# Essays in Sustainable Food and Agricultural Systems

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# Chapter 1

## Introduction

In response to the rapid increase in the world population and the corresponding increase in global demand for food and agricultural products, driven by urbanization and income growth, there is a pressing need to develop more resilient and sustainable agricultural and food systems (Calicioglu et al., 2019). To attain this ultimate goal, a greater quantity of high-quality data and more extensive research will be needed. Although there is existing evidence on the impact of various factors on agriculture and food availability in different settings, a considerable amount of uncertainty still surrounds these issues, leaving many aspects unknown. This uncertainty can be attributed to the inherent complexity of these problems, which demand a holistic, systems-thinking approach for in-depth analysis and effective solutions. This dissertation addresses two such concerns in the United States: municipal solid waste (MSW) generation and pesticide resistance, both presenting distinct challenges that demand effective and innovative solutions. It comprises two papers, with the first focusing on an experimental study exploring informational interventions to encourage households to recycle organic materials, and the second presenting empirical models on understanding farmers' management practices in response to emerging pesticide-resistant soybean aphid.

The first paper addresses the critical issue of MSW generation and its environmental impacts. In the United States, large amounts of MSW are generated annually, leading to numerous environmental problems, including greenhouse gas emissions and contamination of landfills. Organic waste, mainly composed of food waste, constitutes a significant portion of MSW. Despite the potential for recycling and composting, a significant amount of organic waste still ends up in landfills.

In Chapter 2, I explore the role of educational and social influence interventions in encouraging households to recycle organic materials effectively. The study focuses on two cities in Minnesota with different organics recycling programs: one following an opt-in approach and the other implementing an opt-out program. By testing these interventions, the research aims to offer practical insights for other suburban areas and inform policy design at the municipal level. The effectiveness of interventions varied based on participant characteristics and program design. Participants with less than two years of experience exhibited more significant responses to the educational intervention in inducing favorable behavioral changes, while social influence interventions had a limited impact on behavioral outcomes in both opt-in and opt-out programs. Regarding the content of generated organics, the results of the social influence intervention in the opt-out program indicated a potential positive spillover effect, as engaging in organics recycling led to a reduction in overall food waste generation.

In Chapter 3, I investigate how pesticide resistance impacts farmer management practices, specifically in the context of pyrethroid-resistant soybean aphids. Pesticide resistance poses a significant challenge to intensive agriculture, leading to increased production risks and economic losses. To assess how farmers adapt their management practices in response to pesticide resistance, the study proposes a survey protocol designed to capture decision-making processes during the emergence of new challenges like pesticide resistance.

This study investigates the adoption of an integrated pest management (IPM) approach by farmers in Minnesota and North Dakota as a means of managing insecticide resistance in a more resilient and sustainable manner. The research entails an analysis of survey data collected from soybean farmers in these regions, employing instrumental variables to mitigate endogeneity concerns and facilitate the estimation of causal relationships. The results suggest a causal relationship between reports of a change in management due to insecticide resistance and positive developments for the management of soybean aphid resistance, including increased field scouting, increased field scouting frequency, and increased use of organophosphate insecticides.

This dissertation makes a significant contribution to the field of food and agricultural economics by providing valuable insights into encouraging household recycling of organic materials and understanding farmers' responses to pesticide resistance. A unifying theme throughout the dissertation is the development and application of original survey methods, carefully designed to capture realistic decision-making processes.

These survey methods offer a novel perspective on the complex dynamics at play within both households and farming communities. By examining the decision-making processes of households regarding organic material recycling and farmers' responses to pesticide resistance, this research clarifies on critical aspects of sustainable agriculture and resource management. The following chapters delve deeper into the methodologies, results, and implications of each paper, with a focus on how the original survey methods contribute to a comprehensive understanding of these pressing issues.

# Chapter 2

# Effects of social influence and educational interventions on household organics recycling: Evidence from two municipal curbside organics recycling programs

## 2.1 Introduction

Municipal solid waste (MSW) generation is a significant environmental concern in the United States. In 2018, the country produced a total of 292.4 million tons of MSW, equivalent to 4.9 pounds per person per day. Of this amount, only 32.1% (94 million tons) were recycled or composted, while more than 50% (146 million tons) were sent to landfills. This leads to a myriad of environmental problems, as landfills provide an ideal environment for the decomposition of organic materials, which constitute approximately one third of the total MSW (Buzby et al., 2014). According to the Environmental Protection Agency (EPA), landfills are the third largest source of human-related methane emissions, accounting for 14.5% of methane emissions in the United States in 2020 (Kaza et al., 2018; Zhang et al., 2010; EPA, 2020).

Food waste, referring to consumable parts and inedible components that are discarded before or after spoilage, accounts for the majority of organic waste (Ishangulyyev et al., 2019). Approximately 30-40% of food produced in the US is discarded in landfills. According to the EPA's estimates in 2010, the average amount of food waste per person sent for disposal was approximately 218.9 pounds, with a corresponding economic value of $161 billion (EPA, 2020). To mitigate these negative effects, it is essential to reduce food waste generation and redirect organics from landfills through recycling and composting. Composting systems, in particular, represent a cost-effective and environmentally sustainable method to break down organic material to produce biogas, fertilizer, and soil amendments that enhance soil texture and fertility (Cerda et al., 2018; Mu et al., 2017).

Given that a substantial portion of organic waste is generated by households and consumers [1] (Jörissen et al., 2015; Qi and Roe, 2016), it is crucial to promote the recycling of organic materials, proper waste sorting, and reducing food waste at the household level to address the issue of municipal solid waste and improve environmental quality. Extensive scholarly research has been dedicated to examining various psychological and contextual factors that shape household recycling behavior. These factors include intrapersonal dimensions such as attitudes, beliefs, and motivations; interpersonal interactions such as peer effects and social norms; and contextual factors such as characteristics of recycling services (e.g., mandatory vs. voluntary), the availability of curbside collection, and the provision of waste separation bins (Berger, 1997; Timlett and Williams, 2009; Saphores and Nixon, 2014; Varotto and Spagnolli, 2017; Geiger et al., 2019).

In recent years, many local governments have introduced or considered offering residential organics recycling services to their residents as an effective means of diverting organic waste from landfills (EPA, 2020). While the lack of necessary contextual factors,

[1] Based on EPA's estimations of food waste generation in the United States in 2019, the food manufacturing and processing sector emerge as a prominent contributor to the nation's food waste, constituting approximately 39% of the total. Although the commercial operations of the food retail and food service sectors together represent the second largest source of food waste in the country, their individual contributions are comparable to that of the residential sector. Specifically, the residential sector contributes approximately 25%, while the contribution of the food service sector and the food retail sector is 25.2% and 12.2% to the national food waste, respectively (EPA, 2023).

specifically the infrastructure and service provision, emerges as a significant barrier that impedes household participation in recycling activities (Tonglet et al., 2004; Timlett and Williams, 2009), motivations are intended to be more powerful determinants of changing individual attitudes and behavior toward recycling (Schultz et al., 1995; Miafodzyeva and Brandt, 2013; Varotto and Spagnolli, 2017). Several interventions including behavioral, informational, contextual and financial have been investigated in the literature to promote behavior change regarding pro-environmental practices. In the field intervention strategies, appropriate persuasive interventions can be designed to target psychological factors, specifically intrapersonal dimensions and interpersonal interactions, to promote the adoption of pro-environmental behaviors among households. Two such interventions that have received considerable attention are educational interventions and social norms interventions (Frederiks et al., 2015; Osbaldiston and Schott, 2012; Varotto and Spagnolli, 2017).

Educational interventions can affect behavioral habits change through several mechanisms. According to Bandura (2002), among various self-regulation mechanisms, self-efficacy serves as the most accurate predictor of an individual's inclination to participate in an activity, especially if the activity necessitates substantial personal effort. Self-efficacy is the belief in one's ability to perform the behavior or carry out the required actions appropriately (Bandura et al., 1999). In the context of organics recycling, this can be achieved by providing clear and concise guidance on correctly recycling organic materials and avoiding contaminating the recycling stream with incorrect or non-recyclable items. Ultimately, individuals can raise their confidence in their ability to perform recycling tasks successfully, which in turn improves their self-efficacy. Then, increased self-efficacy can lead to increased intention to perform the behavior and a greater likelihood of engaging in recycling (Schultz, 2002; Varotto and Spagnolli, 2017; Barr, 2007; Geiger et al., 2019; Abrahamse et al., 2005; Sherer et al., 1982; Steg and Vlek, 2009; Tabernero, 2015).

A vast body of empirical evidence demonstrates that an individual's behavior is positively correlated with their beliefs about the behavior of others. In the realm of pro-environmental behavior research, households' environmental attitudes and behaviors have been shown to be highly influenced by social factors or social influence (Southerton et al., 2011; Viscusi et al., 2011; Delmas et al., 2013; Farrow et al., 2017; Geiger et al., 2019).[2] This phenomenon is often linked to social norms, which are the expectations that govern how people should behave in a particular social context (Zhang et al., 2022; Abrahamse et al., 2005; Schultz, 2014).

Social influence interventions are designed to promote individual behavior change by targeting social identity, a process in which individuals define themselves in relation to social communities or groups. In order to shape their behavior, individuals often engage in social comparisons, observe the behavior of others, and conform to social norms (Feldman, 1984; Cialdini and Trost, 1998). One effective way of using social identity for improving behavior shaping is through descriptive norms, which motivate individuals by providing suggestions about effective and adaptive behavior (Frederiks et al., 2015; Cialdini and James, 2009). This normative social influence intervention would be designed by the involvement of well-known community members as social role models (Wolske et al., 2020). These individuals are respected and admired within their community, and their behavior is seen as desirable and worthy of emulation. By highlighting the pro-environmental behavior of these community members and framing it as a reflection of a shared social identity, social influence interventions can increase efforts on waste management practices and induce more sustainable behavior practices within the community (Wolske et al., 2020; Frederiks et al., 2015).

Despite decades of research evaluating interventions to encourage pro-environmental

[2] In the literature on social influence, a significant distinction is made between injunctive norms and descriptive norms. Injunctive norms relate to what significant others believe an individual should do, while descriptive norms refer to what significant others themselves do (Rivis and Sheeran, 2003). These are considered separate sources of motivation, according to the work of Deutsch and Gerard (1955). The subjective norm component of the Theory of Planned Behavior (TPB) is an example of an injunctive social norm, as it pertains to the perceived social pressure on an individual to engage in a particular behavior based on the potential for gaining approval or facing sanctions from significant others. Descriptive norms, on the other hand, involve perceptions of significant others' attitudes and behaviors in a specific domain (Conner et al., 2002; Rivis and Sheeran, 2003).

behavior among urban residents by many authors, there is no unanimous approach and sufficient evidence to favor one approach over another to make optimal shifts in individuals' behavior (Nomura et al., 2011; Varotto and Spagnolli, 2017; Milford et al., 2015; Geiger et al., 2019; Parizeau et al., 2015; Knickmeyer, 2020). This study presents the results of a field experiment designed to evaluate the effectiveness of educational and social influence interventions for encouraging households to separate organic materials for recycling in two cities in Minnesota. Specifically, the primary aim of the study is to examine the impact of educational and social influence interventions on the behavior of participants towards organics recycling practices, which includes participants' effort level, habitual forming, and confidence levels related to the proper practice of organics recycling. Furthermore, the study seeks to investigate the effect of these interventions on the amount of organic waste generated by participants, measured in both weight (lbs) and the number of organic items placed in the recycling bin.

The educational intervention in this field experiment involved the use of 2-minute video clips provided weekly by the city's organics recycling coordinator, which aimed to educate participants on the appropriate items that can and cannot be placed in organics recycling bins. This intervention aimed to increase participants' knowledge and understanding of organics recycling guidelines, in order to promote more accurate and effective recycling behaviors. The social influence intervention in this experiment involved using community leaders to model and promote the desired behavior of organics recycling. The influencers provided a 2-minute video clip for each week of the study period, emphasizing the ease and convenience of recycling organics.

The study takes place in Hennepin County, Minnesota, where in November 2018, ordinance N13 was passed, requiring cities with populations greater than 10,000 to implement curbside collection of organic materials for residential households by January 2022. The city of St. Louis Park began offering an opt-in program for organics recycling curbside collection in October 2013, preceding the ordinance, and by the end of summer 2020, it had a participation rate of 37.7%. In contrast, the city of Edina launched a city-wide residential curbside collection program for organics recycling in June 2020 in response to the ordinance, with every household receiving an organics recycling cart and a participation rate of about 30% as of the time of the study. Both cities are suburbs of Minneapolis and comparable in size.[3] This provides an opportunity to investigate the effectiveness of the study interventions in different organics recycling settings. By testing informational interventions in these municipalities, the research aims to provide practical insights for other suburban areas and inform policy design at the municipal level. Especially by comparing the results from two distinct organics recycling programs, opt-in and opt-out programs, the study would support evidence-based program design for effectively achieving environmental goals.

## 2.2 Background

In recent decades, researchers have focused extensively on identifying and characterizing the key determinant factors influencing individuals to engage in pro-environmental actions, such as organics recycling. These factors include but are not limited to socio-demographics, psychological and contextual factors (Huffman et al., 2014; Geiger et al., 2019; Klöckner and Matthies, 2004; Li et al., 2017; Schultz et al., 1995). The relationship between demographic factors such as socioeconomic status, age, gender, household size, housing type, and cultural background with waste separation remains inconclusive and inconsistent due to mixed findings across various studies (Huffman et al., 2014; Varotto and Spagnolli, 2017; Farley et al., 2018; Brandon and Lewis, 1999). However, in order to develop effective interventions aimed at promoting sustainable recycling behavior and minimizing waste generation, it is important to take into account a range of psychological and contextual factors. These factors encompass individual attitudes and beliefs, knowledge and information, social norms, as well as the convenience of recycling programs, including factors such as access to recycling facilities, ease of the sorting process,

[3] Edina, with a population of approximately 53,059, and St. Louis Park, with a population of approximately 49,539 (American Community Survey 5-year estimate, 2021).

and proximity to collection points (Knickmeyer, 2020; Miafodzyeva and Brandt, 2013; Wan et al., 2017; Timlett and Williams, 2009; Varotto and Spagnolli, 2017).

Behavior-change interventions aimed at promoting household recycling and waste sorting behavior are commonly based on the well-established Theory of Planned Behavior (Ajzen, 1991; Schwartz and Howard, 1981). This theory suggests that recycling intentions can be predicted by three key factors: a positive attitude towards recycling, social norms that reflect the expectations of relevant individuals, and perceived behavioral control, which pertains to an individual's belief in their ability to engage in the desired recycling behavior (Knickmeyer, 2020; Klöckner and Matthies, 2004; Wan et al., 2017; Yuriev et al., 2020).

Educational interventions can affect behavioral habits change by increasing information and knowledge. These interventions involve providing individuals with information on recycling, which can be provided in traditional methods of written or face-to-face, or supplemented with online methods by SMS and Emails (each approach has its unique set of benefits and barriers) (Schultz, 2002; Timlett and Williams, 2008; Bernstad et al., 2013; Varotto and Spagnolli, 2017). This increased knowledge can lead to positive attitudes and intentions toward the environment and, consequently, recycling more (Schultz, 2002; Steg and Vlek, 2009; Varotto and Spagnolli, 2017). Previous studies have shown that educational campaigns, awareness-raising, and information dissemination have proven to be successful in motivating communities to participate in municipal recycling programs and improving recycling quality (disposing all recyclable items without contaminants) (Grodzińska-Jurczak et al., 2006; Dolloff, 2017; Issock et al., 2020; Ma et al., 2020; Schanes et al., 2018; Perrin and Barton, 2001; Evison and Read, 2001; Smeesters et al., 2003).

However, it is important to note that simply providing information alone may not guarantee action and may not be sufficient to drive recycling behavior. Consumers may struggle to understand general information, or they may choose not to engage with the information provided (Ojala, 2008; Refsgaard and Magnussen, 2009). To maximize the effectiveness of educational campaigns, it is crucial to tailor the information to the specific characteristics of the target group. For example, individuals with low recycling experience or no recycling behavior may benefit more from practical guidance on how to carry out recycling appropriately, while those with established recycling habits may be more interested in learning about the outcomes of recycling (Varotto and Spagnolli, 2017). By aligning the information provided with the specific needs and interests of the target audience, the strength of the educational campaign can be enhanced. This approach is particularly relevant during the initial stages of a new recycling program or when significant changes are made to an existing program, as individuals may require clear instructions and support to adapt to the new system (Steg and Vlek, 2009).

In a study, Timlett and Williams (2008) examined the relationship between public participation and recycling performance in England, specifically focusing on the effectiveness of various behavior change based tools.[4] The finding suggests that while some interventions, such as providing personalized incentives and feedback on recycling performance, were effective at improving recycling quality and reducing the contamination rate, they may not necessarily result in significant changes in recycling participation. This could be attributed to the initially high level of participation.

To implement a successful source-separation organics recycling program, households who participate in organics recycling need to be knowledgeable about organic materials and less likely to contaminate their organics recycling bin with unacceptable non-organic materials. The level of households' knowledge regarding the items that can and cannot be included in organics recycling plays a crucial role in determining households' confidence and effort levels towards participating in organics recycling through increasing their self-efficacy and positive attitudes toward waste separation practices (Aschemann-Witzel et al., 2015; Qi and Roe, 2016). However, previous studies highlighted a gap between

[4] The paper details the outcomes of three approaches to stimulating behavior change aimed to increase participation in the recycling collection and to reduce the inclusion of contaminant materials, in Portsmouth city in England, between 2005 and 2006. The project employed behavior change based approaches, including face-to-face doorstepping campaigns, positive incentives (rewards), and personalized feedback (Timlett and Williams, 2008).

theoretical predictions and actual practice that was having a positive attitude toward recycling might not necessarily translate into actual recycling behavior based on self-reported measures (Li et al., 2017).

Several studies suggest that habits serve as strong barriers to making lifestyle changes, as they tend to solidify and perpetuate existing behaviors. Consequently, numerous interventions, such as informational interventions, often prove ineffective due to their limited ability to break the established habits (Marechal and Lazaric, 2010; Whitmarsh et al., 2021; Verplanken et al., 1997). Habits are defined as persistent behaviors that become automatic through repeated exposure to contextual cues (Kurz et al., 2015). However, since habits are cued by stable contexts, successful habit change interventions involve changing in context and disrupting the environmental factors that automatically trigger habitual behavior. This understanding has led to the identification of significant life events or structural disruptions as key opportunities to change behaviors more effectively (Verplanken and Wood, 2006; White et al., 2019).

On the other hand, there is increasing emphasis on incorporating insights from social influence theories [5] and individual perceived self-efficacy in the development and shaping of informational interventions, particularly those focused on educational messages and social influence (Timlett and Williams, 2009; Abrahamse and Steg, 2013). The presence, behaviors, and expectations of others often play a crucial role in driving changes in sustainable behavior through increasing individuals' perceived self-efficacy or their belief in their ability to engage in recycling behavior (Steg and Vlek, 2009; Abrahamse et al., 2005; Varotto and Spagnolli, 2017; Wolske et al., 2020).

One of the most prevalent and effective social influence approaches is the use of social norms in information provision for promoting behavior change. Social norms encompass the rules and standards that are collectively understood and followed by a group, playing

[5] In a study by Abrahamse and Steg (2013), they have identified six social influence approaches that are frequently used in the psychology literature including (i) the use of social norms in the provision of information and feedback, (ii) the involvement of block leaders and social networks, (iii) the establishment of public commitments, (iv) modeling, (v) the incorporation of social comparison in the provision of feedback regarding group performance.

a guiding and constraining role in shaping human behavior (Cialdini and Trost, 1998). For instance, Nomura et al. (2011) randomly assigned 318 streets in Oldham, Greater Manchester, to a treatment and control group. In this randomized controlled trial, the treatment group households were provided with postcards that delivered feedback regarding their street's performance in food waste recycling relative to the neighborhood average. They examined the effects of activating the collective norm through feedback on recycling behavior. Their results proved that providing repeated positive feedback on their street's food waste recycling rate compared with others affected food waste participation by approximately 2.8% compared with the control group.

Block leaders are individuals who voluntarily assume the role of disseminating information within their social network (Abrahamse and Steg, 2013). Social influence interventions, those involving block leaders, are built upon the understanding that information is more influential when it is conveyed by someone within the same social network, emphasizing the significance of peer influence and the strength of social connections in shaping behavior(Bandura and Walters, 1977; Osbaldiston and Schott, 2012). The effectiveness of block leaders can be attributed to the principle of liking and the perception of similarity between individuals.[6]

Previous research showed individuals are more willing to engage in organics recycling when approached by a block leader from their community, as motivational strategy by utilizing respected community members as role models (Burn, 1991). This approach involves community members who are already involved in waste separation activities acting as social models or block leaders, inspiring others to adopt sustainable behaviors by establishing social normative pressure and fostering a sense of community support for the behavior (Xu, 2018; Osbaldiston and Schott, 2012; Frederiks et al., 2015).

A study by Wolske et al. (2020) comprehensively investigated the ways in which individual actions impact others and shape a social influence framework for understanding

[6] People are more inclined to comply with requests when they perceive a sense of similarity, including spatial (others who live in my neighborhood), social (others who are in my social network), or demographic and attitudinal similarities (Wolske et al., 2020).

peer effects in energy-related decisions. They defined peer effects as the direct outcome of two different social influence processes including interpersonal communication and persuasion, and social norms. Interpersonal communication focuses on direct or indirect communication that can occur among peers, including one-on-one conversations, group meetings, and online discussions. This method involves social learning and the observation of others' behavior. On the other hand, normative social influence explores the role of social norms in shaping energy-related decisions and can lead individuals to conform to the group norm. While interpersonal communication involves deliberate efforts to influence others, normative social influence can operate more passively through the influence of social norms.

In another study by Nolan et al. (2008), they sought to investigate the extent to which individuals are influenced by normative social influence and whether this influence is often underdetected. The research was conducted as a field experiment in which they attempted to reduce energy usage among homeowners by informing them that their neighbors were using less energy. The result showed a significant decrease in energy consumption among the treatment group who received this information, indicating the powerful influence of normative social influence. However, when participants were asked whether they thought their neighbors' behavior influenced them, only a small minority acknowledged this influence, highlighting the underdetection of normative social influence.

Although previous research has provided valuable information on the effectiveness of different intervention strategies to promote participation in organic recycling, the current study aims to make a unique contribution by examining the impact of behavioral-related interventions on a wide range of outcomes, including effort level, habit strength, and confidence level in the context of organic recycling practices. Additionally, the study seeks to investigate the effect of these interventions on the amount of organic waste generated by participants, measured in both weight (lbs) and the number of organic items placed in the bin. This is an important contribution to the field, as measuring accurately the weight of generated organic waste is a limited factor in evaluating the success of organic recycling programs. By exploring these outcomes, the study seeks to shed light on the mechanisms underlying the success of different intervention strategies and provide more nuanced guidance for policymakers and practitioners seeking to promote sustainable waste management practices. Thus, the present study builds on the existing literature by providing a more comprehensive understanding of the effects of behavioral interventions on organics recycling behavior, which can help inform future intervention design and implementation efforts.

## 2.3 Hennepin County Organics Recycling Program

In 2014, the Legislature raised the recycling targets for counties within the Twin Cities metropolitan area. The new mandate stipulates that by 2030, these metropolitan counties must achieve a recycling rate of 75 percent for the total solid waste generated, measured by weight (Office of the Legislative Auditor(OLA), 2015). The newly established recycling goal, which encompasses both traditional recycling and organics, reflecting a commitment to conserving natural resources, preserving the environment, and ensuring public health and safety (Solid Waste Management Policy Plan, MPCA, 2016). In 2021, Hennepin County generated approximately 1.3 million tons of solid waste, including recycling, organics, and trash, which is a 5% increase from 2020, or roughly 64,500 tons more. Out of the total waste generated, only 39% was managed through recycling and organics programs (Recycling Progress Report, 2022). The Hennepin County Organics Recycling Program is a county-wide initiative to divert organic waste from landfills and incinerators, reduce greenhouse gas emissions, and create a valuable resource for soil health. The program accepts a variety of organic materials, including all food scraps, food-soiled paper products, certified compostable products, and other compostable household items. Over the past 15 years, a significant trend has been observed as the steady rise in the amount of organic waste. This growth is attributed to multiple factors, such as the expansion of the commercial organic waste collection, the implementation of new curbside organic waste programs by several cities, and the Minnesota Pollution Control Agency's decision to include yard waste in the organic waste category (Recycling Progress Report, 2022).

