THREE ESSAYS ON THE ECONOMICS OF PESTICIDE USE

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

THREE ESSAYS ON THE ECONOMICS OF PESTICIDE USE

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a candidate for the degree of doctor of philosophy,

and hereby certify that, in their opinion, it is worthy of acceptance.

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DEDICATION

This dissertation is specially dedicated with love and affection

to

My father Lam Tran and my mother Ha Nguyen

My wife Tu Vu

My beloved children Vu, Dang, Minh, Anh

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Lan The Tran (Columbia, July 2022)

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ABSTRACT

Pesticides primarily benefit humans in terms of protection of food production, prevention of diseases, and weed control, but also potentially harm people and the environment. Given increasing current interest in human health and environmental quality, pesticide usage has become more controversial. This dissertation investigates the use of pesticides and their alternatives from household, producer, and consumer perspectives to obtain insights about their behaviors and preferences. For households, the adoption of organic pesticides in lawns and gardens is examined. A multinomial logit model is applied to analyze factors affecting adoption versus being in distinct non-adopter categories using a dataset from a survey of 661 residents in Missouri. The organic pesticide adoption rate is low (17.7%) and found to be positively associated with pro-environmental attitudes and gardening behaviors but negatively correlated with concerns of neighbor's opinions on the homeowner's lawn appearance or management. Non-adopters differ, e.g., people who have never heard of the practice versus those know it well are predicted by different factors, implying demand for targeted educational campaigns or dissemination of information on effective practices as well as developing or labelling organic and environmentally-friendly products.

Chemical pesticides are widely used for their effectiveness in terms of pest control as farmers have experienced in agricultural production since the 1950s. However, improper use of pesticides may result in inefficiency, thus reducing farm profitability, in addition to external effects of pesticide use on environmental and human health. Using a directional distance function framework on rice and fruit farm data from the 2016 Vietnamese Household Living Standards Survey, the dissertation finds inefficiency of pesticide use, especially in rice production. In addition, although both rice and fruit farms in the sample underused pesticides on average, about one-third of farms overused them and these were more likely to have higher off-farm income or be located in the Mekong Delta (the "Rice Bowl" of Vietnam) for rice farms or be younger, more educated and with more debt for fruit farms. These findings suggest pro-environmental policies need to take into account heterogeneity in the use of pesticides, addressing both underuse and overuse in developing countries, and feasibility of pesticide reduction that can reduce both input costs and environmental impacts.

Consumer preferences are also crucial in the analysis of pesticide use since they provide farmers or producers information on preferred practices. In addition to households with lawns mentioned above, this dissertation incorporates insights on food consumption in an era when consumers have increasing concerns about exposures to pesticide residue in their diets. Specifically, discrete choice modeling is employed to investigate consumer preferences for different tomato purchase options regarding pesticide use. The data come from online survey responses of 343 Missourians. Results show positive preferences for tomatoes produced using 50% less pesticides as usual, but the willingness-to-pay for these tomatoes is only 6% above conventional tomatoes

compared to 28% for organic produce on average. The results also indicate complementary effects between the reduced pesticide attribute and local or Missouri Grown labels. This implies strategies for labelling and reducing pesticides for local or Missouri Grown growers and policy makers. Furthermore, the examination of heterogeneity in consumer preferences for a reduction in pesticides illustrates areas where consumers prefer reduced pesticide tomatoes but not organic ones, implying the presence of different environmental preferences as well as a need for further studies for this niche market.

Keywords: Pesticides, adoption, efficiency, overuse, choice experiment, willingness-to-pay, heterogeneity, residential lawn, food production, Vietnam.

CHAPTER 1. INTRODUCTION

For the past several decades, use of pesticides has been increasing as the major method for pest control and management in many areas such as landscaping, railroad rights-of-way, public buildings, parks, sport fields, and especially agriculture. “Pesticides” is a general term that encompasses several products, including insecticides (insect control), fungicides (fungus control), herbicides (weed control), rodenticides (mice/rat control), and others. The term “pesticides” literally refers to chemical agents that kill pests, but their purpose can extend to preventing or repelling pests, mitigating pest problems, or plant regulation (7 U.S.C 136(w), 2022). Benefits of pesticides relate to crop protection or productivity improvement, labor, machinery and energy cost reduction, disease control, guaranteed appearance, landscaping maintenance and lower food costs (e.g., Pimentel et al., 1978; Braman, Oetting, & Florkowski, 1997; Fernandez-Cornejo, Jans, & Smith, 1998; Aktar, Sengupta, & Chowdhury, 2009; or a review by Tudi et al., 2021). However, pesticide solutions often come with potential risks and adverse effects on human health and environmental quality, typically including cancer, exposure of children, water and soil pollution, and biodiversity loss (U.S. Geological Survey [USGS], 2000; Cassou, Jaffee, & Ru, 2018; WHO-FAO, 2019).

Despite growing concerns about possible negative impacts of pesticides and the rise of organic and pesticide management practices, there has been increasing reliance on pesticide usage across countries. In the United States, the world’s second largest pesticide consumer (after China), pesticide use in agriculture has been remained over one billion pounds annually (USGS, 2017). This has increased interest in pesticide use, especially regarding alternative methods that may reduce negative health and environmental impacts.

This three-essay dissertation studies several key issues of pesticide use from economic perspectives. The first essay investigates determinants of households' adoption of organic pesticides for lawns and gardens using evidence from residential lawn management in Missouri, USA. The second one measures efficiency of pesticide use of rice and fruit farms in Vietnam, determine the overuse, and characterize overusing farms in each production system. The third study estimates consumer preferences and willingness-to-pay for reduced pesticide produce and evaluates consumer segments for this product relative to organic and conventional ones using an online choice experiment of Missouri's tomato consumers. In doing so, the dissertation presents a diversified and coherent approach for a range of stakeholders in pesticide management: household pesticide users (essay I), producers or farmers (essay II), and consumers (essay III). In particular household decisions are analyzed in terms of both production and consumption aspects of lawns and gardens. Moreover, provided the term "organic pesticides" (essay I) and "reduced pesticide" (essay III), evaluation of pesticide use can be compared to its alternatives throughout the thesis. Finally, the analyses of adoption, efficiency, and WTP decisions show how powerful economics tools can help to understand the behavior of economic agents and provide insights on a wide range of questions.

After the Green Revolution, pesticides were used intensively and extensively not only in agriculture but also in other domains. Lawn care management in the United States has relied on chemical pesticides for a long time. According to U.S. Environmental

Protection Agency [EPA] (2017), about 88 million households in the U.S. use pesticides around their home, especially herbicides with over 28 million pounds applied on lawns and gardens in 2012. While pesticides help homeowner save time for insect and weed control and maintain their lawns and gardens in good shape and high quality, there are numerous serious negative effects of pesticide use such as killing bees, exposures of children, or contamination of ground water and nearby lakes and ponds (see reviews of Robbins & Sharp, 2003; Beyond Pesticides, 2017). Therefore, there is an increasing interest in alternatives like “organic pesticides” which seem to be safer than chemical ones in terms of environmental impacts, and possibly even health. The term organic pesticide refers to a potential solution that may carry both “organic” and “pesticide” meaning. Labelling of organic pesticides and organic products is regulated in the U.S. While homeowners are buyers of organic pesticides, they are also producers who use organic pesticides to provide nice lawns or gardens for themselves. Given this consideration, “safer than synthetic chemicals” and “ready to use” are potentially good reasons for organic pesticides being of interest. However, compared to the current dominance of chemical pesticides, the adoption rate of organic pesticides is low in residential lawn management (Levy, 2018). The first essay employs a multinomial logit model (MNL) that considers factors underlying adopters and distinct categories of non-adopters to examine determinants of organic pesticide adoption in residential lawn care management using the dataset of Hinkson Creek Survey, 2014. Better understanding about the adoption process may improve the development of organic and environmentally friendly products while maintaining the effectiveness for pest control, and suggest important implications for pro-environmental policies, especially in landscaping areas.

In areas where pests are especially prevalent, efficacy of pesticides is especially important. Asian developing countries like Vietnam often use pesticide intensive methods for agricultural production. For example, the application rate of pesticides in Vietnam is the highest in the world, about 1.5 times the global average of 2.57 in 2016. In order to meet growing demands in agriculture, pesticide import have been increasing, from about 22 million U.S. dollars in 1991 to near 800 million U.S. dollars in 2015 (FAOSTAT, 2019). Among the agricultural crops, while rice farms were the biggest consumption of pesticides, fruit production has the highest pesticide expenditure per farm (GSO, 2017). There is an intense debate in the literature on efficiency of pesticide use and the widespread overuse among farms in developing countries. The second essay contributes to the discussion by showing pesticide efficiency scores of rice and fruit farms, and characterizing the overusing farms, using farm data in Vietnam in 2016.

More than ever before, increasing consumer concerns toward health and environmental quality provide food producers important insights into pesticide use. While the dissertation looks at organic pesticides in the first essay, reduced pesticide alternatives like integrated pesticide management (IPM) practices are considered in the third essay. Along a continuum of pesticide use, reduced pesticide production may have potential as a compromise between conventional (lower cost, higher health and environmental risk) and organic (higher cost, lower risk) methods. However, there is a gap relating to the evaluation of consumer preferences for reduced pesticide food due to the lack of an actual market or clear terminology for reductions in pesticides. Most food products are differentiated from conventional ones by using general terms such as natural, green, sustainable, eco-friendly, etc., and certainly organic. Using a discrete choice experiment (DCE), the third essay develops a hypothetical label of "50% reduced pesticide use as usual" to investigate consumer preferences and estimate willingness-to-pay (WTP) for this claim with regard to conventional tomatoes. In addition, this essay also reveals differences between reduced pesticide use and organic produce from consumer perspectives, suggesting implications for the development of IPM and sustainable practices that specifically reduce pesticides but not fully organic.

The rest of this dissertation is structured as follows:

Chapter 2 is essay I, determinants of households' adoption of organic pesticides, in which the potential factors are suggested by synthesizing the literatures of organic consumption, organic farming as well as IPM practices, and lawn care management practices, and their effects on the homeowners' adoption behavior are examined on the basis of the MNL.

Chapter 3 is essay II, efficiency of pesticide use and determinants of the overuse, in which pesticide use efficiency measurements are estimated by using the directional distance function, the overuse is implied by shadow value of pesticides, and characteristics of the overusing farms are examined on the basis of the probit model.

Chapter 4 is essay III, consumer preferences and WTP for reduced pesticide tomatoes, in which consumer responses are collected in the discrete choice experiment, preferences and WTP are estimated by using the mixed logit model, and the determinants of the heterogeneity in consumer preferences are examined on the basis of the MNL.

Chapter 5 concludes the dissertation.

References

[1] Aktar, W., Sengupta, D. & Chowdhury, A. (2009). Impact of pesticides use in agriculture: their benefits and hazards. *Interdisciplinary Toxicology, 2*(1), 1-12. doi:https://doi.org/10.2478/v10102-009-0001-7

[2] *Beyond Pesticides*. (2017). Retrieved from Lawn & Garden Pesticides: Facts & Figures. https://www.beyondpesticides.org/assets/media/documents/lawn/resources/bp-fact-lawnpesticides.081417.pdf

[3] Braman, S.K., Oetting, R.D., & Florkowski, W.J. (1997). Assessment of Pesticide Use by Commercial Landscape Maintenance and Lawn Care Firms in Georgia. *Journal of Entomological Science, 32*, 403-411.

[4] Cassou, E., Jaffee, S., & Ru, J. (2018). *The Challenge of Agricultural Pollution.* World Bank Publications.

[5] *FAOSTAT* (2019, 9 2). Retrieved from http://www.fao.org/faostat/en/#data/RP

[6] Fernandez-Cornejo, J., Jans, S., & Smith, M. (1998). Issues in the Economics of Pesticide Use in Agriculture: A Review of the Empirical Evidence. *Review of Agricultural Economics. Vol. 20, No. 2*, 462-488.

[7] General Statistics Office of Vietnam (2017). *Vietnam Household Living Standard Survey 2016.* Hanoi: Statistical Publishing House.

[8] Levy, N. (2018). *Louisiana Urban and Suburban Homeowners' Fertilizer Management Behavioral Beliefs, Intentions, and Past Behaviors*. Louisiana State University: *LSU Doctoral Dissertations. 4687.* Retrieved from https://digitalcommons.lsu.edu/gradschool_dissertations/4687

[9] Pimentel, D., Krummel, J., Gallahan, D., Hough, J., Merrill, A., Schreiner, I., ... & Fiance, S. (1978). Benefits and costs of pesticide use in US food production. *BioScience, 28*(12), 772-784.

[10] Tudi, M., Daniel Ruan, H., Wang, L., Lyu, J., Sadler, R., Connell, D., Chu, C., & Phung, D. T. (2021). Agriculture Development, Pesticide Application and Its Impact on the Environment. *International journal of environmental research and public health*, 18(3), 1112. https://doi.org/10.3390/ijerph18031112

[11] U.S.C (the United States Code). (2022). *Office of the Law Revision Counsel.* Retrieved from Title 7-Agriculture. Section 136-Definitions: https://uscode.house.gov/

[12] USGS (2000). *The United States Geological Survey Report, 1999.* Washington, D.C.: U.S. Government Printing Office.

[13] USGS (2017). *The United States Geological Survey Report, 2016.* Washington, D.C.: U.S. Government Printing Office.

[14] WHO-FAO. (2019). *Global situation of pesticide management in agriculture and public health.* Geneva: Licence: CC BY-NC-SA 3.0 IGO.

CHAPTER 2. DETERMINANTS OF HOUSEHOLDS' ADOPTION OF ORGANIC PESTICIDES FOR LAWNS & GARDENS

The chapter is modified from Tran, L., McCann, L.M., & Shin, D.W. (2020). Determinants of Households' Adoption of Organic Pesticides for Lawns and Gardens. Journal of Environmental Protection, 11, 269-298.

This study investigates determinants of organic pesticide adoption in residential lawn care management. Mail survey data from Missouri indicates an adoption rate of 17.7 percent. This dataset also allows us to differentiate distinct non-adopters by familiarity with the practice as well as non-use of any pesticides. Multinomial logit regressions find environmental concerns, awareness of neighbor's opinions, and gardening behaviors as significant determinants. The effects on relative probability of being an adopter are large: 18 times more likely for people with serious environmental concerns or 5 times more likely for those spending more than 15 hours a month on lawn care.

2.1. Introduction

Lawns and gardens are popular in the United States; they are a source of enjoyment, a hobby and a source of home value. Homeowners in the U.S. spent about $47.8 billion on lawn and garden retail sales in 2016, with a record average expenditure of $503 per household (Cohen, 2018). Pesticides are an important component; the home and garden sector accounted for about 6% of total U.S. pesticide usage in 2012, valued at about 24% of conventional pesticide sales, compared to 66% by agriculture (Adwood & Paisley-Jones, 2017). The highest expenditure was for insecticides, approximately 80% of the total amount spent by households. Pesticides are used to prevent, destroy, repel, or mitigate weeds, insects and other pests, and thus maintain the aesthetic value of lawns and gardens, as well as providing an ideal setting for outdoor recreation, entertainment and relaxation. However, the negative impacts of pesticides include water pollution, biodiversity loss and exposures in children (Robbins & Sharp, 2003). Therefore, there has been increasing interest in less toxic or organic pesticides or pesticide-free practices for use in residential lawn care management (Marshall et al., 2015).

Potential strategies to reduce use of conventional pesticides are integrated pest management (IPM) (pesticide applications based on monitoring and thresholds), organic (monitoring and need-based organic and natural product applications), and non-use or untreated lawn care techniques. In fact, there are overlaps among these three approaches. Using no pesticides or using organic pesticides can be part of IPM. Organic pesticides are appealing because of their less toxic and ready-to-use characteristics, although a few studies show that organic pesticides may have similar or even greater negative impacts than synthetic ones (Bahlai et al., 2010). Homeowners can apply organic pesticides by themselves (following instructions on the label) or request professional services for this purpose (Alumai et al., 2009). While there has been increasing interest in organic lawn management in the U.S., with widespread adoption of organic management practices in public spaces (Marshall et al., 2015), the adoption rate of these practices for households is relatively low (Levy, 2018).

This leads to our research question: what factors prevent organic pesticide adoption and use in lawn care management regardless of the relative safety offered by these products? A fairly extensive literature examines adoption of best management practices (BMPs) by farmers. Typically, profitability, risk, environmental and health concerns, and some demographic factors are important determinants of BMP adoption (Prokopy et al., 2008). For organic lawn care management, the story may be a bit different. Differences include the aesthetic value of a weed-free lawn to the homeowner and in the eyes of neighbors, the impact on the health of family members and pets, and the fact that gardening and lawn care are a hobby for some.

This paper explores determinants of household's adoption of organic pesticides in lawn care management using evidence from a mail survey in Missouri. A better understanding about factors affecting adoption from a homeowner perspective is necessary for gardeners, policy makers, environmentalists and companies. The existing literature on pesticides often focuses on agriculture rather than residential contexts, and on practices rather than products. On the other hand, the literature on organic products focuses on food consumption rather than use of items like cleaning or lawn-care products. This paper contributes to the literature on adoption of organic pesticide practices in lawn care management by synthesizing empirical studies on both organic consumption and organic farming/IPM in order to develop potential factors affecting adoption. In addition, comparing and contrasting adopters and types of non-adopters for organic pesticide practices provides deep insights about the characteristics of each group.

In the next section, we present definitions of organic pesticides and factors affecting household's adoption of organic pesticides extracted from the previous literature. In the subsequent section, we describe the research methodology applied in this particular study, including the conceptual framework, empirical model, and the unique dataset used in the study. Next, we report summary statistics of the data and the main empirical results of the model. The chapter ends with a summary and a discussion of the implications and limitations of the study of organic pesticide adoption.

2.2. Definitions and factors affecting household's adoption of organic pesticides

2.2.1. Definitions of organic pesticides

Merriam-Webster has definitions of organic that relate to organs, organisms, or carbon compounds, but the relevant one in this context is "of, relating to, yielding, or involving the use of food produced with the use of feed or fertilizer of plant or animal origin without employment of chemically formulated fertilizers, growth stimulants, antibiotics, or pesticides." The USDA National Organic Program only certifies agricultural products as organic if the products are produced using allowed substances in the *National List of Allowed and Prohibited Substances*, along with suitable production methods and third-party verification. However, there may be non-USDA certified organic products such as organic pesticides.

The National Pesticide Information Center (NPIC), a cooperative agreement between Oregon State University and the U.S. Environmental Protection Agency, provides an open list of commercial and homemade organic pesticides: bleach, pyrethrin, iron sulfate, copper sulfate, neem oil, vinegar, canola oil, salt, garlic, lemon grass, thyme, peppermint oil, etc., in which the overlaps between organic pesticides, biopesticides and minimum risk pesticides are acknowledged. The Organic Gardener's Handbook of Natural Insect and Disease Control (Ellis & Bradley, 1996) refers to organically acceptable pesticides as organic control products used in gardens that have three characteristics: derived from natural substances, less toxic to humans than synthetic pesticides, and quickly breaking down in the environment to harmless substances. Hence organic pesticides generally come with specific target pests, slow effectiveness, low residue levels with short persistence, and are thus likely to be safer than synthetic pesticides when their applications follow the label instructions carefully (Ellis & Bradley, 1996). In summary, given the various definitions of organic pesticides, gardeners may interpret the term slightly differently.

2.2.2. Factors affecting household's adoption of organic pesticides

The literature on residential adoption of organic pesticides used in lawn care is complex. Households buy organic pesticides to use as inputs in a home production activity like lawn care and then enjoy their lawn on a regular basis. The adoption of inputs like organic pesticides in home production can related to organic agriculture or IMP production practices while the purchase of products like organic pesticides by end users may be related to organic consumption perspectives. Hence, the literature herein covers studies of both organic consumption and organic or IPM practices in agriculture. Most studies of household organic purchases examine consumers of food (e.g. Li et al., 2007, Asif et al., 2018, Janssen, 2018), or specific kinds of food like fresh vegetables or fruits (e.g., Boccaletti & Nardella, 2001, Saba & Messina, 2003, and Bond et al., 2008), and drinks (Schäufele & Hamm, 2018), but only few cases examine products for other purposes (Van Doorn & Verhoef, 2015). On the other hand, studying determinants of adoption of pesticide best management practices, work has primarily focused on farmers or agricultural producers rather than households (Prokopy et al., 2008, Baumgart-Getz et al., 2012, Rofle & Gregg, 2015). For a comprehensive literature review of organic pesticide adoption in lawn care from a household's perspective, this paper also examines other studies that explore demand or preferences of households for organic cleaning products (Bach & Rosner, 2008, Steingraber, 2011, Laferriere et al., 2014) or organic lawn care practices in general (Tukey, 2007, Morris & Bagby, 2008, Pennington, 2010, Larson, 2017, Burr et al., 2018, McCann & Shin, 2018). The following review integrates these literatures to develop a comprehensive set of potential determinants.

In empirical models, some socio-demographic characteristics have impacts on adoption. In the literature on organic purchases, for example, women may be more likely to buy organic products, because they express more concern for communal goals than men (Winterich et al., 2009) or they want to protect their children from harmful effects of chemical products (Laferriere et al., 2014). In the context of organic production, women are also likely to be organic producers for the same reasons (Veldstra et al., 2014).

Household income level consistently shows a positive effect on adoption of both organic purchases (Janssen, 2018, Van Doorn & Verhoef, 2015, Shashi et al., 2015) and best management practices such as organic agriculture and IPM (Prokopy et al., 2008, Blaine et al., 2012) because this helps adopters overcome financial constraints related to organic products/inputs. We will leave cost issues of organic pesticides to a discussion of price consciousness at the end of this review.

There are not such clear effects for household size, age, and education in empirical studies of organic adoption. Larger households may be less likely to purchase organic products (Van Doorn & Verhoef, 2015), but it does not affect adoption of organic production. The number of children may have competing effects; it is highly correlated with household size, potentially reducing organic consumption, however having children may increase adoption due to health and safety concerns (as discussed below). Young people are likely to buy organic food than older people (Dettmann & Dimitri, 2009, Yadav & Pathak, 2015) and they might be more likely to adopt organic farming methods than older farmers (Veldstra et al., 2014), but the relationship between age and probability of BMP adoption is sometimes insignificant (Brehm et al., 2013). Similarly, higher educational level of homeowners tends to result in pesticide-free purchases (Ngobo, 2011, Shashi et al., 2015, Janssen, 2018) or use of organic practices (Genius et al., 2006), but the relationship is insignificant in other studies (Veldstra et al., 2014).

While education level does not always affect organic adoption, environmental knowledge and attitudes usually are identified as critical drivers of adoption. Most empirical studies of organic consumption show positive effects on purchase intention of knowledge about organic products, awareness of threats from using synthetic pesticides, concerns about current quality of soil and water, or general attitudes of environmental protection (Magnusson et al., 2003, Dreezens et al., 2005, Lea & Worsley, 2005, Hughner et al., 2007, Jassen, 2018). However, the approach based on intended purchase is problematic because of the gap between behavior and attitudes toward organic products (Vermeir & Verbeke, 2006) or potential biases relating to environmentally friendly purchasing behavior (Moser, 2016). A few studies show that environmental knowledge and attitudes do not positively affect actual purchase of organic products (Jassen, 2018), and consumers might overestimate their organic purchases (Hughner et al., 2007).

In the literature on organic farming, environmental knowledge and attitudes also play an important role in the adoption of organic and IPM practices (Prokopy et al., 2008, Reimer et al., 2012, Riar et al., 2017). However, the impacts on a farmer's adoption differ from a consumer's purchase of pesticide-free or lower pesticide products in terms of sensitivity. Consumers are likely to alter their behavior more easily than farmers do under awareness of serious environmental degradation, strict subjective norms, and high expectation of environment quality (Beedel & Rehman, 2000, Reimer et al., 2012). The effect of knowledge on farmers' environmental behavior may also differ based on personal beliefs and emotions (Grob, 1995), lack of trust in information sources (Jin et al., 2014), and uncertainty and complexity (Philbert et al., 2014). Extending the concept of organic agriculture to lawn care management, households with more knowledge of lawn care are more likely to adopt BMPs (Brehm et al., 2013).

In the adoption literature, personally/individually perceived benefits and costs associated with the implied innovation are the main factors affecting the adoption decision. While environmental knowledge and attitudes express public or general benefits, personal health and safety represent individual benefits. Organic products often are perceived as healthier or safer than conventional ones (Magnusson et al., 2001, Lea & Worsley, 2005), which leads to higher adoption of organic products to avoid health risks (Makatouni, 2002, Padel & Foster, 2005). This is related to why women, especially those with children, often show preferences for organic products, as noted in the demographic section. Many studies show that organic agriculture and IPM techniques help farmers reduce or avoid threats of chronic poisoning or cancer due to direct or indirect exposure to chemicals while farming (Singh et al., 2007).

In the context of lawn care, health issues become important since household members experience a lawn treated with pesticides (USGS, 1999, Robbins & Sharps, 2003) which leads to adoption of organic lawn care. Children are highly exposed to these chemicals because they often play in yards and pesticide residue may touch their skin. Hence, households who have children tend to adopt organic and natural pesticides rather than conventional ones (Davis et al., 1992, Alumai et al., 2009). However, the number of children may negatively affect organic pesticide adoption as discussed above due to a possible interaction effect with average income, which implies more research is needed on this relationship (Janssen, 2018, Boizot-Szantai et al., 2017).

In addition to safety, expected quality of products can affect adoption. Past studies on organic purchase and organic production often view organic products as having better flavor (Radman, 2005), higher vitamins (Lea & Worsley, 2005) as well as lower pesticide residues (Gomiero, 2018), which may lead to consumers buying organic rather than conventional products (Huang, 1996, Lockie et al., 2002, Baker et al., 2004).

Regarding lawns, the concept of quality may include property value and aesthetic value (lawn appearance). In general, households who expect that organic lawn management may improve their property values are more likely to adopt this practice (Blaine et al., 2012). On the other hand, if the household prioritizes the appearance of the lawn, they might be more likely to purchase chemical pesticides, or hire commercial firms to effectively treat a problem such as grubs (Alumai et al., 2009). Perceptions of neighbors' attitudes about practices are considered in the adoption literature, with conflicting effects. From the neighbors' viewpoint, increased chemical pesticide use causes loss of biodiversity, landscape simplification and other harmful impacts (Meehan et al., 2011), as a result, homeowners may adopt pesticide restriction techniques to reduce these negative impacts (Nassauer et al., 2009, Reimer & Prokopy, 2012). On the other hand, a focus on the appearance of the lawn to comply with neighborhood norms may have the opposite effect. Whether households employ a lawn care company for applying chemicals and pesticides depends on whether neighbors use them (Blaine et al., 2012). If people in a neighborhood tend to share the same aesthetic values regarding lawns and gardens, it may lead to favoring chemical pesticides which are perceived to be very effective. Hence, the effect of perceptions of neighbors' attitudes and practices on organic pesticide adoption is ambiguous: it is negative for yard or landscape appearance, and it is positive for environmentally friendly landscaping.

Individual preference that relates to enjoyment of yard work or gardening may affect the adoption of organic lawn management. For example, people who are more interested in gardening and able to do yard work tend to adopt alternative lawn care practices (McCann & Shin, 2018) because they may be more aware of, and gain more utility from using, best management practices.

While safety and high quality or enjoyment of an organic lawn delivers benefits to households, the price of organic products or cost of using organic methods presents a barrier to their adoption. Consumers often perceive organic products as expensive compared to conventional ones, which implies price negatively affects organic purchases (Magnusson et al., 2001, Lea & Worsley, 2005). For households, commercial lawn management is the most expensive, followed by homeowner use of synthetic pesticides, and IPM or organic lawn management, which may include homemade organic pesticides (Alamui et al., 2009). Using no products obviously has not out-of-pocket costs. However, cost needs to be considered along with the associated quality or outcome. In the context of agriculture, the total cost of IPM or organic practices can potentially be lower, although farmers often pay more for labor as a substitute input. Availability of cheap labor relative to pesticide cost might positively affect adoption of organic agriculture (Gudade et al., 2014).

Besides cost issues, convenience has been considered a barrier to organic adoption. The concept of convenience refers to the amount of time involved with new practices.

Studies found that consumers did not switch to organic food products due to convenience reasons like availability of organic products (Magnusson et al., 2001) or search time (Jolly, 1991). However, the implementation of USDA's national organic labeling standards in 2002 has helped to address these issues by providing quality assurance for organic foods (Greene & Kremen, 2003). Additionally, since 2006, the "Walmart effect" on the organic product market alleviated convenience issues (Li et al., 2007, Constance & Choi, 2010). Regarding organic production, convenience may be related to availability of labor (Gudade et al., 2014) or other inputs. Lawn care and pesticide use can be analyzed in the household production-consumption model of Becker (1965) (Templeton et al., 1999). In this model, the indirect utility of the household decreases with chemical pesticide use, but increases with leisure hours, and has a mixed relationship with lawn care depending on each household. Hence, time scarcity may negatively affect the adoption of organic lawn products.

Organic pesticides are potential replacements for conventional ones for residential use because of their safer yet ready-to-use characteristics. However, the household adoption rate of organic pesticides is currently low. By merging the literatures of organic consumption, organic farming as well as IPM practices, and lawn care management practices, this paper extracts hypotheses for potential determinants of organic pesticide adoption in lawn care from the household's perspective as summarized in table 2.1. Demographic variables like female gender and higher income level show positive effects on organic adoption while the effects of age and education are less robust. Environmental knowledge and attitudes, personal safety, and enjoyment of gardening may positively affect the use of organic pesticides while yard appearance/neighborhood norms and time scarcity have potentially negative impacts on adoption. There are various combinations of those attributes or dimensions, leading to difficulties in the classification of adopters for organic pesticides. There exist gaps in the literature regarding the role of children, perception of neighborhood attitudes, convenience, and knowledge on residential organic pesticide adoption.

Table 2.1. Hypothesized effects on organic pesticide adoption

	Organic consumption	**Organic agriculture/ IPM**
Demographic variables		
- Younger age	(+)	(+)
- Female	+	+
- Higher education	(+)	(+)
- Higher income	+	+
- Larger household	-	-
Environmental knowledge/attitudes	+	(+)
Perceptions of neighborhood attitudes	+/-	+/-
Personal health and safety concern	+	+
- Having children	(+)	
Lawn quality		
- Yard appearance		-
- Enjoyment		+
Price consciousness	-	-
Desire for convenience/time scarcity	-	-

Note: The plus "+" sign means the effect is positive; the minus "-" sign means the effect is negative. The sign in parentheses like "(+)" or "(-)" means the effects are insignificant in some studies. The plus/minus "+/-" means the direction of the effect is indeterminate (i.e., some studies have found a positive effect and others have found a negative effect).

