Preference Estimates.

Interactions (Attributes * Income)	Coefficient	Standard Error
Lot size * Income	0.3850	(0.0033)***
House age * Income	-0.0084	(0.0000)***
Number of Bedrooms * Income	0.0898	(0.0016)***
% Water * Income	0.8440	(0.0613)***
% Impervious surface * Income	-1.1152	(0.0548)***
% Trees & forest * Income	1.1122	(0.0543)***
% Grass & herbaceous * Income	0.4675	(0.0559)***
% Agriculture * Income	-0.7532	(0.0615)***
% Wetlands * Income	1.0795	(0.0560)***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Table 3.3: Second-Stage Mean Utility Decomposition Estimates.

Variable	Coefficient	Standard Error
Price ($10k)	-0.4042	(0.0202)***
Lot size (acres)	4.7223	(0.1615)***
House age	-0.0656	(0.0018)***
Number of bedrooms	1.7684	(0.0568)***
% Water	14.8144	(1.6866)***
% Impervious surface	-2.3618	(1.4447)
% Trees & forest	11.0411	(1.4395)***
% Grass & herbaceous	5.2516	(1.4710)***
% Agriculture	3.7745	(1.8770)**
% Wetlands	14.8450	(1.5551)***
% White population	2.5841	(0.1437)***
% Education	5.8220	(0.2552)***
% Owner-occupied houses	2.0816	(0.1351)***
% Vacant houses	-4.9391	(0.7860)***
Constant	-7.7343	(1.4374)***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. The omitted land cover attribute is soil & barren.

Table 3.4: Marginal Willingness to Pay (MWTP) Estimates Heterogeneity.

	Min	Mean	Max
Income ($10k)	0.9030	5.9741	18.4250
Variable change (Marginal Change)	MWTP	MWTP	MWTP
Lot size (0.1)	$12,543	$17,373	$29,232
House Age (1)	-$1,809	-$2,860	-$5,439
Number of bedrooms (1)	$45,754	$57,017	$84,671
% Water (1%)	$3,854	$4,912	$7,512
% Impervious surface (1%)	-$833	-$2,232	-$5,667
% Trees & forest (1%)	$2,980	$4,375	$7,801
% Grass & herbaceous (1%)	$1,404	$1,990	$3,430
% Agriculture (1%)	$766	-$179	-$2,499
% Wetlands (1%)	$3,914	$5,268	$8,593
% White population (1%)	$639	$639	$639
% Education (1%)	$1,440	$1,440	$1,440
% Owner-occupied houses (1%)	$515	$515	$515
% Vacant houses (1%)	-$1,222	-$1,222	-$1,222

Table 3.5: Comparison of Sample Statistics for Transactions Data and Merged Data for Milwaukee, WI.