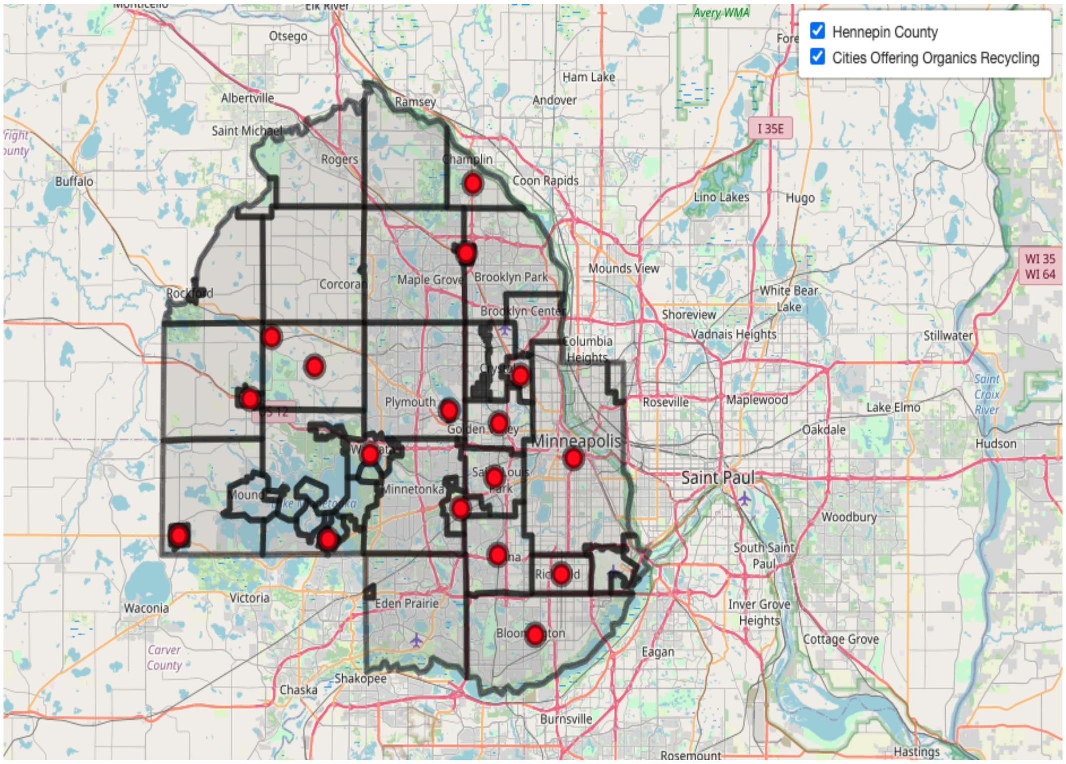
Various participation options are available for residents, including citywide curbside collection and drop-off sites. In November 2018, cities with populations over 10,000 were required to provide curbside collection of organic materials for their residential households (single-family through fourplex) by January 2022. This requirement was part of revisions the county made to its recycling ordinance (Ordinance 13) in November 2018 (Ordinance 13-Hennepin County, 2018).[7] The collection is to be carried out on a weekly basis, year-round. The county left it to each individual city to determine the method and cost for implementing the service of organics recycling.[8] As of June 2021, 17 cities of Hennepin County (or 37%), including St. Louis Park and Edina, have implemented the curbside collection of organics recycling program for their residents, with more than 80,000 households (23% participation rate) across Hennepin County participating (Recycling Progress Report, 2022).[9] The figure 2.1 illustrates cities within Hennepin County that provide organics recycling services to their residents by 2021.

[7] This is part of the Amended to Ordinance 13 on November 27, 2018. The Ordinance 13, Recycling for Hennepin County, was adopted by the Hennepin County Board of Commissioners in 1986, to regulate the separation of mixed recyclables and organic material from Waste by generators. This ordinance is consistent with County adopted goals established by the Minnesota Pollution Control Agency in its Metropolitan Solid Waste Management Policy Plan and mandated by Minnesota Statute, requiring a 75% recycling rate by 2030.

[8] Some cities require all residents to pay a flat fee for the curbside collection service, while others provide the service as an opt-in option for those who voluntarily sign up for it.

[9] In 2021, the county expanded its organics recycling drop-off sites to 38 sites, including those at the Bloomington and Brooklyn Park drop-off facilities.

Figure 2.1: Cities within Hennepin County that offer organics recycling to their residents by 2021.




The city of St. Louis Park, Minnesota, has been offering organics recycling curbside collection to its residents since October 2013. This program in St. Louis Park was set up as an opt-in program, where residents were asked to enroll and pay a fee to receive the service, with a 6% participation rate in the first year. One year later, in 2014, the participation rate for the program stayed at 6% (794 households participating). In January 2017, the city removed the additional fee in an effort to encourage greater participation, resulting in almost double the participation rate within a year, from 16% (1,982 households) in 2017 to 30% (3,754 households) in 2018. By the end of summer 2020, although it has been more than six years since the city has offered organics recycling curbside collection, the participation rate has stayed at about 37.7% with 4,643 households participating. After signing up for the program, participants receive an organics cart (30 or

60 gallons) and a yearly allotment of compostable bags at no additional cost from the city.[10]

On the other hand the City of Edina, was the first city to offer curbside organics recycling collection in response to the County's mandate, rolling out an opt-out program in June 2020. According to this new city-wide residential curbside collection program, all single-family, double and multi-unit properties up to eight received an organics recycling cart in early June 2020. Organics collection begun once carts had been delivered to all homes. Households' quarterly utility bill that included the traditional recycling fee increased by $5.50 per month per household. Households who are not willing to participate can decline and return their carts to the City Council, or they could choose not to put the cart out for organics collection. Regardless of whether households chose to keep or return the cart, the additional fee for the organics recycling program could not be removed from their utility bill as it was considered a citywide utility service. Despite the fact that every household in the city received an organics recycling cart, only about 30% households participated in the program as of June 2021.[11]

## 2.4 Experimental Design

This study aimed to estimate the impact of educational and social influence interventions on individuals' behavior in terms of sorting organics waste, including effort level, habit formation, and confidence in appropriate source separation of organic waste. Additionally, the study aims to investigate the impact of these interventions on the weekly amount of organic waste generated. The study was purposefully conducted in two different cities with different levels of experience in offering organics recycling curbside collection to their residents, so there was enough variation in the experience level of

[10] Organics collection is not commonly available at multifamily buildings. To provide the opportunity for organics recycling, the city has implemented a program that allows residents of multifamily buildings to drop off their organics at designated sites. This program is offered free of charge to these residents. It is required to use certified compostable bags for the collection of organics.

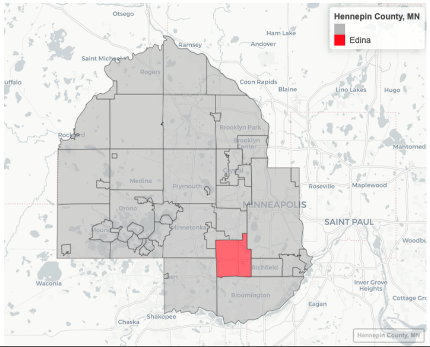
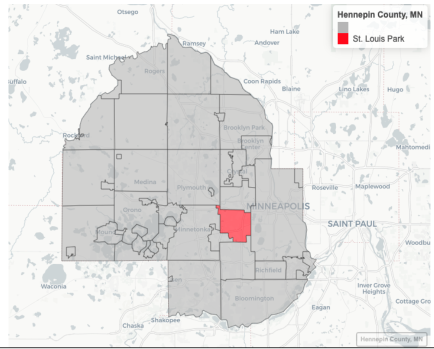
[11] Since the launch of the program in June 2020, Edina residents have diverted a total of 2,939.68 tons of organics from landfills.

participants. This design allowed for a more robust evaluation of the effectiveness of the educational and social influence interventions across the two different settings and helped to surmount the weak variation problem commonly found in studies evaluating the impact of social influence or peer effects (Angrist, 2014).

### 2.4.1 Study Sites

This study was conducted in collaboration with the cities of Edina and St. Louis Park, which are suburbs of the Minneapolis-Saint Paul metropolitan area in Hennepin County, Minnesota. Edina had rolled out their program in June 2020, where the city distributed the organics recycling bins to all residents, who could return them to the city if they wanted to opt-out. St. Louis Park has been the county's oldest curbside organics recycling program, in which residents sign up to participate. Edina, with a population of 53,059 individuals, is the eighth most populous city among the 45 cities in Hennepin County. St. Louis Park, on the other hand, has a population of 49,539 individuals, ranking as the ninth most populous city within Hennepin County. Median household income for residents of Edina and St. Louis Park were $115,047 and $87,639, respectively, in 2021. Furthermore, these two cities are adjacent to each other geographically (See more demographic descriptions of these two cities in the table A.1 in Appendix A).

Table 2.1: Organics recycling study sites: Edina and St. Louis Park, Hennepin County

| **Edina** | | **St. Louis Park** | |
|---|---|---|---|
|  | |  | |
| **Population:** | 53,059 | **Population:** | 49,539 |
| **Median Household Income:** | $115,047 | **Median Household Income:** | $87,639 |
| **Total Area:** | 15.4 sq. mi. | **Total Area:** | 10.6 sq. mi. |
| **Population Density:** | 3321/sq.mi. | **Population Density:** | 4568/sq.mi. |

Source: American Community Survey 5-year estimate 2021.

Materials accepted for organics recycling are important to any organics recycling program. The cities of St. Louis Park and Edina have a comprehensive list of accepted organic materials that can be included in their curbside collection program or dropped off at designated locations. Table 2.2 displays the list of acceptable organics materials and what can and will be diverted as organic waste within the cities of St. Louis Park and Edina. The list of accepted materials for these two cities are the same because the organics collected curbside are hauled to the same commercial facility named Shakopee Mdewakanton Sioux Community (SMSC) in Shakopee, Minnesota. In this facility, the organics are recycled into compost to use in landscaping and road construction projects to improve soil.

Table 2.2: Acceptable Organics Materials that can go in the organics cart for St. Louis Park and Edina

| **Materials accepted for organics recycling** |
|---|
| **All food scraps, cooked and uncooked** |
| Fruits and vegetables |
| Bread and cereal |
| Dairy products |
| Eggs and eggshells |
| Meat, fish, shellfish and bones |
| Nuts and shells |
| **Food-soiled and compostable paper** |
| Pizza delivery boxes |
| Paper egg cartons |
| Napkins and paper towels |
| Toilet paper tube/roll and paper towel tubes/roll |
| **Other compostable household items** |
| Coffee grounds, filters, tea leaves, and tea bags |
| Cotton balls and cotton swabs (paper middle) |
| Hair and nail clippings |
| House plant trimmings and flowers |
| Wooden chopsticks, popsicle sticks, and toothpicks |
| Carved pumpkins and ornamental gourds |
| Certified compostable products |
| **Certified compostable products** |
| All cups, plates, bowls, containers, parchment, and wax paper, utensils, straws, and bags with BPI-certified compostable products |

Notes: All accepted organic materials (except pizza delivery boxes and egg cartons) must be placed in compostable bags and tied before placing them inside the organics cart.
Source: Cities of St. Louis Park and Edina, (2022). Acceptable Organics Materials for St. Louis Park and for Edina.

### 2.4.2 Randomization

The study was conducted as a randomized controlled trial, where households were randomly assigned to either control or one of two treatment groups. Participants were recruited from Edina and St. Louis Park residents through recruitment messages distributed by the cities using their communication networks.[12] The recruitment materials directed interested individuals to an online registration survey to express their interest in participating in the research.[13] The front page of this survey included all items about the study requirements and procedures, required by the Institutional Review Board (IRB) to ensure that potential participants were fully informed before enrolling, followed by a block of screening questions to identify respondents for eligibility to participate in the experiment.[14] This study was designed to have single enrollment from people living together at a given address. The study eligibility criteria included the registrant to reside in either city in the study, be at least 18 years old, and have access to an active email address, internet connection, and device of communication with the research team during the research period. After passing the screening process of registered households for the experiment, eligible representatives from each participating household were randomly assigned into one of these three groups for each city so that each treatment group and comparison group comprised one-third of the enrolled households from each city.

The recruitment messages were sent to 4,000 households in St. Louis Park and 3,000 households in Edina. From these invitations, 911 households in St. Louis Park and 1,015 households in Edina registered their interest in participating in the research experiment.

[12] Recruitment materials, E-recruitment, and short flyers were prepared by the university research team indicating eligibility criteria, a summary of participants responsibilities over the research period, and availability of a stipend for those who would complete all research components. Both E-recruitment and short flyers included a URL link and QR code to locate interested participants to the study registration page.

[13] St. Louis Park used e_recruitment by sending recruitment messages to the e-mail list of households participating in the organics recycling program on May 12, 2021. Edina recruited households by affixing short flyers on the garbage bins of the city residents for a week from May 12, 2021, to May 18, 2021.

[14] The cover page provided detailed information about the organics recycling study, research team, project description and procedures, eligibility, participant stipend, confidentiality, and voluntary nature of the study.

Of those who registered, 367 households in St. Louis Park and 280 households in Edina completed the baseline survey. In total, 276 households in St. Louis Park and 197 households in Edina completed all research components, including the baseline survey, six-week research materials, and endline survey. The net response rate for this study was 6.9% in St. Louis Park and 6.6% in Edina. Despite the relatively low response rate, the study had a large enough sample size to draw statistically reliable conclusions about the effectiveness of the different interventions in promoting organics recycling. Table 2.3 summarizes the recruitment processes and the study surveys response rate.

Table 2.3: Surveys response rate

| | **Edina** | **St.Louis Park** | **Total** |
|---|---|---|---|
| Total invitation sent out † | 3,000 | 4,000 | 7,000 |
| Total registered households | 1,015 (33%) | 911 (22%) | 1,926 (27%) |
| Total completed baseline survey | 280 (9.3%) | 367 (9.1%) | 647 (9.2%) |
| Total completed all research requirements | 197 (6.5%) | 276 (6.9%) | 473 (6.7%) |
| Educational intervention | 70 | 84 | 154 |
| Social influence intervention | 67 | 102 | 169 |
| Control group | 60 | 90 | 150 |

† St. Louis Park used e-recruitment by sending recruitment messages to the e-mail list of households participating in the organics recycling program on May 12, 2021. Edina City recruited households by putting short flyers on the garbage bins of the city residents for a week from May 12, 2021, to May 18, 2021.

Two types of informational messaging were used as treatments: educational and social influence. Educational messaging informed targeted households by naming specific items that should be added to or excluded from organics recycling. Organic recycling programs provide instructions to ensure that inappropriate materials are separated from organic recyclables while encouraging households to include all appropriate materials. Yet, such rules likely remain vague to many individuals, leading to limited amounts of organics recyclables or psychological costs of participating in the program. The educational messaging is designed to provide concrete examples associated with types of materials that could be recycled or should be avoided to solidify their understanding. For social influence intervention, we recruited one to three persons from each city who had experience participating in the city's organics recycling program and were asked to record video messages in an inviting and encouraging tone regarding the ease and benefits of organics recycling. The messages were delivered to households through 1- to 2-minute-long video clips created by the city staff and residents (See TableA.27 in AppendixA for the YouTube links of video clips).[15]

The experiment's total procedure consisted of a week of recruitment, during which eligible participants were sent the link to the baseline survey.[16] Participants had two weeks, from May 15 to May 31, to complete the baseline survey, which covered topics related to food and eating habits, environmental attitudes and behavior, and organics recycling practices.[17] Following this, the six-week experiment began, during which participating households received intervention messages and completed weekly surveys to report their organics recycling practices. Upon completion of the six-week experiment, all participants who had finished all research requirements received the link to the endline survey, which they had two weeks to complete.[18] The study ran from May 12 to

[15] The cities were involved in the study by creating the educational and social influence videos used in this study. In total, the experiment utilized 24 video clips, consisting of six educational messaging videos for the educational treatment groups in the two cities, six social influence videos featuring community-known persons from Edina for the social influence intervention group in Edina, six social influence videos featuring community known persons from St. Louis Park for the social influence intervention group in St. Louis Park, and six control group videos for both cities.

[16] At the outset of the study, all participants provided informed consent by affirming consent before completing the baseline survey.

[17] These blocks were divided into the following categories: 1) Introduction, 2) Household compositions, 3) Eating and shopping habits, 4) Time use, 5) Attitudes to the environment, 6) Waste sorting behavior, 7) Practice of organics recycling, 8) Knowledge level towards organic materials, 9) Sense of community, and 10) Demographics.

[18] The final research sample consisted of 473 participants from the two cities. Out of these 473 participants, 58 households did not complete all research requirements. Specifically, 2 and 7 households did not complete three and two of the six weekly surveys, respectively, while the remaining 49 households did not complete one of the six weekly surveys. Therefore, the total number of completed surveys for each phase and each group of the study was summarized by a total of 276 households from St. Louis Park and 197 households from Edina. For a detailed breakdown of the number of participants in each week and group of the experiment, please refer to AppendixA table A.26.

July 26, and each participant received $100 for their time and effort. Table 2.4 shows a summary of the weekly requirements of three different groups of study over the six-week period.

Table 2.4: Three different study groups with their weekly requirement description

| | **Description** |
|---|---|
| **Treatment group1:** Educational intervention | Watched a 1-2 min video clip at the beginning of each week for a 6-week period with educational messaging about what can and cannot be in the organics bin through the video clip. Received a survey link to complete the weekly surveys every week. |
| **Treatment group2:** Social influence intervention | Watched a 1-2 min video clip at the beginning of each week for a 6-week period with messages with an inviting and encouraging tone regarding the ease and benefits of organics recycling through the video clip. Received a survey link to complete the weekly survey every week. |
| **Control group:** Comparison group | Watched a 1-2 min video clip at the beginning of each week for a 6-week period with some filler information about agricultural activities and the food supply system (no information about organics recycling) through the video clip. Received a survey link to complete the weekly survey every week. |

### 2.4.3 Experiment period

The experiment was held in a 6-week period from Tuesday, June 1, 2021, until Saturday, July 10, 2021. The weeks were defined in this study based on the participating households' organics collection days, where a week would start on the day of their organics recycling collection day and end on the day before their next organics recycling collection day.[19] The purpose of the weekly surveys was to track participating households'

[19] For example, for those of participating households with their collection day on Thursday, June 3, 2021, their first week would be defined as from June 3, to Wednesday, June 9, 2021, a day before their next collection day; Table A.28 shows all study weeks' timeline for each organics recycling pick-up day.

organics recycling and related activities at their home during the study period. Each weekly survey began with a short (1-2 min) video clip according to the study groups they were assigned to (i.e., the educational video clip for the educational treatment group, the social video clip for the social treatment group, and a control video clip for the comparison group); all video also varied from one week to the next week. These videos were hosted on YouTube, and research participants were provided with private direct links through the weekly surveys. The weekly surveys were designed so participants could only proceed after the video clips played. Subsequent sets of questions were the same for all six weekly surveys.

Surveys were sent to participants each week on the afternoon of their first days of weeks (pickup day) and were designed to stay open until the end of the day before their next organics recycling collection. Thus, participants started the survey on the first day of the study week to watch the video clip. They returned to the survey to log their organics recycling activities throughout the week, including biodegradable bag weight and content discarded during the week, and then submitted the complete survey at the end of the study week.[20] Weekly surveys were designed in seventeen blocks of questions after the front page, where the first block included a link to direct participants to the video clip for the week. Blocks 2 to 11 of the weekly surveys were designed for participants to report their compostable bags when they were full and ready to be put in their organics recycling bin. Each block was designed for reporting one filled compostable bag, with assuming a maximum of 10 bags set out by a household each week. In addition to the number of bags, participants were asked to report the weight, size, or capacity of the bag and the degree of fullness of the bag. Moreover, they were required to upload a picture of the bag's contents before tying it and putting it in the organics bin. The remaining blocks of the weekly survey questionnaire aimed to explore any changes or levels of the following factors during the study period: household composition, eating

[20] Weekly survey included a front page to explain all details on the weekly survey, on how to track the organics recycling activities and a table that defined the first and last days of the study week based on the collection days of participating households.

and shopping habits, time use, organics recycling practices, sense of community, and knowledge levels related to organics recycling.

### 2.4.4 Data

In this study, data were obtained from surveys designed to elicit information regarding research participants' engagement in organics recycling. The surveys were administered using an online platform (Qualtrics) and comprised various online questionnaires. The baseline survey collected information on participants' demographics and prior experience with organics recycling. Table A.2 and table A.3 in Appendix A show the demographic distribution of research participants and their households in Edina and St. Louis Park, respectively. In both cities, more than 70% of household representatives were female, and more than 90% of them were white and had bachelor's degrees or higher professional degree education. Comparing the demographic distribution of the research participants to the broader population demographics of Edina and St. Louis Park, it is evident that the participant sample effectively reflects the composition of the population in both cities, with approximately 50% of the total population is female, while over 80% of the population is classified as white, and more than 70%, of the population holds a bachelor's degree or higher professional degree education.

In the following subsections, I describe the outcome variables of this study. To measure participants' organics recycling practices, different types of questions were employed to capture changes in participants' organics-recycling-related performance behaviors and the quantity of organics recycled by research participants during the study period. These are grouped into two categories to examine the effectiveness of informational interventions on organics recycling practices. Behavioral outcomes measure the changes in self-reported measurements of participants' effort, habitual formation, and confidence levels in performing organics recycling collection. The other set of outcomes is the amount and content of organics recycling generated by research participants. The outcome variables measuring the amount and content of generated organics recycling included the self-weighed weight of organics brought out for recycling, the count of recycled organic items, and decomposing organic items in food and non-food items.

### 2.4.5 Behavioral outcomes

The behavioral outcome variables consisted of self-reported effort level, strength of the habitual formation, and confidence level in doing organics recycling appropriately. The weekly surveys asked participants to rate their practice of organics recycling on a scale of 1 to 10, where one is minimal, and ten is the maximal score for each question. Behavioral outcomes data collected from responses to the four questions included in all surveys as follows:

- **The amount of efforts**:

  *"During this week, how would you rate the amount of effort you and your household put in for organics recycling? (On a scale of 1 to 10, where one is minimal and ten is maximal possible)"*

- **The strength of doing organics recycling as habit**:

  *"During this week, how would you rate the strength of doing organics recycling as a habit for you and your household? (On a scale of 1 to 10, where one is very weak and ten is as strong as a habit can be)"*

- **The level of confidence**:

  *"During this week, how would you rate your level of confidence that **you are putting out as much organics as possible**? (On a scale of 1 to 10, where one is no confidence and ten is fully confident)"*

- **The level of confidence**:

  *"During this week, how would you rate your level of confidence that **you did not include non-acceptable items in the organics recycling cart**? (On a scale of 1 to 10, where one is no confidence and ten is fully confident)"*

The effort level can be specifically defined as the perceived level of physical and mental exertion or inconvenience that participants associated with the act of separating food waste and organic materials from their regular trash. In our baseline survey, we asked participants about the factors that influenced their waste sorting habits when they first started recycling organics. Notably, one of these factors involved gauging the importance of 'The difficulty of separating organic materials (it takes too much effort to separate food waste and organic materials from trash).' The responses to this question revealed that more than 60 percent of participants regarded this factor as extremely to slightly important, refer to figure A.2. This underscores the significance of effort cost in influencing participants' decisions and behaviors regarding organics recycling. In essence, it reflects the extent to which individuals perceive the process of segregating food waste as laborious or time-consuming, and such perceptions can have a profound impact on their willingness and commitment to engage in sustainable recycling practices. Table 2.5 shows the summary statistics of each city's main behavioral outcomes of interest variables and the total sample.

### 2.4.6 The amount and content of generated organics outcomes

Measuring the amount and content of generated organics waste by participants is a critical outcome measure to assess the effectiveness of organics recycling interventions. In accordance with the study's objective of examining the effectiveness of interventions aimed at promoting organic waste recycling, we asked all households to track weekly all their compostable bags with organics recycling they put out in the organics cart for collection.[21] For the weight, we asked them to weigh the bag after they tied it before putting it in their organics recycling cart. While we asked for the use of a scale, if available, to give us the exact weight of the bag, we provided them with different weight

[21] Participants were asked to provide weekly reports on the size, capacity, and weight of the compostable bags they placed in their organics carts. A descriptive summary of the total compostable bags, a summary of the percentage of different biobag sizes used by research participants, and a summary of the degrees of the fullness of the compostable bags reported by each participant throughout the study period are presented in Tables A.4, A.5, A.6 in Appendix A, respectively.

Table 2.5: Summary Statistics of behavioral outcome variables for each city and total sample over the study period

| **The practice of organics recycling Behavioral Outcome variables:** | **Edina** mean (sd) | **St. Louis Park** mean (sd) | **Total sample** mean (sd) |
|---|---|---|---|
| The amount of effort | 6.86 (2.63) | 6.98 (2.81) | 6.93 (2.74) |
| The strength of doing organics recycling as a habit | 8.42 (1.73) | 8.73 (1.77) | 8.60 (1.76) |
| The level of confidence in putting out as much organics as possible | 7.82 (2.03) | 8.13 (2.04) | 8.00 (2.04) |
| The level of confidence did not include non-acceptable items in organics cart | 8.76 (1.36) | 9.12 (1.26 ) | 8.97 (1.31) |
| Observations | 1,230 | 1,656 | 2,886 |

categories, including Extra-heavy, Heavy, Medium, and Light, to select between based on their estimation of how heavy or light the bag is.[22] The question was multiple-choice and open-ended, which asked participants to explain the weight if they had the exact weight. We received reports of tracking 6,027 compostable bags of organics recycling in total over the whole period of the study. Of these, we obtained the scale-based weight of 1,203 (19.9%) compostable bags, and the weight of the remaining 4,824 (80.1%) bags indicated by categorical weight options. Table A.7 in Appendix A shows the summary of the total number of reported compostable bags and the proportion of bags with self-reported scale-based weights by participants in both cities over the six weeks of the study.