2.3. Conceptual framework

The study employs a discrete choice framework to examine determinants of organic pesticide adoption from the household perspective. For simplicity, household decisions are considered as individual choices as usual in adoption studies. We thus ignore intrahousehold factors that may affect household decisions. Rogers (1962) provided a foundation for understanding adoption and diffusion of innovations. Adoption is an individual choice of accepting or rejecting an innovation that can be an object, technology, practice, etc., perceived as new to potential adopters (Rogers, 2003, Straub, 2009). In this study, the innovation is use of organic pesticides in lawn care.

Discrete choice models can be derived from a utility maximization approach. Depending on whether use or non-use of the organic pesticide delivers greater utility (indirect utility value), households decide to be adopters or non-adopters. This paper uses a random utility-based discrete choice model (RUM), which includes stochastic or latent attributes of alternatives and individual characteristics (McFadden, 1974, 1981), and has several advantages. First, the model can cover some components of preferences, which are unobservable to the researcher (Thurstone, 1927, Luce, 1959, McFadden & Train, 2000). Second, the RUM has a firm foundation in economics (Small & Rosen, 1981). Another advantage is that the derived logit model is easily tractable with good empirical performance (McFadden, 1974, Ben-Akiva & Lerman, 1985, and Train, 2009).

The indirect utility of a typical RUM can be approximated by an appropriate linear function of observed characteristics of the alternatives, the individual, and the economic environment, and random error representing unobserved factors (McFadden, 1981). For multiple discrete choices, we have a set of random utilities associated with corresponding alternative choices for an individual. The derived logit model, also known as a multinomial logit model (MNL), is widely used to predict the probability or likelihood of the choice that yields the greatest utility among alternatives given a set of observed characteristics hypothesized to affect perceived utility. Specifically, MNL models require that random errors in the RUM are independently distributed and follow type 1 extreme value or log-Weibull distribution for a closed form likelihood expression of the integration (McFadden, 1981). Another important assumption of MNL models is the axiom of independence from irrelevant alternatives (IIA) (Luce, 1959). The IIA assumption is to model individual choice probabilities, and this can be tested by the Hausman-McFadden test (Hausman & McFadden, 1984) or the Small-Hsiao test (Small & Hsiao, 1985). Maximum likelihood estimation (MLE) is considered to be the most common method to estimate MNL models (McFadden, 1974).

Estimation of the MNL model provides estimates of parameters or weights of observed characteristics used in the RUM (McFadden, 1981). Based on the results of the model, specific hypotheses extracted from the literature review are tested.

The main interest of this study is to examine the effects of environmental knowledge and attitudes, importance of neighbors, health concerns, and lawn care behaviors on a household's organic pesticide adoption decision. We hypothesize that pro-environmental attitudes positively affect adoption. Specifically, households who care more about the environment are more likely to adopt organic pesticides than conventional ones. This effect may be less for residents not applying any pesticides to their lawns. We also expect that households with more knowledge about the environment, and who are more familiar with organic pesticides will be more likely to be adopters. However, the importance given to the opinions of neighbors may negatively affect adoption; if it is important to them that their neighbors think they have a nice lawn they will prioritize aesthetic values over environmental ones.

Based on the previous literature, we assume that families with young children have more health concerns regarding the safety of pesticides applied to their lawns. Given this assumption, we predict a positive effect of young children on adoption of organic pesticides. Other demographic variables are included as controls.

Gardening behavior is expected to influence households' adoption choices because this relates to personal preferences. In this study, dimensions of lawn care behavior are conceptualized by time spent on lawn care and use of professional services for pest control. People often spend more time on yardwork if they enjoy gardening, and thus are expected to be more likely to be aware of and adopt environmentally friendly practices. On the other hand, households who use professional services for pest control will be less likely to adopt organic pesticides.

2.4. Empirical model

We build a multinomial logit model to test our hypotheses of organic pesticide adoption using a sample of households obtained by the 2014 Hinkson Creek Household Survey. The survey was mailed to single-family detached homes in Columbia, Missouri using a random sample of 2000 residences provided by Survey Sampling International. The Dillman method was used with four waves of contact: a postcard notice, a cover letter and survey packet, a reminder postcard, and a final complete survey packet. The person most responsible for gardening was asked to respond to the questionnaire. After removing invalid addresses, deceased residents, and those without yards, there were 1773 potential respondents. We received 783 completed surveys resulting in an effective response rate of 44.1%.

The MNL model uses variables constructed from the survey results. Assuming revealed preferences of decision makers for conservation practices (Lichtenberg, 2004), the dependent variables related to the respondent's knowledge/experience of using organic pesticides. The choices included "*Not applicable*", "*Never heard of it and not using it*" (Never heard), "*Somewhat familiar with it but not using it*" (Know somewhat), "*Know how to use it but not using it*" (Know well), and "*Currently use it*" (Adopter). We do not eliminate "*Not applicable*" because this choice accounts for a substantial number of observations, 184 respondents, and it may imply various latent possibilities for not adopting organic pesticides, including: not using any pesticides, no availability of necessary organic pesticides, using professional pest control companies, etc. Of these 184 "*Not applicable*" cases, there are 61 residents who did not use professional services for pest control, never apply fertilizers to their lawns, and said "not applicable" for reading and following pesticide application instructions for their yards or gardens. Given these responses, we assume that these 61 households did not use any pesticides at all for their lawns. Thus, we put these non-adopters into a separate group called "Not using any pesticides" to distinguish them from other "Not applicable" non-adopters. In this way, the dataset enables us to differentiate five distinct types of non-adopters in the context of the MNL model.

Explanatory variables of the model describe observable attributes affecting the choice outcome, and are based on respondents' answers. We operationalize these variables to employ them in the MNL model. For seriousness of environmental concerns regarding locally excessive use of pesticides, the survey responses included: "*not a problem*", "*slight problem*", "*moderate problem*", "*severe problem*", and "*don't know,*" accounting for 19, 130, 276, 221, and 109 cases, respectively. We combine the first two categories into "not or slight problem" and use it as the base category. Agreement with the statement "It is important that my neighbors think I have a nice lawn" was assessed using a five-point Likert scale, from "*strongly disagree*" to "*strongly agree.*" There were 61, 159, 251, 257, and 24 respondents for the respective categories. We merge "strongly disagree" and "disagree" into a disagree category, and similarly form an agree category, while keeping "neutral" answers separate. To get at health concerns of pesticide use on young children we asked for the number of children under 12 and created a dummy variable for whether the household has at least one child in that age group.

Time spent gardening, one of two aspects of gardening behavior, was measured by four time-interval categories: "*0-5 hours*", "*6-10 hours*" (the base category), "*11-15 hours*", and "*more than 15 hours.*" We keep this variable as described in the survey to represent household's monthly hours spent on gardening and lawn care during the growing season, which may indicate preferences for gardening as a hobby. We also examined the professional lawn care services used by the household; the options included: "*No*", "*Yes, just for mowing*", "*Yes, for mowing and fertilizing*", "*Yes, just for fertilizing and pest control*", and "*Yes, for mowing, fertilizing, and pest control*" accounting for 522, 50, 36, 105, and 40 cases, respectively. We constructed a dummy variable by combining the first three responses into "not using pest control services," while the last two responses became "using a pest control service."

To increase the explanatory power of the model, we added specific attributes of the background environment and demographic variables (McFadden, 1981, Curtis, McCoy, & Aravena, 2018, Shin & McCann, 2018). The need for effective pest control is proxied by weed density in the lawn; we expect low weed density to be associated with organic pesticide adoption and for high weed density to be associated with non-adoption. Alternatively, this variable may represent previous use of effective synthetic pesticides in which case the effect on adoption would be opposite. In the dataset, the weed density measured by the average number of weeds per square yard is represented by five options: "*None*", "*1 to 10*", "*11 to 40*", "*More than 40*" weeds, and "*Don't know*" resulting in 50, 259, 151, 37, and 254 cases, respectively. We combine the categories of "*None*" and "*1 to 10*" into "Less than 10" and use that as the base category.

For demographic variables, we choose gender, age, annual household income and educational attainment which theoretically affect the adoption choices in our model. (The presence of young children is included above.) Gender is a dummy variable with female as the base. The survey contained four age intervals: "*18-30 years*", "*31-45 years*", "*46-60 years*", and "*Over 60 years*" (the base category). Educational attainment consists of five possible categories: "*Some formal schooling*", "*High school diploma or GED*", "*Some college or 2 year college degree*", "*4 year college degree*", and "*post-graduate degree*" with 8, 72, 154, 254, and 265 cases, respectively. We combined the first two categories into a "High school or less" base category. Annual household income included five options: "*less than $24,999*", "*$25,000-$49,999*" (the base), "*$50,000-$74,999*", "*$75,000–$99,999*", and "*$100,000 or more.*"

To sum up, the empirical MNL model is specified as follows:

$$P(y_i = k) = \frac{exp(\mathbf{x}_i \boldsymbol{\beta}_\mathrm{k})}{\sum_{j=1}^{6} exp(\mathbf{x}_i \boldsymbol{\beta}_\mathrm{j})}$$

The model takes a simple form of Luce model (e.g. Luce, 1959, McFadden, 1981, Greene, 2003) to predict the probability or the likelihood that choice "y_i" made by household “i" occurs over the sample of size “n.” “k” represents alternative organic pesticide adoption choices: “adopt”, and five non-adopter alternatives: “never heard”, “know somewhat”, “know well”, “not use any pesticides”, and “other N/A.” We can thus classify households as adopters and distinct types of non-adopters. Since we distinguish among various types of non-adopters, we use “adopters” as the base of the model, which differs from traditional adoption studies.

In the model, “**x**” is a vector of explanatory variables from household “i” responses while “**β**” is vector of corresponding parameters in the model. Since all variables used categorical data, we choose a specific reference category for each variable for estimation and interpretation of the MNL model. In a base model, “**x**” includes these variables: Seriousness of environmental concerns (base: not or slight problem), Importance of neighbors’ perception of nice lawn (base: agree), Having at least one child under 12 (base: no), Monthly hours spent on lawn (base: 6-10 hours), Using professional pest control services (base: no), Weed density (base: less than 10 weeds per square yard), Male (base: Female), Age (base: above 60 years), Education (base: high school or less), Household income (base: $25,000-49,000).

2.5. Data description

Summary statistics for the data used for the regression model can be found in table 2.2. These statistics are reported for the dataset as a whole as well as separately for adopters and different types of non-adopters. (Column percentages by each variable category sum to 100%.) After removing missing data of the outcome variable (28 observations), the adoption rate for organic pesticides is 17.7% while non-adoption rates of “Never heard”, “Know somewhat”, “Know well”, “Not use any pesticides”, and

"Other N/A" groups are 5.5%, 28.8%, 23.7%, 8.0%, and 16.3% respectively. Compared to the adoption rate of residential organic lawn care in Louisiana of 15.6% (Levy, 2018), the adoption rate in this sample is slight larger.

Table 2.2. Summary statistics

Variables	**Sample Proportions***		**Adopters**	**Non-Adopters**				
	Mean	**Std. Dev.**		**Never heard**	**Know somewhat**	**Know well**	**Not use any pesticides**	**Other not applicable**
Dependent Variable			17.7%	5.5%	28.8%	23.7%	8.0%	16.3%
Predictors								
Seriousness of environmental concerns								
Not or slight problem (base)	0.197	0.014	9.8%	26.2%	23.4%	18.0%	13.1%	27.6%
Moderate problem	0.366	0.018	37.6%	35.7%	38.5%	39.9%	23.0%	34.1%
Severe problem	0.293	0.017	40.6%	11.9%	27.5%	30.9%	39.3%	18.7%
Don't know	0.144	0.013	12.0%	26.2%	10.6%	11.2%	24.6%	19.5%
Neighbors' opinion of lawn important								
Disagree	0.375	0.018	30.3%	38.1%	39.8%	44.4%	9.8%	44.7%
Neutral	0.292	0.017	33.3%	21.4%	26.9%	27.2%	47.5%	25.2%
Agree (base)	0.333	0.017	36.4%	40.5%	33.3%	28.3%	42.6%	30.1%
Have children under 12	0.242	0.016	19.4%	29.3%	25.1%	27.5%	26.7%	19.8%
Monthly hours spent on gardening/lawn								
0-5 hours	0.195	0.014	9.8%	26.2%	18.1%	14.0%	37.3%	29.8%
6-10 hours (base)	0.347	0.017	25.0%	47.6%	38.6%	34.3%	32.2%	35.5%
11-15 hours	0.221	0.015	25.0%	14.3%	22.3%	27.0%	13.6%	18.2%
More than 15 hours	0.237	0.016	40.2%	11.9%	20.9%	24.7%	16.9%	16.5%
Hire pest control services	0.193	0.014	22.0%	21.4%	20.6%	17.9%	0.0%	24.8%
Lawn attributes								
Number of weeds per square yard								
Less than or equal to 10 weeds (base)	0.411	0.018	45.4%	38.1%	38.2%	45.8%	26.2%	43.4%
11-40 weeds	0.201	0.015	19.2%	11.9%	12.7%	23.5%	26.2%	13.1%
> 40 weeds	0.049	0.008	4.9%	2.4%	6.9%	2.8%	1.6%	4.9%
Don't know	0.338	0.017	28.5%	47.6%	33.2%	27.9%	45.9%	38.5%
Demographic characteristics								
Male	0.632	0.018	57.1%	66.7%	68.1%	67.4%	45.9%	62.8%
Age								
18-30 years	0.085	0.010	4.5%	9.5%	9.7%	6.2%	14.8%	10.7%
31-45 years	0.253	0.016	23.3%	28.6%	25.8%	27.5%	29.5%	19.8%
46-60 years	0.307	0.017	29.3%	33.3%	33.6%	27.0 %	29.5%	32.2%
Above 60 years (base)	0.355	0.017	42.9%	28.6%	30.9%	39.3%	26.2%	37.2%
Educational attainment								
High school or less (base)	0.106	0.011	7.5%	9.8%	10.1%	10.6%	8.2%	16.5%
2-year or some college	0.205	0.015	23.3%	22.0%	18.0%	22.2%	23.0%	17.4%
4-year college	0.337	0.017	33.1%	34.1%	36.9%	34.4%	31.1%	28.9%
Post-graduate	0.352	0.017	36.1%	34.1%	35.0%	32.8%	37.7%	37.2%
Household income								
$0- $24,999	0.076	0.010	4.0%	17.6%	5.5%	4.0%	17.2%	7.5%
$25,000-$49,999 (base)	0.201	0.015	21.6%	23.5%	15.6%	21.6%	31.0%	25.2%
$50,000-$74,999	0.264	0.017	28.8%	14.7%	26.6%	25.3%	27.6%	28.0%
$75,000-$99,999	0.172	0.014	14.4%	23.5%	19.6%	17.6%	15.5%	14.0%
$100,000 and above	0.287	0.017	31.2%	20.6%	32.7%	32.9%	8.6%	25.2%

Note: (*) For categorical variables, the fractions are defined on the domain (0, 1)

The summary statistics in table 2.2 show that adopters look different from the sample in seriousness of environmental problems regarding pesticides, neighbor opinions of their lawn being important, and time spent gardening. There are also several noticeable differences across distinct types of non-adopters. For example, "*severe*" is the most common response regarding pesticide problems for adopters and for those who use no pesticides, 40%, compared to 29% for the whole sample. Compared to the whole sample (38%), a lower percentage of adopters (30%) disagree that neighbors' opinions are important, but this difference masks the much lower level of disagreement among those not using any pesticides (10%) and the much higher disagreement (over 44%) of non-adopter categories know well and other N/A. This data highlights the importance of distinguishing among types of non-adopters and separating those who use no pesticides from other responses. About 40% of adopters spent more than 15 hours per month gardening while the most common response overall was 6-10 hours. The most common response for those who do not use pesticides was 0-5 hours, which was the second most common for never heard and other N/A categories (26% and 30%). The weed question is also interesting; 28% of adopters did not know how many weeds they had, but for those who had never heard of organic pesticides and those who do not use pesticides, over 45% didn't know. This may indicate that these non-adopters are more generally not interested in gardening and lawn care.

Demographic statistics indicate that adopters are somewhat less likely to be male than all non-adopter categories other than those who use no pesticides. They are also less likely to have young children. Adopters are older than the sample as a whole, especially compared to those who use no pesticides. Educational levels for adopters and those using no pesticides are fairly similar, but those who use no pesticides are much more likely to be in the lower income categories than adopters. Given the population for this dataset (those living in homes with yards), respondents being older, richer, and more educated than the relevant Census data is reasonable (Shin & McCann, 2017). In table 2.2, we also see the standard deviations of the sample averages are small: less than 0.02 and about 10% of the corresponding sample means. This implies the sample means are statistically robust, and thus the dataset is appropriate for further analyses of the determinants of organic pesticide adoption.

2.6. Estimation results and discussion

We begin this section by discussing the way the regression results are reported and interpreted. For our empirical MNL model where adopters are the base and distinct types of non-adopters represent alternatives, there are separate outcomes for each type of non-adopter category as if we independently estimated logistic regressions for each group of non-adopters compared to adopters. In other words, the model results include estimated coefficients, significance levels, and goodness-of-fit statistics for non-adopter types of "never heard", "know somewhat", "know well", "not use any pesticides", and "other N/A", compared to the base of adopters. Since all explanatory variables are categorical, a coefficient is interpreted as the difference in the logit or log-odds of being a specific type of non-adopter rather than an adopter, due to the effect of that response category versus the base category, all else equal. The exponential of an estimated coefficient can be interpreted as how many times more/less likely it is to be a specific non-adopter type versus an adopter of organic pesticide practices. A positive coefficient means the odds are greater than 1: the respondent is more likely to be a non-adopter than adopter if they chose that response category rather than the base category for that variable. A negative coefficient implies the respondent is less likely to be a non-adopter than an adopter based on that variable. Again this differs from typical adoption studies; negative coefficients imply that variable positively affects adoption.

Regression results of the preferred model are reported in table 2.3. In terms of goodness-of-fit of the MNL model, the McFadden pseudo R^2 is 10.8% (the alternatives Nagelkerke or Cox & Snell pseudo R^2 are about 30%). Since the model uses the MLE method to calculate estimates, the pseudo R^2 implies a different interpretation from that of ordinary least squares (OLS), but in general, the higher the pseudo R^2 value, the better the fit of the model. While the low pseudo R^2 implies the model might be improved by adding more explanatory variables, it is acceptable relative to other empirical studies (Shin & McCann, 2017). Moreover, the likelihood ratio test for the model is highly significant, α-level = 1% confirming that the model significantly predicts the likelihood of organic pesticide non-adoption.

Table 2.3. Multinomial Logit Results for the Full Model (Base: Adopters)

Independent Variables (Factors)	**Non-Adopters**				
	Never heard	***Know somewhat***	***Know well***	***No Pesticides***	***Other N/A***
<u>Personal attitude measures</u>					
Environmental concerns (base: Not or slight problem)					
Moderate problem	-1.365**	-0.976**	-0.834*	-1.413**	-1.492***
Serious problem	-2.692***	-1.227***	-0.842 *	-0.819	-2.039***
Don't know	-0.288	-0.663	-0.398	-0.044	-0.699
Neighbors' opinion of lawn important (base: Agree)					
Disagree	-0.900	-0.782**	-0.763**	0.769	-1.133***
Neutral	-0.198	-0.509	-0.633**	1.039*	-0.824**
Having children under 12 (base: No children)					
At least 1 child	0.495	0.095	0.188	0.357	0.019

Gardening behaviors					
Monthly hours spent gardening (base: 6-10 hours)					
0-5 hours	0.713	0.334	0.112	0.775	0.747
11-15 hours	-1.118**	-0.613**	-0.315	-0.835	-0.853**
More than 15 hours	-1.661***	-1.245***	-1.015***	-1.580***	-1.500***
Pest control services hired (base: No)					
Use service	-0.013	-0.139	-0.423	-16.269	0.168
Lawn attributes					
Number of weeds per square yard (base: < 10 weeds)					
10-40 weeds	0.297	0.491	0.251	0.972**	0.085
More than 40 weeds	-15.790	0.710	-0.546	-1.232	0.388
Don't know	0.711	0.457	0.097	0.944**	0.413
Demographic characteristics					
Male	0.522	0.436	0.433	-0.278	0.358
Age (base: > 60 years)					
18-30 years	0.923	0.851	0.138	1.267*	0.944
31-45 years	0.147	0.184	0.017	0.423	-0.005
46-60 years	1.051*	0.421	-0.065	0.830*	0.489
Educational attainment (base: High school or less)					
Some college or 2-year college	-0.500	-1.094**	-0.878*	-0.703	-1.135**
4-year college	-0.121	-0.409	-0.616	-0.061	-0.710
Post-graduate	-0.151	-0.640	-0.790	-0.046	-0.540
Household income (base: $25,000-$49,999)					
< $24,999	0.802	-0.024	0.269	0.465	-0.317
$50,000-$74,999	-1.212*	-0.144	-0.048	-0.526	-0.556
$75,000-$99,999	0.014	0.312	0.309	-0.207	-0.503
> $100,000	-1.360*	-0.178	0.044	-1.530**	-1.087**
Constant	0.413	2.099***	2.179***	-0.482	2.793***
Goodness-of-fit					
N			661		
LR ChiSquare (120)			236.35		
Pr(>Chisquare)			1.283e-09 ***		
AIC			2208.599		
BIC			2770.318		
McFadden's Pseudo R^2			10.8%		
Cox & Snell Pseudo's R^2			30.1%		
Nagelkerke's Pseudo R^2			30.1%		

Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.

From table 2.3, we can see important variables in the model. Only statistically significant results are discussed. As expected, perceived seriousness of environmental problems related to pesticides affects adoption of organic pesticides. The estimated coefficients are negative, implying those who indicated "*moderate problem*" rather than the base "*not or slight problem*" are less likely to be non-adopters, or in other words, they tend to be adopters. If they indicated it is a "*serious problem*" they are less likely to be a non-adopter, except those who use no pesticides, and the effects are generally larger. For example, the estimate for "never heard" is the largest at 2.7, followed by "other N/A" at 2.0. An alternative interpretation using these exponents is that if a respondent indicates that pesticides are a serious problem (versus the base), the probability of being non-adopter type "never heard" is 15 times less likely than being an adopter, and being "other N/A" is 7 times less likely. The effects are smaller for "know somewhat" and even smaller and less significant for "know well". These results hint at the role of environmental knowledge, in addition to concern, that is highlighted in the organic literature. Households who are more familiar with organic pesticides could more easily transition to being adopters. The fact that those who indicate it is a serious problem are not significantly less likely to not use pesticides than to adopt organic ones implies that at least some people do not use pesticides due to environmental concerns.

For the importance given to neighbors' perceptions of their lawn, if people disagree this is important (versus agree) they are less likely to be in the "know somewhat," "know well," or "other N/A" categories than to be adopters. In other words, adopters put less weight on the opinions of their neighbors than these categories. The lack of adoption by those who care what the neighbors think may relate to the perceived lower effectiveness of organic products, but examining the summary statistics, adopters do not have weedier lawns. The magnitude of the effect for the two non-adopter categories with some knowledge is similar; they are about two times (= $e^{0.8}$) less likely to be adopters. The effect of disagreeing with the statement is the highest for the "other N/A" category. Households who are not using any pesticides are distinct from other non-adopters since the coefficients are positive, and for the neutral response, significant. In other words, if they are neutral they are more likely to not apply pesticides than to be adopters. This may indicate that they don't care about either their lawn or their neighbors.

The effect of health concerns represented by whether households have children under 12 is not significant in this study, although estimated coefficients are positive for every type of non-adopters This result is unexpected and robust to an alternative specification of dropping a somewhat correlated variable, age. As indicated in the literature review, there are two counteracting effects, health concern and the financial effect of having a larger family. The role of children regarding organic purchases is still not clear in the literature (Boizot-Szantai et al., 2017).

Gardening behaviors, defined by time spent gardening and use of pest control services, have different effects on adoption. Similar to the results regarding perceived seriousness of environmental problems, those indicating they spent "*more than 15 hours*" gardening versus the base category of "*6-10 hours*" were significantly less likely to be in any of the non-adopter categories. In other words, serious gardeners are more likely to use organic pesticides, as expected from the literature. The magnitudes are large: the biggest effect is for "never heard," followed by "no pesticides," "other N/A," "know somewhat," and "know well". Thus, the probability of non-adoption relative to adoption would be from 3-5 times less than for gardeners spending more than 15 hours a month for lawn care. The probability is smallest for those with the most knowledge and largest for those with the least knowledge. Note that time can be also treated as a substitute input for pesticides in the household model proposed by Templeton et al. (1999). Holding other factors constant, the other gardening behavior, use of pest control services, is not significant in the study.

There is only one type of non-adopter category for which weed density is significant. Households whose lawn has *10-40 weeds* per square yard (versus less than 10) or simply *don't know* are more likely to be non-adopters who don't use pesticides rather than being adopters. The results support the hypothesis that not using any pesticides (or not caring) may have allowed the proliferation of weeds, rather than weeds representing a need for effective herbicides/pesticides. The estimates are approximately 0.95 implying the probability of not using any pesticides is 3 times more likely than adoption for those response categories. The effect of "*greater than 40 weeds*" is not significant which may be partly due to the low number of responses in this category.

Demographic variables do not seem to have much impact on organic pesticide adoption. While the signs for male versus female generally align with the literature, there are no significant effects, *ceteris paribus*. This result is similar to Shin and McCann (2017) for the adoption of watershed conservation practices. Regarding age, compared to those over 60, those 18-30 are more likely to not apply pesticides than to adopt organic ones. They may be new to having a home and yard and starting their careers. The middle-aged category, versus over 60, is more likely to have never heard of organic pesticides or to not apply any pesticides than to adopt. The probability of being these non-adopter types is about 3 times more likely than being an adopter. In other words, there is some evidence that those over 60 are more likely to adopt.

If a respondent had some college versus a high school diploma or less, they are somewhat more likely to be adopters. From table 2.3, the significant coefficient estimates are -1.09, -0.88, and -1.14 for “know somewhat”, “know well”, and “other N/A” non-adopters, respectively. That means they are about 3 times less likely to be adopters. These results support studies which imply positive effects of educational level on adoption in the organic literature. However, there are no significant effects for higher educational levels.

The main reason for the positive effect of income on adoption in the literature is costly new technology or products being more expensive, but it may be not the case for organic pesticides because there are some cheap home-made pesticides such as vinegar. There are few significant income effects. Compared to the base of $25,000 – 49,999, those earning the next larger income are less likely to have never heard of organic pesticides than to be adopters. Those earning the highest income level are generally more likely to adopt, which is in line with the literature. Looking at the table, those who earn more than $100,000 (versus the base) are less likely to be the never heard, no pesticides or other N/A types of non-adopters than to adopt. The largest effect is for no pesticides with a coefficient of -1.53. The probability of being in these categories of non-adopters is 3-4 times less likely than being an adopter.

Robustness checks

The regression analyses show that the main interest variables including seriousness of environmental concerns, importance of neighbors’ opinions, and time spent gardening are important factors affecting the adoption of organic pesticide practices for lawn care. However, contrary to expectations, factors such as having children under 12 and hiring professional pest control services are not significant while the effects of a specific attribute of the lawn like weed density and demographic characteristics are not clear or consistent in this study. We also examine several alternative models to see whether the results are robust to different model specifications.

First, we test for multicollinearity. The correlation matrix of categorical variables used in the full model are reported in appendix 1. Almost all correlation coefficients are smaller than 0.3 except for age and having children under 12 (0.6). Using a Chi-square test for independence, we find that these two variables are significantly correlated ($p<0.0001$). In addition, the variance inflation factors (VIF) of all predictors are presented in appendix 2. Since all the VIF are less than the standard cutoff of 10, there is no evidence of multicollinearity in the full model.

Second, based on the correlation between age and children, we ran two reduced models. The first model is defined by excluding the children under 12 variable while the second one leaves the age variable out of the set of explanatory variables. The estimation results of these models are reported in appendices 3 and 4. The results are in general robust regarding signs and significance. More specifically, the children under 12 variable is still not significant after dropping age. For both alternative models, the neutral response regarding neighbors became significant at the 10% level for the "know somewhat" type of non-respondent, and 0-5 hours spent gardening became significant at the 10% level for the "other N/A" type. When the variable relating to young children was dropped, there were minor changes to the age variables, the 18-30 category is no longer significant at the 10% level for those using no pesticides, and the 46-60 age category for "never heard" went from 10% to 5% level of significance.

We consider McFadden's pseudo R^2, Nagelkerke's pseudo R^2, and information measures like the Akaike information criterion (AIC) and Bayesian information criterion (BIC) to assess which model is a better fit given the dataset. We find that the full model has the largest pseudo R-squared values, followed by the model excluding children and the one excluding age. The smallest AIC and BIC are for the model removing age, followed by the one removing children and the full model. We cannot improve AIC and BIC without reducing the pseudo R-squared values. For consistency with other studies, we prefer using pseudo R-squared to evaluate the models. The full model would be the best in this regard, offering more explanatory power than the other models.

Third, we compare the full model to one keeping all "not applicable" respondents lumped together, rather than separating out those who apparently use no pesticides. The results of this model are reported in appendix 5. In general, the significant coefficients of the other non-adopter groups ("never heard", "know somewhat", and "know well") are the same in sign and magnitude. The model without identifying those using no pesticides has lower pseudo R-squared values than the full model: 8.4% vs 10.8%, and 22.4% vs 30.1%, for the McFadden's and the Nagelkerke's measures, respectively. Also, as indicated by the results of the full model, there are cases where the results of the no pesticide group are opposite to those of the other N/A respondents.

2.7. Conclusions, implications, and limitations

The low adoption rate of residential lawn care BMPs such as organic pesticides means that further environmental improvement is possible if we can identify factors that could lead to improved management practices. In this paper we examine different characteristics of adopters and non-adopters to identify important drivers of organic pesticide adoption. Given the paucity of research on organic practices in residential lawn care, possible determinants are extracted from multiple literatures. Using unique household data from Missouri, the study also distinguishes five distinct non-adopter groups for a deeper understanding of the factors affecting the adoption. A standard multinomial logistic regression is employed to test significance of these determinants and explain household behavior regarding organic pesticides.