	Mean	Std. Dev.	Min	Max
Merged data with the HMDA:				
(N=12,788)				
Sale price ($10k)	17.2630	8.3261	2.3605	111.5361
Lot size (acre)	0.2649	0.3375	0.0275	13.6900
Living square footage	1504.6320	594.2013	544.0000	7664.0000
House age	54.9970	24.7165	0.0000	177.0000
Number of bedrooms	3.0841	0.6699	1.0000	10.0000
Number of bathrooms	1.6156	0.6104	1.0000	5.5000
0-100m buffer ring:				
% Water	0.0004	0.0078	0.0000	0.3813
% Impervious surface	0.3586	0.1421	0.0000	0.8312
% Trees & forest	0.3971	0.1854	0.0020	0.9814
% Grass & herbaceous	0.2356	0.1102	0.0000	0.7584
% Agriculture	0.0010	0.0140	0.0000	0.4320
% Wetlands (Woody or Emergent)	0.0070	0.0392	0.0000	0.8882
101-500m buffer ring:				
% Water	0.0044	0.0233	0.0000	0.4349
% Impervious surface	0.3644	0.1334	0.0209	0.7468
% Trees & forest	0.3541	0.1368	0.0548	0.8261
% Grass & herbaceous	0.2454	0.0836	0.0214	0.6335
% Agriculture	0.0051	0.0228	0.0000	0.4195
% Wetlands (Woody or Emergent)	0.0251	0.0529	0.0000	0.5331
501-1000m buffer ring:				
% Water	0.0118	0.0460	0.0000	0.4953
% Impervious surface	0.3601	0.1239	0.0212	0.6527
% Trees & forest	0.3280	0.1112	0.0742	0.7408
% Grass & herbaceous	0.0085	0.0260	0.0000	0.2801
% Agriculture	0.2527	0.0713	0.0382	0.5224
% Wetlands (Woody or Emergent)	0.0366	0.0560	0.0000	0.5667
Transaction data from 2007-2014:				
(N=40,466)				
Sale price ($10k)	16.8692	8.6357	1.9530	144.9786
Lot size (acre)	0.2602	0.3487	0.0200	14.0000
Living square footage	1501.4500	601.0607	512.0000	11009.0000
House age	54.0508	27.1253	1.0000	177.0000
Number of bedrooms	3.0862	0.6964	1.0000	10.0000
Number of bathrooms	1.6146	0.6203	1.0000	6.5000
0-100m buffer ring:				
% Water	0.0004	0.0071	0.0000	0.3813
% Impervious surface	0.3686	0.1427	0.0000	0.8533
% Trees & forest	0.3801	0.1820	0.0000	1.0000
% Grass & herbaceous	0.2424	0.1099	0.0000	0.7867

% Agriculture	0.0012	0.0163	0.0000	0.7207
% Wetlands (Woody or Emergent)	0.0071	0.0394	0.0000	1.0000
101-500m buffer ring:				
% Water	0.0040	0.0207	0.0000	0.5624
% Impervious surface	0.3717	0.1344	0.0160	0.7468
% Trees & forest	0.3408	0.1337	0.0490	0.8367
% Grass & herbaceous	0.2506	0.0831	0.0214	0.6335
% Agriculture	0.0055	0.0236	0.0000	0.6944
% Wetlands (Woody or Emergent)	0.0259	0.0552	0.0000	0.5331
501-1000m buffer ring:				
% Water	0.0092	0.0356	0.0000	0.4648
% Impervious surface	0.3677	0.1244	0.0280	0.6717
% Trees & forest	0.3238	0.1111	0.0702	0.7322
% Grass & herbaceous	0.2551	0.0707	0.0547	0.5233
% Agriculture	0.0080	0.0240	0.0000	0.3344
% Wetlands (Woody or Emergent)	0.0369	0.0580	0.0000	0.5667

Table 3.6: Descriptive Statistics for The Key Variables Used in Section 3.7.

	Mean	Std. Dev.	Min	Max
Household Demographics ($I = 12{,}788$)				
Annual Income from HDMA ($10k)	7.1076	4.8054	0.6078	85.6408
Housing Types ($H = 5{,}978$)				
Structural attributes				
Lot size (acre)	0.2387	0.2379	0.0281	4.6283
Living square footage	1446.6530	500.7511	544.0000	6621.0000
House age	59.9907	24.2116	0.0000	151.0000
Number of bedrooms	3.0700	0.6161	1.0000	8.0000
Number of bathrooms	1.5456	0.5279	1.0000	5.5000
Land cover (0-100m buffer ring)				
% Water	0.0004	0.0086	0.0000	0.3813
% Impervious surface	0.3697	0.1414	0.0000	0.8031
% Trees & forest	0.3939	0.1755	0.0203	0.9814
% Grass & herbaceous	0.2277	0.1000	0.0000	0.6456
% Agriculture	0.0006	0.0101	0.0000	0.4036
% Wetlands (Woody or Emergent)	0.0044	0.0273	0.0000	0.6312
Land cover (101-500m buffer ring)				
% Water	0.0050	0.0249	0.0000	0.4349
% Impervious surface	0.3822	0.1335	0.0221	0.7468
% Trees & forest	0.3465	0.1342	0.0754	0.8222
% Grass & herbaceous	0.2393	0.0800	0.0214	0.6079
% Agriculture	0.0037	0.0192	0.0000	0.3699
% Wetlands (Woody or Emergent)	0.0202	0.0443	0.0000	0.4611
Land cover (501-1000m buffer ring)				
% Water	0.0142	0.0509	0.0000	0.4591
% Impervious surface	0.3774	0.1224	0.0338	0.6386
% Trees & forest	0.3196	0.1092	0.0817	0.7408
% Grass & herbaceous	0.2483	0.0703	0.0385	0.5224
% Agriculture	0.0066	0.0226	0.0000	0.2752
% Wetlands (Woody or Emergent)	0.0312	0.0509	0.0000	0.4385
Neighborhood characteristics (block group)				
% White population	0.7165	0.2872	0.0026	0.9838
% Education	0.3028	0.1722	0.0032	0.8603
% Owner-occupied houses	0.6763	0.2114	0.0567	0.9941
% Vacant houses	0.0579	0.0372	0.0000	0.3467
Price Index ($10k)	15.8000	7.1651	2.3600	87.9500