To convert the weight of all reported bags to pounds, we utilized the weight distribution of bags reported both by using scale and categorical options. We assigned ranges

[22] We made videos showing different types of compostable bags with different amounts of stuff in them. The videos show how heavy the bags are so people can use them to estimate if they're extra heavy, heavy, medium, or light.

of poundage corresponding to the four weight categories using the weight distribution of the 1,203 biobags that were reported with their exact weight using a scale. Specifically, we determined the weight (lbs) cutoffs for the weight categories based on the cumulative distribution of the categorical responses for 4,824 bags. For example, of these 4,824 categorical responses, 897 (18.6%) bags were reported as "Light". Using the weight distribution of the biobags, we found that the 18.6th percentile was 1.5 pounds, meaning that the weight of the first 18.6th percentile of bags was reported as 1.5 pounds or less than that, which thus defines the cutoff for the "Light" category as bags weighing less than 1.5 pounds. In the next step, the weight of all biobags below 1.5 pounds is averaged to correspond an exact weight assigned to the "Light" group. This average value for the "Light" group is 0.8 pounds.

A similar process was performed for the next weight category, "Medium". According to the reported data from participants, 37.9% (1829) of the categorical weights are in this category. Assigning the next 37.9% of items beyond the previous cutoff (1.5 pounds) in the data for the 1,203 biobags with exact weights to the "Medium" category, we found the upper boundary for this category as 3.0 pounds. The average of all these weights in this interval (1.5 lbs to 3.0 lbs) was 2.3 lbs which become the weight corresponding to the "Medium" Category. The same approach would be applied to obtain weight ranges for the "Heavy" and "Extra-Heavy" categories and calculate the average weight of all reported bags that fell into that interval, converting the categorical reports to their corresponding exact weights in pounds. Table 2.6 shows the cumulative distribution of categorical weight answers and weight cutoffs and assigned weight to each category in pounds. The calculated assigned weights for the Light, Medium, Heavy, and Extra-heavy categories are 0.8, 2.3, 5.2, and 12.3 pounds, respectively.

The weekly average of the total organic waste generated and collected per household and per capita over the study period are presented in Table A.8 in Appendix A. The table reports the average amount of organic waste generated by Edina and St. Louis Park participants for each week of the study. The results show that the lowest amount of

Table 2.6: Cumulative distribution of categorical weight answers and weight cutoffs and assigned weight to each category in pound

| Weight categories | Distribution of categorical weight | Cumulative distribution of categorical weight | Weight cutoffs | Weight (lbs) |
|---|---|---|---|---|
| Light | 897 (18.6%) | Light (18.6%) | Weight $< 1.5$ | 0.8 |
| Medium | 1,829 (37.9%) | Medium (56.5%) | $1.5 \leq$ Weight $\leq 3$ | 2.3 |
| Heavy | 1,767 (36.6%) | Heavy (93.1%) | $3 <$ Weight $< 7.5$ | 5.2 |
| Extra-heavy | 331 (6.9%) | Extra-heavy (100%) | Weight $\geq 7.5$ | 12.3 |

organic waste was generated in the first week of the study in both Edina and St. Louis Park, with an average of 6.3 pounds per week. The greatest amount of organic waste generated was observed in week 5 of the study, with an average of 9.6 pounds for Edina participants and 9.5 pounds for St. Louis Park participants. These findings highlight the variability in the amount of organic waste generated by participants over the course of the study period.

Additionally, we included a table of 19 different kinds of organic items in the weekly surveys and asked participants to choose how they discarded each specific organic item by choosing between options of putting it in the "organics cart", "recycling cart", "backyard compost cart", "trash cart", or using the "garbage disposal". We counted the number of items participants put in the organics cart as the total number of organic items placed in the organic bin. We also decomposed organic items into food and non-food organic items and then counted the number of food and non-food items placed in the organic bin weekly. The average number of organic items, food-organic items, and non-food-organic items collected and placed in organics recycling bins by participants in two cities and the total research sample over the study period is presented in Table A.10 in Appendix A. On average, participants from both cities put a similar number of organic, food, and non-food items in the bin. In general, the average number of organic items discarded in organics recycling bins did not change notably over the six weeks of the study. However, there were some minor fluctuations in the number of items from week to week. Table 2.7 shows the summary statistics of each city's generated organics (amount and content) outcomes of interest variables and the total sample.

Table 2.7: Summary Statistics of generated organics outcome variables for each city and total sample over the study period

| **The practice of organics recycling**<br>**Generated Organics Outcome variables:** | **Edina**<br>mean (sd) | **St. Louis Park**<br>mean (sd) | **Total sample**<br>mean (sd) |
|---|---|---|---|
| Organics (lb) | 8.53<br>(7.12) | 8.34<br>(7.05) | 8.42<br>(7.08) |
| Number of organic items | 10.75<br>(4.01) | 11.10<br>(3.97) | 11.00<br>(4.00) |
| Number of food items | 5.84<br>(2.39) | 6.00<br>(2.18) | 6.00<br>(2.27) |
| Number of nonfood items | 4.90<br>(2.30) | 5.10<br>(2.47) | 5.10<br>(2.40) |
| Observations | 1,152 | 1,617 | 2,769 |

Our analysis employed three distinct samples to assess and estimate the impacts of informational interventions, including educational and social influence, on behavioral outcomes and the quantity of generated organics recycling. These samples encompassed the entire research participant pool, as well as two subsamples: one comprising participants with less than two years of experience in organics recycling, and the other comprising participants with more than two years of experience in organics recycling.

The rationale for utilizing these different subsamples stems from the importance of tailoring the information provided to the specific characteristics and needs of the target audience. In the case of individuals with limited or less than two years of experience in organics recycling, it is crucial to offer practical guidance on proper recycling practices. By providing item-by-item instructions, clear guidelines, and specific examples, these individuals can develop a solid foundation for effective organics recycling behaviors (Varotto and Spagnolli, 2017). In addition, interventions are more effective means to change behaviors, especially in improving habit performance, for individuals facing a change or disrupting old environmental situations or contexts in their life (Verplanken and Wood, 2006).

On the other hand, participants with more than two years of experience in organics recycling form a unique subgroup that has already established familiarity and engagement with recycling practices. For this group, interventions can focus on reinforcing the importance of their continued participation, exploring strategies for waste reduction, and highlighting the broader environmental impacts of their recycling efforts. By providing more advanced information, tailored to their existing knowledge, interventions can further enhance their understanding and engagement with organics recycling (Verplanken and Wood, 2006; Wolske et al., 2020).

Moreover, findings of the spillover effect of pro-environmental behavior by Maki et al. (2019), suggests that engaging in one environmentally conscious behavior can lead to an increase (positive spillover) or decrease (negative spillover) in other environmentally conscious behaviors. In our study, we expected a potential positive spillover effect of the interventions for participants who are relatively new to the organics collection program and may have been more conscious of generating food waste, resulting in an overall reduction in food waste generation and ultimately reducing the amount of organic waste generated by their households. This spillover effect could have significant implications for the cost efficiency and overall effectiveness of behavioral interventions aimed at promoting environmentally conscious behaviors.

To categorize participants based on their experience level, we utilized their responses to a baseline survey question that asked for the date (Month/Year) when they commenced separating organics waste and participating in the City's organics recycling program, resulting in the creation of an experience level variable to distinguish participants with an experience level of less than two years from those with an experience level of more than two years.[23] By examining these two distinct subgroups based on their experience levels in organics recycling, we can gain valuable insights into the development of targeted interventions and educational campaigns tailored to the specific needs and motivations of each group.

Table 2.8 shows the distribution of research participants based on their experience level for each city and the total sample. The mean number of years of experience in organics recycling for the total sample is almost three years. Among the total sample, 55.6% of participants have less than two years of experience in organics recycling, while 44.4% have more than two years of experience. Specifically, in Edina, a significant majority of participants (94.9%) fall into the category of less than two years of experience, whereas in St. Louis Park, the majority (72.5%) have more than two years of experience. This table shows a notable disparity in experience levels between the two cities. As expected, a higher proportion of Edina participants who are relatively new to organics recycling, while St. Louis Park has a larger proportion of participants with more extensive experience. The differences in experience levels can largely be attributed to the timing of program implementation since St. Louis Park has been the county's oldest curbside organics recycling program since 2013, while Edina rolled out their program in June 2020.

## 2.5 Empirical Strategy

In this study, we evaluate the data collected from the randomized controlled trial field experiment to identify the impact of educational and social influence interventions on the organics recycling practices of research participants. By utilizing random assignment of treatments, we can identify the specific impact of these interventions. Our analysis focuses on various outcomes of interest, including behavioral outcomes, the quantity and content of organics waste generated, to estimate the effectiveness of informational

[23] The survey question is: When did your household begin participating in the City's organics recycling program? It was an open-ended question that participants were able to indicate the year and month of beginning participating in the city's organics recycling program.

Table 2.8: Summary Statistics of number years experience and participating in the city's organics recycling program for each city and total sample

| **Experience Level** | **Edina** mean(sd) | **St. Louis Park** mean(sd) | **Total sample** mean(sd) |
|---|---|---|---|
| Number years of experience | 1.27<br>(1.30) | 4.32<br>(2.90) | 3.05<br>(2.83) |
| Experience with less than two years (% of participants) | 94.92 | 27.54 | 55.60 |
| Experience with more than two years (% of participants) | 5.08 | 72.46 | 44.40 |
| Observations | 197 | 276 | 473 |

interventions in promoting proper waste sorting. We conduct this evaluation in two distinct organics curbside collection program settings.

Two distinct specifications were employed using ordinary least squares (OLS) regression to estimate the treatment effects in this study. The first specification involved combining all treatment groups into a single treated group, contrasting it with the control group as the following specification:

$$Y_{iw} = \beta_0 + \beta_1 T_i + \alpha_x \mathbf{X}_i + \gamma_w W_w + \epsilon_{1iw} \tag{2.1}$$

where $Y_{iw}$ represents multiple outcomes of interest, encompassing self-rated performance behavioral and generated organics recycling outcomes by each household $i$ in week $w$; $T_i$ represents the treatment indicator which is a binary variable indicating whether the household belonged to the treated group (either educational treatment or social influence treatment); $\mathbf{X}$ is a vector of control variables to capture various household and individual demographic characteristics including age, education level, gender, race, household income, household size, the number of children, and the number of hosted meals during the week; Additionally, variables capturing the sense of connection to the local community, such as the street, neighborhood, and city, were included; $W_w$ denotes dummy variables for each week to account for potential time trends confounding the intervention effects; $\epsilon_{1iw}$ is unobserved, mean zero random error. $\beta_1$ is the coefficient of interest to examine the impact of the treatment on multiple outcomes of interest.

In an alternative specification, we employed a model that utilized separate dummy variables to estimate the individual effects of specific treatment groups on the primary outcomes of interest. The treatment groups are defined as the educational treatment group, the social influence opt-in treatment group, and the social influence opt-out treatment group. The educational treatment group comprised all participants, regardless of city affiliation, who received educational treatment during the study. The social influence opt-in treatment group consisted of participants who received the social influence intervention in St. Louis Park, while the social influence opt-out treatment group included participants who received the social influence intervention in Edina.

The reason for differentiating the social norm interventions across the opt-in and opt-out groups, but not the educational interventions, lies in the nature of the interventions themselves. The educational intervention was designed to provide consistent and uniform information to all participants, regardless of their city affiliation, with the primary goal of enhancing their knowledge and awareness of organics recycling practices. Since the content and delivery of the educational intervention were consistent for participants in both cities, there was no requirement to differentiate the treatment between the two locations. However, the social influence intervention was designed to leverage the influence of community leaders to promote and model the desired behavior of organics recycling. Since the opt-in group had voluntarily signed up for the organics recycling program, their motivations and perceptions might differ from the opt-out group, who were automatically enrolled in the program. To account for these potential differences and to ensure that the social influence interventions were relevant and effective for each group, separate videos were used to the participants in each city.

$$Y_{iw} = \gamma_0 + \gamma_1 T1_i + \gamma_2 T2_i + \gamma_3 T3_i + \alpha_x \mathbf{X}_i + \gamma_w W_w + \epsilon_{2iw} \tag{2.2}$$

The empirical regression model, as denoted by Equation 2.2, was employed to examine variations in organics recycling practices across the different study groups. The treatment groups denoted as $T1_i$, $T2_i$, and $T3_i$ represented whether household $i$ belonged to the educational treatment group, the social influence opt-in treatment group, or the social influence opt-out treatment group, respectively. Specifically, $T1_i$ is an indicator variable that equals 1 if the participant belonged to the educational treatment group either opt-in or opt-out, and 0 otherwise. Similarly, $T2_i$ and $T3_i$ are indicator variables that equal 1 if the participant belonged to the social influence opt-in and opt-out treatment groups, respectively, and 0 otherwise. The outcomes of interest, control variables, and time trend controls remained consistent with those employed in the previous specification; $\epsilon_{2iw}$ is unobserved, mean zero random error; $\gamma_1$, $\gamma_2$, and $\gamma_3$ are the coefficients of interest to examine the differential impacts of the various treatment groups on the outcome variables of interest.

The two models were estimated using three separate samples in our analysis to evaluate the effects of the interventions and estimate the respective specification models. The samples encompassed the entire research participant pool and were divided into two subsamples: one comprising participants with less than two years of experience in organics recycling and the other consisting of participants with more than two years of experience in organics recycling.

## 2.6 Results

This section presents the results of the study, which are divided into two categories based on the type of outcome: behavioral outcomes and the weekly quantity of generated organics (amount and content of generated organics). Behavioral outcomes include the effort (burden) level participants put into organics recycling activities, the strength of doing organics recycling as habitual behavior, and the confidence level of participants in source sorting of organics recycling appropriately. Behavioral outcomes were measured using self-reported data on a scale of 1 to 10, where one is minimal, and ten is the maximal score of scaling. The weekly quantity of generated organics outcomes include the amount of generated organics measured as self-weighing weekly weight of organic waste and the content of organic waste measured as the total number of different organic items placed in organics recycling bin for collection during the experiment. The following subsections present the study results for all participants from both cities, for the subsample of participants with less than two years of experience, and for the subsample of participants with more than two years of experience.

### 2.6.1 Behavioral outcomes

In Table 2.9, Panel A represents the results of estimating equation 2.1 for all treated participants, where the treatment affects on behavioral outcomes such as effort level, habitual forming, and the confidence level for acceptable and non-acceptable items are shown. The results indicate a significant decrease in the self-reported amount of effort level among all treated participants. Moreover, the treatment overall has a positive effect on the habitual forming, but no significant effects on the confidence level for acceptable and non-acceptable items.

Panel B of the table presents the results of estimating equation 2.2 examining the effects of treatment interventions, including educational intervention, social influence opt-in program, and social influence opt-out program. The results show that educational intervention has a positive effect on confidence level for acceptable items and habitual forming. Social influence interventions are effective in reducing self-reported effort level in both opt-in and opt-out programs. While social influence intervention in opt-out program has no significant effect on any of behavioral outcomes, it has a slightly negative and positive effect (i.e., at a 10 percent significant level) on confidence level for acceptable and non-acceptable items, respectively.

Tables 2.10 and 2.11 present the same information as Table 2.9 but limit the analysis to participants with experience less than two years (Table 2.10) and participants with experience more than two years (Table 2.11), respectively.

As presented in Table 2.10, the treatment had a significant effect in reducing effort level and increasing habitual forming among all treated participants with less than two

Table 2.9: Impact of Different Informational Interventions on Behavioral Responses to Organics Recycling: Total research participants

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| | | **Panel A: All treated participants (Eq: 2.1)** | | |
| Treatment | -0.33*** | 0.11* | 0.07 | 0.06 |
| | (0.11) | (0.06) | (0.08) | (0.05) |
| | | **Panel B: Different treatment groups (Eq: 2.2)** | | |
| Education | 0.06 | 0.21*** | 0.27*** | 0.09 |
| | (0.13) | (0.07) | (0.09) | (0.06) |
| Social_optin | -0.89*** | -0.01 | -0.19* | 0.12* |
| | (0.15) | (0.08) | (0.10) | (0.07) |
| Social_optout | -0.39** | 0.09 | 0.01 | -0.09 |
| | (0.17) | (0.10) | (0.12) | (0.08) |
| Control mean | 7.06 | 8.38 | 7.88 | 8.90 |
| N | 2,616 | 2,616 | 2,616 | 2,616 |

The outcome variables were measured using self-reported data from participants on a scale of 1 to 10. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, years of experience engaging in organics recycling, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

years of experience. In panel B of the table, the educational intervention is effective in improving most behavioral responses to organics recycling among participants with less than two years of experience, with a significant positive effect on confidence levels in knowing both acceptable and non-acceptable items and forming the habit of doing organics recycling. It would be attributed to the fact that most of the participants in this subsample (participants with less than two years of experience) are from Edina city which is very new in offering organics recycling. The social influence interventions in both opt-in and opt-out programs are also effective in reducing effort levels among new participants in doing organics recycling.

Table 2.10: Impact of Different Informational Interventions on Behavioral Responses to Organics Recycling: Participants with experience less than two years

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| | **Panel A: All treated research participants (Eq: 2.1)** | | | |
| Treatment | -0.33** | 0.20** | 0.01 | 0.11 |
| | (0.14) | (0.09) | (0.11) | (0.07) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | 0.05 | 0.35*** | 0.29** | 0.17** |
| | (0.16) | (0.10) | (0.12) | (0.08) |
| Social_optin | -1.26*** | -0.03 | -0.79*** | 0.20 |
| | (0.24) | (0.15) | (0.18) | (0.12) |
| Social_optout | -0.44** | 0.11 | -0.02 | -0.02 |
| | (0.19) | (0.12) | (0.14) | (0.09) |
| Control mean | 7.14 | 8.31 | 7.72 | 8.79 |
| N | 1,439 | 1,439 | 1,439 | 1,439 |

The outcome variables were measured using self-reported data from participants on a scale of 1 to 10. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.11 shows the estimation results for the subgroup of participants who have engaged in organics recycling for more than two years. In Panel A, the results reveal that the treatment variable has a significant and negative impact on the level of effort among all treated participants, indicating a decrease in the level of effort for those who have practiced organics recycling for an extended period. However, the treatment variable did not have a significant effect on the confidence level for both acceptable and non-acceptable items, as well as habitual forming. Moving to Panel B, the findings demonstrate that the effect of the treatment varies across different treatment groups. Specifically, the Education treatment variable has a positive and significant effect on the confidence level for acceptable items, suggesting that participants who received the educational treatment exhibit higher confidence in handling acceptable items. Moreover, the Social opt-in treatment variable has a negative and significant effect on the level of effort, indicating that participants who received social influence treatment from the opt-in program report a lower level of effort. However, the social influence intervention did not have an effective impact on behavioral outcomes as much as the less experienced group for participants from the opt-out program.

Table 2.11: Impact of Different Informational Interventions on Behavioral Responses to Organics Recycling: Participants with experience more than two years

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| | **Panel A: All treated research participants (Eq: 2.1)** | | | |
| Treatment | -0.33* | 0.02 | 0.16 | 0.10 |
| | (0.17) | (0.09) | (0.10) | (0.07) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | 0.15 | 0.08 | 0.29** | 0.11 |
| | (0.20) | (0.10) | (0.12) | (0.08) |
| Social_optin | -0.73*** | -0.05 | 0.08 | 0.09 |
| | (0.20) | (0.10) | (0.12) | (0.08) |
| Social_optout | -0.50 | 0.27 | -0.14 | -0.04 |
| | (0.54) | (0.28) | (0.33) | (0.22) |
| Control mean | 7.41 | 8.9 | 8.12 | 9.10 |
| N | 1,177 | 1,177 | 1,177 | 1,177 |

The outcome variables were measured using self-reported data from participants on a scale of 0 to 10. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

It is evident from the results presented in Tables 9-11 that different types of interventions have varying effects on organics recycling behavior. Educational interventions appear to have a positive impact on confidence levels and habitual forming, while social influence interventions are effective in reducing effort levels, but have minimal effects on habitual forming, and confidence levels. Additionally, the effectiveness of interventions differs based on participant characteristics, such as their level of experience with organics recycling. The educational intervention is an effective intervention in improving most behavioral responses to organics recycling among participants with less than two years of experience, with a significant positive effect on confidence levels in acceptable and non-acceptable items and forming the habit of doing organics recycling. The social influence interventions in both opt-in and opt-out programs had a minimal effect on behavioral responses, regardless of their experience in doing organics recycling. These findings highlight the need for tailored interventions to address the specific needs and behaviors of different participant groups.

### 2.6.2 Generated Organics Outcomes

Table 2.12 presents the impact of different informational interventions on the amount of generated organic waste in terms of weight in pounds and the number of organic items placed in the organic bin by the total research participants from both cities. In Panel A, the results indicate that the overall treatment had no significant effect on the amount and content of organic waste generated by all treated participants. Moving to Panel B, the educational intervention did not significantly affect the amount of organic waste generated or the number of food and non-food items placed in the organic bin. The social influence intervention in the opt-in program had no significant effect on the amount of organic waste generated, the total number of different organic items, or the number of food items but had a significant effect on reducing the number of non-food items placed in the organic bin. On the other hand, the social influence intervention in the opt-out program, which relatively includes participants who are new in doing organics recycling, had a significant effect on reducing the amount of organic waste generated in terms of reducing the weight of generated organic waste and reducing the number of organic items, and the number of food items placed in the organic bin. Overall, the results suggest that the social influence intervention in the opt-out program was effective in reducing the amount of organic waste generated and the number of items placed in the organic bin, while the educational intervention had no significant effect on these outcomes.

Table 2.13 presents the estimate of the impact of different informational interventions on organics recycling, limiting the sample to those with less than two years of experience with organics recycling. Panel A shows that the treatment did not have a significant impact on the amount of organic waste generated by the treated groups. Panel B shows the effects of each intervention separately, including educational and social influence interventions. Educational treatment had a significant positive impact on the total number of food items discarded in organics bins by treated participants but no impact on the other outcomes. Social influence intervention was found to be not effective for less experienced participants in the opt-in program and had a slightly significant effect (at a 10 percent significant level) in reducing the weight of organics recycling generated by participants in the opt-out program.

Table 2.14 displays the estimated effects of the interventions on the quantity of organic waste generated by participants who have more than two years of experience in organics recycling. The findings indicate that the treatment had a significant negative impact (at the 90% confidence level) on the weight of organic waste generated by all treated research participants. However, among the different treatment groups, only the social influence intervention in the opt-in program showed statistically significant effects in reducing the amount of generated organic waste, as measured by both weight and the number of organic and non-food items. The educational and social influence interventions did not have a significant impact on waste generation in any of the outcome measures.