Overall, the estimation results support most of the hypotheses of the study. Perceived seriousness of environmental problems related to pesticides, low importance of neighbors' opinions of their lawn, and time spent gardening are critical factors since they are significantly different between adopters and most non-adopter groups. On the other hand, having children under 12, which represents health concerns of the household is not significant, in line with some previous studies (Janssen, 2018; Boizot-Szantai et al., 2017). Demographic variables are also not generally significant determinants of organic pesticide adoption, *ceteris* paribus. Our results can provide information for researchers, educational outreach organizations, and policy makers.

The study provides some insights for conducting future adoption studies. The differences in coefficients between non-adopter groups imply that distinguishing non-adopters is more meaningful and appropriate than lumping them together as in traditional adoption studies. This information could enable targeting of educational campaigns. For example, people who were most knowledgeable about the practice were often quite different from those who had never heard of it. Distinct characteristics of non-adopter groups can be useful to evaluate the importance of determinants in different contexts to enable a deeper understanding of the adoption process. For example, providing more information to knowledgeable non-adopters is less likely to be helpful than providing information to first-time homebuyers. Those who use no pesticides for environmental reasons may not be aware of environmentally-friendly alternatives. Another innovation was separating out people who seem to not apply any pesticides at all from the "other N/A" group. In some cases, signs and significance differed between these subgroups, which has implications for future studies. However, the remaining not applicable group still represents 16% of respondents so future research to further identify reasons for this response may be worthwhile.

There are also implications that flow from some of our key results. First, there are two groups that are low-hanging fruit, people with pro-environmental attitudes and those whose hobby is gardening. The effects of these characteristics are so dominant that these people may be more likely to adopt organic pesticides and other residential BMPs, regardless of other factors. Environmental organizations that focus on unrelated issues, such as climate change, may be targeted for outreach regarding personal behaviors that affect water quality. People who spent more than 10 hours gardening were more likely to be adopters, and this effect was particularly large for those spending over 15 hours per month. This implies that gardening clubs, magazines, and websites may be a good way to reach people who may be predisposed to environmentally-friendly practices that may not be particularly convenient. They may also gain utility from trying new gardening practices.

The fact that 24% of respondents indicate they know the practice well but have not adopted implies that awareness is not the only barrier. This may relate to perceived or actual problems with effectiveness and convenience of current organic pesticides compared to conventional ones or pesticide free solutions. Non-adopters caring more about what the neighbors think may also be related to the effectiveness issue. To address this issue with cleaning products, the Sierra Club collaborated with Clorox to develop a line of environmentally-friendly products. Research to develop effective and convenient environmentally-friendly products, both commercial and home-made, is needed. Dissemination of information on effective solutions to residents and pest control businesses, including experiences from successful adopters, may increase adoption. Regarding policy, a label for organic or environmentally-friendly household products, similar to the USDA one for food, may be helpful in creating markets for these products.

While using traditional predictors like other adoption studies, the explanatory power of the model is low. Including barriers related to the practice may be helpful; for example, physical limitations may limit the use of some practices by certain individuals. The heterogeneous characteristics of organic pesticides such as price and convenience are not covered in the study. The cost of home-made organic pesticides is often lower while that of commercial products is typically higher than conventional pesticides. The same holds for convenience; many organic pesticides are ready to use but some of them require preparation time or additional equipment. Including these characteristics as well as perceptions could increase the explanatory power of the model. Additional research to examine gardeners who are not using any pesticides and those who adopt environmentally-friendly, but not organic, pesticide management practices may be interesting since the water quality impacts are different from other non-adopters.

References

[1] Cohen, P. (2018). *National Gardening Survey, 2018 edition.* GardenResearch.com.

[2] Adwood, D. & Paisley-Jones, C. (2017). *Pesticides Industry Sales and Usage 2008 - 2012: Market Estimates.* Washington, D.C. 20460: U.S. Environmental Protection Agency.

[3] Robbins P. and Sharp J. (2003). The Lawn-Chemical Economy and Its Discontents. *Antipode,* 35 (5), 955-979.

[4] Marshall, S., Orr, D., Bradley, L., & Moorman, C. (2015). A Review of Organic Lawn Care Practices and Policies in North America and the Implications of Lawn Plant Diversity and Insect Pest Management. *HortTechnology*, 25(4).

[5] Bahlai, C.A., Xue, Y., McCreary, C.M., Schaafsma, A.W., & Hallett, R.H. (2010). Choosing Organic Pesticides over Synthetic Pesticides May Not Effectively Mitigate Environmental Risk in Soybeans. *PLoS ONE*, 5(6).

[6] Alumai, A., Salminen, S.O., Richmond D.S., Cardina, J., & Grewal, P.S. (2009). Comparative evaluation of aesthetic, biological, and economic effectiveness of different lawn management programs. Springer Science + Business Media, LLC.

[7] Levy, N. (2018). *Louisiana Urban and Suburban Homeowners' Fertilizer Management Behavioral Beliefs, Intentions, and Past Behaviors*. Louisiana State University: LSU Doctoral Dissertations. 4687. Retrieved from https://digitalcommons.lsu.edu/gradschool_dissertations/4687

[8] Prokopy, L.S., Floress, K., Klotthor-Weinkauf, D., & Baumgart-Getz, A. (2008). Determinants of agricultural best management practice adoption: Evidence from the literature. *Journal of Soil and Water Conservation*, 63(5), 300–311.

[9] Ellis, W.B. & Bradley, M.F. (1996). *The organic gardener's handbook of natural insect and disease control*. Rodale Press, Inc.

[10] Asif, M., Xuhui, W., Nasiri, A., & Ayyub, S. (2018). Determinant Factors Influencing Organic Food Purchase Intention and the Moderating Role of Awareness: A Comparative Analysis. *Food Quality Prefer*, 63, 144–150.

[11] Janssen, M. (2018). Determinants of organic food purchases: Evidence from household panel data. *Food Quality and Preference*, 68, 19–28.

[12] Li, J., Zepeda, L., & Gould, B.W. (2007). The Demand for Organic Food in the U.S.: An Empirical Assessment. *Journal of Food Distribution Research* (38).

[13] Boccaletti, S. & Nardella, M. (2000). Consumer willingness to pay for pesticide-free fresh fruit and vegetables in Italy. *International Food and Agribusiness Management Review*, 3, 297-310.

[14] Bond, C.A., Thilmany, D., & Bond, J.K. (2000). What to choose? The value of label claims to fresh produce consumers. *Journal of Agricultural and Resource Economics*, 33, 402-427.

[15] Saba, A. & Messina, F. (2003). Attitudes towards organic foods and risk/benefit perception associated with pesticides. *Food Quality and Preference*, 14, 637-645.

[16] Schäufele, I., Pashkova, D., & Hamm, U. (2018). Which consumers opt for organic wine and why? An analysis of the attitude-behaviour link. *British Food Journal*, 120(8), 1901-1914. https://doi.org/10.1108/BFJ-03-2018-0141

[17] Van Doorn, J. & Verhoef, P.C. (2015). Drivers of and Barriers to Organic Purchase Behavior. *Journal of Retailing*, 91(3), 436-450. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S0022435915000184

[18] Baumgart-Getz, A., Prokopy, L.S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: a meta-analysis of the adoption literature. *Journal Environmental Management*, 96(1), 17-25. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301479711003598?via%3Dihub

[19] Bach, D. & Rosner, H. (2008). *Go Green, Live Rich: 50 Simple Ways to Save the Earth and Get Rich Trying*. New York: Broadway Books.

[20] Laferriere, K.A., Crighton, E.J., Baxter, J., Lemyre, L., Masuda, J.R., & Ursitti, F. (2016). Examining inequities in children's environmental health: results of a survey on the risk perceptions and protective actions of new mothers. *Journal of Risk Research*, 19(3), 271-287. Retrieved from https://www.tandfonline.com/doi/full/10.1080/13669877.2014.961518

[21] Larson, J.L., Dale, A., Held, D., McGraw, B., Richmond, D.S., Wickings, K., & Williamson, R.C. (2017). Optimizing Pest Management Practices to Conserve Pollinators in Turf Landscapes: Current Practices and Future Research Needs. *Journal of Integrated Pest Management*, 8(1). https://doi.org/10.1093/jipm/pmx012

[22] McCann, L. & Shin, D.W. (2018). Household Use of Composted Manure and Phosphorous-Free Fertilizers: Feeling Good versus Doing Good. *Journal of Environmental Protection*, 2018, 9, 140-157.

[23] Morris, J., & Bagby, J. (2008). Measuring environmental value for Natural Lawn and Garden Care practices. *The International Journal of Life Cycle Assessment*, 13, 226-234.

[24] Tukey, P. (2007). The Organic Lawn Care Manual: A Natural, Low-maintenance System for a Beautiful, Safe Lawn. Storey Pub.

[25] Winterich, K.P., Mittal, V., & William, T.R. (2009). Donation Behavior toward In-Groups and Out-Groups: The Role of Gender and Moral Identity. *Journal of Consumer Research*, 36(2), 199–214.

[26] Veldstra, M.D., Alexander, C.E., & Marshall, M.I. (2014). To certify or not to certify? Separating the organic production and certification decisions. *Food Policy*, 49, 429–436.

[27] Shashi, A.A., Kottala, S.Y., & Singh, R. (2015). A review of sustainability, deterrents, personal values, attitudes and purchase intentions in the organic food supply chain. *Pacific Science Review B: Humanities and Social Sciences, 1(3)*, 114-123. https://doi.org/10.1016/j.psrb.2016.09.003

[28] Blaine, T.W., Clayton, S., Robbins, P., & Parwinder, G.S. (2012). Homeowner Attitudes and Practices Towards Residential Landscape Management in Ohio, USA. Springer Science+Business Media, LLC.

[29] Dettmann, R.L. & Dimitri, C. (2009). Who's Buying Organic Vegetables? Demographic Characteristics of U.S. Consumers. *Journal of Food Products Marketing*, 16(1), 79-91. https://doi.org/10.1080/10454440903415709

[30] Yadav, R. & Pathak, G. (2016). Young consumers' intention towards buying green products in a developing nation: Extending the theory of planned behavior. *Journal of Cleaner Production*, 135, 732-739. https://doi.org/10.1016/j.jclepro.2016.06.120

[31] Brehm, J.M., Pasko, D.K. & Eisenhauer B.W. (2013). Identifying Key Factors in Homeowner’s Adoption of Water Quality Best Management Practices. *Environmental Management*, 52(1), 113–122.

[32] Ngobo, P. (2011). What Drives Household Choice of Organic Products in Grocery Stores? *Journal of Retailing*, 87(1), 90-100. https://doi.org/10.1016/j.jretai.2010.08.001

[33] Genius, M., Tzouvelekas, V., & Pantzios, C. (2006). Information Acquisition and Adoption of Organic Farming Practices. *Journal of Agricultural and Resource Economics*, 31(1).

[34] Dreezens, E., Martijin, C., Tenbult, P., Kok, G., & Vries, N.K. (2005). Food and values: an examination of values underlying attitudes toward genetically modified and organically grown food products. *Appetite*, 44, 115-122.

[35] Magnusson, M. (2001). Attitudes towards organic foods among Swedish consumers. *British Food Journal*, 103(3), 209-226.

[36] Lea, E. & Worsley, T. (2005). Australians’ organic food beliefs, demographics and values. *British Food Journal*, 107(11), 855-869.

[37] Vermeir, I. & Verbeke, W. J. (2006). Sustainable Food Consumption: Exploring the Consumer "Attitude – Behavioral Intention" Gap. *Journal of Agricultural and Environmental Ethics*, 19. https://doi.org/10.1007/s10806-005-5485-3

[38] Moser, K. (2016). Consumers' purchasing decisions regarding environmentally friendly products: An empirical analysis of German consumers. *Journal of Retailing and Consumer Services*, 31(C), 389-397.

[39] Hughner, R.S., McDonagh, P., Prothero, A., Shultz, C.J., & Stanton, J. (2007). Who are organic food consumers? A compilation and review of why people purchase organic food. *Journal of Consumer Behaviour*, 6, 94-110.

[40] Reimer, A.P. & Prokopy, L.S. (2012). Environmental Attitudes and Drift Reduction Behavior among Commercial Pesticide Applicators in a U.S. Agricultural Landscape. *Egyptian Journal of Environmental Management*, 113, 361-369. https://doi.org/10.1016/j.jenvman.2012.09.009

[41] Riar, A., Mandloi, L.S., Poswal, R.S., Messmer, M.M., & Bhullar, G.S. (2017). A Diagnosis of Biophysical and Socio-Economic Factors Influencing Farmers' Choice to Adopt Organic or Conventional Farming Systems for Cotton Production. *Frontiers in plant science*, 8(1289). https://doi.org/10.3389/fpls.2017.0128

[42] Beedell, J. & Rehman, T. (2000). Using Social-Psychology Models to Understand Farmers' Conservation Behavior. *Journal of Rural Studies*, 16, 117-127.

[43] Grob, A. (1995). A structural model of environmental attitudes and behaviour. *Journal of Environmental Psychology*, 15(3), 209-220.

[44] Jin, S., Bluemling, B., & Mol, A. (2015). Information, trust and pesticide overuse: Interactions between retailers and cotton farmers in China. *Wageningen Journal of Life Sciences*, 23–32.

[45] Philbert, A., Lyantagaye, S., & Nkwengulila, G. (2014). A Review of Agricultural Pesticides Use and the Selection for Resistance to Insecticides in Malaria Vectors. *Advances in Entomology*, 2, 120-128. https://doi.org/10.4236/ae.2014.23019

[46] Makatouni, A. (2002). What motivates consumers to buy organic food in UK? Results from a qualitative study. *British Food Journal*, 104, 345-352.

[47] Padel, S. & Foster, C. (2005). Exploring the gap between attitudes and behavior: Understanding why consumers buy or do not buy organic food. *British Food Journal*, 107, 606-625.

[48] Singh, Y., Singh, B., Pabbi, S., & Singh, P.K. (2007). Impact of Organic Farming on Yield and Quality of BASMATI Rice and Soil Properties. *Scientific Conference on Organic Agriculture*. Retrieved from https://orgprints.org/9783/

[49] USGS (2000). *The United States Geological Survey Report, 1999*. Washington, D.C.: U.S. Government Printing Office.

[50] Davis, J.R., Brownson, R.C., & Garcia, R. (1992). Family pesticide use in the home, garden, orchard, and yard. *Environment Contamination Toxicology*, 22.

[51] Boizot-Szantai, C., Hamza, O., & Soler, L.G. (2017). Organic consumption and diet choice:An analysis based on food purchase data in France. *Appetite*, 117, 17-28. https://doi.org/10.1016/j.appet.2017.06.003

[52] Radman, M. (2005). Consumer consumption and perception of organic products in Croatia. *British Food Journal*, 107(4), 263-273.

[53] Gomiero, T. (2018). Food quality assessment in organic vs. conventional agricultural produce: Findings and issues. *Applied soil ecology*, 123, 714-728. https://doi.org/10.1016/j.apsoil.2017.10.014

[54] Baker, S., Thompson, K., & Engelken, J. (2004). Mapping the values driving organic food choice. *European Journal of Marketing*, 38(8), 995-1012.

[55] Huang, C. (1996). Consumer preferences and attitudes towards organically grown produce. *European Review of Agricultural Economics*, 23, 331-342.

[56] Lockie, S., Lyons, K., Lawrence, G., & Mummery, K. (2002). Eating green: Motivations behind organic food consumption in Australia. *European Society for Rural Sociology*, 41(1), 23-40.

[57] Meehan, T.D., Werling, B.P., Landis, D.A., & Gratton, C. (2011). Agricultural landscape simplification and insecticide use in the Midwestern United States. *Proceedings of the National Academy of Sciences of the United States of America*.

[58] Nassauer, J.I., Wang, Z., & Dayrell, E. (2009). What will the neighbors think? Cultural norms and ecological design. *Landscape and Urban Planning*, 9, 282-292.

[59] Gudade, B.A., Chhetri, P., Gupta U., Deka, T.N., Vijayan ,A.K., & Bhattarai, N.K. (2014). The study of ecofriendly practices of large cardamom cultivation in Sikkim and Darjeeling. *Ecology, Environment and Conservation*, 20(1), 119-123.

[60] Jolly, D. (1991). Differences between buyers and non-buyers of organic produce and willingness to pay organic price premiums. *Journal of Agribusiness,* 9(1), 1-15. https://doi.org/10.22004/ag.econ.62304

[61] Greene, C. & Kremen, A. (2003). *US Organic Farming in 2000-2001: Adoption of Certified Systems*. Washington, D.C.: United States Department of Agriculture, Washington DC.

[62] Constance, D.H. & Choi, J.Y. (2010). Overcoming the Barriers to Organic Adoption in the United States: A Look at Pragmatic Conventional Producers in Texas. *Sustainability*, 2, 163-188.

[63] Templeton, S., Yoo, S., & Zilberman, D. (1999). An Economic Analysis of Yard Care and Synthetic Chemical Use: The Case of San Francisco. *Environmental and Resource Economics*, 14(3), 385-397.

[64] Rogers, E. (2010). *Diffusion of Innovations (5th edition)*. Simon and Schuster.

[65] Straub, E. (2009). Understanding Technology Adoption: Theory and Future Directions for Informal Learning. *Review of Educational Research*, 79(2), 625-649.

[66] McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. *In Frontiers in Econometric*. New York: Academic Press.

[67] Luce, R. (1959). *Individual Choice Behaviour: A Theoretical Analysis*. New York: John Wiley & Sons.

[68] McFadden, D., & Train, K. (2000). Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics*, 15(5), 447-470.

[69] Small, K.A. & Rosen, H.S. (1981). Applied Welfare Economics with Discrete Choice Models. *Econometrica*, 49(1), 105-130.

[70] Ben-Akiva, M.E. & Lerman, S.R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge: MIT Press.

[71] McFadden, D. (1981). Econometric Models of Probabilistic Choice. *In Structural Analysis of Discrete Data: With Econometric Applications* (pp. 198–272). Cambridge, Mass.: MIT Press.

[72] Lichtenberg, E. (2004). Cost-Responsiveness of Conservation Practice Adoption: A Revealed Preference Approach. *Journal of Agricultural and Resource Economics*, 29(3), 420-435.

[73] Shin, D.W. & McCann, L. (2017). Enhancing Adoption Studies: The Case of Residential Stormwater Management Practices in the Midwest. *Agricultural and Resource Economics Review*, 1-34.

CHAPTER 3. EFFICIENCY OF PESTICIDE USE IN AGRICULTURAL PRODUCTION: EVIDENCE FROM VIETNAMESE RICE & FRUITS FARMS

The chapter is modified from the conference paper of Tran, L., McCann, L., and Skevas, T. (2020). Efficiency of pesticide use in agricultural production: Evidence of pesticide overuse from Vietnam. Selected paper presented at the 2020 Agricultural and Applied Economics Association annual meeting[1].

Pesticides have long been important for the development of agricultural production. However, improper use of pesticides may result in inefficiency with respect to farm profitability, in addition to external effects of pesticide use on environmental and human health. This paper employs the directional distance function to estimate efficiency scores of Vietnamese rice and fruit farms, analyzes pesticide efficiency of these two sets of farms, then investigates determinants of pesticide overuse. The empirical application uses data on Vietnamese fruit and rice farms drawn from the 2016 Vietnamese Household Living Standards Survey. Results indicate considerable potential for improving pesticide use efficiency, especially of rice farms. Pesticides were overused by about one-third of both rice and fruit farms, while no farm was found to use pesticides optimally. The results of the determinants of pesticide overuse versus underuse suggest overusing rice farms were more likely to have higher off-farm income or be located in the Mekong Delta. For fruit farms, younger, more educated farmers with more debt were more likely to overuse pesticides.

[1] This work has been also submitted to AJARE for peer-review.

3.1. Introduction

Pesticides are important inputs in modern agriculture for ensuring high quantity and quality of agricultural production. In 2017, about 4.1 million tonnes of pesticides[2] were used in agriculture worldwide (FAOSTAT, 2019). The use of these chemicals has been dramatically increasing during the last three decades especially in developing countries (Ecobichon, 2001; Schreinemachers & Tipraqsa, 2012; Sharma et al., 2019). Despite the benefits of pesticides, their indiscriminate use has led to serious health and environmental risks (Antle & Pingali, 1994; Pingali, 2004; Dasgupta et al., 2007a; Lamers et al., 2013; WHO-FAO, 2019). The growing concerns regarding the environmental and health effects of pesticides have stimulated intensive research efforts into understanding farmers' pesticide use behavior and its determinants.

Vietnam has widely promoted pesticide use in agricultural production since the 1990s (Meisner, 2005). Pesticide consumption drastically increased from about 20,000 tonnes of 96 different pesticide formulations in 1991 to more than 150,000 tonnes of about 4000 formulations in 2017 (GSO, 2018). The rising quantity and types of pesticides indicate the increasingly heavy reliance on pesticides for pest control.

While pesticides indeed have benefited agricultural crop production in Vietnam, their improper use has caused a variety of problems, such as environmental pollution and adverse health impacts on animals and humans. Pesticides, even highly hazardous pesticides, have been misused in Vietnam due to the absence of pesticide regulations, and farmer's lack of knowledge and proper equipment (Hoi et al., 2013; Toan et al., 2013). Minh et al. (2008) showed that in Vietnam, contamination of air, water, and sediment due to persistent organic pollutants, especially organic chlorinated insecticides, are higher

[2] In terms of active ingredients.

than in developed countries like Japan. In another study, Hoai et al. (2010) also indicated many water samples have been seriously polluted with dichlorodiphenyltrichloroethane (DDT), hexachlorocyclohexane (HCH), and endosulfan. According to Dang et al. (2007), improper use of pesticides has been an important factor leading to an increase in non-communicable diseases including neurobehavioral development, cancer, infertility, and other reproductive problems. Vietnamese farmers and their families are directly and indirectly exposed to pesticides from their work in fields, their contaminated clothes, or the pollution of local water supplies. They are faced with multiple symptoms of chronic poisoning: skin irritation, headache, dizziness, eye irritation, and respiratory problems (Murphy et al., 2002; Dasgupta et al., 2007a). Continuous misuse and overuse of pesticides have also caused negative effects on fish or shrimp farming which are often combined with rice cultivation in the Mekong Delta (Berg, 2001; Klemick and Lichtenberg, 2008; Tam et al., 2015).

Understanding pesticide use efficiency in Vietnam is thus important for farmers' incomes and health status, as well as the environment. Identifying significant factors affecting overuse of pesticides is also important for designing improved policies and educational efforts in Vietnam aimed at improving pesticide use efficiency and protecting public health and the environment. We choose rice and fruit farming for this study because they have special roles in Vietnam's agriculture. Rice is the major crop in Vietnam, grown by 80% of the rural population, and Vietnam is the second largest rice exporter in the world, but fruits have seen considerable growth in recent years (GSO, 2018). Moreover, while rice farms represent 63% of all pesticide consumption by quantity, the largest average expenditure for pesticides is on fruit farms.

In this study, we add to previous research by examining: (a) the technical efficiency of pesticide use in Vietnam's rice and fruit cultivation, (b) whether pesticides are over- or underused in these crops under profit maximizing behavior, and (c) the factors leading to pesticide over- or underuse. To address the two first questions, this study utilizes a directional distance function (DDF) to measure performance of rice and fruit farms. The DDF allows the calculation of pesticide shadow prices which are then compared to market prices to infer whether pesticides are over- or underused. A probit model is then used to examine the determinants of pesticide overuse versus underuse. This research contributes to the literature in several ways. First, it provides the first assessment of pesticide use efficiency in Vietnamese farming. Second, unlike other pesticide use efficiency studies focusing on relatively homogeneous groups of crops such as vegetables (Fernandez-Cornejo, 1994; Singbo et al., 2015) or arable crops (Lansink and Silva, 2004; Skevas et al., 2012), this study examines pesticide use efficiency in two important but divergent crops, rice and tree fruits. Third, it adds to the scarce literature on the determinants of pesticide overuse in agriculture (Wang et al., 2018; Schreinemachers et al., 2020)[3].

In the next section, we present relevant empirical studies and theoretical literature about pesticide use in crop production, especially in developing countries. We then describe the methodology used and provide data descriptions for the study. In the subsequent section, we report empirical results of efficiency measures and present significant factors affecting pesticide overuse. The chapter ends with conclusions and implications of the study, especially in the developing country context.

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[3] As will be made clear later, our study differs from the studies of Wang et al., (2018) and Schreinemachers et al., (2020) not only in terms of the application (i.e., country and crops studied) but also by using a non-parametric modeling approach to identify pesticide overusing farms.

3.2. Literature review of pesticide efficiency and overuse

3.2.1. Measuring pesticide efficiency and determining overuse

Agricultural production has always involved the use of resources or inputs such as farmland, labor, physical capital, and variable inputs such as fertilizers, pesticides, energy, and custom services to produce outputs (e.g., crops). From an input perspective, technical efficiency is defined as the producer's ability to reduce the use of inputs to achieve a certain level of production. When input technical inefficiency is present in production, the use of inputs can be reduced without reducing outputs. This could, in turn, lead to reduced production costs and, in the case of polluting inputs such as pesticides, higher environmental quality. Since the Green Revolution, there have been considerable changes in input use in agriculture (e.g., increased use of fertilizers and pesticides, and decreased use of labor and land) (Wang et al., 2015). Efficiency of input use has become a focus for enhancing agricultural productivity growth, especially in developing countries where existing technology has usually not been used efficiently (Belbase & Grabowski, 1985; Fan et al., 2011; Bravo-Ureta & Pinheiro, 2016).

Pesticides have been widely used in agriculture for crop productivity/protection and as a labor-saving technology in the presence of pests (Cassou et al., 2018). Thus, pesticides contribute to agricultural productivity growth. In recent decades, the reliance on pesticides has been growing around the world (see reviews by Popp et al., 2013 and Sharma et al., 2019).

Previous studies often have evaluated pesticide performance in agricultural production by measuring marginal productivity of pesticides. Early research (e.g., Headley et al., 1968) considered pesticides as regular inputs (e.g., fertilizers, farm machinery), and thus assumed a positive value of marginal product (VMP) of pesticides in production. This empirical research tended to find VMP estimates which were higher than the marginal cost of pesticides, which supported the positive impacts of pesticide use on crop yields, and implied pesticide use was lower than the optimal level. In another words, pesticides were underused in production, and farmers could improve efficiency by increasing their pesticide use.

Later research disputed this view. Based on agronomic evidence, pesticides are damage reducing rather than productive (productivity increasing) inputs[4], which suggests an output damage abatement specification for pesticides (Lichtenberg and Zilberman, 1986). Stemming from the seminal contribution of Lichtenberg and Zilberman (1986), numerous studies applied various damage abatement specifications and reported mixed findings of pesticide over- or underuse (e.g., Carrosco-Tauber and Moffit, 1992; Lin et al., 1993; Antle and Pingali, 1994; Lansink and Carpentier, 2001; Guan et al. 2005; Skevas et al. 2013; Wang et al, 2018; Sun et al., 2020; Schreinemachers et al. 2020). The results indicate the VMP estimates are generally sensitive to the functional forms specified for the damage abatement function in parametric estimations, which may limit insights of the estimates for pesticide performance.

Efficiency of pesticide use can also be examined using a non-parametric approach like data envelopment analysis (DEA). Based on linear programming and not requiring

[4] Strictly speaking, pesticides are used directly for protecting crop yield from damages causes by pests, which is different from standard inputs (seeds, fertilizers, land, etc.) which increase potential output. In this regard, Lichtenberg and Zilberman (1986) distinguished the contribution of damage control agents like pesticides to production by incorporating a damage control specification into a standard production function (i.e., specifying $f(X, Z)=f(X, g(Z))$ where X are productive inputs, Z are pesticide inputs, f(.) represents traditional production function (e.g., Cobb-Douglas), and g(.) represents damage control or damage abatement function). The new production function allows estimation of pesticide productivity to be able to explain the fact that pesticides are often overused rather than underutilized in the biological and behavioral literature on pesticide use.

any assumptions on the functional form of the production frontier and the distribution of efficiency, DEA avoids misspecification and distribution errors, which might arise with parametric approaches. DEA can estimate input-specific technical efficiency measures. Moreover, the dual values of its input and output constraints can be used to estimate the VMPs of inputs and investigate whether inputs are being used optimally. Several studies have examined pesticide use efficiency in agricultural production using DEA, with most of these studies undertaken in developed countries (Fernandez-Cornejo, 1994; Lansink and Silva, 2004; Skevas et al., 2012) and less in the developing world (Singbo et al., 2015). All these studies measured farm-level efficiency scores, which represent how efficiently pesticides are used relative to the best practice observed in a sample and describe the potential to reduce pesticide use while producing the same output. Some of these studies have also computed the VMP of pesticides, also known as the shadow price of pesticides, and compared it with the pesticide market price to determine which farms in the sample are over- or underusing pesticides (Lansink and Silva, 2004; Skevas et al. 2014; Singbo et al., 2015).

In an era of increasing awareness of the negative side effects of pesticide use and growing concerns about reducing the dependence on pesticides, determining overuse of pesticides is useful information for policy and educational programs. The term “overuse” has been presented in a large number of pesticide studies, especially in developing countries, but with different definitions. Legally, “overuse” refers to pesticide applications that exceed the standard dosage recommended by the pesticide label or experts like agronomists, extension agents or retail sellers (e.g., Jallow et al., 2017). This definition conforms to pesticide laws and regulations, a description of agrochemical companies, and farmers' knowledge. From an economic point of view, pesticide overuse occurs when the amount used is greater than the economic optimum or the profit maximizing level of pesticides (e.g., Schreinemachers et al., 2020). The estimated VMP and marginal cost of pesticides are crucial to determine the presence of pesticide overuse. When the estimated VMP is lower (higher) than the marginal cost, pesticides are overused (underused) according to the economic approach.

Various attempts have determined pesticide overuse in the literature. Most studies found overuse of pesticides is common in Asian developing countries, either using the agronomic approach (Shetty, 2004; Dagupsta et al., 2007; Khan et al., 2015; Zhang et al., 2015; Jallow et al., 2017; Wu et al., 2018; Qin & Lu, 2020) or the economic approach in a parametric framework (Wang et al., 2018; Schreinemachers et al., 2020). While beyond the scope of our research, several studies also accounted for the negative effects of pesticide use on human health and/or the environment (e.g., Pimental et al., 2005; Grovermann et al., 2013; Veettil et al., 2017). A few studies examined pesticide overuse in a non-parametric framework by computing the VMP of pesticides (using the dual values of the pesticide and output constraints of DEA specifications) and comparing it with the unit cost of pesticides (Skevas et al., 2014; Singbo et al., 2015). Skevas et al. (2014) showed pesticides on average are overused in cash crop farms in the Netherlands, although there are a small number of farms that underuse insecticides and fungicides. Singbo et al. (2015) also found the general presence of pesticide overuse in vegetable production in Nigeria.