Note: % Education refer to the percent of people of age older than 25 years with bachelor's degree. Land cover percentage is shown as decimal fractions.

Table 3.7: First-Stage Heterogeneous Preference Estimates.

Interactions (Attributes * Income)	Coefficient	Standard Error
Lot size * Income	0.0476	(0.0045)***
House age * Income	-0.0010	(0.0001)***
Number of Bedrooms * Income	0.0841	(0.0019)***
% Water (0-100m) * Income	-0.0648	(0.0966)
% Trees & forest (0-100m) * Income	-0.1060	(0.0147)***
% Grass & herbaceous (0-100m) * Income	0.0211	(0.0222)
% Agriculture (0-100m) * Income	-0.6000	(0.1430)***
% Wetlands (0-100m) * Income	-0.1178	(0.0406)***
% Water (101-500m) * Income	0.0351	(0.0566)
% Trees & forest (101-500m) * Income	0.1250	(0.0249)***
% Grass & herbaceous (101-500m) * Income	-0.0055	(0.0336)
% Agriculture (101-500m) * Income	-0.1095	(0.0703)
% Wetlands (101-500m) * Income	0.1763	(0.0328)***
% Water (501-1000m) * Income	0.7211	(0.0315)***
% Trees & forest (501-1000m) * Income	0.3893	(0.0248)***
% Grass & herbaceous (501-1000m) * Income	0.0726	(0.0340)***
% Agriculture (501-1000m) * Income	0.5109	(0.0538)***
% Wetlands (501-1000m) * Income	0.3376	(0.0298)***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Table 3.8: Second-Stage Mean Utility Decomposition Estimates.

Variable	Coefficient	Standard Error
Price ($10k)	-0.3323	(0.0207)***
Lot size (acres)	2.0728	(0.2394)***
House age	-0.0278	(0.0021)***
Number of bedrooms	1.6457	(0.0775)***
% Water (0-100m)	13.0347	(4.1548)***
% Trees & forest (0-100m)	-0.7543	(0.2658)***
% Grass & herbaceous (0-100m)	1.8393	(0.3840)***
% Agriculture (0-100m)	-4.5663	(2.6551)*
% Wetlands (0-100m)	1.0282	(1.3303)
% Water (101-500m)	-0.2959	(2.4654)
% Trees & forest (101-500m)	1.5955	(0.4747)***
% Grass & herbaceous (101-500m)	-0.2483	(0.5024)
% Agriculture (101-500m)	-1.4721	(1.9398)
% Wetlands (101-500m)	2.7283	(0.8650)***
% Water (501-1000m)	13.8924	(1.2125)***
% Trees & forest (501-1000m)	4.1178	(0.4732)***
% Grass & herbaceous (501-1000m)	-1.0170	(0.5357)*
% Agriculture (501-1000m)	9.9219	(1.5946)***
% Wetlands (501-1000m)	3.3134	(0.8357)***
% White population	1.8072	(0.1615)***
% Education	4.6445	(0.2993)***
% Owner-occupied houses	1.9719	(0.1709)***
% Vacant houses	-2.2002	(0.6959)***
Constant	-2.0028	(0.2817)***

Note: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels. The omitted land cover attribute is impervious surface.