Table 2.12: Impact of Different Informational Interventions on Generated Organics Recycling: Total research participants

| | (1) Organics (lb) | (2) Number of organic items | (3) Number of food items | (4) Number of nonfood items |
|---|---|---|---|---|
| | **Panel A: All treated research participants (Eq: 2.1)** | | | |
| Treatment | -0.32 | -0.15 | 0.01 | -0.15 |
| | (0.28) | (0.16) | (0.09) | (0.10) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | -0.21 | 0.04 | 0.13 | -0.09 |
| | (0.33) | (0.18) | (0.10) | (0.11) |
| Social_optin | -0.14 | -0.20 | 0.08 | -0.28** |
| | (0.38) | (0.21) | (0.12) | (0.13) |
| Social_optout | -0.86** | -0.52** | -0.40*** | -0.12 |
| | (0.44) | (0.25) | (0.14) | (0.15) |
| Control mean | 8.13 | 10.87 | 5.81 | 5.04 |
| N | 2,752 | 2,752 | 2,752 | 2,752 |

The outcome variables include organics which is self-weighed generated organics waste (lb), number of organic items, food items, and nonfood items which are self-reported counting of different items put out for collection. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, years of experience engaging in organics recycling, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.13: Impact of Different Informational Interventions on Generated Organics Recycling: Research participants with experience less than two years

| | (1) Organics (lb) | (2) Number of organic items | (3) Number of food items | (4) Number of nonfood items |
|---|---|---|---|---|
| | **Panel A: All treated research participants (Eq: 2.1)** | | | |
| Treatment | -0.15 | 0.04 | 0.13 | -0.08 |
| | (0.37) | (0.21) | (0.13) | (0.12) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | 0.23 | 0.35 | 0.34** | 0.02 |
| | (0.43) | (0.24) | (0.14) | (0.14) |
| Social_optin | 0.02 | 0.03 | 0.24 | -0.21 |
| | (0.64) | (0.36) | (0.22) | (0.21) |
| Social_optout | -0.82* | -0.41 | -0.23 | -0.18 |
| | (0.48) | (0.27) | (0.16) | (0.16) |
| Control mean | 7.86 | 10.31 | 5.64 | 4.67 |
| N | 1,527 | 1,527 | 1,527 | 1,527 |

The outcome variables include organics which is self-weighed generated organics waste (lb), number of organic items, food items, and nonfood items which are self-reported counting of different items put out for collection. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.14: Impact of Different Informational Interventions on Generated Organics Recycling: Research participants with experience more than two years

| | (1) Organics (lb) | (2) Number of organic items | (3) Number of food items | (4) Number of nonfood items |
|---|---|---|---|---|
| | **Panel A: All treated research participants (Eq: 2.1)** | | | |
| Treatment | -0.33* | 0.16 | 0.10 | 0.02 |
| | (0.17) | (0.10) | (0.07) | (0.09) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | -0.71 | -0.40 | -0.10 | -0.31* |
| | (0.52) | (0.29) | (0.15) | (0.18) |
| Social_optin | -0.90* | -0.49* | -0.17 | -0.32* |
| | (0.50) | (0.28) | (0.14) | (0.18) |
| Social_optout | 1.35 | 0.09 | -0.36 | 0.45 |
| | (1.37) | (0.76) | (0.40) | (0.49) |
| Control mean | 8.50 | 11.57 | 6.04 | 5.52 |
| N | 1,225 | 1,225 | 1,225 | 1,225 |

The outcome variables include organics which is self-weighed generated organics waste (lb), number of organic items, food items, and nonfood items which are self-reported counting of different items put out for collection. The treatment variable in the first specification (reported results in Panel A) is a binary variable indicating whether the household belonged to the treated group either educational treatment or social influence treatment. The different treatment groups in the second specification (reported results in Panel B) are binary variables including the educational treatment variable equals 1 if the participant belonged to the educational treatment group (regardless of city affiliation); the social influence opt-in and social influence opt-out treatment groups equal 1 if the participant belonged to the social influence group in St. Louis Park City and in Edina City, respectively. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, the number of hosted meals, sense of connection to the group of people living in their home street, neighborhood, and city, and weeks fixed effect to control time trend. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

## 2.7 Discussion

The aim of this study was to investigate the effects of social influences and educational interventions on household organics recycling practices including behavioral aspect of households and organics recycling generation rate in the residential sector of two municipal curbside recycling programs. The household study revealed several key findings regarding the participants and their organic waste management practices. The average household size was reported 2.8 people, with a median of 3 people. Typically, households consisted of on average two adults and 0.8 children under the age of 18. Participant households had been living in the municipality (Edina or St. Louis Park) for 16 years on average. A majority of the survey respondents were female, equivalent to 72% of the research sample.

In terms of organic waste disposal in the organics waste stream, surveyed households placed an average of 2.1 bags in the organics recycling cart for curbside collection per week. The study observed an average weekly household organics waste production of 8.4 pounds per household and 3.3 pounds per person per week (equivalent to 171.6 pounds per person annually).[24] Our research findings of an average annual organics waste disposal of 171.6 pounds per person, which aligns with the EPA's estimates for food waste sent for disposal. The EPA's baseline estimate for 2010 was 218.9 pounds of food waste per person annually, while their 2030 goal aims to reduce this figure by 50 percent to 109.4 pounds per person (EPA, 2020). Comparing our results to the EPA's benchmark, it is evident that our findings are consistent with the reduction trend in food waste production within the residential sector, demonstrating the progress made by our study participants in reducing the amount of food waste sent to landfills. The study examined the composition of organics waste by counting the number of different types of organics

[24] These results were consistent with the scale of organics production in the cities of Edina and St. Louis Park. We checked the average organics waste production per week by research households with organics recycling coordinators from both cities of St. Louis Park and Edina and it was found that our research results were aligned with their data on average organics recycling generation across cities residential households.

items placed in the organics cart on a weekly basis. On average, households included 10.9 different types of organics items. This included an average of 5.9 food organic items and 5.9 non-food organic items placed in organics cart per week by research households.

The results of our study revealed a notable decrease in the quantity of generated organics waste among participants who received the social influence in the opt-out program, suggesting a potential positive spillover effect for these findings. The presence of a positive spillover effect of interventions can be shown by the self-reported increase in the frequency of recycling and reducing trash production by research participants at the end of the study. They were asked, in the endline survey, to reflect on changes in the frequency of recycling items such as paper, plastic, and metal compared to the beginning of the study, on a rating scale of -3 to 3, where -3 indicated a significant decrease and 3 indicated a significant increase, and 0 the same. The average rating was 2.1 which is significantly greater than zero and with a standard deviation of 1.4. Notably, participants also rated their reflection on garbage production relative to the beginning of the study, yielding an average of -0.44. This also aligns with the statistically significant negative effect of the research treatments on the number of organic items placed in the trash bin during the study period (see the Tables A.19 and A.20).

Moreover, our study suggests that engaging in organics recycling can have an effect on participants' overall environmental awareness and consciousness. By actively participating in a pro-environmental activity such as organics recycling, individuals may experience changes in their beliefs and attitudes towards other environmental behaviors. Especially for participants who are new to such activities, as they may become more environmentally conscious through their engagement in organics recycling. The findings of our study showed a high level of changes in environmental consciousness and commitment among research participants. In the endline survey, they were asked to reflect on changes in their environmental attitudes regarding a set of environmental statements relative to the beginning of the study on a scale of -3 to 3 where equivalent to a lot less strongly and a lot more strongly about their agreement/disagreement respectively. The average rates were positive for statements of their commitment to helping to protect the environment, to make efforts to reduce the amount of waste they generate, and to think about the environment when they throw away food (see Table A.15 in Appendix A). These findings highlight the positive changes in participants' environmental attitudes and behaviors. Furthermore, participants' ratings of their eating and shopping behavior showed positive changes to their behavior and practices compared to the beginning of the study. These behaviors included the frequency of saving leftover food, reusing leftovers, making shopping lists, and seeking compostable materials during shopping (see Table A.14 in Appendix A). Ratings were greater than zero on the -3 to 3 scale, indicating changes in participants' environmental-related behaviors and consequently may result in reduced food waste and fewer organics produced.

The second potential explanation for these results would be the underestimated self-report of organic waste generation and the research participation effect. It is important to recognize that self-reported mechanisms for measuring the quantity of waste may have inherent limitations and can potentially underestimate the actual amount of waste. This can be attributed to the biases introduced by research participation effects. The Hawthorne effect, referring to the alteration of behavior due to the awareness of being observed or studied, is a relevant consideration in our study (McCambridge et al., 2014). Within the context of this research, the consequences of research participation on the behaviors under investigation were found. In the endline survey, respondents were asked to identify the most influential aspect of the study that prompted changes in their level of effort, the strength of organics recycling as a daily habit, and confidence in doing organics recycling appropriately. While a substantial portion (more than 40%) reported no change in their behavior, around 30% and 25% of participants indicated the need to report their recycling activities to someone influences their effort level and the strength of their recycling habit, respectively. Additionally, 17.7% of participants acknowledged that the weekly videos were influential to make them feel more confident in performing organics recycling more effectively (see Tables A.16, A.17, and A.18 in Appendix A).

### 2.7.1 Limitations and direction for future studies

A limitation of this study is the external validity of the findings, as the results are specific to the residents of Edina and St. Louis Park who are already engaged in the organics recycling program. The participants in this study may not be representative of households in other parts of Minnesota or the country. Therefore, generalizations based solely on this study should be made with caution.

One noteworthy limitation of our study is the observed variability in the effectiveness of educational intervention across cities. In our primary model with the total sample of the study, we identified a statistically significant overall effect of the educational intervention on habitual forming and confidence level, signifying its effectiveness in promoting desired outcomes. We defined a regression model that includes the interaction term of educational intervention with cities to examine whether the effects of educational interventions depend on the communities participants belong to; according to the results of this regression model in Table A.25, we found that the coefficient of the interaction term was also slightly significant for habitual forming and confidence level, indicating that the intervention's impact varies significantly among communities. This divergence in results highlights the complex nature of our findings and raises questions regarding the driving factors behind this variation. This variability would be attributed solely to community-specific characteristics. Participants in some communities may exhibit different organics recycling behaviors due to community characteristics. This presents a challenge in the interpretation of the main effect of educational intervention on the desired outcomes, as it is challenging to disentangle the unique contributions of community attributes and individual behaviors. To address this limitation comprehensively, future research endeavors could extend the study to include multiple communities with diverse levels of experience and explore the nuanced dynamics between community contexts and educational interventions.

Another limitation is the short duration of the study. With only a 6-week experiment, it is challenging to assess the long-term sustainability of individual behaviors. Even individuals who possess the knowledge and motivation to act in more sustainable ways may struggle to sustain these behaviors over a longer period. Furthermore, human behavior is highly complex and varies across time, situations, and individuals. This study was conducted during the summer of 2021, which coincided with the second year of the COVID-19 pandemic and the rollout of vaccination phases. This context could have influenced participants' behaviors and limited the generalizability of the findings to other time periods.

In terms of future research, long-term follow-up studies can assess the sustainability of behavioral changes and explore potential barriers or facilitators to their maintenance. Additionally, comparative studies across different regions and program designs can provide insights into the generalizability of our findings and inform the development of best practices in waste management strategies.

Furthermore, future research should aim to understand not only what predicts changes in behavior but also when, where, how, why, and for whom these effects occur. Additionally, more emphasis should be placed on identifying the critical measures of potential moderator and mediator variables, enabling an investigation of the circumstances in which informational intervention approaches are most effective in real-world settings.

To comprehensively evaluate the more precise impact of public policy interventions on promoting desired behavioral shifts, it is suggested to employ a large and diverse sample that represents the target population. By utilizing a substantial sample size, researchers can tailor interventions to target specific participant groups and obtain more reliable and generalizable findings that reflect the impact of the interventions on a broader scale. Overall, while this study provides valuable insights, it is important to consider these limitations when interpreting the results and applying them to different contexts and populations.

## 2.8 Conclusion

In this study, we examined the effects of social influence and educational interventions on household organics recycling practices in terms of behavioral change and the amount of generated organics in two municipal curbside recycling programs. Our findings shed light on the effectiveness of different interventions and their implications for promoting sustainable waste management practices.

First, our results demonstrated that both educational and social influence interventions were effective in inducing desirable behavioral changes among participants. The educational messages positively influenced participants' confidence levels and habitual formation in organics recycling, particularly among those with less than two years of experience. On the other hand, the social influence approach was effective at changing the perceived effort level of recycling, especially among households that are required to explicitly register or indicate their desire to receive the offered service (households in the opt-in program).

Second, the findings of this study for the total research sample showed a significant decrease effect in the quantity of generated organics waste among participants who received the social influence-opt-out treatment. This treatment specifically targeted individuals who were part of an opt-out program, wherein they were automatically enrolled in the program and they are relatively new to this program. A reduction in both overall generated organics waste and the number of food items were shown as the effect of social influence intervention for these participants. Furthermore, when examining the subsamples based on participants' experience level, the educational intervention demonstrated positive effects for individuals with less than two years of experience in organics recycling. This intervention increased the number of food-item organic waste put out for collection by less-experienced participants, indicating a change in their organics recycling contents. However, it should be noted that the interventions, overall, did not significantly impact the quantity and contents of generated organics waste across the samples.

Our study revealed that the effectiveness of interventions varied depending on participant characteristics and program design. Participants with less than two years of experience showed stronger responses to the educational intervention, while social influence interventions had a minimal impact on behavioral outcomes across both opt-in and opt-out programs. In terms of the content of generated organics, the results of the social influence intervention in the opt-out program suggested a potential positive spillover effect, where engaging in organics recycling reduced overall food waste generation. Such spillover effects have important implications for cost efficiency and the overall effectiveness of behavioral interventions aimed at promoting environmentally conscious behaviors. This highlights the need for tailored interventions that consider participants' experience and specific needs in promoting organics recycling behaviors.

In conclusion, this study contributes to the growing body of literature on behavioral interventions for promoting waste management practices. The findings underscore the effectiveness of educational and social influence interventions in inducing desirable behavioral changes in organics recycling. By highlighting the importance of tailored interventions and considering participant characteristics and program design, this research provides valuable guidance for policymakers aiming to enhance household waste diversion efforts and move towards more sustainable waste management systems.

# Chapter 3

# Do farmers respond to the emergence of pesticide resistance? The Case of Pyrethroid Resistant Soybean Aphid

## 3.1 Introduction

In the context of intensive agriculture, where the reliance on relatively cheap and efficacious pesticides, including plant-incorporated pesticides, is widespread, pesticide resistance (e.g., glyphosate-resistant pigweed, ampicillin-resistant salmonella, Cry1Ab-resistant corn earworm, and pyrethroid-resistant soybean aphid) poses significant challenges. While proactively managing pesticide resistance can increase farm profitability over time, it also increases immediate costs and complexity, so it is not widely practiced, particularly in lower-value commodity crops. As a result, agriculture has suffered from reoccurring cases of pesticide resistance resulting in increased production risks including cost spikes and lower yields. Furthermore, in the realm of soybean farming in the United States, a specific and pressing challenge has emerged. By the end of the 2000 growing season, soybean aphids had been reported in research plots, commercial fields, and soybean farms across the 10 primary soybean-producing states in the Northland region. This rapid expansion and the heavy reliance on insecticide-based applications in soybean production led to aphids developing resistance to these chemical treatments. These negative shocks have drawn the attention of agricultural policymakers seeking to mitigate the harm.

Integrated Pest Management (IPM) strategies are essential components of modern agriculture, designed to address the unique challenges posed by various pests in different crops. The approach to IPM can vary significantly depending on the specific pest-crop interactions in question. When it comes to managing soybean aphids in soybean fields, IPM strategies are characterized by distinct practices. In this context, the core of IPM revolves around scouting, aphid population thresholds, and rotation of chemical management. Unlike some other crops where seed treatments play a prominent role, seed treatments for soybean aphids are of limited value due to the delayed appearance of aphids, typically occurring after the seed treatment's effectiveness has waned. Instead, soybean aphid IPM emphasizes regular field scouting to monitor aphid populations. When the number of aphids reaches a predetermined threshold, usually around 250 aphids per plant, it triggers the use of foliar insecticides. Furthermore, to mitigate the development of insecticide resistance, IPM in soybeans encourages the rotation of different classes of insecticides, discouraging the repeated use of the same chemical agents to minimize environmental impact, and promoting long-term sustainability in agriculture.

To determine what policy interventions can effectively mitigate the harm of reoccurring cases of pesticide resistance, policymakers have turned to researchers to understand how pesticide resistance impacts farmers' management practices. Despite the availability of econometric methods that can help in the evaluation of the impact of pesticide resistance on farmers' management practices (e.g., the application of difference-in-difference or random discontinuity models to panel data that includes observations before and after the emergence of pesticide resistance), appropriate data is often unavailable because the available panel datasets, like the Agricultural Resource and Management Survey dataset curated by the USDA's National Agricultural Statistics Service, were originally collected for other purposes and seldom include necessary case-specific information. Therefore, there is a need to create new data sources or data collection protocols that can be used to inform agricultural policies when new instances of pesticide resistance are observed to emerge.

To address the growing concerns related to pesticide resistance in agriculture, this research proposes a survey protocol aimed at collecting valuable data on how the emergence of pesticide resistance is influencing farmers' management practices. This critical inquiry seeks to provide policymakers and researchers with essential data to inform potential measures aimed at mitigating the detrimental impacts of this issue. The imperative nature of this research is underscored by the contemporary and significant case study of pyrethroid-resistant soybean aphids, which has become demonstrative of the broader challenges posed by pesticide resistance. In 2015, a notable reduction in the efficacy of pyrethroid-based insecticides for soybean aphid management was reported in commercial soybean fields, initially concentrated in counties across southwest Minnesota.

In light of this context, the main questions of this research are: have Minnesota and North Dakota farmers changed their soybean aphid management approach in response to insecticide-resistant soybean aphid concerns? and do they use an integrated pest management (IPM) approach on their farms? The practices that were explored in this study included foliar insecticide use in the past five years, insecticide treated seed use, field scouting, and pyrethroid or organophosphate insecticide applications. The frequency of field scouting was also determined for those who did it. Management practices were compared between farmers who did and did not report a change due to pyrethroid resistant soybean aphid concerns. This strategy raises typical endogeneity concerns, especially reverse causality concerns. To address endogeneity, farmers' self-identified level of concern about insecticide-resistant soybean aphid was used as an instrumental variable. We also drew upon an external data set that recorded the location of commercial soybean farms in Minnesota and North Dakota that experienced pyrethroid insecticide failures in controlling soybean aphid between 2015 and 2020. This data set was used to estimate the average distance between each surveyed farm county and the counties with pyrethroid failures. This average distance was used as another instrumental variable to explore the robustness of our analysis. Assessing the proposed instrumental variables based on relevance and exclusion conditions suggests that while the survey-based instruments (i.e., pesticide resistance concern levels) appear to satisfy relevance, satisfaction of the exclusion condition is more tenuous. The instrument that is measured independent of the survey (i.e., the average distance between surveyed farms county and counties with pyrethroid failures) appears more likely to satisfy the exclusion restriction but seems less relevant (i.e., it appears to be a weak instrument).

The analysis results suggest a causal relationship between reports of a change in management due to insecticide resistance concerns and positive developments for soybean aphid resistance management including increased field scouting, increased field scouting frequency, and increased use of organophosphate insecticides. However, the results reveal that farmers who changed management also increased pyrethroid insecticide use, which could exacerbate pyrethroid resistance.

The contributions of this research are both methodological and practical in nature. It effectively demonstrates how cross-sectional surveys can be thoughtfully designed to capture farmers' decision-making process during the emergence of new challenges in their production environment. Given the scarcity of panel data for other causal evaluation methods, the proposed survey protocol in this study provides a viable approach. Considering the ongoing challenges posed by pest pesticide resistance globally, these research findings hold immediate implications for developing public and private incentive programs. These programs can be designed to increase in farmers' awareness and concerns of insecticide resistance and lead to promote more resilient agricultural supply chains and facilitate the adoption of sustainable agricultural practices in response to the growing threat of pest pesticide resistance.

This chapter is organized into seven sections. The following section provides an overview of the soybean aphid infestation context, including the economic losses associated with the infestation and the importance of pest management practices. Section 3 Background of Literature presents a summary of various strategies employed to control soybean aphids, highlights the consequences of heavy reliance on chemical-based practices, and emergence of insecticide resistant aphid. In section 4 Materials and Methods, we outline the study design, sampling strategies, survey overview and the data. The subsequent section, section 5 Empirical Strategy provides the identification strategies and empirical models employed for estimation, and section 6 Results presents the estimation results. Finally, conclusions are found in the last section.

## 3.2 Context

The USA produces more than one-third of the world's soybean grown on over 80 million acres, with an average value of $40 billion annually (USDA-NASS, 2017). Soybean contains oil and protein and is considered one of the world's largest sources of vegetable oil and animal protein (USDA-ERS, 2020). The soybean aphid (*Aphis glycines Matsumura*), an insect native to Asia, is the soybean's primary insect pest and the most damaging pest to soybean farms. Soybean aphid was first detected on soybean farms in North America by University of Wisconsin extension researchers in July 2000 (DiFonzo, 2009). By the end of the 2000 growing season, soybean aphid was reported in research plots, commercial fields, and soybean farms from the 10 primary northland soybean producing states. The colonization of aphid can significantly damage soybean production, including a reduction in the number of soybean pods and seed coat quality, seed size, and plant height (Musser et al., 2022; Ragsdale et al., 2007). The soybean plant serves as a secondary host for soybean aphid.[1] Given the million acres of soybean farms in the Midwest, along with the comparable climate conditions to the original habitats of soybean aphid

[1] The primary host for soybean aphids is the common buckthorn (Rhamnus cathartica) in North America (Ragsdale et al., 2004).

(Eastern Asia), the Midwest has emerged as a suitable habitat for these insect pests. As a consequence, less than one decade after the detection of soybean aphids, over 42 million acres of soybean-planted areas in the North Central region were infested by aphids (Ohnesorg et al., 2009).

The high infestation level of soybean aphid had become a significant source of economic loss in Midwest soybean production, resulting in up to 40% soybean yield loss (Ragsdale et al., 2007). The estimated yield losses caused by soybean aphid was 6-13 bu/acre in 2003, equivalent to a reduction in US national average soybean yield by 11% compared to the years before 2000 (Song and Swinton, 2009).[2] As well as reducing yield, soybean aphid outbreak increases the production cost. The insecticide-based applications and soybean farm acreage treated by insecticides has surged considerably to control soybean aphid. In 1999, the year before soybean aphid discovery, less than 1% of the planted soybean acreage was treated with insecticides in the 5 main soybean producing states (DiFonzo, 2009).[3] By 2010, a 130-fold increase in insecticide-treated planted acres in Midwest states had been reported, increasing production cost by about $10-20 per acre (Song and Swinton, 2009).[4]

As the potential severe economic impact of soybean aphid infestation began to be understood at the beginning of the 2000s, entomologists and university extensions have been recommending and incorporating multiple pest management practices to improve long-term aphid infestation management. Integrated pest management recommendations to control the widespread outbreaks of pests are comprised of different techniques categorized by cultural, genetic, and chemical factors (Hodgson et al., 2012). While different insect management such as host-plant resistance or biological control are available, soybean farmers continue to rely on chemical-based insecticides including foliar-applied and

[2] Estimate of the average soybean yield per acre production in the United States was 33.9 bu/acre in 2003 and it was increased to 51.6 bu/acre in 2018 (USDA-NASS, 2019).

[3] Illinois, Indiana, Michigan, Minnesota, and Ohio.

[4] Insecticide use increased from less than 1% to more than 20% in Iowa, Illinois, Indiana, Michigan, Minnesota, and Ohio from 1999 to 2005 (Song and Swinton, 2009).

seed-applied insecticides to manage soybean aphids (Ragsdale et al., 2011). Organophosphate and pyrethroids are the two major groups of foliar insecticides that have become the primary management tools for soybean aphid control (Ragsdale et al., 2011).

The heavy reliance on insecticide-based applications in soybean production resulted in aphid developing insecticide resistance. Insecticide resistance is defined as a genetic makeup change in the pest making it less susceptible to pesticides (Tabashnik and Carrière, 2017). In 2015 and 2016, there had been reports mostly from southwest Minnesota that soybean aphid had developed resistance to pyrethroid insecticides. In subsequent years, evidence of pyrethroid insecticides failing to control aphid expanded over most upper Midwest soybean producing states including North Dakota, South Dakota, and Iowa. In addition, there is the risk of insecticide-resistant aphid infesting the entire Midwest because of the high mobility of winged aphid (Koch et al., 2018). This has resulted in many research and extension programs recommending diverse strategies for pest management to reduce insecticide use in soybean production.

## 3.3 Background of Literature

This section aims to provide a comprehensive background on soybean aphid control strategies. The section begins by examining how to control aphid. It then investigates the critical issue of the risk of resistance with chemically based practices and evidence of pyrethroid-resistant soybean aphid.

### 3.3.1 Soybean aphid management practices

The commonly recommended aphid management strategies are agronomic practices, chemical-based insecticide applications (foliar and seed insecticide treatment), economic practices (using economic injury level and foliar insecticide application thresholds), scouting, and host plant resistance (Tilmon, 2019).

In the context of agronomic practices for soybean aphid management, the selection of high-yielding seed or changing the potassium levels in leaves can foster resilient plants that can withstand environmental stressors like soybean aphid (Hodgson et al., 2012; Walter and Difonzo, 2014).[5] In addition, cultural control such as manipulating the planting date and adjusting row spacing are proposed as a sustainable IPM program for controlling soybean aphid. However, altering the planting date to find an optimal planting window to avoid soybean aphid colonization proves challenging, as research on variable planting dates have been inconsistent and contradictory. The influence of row spacing, a common agronomic factor studied for optimizing yields in relation to weed control, on soybean aphid population growth or yield impacts also remains inconclusive (Johnson et al., 2009; Hodgson et al., 2012; Hurley and Mitchell, 2020). However, studies have identified the presence of beneficial species, including predators, parasitoids, and pathogens as natural enemies, that can reduce soybean aphid establishment and overall population growth across different production systems (Nielsen and Hajek, 2005; Noma and Brewer, 2008; Ohnesorg et al., 2009).

The labeled active chemical ingredients for soybean aphid control can be applied as a seed coating or as a foliar spray with each targeting a different soybean growth stage. Currently, the chemical insecticides available for soybean aphid management are restricted to three different insecticide groups (1, 3, and 4) and six different subgroups, including 1A. carbamates, 1B. organophosphates, 3A. pyrethroids, 4A. neonicotinoids, 4C. sulfoxamines, and 4D. butenolides (Koch et al., 2018).

Insecticide seed coating is considered a management strategy against pest infestations in the early soybean growth stages. Insecticidal seed coatings lose the toxin's effectiveness shortly after planting. Therefore, seed coatings are most effective and beneficial in mitigating crop damage if soybean aphid population colonization occurs during the vegetative stages[6] or up to 49 days after seed planting (McCornack and Ragsdale,

[5] Experimental studies evaluating potassium levels in leaves have shown that potassium deficiencies in leaves can lead to higher soybean aphid populations through plant effects. One possible mechanism for this relationship is related to nitrogen nutrition or the N-limited nature of soybean aphids; The potassium deficiency can improve the nitrogen nutrition of these N-limited insects. Consequently, allowing soybean aphid populations to reach higher levels more rapidly in the farm (Walter and Difonzo, 2014).