3.2.2. Determinants of pesticide overusing farms/farmers

While measuring overuse of pesticides is an evolving area of research, there are numerous studies examining factors affecting pesticide use in agriculture but fewer studies assessing the determinants of pesticide overuse. In this review, we therefore examine previous research on determinants of pesticide use and overuse based on both agronomic and economic considerations in order to develop a robust set of potential determinants. Factors which increase pesticide quantity/expenditure may be potential determinants of overuse since they positively affect the amount of pesticides used in the agronomic approach or decrease the VMP as an economic criterion of overuse. The following review integrates all these perspectives to develop potential determinants of pesticide overuse (Table 3.1).

Several socio-demographic characteristics such as gender, age, education, household size, and household income may have impacts on overuse of pesticides in agriculture. The effect of gender is not clear; for example, Wang et al. (2018) found men are less likely to overuse pesticides compared to women because most female farmers are less experienced in developing countries like China. This result is contrary to the finding of Schreinemachers et al. (2020) for female farmers in Southeast Asia. Rahman and Chima (2018) also suggest female headed households have lower access to modern inputs like pesticides than male ones in Nigeria.

Table 3.1. Factors affecting pesticide use (quantities/overuse) in agricultural production.

No.	Determinants	Quantity/Expenditure of pesticides		Overuse of pesticides by agronomic/legal definition		Overuse of pesticides by economic criteria	
		Effect	Articles	Effect	Articles	Effect	Articles
Demographic characteristics							
1	Male	+	Rahman&Chima (2018)			- +	Wang et al. (2018) Schreinemachers et al. (2020)
2	Age	+/-	Huang et al. (2000); Zheng et al. (2020); Migheli (2017)	+	Dagupsta et al. (2007)	+	Huang et al. (2020)
3	Farming experience	+	Rahman&Chima (2018)	-	Jallow et al. (2017)	+ -	Huang et al. (2020); Wang et al. (2018)
4	Education			-	Khan et al. (2015); Jallow et al. (2017)		
5	IPM Training			+	Khan et al. (2015); Jallow et al. (2017)	-	Wang et al. (2018)
6	Household size (working on farm)	-	Migheli (2017)				
7	Income	-	Migheli (2017)			+	Huang et al. (2020)
8	Off-farm income	-	Migheli (2017)				
Farmer/Farm characteristics							
9	Risk averse	+	Huang et al. (2000); Mariyono et al. (2018);	+	Qin & Lu (2020); Jallow et al. (2017)		
10	Farm/Land Ownership	+	Migheli (2017)	+	Dagupsta et al. (2007)		
11	Farm size			+/-	Qin & Lu (2020); Wu et al. (2018)	- +	Huang et al. (2020); Schreinemachers et al. (2020)
12	Crop	+/-	Migheli (2017); Douglas&Tooker (2015)	+/-	Dagupsta et al. (2007)		
15	Location (climate, pest population …)			+/-	Dagupsta et al. (2007); Shetty (2004)		
16	Debt	+	Migheli (2017)				
13	Retailer's information			+	Jallow et al. (2017)	+	Schreinemachers et al. (2020)

No.	Determinants	Quantity/Expenditure of pesticides		Overuse of pesticides by agronomic/legal definition		Overuse of pesticides by economic criteria	
		Effect	Articles	Effect	Articles	Effect	Articles
17	Joining cooperatives			-	Qin & Lu (2020)	-	Huang et al. (2020)
18	Extension accessibility			-	Jallow et al. (2017)	-	Schreinemachers et al. (2020)

Notes: All effects are statistically significant at least at the 10% level. The plus "+" sign means the effect is positive; the minus "-" sign means the effect is negative; the plus/minus "+/-" means the direction of the effect is indeterminate (i.e., some studies have found a positive effect and others have found a negative effect).

The effect of age is fairly clear in pesticide overuse studies. Older farmers tend to overapply pesticides compared to younger farmers because they do not follow the standard dosage (Dasgupta et al., 2007) or they do not easily change their habits regarding pesticide application (Huang et al., 2020). This may relate to older farmers in general making farming decisions based on their experience rather than regulations or economic efficiency. However, experienced farmers may have knowledge about how to control pests without heavy reliance on pesticides, ensuring a high VMP of pesticides, and thus less overuse (Jallow et al., 2017; Wang et al., 2018).

More educated farmers are less likely to overuse pesticides, which is expected because they tend to follow the instructions on pesticide labels or given by agronomic experts (Khan et al., 2015; Jallow et al., 2017). However, the effect of educational programs like integrated pesticide management (IPM) or good agricultural practices (GAP) trainings on pesticide overuse is indeterminant (Wang et al., 2018; Jallow et al., 2017).

The effects of household size and income on pesticide overuse are not clear. Family farms with more members working in the fields tend to have decreased use of pesticides, possibly implying lower probability of pesticide overuse (Migheli, 2017). However, this has not been directly examined in pesticide overuse studies yet. Higher income households can afford to buy more pesticides (quantity and type), leading to higher probability of pesticide overuse (Huang et al., 2020). This may contradict the result of Migheli (2017) that suggests higher income can reduce pesticide use and enable more expensive solutions like organic or biological controls. On the other hand, off-farm income, as a portion of total income, represents both affordability and farm labor substitution, and negatively affects the use of pesticides (Migheli, 2017), potentially implying lower probability of pesticide overuse for higher off-farm income due to the substitution effect.

Farmer/farm attributes such as risk aversion, the ownership of farm/land, farm size, crop, and location have been introduced as potential determinants of pesticide overuse. A risk averse farmer mostly uses pesticides for crop protection. The literature shows that they tend to use more pesticides than required, leading to higher probability of pesticide overuse (Jallow et al., 2017; Qin & Lu, 2020).

Land ownership may positively impact pesticide overuse. Farmers who own the farm are more likely to overuse pesticides since they are fully responsible for farm performance, and there has been a widespread belief that increasing pesticides improves the production performance (Dasgupta et al., 2007). Landowners would thus use more agrochemicals (including pesticides) compared to renters because the owners look for productivity increases in the short run (Migheli, 2017), potentially leading to overuse of pesticides.

The effect of farm size on overuse in general is indeterminant. In the paper by Wu et al. (2018), small farms in China, typically about 0.1 ha for each parcel, were strongly related to overuse of pesticides because of lack of farming knowledge and management skills. In contrast, Qin & Lu (2020) found large scale rice farms tend to overuse pesticides compared to small scale rice farms because of differences in market orientation of these farms. In particular, the probability of pesticide overuse among small farms is lower than that among large farms when the rice eaten by households is a large proportion of their yield.

Empirical studies have shown crop and locational factors as significant determinants of pesticide overuse (e.g., Shetty, 2004; Dasgupta et al., 2007; Migheli, 2017). Different crops require different pesticides, since there are a range of pests and diseases for each crop. For example, rice versus fruit (apples, peaches, strawberries) production often are faced with different kinds of insects and diseases. Locational factors relate to climate, rainfall (drought), temperature, and pest population, as well as pesticide availability, which affect the use of pesticides and overuse.

Additional socioeconomic factors such as debt, access to retailers' information, membership in agricultural cooperatives, and extension availability have also been possible determinants of the pesticide overuse. Migheli (2017) showed farmers who have informal debt are more likely to increase the quantity of pesticides used compared to those who have formal debt (given the same total of debt) because formal institutions have more credit constraints. This empirical result may imply the relationship of holding debt and affordability: farms without debt are more able to buy pesticides, leading to a higher probability of pesticide overuse.

Farmers who more easily receive retailers' information tend to apply pesticides at more than the recommended dosage (Jallow et al., 2017) or more than the optimal use (Schreinemachers et al., 2020). Retailers have an incentive to sell more inputs to farmers.

In contrast, farmers who are members of a cooperative and have more access to extension are less likely to overuse pesticides (Jallow et al., 2017; Qin & Lu, 2020), and are able to improve VMPs of pesticides (Huang et al., 2020; Schreinemachers et al., 2020).

The literature on pesticide use efficiency shows discrepancies in empirical results and insights for the use of pesticides in agricultural production. There have been differences in determining overuse of pesticides, depending on whether the agronomic or economic approach is used. Within the economic efficiency approach, the discrepancies arise from the way pesticides are treated: productive versus damage abatement inputs, and the estimation method used: parametric or non-parametric approach. Although numerous studies indicate the presence of pesticide overuse in developing countries, there is little research on determinants of overuse. By merging the literature on studies determining overuse of pesticides and studies quantifying the amount of pesticides used in agricultural production, the paper contributes to the literature of determinants of pesticide overuse by extracting hypotheses about potential determinants from demographic characteristics and farmer/farm attributes. Demographic variables like age and household income are more likely to relate to pesticide overuse while more education is less likely to be associated with pesticide overuse. Farmer/farm attributes such as risk aversion, land ownership, crop, and location are potentially significant factors leading to the overuse of pesticides. There are gaps in the literature regarding possible determinants that can be fruitfully examined from the efficiency perspective.

3.3. Methodology

3.4.1 Measuring pesticide use efficiency and overuse

Following Skevas et al. (2012) and Singbo et al. (2014), with some adjustments to fit the context of our study, we model how to measure pesticide efficiency and determine pesticide overuse.

Consider a farmer i ($i = 1, \ldots, I$) who produces output y ($y \in R_{+}$) using pesticides ($z \in R_{+}$), variable inputs other than pesticides x ($x \in R_{+}$), and a vector of fixed inputs $\boldsymbol{q}$ ($\boldsymbol{q} \in R_{+}^{C},\ c = 1, \ldots, C,\ with\ C = 3$). The production technology T is then defined by all $(z, x, \boldsymbol{q}, y)$ such that z, x and $\boldsymbol{q}$ can produce y:

$$T(z, x, \boldsymbol{q}, y) = \{(z, x, \boldsymbol{q}, y): z, x, \boldsymbol{q}\ can\ produce\ y\} \qquad (1)$$

T is assumed to be non-empty, convex and compact. Further, it is assumed that T satisfies variable returns to scale and allows for strong disposability of output and all variable inputs (i.e., z and x). Fixed inputs $\boldsymbol{q}$ (e.g., farm capital) are assumed to be weakly disposable, because farmers cannot easily adjust these inputs in the short run.

A primal characterization of T is the following directional distance function (DDF) (Chambers et al., 1998):

$$\vec{D}(z, x, \boldsymbol{q}, y) = \max_{\boldsymbol{\beta}}\{\boldsymbol{\beta}: (z, x, y) + \boldsymbol{\beta}\boldsymbol{g} \in T\} \qquad (2)$$

where $\boldsymbol{g}$ denotes a directional vector, $\boldsymbol{\beta}$ is the portion of the directional vector $\boldsymbol{g}$ that must be added to output, pesticides and other variable inputs, to bring them exactly onto the boundary of T. By defining $\boldsymbol{g} = \left(g_y, -g_z, -g_x\right)$, the DDF in (2) seeks to simultaneously increase output and decrease pesticides and other variable inputs. The choice of $\boldsymbol{g}$ is driven by the production technology under investigation. Farmers seek to produce as much output as possible, with minimal input use.

we empirically approximate eq. 2 using data envelopment analysis (DEA), as follows:

$$\vec{D}(z, x, \boldsymbol{q}, y) = \max_{\beta_{1i}, \beta_{2i}, \beta_{3i}, \lambda} \{\beta_{1i} + \beta_{2i} + \beta_{3i}\} \qquad (3)$$

subject to:

$$\sum_{i=1}^{I} \lambda_i \, y_i \geq y_i + \beta_{1i} g_y \qquad \text{(i)}$$

$$\sum_{i=1}^{I} \lambda_i \, x_i \leq x_i - \beta_{2i} g_x \qquad \text{(ii)}$$

$$\sum_{i=1}^{I} \lambda_i \, q_{ic} = q_{ic}, \; c = 1, \ldots, C \qquad \text{(iii)}$$

$$\sum_{i=1}^{I} \lambda_i \, z_i \leq z_i - \beta_{3i} g_z \qquad \text{(iv)}$$

$$\sum_{i=1}^{I} \lambda_i = 1 \qquad \text{(v)}$$

$$\lambda_i \geq 0 \qquad \text{(vi)}$$

where β_{1i}, β_{2i} and β_{3i} are the farm-specific technical inefficiency scores of output, variable inputs, and pesticides, respectively. They represent the largest possible expansion of output and contraction of variable inputs and pesticides. λ_i are the farm weights that define the reference technology. Variable returns to scale are imposed by using the constraint (v). The equality constraint (iii) implies that fixed inputs are considered weakly disposable. The directional vectors g_y, g_{x}, and g_z are defined as the farm-specific quantities of output, variable inputs, and pesticides, respectively. This allows the convenient interpretation of the technical inefficiency scores in terms of percentages (Chambers et al., 1998). Eq. 3 was estimated separately for each sample farm. For the ease of interpretation, we convert inefficiency scores to efficiency by subtracting the level of inefficiency from unity. By doing so, farms with an efficiency score of 1 are characterized as fully efficient.

Estimation of eq. 3 allows one to obtain a set of dual variables for each observation. Using these dual variables, which account for the impact on inefficiency of a change in each technological constraint, the value of the marginal product (i.e., shadow value) for each input can be generated. As in Ball et al. (1994), Skevas et al. (2014), and Singbo et al. (2015), the input-specific marginal products (MP) are obtained by taking the first derivative of output with respect to each input. In the case of pesticides, which is the focus of this study, the mathematical expression of the MP is as follows:

$$MP_i = \partial y_i / \partial z_i = -\frac{\partial \beta_{3i} / \partial z_i}{\partial \beta_{1i} / \partial y_i} \qquad (4)$$

where the quantities $\partial \beta_{3i} / \partial z_i$ and $\partial \beta_{1i} / \partial y_i$ are the dual variables obtained from solving eq. 3, and they are associated with the constraints on pesticides and output, respectively. The shadow value (SV) of pesticides for each farm i is then obtained as follows:

$$SV_i = VMP_i = p * MP_i \qquad (5)$$

where p is the observed output price.

The extent to which pesticides are over- or under-used is inferred from a comparison of SV_i with the pesticide market price. Profit maximization implies the marginal product or shadow value of pesticides must equal the market price of pesticides (Lansink and Silva, 2004). If the pesticide market price is greater (lower) than the SV_i then pesticides are overused (under-used).

3.3.2 Assessing the factors that affect pesticide over- or under-use

We use a probit model to understand what factors or farm/farmer characteristics might be associated with over- or under-use of pesticides. The dependent variable in this model is a dummy variable that takes the value of 1 if the farmer under investigation overuses pesticides and zero if he/she underuses pesticides[5]. The specification of the probit model is as follows:

$$Pr(D_i = 1|\mathbf{h_i}) = \Phi(\frac{\boldsymbol{\gamma_k} * \boldsymbol{h_i'}}{\sigma_k}) \quad (5)$$

where Pr denotes probability, D is the binary variable of farmer i over- (1) or underusing pesticides (0), Φ is the normal cumulative distribution function, $\mathbf{h}$ is a vector of explanatory variables, $\boldsymbol{\gamma_k}$ is a vector of parameters to be estimated, and σ_k is the standard deviation for the overuse model. Eq. 5 is estimated using the maximum likelihood estimation approach.

3.4. Data Description

The data used in this study comes from the 2016 Vietnamese Household Living Standard Survey (GSO, 2017). The survey dataset includes 5,552 farm households which were randomly sampled from a list of 33,480 active Vietnamese farms in 2016. All agricultural crops produced in Vietnam are included in the dataset, grouped in the survey instrument as rice, fruit trees, industrial crops, staple, non-staple food crops, and others.

According to the dataset, 70% of sample farms produced multiple crops in the same year, which means these farms produced more than two out of the six category crops in 2016. With the intention of focusing on farms engaged primarily in rice and fruit production, we selected farms for the analysis whose revenues from sales of rice and fruit, respectively, comprised at least 80% of their total annual revenues[6]. After imposing

[5] As will become clear in the Results section, no sample farmer is using pesticides at the optimal level.
[6] This is necessary because the data on input use is not separated by crop.

these requirements and excluding all missing and zero[7] observations, the final dataset used in this study consists of 1,368 rice farms and 158 fruit tree farms.

Summary statistics for the data used in our study and for each group of farms (i.e., rice and fruit farms) can be found in Table 3.2. For the inefficiency analysis, one output and 5 inputs are distinguished. Output or farm revenue (y) is defined as the revenues in Vietnamese dong from the sales of all crop products. Following the DEA literature, output price index includes consumer price index of rice and fruits in 2016 with the base of 2014. Inputs are categorized into three groups: fixed inputs (q), pesticides (z), and other variable inputs (x). Fixed inputs include land, labor, and capital. Capital represents the value of tools, machinery, and asset depreciation. Land represents the total area used for all crop production and is measured in hectares (ha). Labor represents the working time of farm household members and hired workers and is measured in man-year units. Pesticides are defined as the amount of money a farm spent on herbicides, insecticides, and fungicides. Pesticide price index is the producer price index (PPI) of agrochemicals[8] in 2016 with the base of 2014. Finally, other variable inputs include the cost of seeds, seedlings, energy, irrigation, hired cattle traction, and other costs.

[7] We exclude observations that report zero values for output and principal inputs (e.g., land, labor) because no farm can be assumed to be in operation without reporting positive values for such measures. Further, from a theoretical standpoint, farms that can produce the given output from zero values of some inputs use a different production technology than those that use at least some amounts of those inputs to produce the same output. Including such farms in the efficiency analysis may lead to biased efficiency estimates (Mukherjee et al, 2010). Therefore, farms that report zero values for inputs are excluded from the analysis.

[8] Agrochemicals include fertilizers and pesticides. In Vietnam, about 90% of active ingredients have been imported for the agrochemical industry. By doing this, we assume the producer price indices of fertilizers and pesticides are the same, and equal to the PPI of the industry in this study.

Table 3.2. Description of data (1,526 observations)

Variables	Rice Sample		Fruit Sample	
	Mean	SD	Mean	SD
Farm output-input variables				
Revenue *(100,000 dong)*	419.42	*19.73*	979.33	*97.50*
Output price (*index)*	0.984		1.037	
Capital *(100,000 dong)*	3.82	*6.54*	41.8	*5.38*
Land *(ha)*	1.01	*1.64*	1.36	*0.58*
Labor *(Man-years)*	0.59	*0.45*	1.03	*0.06*
Other variable inputs *(100,000 dong)*	123.40	*211.82*	211.37	*23.39*
Pesticides *(100,000 dong)*	29.08	*78.77*	45.31	*5.16*
Pesticide price *(index)*	0.906		0.906	
Farm characteristics				
Female gender *(base: Male)*	0.837	0.010	0.785	0.033
Age (in years)	51.12	*12.65*	53.25	*13.11*
Education				
No qualified	0.213	*0.011*	0.272	*0.035*
Primary school	0.260	*0.012*	0.253	*0.035*
Middle school	0.395	*0.013*	0.329	*0.037*
High school and above	0.133	*0.009*	0.145	*0.028*
Household size (No. of people)	3.93	*1.44*	4.13	*1.43*
“Poor” economic status (base: above Poor)	0.124	0.009	0.056	0.018
Off-farm income *(100,000 dong)*	8.60	*26.55*	7.29	*15.01*
Contract agricultural work (base: No)	0.696	*0.012*	0.722	*0.036*
Debt (base: No debt)	0.760	*0.012*	0.772	*0.033*
Region				
Mekong Delta	0.208	*0.011*	0.494	*0.040*
Red River Delta	0.316	*0.013*	0.095	*0.023*
Northern Mountainous Areas	0.152	*0.010*	0.196	*0.032*
Northern & Coastal Centre Areas	0.300	*0.012*	0.171	*0.030*
Others	0.024	*0.004*	0.044	*0.016*
No. of farms	**1368**		**158**	

Note: 1 USD = 21,138 VND (dong) in 2014. Price indexes from are obtained from GSOstats (Vietnam).

The determinants of pesticide over- or underuse include nine variables: gender, age, educational attainment, household size, “poor” economic status, off-farm income, contract agricultural work, debt, and region. Gender is a dummy variable with male as the base. Age is defined as the age in years of the head of the household. Educational attainment is operationalized to match Vietnam education in the past, consisting of four possible categories: no qualified (base category), primary school, middle school, high school and above. Household size is the number of household members, including children. Off-farm income includes all cash money received from non-agricultural wage employment. Economic status is a dummy variable that takes the value 1 if a farm household is considered “poor” under the Vietnamese standard, and 0 if above that level. Contract agricultural work is a dummy variable that takes the value 1 if a farmer provides agricultural services to other farmers and 0 otherwise. Debt is a dummy variable that takes the value 1 if a farmer is in private debt, and 0 otherwise. Region is a dummy variable indicating the region where the farm household operates. These regions include the Mekong Delta (base), Red River Delta, Northern mountainous areas, Northern & Coastal central areas, and Others.

Table 3.2 indicates that the mean sales of fruit farms in 2016 were more than double those of rice farms. Concerning input use, fruit farms spent more on pesticides and other variable inputs and were more capital and labor intensive than rice farms. There were no substantial differences in terms of farm or farmer characteristics between these groups of farms. Most fruit farms were located in the Mekong Delta, while most rice farms operated in the Red River Delta, and Northern and Coastal Centre areas (Figure 3.1).

Figure 3.1. Rice, fruit, and other crops in Vietnam

Source: The Voyage to Vietnam Project

3.5. Results of efficiency and determinants of pesticide overuse

3.5.1. Estimates of farm efficiency and pesticide over- or under-use

Figure 3.2 and Figure 3.3 show efficiency scores for output, pesticides and other variable inputs (V-inputs), for rice and fruit farms, respectively. Efficiency estimates were obtained using the GAMS programming software. For rice producers, the average efficiency score for output, pesticides and other variable inputs is 90%, 51% and 69%, respectively. These results imply that rice farmers can increase output by 10% while reducing pesticides and other variable inputs by 49% and 31%, respectively. The output efficiency reported here is higher than what was found in previous Vietnamese studies. More specifically, Linh (2017) report output efficiency scores in the range of 70% to 80%. One should keep in mind that our efficiency results are not directly comparable with those of these two studies because of differences in modeling approaches (e.g., parametric versus nonparametric efficiency models) and assumptions, data, and period under study. Note that the graphs of pesticide and other variable inputs efficiency show a bimodal distribution with some farms operating on or very close to the production frontier and others operating far from the frontier. The bimodality of efficiency scores is more prominent for pesticide efficiency, implying a considerable scope for improving pesticide efficiency in Vietnamese rice farming.

Figure 3.2. Efficiency scores in rice production

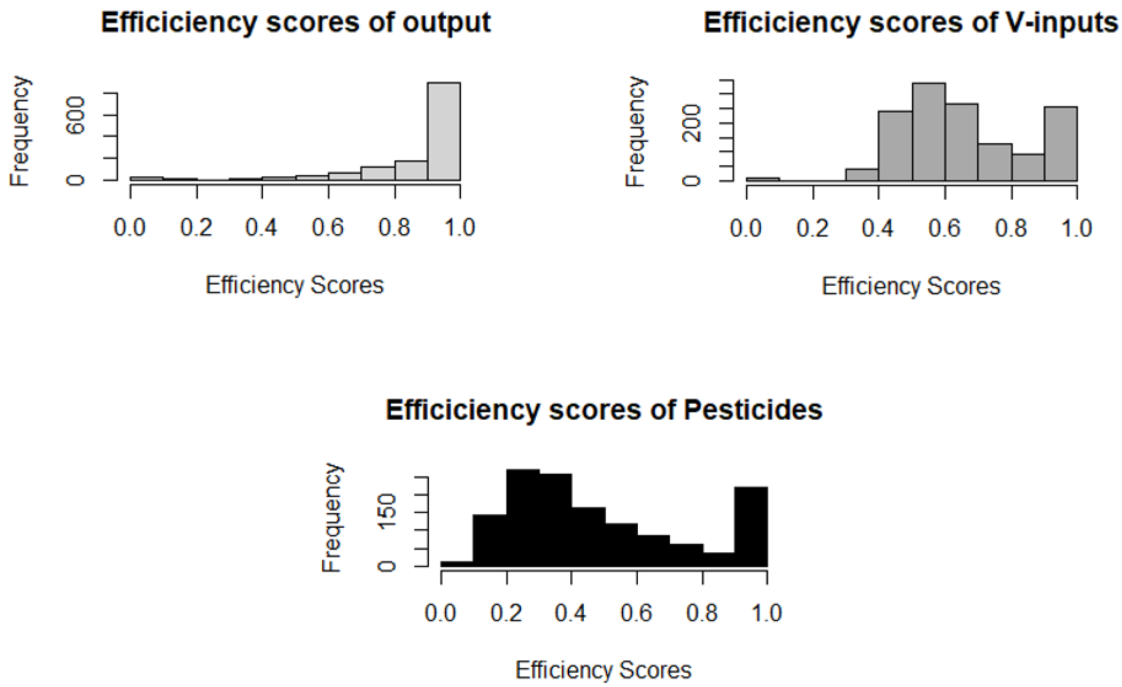
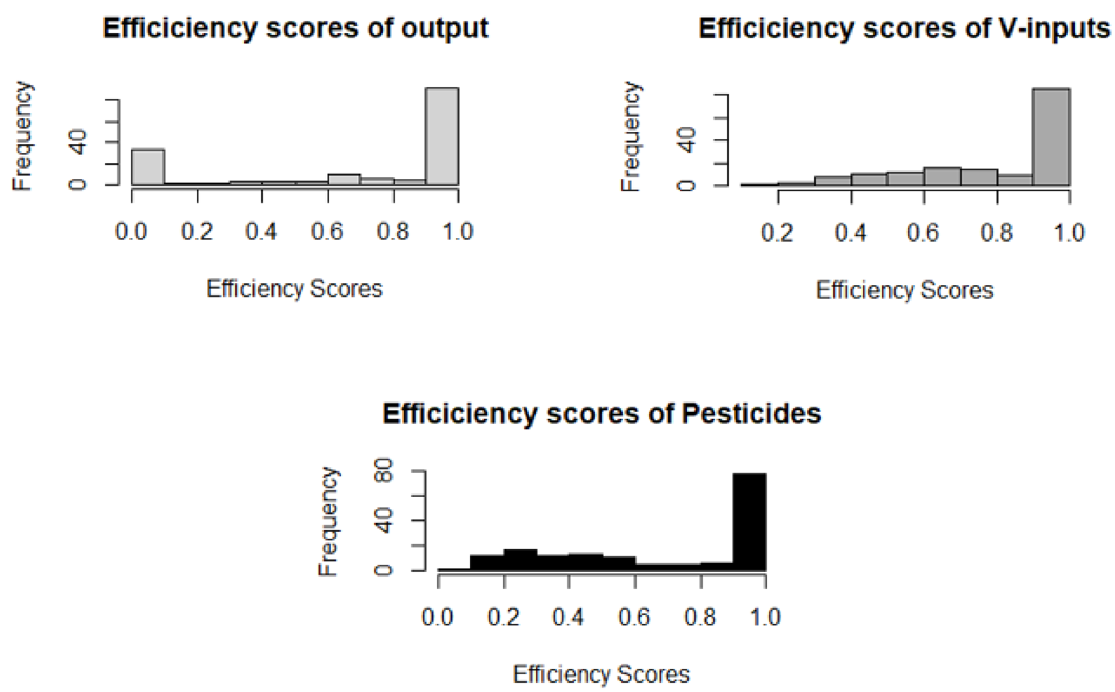


Figure 3.3. Efficiency scores in fruit production



Moving to the efficiency results for fruit farmers, the average output, pesticide and other variable inputs efficiency are 70%, 70%, and 81%, respectively. These results imply that fruit farmers can, on average, increase fruit production by 30% while reducing pesticides and other variables inputs by 30 and 19%, respectively, holding fixed inputs constant. Results further show that about 30% of fruit farms have relatively low pesticide efficiency scores (scores < 0.6), while about 58% of total fruit farms operate close to or on the best practice frontier (scores > 0.9).

Table 3.3 presents the average shadow values of pesticides using an output price index of 0.984 and 1.037 for rice and fruit production, respectively. The mean shadow price of pesticides for both farm types was found to be higher than the pesticide price of 0.906, indicating that pesticides are under-used by the rice and fruit farmers in the sample on average. This result seems surprising given the common perception that pesticides are overused in agricultural production in Vietnam. However, this can be explained by the fact that we are focusing on "single" crop farms in the sample, and these farms might have higher marginal product of pesticides than multi-crop farms because of lower cost and avoidance of misuse in terms of pesticides (Hoi et al., 2013). Additionally, pesticides being underused at the farm level on average does not necessarily imply an increase in pesticide use to reach optimality, especially when environmental and human health effects caused by highly toxic pesticides or misuse of pesticides are taken into account. On the other hand, the statistics show that about 48% and 38% of farms used less than 20% of the sample average expenditure for rice and fruit crops, respectively, indicating heterogeneity exists in the sample in term of pesticide use. This might be explained by differences in accessibility of pesticides among rice and fruit farms across the country.

Farms located in the Northern Mountainous areas have less accessibility than ones in the Mekong Delta and Red River Delta, which are completely covered by the distribution network of the 5 biggest chemical companies in Vietnam (StoxPlus, 2018). Additionally, differences in household income and credit constraints between areas might affect affordability of pesticides. Poor farmers and those with little access to credit may not be able to afford the up-front cost of pesticides. These reasons may lead to the underuse result on average.

Table 3.3. Average shadow value of pesticides for rice and fruit farms

Sample	Shadow Price	Pesticide Price Index	% farms overusing pesticides
Rice farms	1.90	0.906	33.8%
Fruit farms	2.08	0.906	38.6%

Note: Pesticide Producer Price indexes are obtained from GSOstats (Vietnam) using base year of 2014

Our shadow value results further show that 38.6% of fruit farms and 33.8% of rice farms overused pesticides (i.e., their pesticide shadow price was lower than the pesticide market price) in the sample. This result supports the above argument of heterogeneity in pesticide use in agricultural production in Vietnam. Results also show that no farms have a shadow value exactly equal to the pesticide price index. The next section sheds light on the factors that influence pesticide overuse.