Table 3.9: Marginal Willingness to Pay (MWTP) Estimates Heterogeneity.

	Min	Mean	Max
Income ($10k)	0.6078	7.1076	85.6408
Variable change (Marginal Change)	MWTP	MWTP	MWTP
Lot size (0.1)	$6,325	$7,255	$18,497
House age (1)	-$857	-$1,059	-$3,503
Number of bedrooms (1)	$51,065	$67,524	$266,390
Land cover (1%):			
% Water (0-100m)	$3,923	$3,923	$3,923
% Trees & forest (0-100m)	-$246	-$454	-$2,958
% Grass & herbaceous (0-100m)	$553	$553	$553
% Agriculture (0-100m)	-$1,484	-$2,658	-$16,838
% Wetlands (0-100m)	$288	$57	-$2,727
% Water (101-500m)	-$89	-$89	-$89
% Trees & forest (101-500m)	$503	$748	$3,703
% Grass & herbaceous (101-500m)	-$75	-$75	-$75
% Agriculture (101-500m)	-$443	-$443	-$443
% Wetlands (101-500m)	$853	$1,198	$5,364
% Water (501-1000m)	$4,313	$5,723	$22,766
% Trees & forest (501-1000m)	$1,310	$2,072	$11,272
% Grass & herbaceous (501-1000m)	-$293	-$151	$1,564
% Agriculture (501-1000m)	$3,079	$4,079	$16,152
% Wetlands (501-1000m)	$1,059	$1,719	$9,697
% White population (1%)	$544	$544	$544
% Education (1%)	$1,398	$1,398	$1,398
% Owner-occupied houses (1%)	$593	$593	$593
% Vacant houses (1%)	-$662	-$662	-$662

Appendix

Table A1: Definition of Land Cover Types in the Metro Milwaukee Area.

Land Cover Type	Detail
Water	All surface waters including streams, rivers, canals, ponds, reservoirs, lakes, bays, estuaries, and coastal waters. For cases of ephemeral changes in water level and extent such as tidelands and some lakes, the waterline at the time of photo acquisition is used to define the extent of the water feature.
Impervious Surface	Impervious Surface is a landscape feature that prevents or substantially limits rainfall from infiltrating into the soil, including: paved roads, parking lots, driveways, sidewalks, roofs, swimming pools, patios, painted surfaces, wooden structures, and most asphalt and concrete surfaces. Many dirt and gravel roads, and railways, are functionally impervious or semi-impervious and are included in the impervious surface class. Most impervious surfaces are anthropogenic. When trees overhang streets and other impervious surfaces, those pixels are assigned to the Tree class rather than the underlying Impervious class. This assignment reflects the EnviroAtlas emphasis on ecosystem services, and the importance of street trees in urban areas.
Soil & Barren	The Soil and Barren includes soil, bare rock, mud, clay and sand. This class includes bare fields, construction sites, quarries, gravel pits, mine lands, golf sand traps, stream and river sand bars, beaches and other bare soil and gravel surfaces. Soil and Barren includes natural areas with widely spaced or no vegetation cover.
Trees & Forest	The Trees and Forest class includes trees of any kind, from a single individual to continuous canopy forest. If a vegetation object casts a shadow longer than a few meters, it is usually classified as a tree. Large shrubs fall in this class.
Grass & Herbaceous	The Grass and Herbaceous includes the graminoids, forbs and herbs lacking persistent woody stems. Grass includes residential lawns, golf courses, roadway medians and verges, park lands, transmission line, natural gas corridors, recently clear-cut areas, pasture, grasslands, prairie grass, and emergent wetlands vegetation. Small shrubs fall into this category.
Agriculture	The Agriculture includes herbaceous vegetation planted or being managed for the production of food, feed, or fiber. Agriculture includes cultivated row crops and fallow fields that are being actively tilled. Agriculture is typically a relatively rare class in