[6] The vegetative stage of soybean plant is determined based on the count of fully expanded trifoliate. Trifoliate leaves are present on the nodes above the unifoliate leaves, and the vegetative development identified from V2, which represents the node with the first trifoliate leaf and extends to the topmost

2006; Hodgson et al., 2012). In 2013, neonicotinoid seed treatments emerged as the predominant insecticide utilized in US soybean production (Hurley and Mitchell, 2017).

Hurley and Mitchell (2017) estimated the benefits of neonicotinoid insecticide seed coatings to soybean farmers using a dataset of surveyed soybean farmers in the Midwest. Of the surveyed farmers, 51% indicated that they used insecticide seed coatings in the 2013 growing season. The authors used farmer-reported average yield information and estimated an average yield gain of 128 kg/ha or about $US 42.20 per soybean planted hectare with insecticide coated seed.

To maximize the potential yield benefits provided by insecticide seed coating, it is recommended to complement them with the application of foliar insecticides. This combination of insecticidal seed coatings and foliar insecticide has been shown to enhance the overall yield improvements associated with insecticide seed coatings (Johnson et al., 2009; Ohnesorg et al., 2009). While seed coatings containing neonicotinoids (Group 4A) are commonly used in soybean, formulations of insecticides from three different groups (1,3, and 4) are often available as foliar sprays for soybean aphid. However, the predominant foliar sprays used for soybean aphid management are formulations of organophosphate (Group 1B) or pyrethroid (Group 3A) insecticides.

Since the timing of colonization of soybean aphid is sporadic over the growing seasons and can include immigration of winged aphids (Favret, 2000), it is essential to identify the optimal time for spraying a foliar insecticide to effectively suppress soybean aphid and protect soybean yield (Hurley and Mitchell, 2017; Koch et al., 2016; Rice et al., 2007; Ragsdale et al., 2007). For most regions in the United States including Minnesota, it is essential to have regular sampling after the bloom stage (R1) through the reproductive stage (R5).[7] Research by Ragsdale et al. (2007) indicates that during the early vegetative to pod set (R4) stage, soybean aphids can cause a 6% reduction in yield for

node of the plant (Rutledge and O'Neil, 2006).

[7] The reproductive growth stages of a soybean plant are classified based on its flowering and subsequent development until maturity. The reproductive growth stage scheme assigns the following designations to each stage: R1, one flower; R2, more than one flower; R3, pod formation; R4, pod elongation; R5, pod fill; R6, green pod; R7, pod maturation; and R8, mature, harvestable pods (Rutledge and O'Neil, 2006).

every 10,000 cumulative aphid days (CAD).[8]

Scouting, or the regular sampling of soybean aphids, improves the timing of management decisions. The most common sampling method involves counting the number of aphids on each plant and calculating the average aphid count per plant (Hodgson et al., 2004).[9] Determining the economic injury level (EIL) and economic threshold (ET) for soybean aphids necessitates an understanding of their growth dynamic and damage potential. Treatment decisions based on the EIL represent the point at which the yield loss from insect damage equals the cost of implementing management actions. Approximately 423 aphids per plant are required for the value of soybean yield loss to exceed the cost of a foliar insecticide spray.[10] Ragsdale et al. (2007) developed an ET using a dataset of 19 experiments over three years in six north-central states. In this study, the estimated economic threshold of 250 aphids per plant was conducted over a wide range of yield, price expectations, and control costs. Despite variations in crop value and input costs, the applicability of this ET remains effective in managing soybean aphids (Ragsdale et al., 2007; Hodgson et al., 2012; Koch et al., 2016). So, growers are recommended to apply a foliar insecticide when the soybean aphid population exceeds the ET of 250 aphids per plant between the flowering (R1) and early seed stages.

Speed scouting for soybean aphid is an alternative approach that is designed to be more efficient and conservative. Instead of trying to estimate the average number of aphids per plant in a random sample of plants, the number of plants with 40 or more aphids in sequential random samples of plants is used to determine when a foliar insecticide should be sprayed (Hodgson et al., 2012; Koch et al., 2018).

[8] According to Ragsdale et al. (2007), cumulative aphid-days is a single value to quantify aphid abundance over time, and it can be calculated on a weekly basis during the sampling period using the following equation:

$$CAD = \sum_{i=1}^{\infty} \left[ \frac{(x_{(i-1)} + x_i)}{2} \right] \times t \tag{3.1}$$

where $x$ is the mean number of aphids on sample day $i$, $x_{i-1}$ is the mean number of aphids on the previous sample day, and t is the number of days between samples $i-1$ and $i$.

[9] For soybean aphids, sampling 38 whole plants per 50 acres (20 hectares) is the most efficient use of time (Hodgson et al., 2004).

[10] This estimation is based on considering a control cost of \$24.51/ha, a market value of \$238.83/ton, and an estimated yield potential of 4.04 ton/ha.

The emergence of pyrethroid-resistant soybean aphid has renewed interest in the use of host plant resistance as a valuable pest management tool. The incorporation of host plant resistance marked a significant milestone in soybean aphid management. However, the commercial adoption of resistant varieties has been limited, particularly among conventional farmers, primarily due to the emergence of aphid biotypes that can overcome the soybean plant's natural defenses, which have been enhanced by soybean breeders (Tilmon, 2019). Despite the underutilization of this approach, the implementation of an effective insect management strategy could incentivize greater commercial development and adoption of aphid-resistant soybean varieties.[11]

### 3.3.2 The emergence of insecticide resistance

The emergence of insecticide resistance has become a growing concern for various industries, including agriculture, forestry, and public health (Silva et al., 2012). Insecticide resistance is defined as a genetically based decrease in susceptibility to pesticides (Tabashnik and Carrière, 2017). An example of micro-evolution that is widely observed is the evolution of pest resistance due to the widespread use of insecticides (Connor et al., 2011).[12]

Over time, the repeated application of insecticides led to the evolution of insecticide resistance in the soybean aphid population in the U.S. The reduced efficacy of a pyrethroid-based insecticide to manage soybean aphids in commercial soybean fields was first reported in North America in 2015, mainly in southwest Minnesota counties. Furthermore, the results of evaluating the vulnerability of aphids to insecticides in small-plot and laboratory studies showed clear indications of growing insecticide resistance within the soybean aphid population (Hanson et al., 2017).

[11] Recent advancements in aphid genetics and markers, and plant gene expression, along with the concept of in-plant refuges may provide the potential to promote the wider commercialization of aphid-resistant soybean varieties (Tilmon, 2019).

[12] Microevolution refers to the small-scale changes in the genetic makeup of a population over time, often in response to environmental pressures such as the widespread use of insecticides, which leads to the selection and survival of pests that are resistant to the insecticides. These resistant pests then pass on their resistance genes to future generations, leading to the gradual evolution of the pest population and the development of insecticide resistance (Silva et al., 2012; Ffrench-Constant et al., 2004).

Hanson et al. (2017) performed laboratory bioassays to compare the rate of insecticide-caused death of field-collected aphids from Minnesota and northern Iowa to that of laboratory aphid colonies that had not been exposed to insecticides in 2015 and 2016. They tested the susceptibility of the aphids to pyrethroid insecticides, and their findings indicated the emergence of insecticide resistance among the aphids collected from locations where insecticides were failing to effectively control soybean aphids.

Ribeiro et al. (2018) reported a moderate level of resistance to neonicotinoid insecticides among soybean aphid population in the North Central region of the US. However, the emergence of insecticide resistance in soybean aphid is not surprising, considering the limited number of chemical-based insecticides available for their management (Koch et al., 2018).

The ability of winged soybean aphids to move and migrate from neighboring fields raised the likelihood of the spread of insecticide-resistant aphid populations to soybean fields throughout the Midwest. This was demonstrated by the growing geographical reach of pyrethroid insecticide resistance, which expanded to include Minnesota, Iowa, North Dakota, South Dakota, and Manitoba by 2017 (Koch et al., 2018). The production cost imposed by developing the insecticide-resistant soybean aphid is two-fold: first, it reduces yield and the quality of crop products; and second, it increases the production cost by requiring additional insecticide applications to compensate for the poor efficacy of the insecticides. Therefore, this issue has raised concerns and led to soybean growers changing their aphid management practices.

## 3.4 Materials and methods

### 3.4.1 Study design

This study is interested in identifying how soybean farmers are changing their management practices in response to the emergence of pyrethroid resistant soybean aphid. To accomplish this objective, the initial strategy planned to first ask farmers about their management practices in the most recent growing season. It then planned to ask them if they have changed their management practices in response to pyrethroid resistant soybean aphid. Farmers who reported a change would then be asked to detail their management practices before the change. An important strength of such a strategy is that it can provide compelling within-subject comparisons of management before and after a change due to pyrethroid resistant soybean aphid.

There are also important weaknesses in the initial plan. First, farmers must be able to accurately detail their management practices before and after the change, which can be particularly difficult depending on how long ago the change took place. Second, when the possibilities for management are complex, as they are with soybean aphid management, asking farmers to detail their management practices before and after a change based on recall can be overly burdensome, discouraging farmer participation. Given recent evidence of the potential for bias with recall data (Beegle et al., 2012; Raphael, 1987; Lee et al., 2005) and diminishing response rates on farmer surveys (Dillman et al., 2014), follow up questioning was dropped from the initial plan. The weakness introduced by dropping these follow-up questions for farmers who reported changing management is that identification must now rely on between-subject comparisons. For such a comparison to be valid, the treatment, a change in management due to pyrethroid resistance, must be conditionally independent of farmers' management practices or statistical methods that can account for possible dependencies must be employed. This study employs instrumental variable methods with two different instruments to account for biases that could be introduced from a lack of conditional independence.

### 3.4.2 Sampling Strategy

According to Table 3.1, 78% of soybean farmers in Minnesota in 2017 operated relatively small farms with less than 1,000 acres, while accounting for 39% of soybean acres harvested in the state. Conversely, about 22% of soybean farmers operated relatively large farms, with 1,000 or more acres, accounting for 61% of harvested soybean acres in the state. In contrast, almost half of the soybean farmers (50%) in North Dakota in 2017 operated relatively large farms with more than 2,000 acres covering nearly 77% of the state's total soybean acres harvested. In comparison to about 49% of soybean farmers operated relatively small farms with less than 2,000 acres covering almost 23% of the state's total soybean acres harvested.

Accounting for the fact that relatively large farmers harvest most of the soybean acreage and in order to obtain a sample representative of the average acre of harvested soybean for our results, the present study sent out surveys to 2,300 soybean farmers in Minnesota, including 920 farmers who operated relatively small farms and 1,380 farmers who operated relatively large farms. This sample represented 4.2% and 23% of the total population of farmers with small and large operations in the state, respectively. Similarly, the surveys were sent to 173 soybean farmers operating relatively small farms in North Dakota (representing 4.1% of all small farms) and to 518 farmers operating relatively large farms in the state (representing 12.3% of all large farms).

Table 3.1 compares the characteristics of soybean farms in Minnesota and North Dakota with the 2017 U.S. Census of Agriculture and this study's survey sample. The table shows oversampling from farmers operating on large farms in both states. To address this issue, we constructed the survey design weights. The weights were calculated based on the inverse of the probability of selection considering the sample design's stratification. By adopting this approach, we ensure that our results accurately reflect the characteristics and conditions typically encountered on an average acre of harvested soybean.

### 3.4.3 Survey Administration

The survey sample was obtained from Farm Market ID, a commercial agricultural data service provider, which is now owned by DTN.[13] The recruitment processes included

[13] Farm Market ID maintains an extensive proprietary database encompassing over two million farm operators and owners, which accounts for more than 95% of all U.S. farm operations. This comprehensive database is regularly updated using information sourced from the U.S. Department of Agriculture, state and local governments, and various private sources (DTN).

Table 3.1: Characteristics of Soybean Farm Operations in MN and ND, in 2017.

| | USDA NASS | | Survey Sample | |
|---|---|---|---|---|
| | Total Area Operated (acres) | Total Farmers | Survey Sample | % of the Total Farmers |
| **Panel A: Minnesota** | | | | |
| Small farms: Below 1,000 acres operated | 3,126,052 (38.39%) † | 21,888 (78.55%) | 920 | 4.20% |
| Large farms: 1,000 acres operated and above | 5,016,420 (61.61%) | 5,977 (21.45%) | 1380 | 23.09% |
| **Panel B: North Dakota** | | | | |
| Small farms: Below 2,000 acres operated | 1,588,333 (22.41%)† | 4,179 (49.77%) | 173 | 4.13% |
| Large farms: 2,000 acres operated and above | 5,497,407 (77.58%) | 4,217 (50.23%) | 518 | 12.29% |

† In 2017, the total area of soybean farming operations in Minnesota and North Dakota amounted to 8,142,472 and 7,085,740 acres, respectively.
(USDA National Agricultural Statistics Service, 2017 Census of Agriculture.)

sending out a total of 2991 invitation postcards randomly to Minnesota and North Dakota soybean farmers in early November 2021, specifically, the surveys were mailed to 2300 farmers in Minnesota and 691 farmers in North Dakota. The criteria to be eligible as survey respondents in this study included being an owner or operator of a farm that had a recent history of producing soybean in either Minnesota or North Dakota. Table 3.2 provides a timeline of survey administration, starting from the initial invitation postcards sent out to the final reminder to complete the survey.[14]

Out of the total 2991 mailed surveys, 2963 (99%) farmers were recorded as having received the survey, with 28 (1%) surveys undelivered. The response rate for this study was 20.35% as 603 farmers out of 2963 participated and completed the survey. However, for this study, responses from individuals who were not soybean farmers, such as

[14] The University of Minnesota's Institutional Review Board (IRB) reviewed and approved of the survey instrument and this administration protocol.

Table 3.2: Timeline of the survey administration.

| Survey timeline | Number of postcards/surveys | | Date |
|---|---|---|---|
| | Minnesota | North Dakota | |
| Initial invitation postcards sent out | 2300 | 691 | November 3, 2021 |
| First survey mailing | 2300 | 691 | November 11-12, 2021 |
| Second invitation postcards sent out | 2300 | 691 | November 18, 2021 |
| Final survey mailing | 1765 | 595 | December 20, 2021 |

crop consultants or agronomists, retired farmers, or those who rent their land, were considered ineligible participants and excluded from the analysis. Finally, among the 603 responses, 399 (66.1%) survey responses were deemed adequate and eligible for the study, consisting of 352 (88.22%) soybean farmers from Minnesota and 47 (11.77%) from North Dakota. Table B.7 in the appendix shows the response rates for different categories of farmers (owners, owner-operators, and operators) in Minnesota and North Dakota. The calculation of the gross responses rate in this table involved the inclusion of all returned responses, regardless of their eligibility, while considering the total number of surveys that were successfully delivered. It is important to note that the survey was distributed to owners who were not operators and that these farmers were less likely to respond because the survey was likely not relevant to them. The data presented in Table B.7 in the appendix show that the response rates for non-operator owners in Minnesota and North Dakota were 18.2% and 9.4% respectively. These response rates were lower compared to the response rates for farm operators in both states, which were approximately 24% for Minnesota and 14% for North Dakota. Consequently, the response rates would have been increased if we did not sample owners.

### 3.4.4 Survey overview

The survey instrument employed in this study was specifically designed to collect primary data on pesticide resistance's impact on soybean farmers' management practices in Minnesota and North Dakota. To gauge changes in management practices in response to the emergence of pesticide resistance, the survey measured the utilization of relevant management practices and whether these practices had undergone any changes due to insecticide resistance concerns. Comparing management practices between farmers who did and did not change management due to insecticide resistance concerns provides an estimate of the impact of insecticde resistance on farmers soybean aphid management.

The survey instrument was constructed with multiple sections, each intended to gather information on various aspects of soybean farming practices. Each section of the survey was designed to be clear, concise, and easy to understand to encourage maximum participation from the targeted population.

The survey's five sections were: (1) Farm characteristics, (2) Soybean aphid management, (3) Foliar insecticides used to manage soybean aphids over the past five years, (4) Farmers' thoughts about pesticide resistance, and (5) Farmers' characteristics. The survey was administered in the fall of 2021 after the growing season and asked questions about the farmers 2021 growing season and practices during the previous four seasons.

### 3.4.5 Response variables: Soybean aphid management practices

The survey instrument included a set of questions designed to derive the response variables of interest and aimed to capture information on farmers' management strategies for controlling soybean aphid on their farms. The main question of the survey asked farmers to indicate which practices they used to control soybean aphid. The question was formulated as follows:

---

*"What practices did you use to manage soybean aphids in 2021? Please check all that apply."*

- *Applied a foliar insecticide*
- *Conserved natural enemy (e.g., parasitic wasps or other aphid predators) population*

- *Planted insecticide-treated soybean seed*
- *Planted soybean seed variety with resistance or tolerance to soybean aphid*
- *Scouted fields*

---

Additionally, farmers were asked whether they have used foliar insecticides to manage soybean aphids in the past five years. The following survey question filtered out a subsample of respondents who answered "Yes" to this specific question.

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*"In the past five years, have you used foliar insecticides to manage soybean aphids?"*

- *Yes*
- *No*

---

For those farmers who answered "Yes", an additional subset of questions was asked to assess and monitor their use of foliar insecticides in greater detail. These questions pertained to their scouting practices, frequency of field scouting, and the type of foliar insecticides they employed for controlling the soybean aphids on their farms.

Soybean farmers commonly use different commercialized foliar insecticides that are labeled with different active ingredients for controlling soybean aphids. A list of the labeled mode of action was provided in the survey, and farmers were asked to select the ones used as foliar insecticides. Their responses were classified into six main groups of insecticides, and two dummy variables were constructed for the two most frequently used insecticide groups: organophosphates (Group 1B) and pyrethroids (Group 3A). A value of 0 indicated non-usage, while one stated the usage of pyrethroids/organophosphate insecticides on their farms in the past five years.

This study's response variables included five dummy variables and one ordinal variable with five categories.[15] Dummy variables were constructed for foliar insecticide use in the past five years, insecticide-treated seed, scouting farms, pyrethroid use, and organophosphates use, and the ordinal variable was used for frequency of the field scouting per year, including the categories of once-a-year, twice a year, 2 to 5 times a year, 6 to 10 times a year, and more than ten times a year. We used the total sample of survey responses to examine the first three response variables (foliar insecticide use in the past five years, insecticide-treated seed, and scouting farms). A subsample of survey respondents who reported using foliar insecticides in the past five years was used to analyze three response variables: pyrethroids use, organophosphate use, and frequency of field scouting per year. This subsample was selected to focus specifically on farmers who had direct experience with soybean aphid management using foliar insecticides.

Despite the prevalence of pyrethroid resistance in soybean fields, some farmers still employ pyrethroid insecticides for the management of soybean aphids. Table 3.3 summarizes the distribution of the main outcomes of interest as different soybean aphid management practices including using insecticide-treated soybean seed, field scouting, using foliar insecticide in the past five years, using pyrethroids and organophosphates insecticides, and frequency of field scouting during the 2021 growing season. It shows a heavy reliance on insecticides with more than 72% of farmers using foliar insecticides to manage soybean aphid during the past five years. More specifically, 76% and 56% of farmers said that they used pyrethroid and organophosphate insecticides. Of total survey respondents, 30% of farmers reported using insecticide-treated soybean seed in the 2021 growing season. Scouting fields was reported by most farmers (about 70%), while 13%, 51%, 25%, and 9% of farmers reported the frequency of field scouting twice

[15] While farmers were asked if they applied a foliar insecticide in 2021 for completeness, we instead focus our analysis on whether they applied a foliar insecticide in the past 5 years because not to applying a foliar insecticide in 2021 could be attributable to a farmer choosing not to use foliar insecticides or choosing to use them conditionally, but not observing the conditions that would trigger an application. We also do not report results for a farmer's use of a soybean seed variety with resistance or tolerance to soybean aphid, or conservation of natural enemy populations because these practices were rarely used (13% and 7% of farmers) and did not vary with the independent variables of primary interest in our preliminary analysis.

a year, 2 to 5 times a year, 6 to 10 times a year, and more than 10 times a year.

We explored the most relevant management changes by focusing our attention on the most commonly used management practices: foliar insecticide use in the past five years, use of insecticide-treated soybean seed, and field scouting. For the subsample of farmers who reported using foliar insecticide in the past five years, attention was focused on pyrethroid use, organophosphate use, and frequency of field scouting per year.

Table 3.3: Distribution of response variables: Farmer use of alternative soybean aphid management practices in growing season of 2021.

| | **Minnesota** | **North Dakota** | **Total sample** |
|---|---|---|---|
| **Total sample** † | **(Percentage of survey respondents)** | | |
| Planted insecticide-treated soybean seed | 31.8 | 27.6 | 31.3 |
| Scouted fields | 71.8 | 57.4 | 70.1 |
| Foliar insecticides in the past five years | 78.1 | 33.3 | 72.8 |
| **Subsample of participants who used foliar insecticides in the past five years** †† | | | |
| Pyrethroid insecticides | 77.0 | 66.6 | 76.4 |
| Organophosphate insecticides | 55.5 | 66.6 | 56.1 |
| Field scouting frequency | | | |
| Once a year | 1.0 | 0 | 1.0 |
| Twice a year | 13.3 | 14.2 | 13.3 |
| 2 to 5 times a year | 51.0 | 50.0 | 51.0 |
| 6 to 10 times a year | 25.5 | 21.4 | 25.3 |
| More than 10 times a year | 8.8 | 14.2 | 9.1 |

† The total number of survey responses is 399, with 352 responses from Minnesota and 47 responses from North Dakota. †† The following analysis focuses on the subsample of participants who responded positively to the question regarding the use of foliar insecticides in the past five years. Out of the total number of participants who responded to this question (n=391), 285 reported using foliar insecticides in the past five years. Of these 285 respondents, 270 were from Minnesota and 15 were from North Dakota.

Response variables in this study include five dummy variables and one ordinal variable with five categories. Five dummy variables were constructed for foliar insecticide use in the past five years, insecticide-treated seed, scouting farms, pyrethroid use, and organophosphates use with a value of 0 indicating non-usage of the corresponding management practice and 1 indicating its usage by the farmer in the growing season of 2021; and the ordinal variable was used for frequency of the field scouting per year, including the categories of once-a-year, twice a year, 2 to 5 times a year, 6 to 10 times a year, and more than ten times a year.

### 3.4.6 Explanatory variables

The primary focus of this study is to examine the adoption of different soybean aphid management strategies by farmers who changed their management practices due to insecticide resistance concern. This was conducted by utilizing the survey question:

---

*"Have you changed how you manage soybean aphids over the past five years due to insecticide-resistance concerns?"*

- *Yes*
- *No*

---

We used the responses to this question to create our treatment variable as an indicator variable that was set to 1 for respondents who answered "Yes" and changed their pest management practices due to concerns about insecticide resistance (0 otherwise). Table 3.4 shows that almost 30% of farmers changed their practices due to insecticide resistance concerns.

This study employed a set of control variables including farmers and farm environment such as farmer's education level, experience, age, planted acres, risk aversion, and patience level to control factors affecting farmers' practices choices for managing soybean aphid.

Educational attainment is used in literature as a proxy for broadly applicable skills and knowledge, while farming experience aimed to measure farmer's specific skills and knowledge, such as decision-making, problem-solving, and overall farm management techniques (Miyittah et al., 2022; Hurley and Mitchell, 2020; Frisvold et al., 2009). Farmer age was also included to account for potential differences between new entrants in soybean farming and those who have been engaged in this practice for a longer period. Furthermore, total cropland was used to capture the additional time constraints and complexities of managing larger farm operations (Hurley and Mitchell, 2020; Dong et al., 2016).

Following Dohmen et al. (2011), farmers were asked to rate their willingness to take a risk and their patience on 11-point scale to capture farmers' attitudes toward risk and time preferences. Farmers' risk tolerance and patience level are important factors in agricultural decision-making due to farming practices' inherent uncertainties and long-term implications.[16] Variables to control for variations in farmers' risk tolerance and patience level were derived from responses to the following questions.

---

- ***Risk tolerance question:***
  *"Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? (On a scale of 0 to 10, where 0 is not at all willing to take risks and 10 is Very willing to take risks)"*

- ***Patience question:***
  *" Are you generally an impatient person or someone who always shows great patience? (Please circle the number that best applies on a scale from 0 Very impatient to 10 Very patient)"*

---

Table 3.4 presents a summary of the key variables of farmers and farm operation characteristics of the final sample analyzed in this study. It shows the sample of farmers used in this research analysis on average have 40 years of farming experience and more than half of them have a college degree. They planted on average 732 acres soybean during 2021 growing season.

[16] Risk tolerance and patience are frequently identified as key factors influencing production decisions in farming due to the unpredictable nature of crop yields and prices during the planting phase (Hurley and Mitchell, 2020; Bozzola and Finger, 2021).