3.5.2. Analysis of determinants of pesticide overuse

Next, we turn to investigating how farm/farmer specific variables and locational factors proxied by region are affecting overuse of pesticides in rice and fruit farming systems in Vietnam. Before conducting regression analyses, pair correlations among explanatory variables used in the probit models were examined. In general, the correlation coefficients were less than 0.25, and thus acceptable for the model estimation[9]. Tables 3.4 and 3.5 report results of the probit model and relevant statistics by crop[10]. In terms of goodness-of-fit, the McFadden pseudo R^2 values of the probit models for rice and fruit crops are 15.8% and 20.8%, respectively (the Cox & Snell pseudo R^2 values are about 18.3% and 24.2%). Such values of pseudo R^2 are acceptable for empirical studies of determinants (e.g., Wang et al., 2018). Moreover, the likelihood ratio tests for the models are highly significant, α-level = 1% confirming that the two models significantly predict the likelihood of pesticide overuse versus underuse.

Table 3.4. Probit regression with "underuse of pesticides" as the base: Rice farm

Independent Variables (Factors)	**Reduced Model**		**Full Model**	
	Coefficient	Std. Err	Coefficient	Std. Err
Female gender *(base: Male)*	0.022	*0.107*	0.022	*0.108*
Age	0.002	*0.003*	0.002	*0.003*
Education (base: No qualified)				
Primary school	0.169	*0.115*	-0.279	*0.327*
Middle school	0.082	*0.113*	0.407	*0.296*
High school and above	0.057	*0.143*	-0.154	*0.412*
Household size	-0.010	*0.027*	0.008	*0.054*
"Poor" economic status *(base: Above "poor")*	-0.239*	*0.142*	-0.247*	*0.144*
Off-farm income	0.004**	*0.002*	0.005**	*0.002*
Debt *(base: No debt)*	0.117	*0.091*	0.112	*0.091*
Contract agricultural work *(base: No)*	0.124	*0.088*	-0.185	*0.191*
Region (base: Mekong Delta)				
Red River	-0.560***	*0.108*	-0.555***	*0.108*
Northern Mountainous Areas	-0.992***	*0.128*	-0.984***	*0.128*
Northern & Coastal Centre	-1.598***	*0.117*	-1.595***	*0.118*
Others	-1.085***	*0.261*	-1.079***	*0.263*
Interaction Effects				
Primary school * Contract agricultural work			0.072	*0.076*
Middle school * Contract agricultural work			-.010	*0.069*
High school & above*Contract agricultural work			0.008	*0.095*
Primary school * Household size			0.571	*0.249*
Middle school * Household size			0.210	*0.229*
High school & above * Household size			0.509*	*0.282*
Intercept	0.094	0.247	0.123	0.306

9 See appendix for the table of correlations.

10 We also implemented the probit model using a dummy variable for crop, but the results had high AIC and BIC and pseudo R^2, implying multicollinearity because of crop and region as indicated by the literature. See appendix.

Goodness-of-fit		
Sample size	1368	1368
LR ChiSquare (df)	263 (14)	277 (20)
Pr(>ChiSquare)	.000***	.000***
AIC	1517	1514
BIC	1595	1624
McFadden's Pseudo R^2	15.0%	15.8%
Cox & Snell's Pseudo R^2	17.5%	18.3%

Table 3.5. Probit regression with "underuse of pesticides" as the base: Fruit farm

Independent Variables (Factors)	Reduced Model		Full Model	
	Coefficient	Std. Err	Coefficient	Std. Err
Female gender *(base: Male)*	0.165	*0.288*	0.303	*0.321*
Age	-0.016*	*0.009*	-0.013*	*0.010*
Education (base: No qualified)				
Primary school	-0.260	*0.318*	0.981	*0.936*
Middle school	0.040	*0.315*	-1.347	*1.081*
High school and above	-0.701*	*0.386*	3.110**	*1.406*
Household size	-0.085	*0.078*	0.236	*0.172*
"Poor" economic status *(base: Above "poor")*	-1.017	*0.655*	-1.120	*0.689*
Off-farm income	0.003	*0.008*	0.005	*0.008*
Debt *(base: No debt)*	-0.646**	*0.284*	-1.024***	*0.339*
Contract agricultural work *(base: No)*	0.427	*0.276*	-0.215	*0.714*
Region (base: Mekong Delta)				
Red River	-0.164	*0.407*	-0.425	*0.474*
Northern Mountainous Areas	0.397	*0.305*	0.590*	*0.342*
Northern & Coastal Centre	-0.198	*0.304*	-0.294	*0.329*
Others	0.041	*0.555*	0.110	*0.607*
Interaction Effects				
Primary school * Contract agricultural work			0.319	*0.218*
Middle school * Contract agricultural work			0.331	*0.263*
High school & above*Contract agricultural work			-0.876**	*0.346*
Primary school * Household size			0.847	*0.852*
Middle school * Household size			0.963	*0.817*
High school & above * Household size			-0.424	*1.035*
Intercept	0.297	0.654	-0.426	0.914
Goodness-of-fit				
Sample size	158		158	
LR ChiSquare (df)	21 (14)		44 (20)	
Pr(>ChiSquare)	.115		.002***	
AIC	220		208	
BIC	266		273	
McFadden's Pseudo R^2	9.7%		20.8%	
Cox & Snell's Pseudo R^2	12.2%		24.2%	

*Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.*

In Table 3.6, marginal effects and the relevant errors of the explanatory variables used in the full models of rice and fruit crops are presented. Only statistically significant results are discussed. Overall, poverty, off-farm income, region, and the interaction effect of high school education (versus none) and household size have significant effects on the likelihood of pesticide overuse in rice farming. On the other hand, age, high school education, poverty, debt, northern mountainous areas, and interaction effects of high school education and agricultural contract work significantly affect the probability of overuse in fruit crop production.

Table 3.6. Marginal Effects of Determinants on Overuse[i]

Independent Variables (Factors)	Rice		Fruit	
	Effect	Std. Error	Effect	Std. Error
Gender *(base: Male)*	0.008	0.038	0.116	0.124
Age	0.001	0.001	-0.005*	0.004
Education (base: No qualified)				
Primary school	-0.094	0.106	0.373	0.339
Middle school	0.145	0.107	-0.427	0.271
High school and above	-0.052	0.136	0.785***	0.102
Household size	0.003	0.019	0.088	0.064
"Poor" economic status *(base: Above "poor")*	-0.082*	0.045	-0.298**	0.106
Off-farm income	0.002**	0.001	0.002	0.003
Debt *(base: No debt)*	0.040	0.033	-0.322***	0.084
Agricultural contract work *(base: No)*	-0.064	0.064	-0.078	0.254
Region (base: Mekong Delta)				
Red River	-0.183***	0.033	-0.145	0.145
Northern Mountainous Areas	-0.272***	0.026	0.228*	0.133
Northern & Coastal Centre	-0.438***	0.024	-0.105	0.111
Others	-0.257***	0.034	0.042	0.233
Interaction effects				
Primary school * Ag contract work	0.025	0.027	-0.119	0.081
Middle school * Ag contract work	-0.035	0.024	0.123	0.098
High school & above*Ag contract work	0.003	0.033	-0.326**	0.127
Primary school * Household size	0.218	0.098	0.328	0.312
Middle school * Household size	0.076	0.086	0.37	0.291
High school & above * Household size	0.194*	0.112	-0.144	0.31-
Intercept	0.043	0.108	0.116	0.124

*Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively. (i) Simple models without interactions are examined but perform worse than the model with the interactions from goodness-of-fit perspective.*

The effect of age is positive in previous studies determining pesticide overuse but indeterminant in studies of pesticide quantity. We find the effect of age is significant and negative for fruit farms, but not for rice farms. The marginal effect is -0.05 implying older farmers are less likely to overuse pesticides in fruit production, although the effect is small, 0.5% for one year increase in age. The result is in line with Huang et al. (2000) which showed older farmers tend to use less pesticides than young farmers given the same application frequency. Older farmers probably have more farming experience which tends to be positively associated with higher efficiency of specific inputs like pesticides for fruit crops.

Previous studies suggest more educated farmers are less likely to overuse pesticides because they often follow instructions provided on the pesticide label or enforced by law or regulations. Surprisingly, our results for fruit production contradict the literature; farmers with high school and above educational attainment (versus no education) have a 78.5% higher probability of overuse. On the one hand, this result may indicate less educated farmers better follow pesticide regulations than some educated ones. On the other hand, it may imply education may not always be useful from an efficiency perspective. To check this, we consider the interaction of “high school and above” education and agricultural contract work which may represent farming experience or professional knowledge in agriculture. The effect is significantly negative at -0.326, implying the educated farmers who provide contract services are less likely to overuse pesticides (versus non-educated people who also have agricultural contract work). The result suggests the important role of experience or farming knowledge versus general educational attainment regarding efficiency of pesticide use.

The effect of the economic status of the household on pesticide use can be explained by the income effect or affordability. Households who are designated as “poor” by the Vietnamese government standard would probably be less able to afford pesticides and hence be less likely to overuse them. However, “poor” farms are also motivated to increase pesticide use when they consider pesticides as productive factors for their income growth. The model results show that “poor” farms have a lower probability of overuse than “not poor” farms by 8.2% and 29.8% for rice and fruit farms respectively, confirming the effect of affordability especially for fruit farms.

Farmers who have higher off-farm income are more likely to overuse pesticides due to the income effect and affordability. Higher off-farm income also implies the farmers have less time to spend on crop production and may be more likely to overuse pesticides as a substitute for labor. We find off-farm income has a small (0.008) but significant effect on overuse of pesticides in rice farming.

The effect of debt on pesticide overuse has not been examined in the literature, except the possible relationship between debt and affordability. In this study, the effect of “debt” versus “no debt” is found to be significant at -0.322 for fruit farms only, indicating farmers who have debt are less likely to overuse pesticides. This result confirms that affordability matters for pesticide overuse.

The region variables, representing locational factors, are found to have important effects on overuse. In this study, we find all regions (relative to the base of the Mekong Delta) are significantly less likely to overuse pesticides on rice. In other words, pesticide overuse is more likely in the Mekong Delta region which is widely known as having the highest density of rice farms. The difference in the likelihood of pesticide overuse ranges from 18% to 44% across regions. It is intuitive and reasonable that the lowest difference is for the comparison between Mekong Delta and Red River Delta, the second most dense area of rice production. For fruit farms, the Northern Mountainous areas are actually more likely to overuse pesticides than those in the Mekong Delta.

3.6. Conclusions and Implications

Understanding pesticide efficiency and determinants of overuse is critical to farmer's income, health status, and the environment in Vietnam. We focus on rice and fruit farms since government data indicate 80% of farms grow rice and these farms use more than 60% of total pesticides whilst fruit farms are the biggest consumers in terms of average expenditure. This study represents the first assessment of pesticide use efficiency in rice and fruit production in Vietnam. The results are important for farmers and policy makers in Vietnam as well as other developing countries.

We employ a DEA model to measure output, variable input, and pesticide efficiency using a 2016 national dataset of 1,368 rice farms and 158 fruit farms. We then estimate the shadow value of pesticides for each rice and fruit farm to determine overuse. Given observed demographic characteristics and farmer/farm attributes, a standard binary probit model is applied to test for significant determinants of pesticide overuse.

Results show that about 70% of rice farms and almost all fruit farms operate close to or on the best practice frontier in terms of output efficiency. However, 49% of rice farms and 30% of fruit farms are very inefficient in their use of pesticides, which implies considerable scope for improvement in pesticide use, especially in rice farming. This is important due to the large numbers of hectares and farms involved with rice production in Vietnam. The shadow value results show that both fruit and rice farms in the sample underused pesticides, on average. About 33.8% of rice farms and 38.6% of fruit farms were found to overuse pesticides, while no fruit or rice farm was found to use pesticides optimally. These results suggest that policies need to be designed to address both underuse and overuse, an important implication in the developing country context. Another implication is that reduction in pesticide use is feasible and can reduce both input costs and environmental impacts. The government can take this information into account when designing pro-environmental policies, especially in regions where overuse is prevalent, such as the Mekong Delta and Red River Delta.

Regarding the determinants of pesticide overuse, the results show that age, education, low economic status, off-farm income, debt, contract agricultural services, and region affect pesticide overuse. Fruit farmers overusing pesticides are likely to be highly educated and operating in the Northern mountainous areas of the country. On the other hand, rice farmers overusing pesticides are likely to earn higher off-farm income and are located in the Mekong Delta. The latter result is in line with findings of earlier studies reporting excessive use of pesticides on farms in the Mekong Delta (Tran, 1998; Klemick and Lichtenberg, 2008, Migheli, 2017). Results further show that poorer rice and fruit farmers, and older and more indebted fruit farmers were less likely to overuse pesticides. The fact that poor farmers are less likely to overuse pesticides, in conjunction with the positive effect of off-farm income on pesticide overuse, suggests that pesticide affordability might be an issue in Vietnamese farming. This result further shows the limited ability of poor farmers and those in the least developed areas of Vietnam to improve their agricultural income with pesticides. Improving education of farmers in terms of professional knowledge of pesticide use through practical training programs is warranted. For low-income farmers, these training programs could be linked to temporary subsidies for pesticides.

This research used existing data that was not specifically designed to study pesticide use. Further research could collect data to examine affordability of pesticides accounting for the impacts of education, credit constraints, crop characteristics, and regional factors. The impact of accessibility could also be examined in more detail since pesticides may be less available in some remote areas than in the Mekong Delta. Data that separated pesticide inputs by crop would enable the study of pesticide efficiency in multi-crop farms, controlling for farmer characteristics. Separating different types of pesticides, versus combining insecticides, herbicides and fungicides, may also lead to more detailed recommendations.

References

[1] Babcock, B. A., Lichtenberg, E., & Zilberman, D. (1992). Impact of damage control and quality of output: estimating pest control effectiveness. *American Journal of Agricultural Economics*, 74(1), 163-172.

[2] Balendres, M. A. & Bengoa, J. C. (2019). Diseases of dragon fruit (Hylocereus species): Etiology and current management options. *Crop Protection*. doi:https://doi.org/10.1016/j.cropro.2019.104920

[3] Ball, V. E., Lovell, C. A., Nehring, R. F., & Somwaru, A. (1994). Incorporating undesirable outputs into models of production: an application to US agriculture. *Cahiers d'Economie et de Sociologie Rurales (CESR)*, *31*(905-2016-70233), 59-74.

[4] Berg, H. (2001). Pesticide use in rice and rice-fish farms in the Mekong Delta, Vietnam. *Crop protection, 20*(10), 897-905. Retrieved from https://doi.org/10.1016/S0261-2194(01)00039-4

[5] Brehm, J.M., Pasko, D.K., and Eisenhauer, B.W. (2013). Identifying Key Factors in Homeowner's Adoption of Water Quality Best Management Practices. *Environmental Management* 52 (1): 113–122.

[6] Carrasco-Tauber, C., & Moffitt, L. J. (1992). Damage control econometrics: functional specification and pesticide productivity. *American Journal of Agricultural Economics*, 74(1), 158-162.

[7] Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, directional distance functions, and Nerlovian efficiency. *Journal of optimization theory and applications*, *98*(2), 351-364.

[8] Dang, V. H., Nguyen, T. H., Choi, K. C., and Jeung, E. B. (2017). Unexpected estrogenicity of endocrine disruptors may evoke a failure of pregnancy derived from uterine function: overview of their possible mechanism(s) through steroid receptors. *Journal of Embryo Transfer, 22*(4), 199-208.

[9] Dasgupta, S., Meisner, C., Wheeler, D. (2007). Is environmentally friendly agriculture less profitable for farmers? Evidence on integratedpest management in Bangladesh. *Review of Agricultural Economics*, *29*(1), 103-118. doi:https://doi.org/10.1111/j.1467-9353.2006.00332.x

[10] Ecobichon, D. J. (2001). Pesticide use in developing countries. *Toxicology, 160*(1-3), 27-33. Retrieved from https://doi.org/10.1016/s0300-483x(00)00452-2

[11] FAOSTAT (2019, 9 2). Retrieved from http://www.fao.org/faostat/en/#data/RP

[12] Fernandez-Cornejo, J. (1994). Nonradial Technical Efficiency And Chemical Input Use In Agriculture. *Agricultural and Resource Economics Review, 23*(1), 1-11. doi:10.22004/ag.econ.31322

[13] Gong, J.H.; Huang, M.S.; Ma, Y.S.; Sun, J (2016). Cultural background, Eco-environment awareness and pesticide application behavior of farmers. *J. Ecol. Rural Environ*, *32*, 546–551.

[14] GSO (2017). *Vietnam Household Living Standard Survey, 2016*. Statistical Publishing House, Hanoi, Vietnam.

[15] GSO (2018). *Statistic yearbook of Vietnam 2017.* Hanoi: General Statistics Office of Vietnam.

[16] Guan, Z., Lansink, A.O., Wossink, A., & Huirne, R. (2005). Damage control inputs: a comparison of conventional and organic farming systems. *European Review of Agricultural Economics*, 32(2), 167-189.

[17] Hoai, P. M., Ngoc, N. T., Minh, N. H., Viet, P. H., Berg, M., Alder, A. C., et al. (2010). Recent levels of organochlorine pesticides and polychlorinated biphenyls in sediments of the sewer system in Hanoi, Vietnam. *Environmental Pollution, 158*, 913-920. doi:10.1016/j.envpol.2009.09.018

[18] Hoi, P. V., Mol, A., and Oosterveer, P. (2013). State governance of pesticide use and trade in Vietnam. *Wageningen Journal of Life Sciences*, *67*, 19-26. Retrieved from https://doi.org/10.1016/j.njas.2013.09.001

[19] Huy H.T., 2009. Technical efficiency of rice in the Mekong delta of Vietnam. *Asian Journal of Agriculture and Development*, 6(2): 35-50.

[20] John M. Antle & Prabhu L. Pingali. (1994). Pesticides, Productivity, and Farmer Health: A Philippine Case Study. *American Journal of Agricultural Economics* , 76(3), 418-430.

[21] Klemick, H. & Lichtenberg, E. (2008). Pesticide Use and Fish Harvests in Vietnamese Rice Agroecosystems. *American Journal of Agricultural Economics*, 90, 1-14. doi: 10.1111/j.1467-8276.2007.01059.x.

[22] Lamers M., Schreinemachers P., Ingwersen J., Sangchan W., Grovermann C., Berger T. (2013). Agricultural Pesticide Use in Mountainous Areas of Thailand and Vietnam: Towards Reducing Exposure and Rationalizing Use. In S. P. Fröhlich H.L., *Sustainable Land Use and Rural Development in Southeast Asia: Innovations and Policies for Mountainous Areas.* Springer Environmental Science and Engineering. Springer, Berlin, Heidelberg. doi:https://doi.org/10.1007/978-3-642-33377-4_4

[23] Lansink, A.O., Silva, E. (2004). Non-Parametric Production Analysis of Pesticides Use in the Netherlands. *Journal of Productivity Analysis*, *21*, 49-65. Retrieved from https://doi.org/10.1023/B:PROD.0000012452.97645.30

[24] Lansink, O. & Carpentier, A. (2001). Damage control productivity: An input damage abatement approach. *Journal of Agricultural Economics*, 52 (3), 11-22. doi:10.1111/j.1477-9552.2001.tb00935.x

[25] Lichtenberg, E. & Zilberman, D. (1986). The econometrics of damage control: Why specification matters? *American Journal of Agricultural Economics, 68* (2), 261-273. Retrieved from https://doi.org/10.2307/1241427

[26] Linh V.H. (2012). Efficiency of rice farming households in Vietnam. *International Journal of Development Issues*, 11(1): 60-73.

[27] Meisner, C. (2005). *Poverty-environment report: pesticide use in the Mekong Delta, Vietnam.* Washington DC: World Bank.

[28] Migheli, M. (2017). Land ownership and use of pesticides. Evidence from the Mekong Delta. *Journal of Cleaner Production, 145*, 188-198. Retrieved from https://doi.org/10.1016/j.jclepro.2017.01.045

[29] Minh, T. B., Iwata, H., Takahashi, S., Viet, P. H., Tuyen, B. C., and Tanabe, S. (2008). Persistent organic pollutants in Vietnam: environmental contamination and human exposure. *Reviews of Environmental Contamination and Toxicology*, *193*, 213-290. doi:http://doi.org/10.1007/978-0-387-73163-6_4

[30] Mukherjee, K., Santerre, R. E., & Zhang, N. J. (2010). Explaining the efficiency of local health departments in the US: an exploratory analysis. *Health Care Management Science*, 13(4), 378-387.

[31] Murphy, H. H., Hoan, N. P., Matteson, P., & Abubakar, A. L. (2002). Farmers' self-surveillance of pesticide poisoning: a 12-month pilot in northern Vietnam. *International journal of occupational and environmental health*, *8*(3), 201–211. Retrieved from https://doi.org/10.1179/107735202800338894

[32] Pingali, P. L. (2001). Environmental consequences of agricultural commercialization in Asia. *Environment and Development Economics*, *6*(4), 483-502. Retrieved from https://doi.org/10.1017/S1355770X01000274

[33] Pingali, P. L. (2004). Environmental consequences of agricultural commercialization in Asia. *Environment and Development Economics*, *6*(4), 483-502. doi:https://doi.org/10.1017/S1355770X01000274

[34] Prokopy, L.S., Floress, K., Klotthor-Weinkauf, D., & Baumgart-Getz, A. (2008). Determinants of agricultural best management practice adoption: Evidence from the literature. *Journal of Soil and Water Conservation*, 63(5), 300–311.

[35] Reimer, A.P. and Prokopy, L.S. (2012). Environmental Attitudes and Drift Reduction Behavior among Commercial Pesticide Applicators in a U.S. Agricultural Landscape. *Egyptian Journal of Environmental Management*, 113, 361–369. https://doi.org/10.1016/j.jenvman.2012.09.009

[36] Riar, A., Mandloi, L. S., Poswal, R. S., Messmer, M. M., & Bhullar, G. S. (2017). A Diagnosis of Biophysical and Socio-Economic Factors Influencing Farmers' Choice to Adopt Organic or Conventional Farming Systems for Cotton Production. *Frontier Plant Science*, 8, 1289. doi: 10.3389/fpls.2017.01289

[37] Sarter, S., Ha, H.P., & Anh, T.K. (2012). Current situation of Food Safety in Vietnam. *1st FOODSEG Symposium*. Berlin.

[38] Schreinemachers, P. & Tipraqsa, P. (2012). Agricultural pesticides and land use intensification in high, middle and low income countries. *Food Policy, 37*(6), 616-626. https://doi.org/10.1016/j.foodpol.2012.06.003

[39] Schreinemachers, P., Grovermann, C., Praneetvatakul, S., Heng, P., Nguyen, T. T. L., Buntong, B., ... & Pinn, T. (2020). How much is too much? Quantifying pesticide overuse in vegetable production in Southeast Asia. *Journal of Cleaner Production*, 244, 118738. https://doi.org/10.1016/j.jclepro.2019.118738

[40] Sharma, A., Kumar, V., Shahzad, B. et al. (2019). Worldwide pesticide usage and its impacts on ecosystem. *SN Applied Sciences 1*, *1446*.

[41] Singbo, A. G., Lansink, A. O., & Emvalomatis, G. (2015). Estimating shadow prices and efficiency analysis of productive inputs and pesticide use of vegetable production. *European Journal of Operational Research*, *245*(1), 265-272.

[42] Skevas, T., Lansink, A. O., & Stefanou, S. E. (2012). Measuring technical efficiency in the presence of pesticide spillovers and production uncertainty: The case of Dutch arable farms. *European Journal of Operational Research*, 223(2), 550-559.

[43] Skevas, T., Stefanou, S. E., & Lansink, A. O. (2014). Pesticide use, environmental spillovers and efficiency: A DEA risk-adjusted efficiency approach applied to Dutch arable farming. *European Journal of Operational Research*, *237*(2), 658-664.

[44] Sun, S., Zhang, C. & Hu, R. (2020). Determinants and Overuse of Pesticides in Grain Production: A Comparison of Rice, Maize and Wheat in China. *China Agricultural Economic Review*, *12*(2), 367-379. doi:https://doi.org/10.1108/CAER-07-2018-0152

[45] Tam, N. T., Berg, H., Hang, N. & Cong, N. (2015). Effects of chlorpyrifos ethyl on acetylcholinesterase activity in climbing perch cultured in rice fields in the Mekong Delta, Vietnam. *Ecotoxicology and Environmental Safety*, *117*, 34-40. Retrieved from https://doi.org/10.1016/j.ecoenv.2015.03.020

[46] Thanassoulis, E., Portela, M.C.S. & Despic, O. (2008). The Measurement of Productive Efficiency and Productivity Growth, Oxford University Press, chap. *Data Envelopment Analysis: The Mathematical Programming Approach to Efficiency Analysis*. pp. 251–420.

[47] Thanh P.C., Tan V.P., and Thu P.X. (2015). Vietnamese Fruits Production and Exports Based on The Global Gap & ISO 22000 Standard Towards Faster and Sustainable Development. Available at http://www.vietnamquality.org.vn/uploads/phocadownload/vien-kiem-dinh-va-phat-trien-chat-luong/cac-bao-cao-khoa-hoc-da-cong-bo-quoc-te/13.Fullpaper_P0285_Oral_VQAH.pdf

[48] Toan, P. V., Sebesvari, Z., Blasing, M., Rosendahl, I., and Renaud, F. G. (2013). Pesticide management and their residues in sediments and surface and drinking water in the Mekong Delta, Vietnam. *The Science of the total environment*(452-453), 28-39. Retrieved from https://doi.org/10.1016/j.scitotenv.2013.02.026

[49] Tung D.T., 2013. Changes in the technical and scale efficiency of rice production activities in the Mekong delta, Vietnam. *Agricultural and Food Economics*, 1(1): 16.

[50] Veettil, P. C., Krishna, V. V., & Qaim, M. (2017). Ecosystem impacts of pesticide reductions through Bt cotton adoption. *Australian Journal of Agricultural and Resource Economics*, 61(1), 115-134.

[51] VIPA (2019). Vietnam Agricuture and Status of Pesticides Market. *8th CAC Asia Summit*. Bangkok, Thailand: Vietnam Pesticide Association. Retrieved from http://www.cacasiasummit.com/Uploads/Download/7-Vietnam%20Agricuture%20and%20Status%20of%20Pesticides%20Market.pdf

[52] Wang, J, Chu, M. & Ma, Y. (2018). Measuring Rice Farmer's Pesticide Overuse Practice and the Determinants: A Statistical Analysis Based on Data Collected in Jiangsu and Anhui Provinces of China. *Sustainability, 10*(3), 1-17.

[53] Wilson, C. & Tisdell, C. (2001). Why farmers continue to use pesticides despite environmental, health and sustainability costs. *Ecological Economics, 39*(3), 449-462. doi:http://dx.doi.org/10.1016/S0921-8009(01)00238-5

[54] World Bank (2017). *Food safety risk management in Vietnam: Challenges and opportunities*. Washington, D.C.: World Bank Group. Retrieved from http://documents.worldbank.org/curated/en/157501490724011125/Vietnam-food-safety-risks-management-challenges-and-opportunities-policy-note

[55] Xu, R., Kuang, R., Pay, E., Dou, H. & de Snoo, G. R. (2008). Factors contributing to overuse of pesticides in western China. *Environmental Sciences, 5*(4), 235-249. Retrieved from https://doi.org/10.1080/15693430802346543

CHAPTER 4. CONSUMER PREFERENCES FOR REDUCED VEGETABLE PRODUCTION: EVIDENCE FROM DISCRETE CHOICE EXPERIMENT IN MISSOURI

The chapter is modified from the conference paper of Tran, L., Su, Y., and McCann, L., (2022). Consumer Preferences for Less Pesticide Produce: A Choice Experiment in Missouri. Selected paper presented at the 2022 Agricultural and Applied Economics Association annual meeting.

There have been growing concerns about exposures to chemical pesticides in fresh produce like fruits and vegetables, which are an important part of a healthy diet. This study investigates consumer preferences for reduced pesticide produce using a discrete choice experiment. An online survey of fresh tomato purchases was conducted in Missouri in spring of 2022 to collect choice data, demographic information, and private health and environmental attitudes of decision makers. We found positive preferences for 50% reduced pesticide use as usual, but a low premium of 6% compared to a premium of 28% above conventional price for organic produce. Also, we found complementary effects between the reduced pesticide attribute and local or Missouri Grown labels, suggesting important implications for local/ Missouri Grown producers, retailers, and policy makers. Further, we analyzed heterogeneity in consumer preferences for a reduction in pesticides, which differs from organic, implying further studies for determinants of this niche market.

4.1. Introduction

Changes toward healthier and environmentally friendly food consumption have been highlighted in business practice and academic research (e.g., Li & Kallas, 2021; Miller et al., 2021; Su et al., 2019). While eating fresh vegetables and fruits is always considered an important part of a healthy diet (e.g., Lee et al., 2022; Wallace et al., 2020; WHO, 2020), one of the concerns is possible exposure to harmful pesticide residues (Consumer Reports, 2020). In the United States, pesticides were found in 87.4% of fresh fruits, and 52.1% of vegetables (FDA, 2019). While the FDA indicates the levels of these chemicals are acceptable in most cases, there may be demand for produce with reduced pesticide use, which may also reduce negative environmental impacts (Milford, Trandem, & Pires, 2021; Khachatryan, Wei, & Rihn, 2020).

Organic produce has very little pesticide residue[11], but it is not always an option for consumers because of its high price compared to conventional products (Aschemann-Witzel & Zielke, 2017). Reduced pesticide production for vegetables and fruits may have potential as a compromise between conventional (lower cost, higher health and environmental risk) and organic (higher cost, lower risk) methods. However, the market for reduced or lower pesticide produce is vague; there is a lack of clear terminology and definitions. Sustainable claims such as “natural”, “green”, “eco-”, “environmentally friendly,” etc. generally imply zero or lower pesticide use without indicating specific reduction of pesticides in production (Li & Kallas, 2021). Thus, reduced pesticide vegetable or fruit production represents a puzzle since there is little knowledge about how much reduction is feasible for producers, and how consumers respond to various reductions in pesticide use.

Previous studies have shown consumers have positive preferences for organic and sustainable food. Several attempts have addressed consumer preferences towards

[11] In the U.S., synthetic pesticide use in organic production is not allowed but some pesticides are allowed, such as plant oils, vinegar, etc.

pesticide reduction in vegetable and fruit purchasing behavior. In this regard, reduced pesticide produce has been specifically associated with integrated pesticide management (IPM) practices (Govindasamy & Puguri, 2008; Moser, Raffaelli, and Notaro, 2010; Biguzzi et al., 2014). However, past surveys have indicated problems with IPM due to the fact that it does not result in specific or consistent pesticide reductions (Alwang et al., 2019, Durham & Mizik, 2021; Moser & Raffaelli, 2012). Moreover, pesticide reduction from genetically modified organism (GMO) techniques may not be preferred by consumers (see reviews by Dannenberg, 2009; Hess et al., 2016), leading to complexity for evaluations of consumer preferences toward reduced pesticide produce. While reduced pesticide use is of interest, few studies have assigned it as a food attribute to compare it with preferences for organic and conventional production methods.