	urban areas, but may occur with greater frequency in exurban regions away from the urban core. The US Census Urban Areas can be large in aerial extent, and may encompass significant amounts of agricultural land. The Atlas treats agricultural lands primarily in a land cover sense as Grass-Herbaceous, Trees, Shrubs or Soil, and secondarily as Agriculture land use.
Woody Wetlands	Woody Wetlands are wetlands dominated by tree and forest species. Typically these are identified using ancillary GIS layers (e.g., National Wetlands Inventory).
Emergent Wetlands	Emergent Wetlands are wetlands dominated by grass and herbaceous species. Typically these are identified using ancillary GIS layers.

Source: EnviroAtlas, EPA, please refer to https://www.epa.gov/enviroatlas/milwaukee-wi-mulc-metadata

CHAPTER 4
Conclusion

This dissertation focuses on the applications of economic theories and empirical analyses on environmental issues in the United States. The first study presented in Chapter 2 analyzes the financial feasibility and cost-effectiveness of water-recycling technology with consideration of plant eco-labeling program and consumer premiums on plants produced with recycled water. The second study presented in Chapter 3 adopts a novel research method, i.e., the horizontal residential sorting model, to determine the impact of tree cover on residential property value in urban landscape and further elicit property owners' demand for tree cover and other land cover attributes.

Chapter 2 aims to determine whether consumer premiums for plants grown with recycled water are sufficient to make WRT economically feasible. Specifically, this study evaluates the economic effects of labeling plants grown with WRT practices in selected nursery operations in the Mid-Atlantic region of Virginia, Maryland and Pennsylvania. Partial budgeting, whole enterprise-level budgeting, sensitivity and break-even analyses are conducted to estimate the economic feasibility of water-recycling technology combined with plant eco-labeling program, and to determine the influence of consumer premiums generated from such a program on greenhouse/nursery production costs, gross revenues and net revenues. It is concluded that consumer premiums for plants grown with recycled water could offer nursery growers a method to improve their net returns while reducing pollution runoff and improving irrigation water usage efficiency. This finding holds when only a fraction of the premiums is returned to growers. While numerous studies have investigated consumer willingness to pay premiums for environmental amenities, few studies have compared such premiums with costs of producing such amenities. This study helps fill that gap for horticultural products, an important and growing part of the U.S. agricultural sector. The results can help nursery growers and policy makers assess WRT adoption to improve irrigation water use efficiency and reduce pollution of surface waters.

Chapter 3 is an application of residential sorting model on non-market valuation of environmental (dis)amenity. This chapter investigates how tree cover and other land cover attributes affect housing property value and recovers households' demand for these land cover attributes. Through imposing the "horizontal preference structure", heterogeneous preferences for tree cover which vary by observable household demographic characteristics are estimated. It is concluded that housing property owners positively value the "community trees" measured at the census block group level. Providing positive externalities, tree cover has a positive impact on property value. In addition, income is found to be a strong demand shifter which leads to the heterogeneous preferences for tree cover. For example, when income increases, households would prefer to live in a neighborhood covered by more trees but less impervious surface. Besides focusing on "community trees", this chapter further incorporates heterogeneity of tree cover measurement at different spatial scales into the analysis. Nearby trees and distant trees are measured within 0-100m, 101-500m and 501-100m buffer rings, respectively. It is found that different spatial scales of land cover measurement results in heterogeneous preferences for tree cover when household demographic characteristics are controlled. To sum up, Chapter 3 concludes that preferences for urban tree cover not only vary by household annual income, but also differ across spatial scales of the tree cover measurement. The findings offer suggestions and important policy implications on urban trees and forestry programs.