Table 3.4: Descriptive statistics of farm and farmers characteristics (explanatory covariates).

| **Total sample** | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|
| Years of farming | 40.07 | 12.31 | 9 | 84 |
| Age (years) | 60.76 | 10.18 | 31 | 89 |
| Risk aversion (0-10 scale) | 5.98 | 1.88 | 0 | 10 |
| Patience tolerance (0-10 scale) | 6.09 | 2.11 | 0 | 10 |
| Total soybean acres planted | 732 | 3,500 | 0 | 71,000 |
| Change management practices due to insecticide resistance concerns (%) | 29.58 | | | |
| Education (%) | | | | |
| Completed High School | 35.59 | | | |
| Attended Vocational/Technical | 1.00 | | | |
| Completed College | 61.40 | | | |
| Completed Graduate School | 2.01 | | | |

Total sample responses:399.

## 3.5 Empirical Strategy

### 3.5.1 Identification strategy: Instrumental variable approach

This study aims to measure changes among Midwest farmers in their adoption of different management practices due to emerging insecticide-resistant soybean aphid. It is of interest to know how the adoption of different management practices ($MP$) differs between farmers who have changed their practices due to insecticide resistance concerns ($\Delta MP$) and those who have not. A naïve approach to study this hypothesis is to use ordinary least squares ($OLS$) for each response variable to estimate the regression equation:

$$MP_{ip} = \beta_0 + \beta_1 \Delta MP_i + \alpha_k X_{ki} + \epsilon_i \tag{3.2}$$

where $MP_{ip}$ represents the response of interest of farmer $i$ for management practice $p$ (i.e., using foliar insecticide in the past five years, using seed treatment, field scouting, using pyrethroid or organophosphate foliar sprays, and field scouting frequency over a year);[17] $\Delta MP_i$ is the treatment variable as an indicator variable that equals one if a farmer changed soybean aphid management practice due to insecticide resistance concerns, and 0 otherwise; $X$ is a vector of control variables including farmers and farm operation characteristics;[18] and $\epsilon_i$ is unobserved, mean zero random error.

This naïve specification may be viewed with skepticism due to endogeneity issues. Specifically, the potential endogeneity through omitted variables or unobserved confounders that may jointly affect the two main variables of interest (choosing alternative management practices, $MP$, and changing management practices due to insecticide resistance concern, $\Delta MP$) could lead to biased and inconsistent coefficients in the estimation. To address the endogeneity concern, the present study employs the instrumental variable method. Two potential instrumental variables are proposed: a farmer's pesticide resistance concern level and a farm operation's proximity to reported counties with confirmed cases of insecticide resistant soybean aphid. The first variable is measured by the survey and the second variable is constructed independently of the survey with the evidence of insecticide resistance that raised university researchers' and policy makers' concerns. The following survey question asked farmers to rate their level of concern regarding insecticide-resistant soybean aphid.

*"How concerned are you about insecticide-resistant soybean aphids? (On a scale of 0 to 10, where 0 is not at all concerned and 10 is very concerned)"*

[17] Field scouting frequency includes 5 different categories including once a year, twice a year, 2 to 5 times a year, 6 to 10 times a year, and more than 10 times a year.

[18] Farmer's education level, age, years of experience, total planted crop acres, farmer risk aversion and farmer patience level were controlled in all estimations.

The response to the question is used as an instrumental variable ($IV$) or a source of exogenous variation to address the potential endogeneity problem. For the second, we employ an average distance variable. For this variable, we obtained an external dataset that provides information on the counties in Minnesota and North Dakota where cases of insecticide-resistant aphid on soybean farms were confirmed between 2015 and 2020.[19] Using the geographical coordinates (latitudes and longitudes) of these counties, we calculated the proximity of each surveyed farmer's farm to these locations. Specifically, we measured the distance between each surveyed farmer's farm county and each reported insecticide-resistant county. By averaging these distances across all counties with reported pyrethroid failures, we derived a variable that represents the average proximity of the farms to the counties where insecticide resistance was observed.[20] We exploit the exogenous variation of this variable to isolate the part of endogenous variable $\Delta MP$ that is driven by the instrumental variable (see Figure B.2 in the appendix B which shows a map of surveyed farmers' county location and the county reported insecticide failure to control aphids on their farms).

A potential concern with using the self-reported farmer's insecticide resistance concerns as an instrumental variable is that it may not be exogenous as it is measured with the same survey instrument as the response and treatment variables. Consequently, there

[19] This dataset obtained from the report were received documenting instances of pyrethroid insecticides failing to effectively control soybean aphids in the field, with a particular focus on southwest Minnesota. In response to these reports, soybean aphid populations were collected from various soybean fields within the affected geographic area. These collected populations were then subjected to laboratory assays to determine their susceptibility to two commonly used pyrethroid insecticides, namely bifenthrin and lambda-cyhalothrin. The results of these bioassays confirmed the presence of resistance to these insecticides among soybean aphid from multiple locations across the region. By 2017, the scope of reported insecticide failures and confirmed resistance expanded to encompass a broader geographic area that included Minnesota, Iowa, North Dakota, South Dakota, and Manitoba. Subsequent investigations in 2018 revealed the continued presence of insecticide-resistant soybean aphid populations across a wide range of locations within Minnesota (Hanson et al., 2017; Koch et al., 2018).

[20] Among the reported cases of insecticide failure, a total of 43 counties were identified for Minnesota and North Dakota. It was found that out of these 43 counties, 4 counties reported insecticide failure for two different years, indicating a sustained issue in those areas. Additionally, 4 counties reported insecticide failure for three different years, suggesting an ongoing and recurring problem. The remaining 35 counties reported insecticide failure for only one year, indicating isolated incidents in those regions. These findings emphasize the varying degrees of prevalence and persistence of insecticide failure across different counties.

is a concern that they may not satisfy the untestable exclusion assumption required for it to be a valid instrument. To address this concern, the average distance variable was introduced as a potential instrument, as it satisfies the assumption of being uncorrelated with the primary management practices.

Table 3.5 shows the descriptive statistics for three variables resistance concern, change management due to resistance concern, and average distance for the subsamples from Minnesota and North Dakota as well as the pooled sample.

Table 3.5: Descriptive statistics for main variables of interest.

| **Total sample** | Mean proportion | Standard deviation | Min | Max |
|---|---|---|---|---|
| Change management (%) | 29.5 | | | |
| Insecticide resistance concern (0-10) | 5.8 | 2.3 | 0 | 10 |
| Average distance (in Miles) | 169.12 | 47.63 | 122.34 | 416.46 |
| **Minnesota** | | | | |
| Change management (%) | 31.9 | | | |
| Insecticide resistance concern | 5.8 | 2.2 | 0 | 10 |
| Average distance (in Miles) | 158.16 | 29.09 | 122.34 | 247.43 |
| **North Dakota** | | | | |
| Change management (%) | 11.3 | | | |
| Insecticide resistance concern | 5.5 | 2.8 | 0 | 10 |
| Average distance (in Miles) | 251.21 | 73.29 | 148.24 | 416.46 |

Total sample responses:399, Minnesota responses 352, North Dakota responses: 47.

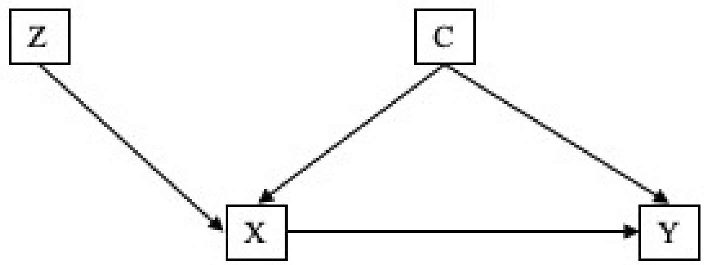
### 3.5.2 Research Design

Using an instrumental variable is a distinct approach in causal analysis and it is used to estimate the coefficients of the model and provides an effective means of addressing endogeneity concerns. The $IV$ method enables the use of instrumental variables that are correlated with the endogenous variable but not with the error term to estimate the model parameters. While the use of $IV$ methods can produce unbiased and consistent estimates of coefficients, it may come at the cost of reduced efficiency compared to standard $OLS$ regression (Angrist et al., 1996). The research design and analysis in this study are guided by Figure 3.1 which depicts a Directed Acyclic Graph (DAG) (Pearl, 2009). This framework provides a foundation for understanding the relationships among variables and guides the interpretation of the results. In a DAG, a line between variables with an arrow pointing at one of the variables depicts a causal relationship. For example, the line between X and Y with an arrow pointing at Y implies that X has a causal effect on Y. A set of lines that connects two variables, possibly indirectly, is referred to as a path. For example, the line in Figure 3.1 between X and Y forms a path between X and Y. The line between C and X and the line between X and Y form a path between C and Y as does the line between C and Y. The difference between these two paths is that the line between C and Y depicts a direct causal relationship between C and Y, while the lines between C and X and X and Y depict an indirect causal relationship between C and Y through X.

According to Figure 3.1, when estimating the effect of X on Y while controlling for variable C, we include C as a covariate in the model and then remove the explained parts, both direct and indirect. This helps us close any potential backdoor paths that pass through C and can confound our results. However, when employing an instrumental variable like Z to estimate the effects of X on Y, we utilize it as a proxy for X and to find an exogenous source of variation that explains Y only by way of the causal variable X, thereby removing the unexplained portions. By doing so, we focus solely on the causal paths originating from Z, effectively bypassing any confounding variables. The portion of X and Y that is explained by Z represents the part with no back doors, an effect that is not confounded by other variables, enabling us to obtain unbiased estimates of the causal relationship between X and Y (Huntington-Klein, 2021; Morgan and Winship, 2015; Pearl and Mackenzie, 2018).

Figure 3.2 (a) depicts the primary relationship that is the focus of interest in this

Figure 3.1: Graph depicting the ideal case of Z as a potential valid instrumental variable (IV).




study: how soybean aphid management practices ($MP$) differ between farmers who have changed their practices ($\Delta MP$) due to insecticide resistance concerns and those who have not. This relationship represented by the line connecting $\Delta MP$ and $MP$, indicates that there exists a causal effect of changes in soybean aphid management $\Delta MP$ on soybean aphid management practices $MP$. However, comprehensively understanding this relationship is challenging due to the joint influence of other factors known as the Farmer and Farm Environment ($FFE$) and Omitted Variables ($OV$). The $FFE$ encompasses various elements, including farmers' characteristics such as age, human capital, experience, risk aversion, and patience tolerance, as well as farm characteristics like farm acre size (Pannell and Zilberman, 2001). Figure 3.2 (b) illustrates the presence of common causes that affect both $\Delta MP$ and $MP$, represented by the inclusion of $FFE$ and $OV$ in the graph. This is depicted by lines with arrows running from $FFE$ and $OV$ to both $\Delta MP$ and $MP$. To account for $FFE$, we include $FFE$ as a covariate in the model and subsequently eliminate any mediated influences by blocking potential backdoor paths that may pass through $FFE$. To address the anticipated common causes of omitted variables and endogeneity, the survey included a measure of farmers' Insecticide Resistance Concerns ($IRC$) with the purpose of utilizing it as an instrumental variable, see Figure 3.2 (c). The aim to employ $IRC$ as an instrumental variable to estimate the effects of $\Delta MP$ on $MP$, is to utilize $IRC$ as a proxy for $\Delta MP$ and to find an exogenous source of variation that explains $MP$ only by way of the causal variable $\Delta MP$, thereby removing the unexplained portions. By doing so, we focus solely on the causal paths originating from $IRC$, effectively bypassing any confounding variables. The portion of $\Delta MP$ and $MP$ that is explained by $IRC$ represents the part with no back doors and the effect that is not confounded by other variables, enabling us to obtain unbiased estimates of the causal relationship between $\Delta MP$ and $MP$ (Huntington-Klein, 2021; Pearl and Mackenzie, 2018; Morgan and Winship, 2015). However, the potential issue of using self-reported farmer's insecticide resistance concerns as an instrumental variable raises, as it may not be exogenous since it is measured using the same survey instrument as $FFE$ may jointly influence it. Therefore, the average distance ($AD$) variable was used as another potential instrument, as it satisfies the assumption of being uncorrelated with the primary management practices.

The conditions for the instrument to be valid are: (i) there is enough correlation between instrument variables and $\Delta MP$ variable or instruments help to explain the variation in the endogenous variable that is not accounted for by other factors (relevance assumption), and (ii) the instrument variables are not directly correlated with main outcome of interest ($MP$) or an unobserved determinant (exclusion assumption)(Angrist and Pischke, 2009). To satisfy this exclusion restriction assumption for using instrumental variables ($IV$) requires adjusting for all open paths (i.e., backdoor) between $IV$ and $MP$ in the hypothesized model in the Structural Causal Model with common causes in Figure 3.3:

1. $IV \rightarrow \Delta MP \rightarrow MP$
2. $IV \rightarrow \Delta MP \leftarrow$ Omitted variables ($OV2$) $\rightarrow MP$

Figure 3.2: (a) Primary Relation of Interest, (b) Primary Relation of Interest with Farmer  Farm Environment and Omitted Variables Confounding, and (c) Primary Relation of Interest with Farmer  Farm Environment, Omitted Variables Confounding and Instrumental Insecticide Resistance Concern Variable for Identifying the Causal Effect.

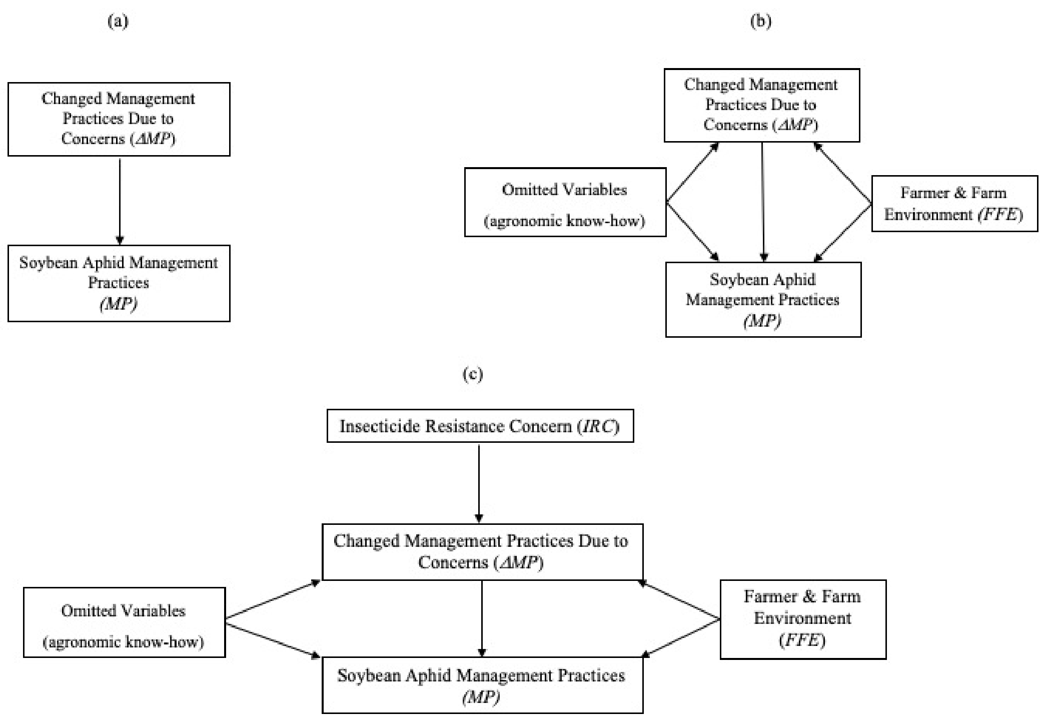
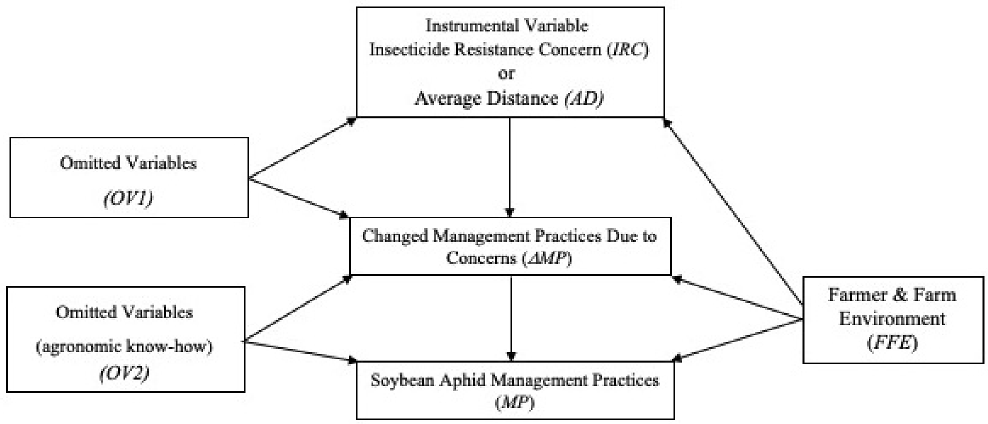


Figure 3.3: Hypothesized Structural Causal Model.




3. $IV \leftarrow$ Omitted variables $(OV1) \rightarrow \Delta MP \rightarrow MP$

4. $IV \leftarrow$ Omitted variables $(OV1) \rightarrow \Delta MP \leftarrow$ Omitted variables $(OV2) \rightarrow MP$

5. $IV \leftarrow FFE \rightarrow \Delta MP \rightarrow MP$

6. $IV \rightarrow \Delta MP \leftarrow FFE \rightarrow MP$

7. $IV \leftarrow FFE \rightarrow MP$

To account for these indirect paths and use $IV$, a group of control variables must be determined that can effectively block them. It is necessary to ensure that all paths from $IV$ to $MP$ incorporate the $\Delta MP$ variable, as isolating the variation in $\Delta MP$ caused by $IV$ renders any other paths or arrows leading to $\Delta MP$ insignificant.[21] The first six paths are blocked by $\Delta MP$ and the only way to block path (7) is by using

[21] To use $IV$, we need to have all open paths from $IV$ to $MP$ to contain $\Delta MP$ variable because once we isolate the variation in $\Delta MP$ driven by $IV$, there is no association between $IV$ and $MP$ and because $\Delta MP$ is a collider variable along all of them (i.e., it is a way to isolate the covariation in $\Delta MP$ and $MP$ that is causal and ignore the other covariation in $\Delta MP$ and $MP$ that is noncausal or any other arrow leading to $\Delta MP$ basically doesn't matter anymore) (Morgan and Winship, 2015; Huntington-Klein, 2021).

farm and farmer characteristics as a control variable; so the validity of $IV$ variable holds conditional on farm and farmers features. In other words, the decision to change management due to insecticide resistance concerns is associated with the instrumental variable. However, the instrumental variable is not expected to directly affect management practices, except through its impact on the decision to change management due to insecticide resistance concerns (Huntington-Klein, 2021; Pearl, 2009). We refer to a conceptual framework illustrated by Huntington-Klein (2021) and emphasize a key assumption that underly the effectiveness of using an instrument. As depicted in the figure 3.3, the crucial assumption is that there should be no omitted variables that span across the pathway from the instrument, in this case, insecticide resistance concerns, to the response variable, which represents changes in farmers' management practices. If such omitted variables were present, they could potentially confound the relationship between the instrument and management practices, rendering the IV less effective.

To clarify, this assumption implies that the instrument, in this case, resistance concerns (IV), should not directly impact management practices. However, we designed our survey question to strategically intercept this potential causal pathway. The survey question explicitly asked whether farmers had changed their management practices due to concerns about insecticide resistance. This design was intended to break the direct link between resistance concerns and management practices, allowing us to effectively use resistance concerns as an instrument.

Nevertheless, it is important to acknowledge potential sources of error or bias that might affect the effectiveness of this instrument. Mainly, surveys inherently introduce some degree of measurement error, which can lead to correlated errors across survey responses. Therefore, we have also employed the exogenous average distance variable as an alternative instrument to cross-verify our findings and ensure the robustness of our conclusions. This variable, reflecting farmers' proximity to incidents of resistance, is likely to evoke concerns when resistance is observed and potentially trigger adjustments in management practices.

The use of the average distance to counties reporting insecticide-resistant aphids as an instrumental variable (IV) in our analysis is based on several compelling arguments that attest to its validity. One is that these geographical distance data met the assumption of being uncorrelated with the outcome responses since it is from an external data source. Furthermore, a compelling argument for the validity of the average distance as an instrument variable is from the nature of resistance evolution itself. Resistance in aphids, as in many cases, initiates with a random mutation of a gene. The occurrence of such mutations and subsequent resistance events can be viewed as a somewhat random process. Therefore, the counties where resistance emerges can be considered, to some extent, a random outcome of this mutation process. In other words, the selection of counties with resistant aphids is not influenced by farmers' management practices, but rather by the stochastic nature of genetic mutations. This multifaceted approach enhances the reliability of our analysis and strengthens the validity of our instrumental variable models.

This leads to the first and second stages of the equations as the following specifications to estimate the relationship:

$$\Delta MP_i = \delta_0 + \delta_1 IV_i + \delta_k X_{ki} + \zeta_i \tag{3.3}$$

$$MP_{ip} = \beta_0 + \beta_1 \widehat{\Delta MP_i} + \alpha_k X_{ki} + \epsilon_i \tag{3.4}$$

where $IV_i$ represents the instrument variable including a farmer's pesticide resistance concerns; and a farm operation's proximity to reported counties with confirmed cases of pesticide resistance; $MP_{ip}$ represents the outcome of interest of farmer $i$ for each management level of $p$ (i.e., using foliar in the past five years, using insecticide-treated soybean seed, scouting the fields, using pyrethroid and organophosphate as foliar insecticides, and field scouting frequency); $\Delta MP_i$ is indicator variable that equals one if a farmer $i$ changed soybean aphid management practice due to insecticide resistance concern, and

0 if the farmer did not change soybean aphid management practice due to insecticide resistance concern; $X$ is a vector of control variables including farmers and farm operation environment; $\epsilon_i$ is unobserved, mean zero random error. $\beta_1$ is the coefficient of interest to examine the association of changing insect management due to resistance concern with the adoption of appropriate management practices.

## 3.6 Results

The study aimed to investigate the relationship between farmers who indicated a change in their management practices due to concern about insecticide resistance in soybean aphid and their adoption of alternative pest management strategies. Specifically, we investigate the extent to which farmers who express insecticide resistance concern are more likely to adopt alternative management practices.

The results presented in this section are from the estimation of equations 3.3 and 3.4 where the response variables are the different recommended management practices, and the endogenous variable is an indicator for a change in management due to pesticide resistance concern.

For the estimation of model parameters, we focus on two different sets of outcome variables. The first set consists of dummy variables, namely Foliar_5years (using foliar insecticide in the past five years), Insecticide treated seed, and Scouting. We used the total sample of surveyed farmers to estimate the parameter for the change management due to insecticide resistance concern for this set of outcome variables. The second set includes dummy variables representing pyrethroid use, organophosphate use, and an ordered variable indicating the frequency of scouting per year. We use a subsample of survey farmers who reported using foliar insecticide in the past five years to estimate the model parameter for this set of outcome variables.

Panels A, B, and C in Table 3.6 report the results of model estimation with dependent variables as Foliar_5years, Insecticide treated seed, and Scouting, respectively. Column 1 reports the naïve (reduced form) regression result. Columns 2 and 3 present 2SLS regression results using different variables as instrumental variables. In panel A, the reduced form estimation coefficient on change management is 0.15 and strongly significant, implying that farmers who change their management due to insecticide resistance concern are more likely to have used a foliar insecticide in the past five years. The second stage regression result of instrumenting a change in management with the resistance concern level shows a positive, though not significant coefficient. However, in column 3, the result of second stage regression of using average distance as an instrument shows positive and strongly significant coefficient suggesting a causal effect that farmers who change their management due to insecticide resistance are more likely to have used a foliar insecticide in the past five years. This suggests that these farmers relied on chemical-based insecticides for soybean aphid control, despite the emergence of resistance. Similarly, panel B of Table 3.6 shows the estimation results for insecticide treated seed are positive and significant for the naïve regression, but not significant for the IV regressions.

For the dependent variable Scouting in Panel C of Table 3.6, the coefficient on change in management in the naïve (reduced form) regression is negative and statistically insignificant. Moving to the instrumental variable ($IV$) regressions, the second stage regression using the resistance concern level as an instrument yields a positive estimate that is statistically significant at the 5% level. This result suggests that farmers who made changes to their pest management strategies due to insecticide resistance concerns are more likely to engage in scouting activities. However, when employing the average distance as an instrument in the second stage regression, the coefficient is positive, but not statistically significant.

Table 3.7 presents the findings from the analysis conducted on the subsample of farmers who reported using a foliar insecticide in the past five years. This analysis aimed to gain insights into their practices regarding the utilization of diverse chemical-based insecticides and the frequency of farm scouting per year.