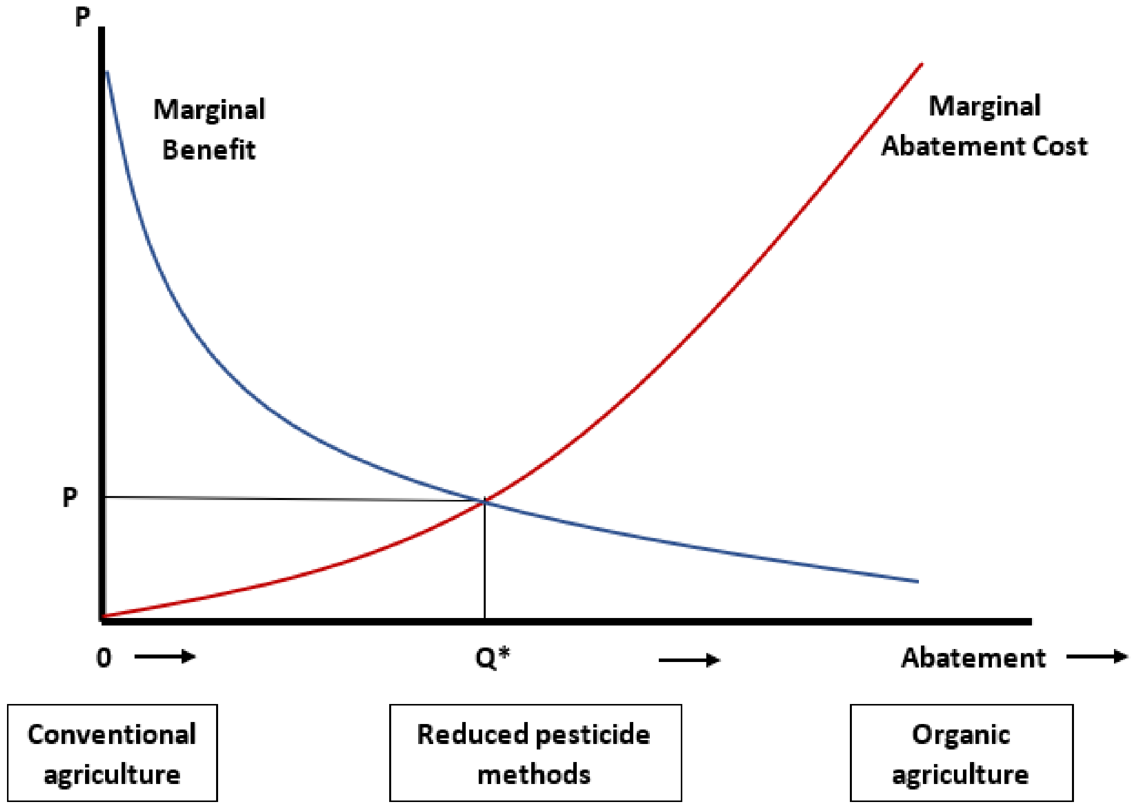
This research has attempted to evaluate consumer preferences and estimate willingness-to-pay (WTP) for reduced pesticide tomatoes, and to explain how demand differs from organic tomatoes. We implemented a discrete choice experiment (DCE) to analyze consumer preferences along a continuum of pesticide use: conventional, 50% reduced pesticide use, and organic. In doing so, we add to the scarce literature on pesticide use from the consumer side. Also, our findings provide valuable implications for policy makers and farmers regarding potential markets for reduced pesticide produce.

The rest of the paper is structured as follows. Section 2 presents a literature review of previous pesticide research. Section 3 describes the design of the choice experiment, the dataset, and the empirical model. Section 4 presents the estimation and results. Finally, we draw conclusions and implications of our findings in Section 5.

4.2. Literature Review

Increasing attention has been paid to production methods and food purchasing behavior. After the Green Revolution, food crop production systems known as conventional agriculture (CA) became the norm. They are typically characterized by mechanization, improved varieties, and intensive input use, including synthetic fertilizers and pesticides, for improved output. Regarding pesticide use, the main interest of the study, previous research considers pesticides to be crop-protective (damage reducing) rather than productive (productivity increasing) inputs (Lichtenberg & Zinberman, 1986) (noting that the effect of damage from pests on yields would be generally irrefutable in agricultural crops). Also, it is commonly agreed that pesticides can have potential negative impacts on human health, the environment, and the food production system (WHO-FAO, 2019). In this regard, theoretically the optimal pesticide abatement for society may be somewhere between the lower pesticide use systems like organic agiculture (OA) and the status quo higher pesticide ones (CA), leading to demand for reduced pesticide methods (Figure 4.1). As an example, an experiment of conventional and organic tomato cultivation in Arkansas found yields could be maintained at a higher cost (Francis & Stark, 2012). It is feasible to reduce pesticide use without decreasing output as indicated by IPM methods which provide an approximately 20% reduction in pesticides on average (Freier & Boller, 2009).

Figure 4.1. Abatement Diagram for Pesticide Use



Note: In Figure 4.1, the origin represents the status quo or CA production system where producers are using pesticides without taking into account any environmental impacts. Benefits of reducing pesticides from these levels are relatively high. The optimal abatement level, Q may be somewhere between the lowest and the highest abatement of pesticides, implying reduction in pesticides with respect to CA. Organic production tends to be more labor intensive and thus is typically assumed to be more costly.*

The importance of reduced pesticide use from the individual perspective also relates to pesticide residue levels in fresh produce. The literature indicates there has been growing interest in the importance of environmental sustainability and health attributes on food choice so that consumers are willing to pay premium for these attributes (e.g., Ballen et al., 2021, Moser et al., 2012). Consumers may consider pesticide residue levels in vegetables and fruits as a credence attribute[12] regarding health and environmental concerns. While the examination of pesticide residue levels is prohibitively expensive for consumers, labels or information regarding production methods or pesticide management practices can be provided since pesticide residue depends on pesticide use. Following a review of Garcia & Teixeira (2017), CA using pesticides for high yields may lead to high pesticide residue while OA avoids chemicals resulting in low or very low pesticide residue on fresh produce. IPM can be a "middle" choice that differentiates reduced pesticide produce from conventional and organic.

There is a large body of literature on organic and sustainable practices from the consumer side (e.g., reviews of Li & Kallas, 2021; Katt & Meixner, 2020; Cecchini et al., 2018). Previous studies generally found that consumers are willing to pay a premium for organic and sustainable food attributes (e.g., Aryal et al., 2009, Bazzani et al., 2017). Based on empirical studies implemented around the world from 2000-2020, Li & Kallas (2021) reported the overall average WTP is about 30% (in percentage terms). However, the premiums differ under various considerations in terms of food categories, sustainable attributes, certification, region or country, and their heterogeneity across consumers. For example, the estimated premium for organic tomatoes ranges from 10% for uncertified organic in Ghana (Owusu & Dadzie, 2021) to 100% for certified organic in Myanmar (Aye et al., 2019).

Several attempts have examined consumer preferences for a reduced pesticide attribute of fresh produce. Moser et al. (2010) estimated WTP for apples produced by

[12] A credence attribute of a product is unobservable or cannot be ascertained by consumers even after purchase. For example, consumers who are buying a tomato can evaluate its shape, color, freshness, and taste through search and experience, but cannot evaluate credence attributes such as environmental impacts, health, safety, etc. despite their presence (Fernqvist & Ekelund, 2013).

four methods: conventional, integrated (IPM), innovative (IPM with biological control), and organic production, and only found a significant WTP for organic apples. Marette, Messean, & Millet (2012) developed a new label of "few pesticides" for apples (50% reduction in the pesticide use compared to conventional apples), and found these apples are preferable to conventional ones. Kiruthika & Selvaraj (2013) evaluated drivers of WTP for IPM produce given direct information of WTP, and then found significant effects of age and income on WTP for IPM produce. Biguzzi et al. (2014) implemented a lab experiment on tomato purchases to investigate the role of IPM information on the food label and found that WTP for IPM was higher than WTP for organic tomatoes provided IPM information, and vice versa. Chen et al. (2018) found WTP for fresh strawberries from a production method that uses less pesticides than the industry average is higher than other sustainable practices (less fertilizer, less negative impacts on water quality, less negative impacts on soil quality, less negative impacts on air quality). These studies suggested reduced pesticide produce is differentiated from conventional and possibly organic ones.

While in the U.S. the "certified organic" attribute indicates little or no pesticide residue on food, implying a wide range of health and environmental benefits for consumers, "reduced pesticide" outcomes obtained by IPM and other practices may not be similarly informative. First, IPM systems generally have no clear commitments about how much pesticide reduction would occur nor the effects of the reduction on health and environment outcomes (e.g., Alwang et al., 2019). Second, there is currently no physical market for IPM produce, suggesting potential biases for a hypothetical approach based on intended purchase behavior (Moser, 2016). Third, previous studies have shown a majority of consumers do not know what IPM is (Biguzzi et al., 2014), and labelling IPM practices on food may not affect consumers at the purchasing stage because they do not have a clear idea about its benefits (Moser & Raffaelli, 2012). The effect of "reduced pesticide" may be more complex than "organic" when it comes to consumer preferences for GMO food products. Several studies have shown GMO food is less preferred to its non-GMO counterparts (see review by Hess et al., 2016). Therefore, if reduced pesticide use is enabled by GMO technology, there are conflicting preferences. Thus, it is critical to examine the reduced pesticide attribute compared with preferences for organic and conventional production methods.

The literature has also offered multiple explanations for factors affecting willingness-to-pay (WTP) for organic and sustainable produce as well as factors driving the growth of these practices. From demographic perspectives, consumers having higher income, higher education, stronger pro-environmental attitudes, or having children are more likely to purchase organic and sustainable foods. The effects of age, gender, and household size are indeterminant while other factors: employment, marital status, living in rural areas, and home ownership did not suggest significant effects on WTP for organic and sustainable food (see a systematic review by Katt & Meiner, 2020).

4.3. Experimental Design, Data Collection, and Empirical Models

4.3.1. Experimental Design

Numerous methods have been used to elicit consumer preferences or estimate WTP for product attributes. Generally, they can be grouped into two categories: stated preference and revealed preference approaches. In the stated preference (SP) approach, consumers are asked to make hypothetical choices in a survey, for example. The most common SP approaches are contingent valuation, discrete choice experiment (DCE), and conjoint analysis. In the revealed preference (RP) approach, consumers reveal their WTP in a real purchase or simulated situation which is very close to real life. RP that use available market data have much lower costs than those that use laboratory or field experiments (Katt & Meiner, 2020).

This study uses DCE as a stated preference survey to elicit consumer preferences for organic, reduced pesticide, and conventional tomatoes. The popularity of DCE comes from its advantages: flexibility, avoiding bias from direct elicitation of WTP, straightforward application for attributes of interest, strongly grounded in random utility theory, and good properties of estimation (Carson & Louviere, 2011). In the present DCE, consumers were repeatedly asked to choose their preferred option among several various fresh tomato options given the same quantity, one pound of tomatoes. We selected fresh tomatoes because it is a typical product that can be obtained by various production methods and can be purchased through different marketing channels (farm stands, farmers markets, supermarkets, natural stores, and online).

The tomato options differed in terms of three attributes: production method, place of origin, and price. The production method was assigned three levels: organic, 50% reduced pesticide use as usual (e.g., comparing to the ordinary or conventional use), and conventional methods. Several studies indicated some U.S. farmers, including in Missouri, are reducing pesticide use in crop production; they are not yet organic, but are not conventional anymore (Piñero & Keay, 2018). We focused on a 50% reduction in pesticides as suggested by Marette et al. (2012) for a new apple that has higher quality (less pesticide) than a conventional one but is cheaper than an organic one, and Chen et al. (2018) for a reduction as an average use of pesticides in the strawberry industry. This enables comparison of our results to these studies' findings. Three label levels were set for place of origin: local, Missouri Grown, and other. While "Missouri Grown" tomatoes indicate their producers are Missouri Grown program[13] members, the "local" tomatoes are produced within some specific geographical boundaries around the consumer's residence, like within 100 miles, and the "other" tomatoes are from other U.S. states or imported. The price attribute includes three levels: $1.99, $2.99, $3.99, that were established through collecting and analyzing the market prices of fresh tomatoes observed at grocery stores (Hy-Vee, Schnucks stores in Columbia, MO), farmers markets, and online purchases at the time of the study. Table 4.1 reports the attributes and attribute levels used in this study.

Table 4.1. Attributes and levels of tomato options

Attributes	**Levels**		
	Level 1	***Level 2***	***Level 3***
Production method	organic	50% reduced pesticide*	conventional
Label	Local	Missouri Grown	Neither "Local" nor "Missouri Grown"
Farm type	Small & medium family	Large family	Large corporation
Price of tomatoes	$1.99/lb.	$2.99/lb.	$3.99/lb.

Notes: (*) the 50% reduced pesticide techniques can be defined as the methods help farmers reduce a half of pesticide amounts used as usual in tomato cultivation.

We applied the Bayesian D-efficient design procedure to generate optimal design for the above choice problem of 4 attributes with 3 levels each. The obtained design results in 9 choice sets with 4 options per set, including three alternative and one opt-out (not

[13] Missouri Grown an outreach program through the Missouri Department of Agriculture that promotes products grown, raised, or produced and processed in Missouri. Paid members of the program can use Missouri Grown logo or label on their products (Missouri Grown USA, 2022).

buy) option. It is a kind of blocked fractional factorial design. The Bayesian D-error is 0.71 and the efficiency is 98.6% for this design. In particular, respondents are asked to choose one option or opt-out for buying fresh tomatoes over the 9 following scenarios (the questions and the options are randomized on the Qualtrics platform). For example (Figure 4.2):

Figure 4.2. A Scenario in Choice Experiment for Tomato Consumers

	Option A	Option B	Option C
Method	**Conventional**	**50% Reduced pesticide**	**Organic**
Label	**Missouri Grown**	**Local**	**No Local or Missouri Grown**
Farm	**Small & medium family**	**Large Corporation**	**Large Corporation**
Price	**$3.99/lb**	**$2.99/lb**	**$3.99/lb**

Which choice for buying tomatoes would you prefer?

○ Option A ○ Option B ○ Option C ○ None of them

4.3.2. Data Collection

Prior to conducting the survey, it was approved by the Lincoln University Institutional Review Board (IRB) to ensure the protection of human participants in the research. There were 530 Missouri respondents who participated in the experiment on Amazon's Mechanical Turk (MTurk), an online survey platform. As suggested by recent studies, Mturk samples are found to be a robust alternative to other common samples for healthy eating messages (Ouyang & Sharma, 2019) and especially useful for grocery shopping preference studies regarding effects of the COVID-19 pandemic (Grashuis, Skevas, & Segovia, 2020). MTurk's respondents needed to satisfy the following requirements: at least 18 years old, residents of Missouri, primary grocery shoppers of their households, and consumed tomatoes in the past 12-month period.

After data cleaning, 343 respondents were valid for the study. Because respondents stated their choices over 9 scenarios, the total number of unique choice observations for the full sample is 343*9 = 3,087. The dataset also included demographics of the respondents (Table 4.2).

Table 4.2. Summary Statistics

Demographic Characteristics	Sample	Missouri
Gender		
Male	43.2%	48.6%
Female	56.0%	51.4%
Age		
Under 34	36.7%	27.7%
34-54	45.5%	40.8%
Above 54	17.8%	31.5%
Education		
High school and less	21.0%	59.0%
2 year / Associate's degree	13.1%	11.0%
4 year / Bachelor's degree	41.7%	20.0%
Graduate or professional degree	24.2%	10.0%
Income		
Less than $25,000	12.0%	
$25,000-$50,000	32.7%	
$50,000-$75,000	21.9%	
$75,000-$100,000	16.1%	
$100,000 and above	17.3%	
Ethnicity		
Caucasian	79.0%	88.0%
African American	12.0%	8.0%
Others	9.0%	4.0%
House location		
Rural	25.1%	
Suburban	41.7%	
Urban	33.2%	
Children		
No children	51.5%	68.1%
At least 1 child under 17	48.5%	31.9%

Source: Missouri statistics (U.S. Census Bureau, 2022, July 7)

Table 4.2 reports summary statistics for the demographic variables in the sample. A slight majority of respondents are female (56.0%). Among respondents, 45.5% are 35-54 years and 17.8% are 55 and older. For educational attainment, 65.9% of the sample had bachelor's degrees or higher. The most common annual incomes, reported by 32.7%, was $25,000-$49,999. A majority of respondents are Caucasian (79%). Nearly half of respondents live in a suburban area. Additionally, 48.5% of respondents indicated they have at least one child under age 17. The summary statistics show that respondents tend to be younger and more educated than the demographics of Missouri, but this is expected for an online choice experiment survey, and the target population (grocery shoppers for the family and tomato consumers) might not necessarily be the same as the state's general population.

4.3.3. Empirical models

Analysis of consumer preference for food attributes using the DCE data is strongly grounded in Lancaster Consumer Theory (Lancaster, 1966) and Random Utility Theory (McFadden, 1974). In our experiment, hypothetical consumers or participants make discrete choices among tomato options that vary in levels of production method, origin location, producer type, and price attributes. Thus, assuming preferences are randomly distributed over subjects and heterogenous across consumers, the random utility model is an appropriate econometric approach to obtain estimates of consumer preference parameters and their WTP for "50% reduced pesticide use," all else equal.

Typically, the utility of respondent "i" choosing alternative "j" in the choice task "t" can be partitioned into two separate components: an observed component V_{ijt} and an unobserved component ε_{ijt}, so that $U_{ijt} = V_{ijt} + \varepsilon_{ijt}$ (1). The discrete choice modeling of the utility can be described as: $U_{ijt} = ASC + \beta' x_{ijt} + \varepsilon_{ijt}$ (2) where ASC is an alternative-specific constant representing the opt-out option; x_{ijt} are observed or determined attributes of the alternative; β' are alternative specific attribute parameters; ε_{ijt} are random errors that follow N(μ, σ).

Given the attributes of the study, the basic model (Model 1) is specified as below:

$$Utility\ (choice) = OptOut + \beta_1 Price + \beta_2 Organic + \beta_3 50\% ReducedPesticide + \beta_4 Local + \beta_5 MissouriGrown + \beta_6 SmallFamily + \beta_7 LargeFamily + \varepsilon$$

Where *OptOut* is an intercept term that captures the utility associated with the opt-out option, β_k $(k = 1, \ldots, 7)$ represents the utility model coefficients associated with price and non-price attributes, and ε is the error term. The utility model advanced the mixed logit approach whereas *OptOut* and price coefficient are fixed effects, and the other parameters are assumed to be random effects ~ N(μ, σ^2) for assumption of heterogeneity in consumer preferences (Bansai, Daziano, & Achtnicht, 2017).

Also, an extended model is specified by adding interaction terms between production methods and locally produced labels to Model 1 to examine WTP for combinations of 50% reduced pesticide and local or Missouri Grown and how they differ from organic. As previously mentioned in the literature, there has been empirical evidence that organic and local attributes can be additive or subtractive due to complementary or substitution effects (e.g., Gracia, Barreiro-Hurlé, & López Galán, 2014; Meas et al., 2015; Winterstein & Habisch, 2021).

$$\begin{aligned} Utility\ (choice) = {} & OptOut + \beta_1 Price + \beta_2 Organic + \beta_3 50\% ReducedPesticide \\ & + \beta_4 Local + \beta_5 MissouriGrown + \beta_6 SmallFamily + \beta_7 LargeFamily \\ & + \beta_8 Organic * Local + \beta_9 50\% ReducedPesticide * Local \\ & + \beta_{10} Organic * MissouriGrown + \beta_{11} 50\% ReducedPesticide * MissouriGrown + \varepsilon \end{aligned}$$

The WTPs for an attribute in the basic and extended models are derived from estimated distributions of the attribute coefficient and price coefficient. Under our specifications, WTP for the attribute is a ratio of the attribute coefficient to the price coefficient and is normally distributed (e.g., Hensher, Rose, & Green, 2015; Train, 2009).

4.4. Results and Discussion

Results of the empirical models are obtained by the Maximum Likelihood Estimation method. Estimates of preference parameters, derived WTPs for the attributes, and statistics for each model are presented in Table 4.3. The two models are statistically significant at the 1% level, confirming the specifications are acceptable. Also, most standard deviations of the attribute coefficients are significant, indicating heterogeneity in consumer preferences as expected (Bansai et al., 2017), which implies the adequacy of the mixed logit approach for the study. Looking at pseudo-R^2, Log-likelihood, and AIC statistics, Model 2 fits better than Model 1. Given that fact that the estimates are robust across the models, model performance can be improved when accounting for the interactions of interest, which also provides more policy-relevant implications.

Table 4.3. Mixed Logit Regression Results

Attribute-specific variables	Model 1		Model 2	
	Preferences	WTP	Preferences	WTP
Opt-out	-4.398***		-4.738***	
Price	-0.797***		-0.915***	
Organic	0.459***	0.576***	0.509***	0.556***
50% reduced pesticide use	0.126**	0.158**	0.097**	0.106**
Local	0.109***	0.137***	0.154***	0.168***
Missouri Grown	0.440***	0.551***	0.513***	0.561***
Small, medium family farm	0.278***	0.277***	0.258***	0.282***
Large family farm	0.295***	0.315***	0.294***	0.322***
Interaction terms				
Organic * Local			-0.227***	-0.249***
50% reduced pesticide use * Local			0.143**	0.157**

Organic * Missouri Grown			0.021	0.023
50% reduced pesticide use * Missouri Grown			0.110*	0.120*
Heterogeneity (Standard Deviation)				
Organic	0.634***	0.710***	0.629***	0.658***
Reduced 50% pesticide use	0.355***	0.397***	0.368***	0.385***
Local	0.245**	0.275**	0.232**	0.242**
Missouri Grown	0.415***	0.465***	0.429***	0.449***
Small, medium family farm	0.541***	0.606***	0.529***	0.553***
Large family farm	0.055	0.062	0.061	0.064
Model Statistics				
Log-likelihood	-3161		-3153	
Wald χ^2 (df)	211(6)		206(6)	
Pr ($>\chi^2$)	0.000***		0.000***	
AIC	6349		6341	
Pseudo-R^2	23.8%		24.0%	
Number of observations	3087		3087	

Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

4.5.1. Preferences

In Model 2, all the estimates (except the interaction between organic and Missouri Grown) are statistically significant at conventional critical levels. The constant for the opt-out option is negative indicating a lower utility associated with "none of the presented options" choice. This is a common result in past studies using DCE where consumers are expected to prefer buying rather than choosing opt-out (e.g., Bazzani et al., 2017). Also, the price coefficient is negative, implying decreased utility for an increase in price. Consumers will prefer the lower priced option, all else equal. As for non-price attributes, their coefficients are positive, and therefore suggesting higher perceived utility derived from these attributes, compared to the corresponding reference attribute levels. Consumers have higher preferences for tomatoes carrying organic, 50% reduced pesticide use, local, and Missouri Grown label, or those produced by small, medium, and large family farms. Put differently, using "conventional" as the reference level for production method, consumers are more likely to choose organic or 50% reduced pesticide use rather than conventional fresh tomatoes. The findings are consistent with previous studies even though most studies had only two production method attributes versus the three in our study (e.g., Biguzzi et al., 2014; Skreli et al., 2017; Printezis & Grebitus, 2018). Regarding origin label, consumers are more likely to buy local or Missouri Grown tomatoes than non-local or non-Missouri Grown ones. These results are in line with the literature of consumer preferences for local food where consumers show their support to the local economy and community (e.g., Carroll, Bernard, & Pesek, 2013; Meyerding, Trajer, & Lehberger, 2019; Grahuis & Su, 2022). We note the fact that the study sample includes consumers in Missouri only, and 64% of these consumers agree it is important to support local farms and communities when shopping for fresh produce (data not shown). Finally, considering "large corporation" as the reference level for type of producers, consumers are more likely to choose small & medium or large family farms rather than large corporations for tomato purchases. These findings can be also explained by the fact that the consumers in the study mostly support local farms, which generally are owned by families, which may help strengthen local community ties (e.g., see review of Enthoven & Van den Broeck, 2021).

Regarding our focus on reduced pesticide attributes, "organic" has a bigger effect on consumer preferences than "50% reduced pesticide use" on average, 0.509 versus 0.097, with respect to conventional fresh tomatoes. This is not surprising since organic food has broader benefits than "reduced pesticide" since synthetic fertilizers and GMOs are also not allowed. Consumers may consider organic to have health and environmental benefits while also being potentially being more nutritious and fresher than "non-organic" (e.g., Magkos, Arvaniti, & Zampelas, 2003; Lairon, 2011; Vinha et al., 2014). Since most past comparisons were made between organic and conventional foods, there is little evidence on reduced pesticides. Given the absence of knowledge and information of “50% reduced pesticide use” produce, our result is in line with Biguzzi et al. (2014) that showed consumers prefer organic to IPM tomatoes, even if organic tomatoes are more expensive.

While “50% reduced pesticide use” is less important than “organic” in driving consumer preferences for fresh tomatoes in terms of production method, the combinations of this attribute and local or Missouri Grown label have complementary effects. A positive interaction effect between “50% reduced pesticide use” method and “local” origin label indicates consumers prefer “local,” “50% reduced pesticide use” tomatoes over “50% reduced pesticide use” ones that are not locally produced. Similarly, consumers prefer “Missouri Grown,” “50% reduced pesticide use” tomatoes rather than ones from other states or countries. As previously mentioned, the sample of consumers supports local and Missouri Grown produce, and there is significant complementarity to “50% reduced pesticide use” tomatoes, with little difference between local (0.143) and Missouri Grown (0.110). However, surprisingly, this is not the case for organic tomatoes. The results of Model 2 show a negative interaction effect between “organic” and “local” of (-0.227), suggesting consumers have a lower preference for local organic tomatoes compared to those without a local or Missouri Grown label. The interaction between “organic” and “local” has been examined but remains indeterminant in the literature. In some past studies, the interaction between organic and local attributes is not statistically significant (e.g., Onozaka & McFadden, 2011; Bazzani et al., 2017). In other studies, the interaction is significantly positive (e.g., Gracia et al., 2014; Winterstein & Habisch, 2021) or significantly negative (e.g., Meas et al., 2015). In our study, the result is in line with the studies showing a substitute rather than a complement between “organic” and “local” claims. The substitution effect may exist when consumers consider “local” to share several characteristics of “organic” and vice versa (USDA, 2016), or the existence of a third factor that implies both “organic” and “local” like supporting small or family-owned farms (Meas et al., 2015), or due to heterogeneity in consumer preferences for “organic” where consumers who support “local” do not prefer “organic” (Govindasamy et al., 2017; Kim, Brorsen, & Lusk, 2018). Thus, “50% reduced pesticide use” tomatoes differ from organic ones, where the “reduced pesticide” and “local/ Missouri Grown” attributes are complements while the “organic” and “local” claims are substitutes in this study.

As expected for the mixed logit approach, model 2 captures unobserved heterogeneity in consumer preferences. In particular, there are significant standard deviation estimates for “organic”, “50% reduced pesticide use”, “local”, “Missouri Grown”, and “small & medium family farm”, suggesting the presence of heterogeneity across the population for these attributes. Put differently, consumer preferences significantly vary for most of the attributes in that some do prefer “organic”, or “reduced pesticide”, or “local” but this does not necessarily hold for all consumers. The finding that consumer preferences for organic tomatoes are heterogeneous is consistent with past studies, due to differences in demographic characteristics (Pishbahar, Mahmoudi, & Hayati, 2019) or in personal traits (Printezis & Grebitus, 2018). Regarding our interest, the existence of heterogeneity in consumer preferences for “50% reduced pesticide use” tomato is confirmed in this study, but the source of the heterogeneity remains unclear.

4.5.2. Willingness-to-pay

In an analysis of consumer preferences, consumers' WTP is of interest for two essential reasons. First, WTP provides a valuable tool to quantify the value of non-market goods. Second, WTP is measured in monetary terms, which would be useful for marketing strategies and relevant policies. Using the standard approach for derivation of WTP in preference space as described by Train (2009), we calculated the mean and standard deviation of WTP values for each coefficient estimate (noting that given the assumptions of the empirical models, the WTP estimates follow a normal distribution). The results in table 4.3, Model 2 show most WTP values are statistically significant and consistent with the preference results.

Among attributes, the highest mean WTP is for “Missouri Grown” at 56 cents/lb., followed by “organic”, “large family”, “small & medium family”, “local”, and “50% reduced pesticide use” of 56 cents/lb., 32 cents/lb., 28 cents/lb., 17 cents/lb., and 11 cents/lb., respectively. Regarding production method attributes, the mean WTP results indicate consumers would pay a much higher premium for “organic” than “50% less pesticide” compared to conventional, e.g., 56 cents/lb. for organic tomatoes vs. 11 cents/lb. for “50% less pesticide” ones. Using a reference price of $1.99/lb. for conventional tomatoes, this is equivalent to a premium of 28% for “organic” vs. 6% for “50% reduced pesticide”. The findings are consistent with past studies that found the premium for “organic” is about 30% of the regular price on average (Li & Kallas, 2021), and the price for “reduced pesticide” produce is closer to the price of conventional compared to the price of organic (Marette et al., 2012). For the other attributes, the results also show big differences in the premium for “Missouri Grown” vs. “local”, e.g., 56 cents/lb. for Missouri Grown tomatoes vs. 17 cents/lb. for local ones, while family farms receive the same premiums of about 30 cents/lb. with respect to large corporation.

A positive (negative) interaction term of WTP results suggest a higher (lower) WTP for the interaction than the sum of WTP associated with the attributes. In this regard, there would be a bigger premium for “50% reduced pesticide use” tomatoes that are local or Missouri Grown label, which have positive interactions. In particular, the mean WTP for a combination of “reduced pesticide and local” is 16 cents/lb. higher than the sum of WTP associated with “reduced pesticide” and “local” tomatoes (28 cents/lb.), leading to a WTP for this combination of 44 cents/lb. on average. Similarly, the mean WTP for a combination of “reduced pesticide and Missouri Grown” is 79 cents/lb., which is 12 cents/lb. higher than the sum of WTP associated with “reduced pesticide” and “Missouri Grown” tomatoes (67 cents/lb.). Thus, this implies a possible niche market for reduced pesticide tomatoes. However, it is not the case for “organic”. A negative WTP for “organic and local” of -25 cents/lb. indicates the premium for this combination decreases to 48 cents/lb., given the sum of WTP associated with “organic” and “local” tomatoes (73 cents/lb.). The complements between “reduced pesticide” and “local” or “Missouri Grown” attributes, and the substitutes between “organic” and “local” are present in this study. One possible reason for these results is heterogeneity in consumer preferences which can be seen from individual WTP perspectives as below (Figure 4.2).

Figure 4.2. Individual WTP for organic & reduced pesticide claims

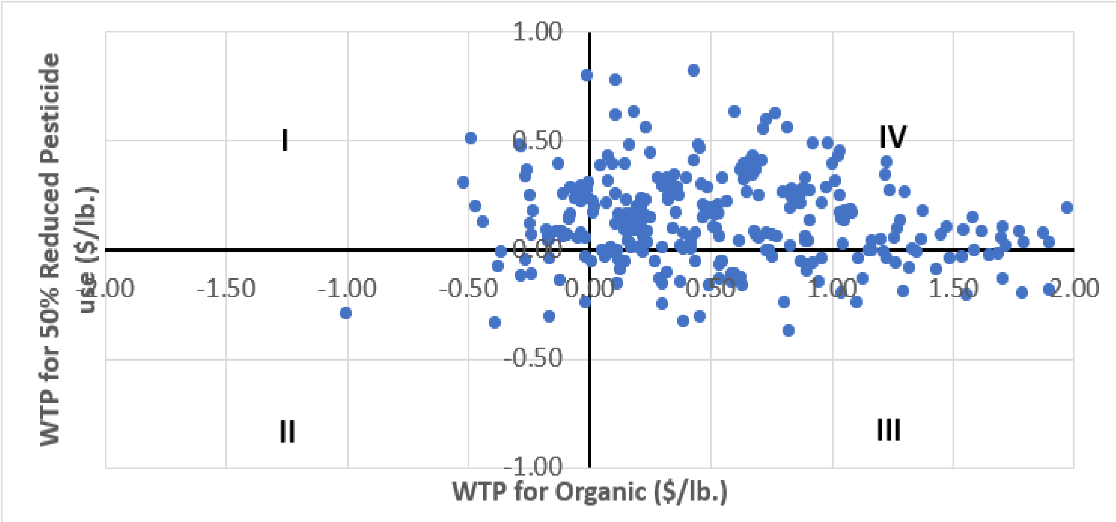


Figure 4.2 shows differences in individual WTP for organic and for 50% reduced pesticide use: 65% of the sample would pay a premium for both production methods (group IV), 18% would only pay extra for organic (group III), 13% would only pay extra for reduced pesticide (group I), and 4% would pay less for both or prefer conventional (group II). Consumers' WTP for organic is more heterogenous than those for the reduction in pesticides. The premium for "organic" can be up to $2/lb., which is equivalent to 100% of the regular price, while the maximum premium for "50% reduced pesticide use" is 80 cents/ lb., which is equivalent to 40% of the regular price in this study. The existence of consumers in group I & group II indicates not all consumers prefer organic to conventional tomatoes as concluded by Kim et al. (2018). In particular, 17% of the sample are not willing to pay any premium for organic tomatoes. Similarly, 22% of the sample, group II & group III, are not willing to pay a premium for reduced pesticide tomatoes. The largest portion of the sample, group IV, is in line with the literature where a majority of consumers have positive preferences for organic and sustainable practices.

We employed a multinomial logit model to investigate determinants of a consumer being in the four consumer segments (group I, II, III, and IV) mentioned above where the popular group (group IV) is used as the reference category. Following Katt & Meiner (2020), some demographic information, as well as health and environmental attitudes could be important factors affecting consumer preferences for organic tomatoes as well as reduced pesticide ones. These drove our analysis using demographics (gender, educational attainment, income, ethnicity, having children under 17, location of residence, and farm origin), private health concerns, and environmentally friendly attitudes as potential determinants to characterize the consumer groups. Specifications and estimation results of the MLM are reported in Table 4.4. Overall, the model is significant at the 5% level with a pseudo R^2 of 10.2%. We found education, ethnicity, having children under 17, location, farm origin, private health concerns, and environmentally friendly attitudes are somewhat significant to predict consumers who would be in group I, II, and III with respect to those in group IV.

Table 4.4. Multinomial Logit Results for the Determinants (Base: Group IV)

Independent variables	Group I	Group II	Group III
Demographic characteristics			
Female (base: male)	-0.298	-0.338	-0.226
Educational attainment (base: High school or less)			
2 year / Associate's degree	0.131	-17.983	0.118
4 year / Bachelor's degree	0.641*	-1.768*	-0.005
Graduate or professional degree	1.255	-1.941*	-0.007
Income (base: $25,000-$50,000)			
< $25,000	-0.305	1.301	0.027
$50,000-$75,000	0.631	-0.280	-0.287

> $75,000[14]	0.192	1.390	-0.330
Ethnicity (base: Caucasian)[15]	0.239	1.588**	-0.263
Having children under 17 (base: No children)	0.196	0.260	0.534*
Location (base: Suburban)			
Urban	0.461	-0.810	0.501
Rural	0.521	-2.491*	0.213
Farm origin (base: No)	0.593	-0.022	0.560*
Private Health Concerns (base: Disagree)			
Neutral	-0.336	0.595	1.122*
Agree	0.017	-0.993	0.648
Environmental Attitudes (base: Disagree)			
Neutral	-1.073	-0.067	1.104
Agree	-0.663	-2.082*	1.445
Constant	-2.409***	-0.459	-3.736***
Model Statistics			
Sample size		343	
LR ChiSquare (57)		66	
Pr(>Chisquare)		0.046**	
AIC		681	
McFadden pseudo R^2		10.2%	

Notes:
- *Private health concern statement: "I am concerned about chemicals (pesticides) and GMO in my food".*
- *Environmental attitude statement: "I would like to buy environmentally friendly products because they are less polluting"*
- *Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.*

Table 4 shows there are few significant differences for comparisons between group I vs. group IV, and group III vs. group IV, while more significant variables can be used to compare group II to group IV in the model. In particular, only education has somewhat significant effect to characterize consumers in group I vs. group IV. The positive

[14] We combined two income groups: "$75,000 – $100,000" and "$100,000 and above" to "> $75,000," which still represents a high annual income in Missouri and preserves more degrees of freedom.
[15] We combined "African American" and "other ethnicity" to "non-Caucasian" due to low percentages of these groups and our interest of "Caucasian" as the base.

coefficient of 4-year college or bachelor degree (i.e., 0.6) indicates these more educated consumers (compared to the reference education level of high school or less), are more likely to pay extra for reduced pesticide but less for fully organic (group I). The rest of the variables are not useful in the prediction of group I membership compared to group IV in this study.

When looking at consumers who prefer conventional over both organic and reduced pesticide tomatoes (group II), several variables are consistent with previous studies. Compared to “high school or less”, educational attainment levels such as four-year college, bachelor and higher degrees have negative estimates (-1.8 and -1.9), implying higher educated consumers are less likely to pay a discount for organic and reduced pesticides. Put differently, consumers in group IV would be more likely to have four year-college, bachelor’s degree, and higher degrees compared to those in group II. Regarding ethnicity, the positive effect of non-Caucasian on group II (i.e., 1.6) is in line with the effect of being Caucasian in the organic literature. In other words, consumers in group IV are more likely to be Caucasian rather than those in group II.

Demographic information relating to where consumers are living contributes to the prediction of consumers being in group II vs. group IV. For current location, there is little difference between consumers living in urban areas and those living in suburbs (reference category); however, compared to “suburban,” rural consumers are less likely to be in group II compared to group IV (the estimated coefficient is -2.5). In other words, group IV would be more likely to live in rural areas than urban/suburban areas compared group II. Finally, while there is no evidence for private health concerns on the prediction of group II vs. group IV, the effect of environmental attitudes is as expected. Consumers who agree that “they would like to buy environmentally friendly products because they are less polluting” are less likely to be in group II (the estimated coefficient is -2.1). In other words, group IV are consumers who have pro-environmental attitudes in comparison with group II.

For consumers who pay extra for organic, but less for reduced pesticide tomatoes versus conventional ones (group III), the predictors are somewhat different. Education, ethnicity, rural, and environmental attitudes are not significant at all, while having children under 17, farm origin, and private health concerns show significant results. Interestingly, the effect of having children under 17 is positive (i.e., 0.5), suggesting consumers who have children tend to pay a discount rather than a premium for reduced pesticides vs conventional even though they have positive preferences for organic. Put differently, group III would be more likely to contain consumers having children under 17 compared to those in group IV. The literature indicates that families with children are more likely to buy organic, believing it to be healthier. The result further confirms reduced pesticide produce is differentiated from organic by some consumers.

Regarding consumer origin, it seems that consumers who were raised on a farm are more likely to be in group III than group IV (the estimated coefficient is 0.6). This finding implies heterogeneity in consumer preferences for pesticide reduction relative to organic. For example, consumers with a farm background and those who are living in rural areas now have some similarities in that they may be more knowledgeable about agricultural practices and pesticide hazards. We had hypothesized that those who were more knowledgeable might be more interested in reduced pesticide use but not fully organic but that was not the case.

We also examined the effects of health and environmental concerns on group III. However, the results show little evidence for private health concerns, all else equal. Only the estimated coefficient of consumers who are neutral rather than disagree that “they are concerned about chemicals (pesticides) and GMO in their food” is significantly positive (i.e., 1.1), indicating these neutral consumers would be in group III vs. group IV. This result on the one hand shows heterogeneity in consumer preferences in pesticide reduction relative to organic with regard to having children and farm origin. Consumers who have children tend to prefer organic, which is probably related to health concerns. On the other hand, the result might support conflicting preferences regarding pesticide use and GMO attributes on personal health concerns as indicated in the literature. This research combined these concerns. Future research could try to separate the reduced pesticide feature from GMO to more clearly examine the reduced pesticide effect on consumer preferences for produce.

The analysis of consumers’ demographic characteristics, health concerns, and environmental attitudes shows reasons underlying the existence of heterogeneity in consumer preferences for organic and reduced pesticides. As expected, there were more significant factors when looking at quite different consumer segments like group II versus group IV where consumers have opposite preferences. Little evidence was found for comparisons between group I vs. group IV, and group III vs. group IV. This is unfortunate since information on factors relating to consumers in group I would enable producers interested in reducing but not eliminating pesticides to find buyers for their produce. Regardless, the distributions of individual WTPs for reduced pesticide tomatoes over different consumer segments have important implications for growers, sellers, and policy makers who are producing or marketing the produce.

4.5. Conclusions and Implications

Along a continuum of pesticide use, reduced pesticide food has been increasingly of interest due to potential welfare gains compared to either organic or conventional food. However, there has not been an actual market for this kind of food. In this research, we attempted to investigate consumer preferences for reduced pesticide fresh produce that is an essential part of a healthy diet. To do this, we employ a DCE for fresh tomatoes possessing different attributes in terms of how they were produced regarding pesticide use, who produced them, where they were produced, and prices. Specifically, we examine three production methods for tomatoes: organic, 50% reduced pesticide use, and conventional, and then we employ a mixed logit model to estimate preferences and measure WTP for "50% reduced pesticide use" tomato and other relevant attributes. In addition, we discuss how reduced pesticide differs from organic tomatoes with respect to conventional ones, and characterize consumers with different preferences for organic, reduced pesticide, and conventional tomatoes using demographic information, health concerns, and environmental attitudes.

Using online choice data collected from the sample of tomato consumers in Missouri, we found that consumers prefer and are willing to pay a small premium for "50% reduced pesticide use" tomatoes, and premiums for other attributes (e.g., organic, local, Missouri Grown, family farms) which are consistent with past studies. This is a contribution to the literature since most studies had only two production method attributes (e.g., organic vs. conventional) versus the three options in our study. However, we also showed that the premium for “50% reduced pesticide use” is very small compared to the one for “organic,” implying the price of reduced pesticide tomato is closer to conventional than organic. This finding is in line with the literature on consumer preferences for IPM, minimized pesticide, or reduced pesticide produce without specific information on pesticide reduction amount. On the one hand, the large premium for “organic” can be explained by a wider range of benefits for “organic” in terms of health and environmental impacts than “reduced pesticide” only. On the other hand, the small premium for “50% reduced pesticide use” may imply consumers don't have a nice, neat utility function regarding pesticides where a little more pesticide is a little less preferred.

Furthermore, we found “reduced pesticide” may differ from “organic” tomato when interacting with origin labels like “local” and “Missouri Grown”. In particular, while “reduced pesticide” and “local” or “Missouri Grown” claims are complements, “organic” and “local” claims are substitutes. These interesting results suggest implications for growers who are producing by reduced pesticide methods; they should also try to market based on location characteristics.

To examine these issues in greater detail, we provided individual WTP for “organic” and “50% reduced pesticide use” tomatoes to examine heterogeneity in consumer preferences. The findings of four different consumer segments provide insights into an investigation of consumer preferences for a continuum of pesticide use, that no longer includes conventional and organic only. We found the traditional set of demographics, private health concerns, and environmental attitudes useful to characterize the traditional comparisons between strictly opposite preferences, for example conventional vs. organic, conventional vs. reduced pesticide, but limited for predicting who have positive preferences for organic but not reduced pesticide and vice versa. Looking for characteristics of all type of consumers have more insightful implications for relevant farmers, companies, and policy makers, but beyond this study's results. In future, we may examine factors affecting WTP for less pesticide produce in comparison with organic, and search for who pay high for less pesticide, but not fully organic produce. Further research may also consider cost of pesticide reduction in tomato production regarding its low reward from consumer side.

References

[1] Alwang, J., Norton, G., & Larochelle, C. (2019). Obstacles to Widespread Diffusion of IPM in Developing Countries: Lessons From the Field. *Journal of Integrated Pest Management.*

[2] Aryal, K.P., Chaudhary, P., Pandit, S., & Sharma, G. (2009). Consumers' Willingness to Pay for Organic Products: A Case From Kathmandu Valley. *Journal of Agriculture and Environment, 10,* 15-26.

[3] Aschemann-Witzel, J., & Zielke, S. (2017). Can't Buy Me Green? A Review of Consumer Perceptions of and Behavior toward the Price of Organic Food. *Journal of Consumer Affairs, 51*, 211-251.

[4] Aye, M.S., Takahashi, Y., & Yabe, M. (2019). Effects of Consumer Preferences on Environmentally Friendly Tomatoes in Myanmar. *Journal of Agricultural Science, 11*(13).

[5] Ballen, F.H., Evans, E.A., & Parra-Acosta, Y.K. (2021). Consumer Preferences for Green Skin Avocados in the US Market: The Role of Experienced Quality Attributes, Credence Attributes, and Demographic Factors. *Journal of Agricultural & Food Industrial Organization, 20,* 15-23.

[6] Bansal, P., Daziano, R.A., & Achtnicht, M. (2018). Extending the logit-mixed logit model for a combination of random and fixed parameters. *Journal of Choice Modelling, 27*, 88-96.

[7] Bazzani, C., Caputo, V., Nayga, R.M., & Canavari, M. (2017). Revisiting consumers' valuation for local versus organic food using a non-hypothetical choice experiment: Does personality matter? *Food Quality and Preference, 62*, 144-154.

[8] Biguzzi, C., Ginon, E., Gomez-y-Paloma, S., Langrell, S.R., Lefebvre, M., Marette, S., Mateu, G., & Sutan, A. (2014). Consumers' preferences for Integrated Pest Management: Experimental insights. *2014 International Congress.* Ljubljana, Slovenia: European Association of Agricultural Economists.

[9] Carroll, K.A., Bernard, J.C., & Pesek, J. (2013). Consumer Preferences for Tomatoes: The Influence of Local, Organic, and State Program Promotions by Purchasing Venue. *Journal of Agricultural and Resource Economics, 38*, 379-396.

[10] Carson, R.T., & Louviere, J. J. (2011). A Common Nomenclature for Stated Preference Elicitation Approaches. *Environmental and Resource Economics, 49,* 539-559.

[11] Cecchini, L., Torquati, B., & Chiorri, M. (2018). Sustainable agri-food products: A review of consumer preference studies through experimental economics. *Agricultural Economics– Czech, 64*, 554-565.

[12] Chen, X., Gao, Z., Swisher, M.E., House, L.A., & Zhao, X. (2018). Eco-labeling in the Fresh Produce Market: Not All Environmentally Friendly Labels Are Equally Valued. *Ecological Economics.*

[13] Cicia, G., Giudice, T.D., Ramunno, I., & Tagliafierro, C. (2006). Splitting consumer's willingness to pay premium price for organic products over main purchase motivations. *EEAE 98th Seminar.* Chania, Crete, Greece: European Association of Agricultural Economists (EAAE). Retrieved from http://dx.doi.org/10.22004/ag.econ.10057

[14] Dannenberg, A. (2009). The dispersion and development of consumer preferences for genetically modified food - A meta-analysis. *Ecological Economics, 68*, 2182-2192.

[15] Durham, T., & Mizik, T. (2021). Comparative Economics of Conventional, Organic, and Alternative Agricultural Production Systems. *Economies, 9*(64).

[16] Enthoven, L., & Broeck, G.V. (2021). Local food systems: Reviewing two decades of research. *Agricultural Systems, 193*, 103226.

[17] Fernqvist, F. & Ekelund, L. (2013). Consumer attitudes towards origin and organic - the role of credence labels on consumers' liking of tomatoes. *European journal of horticultural science*. 78(4) , 184-190.

[18] Francis, P.B., & Stark, C.R. (2012). Heirloom Tomato Production in Conventional and Transitional-organic Managed Systems. *Hortscience, 47*, 1034-1037.

[19] Freier, B. & Boller, E.F. (2009). Integrated Pest Management in Europe – History, Policy, Achievements and Implementation. In R. &. Peshin, *Integrated Pest Management: Dissemination and Impact.* Dordrecht: Springer. Retrieved from https://doi.org/10.1007/978-1-4020-8990-9_14

[20] Garcia, J.M., & Teixeira, P. (2017). Organic versus conventional food: A comparison regarding food safety. *Food Reviews International, 33*, 424 - 446.

[21] Govindasamy, R., & Puduri, V.S. (2008). Consumer Preferences in the United States for Integrated Pest Management Produce: An Econometric Analysis. *The IUP Journal of Agricultural Economics*, 7-16.

[22] Govindasamy, R., Arumugam, S., Vellangany, I., & Ozkan, B. (2017). Willingness to Pay a High-Premium for Organic Produce: An Econometric Analysis. *Journal of Food Distribution Research, 48*, 103-104.

[23] Gracia, A., Barreiro-Hurlé, J., & Galán, B.S. (2014). Are Local and Organic Claims Complements or Substitutes? A Consumer Preferences Study for Eggs. *Journal of Agricultural Economics, 67*, 49-67.

[24] Grashuis, J., & Su, Y. (2022). Consumer Preferences for State-Sponsored Designations: The Case of the Missouri Grown Label. *Journal of Agricultural and Resource Economics*.

[25] Grashuis, J., Skevas, T., & Segovia, M.S. (2020). Grocery Shopping Preferences during the COVID-19 Pandemic. *Sustainability, 12*, 5369.

[26] Hensher, D.A., Rose, J.M., & Greene, W. (2015). *Applied Choice Analysis (2nd ed.).* Cambridge: : Cambridge University Press.

[27] Hess, S., Lagerkvist, C.J., Redekop, W.K., & Pakseresht, A. (2016). Consumers' evaluation of biotechnologically modified food products: new evidence from a meta-survey. *European Review of Agricultural Economics, 43*, 703-736.

[28] Ibrahim, A.B., Hasan, A.L., Arne, H., & Mahmoud, E. (2019). Econometric analysis of consumer preferences and willingness-to-pay for organic tomatoes in Palestine: Choice experiment method. *Journal of Development and Agricultural Economics, 11*(4), 71-81.

[29] Katt, F., & Meixner, O. (2020). A systematic review of drivers influencing consumer willingness to pay for organic food. *Trends in Food Science and Technology, 100*, 374-388.

[30] Khachatryan, H., Wei, X., & Rihn, A.L. (2020). Consumer and Producer Perceptions and Preferences for Pollinator Friendly Labeling Practices in the US Green Industry. *EDIS, 2020*(5). Retrieved from https://doi.org/10.32473/edis-fe1083-2020

[31] Kim, S., Brorsen, B.W., & Lusk, J.L. (2018). Not everybody prefers organic food: unobserved heterogeneity in U.S. consumers' preference for organic apple and milk. *Applied Economics Letters, 25*, 9 - 14.

[32] Kiruthika, N., & Selvaraj, K. N. (2013). An economic analysis of consumer preference towards pest management (IPM) produce. *Journal of Environmental Research and Development, 7*(4A), 1684.

[33] Lairon, D. (2011). Nutritional quality and safety of organic food. A review. *Agronomy for Sustainable Development, 30*, 33-41.

[34] Lancaster, K.J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy, 74*, 132-157.

[35] Lee, S.H., Moore, L.V., Park, S., Harris, D.M., & Blanck, H.M. (2022). *Adults Meeting Fruit and Vegetable Intake Recommendations — United States, 2019.* MMWR Morb Mortal Wkly Rep. Retrieved from http://dx.doi.org/10.15585/mmwr.mm7101a1

[36] Li, S. & Kallas, Z. (2021). Meta-analysis of consumers' willingness to pay for sustainable food products. *Appetite, 163*. Retrieved from https://doi.org/10.1016/j.appet.2021.105239

[37] Lichtenberg, E. & Zilberman, D. (1986). The econometrics of damage control: Why specification matters? *American Journal of Agricultural Economics, 68*(2), 261-273. Retrieved from https://doi.org/10.2307/1241427

[38] Lin, B., Smith, T., & Huang, C. (2008). Organic premiums of US fresh produce. *Renewable Agriculture and Food Systems, 23*(3), 208-216. Retrieved from https://doi.org/10.1017/S1742170508002238

[39] Magkos, F., Arvaniti, F., & Zampelas, A. (2003). Organic food: nutritious food or food for thought? A review of the evidence. *International Journal of Food Sciences and Nutrition, 54*, 357 - 371.

[40] Marette, S., Messéan, A., & Millet, G. (2012). Consumers' willingness to pay for eco-friendly apples under different labels: Evidences from a lab experiment. *Food Policy, 37*, 151-161.

[41] McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., *Frontiers in Econometrics.* New York: Academic Press.

[42] Meas, T., Hu, W., Batte, M.T., Woods, T.A., & Ernst, S. (2015). Substitutes or Complements? Consumer Preference for Local and Organic Food Attributes. *American Journal of Agricultural Economics, 97*(4), 1044-1071.

[43] Meyerding, S.G., Trajer, N., & Lehberger, M. (2019). What is local food? The case of consumer preferences for local food labeling of tomatoes in Germany. *Journal of Cleaner Production., 207*, 30-43.

[44] Milford, A.B., Trandem, N. & Pires, A.J.G. (2021). Fear of pesticide residues and preference for domestically produced strawberries. *Review of Agricultural, Food and Environmental Studies*, 369–391. Retrieved from https://doi.org/10.1007/s41130-020-00134-8

[45] Miller, K.B.; Eckberg, J.O.; Decker, E.A.; Marinangeli, C.P.F. (2021). Role of Food Industry in Promoting Healthy and Sustainable Diets. *Nutrients, 13*. Retrieved from https://doi.org/10.3390/nu13082740

[46] Missouri Grown USA (2022). Retrieved from https://missourigrownusa.com

[47] Moser, A.K. (2016). Consumers' purchasing decisions regarding environmentally friendly products: An empirical analysis of German consumers. *Journal of Retailing and Consumer Services, 31*, 389-397.

[48] Moser, R., & Raffaelli, R. (2012). Consumer preferences for sustainable production methods in apple purchasing behaviour: a non-hypothetical choice experiment. *International Journal of Consumer Studies, 36*, 141-148.

[49] Moser, R., Raffaelli, R., & Notaro, S. (2010). The Role Of Production Methods In Fruit Purchasing Behaviour: Hypothetical Vs Actual Consumers' Preferences And Stated Minimum Requirements. *115th Joint EAAE/AAEA Seminar*. Freising-Weihenstephan, Germany 116426: European Association of Agricultural Economists.

[50] Onozaka, Y. & McFadden, D.T. (2011). Does Local Labeling Complement or Compete with Other Sustainable Labels? A Conjoint Analysis of Direct and Joint Values for Fresh Produce Claim. *American Agricultural & Natural Resource Economics, 93*(3), 693-706.

[51] Ouyang, Y., & Sharma, A. (2019). Consumer-citizen willingness to pay for healthy eating messages. *International Journal of Contemporary Hospitality Management, 31*(2), 890-909. Retrieved from https://doi.org/10.1108/IJCHM-08-2017-0490

[52] Owusu, R., & Dadzie, S.K. (2021). Heterogeneity in consumer preferences for organic and genetically modified food products in Ghana. *African Journal of Agricultural and Resource Economics, 16*(2), 112-125.

[53] Piñero, J.C., & Keay, J.N. (2018). Farming Practices, Knowledge, and Use of Integrated Pest Management by Commercial Fruit and Vegetable Growers in Missouri. *Journal of Integrated Pest Management, 9*.

[54] Pishbahar, E., Mahmoudi, H., & Hayati, B. (2019). The Survey of Heterogeneity on Organic Products Consumers' Preferences Using Mixed Logit and Latent Class Models. *Journal of International Food & Agribusiness Marketing, 32*, 220 - 233.

[55] Printezis, I., & Grebitus, C. (2018). Marketing channels for local food. *Ecological Economics*, 152, 161-171.

[56] Roberts, C. (2020, 8 27). *The Six Most Concerning Pesticides on Produce*. Retrieved from Consumer Reports: https://www.consumerreports.org/pesticides-in-food/most-concerning-pesticides-on-produce/

[57] Skreli, E., Imami, D., Chan, C., Canavari, M., Zhllima, E., & Pire, E. (2017). Assessing consumer preferences and willingness to pay for organic tomatoes in Albania: a conjoint choice experiment study. *Spanish Journal of Agricultural Research, 15*(0114).

[58] Su, C.-H.; Tsai, C.-H.; Chen, M.-H.; Lv, W.Q. (2019). U.S. Sustainable Food Market Generation Z Consumer Segments. *Sustainability, 11*. Retrieved from https://doi.org/10.3390/su11133607

[59] Train, K. (2009). *Discrete Choice Methods with Simulation (2nd ed.)*. Cambridge: Cambridge University Press.

[60] Vinha, A. F., Barreira, S. V., Costa, A. S., Alves, R. C., & Oliveira, M. B. (2014). Organic versus conventional tomatoes: influence on physicochemical parameters,

bioactive compounds and sensorial attributes. *Food and chemical toxicology : an international journal published for the British Industrial Biological Research Association*, 139-144.

[61] Wallace, T. C., Bailey, R. L., Blumberg, J. B., Burton-Freeman, B., Chen, C. O., Crowe-White, K. M., Drewnowski, A., Hooshmand, S., Johnson, E., Lewis, R., Murray, R., Shapses, S. A., & Wang, D. D. (2020). Fruits, vegetables, and health: A comprehensive narrative, umbrella review of the science and recommendations for enhanced public policy to improve intake. *Critical reviews in food science and nutrition*, *60*(13), 2174–2211. Retrieved from https://doi.org/10.1080/10408398.2019.1632258

[62] Wheeler, S.A., Gregg, D., & Singh, M. (2019). Understanding the role of social desirability bias and environmental attitudes and behaviour on South Australians' stated purchase of organic foods. *Food Quality and Preference.*

[63] WHO. (2020, 04 29). *Fact Sheets: Healthy Diet*. Retrieved from https://www.who.int/news-room/fact-sheets/detail/healthy-diet

[64] WHO-FAO. (2019). *Global situation of pesticide management in agriculture and public health.* Geneva: Licence: CC BY-NC-SA 3.0 IGO.

[65] Winterstein, J., & Habisch, A. (2021). Is local the new organic? Empirical evidence from German regions. *British Food Journal, 123*(11), 3486-3501. Retrieved from https://doi.org/10.1108/BFJ-06-2020-0517

CHAPTER 5. GENERAL CONCLUSIONS

From the countryside to cities, from home to business, pesticides have retained their importance in our lives since the “Golden Age of Pesticides” during the 1950s. Evidence for the heavy dependence on conventional pesticides is not only based on the huge amount of pesticide consumption annually, but also the low prevalence of alternatives like organic and IPM practices. Benefits of pesticides are real and not taken for granted in this research. But potential risks to people and the environment are not negligible despite regulated pesticide usage. Chemical companies have developed many new formulations that are safer or better than before, but our environment stresses today are severe with pollution, climate change, loss of biodiversity, public health issues, and overpopulation. These issues and pesticides’ own inconsistencies in combatting pests have not surprisingly created intense debates with numerous questions on pesticide use. With due respect to the diversity and complexity of pesticides, this dissertation, by considering household adoption of organic pesticides, producer decisions for efficient use of conventional pesticides, and consumer preferences for reduced pesticide produce shows how important it is to study real issues from different contexts, how appropriate economic tools can deal with practical problems, and how useful is its intellectual framework in providing insights to applied questions in agricultural economics. Furthermore, this three-essay thesis makes several contributions to the literature.

The importance of different contexts across the three essays relates to how they can complement each other, leading to improved understanding about the results and dealing with data limitations. For example, in the first essay, chemical pesticides are dominant in lawn care due to their observable effectiveness on lawn appearance. In the second essay, the analysis indicates pesticide use efficiency differs in rice and fruit production with farms underusing or overusing pesticides in each crop. Another example is that private health concerns are not examined on household adoption of organic pesticides in essay 1 because of limitations of the dataset, but this is supported by the results in essay 3. Another important and useful finding from the dissertation work is the flexibility and capacity of economic tools in dealing with various applied questions such as estimates of pesticide efficiency (essay 2), WTP (essay 3), utility-based adoption models (essay 1), and discrete choice models (essay 3). Flipping from the production to the consumption side and even both sides like household decision-making makes our understanding of pesticide use more comprehensive, more coherent, suggesting more useful or sharper insights for a wide range of stakeholders.

Given the results throughout the dissertation, there are significant original contributions to the literature. In Chapter 2, the first essay shows how to develop a conceptual framework to analyze adoption of cleaning or lawn-care products like organic pesticides. To our knowledge, this is new since most previous studies focused on pesticide practices in agriculture and organic food consumption. In addition, the study shows different results between non-adopter groups in the adoption process, suggesting a new, more insightful way to investigate determinants of population behavior with distinct characteristics for pesticide use.