Table 3.6: IV regression Two-Stage Least Squares (2SLS) parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **TOTAL SAMPLE**.

| **Panel A: Foliar_5Years** | (1) OLS | (2) 2SLS | (3) 2SLS |
|---|---|---|---|
| | | IV: Resistance Concern Level | IV: Average distance |
| Change Management | 0.15*** | 0.17 | 2.00*** |
| | (0.05) | (0.33) | (0.77) |
| Weak Instruments (∼Robust F test) | | 15.85; p = 0.00 | 8.19; p = 0.00 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 0.03; p = 0.86 | 25.42; p = 0.00 |
| Observations | 368 | 366 | 367 |
| **Panel B: Insecticide treated seed** | | | |
| Change Management | 0.17*** | -0.18 | 0.57 |
| | (0.05) | (0.39) | (0.38) |
| Weak Instruments (∼Robust F test) | | 15.91; p = 0.00 | 8.83; p = 0.00 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 2.81; p = 0.09 | 1.40; p = 0.23 |
| Observations | 371 | 369 | 370 |
| **Panel C: Scouting** | | | |
| Change Management | -0.03 | 0.92** | 0.80 |
| | (0.05) | (0.43) | (0.50) |
| Weak Instruments (∼Robust F test) | | 15.91; p = 0.00 | 8.83; p = 0.00 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 16.36; p = 0.00 | 6.51; p = 0.01 |
| Observations | 371 | 369 | 370 |

Note: Column (1) is Ordinary Least Squares regression and columns (2) and (3) are IV regression results with Two Stage Least Squares (2SLS) parameter estimates for change management due to insecticide resistance concern with farmers' resistance concern level and average distance as instrumental variables, respectively. All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience, and acre planting farm. Standard errors in parentheses are robust to heteroskedasticity. All outcomes of interest are binary variables where it equals 1 if the farmer reported using the insect management practice and 0 otherwise; Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance.

Results obtained from the reduced form regression show a positive and strongly statistically significant increase in the use of pyrethroids and organophosphate. However, an increase in the frequency of scouting did not exhibit a significant association with change management. Turning to the instrumental variable regressions using insecticide resistance concern and average distance as $IV$s, the results show no statistically significant causation between pyrethroid use and a change in management. However, the second-stage $IV$ coefficients for a change in management are positive and statistically significant for organophosphate use, irrespective of what $IV$ variable is employed. This indicates that farmers who modified their management practices in response to resistance concern were more likely to employ organophosphate insecticides. These insecticides serve as an alternative to pyrethroid insecticides for aphid control, suggesting a shift towards diversifying chemical options to combat resistance. Regarding the frequency of scouting, the estimated coefficients in the 2SLS regressions, are positive, but not statistically significant.

Table 3.7: IV regression Two-Stage Least Squares (2SLS) parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **SUBSAMPLE**.

| **Panel A: Pyrethroid Use** | (1) OLS | (2) 2SLS | (3) 2SLS |
|---|---|---|---|
| | | IV: Resistance Concern Level | IV: Average distance |
| Change Management | 0.11** | 0.19 | -1.16 |
| | (0.05) | (0.28) | (1.07) |
| Weak Instruments (∼Robust F test) | | 18.36; p = 0.00 | 2.46; p = 0.11 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 0.11; p = 0.7 | 8.21; p = 0.00 |
| Observations | 276 | 271 | 275 |
| **Panel B: Organophosphates Use** | | | |
| Change Management | 0.17*** | 1.04*** | 2.29* |
| | (0.06) | (0.37) | (1.21) |
| Weak Instruments (∼Robust F test) | | 18.36; p = 0.00 | 2.46; p = 0.11 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 11.81; p = 0.00 | 17.56; p = 0.00 |
| Observations | 276 | 271 | 275 |
| **Panel C: Frequency of Field Scouting** | | | |
| Change Management | 0.14 | 0.08 | 1.26 |
| | (0.11) | (0.70) | (2.25) |
| Weak Instruments (∼Robust F test) | | 20.27; p = 0.00 | 1.70; p = 0.19 |
| Robust Score-Endogeneity $\chi^2(1)$ | | 0.14; p = 0.70 | 1.39; p = 0.23 |
| Observations | 278 | 271 | 277 |

Note: Column (1) is Ordinary Least Squares regression and columns (2) and (3) are IV regression results with Two Stage Least Squares (2SLS) parameter estimates for change management due to insecticide resistance concern with farmers' resistance concern level and average distance as instrumental variables, respectively. All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience, and acre planting farm. Standard errors in parentheses are robust to heteroskedasticity. Pyrethroid and Organophosphate use are binary variables where it equals 1 if the farmer reported using them as a foliar insecticide and 0 otherwise; Frequency of Field Scouting includes 5 different categories of once a year, twice a year, 2 to 5 times a year, 6 to 10 times a year, and more than 10 times a year with order of 1 to 5 accordingly. Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance.

To address the concern of weak instrument bias in this study,[22] additional assumptions regarding the structure of the errors were incorporated, and the Conditional Mixed Process (CMP) estimation model was employed. The CMP approach assumes that the equations (equations 3.3 and 3.4 in this study) are related to each other only through the jointly normal distribution of errors. In other words, the assumption is that the errors in both the first stage and second stage equations follow a multivariate normal distribution. According to Roodman (2011), by introducing additional structure to the instrumental variable system, we can have a combination of structural and reduced form models. In this setup, the reduced form equations provide instrumental variables that aid in identifying the parameters in the structural equations. This setup is similar to the two-stage least squares (2SLS) method. In this case, CMP serves as a limited-information maximum likelihood (LIML) estimator. The LIML estimation focuses on estimating the coefficients in the final stage or stages of the model, which are considered structural. This assumption allows us to model the relationship between the endogenous variable, instruments, and the dependent variable in a way that captures the joint distribution of errors.

Table 3.8 and Table 3.9 present the CMP change in management parameter estimates for equations 3.3 and 3.4 for the set of dependent variables for the total sample (foliar_5years, insecticide treated seed, and scouting) and the set of dependent variables for the subsample of farmers (pyrethroid use, organophosphate use, and frequency of scouting), with insecticide resistance concern level (panel A) and average distance (panel B) as instrument variables (SUR results are reported in Table B.5 and Table B.6 in the appendix B).[23] The first stage regression results in column 1 of these tables show

[22] The first stage F-statistics in the regression results in tables 3.6 and 3.7 are larger than the rule-of-thumb threshold of 10 for using insecticide resistance concern as an instrument. However, using average distance as an instrument results in low F-statistics for the first-stage regressions, which leads to the concern of weak instrument bias.

[23] The results of seemingly unrelated bivariate probit regression parameters for change management due to insecticide resistance with the two different instrumental variables of this study are presented in Tables B.5 and B.6 in the appendix B for total sample and subsample, respectively. The statistically significant results of the first stage regressions in column 1 of these tables show the study instruments are strongly associated with the treatment variable and hold for the relevance condition. The Wald

a strong positive correlation between insecticide resistance concern and change in management, indicating increasing concern level is associated with increasing the likelihood of farmers changing their management. Similarly, strong negative correlation between average distance and change management from the findings of first stage regression indicating farmers located closer to the counties reported insecticide failure is associated with being more likely to change their management. The statistically significant results of first stage regressions (at most 5% significance level) show the study instruments are strongly associated with the treatment variable, supporting the relevance condition. The results from panel A of Table 3.8 and Table 3.9, which utilize insecticide resistance concern as an instrumental variable, reveal strongly significant (at 1% level) and positive coefficients of a change in management for scouting and organophosphate use. Conversely, the change management coefficients in models with foliar_5years, insecticide treated seed, pyrethroid use, and frequency of scouting management practices as dependent variable are found to be statistically insignificant. These outcomes imply that farmers who modified their management prompted by insecticide resistance concern are more inclined to engage in farm scouting activities and utilize organophosphate as a chemical-based insecticide, compared to farmers who did not modify their management practices.

Moving on to panel B, which presents the results based on the average distance instrumental variable, the findings demonstrate strong significance and positive coefficients for change in management across all management practices, except for a negative coefficient observed for pyrethroid use. These findings suggest that farmers who modify their management practices due to the proximity of their farms to counties where insecticide resistance aphids have been reported are more likely to diversify their strategies to control aphids on their farms and reduce their reliance on pyrethroid insecticides.

tests (p-values) test the null hypothesis that the correlation between equations errors is zero and the two equations can be estimated separately. The hypothesis cannot be rejected in most models that used insecticide resistance concern as the instrumental variable. However, when using average distance as the instrumental variable, the Wald tests of the null hypothesis of zero correlations are rejected at all conventional significance levels. This suggests the presence of an endogeneity problem in these models.

Table 3.8: Conditional Mixed Process (CMP) with Probit regression parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **TOTAL SAMPLE**.

| **Panel A: Resistance Concern Level as IV** | (1) First Stage | (2) IV Results | (3) IV Results | (4) IV Results |
|---|---|---|---|---|
| | Change Management | Foliar_5Years | Insecticide Treated Seed | Scouting |
| Change Management | | 0.11 | 0.26 | 1.27*** |
| | | (0.85) | (0.97) | (0.16) |
| Resistance Concern | 0.17*** | | | |
| | (0.04) | | | |
| Observations | 370 | 370 | 370 | 370 |
| **Panel B: Average Distance as IV** | | | | |
| Change Management | | 1.63*** | 2.07*** | 1.28*** |
| | | (0.18) | (0.14) | (0.19) |
| Average Distance | -0.01*** | | | |
| | (0.00) | | | |
| Observations | 370 | 370 | 370 | 370 |

Note: Column (1) is the first stage estimation and columns (2), (3), and (4) are conditional mixed process (CMP) estimators with probit model; All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience, and acre planting farm; All outcomes of interest are binary variable where it equals 1 if the farmer reported using the insect management practice and 0 otherwise; Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance. Standard errors in parentheses are robust to heteroskedasticity.

The focus on insecticide resistance concern as an instrumental variable is rooted in the structure of the survey questions. The aim was to isolate the effect of farmers' concerns by establishing that the only pathway through which their concerns could affect management practices was via the observed change. While the instrumental variable analysis, including the CMP estimation, was conducted, it is crucial to note that the untestable assumption regarding the lack of correlation between concerns and other management practices cannot be verified directly.

Table 3.9: Conditional Mixed Process (CMP) with Probit and order probit regression parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **SUBSAMPLE**.

| **Panel A:** **Resistance Concern Level as IV** | (1) First Stage | (2) IV Results | (3) IV Results | (4) IV Results |
|---|---|---|---|---|
| | Change Management | Pyrethroid Use | Organophosphates Use | Frequency of Field Scouting |
| Change Management | | 0.39 | 1.86*** | 0.73 |
| | | (0.68) | (0.21) | (1.34) |
| Resistance Concern | 0.19*** | | | |
| | (0.05) | | | |
| Observations | 272 | 272 | 272 | 272 |
| **Panel B:** **Average Distance as IV** | | | | |
| Change Management | | -1.04*** | 1.88*** | 1.14*** |
| | | (0.37) | (0.19) | (0.29) |
| Average Distance | -0.01** | | | |
| | (0.00) | | | |
| Observations | 272 | 272 | 272 | 272 |

Note: Column (1) is Ordinary Least Squares regression and column (2) and (3) are conditional mixed process (CMP) estimator with probit model, and (4) conditional mixed process (CMP) estimator with ordered probit model; All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience and acre planting farm; Pyrethroid and Organophosphate use are binary variable where it equals 1 if the farmer reported using them as foliar insecticide and 0 otherwise; Frequency of Field Scouting includes 5 different categories of once a year, twice a year, 2 to 5 times a year, 6 to 10 times a year, and more than 10 times a year with order of 1 to 5 accordingly; Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance. Standard errors in parentheses are robust to heteroskedasticity.

Critics may argue that, given the survey data collection context, all variables are inherently endogenous, rendering them unsuitable as instruments. However, the average distance or proximity variable, being independent of the survey, can be considered exogenous in the survey collection process. There are plausible reasons to view it as a potentially valid instrument, as individuals closer to incidents of resistance are more likely to be aware of them and consequently exhibit greater concern and a higher likelihood of changing their management practices.

Overall, the instrumental variable analysis using different instruments in this study aimed to address endogeneity concerns and isolate the causal effect of interest. While it is important to acknowledge the limitations and assumptions associated with instrumental variable models, the use of exogenous variables such as average distance provides a plausible approach to mitigate endogeneity concerns and strengthen the instrument's validity in this study.

## 3.7 Discussion and Conclusion

The findings of this study shed light on the relationship between change management practices due to insecticide resistance concern and the adoption of alternative pest management practices. The results presented in this research highlight the significance of understanding the farmers' decision-making processes in response to emerging challenges such as insecticide resistance. The investigation into the adoption of alternative management practices aimed to identify potential pathways for sustainable pest management strategies in soybean cultivation. The research survey was distributed to a sample of soybean farmers, which accounted for 4.3% and 23% of the total population of farmers with small and large operations in Minnesota. In North Dakota, the survey was sent to 4.1% of all small farms and 12.3% of all large farms, representing the targeted sample size for each category. The response rate for this study was determined to be 20.35%. A total of 399 (66.1%) survey responses were eligible for inclusion in the study analysis. Among these eligible respondents, 352 (88.2%) were soybean farmers from

Minnesota, while the remaining 47 (11.7%) were from North Dakota. These participants responses were used for the data analysis. The total sample of farmers reported an average of 40 years of farming experience, and they planted approximately 732 acres of soybean in the 2021 growing season. Nearly 30% of the farmers indicated that they made changes to their management practices in response to concerns about insecticide resistance. Among the survey responses, 72.8% of farmers reported the utilization of foliar insecticides in the past five years. Among these groups of farmers, 76.4% indicated that they used pyrethroid insecticides, while 56.1% employed organophosphate insecticides for pest management.

We employed a methodological approach combining cross-sectional survey data, a structural causal model with instrumental variable analysis, and a conditional mixed process model to estimate the causal effect of the emergence of insecticide-resistant soybean aphid on farm production practices. The use of instrumental variables, particularly insecticide resistance concern and average distance, allowed us to establish a causal link between a change in management due to insecticide resistance and the adoption of different pest management practices. The results suggest that farmers who changed their management in response to insecticide resistance were more likely to have used specific alternative management practices, namely increased engagement in scouting activities and a positive shift towards the utilization of organophosphates among farmers. This development is significant due to the challenges associated with the overuse of pyrethroids, which has been a prevalent practice. It signifies a diversification of chemical options for aphid control, potentially mitigating the development of insecticide resistance and promoting more sustainable pest management practices within the soybean aphid context. This suggests that an increase in farmers' awareness and concerns about the harmful effects of insecticide resistance could lead to integrated pest management adoption for pest control.

Interestingly, the study also found that the use of insecticide-treated seed did not exhibit a significant association with farmers who changed their management. This observation may indicate that farmers may not view seed treatment as an effective means to address this issue of aphid resistance. This finding warrants further exploration and could provide insights into the efficacy of various management practices.

Additionally, the positive correlation between changing management due to insecticide resistance concerns and the use of foliar insecticides in the past five years highlights the persistent reliance on chemical-based approaches for aphid control, despite the emergence of resistance. This underscores the need to promote and encourage the adoption of integrated pest management practices that encompass a diversity of strategies beyond chemical interventions.

The inclusion of the conditional mixed process (CMP) estimation model addressed concerns related to weak instrument bias, further strengthening the validity of the instrumental variable analysis. The incorporation of the CMP approach allowed us to model the joint distribution of errors and estimate the coefficients of interest with increased robustness.

Although this study provides valuable insights into the relationship between a change in management due to insecticide resistance concern and choosing alternative pest management practices, it is essential to acknowledge its limitations. One limitation in our study pertains to response rate bias and potential oversampling, as these factors can influence the population distribution of conditioning variables and, consequently, impact analysis within the structural causal model. To mitigate this concern, we utilized crop acres reported by farmers and categorized them into distinct groups based on farm size and integrated the distribution of farm size in the 2017 agricultural census to create survey design weight for our observations. Additionally, the use of self-reported data for insecticide resistance concerns may raise potential endogeneity issue as farmers' perceptions could be influenced by various factors. Moreover, the study's scope is limited to specific geographical regions, and further research in diverse locations would enhance the generalizability of the findings.

In conclusion, this research underscores the importance of considering farmers concerns about insecticide resistance and changing their management due to their concerns in the design and implementation of pest management strategies. The evidence of this relationship emphasizes the need for targeted interventions and educational programs that raise awareness about the issue of emerging insecticide resistant soybean aphid and sustainable pest management techniques. By promoting integrated approaches and facilitating the adoption of diversified strategies, stakeholders in the agricultural sector can collectively work towards mitigating the challenges posed by insecticide resistance and ensuring the long-term sustainability of soybean production.

# Chapter 4

# Conclusion

This dissertation has made significant contributions to the field of food and agricultural economics by examining two critical aspects of sustainable agricultural practices: household recycling of organic materials and farmers' responses to pesticide resistance. Through a combination of empirical analyses and field experimental interventions, valuable insights have been gained, paving the way for a transition to more productive, sustainable, and resilient food and agricultural systems. Firstly, it focuses on promoting sustainable waste practices, including proper organics recycling, and composting to handle waste and food waste in the suburban residential sector in the metropolitan area of Hennepin County, Minnesota. Secondly, it delves into the pursuit of more effective and sustainable pest management by involving strategic efforts to manage insecticide resistance to achieve optimal pest management outcomes while ensuring long-term agricultural and environmental sustainability.

I investigate the effectiveness of different informational messaging strategies on household organic material recycling practices. This study draws on a randomized controlled trial in the cities of Edina and St. Louis Park. The educational and social influence messaging was found to induce desirable behavioral changes. Educational messages increased confidence levels and the strength of the recycling habit, while social influence messages reduced perceived effort among participants. However, the effectiveness of the interventions varied depending on participant characteristics and program design, with educational interventions showing stronger responses among less experienced participants and minimal impact of social influence interventions. This underscores the importance of tailoring interventions to specific participant characteristics and program contexts. Certainly, there are more specific policy implications based on the study's findings:

**Integrated Organic Waste Management Approaches:** The study highlights the value of adopting integrated approaches to promote organics recycling. It's crucial to highlight the distinct impact of educational and social influence treatments. Educational interventions substantially boost participants' confidence levels, empowering them with knowledge and awareness. Conversely, social influence interventions remarkably diminish participants' perceptions of effort cost and the quantity of waste they discard. This leads us to a compelling question: Could this shift in perception be a catalyst for more thoughtful shopping habits, ultimately reducing waste generation by households? Therefore, municipalities like Edina and St. Louis Park should consider implementing both educational and social influence programs. This two-pronged approach could maximize the impact of their initiatives, fostering a culture of sustainable waste management.

**Allocating Resources Strategically:** Given the study's findings, policymakers may consider allocating resources strategically between educational and social influence programs. While both are important, the emphasis could vary based on the community's existing recycling culture and specific needs. A community with a strong existing culture might benefit more from social influence interventions to reduce waste generation, whereas a community new to recycling might require a stronger educational focus to build confidence and habits.

**Spillover Effects for Environmental Consciousness:** The research highlights the presence of spillover effects from organics recycling interventions. Engaging residents in organics recycling not only reduces waste but also positively impacts their overall environmental awareness and consciousness. Therefore, municipalities can view organics recycling as a gateway to fostering broader environmentally responsible behaviors. Encouraging participation in one pro-environmental activity can lead to a ripple effect in other eco-friendly practices.

**Tailoring Programs to Participant Experience:** To enhance the effectiveness of interventions, municipalities should tailor their programs based on participants' experience levels. Less-experienced participants may benefit from detailed educational resources and guidance, while those with more experience might require advanced information. By customizing interventions, municipalities can better meet the specific needs of their residents.

**Continuous Monitoring and Evaluation:** Policymakers should recognize that behavior change is an ongoing process. Therefore, continuous monitoring and evaluation of recycling programs are crucial. Regularly collecting feedback and assessing the impact of interventions can help municipalities make necessary adjustments to optimize their waste management strategies.

In summary, this study suggests that municipalities like Edina and St. Louis Park can achieve the best results by adopting a combined approach to organics recycling, strategically allocating resources, and tailoring programs to participant needs and community contexts. Continuous monitoring and a focus on building environmental consciousness can further enhance the effectiveness of recycling initiatives.

The second essay's research contributions encompass both methodological advancements and practical implications. The study shows the design of cross-sectional surveys to effectively capture farmers' realistic decision-making processes when confronting emerging challenges in their production environments. Throughout the investigation, we employed instrumental variable methods with two distinct instrument variables (farmer's insecticide resistance concern level and average distance of surveyed farms from the counties with confirmed cases of insecticide-resistant soybean aphid) with different regression methods to address potential biases in our analysis. In particular, our results indicate consistent impacts for specific management practices across different regression models.

We observed a pattern of consistently positive and statistically significant outcomes in organophosphate use, while in others, the statistical significance varied. Despite statistical significance was not achieved for some management practices, the consistent positivity observed across various models warrants attention. This consistency prompts a nuanced interpretation, suggesting that farmers who changed their management practices in response to resistance were more likely to adopt integrated pest management strategies for sustainable aphid control on their farms. This adoption was marked by an increased reliance on organophosphate insecticides, aligning with diversifying chemical-based practices associated with IPM principles.

Based on the nuanced findings of this study, several specific policy implications can be derived, addressing key concerns in the management of soybean aphids and pesticide resistance:

**Promoting Diverse Chemical Management Strategies:** The study suggests a positive shift towards organophosphate use among soybean farmers in response to the challenges posed by pyrethroid resistance. Policymakers and agricultural advisors should encourage this transition, possibly by providing information and resources on the proper use of organophosphates and their effectiveness in soybean aphid management.

**Balancing Insecticide Usage:** To mitigate the overreliance on pyrethroids, it is imperative to educate farmers on the importance of rotating chemical treatments. Extension agents and entomologists should work together to develop guidelines and recommendations for implementing effective rotation strategies, thus reducing the risk of further resistance development.

**Enhancing Scouting Practices:** Given the positive correlation between insecticide resistance concerns and increased scouting activities, extension services should prioritize promoting scouting practices among soybean farmers. Training programs and outreach efforts can assist farmers in adopting proactive scouting methods to monitor aphid populations effectively.

**Monitoring Seed Treatment Use:** While the study provides insights into changing insecticide practices, there remains uncertainty regarding the use of seed treatments. Agricultural authorities should consider conducting further research or surveys specific to seed treatment practices to better understand their dynamics. This will enable the development of tailored educational programs if needed.

**Raising Awareness:** The study's results indicate the importance of raising awareness among soybean farmers about the challenges posed by pesticide resistance. Enhanced awareness among farmers regarding the adverse impacts of insecticide resistance has the potential to drive the adoption of integrated pest management (IPM) practices for pest control. Extension agents, entomologists, and policymakers should collaborate to disseminate information about the risks associated with uniform insecticide use and the benefits of diversified pest management approaches.

Incorporating these specific policy recommendations into agricultural extension programs and initiatives can contribute to more effective management of soybean aphids and the mitigation of pesticide resistance, ultimately benefiting soybean farmers and the sustainability of soybean production.

The limitations of both studies are related to the use of self-reported survey answers, which may introduce potential issues due to participants' perceptions being influenced by various factors. The reliance on participants' subjective responses might lead to biased or inaccurate information. Additionally, the scope of the studies is restricted to specific geographical regions, which could impact the generalizability of the findings. To enhance the applicability of the research to a broader context, further investigations in diverse locations would be beneficial. This would allow for a more comprehensive understanding of the topic and increase the external validity of the results.

In conclusion, this dissertation makes important contributions to advancing the pursuit of sustainable and resilient food and agricultural systems. It highlights the necessity of specific actions, such as promoting efficient waste management practices, and proactively managing agricultural resources during the emergence of new challenges in the production system to achieve sustainable outcomes.

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# Appendix A

## Supplementary Materials to Chapter 2

Table A.1: Demographic description of the city of Edina and St. Louis Park with Minnesota Population

| | **Edina** | **St. Louis Park** | **Minnesota population** |
|---|---|---|---|
| **Adult Population** | 39,036 | 39,780 | 4,235,751 |
| **Age** | | | |
| 18 - 24 | 5.4% | 8.3% | 11.9% |
| 25 - 34 | 13.7% | 30.7% | 17.8% |
| 35 - 44 | 16.2% | 15.7% | 16.2% |
| 45 - 54 | 18.9% | 14.1% | 17.1% |
| 55 - 64 | 17.6% | 14.3% | 17.4% |
| 64 and over | 28.2% | 16.9% | 19.6% |
| **Gender** | | | |
| Female | 52.4% | 51.6% | 49.9% |
| Male | 47.6% | 48.4% | 50.1% |
| **Household Income** | | | |
| Less than $35,000 | 15.6% | 15.4% | 20.4% |
| $35,000 to $74,999 | 20.1% | 27.2% | 27.9% |
| $75,000 to $149,000 | 25.1% | 32.2% | 32.9% |
| $150,000 or more | 39.2% | 25.2% | 18.8% |
| **Median Household Income** | $115,047 | $87,639 | $77.706 |
| **Education** | | | |
| High school or equivalent degree | 9.1% | 12.9% | 24.2% |
| Some college or associate's degree | 19.2% | 25.5% | 32.5% |
| Bachelor's degree or higher | 39.7% | 39.0% | 24.2% |
| Graduate or professional degree | 30.2% | 19.1% | 12.5% |
| **Race** | | | |
| Asian | 6.6% | 4.9% | 5.0% |
| Black or African American | 2.3% | 6.2% | 6.6% |
| Other | 5.8% | 7.8% | 7.7% |
| White | 85.3% | 81.1% | 80.7% |

Source: Census Bureau and American (Community Survey 5-year estimate 2018).