In chapter 3, the second essay provides the first assessment of pesticide use efficiency in Vietnamese farming, and the method can apply to pesticide use in multi-cropping production systems that are popular in developing countries. Moreover, by indicating that numerous farms underuse pesticides due to affordability and accessibility issues, which is scarce in the literature, the study implies that different policies should be implemented for overusing and underusing farms.

In chapter 4, the third essay shows heterogeneity in consumer preferences for a reduction in pesticides, which differ from those for organic produce, indicating different styles or levels of environmental preferences. This result is also, to the best of our knowledge, new and provides insights about the potential for niche markets for reduced pesticide products.

Overall, in terms of pest control, the use of pesticides should be analyzed in a system regarding possible factors from both production and consumption sides. While conventional and organic farming represent two extremes of pesticide use, IPM systems have utilized pesticides more judiciously due to improved knowledge and advanced technologies. However, these systems need to determine a way to connect with consumers so that consumers' tastes can be incorporated into these production systems. Furthermore, studies of pesticide use and relevant policy implications enormously need to take producer and consumer heterogeneity into consideration.

APPENDICES

(Additional information of Chapter 2, 3, and 4)

Appendix A2.1. Correlation Matrix of Categorical Variables using Cramer's V

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
X1	1.00	0.10	0.23	0.06	0.07	0.14	0.03	0.05	0.08	0.05
X2	0.10	1.00	0.15	0.60*	0.11	0.05	0.05	0.09	0.10	0.11
X3	0.23	0.15	1.00	0.19	0.21	0.08	0.13	0.14	0.13	0.28
X4	0.06	0.60*	0.19	1.00	0.14	0.03	0.02	0.13	0.06	0.02
X5	0.07	0.11	0.21	0.14	1.00	0.09	0.05	0.09	0.08	0.08
X6	0.14	0.05	0.08	0.03	0.09	1.00	0.12	0.10	0.14	0.07
X7	0.03	0.05	0.13	0.02	0.05	0.12	1.00	0.08	0.12	0.18
X8	0.05	0.09	0.14	0.13	0.09	0.10	0.08	1.00	0.08	0.06
X9	0.08	0.10	0.13	0.06	0.08	0.14	0.12	0.08	1.00	0.17
X10	0.05	0.11	0.28	0.02	0.08	0.07	0.18	0.06	0.17	1.00

X1: Gender
X2: Age
X3: Household income
X4: Having children under 12
X5: Education
X6: Seriousness of environmental concerns
X7: Importance of neighbors' opinion
X8: Time spent gardening
X9: Weed density
X10: Hiring pest control services

*(*) Chi Square test for independence of r24: p value < 0.05, which means there is evidence that Age and Having children under 12 are correlated***.**

Appendix A2.2. Variance Inflation Factor (VIF) of Predictors

	McFadden's pseudo R^2*	VIF**
X1	0.086	1.007
X2	0.207	1.045
X3	0.154	1.024
X4	0.366	1.155
X5	0.111	1.012
X6	0.081	1.007
X7	0.068	1.005
X8	0.066	1.004
X9	0.093	1.009
X10	0.177	1.032

(*): The McFadden's pseudo R-squared is provided for each model which includes the corresponding variable as the dependent variable while other variables are predictors.

(**): VIF of each variable is computed by using the corresponding R^2

Appendix A2.3. Estimation Results of the Reduced “Child Factor” Model (Base: Adopters)

Independent Variables (Factors)	Non-Adopters				
	Never heard	*Know somewhat*	*Know well*	*No Pesticides*	*Other N/A*
Personal attitude measures					
Environmental concerns (base: Not or slight problem)					
Moderate problem	-1.355**	-0.978**	-0.835*	-1.416**	-1.497***
Serious problem	-2.682***	-1.228***	-0.841*	-0.820	-2.042***
Don’t know	-0.267	-0.668	-0.403	-0.031	-0.708
Neighbors’ opinion important (base: Agree)					
Disagree	-0.896	-0.784**	-0.769**	0.756	-1.135
Neutral	-0.212	-0.511*	-0.638**	1.030*	-0.826**
Gardening behaviors					
Monthly hours spent gardening (base: 6-10 hours)					
0-5 hours	0.718	0.336	0.113	0.779	0.755*
11-15 hours	-1.123**	-0.611**	-0.312	-0.850	-0.846**
More than 15 hours	-1.675***	-1.250***	-1.028***	-1.600***	-1.499***
Pest control services hired (base: No)					
Use service	0.0002	-0.140	-0.426	-16.268	0.167
Lawn attributes					
Number of weeds per square yard (base: < 10 weeds)					
10-40 weeds	0.284	0.490	0.248	0.956*	0.084
More than 40 weeds	-15.80	0.709	-0.548	-1.245	0.385
Don’t know	0.703	0.457	0.097	0.944**	0.412
Demographic characteristics					
Male	0.549	0.440	0.441	-0.260	0.356
Age (base: > 60 years)					
18-30 years	1.047	0.865	0.179	1.344	0.933
31-45 years	0.464	0.239	0.133	0.638	0.007
46-60 years	1.108**	0.435	-0.040	0.875*	0.498
Education (base: High school or less)					
Some college or 2-year college	-0.464	-1.089**	-0.870*	-0.671	-1.132**
4-year college	-0.100	-0.402	-0.606	-0.043	-0.702
Post-graduate	-0.126	-0.631	-0.776	-0.028	-0.530
Household income (base: $25,000-$49,999)					
< $24,999	0.813	-0.017	0.275	0.485	-0.307
$50,000-$74,999	-1.183*	-0.145	-0.045	-0.486	-0.560
$75,000-$99,999	0.046	0.323	0.329	-0.160	-0.496
> $100,000	-1.308*	-0.168	0.068	-1.461**	-1.083**
Constant	0.365	2.092***	2.164***	-0.519	2.787***
Goodness-of-fit					
N			661		
LR ChiSquare (120)			235.07		

Pr(>Chisquare)	2.942e-10 ***
AIC	2199.871
AICc	2253.648
BIC	2739.121
McFadden's Pseudo R^2	10.7%
Cox & Snell's Pseudo R^2	29.9%
Nagelkerke's Pseudo R^2	29.9%

*Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.*

Appendix A2.4. Estimation Results of the Reduced "Age Factor" Model (Base: Adopters)

Independent Variables (Factors)	Non-Adopters				
	Never heard	*Know somewhat*	*Know well*	*No Pesticides*	*Other N/A*
Personal attitude measures					
Environmental concerns (base: Not or slight problem)					
Moderate problem	-1.364**	-0.993**	-0.823*	-1.434**	-1.516***
Serious problem	-2.689***	-1.264***	-0.840*	-0.898	-2.083***
Don't know	-0.279	-0.659	-0.389	-0.104	-0.700
Neighbors' opinions important (base: Agree)					
Disagree	-0.830	-0.756**	-0.762	0.843***	-1.110***
Neutral	-0.252	-0.510*	-0.622**	1.040*	-0.844**
Having children under 12 (base: No children)					
At least 1 child	0.359	0.122	0.210	0.416	-0.060
Gardening behaviors					
Monthly hours spent gardening (base: 6-10 hours)					
0-5 hours	0.708	0.343	0.108	0.802	0.753*
11-15 hours	-1.066**	-0.594**	-0.313	-0.800	-0.818**
More than 15 hours	-1.610***	-1.278***	-1.027***	-1.579***	-1.533***
Pest control services hired (base: No)					
Use service	-0.105	-0.166	-0.410	-16.383	0.133
Lawn attributes					
Number of weeds per square yard (base: < 10 weeds)					
10-40 weeds	0.264	0.538	0.276	1.042**	0.133
More than 40 weeds	-15.737	0.733	-0.554	-1.186	0.402
Don't know	0.652	0.444	0.113	0.875**	0.392
Demographic characteristics					
Male	0.474	0.383	0.426	-0.392	0.305
Education (base: High school or less)					
Some college or 2-year college	-0.351	-1.000*	-0.879*	-0.527	-1.027*
4-year college	-0.123	-0.358	-0.605	0.036	-0.655
Post-graduate	-0.189	-0.615	-0.769	0.061	-0.529
Household income (base: $25,000-$49,999)					
< $24,999	0.726	-0.002	0.273	0.413	-0.286
$50,000-$74,999	-1.118*	-0.127	-0.056	-0.519	-0.530
$75,000-$99,999	0.128	0.373	0.294	-0.131	-0.430
> $100,000	-1.110	-0.110	0.019	-1.462*	-0.998*
Constant	0.873	2.303***	2.155***	-0.037	3.015***
Goodness-of-fit					
N			661		
LR ChiSquare (120)			221.71		
Pr(>Chisquare)			2.392-10 ***		

AIC	2193.233
AICc	2237.633
BIC	2687.546
McFadden's Pseudo R^2	10.1%
Cox & Snell's Pseudo R^2	28.5%
Nagelkerke's Pseudo R^2	28.5%

*Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.*

Appendix A2.5. Estimation Results of the Model Without Identification of "Not applicable" (Base: Adopters)

Independent Variables (Factors)	Non-Adopters			
	Never heard	*Know somewhat*	*Know well*	*Not Applicable*
<u>Personal attitude measures</u>				
Environmental concerns (base: Not or slight problem)				
Moderate problem	-1.375**	-0.980**	-0.837*	-1.517***
Serious problem	-2.724***	-1.230***	-0.842*	-1.625***
Don't know	-0.310	-0.663	-0.398	-0.571
Neighbors' opinions important (base: Agree)				
Disagree	-0.908	-0.788**	-0.773**	-0.665*
Neutral	-0.209	-0.509	-0.638**	-0.405
Having children under 12 (base: No children)				
At least 1 child	0.488	0.096	0.188	0.112
<u>Gardening behaviors</u>				
Monthly hours spent gardening (base: 6-10 hours)				
0-5 hours	0.723	0.344	0.116	0.792*
11-15 hours	-1.133*	-0.614*	-0.315	-0.865**
More than 15 hours	-1.664***	-1.244***	-1.013***	-1.509***
Pest control services hired (base: No)				
Use service	-0.039	-0.165	-0.451	-0.181
<u>Lawn attributes</u>				
Number of weeds per square yard (base: < 10 weeds)				
10-40 weeds	0.319	0.504	0.260	0.401
More than 40 weeds	-13.424	0.706	-0.551	-0.147
Don't know	0.713	0.463	0.100	0.567*
<u>Demographic characteristics</u>				
Male	0.540	0.434	0.432	0.143
Age (base: > 60 years)				
18-30 years	0.946	0.866	0.157	1.050*
31-45 years	0.156	0.195	0.027	0.161
46-60 years	1.058*	0.437	-0.055	0.615*
Education (base: High school or less)				
Some college or 2-year college	-0.517	-1.096**	-0.883*	-0.959*
4-year college	-0.128	-0.409	-0.621	-0.495
Post-graduate	-0.158	-0.641	-0.796	-0.372
Household income (base: $25,000-$49,999)				
< $24,999	0.818	0.002	0.291	0.025
$50,000-$74,999	-1.215*	-0.144	-0.046	-0.527
$75,000-$99,999	0.033	0.319	0.318	-0.375
> $100,000	-1.362*	-0.178	0.047	-1.144***
Constant	0.424	2.093***	2.180***	2.629***

Goodness-of-fit	
N	661
LR ChiSquare (96)	167.54
Pr(>Chisquare)	8.624e-06
AIC	2022.232
AICc	2058.404
BIC	2471.707
McFadden's Pseudo R^2	8.4%
Cox & Snell's Pseudo R^2	22.4%
Nagelkerke's Pseudo R^2	22.4%

*Notes: Superscripts *, ** and *** indicate statistical significance at the 10 percent, 5 percent and 1 percent levels, respectively.*

Appendix A3.1. Correlation Matrix of Explanatory Variables

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10
X1	1.00	0.23	-0.19	-0.15	0.06	-0.05	-0.01	-0.05	0.00	0.02
X2	0.23	1.00	-0.17	-0.11	-0.12	0.03	-0.13	-0.06	-0.10	-0.01
X3	-0.19	-0.17	1.00	-0.05	-0.16	0.06	-0.08	0.10	0.05	-0.06
X4	-0.15	-0.11	-0.05	1.00	0.02	0.08	0.11	0.09	0.03	0.04
X5	-0.05	0.03	0.06	0.08	-0.06	1.00	0.04	0.25	-0.06	-0.03
X6	-0.01	-0.13	-0.08	0.11	0.09	0.04	1.00	-0.02	0.10	0.07
X7	0.06	-0.12	-0.16	0.02	1.00	-0.06	0.09	-0.10	0.09	-0.03
X8	-0.05	-0.06	0.10	0.09	-0.10	0.25	-0.02	1.00	-0.07	-0.08
X9	0.00	-0.10	0.05	0.03	0.09	-0.06	0.10	-0.07	1.00	0.25
X10	0.02	-0.01	-0.06	0.04	-0.03	-0.03	0.07	-0.08	0.25	1.00

Notes:

- A set of 10 explanatory variables: gender (X1), age (X2), education (X3), household size (X4), low economic status (X5), off-farm income (X6), debt (X7), contract agricultural work (X8), region (X9), crop (X10)
- Pearson correlations are reported for correlations between two continuous variables or between one continuous variable and one categorical variable, Cramer’s V (0 – 1) is used for categorical variables only.

Appendix A3.2. Probit regression results with "underuse of pesticides" as the base: "Pool" case

Independent Variables (Factors)	Reduced Model		Full Model	
	Coefficient	Std. Err	Coefficient	Std. Err
Female *(base: Male)*	0.057	*0.010*	0.064	*0.010*
Age	-0.000	*0.000*	-0.000	*0.003*
Education (base: No qualified)				
Primary school	0.118	*0.107*	0.110	*0.300*
Middle school	0.045	*0.104*	0.345	*0.277*
High school and above	-0.060	*0.132*	0.191	*0.384*
Household Size	0.001	*0.025*	0.050	*0.050*
"Poor" Status *(base: Above "poor")*	-0.305**	*0.136*	-0.317**	*0.137*
Off-farm income	0.004*	*0.002*	0.004*	*0.002*
Debt *(base: No debt)*	0.058	*0.085*	0.049	*0.085*
Contract agricultural work (*base: No)*	0.126	*0.082*	-0.197	*0.180*
Region (base: Mekong Delta)				
Red River	-0.422***	*0.101*	-0.419***	*0.101*
Northern Mountainous Areas	-0.763***	*0.115*	-0.758***	*0.115*
Northern & Coastal Centre	-1.380***	*0.107*	-1.376***	*0.108*
Others	-0.912***	*0.233*	-0.934***	*0.234*
Crop (*base: rice*)	-0.055	*0.117*	-0.062	*0.117*
Interaction Effects				
Primary school * Contract agricultural work			0.021	*0.069*
Middle school * Contract agricultural work			-0.098	*0.064*
High school & above*Contract agricultural work			-0.092	*0.089*
Primary school * Household size			0.531**	*0.233*
Middle school * Household size			0.326	*0.215*
High school & above * Household size			0.395	*0.265*
Intercept	0.062	0.226	-0.005	0.282
Goodness-of-fit				
Sample size	1526		1526	
LR ChiSquare (df)	237 (15)		248 (21)	
Pr(>Chisquare)	.000***		.000***	
AIC	1756		1758	
BIC	1842		1875	
McFadden's Pseudo R^2	12.1%		12.6%	
Cox & Snell's Pseudo R^2	14.4%		15.0%	

Appendix A4.1. Correlation Matrix of Explanatory Variables

	X1	X2	X3	X4	X5	X6	X7	X8	X9
X1	1.000	0.185	0.107	0.003	0.006	0.142	0.004	0.148	0.088
X2	0.185	1.000	0.218	0.154	0.156	0.278	0.127	0.102	0.114
X3	0.107	0.218	1.000	0.089	0.205	0.135	0.136	0.096	0.104
X4	0.003	0.154	0.089	1.000	0.124	0.197	0.040	0.083	0.045
X5	0.006	0.156	0.205	0.124	1.000	0.070	0.055	0.106	0.027
X6	0.142	0.278	0.135	0.197	0.070	1.000	0.198	0.080	0.088
X7	0.004	0.127	0.136	0.040	0.055	0.198	1.000	0.076	0.110
X8	0.148	0.102	0.096	0.083	0.106	0.080	0.076	1.000	0.176
X9	0.088	0.114	0.104	0.045	0.027	0.088	0.110	0.176	1.000

Note: Cramer's V (0 – 1) is used for the following categorical variables.

X1. Gender (male as base)

X2. Education (high school (1), 2-year (2), bachelor and higher as base)

X3. Income (<25 (1), 25-50 (as base), 50-75 (3), > 75 (4))

X4. Ethnicity (Caucasian as base)

X5. Children (No children as base)

X6. Location (rural (3), suburban (base), urban (2))

X7. Farm origin (not raised on farm as base)

X8. Health concern (disagree (base), neutral (3), agree (5) with the following statement: "*I am concerned about chemicals (pesticides) and GMO in my food*")

X9. Environmental attitude (disagree (base), neutral (3), agree (5) with for the following statement: "*they would like to buy environmentally friendly products because they are less polluting*")

Appendix A4.2. Consumer Survey for Local and Missouri Grown Food

Introduction

You are invited to participate in a survey entitled "Consumer preferences for local and Missouri Grown products." The study is being conducted by the Cooperative Research Program of Lincoln University of Missouri, 820 Chestnut St., Jefferson City, MO, 573-681-5370, suy@lincolnu.edu.

The purpose of the study is to investigate consumer perceptions toward regional and local food like Missouri Grown products and examine factors affecting consumer choice for those foods. A deeper understanding of consumer preferences for Missouri local food will help producers and relevant stakeholders design appropriate strategies to produce and market their products to improve their profitability, promote rural development and serve consumers better.

Your participation in the survey plays a key role in the investigation. It will take about 15 minutes to complete the survey. Your answers are completely confidential and voluntary. The questions in this survey do not ask you to reveal any personally identifying information. You may decline to answer any question, and you have the right to withdraw from participation at any time without penalty

Screening

1. Do you agree that you are:

   (1) 18 years of age or above
   (2) aware that your answers remain anonymous
   (3) and aware that your participation is voluntary?

○ Yes
○ No

2. Are you the primary grocery shopper in your family?

- Yes
- No

3. Which of the following products have you purchased in the past 12-month period? Select all that apply (*all fresh, canned, or frozen products are acceptable*):

- Tomatoes
- Apples
- Corn
- Onions
- Eggs
- None of them
- Chicken
- Pork
- Ground Beef
- Milk
- Honey

Shopping Behavior

4. Where do you plan to do your grocery shopping in the next six months? (*Check all that apply*)

- Farmers' market
- "Natural food" store
- Grocery store/ Supermarket
- Online order, store pickup
- Local store (same town) delivery
- Mail delivery
- Community Supported Agriculture (CSA)*
  Note: CSA is a marketing model whereas consumers prepay local farmers to receive shares in the farm's output periodically throughout the growing season.
- U-Pick, Farm stand pickup, and other direct sales
- Others

5. How often do you shop for fresh fruits and vegetables?

- ○ More than twice a week
- ○ Twice a week
- ○ Once a week
- ○ A few times per month
- ○ Never

6. What are the three most important factors that you consider before buying fresh fruits and vegetables? (please choose three)

- ☐ Certification (e.g., USDA Organic, Non-GMO Verified, Fair Trade Certified, ...)
- ☐ Freshness
- ☐ Nutrition
- ☐ Brand name
- ☐ Place of origin
- ☐ Taste
- ☐ Price
- ☐ Supporting fair wages for farmers (Fair Trade)
- ☐ Appearance

7. Indicate how important these issues are regarding your fresh fruit and vegetable purchases:

	Very important	Important	Somewhat important	Slightly important	Not important	I don't know
Reducing water pollution	○	○	○	○	○	○
Reducing soil erosion	○	○	○	○	○	○
Limiting genetically modified organisms (GMOs) in food	○	○	○	○	○	○
Please choose "Not important"	○	○	○	○	○	○
Minimizing pesticide residue	○	○	○	○	○	○

	Very important	Important	Somewhat important	Slightly important	Not important	I don't know
Supporting local farms and communities	○	○	○	○	○	○
Supporting fair wages for farmers (Fair Trade)	○	○	○	○	○	○

Local food

8. How do you define "local" food?

- ○ "Local" is defined by "geographic" perspectives (a)
- ○ "Local" is defined by "type of producer" perspectives (b)
- ○ Both of the above are relevant to my definition (c)
- ○ None of the above (please indicate):

Note: If you choose the answer (a), please answer the following 8a;
if you choose the answer (b), please skip to 8b.

8a. Choose the one option that most closely matches your definition of local food from "geography" perspectives

- ○ Grown in my state
- ○ Processed in my state but grown elsewhere
- ○ Grown within 50 miles of my home
- ○ Grown within 400 miles of my home
- ○ Grown within 100 miles of my home
- ○ Grown in my county
- ○ Other (please indicate):

8b. Choose the one option that most closely matches your definition of local food from "type of producer" perspectives

- ○ Produced by small or medium family farms
- ○ Produced by any family farms
- ○ Other (please indicate):

9. In the past 12 months, have you purchased local food according to your preferred definition?

- ○ Yes
- ○ No

10. Which of the following describes your reasons for not buying local food in the last year? (*Check all that apply*)

- ☐ Not available in my area
- ☐ Grow it myself
- ☐ Not interested in buying
- ☐ Local food is expensive
- ☐ Not aware of local food
- ☐ Lack of variety/choices
- ☐ Others (please indicate)

11. Where do you purchase local food? (*Check all that apply*)

- ☐ Online order, store pickup
- ☐ Farmers' market
- ☐ Mail delivery
- ☐ U-Pick, Farm stand pickup, and other direct sales
- ☐ Local delivery
- ☐ Grocery store/ Supermarket
- ☐ Community Supported Agriculture (CSA)
- ☐ Natural store
- ☐ Others (please indicate)

12. What motivated you to buy local food? (*Check all that apply*)

- ☐ Price is lower

- ☐ Local food has better quality such as fresher, better flavor
- ☐ Local food is healthier for me and my family
- ☐ Local food is more environmentally-friendly and sustainable
- ☐ Origin of food is clear to me
- ☐ Building relationship with farmers
- ☐ Supporting local small farms
- ☐ Supporting my local community

Missouri Grown Products

This label is created by the Missouri Department of Agriculture to promote the Missouri grown products

13. Have you seen this label before?

- ○ Yes
- ○ No

14. Where have you seen this label? (*Check all that apply*)

- ☐ Directly from producers
- ☐ Facebook
- ☐ Magazines/newspapers
- ☐ Internet
- ☐ Grocery stores/ Supermarkets
- ☐ Farmers markets
- ☐ Others (please indicate):

15. Have you ever bought any products with Missouri Grown label?

- ○ Yes
- ○ No

16. Would you like to buy Missouri Grown Label products if you see them?

- ○ Yes
- ○ No
- ○ Maybe

Note: If you choose Yes, please answer 16a; if you choose No, please answer 16b, otherwise you can answer 16a and 16b.

16a. What are reasons for choosing Missouri Grown products? (*Check all that apply*)

- ☐ Familiar with Missouri Grown products
- ☐ Supporting farms in Missouri
- ☐ Supporting communities
- ☐ Missouri Grown products have better quality
- ☐ Missouri Grown products have lower price
- ☐ Others (please indicate):

16b. What are reasons for NOT choosing Missouri Grown products? (*Check all that apply*)

- ☐ Not interested in local products
- ☐ Familiar with different labels rather than Missouri Grown
- ☐ Missouri Grown products are not different from other products
- ☐ Missouri Grown products have higher price
- ☐ Others (please indicate):

Environmental Attitude

17. Indicate your opinion about the following statements:

	Strongly Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Missouri Grown and local food are the same to me	○	○	○	○	○
Organic and local food are the same to me	○	○	○	○	○
I am concerned about chemicals (pesticides) and genetic modification technologies (GMO) in my food	○	○	○	○	○
It is too expensive to produce green/sustainable/eco-friendly/organic products	○	○	○	○	○
I would like to buy environmentally friendly products because they are less polluting	○	○	○	○	○
I would like to buy environmentally friendly products because they are healthier, safer, and of better quality	○	○	○	○	○
I would be willing to pay more to improve environmental protection (i.e., through local taxes or higher product prices)	○	○	○	○	○
The quality of life in my community depends on good water quality in local streams, rivers, and lakes.	○	○	○	○	○

Choice Experiment Instructions

Imagine you are interested in buying fresh tomatoes. There are four following basic attributes or characteristics to consider when making your purchase decisions.

1. Production method: organic; 50% reduced pesticide (this method means farmers use half of the pesticide amount that is usually used in tomato cultivation); and conventional techniques.

2. Label: local; Missouri Grown; and No local or Missouri Grown label.

3. Farm type: small & medium family farms, large family farms, large corporate farms (by

USDA criteria, family farms are mainly owned or operated by members of a family; small & medium family farms have annual sales less than $350,000)

4. Price: $1.99/lb; $2.99/lb; and $3.99/lb.

There are 3 distinct choices or opt-out option presented over 9 following scenarios.

Choice Experiment: 9 scenarios

18. Scenario 1

	Option A	Option B	Option C
Method	**50% Reduced pesticide**	**Conventional**	**Organic**
Label	**Local**	**Local**	**Missouri Grown**
Farm	**Small & medium family**	**Large family**	**Small & medium family**
Price	**$2.99/lb**	**$1.99/lb**	**$2.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

19. Scenario 2

	Option A	Option B	Option C
Method	**Organic**	**Conventional**	**Conventional**
Label	**Local**	**No Local or Missouri Grown**	**Missouri Grown**
Farm	**Large family**	**Large family**	**Large Corporation**
Price	**$2.99/lb**	**$2.99/lb**	**$1.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

20. Scenario 3

	Option A	Option B	Option C
Method	50% Reduced pesticide	Organic	50% Reduced pesticide
Label	Local	Missouri Grown	Missouri Grown
Farm	Large Corporation	Large family	Small & medium family
Price	$1.99/lb	$1.99/lb	$2.99/lb

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

21. Scenario 4

	Option A	Option B	Option C
Method	Conventional	50% Reduced pesticide	Organic
Label	Missouri Grown	Local	No Local or Missouri Grown
Farm	Small & medium family	Large Corporation	Large Corporation
Price	$3.99/lb	$2.99/lb	$3.99/lb

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

22. Scenario 5

	Option A	Option B	Option C
Method	**Conventional**	**50% Reduced pesticide**	**Organic**
Label	**Missouri Grown**	**No Local or Missouri Grown**	**No Local or Missouri Grown**
Farm	**Large Corporation**	**Large family**	**Small & medium family**
Price	**$2.99/lb**	**$1.99/lb**	**$3.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

23. Scenario 6

	Option A	Option B	Option C
Method	**Organic**	**Conventional**	**50% Reduced pesticide**
Label	**No Local or Missouri Grown**	**Local**	**Missouri Grown**
Farm	**Large family**	**Large Corporation**	**Large family**
Price	**$2.99/lb**	**$3.99/lb**	**$1.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

24. Scenario 7

	Option A	Option B	Option C
Method	**Conventional**	**Organic**	**50% Reduced pesticide**
Label	**Local**	**Local**	**Missouri Grown**
Farm	**Small & medium family**	**Large Corporation**	**Large Corporation**
Price	**$2.99/lb**	**$1.99/lb**	**$3.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

25. Scenario 8

	Option A	Option B	Option C
Method	**Organic**	**Conventional**	**50% Reduced pesticide**
Label	**No Local or Missouri Grown**	**Local**	**Local**
Farm	**Large Corporation**	**Small & medium family**	**Large family**
Price	**$1.99/lb**	**$1.99/lb**	**$3.99/lb**

Which choice for buying tomatoes would you prefer?

O Option A O Option B O Option C O None of them

26. Scenario 9

	Option A	Option B	Option C
Method	**Conventional**	**Conventional**	**Organic**
Label	**No Local or Missouri Grown**	**Missouri Grown**	**Missouri Grown**
Farm	**Small & medium family**	**Large family**	**Large family**
Price	**$1.99/lb**	**$2.99/lb**	**$3.99/lb**

Which choice for buying tomatoes would you prefer?

○ Option A ○ Option B ○ Option C ○ None of them

Demographic information

27. Gender:

○ Male
○ Female
○ Non-binary / third gender
○ Prefer not to say

28. Age:

○ Under 18
○ 18 - 24
○ 25 - 34
○ 35 - 44
○ 45 - 54

- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

29. The Highest Educational Attainment:

- Some high school or less
- High school degree
- 2 year / Associate's degree
- 4 year / Bachelor's degree
- Graduate or professional degree

30. Employment status:

- Full-time employed
- Part-time employed
- Unemployed
- Retired
- Others

31. Annual household income:

- Less than $25,000
- $25,000-$50,000
- $50,000-$75,000
- $75,000-$100,000
- $100,000 and above

32. Ethnicity:

- Caucasian

- African American
- Native American
- Hispanic/ Latino
- Asian/ Pacific Islander
- Other

33. Number of Children under 17:

34. Housing location:

- Urban
- Suburban
- Rural
- Others (please indicate):

35. Were you or your parents raised on farm?

- Yes
- No

Please write down any comments you might have regarding this survey: such as if you had any issues with understanding specific questions, the content or the format of the study.

End of the Survey

This study has been reviewed and approved by the Lincoln University of Missouri Campus Institutional Review Board.
If you have questions regarding your rights as a participant in this study, you may contact the Institutional Review Board (IRB) at (573)681-5151 or e-mail HomannG@lincolnu.edu.
IRB Approval Number IRB F2020-01.

VITA

Tran The Lan, son of Tran The Lam and Nguyen Thi Ha, husband of Vu Thi Cam Tu, and father of Tran Vu, Tran Vu Dang, Tran Vu Dang Minh, and Tran Vu Duy Anh, was born in Hanoi, Vietnam on October 27, 1981. He received his Bachelor of Arts in International Economics and Master of Arts in International Economics from Vietnam National University-Hanoi, Vietnam. Lan then attended University of Missouri-Columbia, where he received master's in economics, master's in Applied Statistics, and worked on his Doctor of Philosophy degree. His general research interests contain environmental and resource economics, individual and household decision making, local food system, efficiency of farm operations, and behavioral health data analytics. Lan is currently working on topics regarding outdoor recreation, eating well, pesticide management practices, state agricultural marketing programs, and data mining applications.