Table A.2: Demographic description of survey respondents and their households: **Edina**

| | Research Participants | U.S. Census |
|---|---|---|
| | Percentage of survey respondents: total respondents: 197 | Census Bureau and American Community Survey 5-year estimate 2018 |
| **Age** | | |
| 18 - 24 | 2.5 | 12.4 |
| 25 - 34 | 8.1 | 17.9 |
| 35 - 44 | 32.4 | 16.3 |
| 45 - 54 | 16.7 | 17.1 |
| 55 - 64 | 18.7 | 16.6 |
| 64 and over | 21.3 | 19.7 |
| **Gender** | | |
| Female | 71.5 | 52.6 |
| Male | 27.4 | 47.4 |
| Prefer not to say | 1.02 | |
| **Race** | | |
| Asian | 3.5 | 8.9 |
| White | 93.4 | 88.1 |
| Other | 3.1 | 3.5 |
| **Education** | | |
| High school or equivalent degree | 0 | 9.1 |
| Some college or associate's degree | 9.6 | 19.2 |
| Bachelor's degree or higher | 40.6 | 39.7 |
| Graduate or professional degree | 49.7 | 30.2 |
| **Household composition** | | |
| Household size | 3.14 | |
| Number of adults | 2.15 | |
| Number of children | 0.98 | |
| **Median Household Income** | $175,000 | $99,295 |

Source: Research Survey and Census Bureau and American (Community Survey 5-year estimate 2018).

Table A.3: Demographic description of survey respondents and their households: **St. Louis Park**

| | **Research Participants** | **U.S. Census** |
|---|---|---|
| | Percentage of survey respondents: total respondents: 276 | Census Bureau and American Community Survey 5-year estimate 2018 |
| **Age** | | |
| 18 - 24 | 0.3 | 12.4 |
| 25 - 34 | 22.4 | 17.9 |
| 35 - 44 | 26.4 | 16.3 |
| 45 - 54 | 16.3 | 17.1 |
| 55 - 64 | 18.8 | 16.6 |
| 64 and over | 15.5 | 19.7 |
| **Gender** | | |
| Female | 72.8 | 51.3 |
| Male | 26.8 | 48.7 |
| Prefer not to say | .3 | |
| **Race** | | |
| Asian | 2.5 | 3.9 |
| White | 95.6 | 82.4 |
| Other | 1.8 | 8.5 |
| **Education** | | |
| High school or equivalent degree | 1.1 | 12.9 |
| Some college or associate's degree | 7.2 | 25.5 |
| Bachelor's degree or higher | 43.4 | 39.0 |
| Graduate or professional degree | 48.1 | 19.1 |
| **Household composition** | | |
| Household size | 2.6 | |
| Number of adults | 1.95 | |
| Number of children | 0.72 | |
| **Median Household Income** | $125,000 | $75,690 |

Source: Research Survey and Census Bureau and American (Community Survey 5-year estimate 2018).

Table A.4: Summary of the number of compostable bags households put out in a given week during the study period

| | Mean | Min | Max |
|---|---|---|---|
| **Panel A: Edina** | | | |
| Educational treatment | 2.2 | 0 | 9 |
| Social influence treatment | 2.3 | 0 | 8 |
| Control | 2.2 | 0 | 9 |
| **Panel B: St. Louis Park** | | | |
| Educational treatment | 2.1 | 0 | 8 |
| Social influence treatment | 2.0 | 0 | 9 |
| Control | 2.1 | 0 | 8 |

Table A.5: Percentage of different compostable bag sizes used by research participants

| | 1 gallon or similar | 3 gallons or similar | 6 gallons or similar | 9 gallons or similar | 13 gallons or similar |
|---|---|---|---|---|---|
| **Edina** | 3.8 | 80.3 | 0.8 | 1.0 | 13.8 |
| **St. Louis Park** | 1.5 | 82.3 | 0.5 | 0.2 | 15.3 |
| **Total** | 2.5 | 81.4 | 0.6 | 0.6 | 14.7 |

The total number of bags from all research participants: 6,027. The total number of bags from Edina city participants: 2,629. The total number of bags from St. Louis Park participants: 3,399.

Table A.6: Degrees of the fullness of the compostable bags

| | Full | More than half | About half | Less than half | Total responses (observations) |
|---|---|---|---|---|---|
| | Percentage of respondents | | | | |
| **Panel A: Edina** | | | | | |
| Educational treatment | 21.4 | 17.0 | 36.8 | 20.0 | 410 |
| Social influence treatment | 29.5 | 15.8 | 29.0 | 18.8 | 392 |
| Control | 32.5 | 19.7 | 23.4 | 18.8 | 350 |
| **Panel B: St. Louis Park** | | | | | |
| Educational treatment | 23.0 | 18.3 | 30.1 | 23.3 | 497 |
| Social influence treatment | 26.8 | 17.7 | 31.8 | 20.2 | 597 |
| Control | 26.7 | 18.9 | 29.2 | 20.2 | 523 |

Table A.7: Summary of the number of reported bags across both cities and weeks of the study.

| Week | Number of all reported compostable bags | | Number of reported bags with their exact weight(% of all reported bags) | |
|---|---|---|---|---|
| | **Edina** | **St. Louis Park** | **Edina** | **St. Louis Park** |
| Week 1 | 369 | 456 | 217 (8.25%) | 272 (8.04%) |
| Week 2 | 443 | 595 | 157 (5.97%) | 187 (5.50%) |
| Week 3 | 468 | 625 | 102 (3.87%) | 87 (2.56%) |
| Week 4 | 444 | 565 | 65 (2.47%) | 41 (1.20%) |
| Week 5 | 469 | 602 | 34 (1.29%) | 14 (0.41%) |
| Week 6 | 436 | 555 | 19 (0.72%) | 8 (0.23%) |
| Total | 2,629 | 3,398 | 594 (22.59%) | 609 (17.92%) |
| | 6,027 | | 1,203 (19.96%) | |

Table A.8: Distribution of average organic waste generated and collected across households in lbs.

| | Week 1 | Week 2 | Week 3 | Week 4 | Week 5 | Week 6 |
|---|---|---|---|---|---|---|
| **Panel A:** | **per household per week** | | | | | |
| **Edina** | 6.3 | 8.5 | 9.1 | 8.5 | 9.6 | 9.1 |
| **St. Louis Park** | 6.3 | 8.4 | 8.9 | 8.4 | 9.5 | 8.3 |
| **Total sample** | 6.3 | 8.4 | 8.9 | 8.5 | 9.5 | 8.6 |
| **Panel B:** | **per capita per week** | | | | | |
| **Edina** | 2.2 | 3.1 | 3.2 | 2.9 | 3.6 | 3.3 |
| **St. Louis Park** | 2.6 | 3.5 | 3.6 | 3.5 | 3.8 | 3.4 |
| **Total sample** | 2.4 | 3.3 | 3.4 | 3.3 | 3.7 | 3.3 |

Table A.9: Distribution of average organic waste generated and collected across study groups in lbs. Total research sample

| | Week 1 | Week 2 | Week 3 | Week 4 | Week 5 | Week 6 |
|---|---|---|---|---|---|---|
| **Panel A:** | **per household per week** | | | | | |
| **Educational treatment** | 6.2 | 8.1 | 9.1 | 8.3 | 9.1 | 8.2 |
| **Social influence treatment** | 6.5 | 9.1 | 8.4 | 8.9 | 9.1 | 8.9 |
| **Control** | 6.2 | 8.3 | 9.2 | 8.2 | 10.2 | 8.5 |
| **Panel B:** | **per capita per week** | | | | | |
| **Educational treatment** | 2.6 | 3.4 | 3.9 | 3.6 | 3.8 | 3.4 |
| **Social influence treatment** | 2.2 | 3.2 | 3.1 | 3.1 | 3.2 | 3.2 |
| **Control** | 2.5 | 3.4 | 3.6 | 3.1 | 4.1 | 3.4 |

Table A.10: Distribution of compositional categories of organic waste placed in organics recycling bin across participants (out of 19 listed organic items)

| | Week 1 | Week 2 | Week 3 | Week 4 | Week 5 | Week 6 |
|---|---|---|---|---|---|---|
| **Panel A:** | The average number of **all organic items** | | | | | |
| **Edina** | 10.5 | 10.8 | 10.6 | 10.6 | 10.9 | 10.8 |
| **St. Louis Park** | 10.7 | 11.3 | 11.1 | 11.0 | 11.0 | 11.2 |
| **Total sample** | 10.7 | 11.3 | 10.9 | 10.8 | 10.9 | 11.1 |
| **Panel B:** | The average number of **food organic items** | | | | | |
| **Edina** | 5.8 | 6.0 | 5.8 | 5.6 | 5.8 | 5.8 |
| **St. Louis Park** | 5.9 | 6.1 | 6.0 | 5.9 | 5.8 | 6.0 |
| **Total sample** | 5.9 | 6.1 | 5.9 | 5.8 | 5.8 | 5.9 |
| **Panel C:** | The average number of **non-food organic items** | | | | | |
| **Edina** | 4.7 | 4.8 | 4.8 | 5.0 | 5.0 | 4.9 |
| **St. Louis Park** | 4.8 | 5.2 | 5.1 | 5.0 | 5.1 | 5.1 |
| **Total sample** | 4.7 | 5.1 | 5.1 | 5.0 | 5.0 | 5.1 |

The 19 listed organic items included Paper egg cartons, Pizza boxes from delivery, Napkins and paper towels without chemicals, Fruits and vegetables, Meat/fish and bones, Dairy products, Pasta/beans, and rice, Eggs and eggshells, Bread and cereal, Nuts and shells, Tea bags without the metal staple, Coffee grounds and filters, Facial tissues without chemicals, Hair and nail clippings, Cotton balls and swabs with paper stems, Houseplants and flowers, Wooden items such as chopsticks/popsicle/sticks and toothpicks, BPI certified compostable products such as cups/plates/bowls/utensils, and containers, Toilet paper/paper towel tubes.

Table A.11: Distribution of compositional categories of organic waste placed in organics recycling bin across study groups (out of 19 listed organic items)

| | Week 1 | Week 2 | Week 3 | Week 4 | Week 5 | Week 6 |
|---|---|---|---|---|---|---|
| **Panel A:** | The average number of **all organic items** | | | | | |
| **Educational treatment** | 11.1 | 11.1 | 10.9 | 11.0 | 11.0 | 11.2 |
| **Social influence treatment** | 10.5 | 11.2 | 11.0 | 10.8 | 11.0 | 10.9 |
| **Control** | 10.5 | 11.1 | 10.8 | 10.7 | 10.8 | 10.9 |
| **Panel B:** | The average number of **food organic items** | | | | | |
| **Educational treatment** | 6.0 | 6.0 | 5.9 | 5.9 | 5.9 | 6.1 |
| **Social influence treatment** | 5.7 | 6.0 | 5.9 | 5.9 | 5.9 | 5.9 |
| **Control** | 5.8 | 6.0 | 5.8 | 5.6 | 5.7 | 5.7 |
| **Panel C:** | The average number of **non-food organic items** | | | | | |
| **Educational treatment** | 4.9 | 4.9 | 5.0 | 5.1 | 5.0 | 5.0 |
| **Social influence treatment** | 4.7 | 5.1 | 5.0 | 4.9 | 5.0 | 5.0 |
| **Control** | 4.6 | 5.0 | 5.0 | 5.0 | 5.1 | 5.2 |

The 19 listed organic items included Paper egg cartons, Pizza boxes from delivery, Napkins and paper towels without chemicals, Fruits and vegetables, Meat/fish and bones, Dairy products, Pasta/beans, and rice, Eggs and eggshells, Bread and cereal, Nuts and shells, Tea bags without the metal staple, Coffee grounds and filters, Facial tissues without chemicals, Hair and nail clippings, Cotton balls and swabs with paper stems, Houseplants and flowers, Wooden items such as chopsticks/popsicle/sticks and toothpicks, BPI certified compostable products such as cups/plates/bowls/utensils, and containers, Toilet paper/paper towel tubes.

Table A.12: Distribution of participants' reflection on recycling materials relative to the beginning of the study

| | **Edina** mean (sd) | **St. Louis Park** mean (sd) | **Total sample** mean (sd) |
|---|---|---|---|
| Reflect on frequency of recycling | 2.4 | 1.9 | 2.1 |
| | (1.4) | (1.4) | (1.4) |
| Observations | 197 | 276 | 473 |

Note: this question in the endline survey asked participants to reflect on frequency of recycling materials such as paper, plastic, glass, and metal relative to the beginning of the study on a scale of -3 to 3, where -3 is a lot less often and 3 is a lot more often, and 0 is about the same.

Table A.13: Distribution of participants' reflection on the amount of garbage generated by their households compared to the beginning of the study

| | **Edina** mean (sd) | **St. Louis Park** mean (sd) | **Total sample** mean (sd) |
|---|---|---|---|
| Reflect on the amount of garbage generated | -0.61 | -0.31 | -0.44 |
| | (0.95) | (0.74) | (0.84) |
| Observations | 197 | 276 | 473 |

Note: this question in the endline survey asked participants to reflect on their garbage generated compare to the beginning of the study on a scale of -3 to 3, where -3 is a lot less amount, 3 is a lot more amount, and 0 is about the same

Table A.14: Distribution of participants' reflection on their eating and shopping habits relative to the beginning of the study

| The eating and shopping habit | Edina<br>mean (sd) | St. Louis Park<br>mean (sd) | Total sample<br>mean (sd) |
|---|---|---|---|
| The frequency of saving leftover food | 0.31<br>(0.63) | 0.31<br>(0.71) | 0.33<br>(0.68) |
| The frequency of reuse/eating leftover food | 0.39<br>(0.65) | 0.43<br>(0.71) | 0.41<br>(0.69) |
| The frequency of making a shopping list before food grocery shopping | 0.33<br>(0.66) | 0.60<br>(0.23) | 0.27<br>(0.62) |
| Looking for compostable materials | 0.96<br>(0.91) | 0.85<br>(0.93) | 0.90<br>(0.92) |
| Observations | 197 | 276 | 473 |

Note: in a set of questions in the endline survey, participants were asked to reflect on the past 7 weeks of the study and evaluate their eating and shopping habits on a scale of -3 to 3, where -3 is a lot less often and 3 is a lot more often.

Table A.15: Distribution of participants' reflection on their environmental beliefs and attitudes relative to the beginning of the study

| The eating and shopping habit | Edina<br>mean (sd) | St. Louis Park<br>mean (sd) | Total sample<br>mean (sd) |
|---|---|---|---|
| I feel obliged to help to protect the environment | 0.84<br>(0.97) | 0.69<br>(0.86) | 0.75<br>(0.91) |
| I make efforts to reduce the amount of waste we generate | 1.10<br>(0.92) | 1.00<br>(0.89) | 1.02<br>(0.90) |
| I think about the environment when we throw away food | 1.00<br>(0.95) | 0.83<br>(0.86) | 0.90<br>(0.90) |
| Other members of my household share these same values | 0.68<br>(1.09) | 0.48<br>(0.84) | 0.57<br>(0.95) |
| Observations | 197 | 276 | 473 |

Note: in a set of questions in the endline survey, participants were asked to reflect on the past 7 weeks of the study and evaluate their environmental statements on a scale of -3 to 3, where -3 is a lot less strongly and 3 is a lot more strongly, and 0 is about the same.

Table A.16: The most influential aspect of the study that made change in **the amount of the effort** put into organics recycling by research participants

| | **Edina** | **St. Louis Park** | **Total sample** |
|---|---|---|---|
| | (Percentage of survey respondents) | | |
| The weekly communication emails | 10.66 | 7.61 | 8.88 |
| Participation sense† | 13.7 | 13.77 | 13.74 |
| The weekly video clips | 16.75 | 9.06 | 12.26 |
| The need to report our recycling activities to someone | 26.40 | 30.43 | 28.75 |
| The need to complete study requirements to receive the stipend | 6.09 | 5.43 | 5.71 |
| No change to our amount of effort | 26.40 | 33.70 | 30.66 |
| Observations | 197 | 276 | 473 |

Note: this question of the endline survey asked participants to choose which aspect of the "Organics Recycling Study" was the most influential in making them change the effort they and their household members put into organics recycling.
† The sense of belonging to a group of people who were also participating in the research study.

Table A.17: The most influential aspect of the study that made change in the **confidence level** of research participants to do organics recycling in an appropriate way

| | **Edina** | **St. Louis Park** | **Total sample** |
|---|---|---|---|
| | (Percentage of survey respondents) | | |
| The weekly communication emails | 14.21 | 13.41 | 13.74 |
| Participation sense† | 8.63 | 11.23 | 10.15 |
| The weekly video clips | 32.49 | 24.28 | 27.70 |
| The need to report our recycling activities to someone | 19.29 | 20.29 | 19.87 |
| The need to complete study requirements to receive the stipend | 3.05 | 2.54 | 2.75 |
| No change to our amount of effort | 22.34 | 28.26 | 25.79 |
| Observations | 197 | 276 | 473 |

Note: this question of the endline survey asked participants to choose which aspect of the "Organics Recycling Study" was the most influential in making them feel differently about their confidence level that they and their household members are doing organics recycling in an appropriate way.
† The sense of belonging to a group of people who were also participating in the research study.

Table A.18: The most influential aspect of the study that made change in the **research participants' strength of habit** of doing organics recycling

| | **Edina** | **St. Louis Park** | **Total sample** |
|---|---|---|---|
| | (Percentage of survey respondents) | | |
| The weekly communication emails | 10.15 | 9.78 | 9.94 |
| Participation sense† | 8.63 | 8.33 | 8.46 |
| The weekly video clips | 13.71 | 9.42 | 11.21 |
| The need to report our recycling activities to someone | 27.92 | 22.83 | 24.95 |
| The need to complete study requirements to receive the stipend | 3.05 | 3.26 | 3.17 |
| No change to our amount of effort | 36.55 | 46.38 | 42.28 |
| Observations | 197 | 276 | 473 |

Note: this question of the endline survey asked participants to choose which aspect of the "Organics Recycling Study" was the most influential in making them feel differently about the strength of their habit of doing organics recycling in their household.
† The sense of belonging to a group of people who were also participating in the research study.

Table A.19: The effect of treatments on the practice of other disposal practices: Total research participants

| | (1) all compost | (2) all recycle | (3) all trash |
|---|---|---|---|
| | **Panel A: All treated participants (Eq: 2.1)** | | |
| treatment | 0.10** | -0.02 | -0.19** |
| | (0.04) | (0.04) | (0.08) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | |
| Education | 0.08* | -0.08* | -0.20** |
| | (0.04) | (0.04) | (0.09) |
| Social_optin | 0.13*** | -0.00 | -0.11 |
| | (0.05) | (0.05) | (0.11) |
| Social_optout | 0.09 | 0.10 | -0.26** |
| | (0.06) | (0.06) | (0.13) |
| Control mean | 0.22 | 0.54 | 1.87 |
| N | 2,575 | 2,575 | 2,575 |

Standard errors in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.20: The effect of treatments on the practice of other disposal practices: Research participants with experience less than two years

| | (1) all compost | (2) all recycle | (3) all trash |
|---|---|---|---|
| | **Panel A: All treated participants (Eq: 2.1)** | | |
| treatment | 0.04 | 0.00 | -0.38*** |
| | (0.06) | (0.06) | (0.11) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | |
| Education | -0.01 | -0.11* | -0.35*** |
| | (0.06) | (0.06) | (0.13) |
| Social_optin | 0.22** | 0.07 | -0.26 |
| | (0.09) | (0.09) | (0.19) |
| Social_optout | 0.02 | 0.14* | -0.47*** |
| | (0.07) | (0.07) | (0.15) |
| Control mean | 0.32 | 0.54 | 2.28 |
| N | 1,412 | 1,412 | 1,412 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.21: The effect of treatments on the practice of other disposal practices: Research participants with experience more than two years

| | (1) all compost | (2) all recycle | (3) all trash |
|---|---|---|---|
| | **Panel A: All treated participants (Eq: 2.1)** | | |
| treatment | 0.14*** | -0.05 | 0.04 |
| | (0.05) | (0.05) | (0.11) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | |
| Education | 0.15** | -0.05 | -0.03 |
| | (0.06) | (0.06) | (0.13) |
| Social_optin | 0.14** | -0.04 | 0.08 |
| | (0.06) | (0.06) | (0.13) |
| Social_optout | 0.08 | -0.04 | 0.45 |
| | (0.16) | (0.16) | (0.35) |
| Control mean | 0.10 | 0.46 | 1.34 |
| N | 1,163 | 1,163 | 1,163 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.22: The reflection of research participants on the changes in their behavioral responses to oragnics recycling practices relative to the beginning of the study: Total research participants

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| | | | **Panel A: All treated participants (Eq: 2.1)** | |
| Treatment | -0.02 | 0.11 | 0.24 | 0.31** |
| | (0.14) | (0.14) | (0.15) | (0.15) |
| | | | **Panel B: Different treatment groups (Eq: 2.2)** | |
| Education | -0.04 | 0.13 | 0.44** | 0.57*** |
| | (0.16) | (0.16) | (0.17) | (0.17) |
| Social_optin | -0.04 | 0.09 | 0.09 | 0.06 |
| | (0.18) | (0.19) | (0.20) | (0.19) |
| Social_optout | 0.05 | 0.07 | 0.01 | 0.09 |
| | (0.21) | (0.22) | (0.23) | (0.23) |
| Control mean | 1.36 | 1.32 | 1.50 | 1.42 |
| N | 470 | 470 | 470 | 470 |

A set of questions in the endline survey asked participants to rate their amount of effort, their strength of doing organics recycling as a habit, their level of confidence that they are putting out as much organics as possible, and their level of confidence that they do not include non-acceptable items in organics recycling carts on a scale of -5 to 5, where -5 is a lot less effort, 5 is a lot more effort, and 0 is about the same. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, changes in their sense of connection to the group of people living in their home street, neighborhood, and city relative to the beginning of the study, and years of experience engaging in organics recycling. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.23: The reflection of research participants on the changes in their behavioral responses to oragnics recycling practices relative to the beginning of the study: Research participants with experience less than two years

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| | **Panel A: All treated participants (Eq: 2.1)** | | | |
| Treatment | -0.05 | 0.11 | 0.21 | 0.38* |
| | (0.20) | (0.21) | (0.21) | (0.20) |
| | **Panel B: Different treatment groups (Eq: 2.2)** | | | |
| Education | -0.05 | 0.13 | 0.48** | 0.64*** |
| | (0.23) | (0.24) | (0.24) | (0.23) |
| Social_optin | -0.29 | 0.14 | -0.17 | -0.00 |
| | (0.35) | (0.36) | (0.36) | (0.34) |
| Social_optout | 0.08 | 0.06 | -0.00 | 0.19 |
| | (0.26) | (0.27) | (0.27) | (0.26) |
| Control mean | 1.63 | 1.64 | 1.74 | 1.65 |
| N | 261 | 261 | 261 | 261 |

A set of questions in the endline survey asked participants to rate their amount of effort, their strength of doing organics recycling as a habit, their level of confidence that they are putting out as much organics as possible, and their level of confidence that they do not include non-acceptable items in organics recycling carts on a scale of -5 to 5, where -5 is a lot less effort, 5 is a lot more effort, and 0 is about the same. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, changes in their sense of connection to the group of people living in their home street, neighborhood, and city relative to the beginning of the study, and years of experience engaging in organics recycling. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.24: The reflection of research participants on the changes in their behavioral responses to oragnics recycling practices relative to the beginning of the study: Research participants with experience more than two years

| | (1)<br>Effort<br>level | (2)<br>Habitual<br>forming | (3)<br>Confidence level<br>(acceptable items) | (4)<br>Confidence level<br>(nonacceptable items) |
|---|---|---|---|---|
| | | | **Panel A: All treated participants (Eq: 2.1)** | |
| Treatment | -0.00 | 0.09 | 0.27 | 0.21 |
| | (0.18) | (0.18) | (0.21) | (0.21) |
| | | | **Panel B: Different treatment groups (Eq: 2.2)** | |
| Education | -0.01 | 0.13 | 0.39 | 0.49** |
| | (0.21) | (0.22) | (0.24) | (0.24) |
| Social_optin | 0.01 | 0.04 | 0.14 | -0.03 |
| | (0.20) | (0.21) | (0.23) | (0.24) |
| Social_optout | -0.10 | 0.28 | 0.52 | 0.06 |
| | (0.57) | (0.58) | (0.65) | (0.66) |
| Control mean | 1.01 | 0.89 | 1.20 | 1.12 |
| N | 209 | 209 | 209 | 209 |

A set of questions in the endline survey asked participants to rate their amount of effort, their strength of doing organics recycling as a habit, their level of confidence that they are putting out as much organics as possible, and their level of confidence that they do not include non-acceptable items in organics recycling carts on a scale of -5 to 5, where -5 is a lot less effort, 5 is a lot more effort, and 0 is about the same. All regressions control for demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, changes in their sense of connection to the group of people living in their home street, neighborhood, and city relative to the beginning of the study, and years of experience engaging in organics recycling. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.25: Regression model with interaction term of educational intervention with cities

| | (1) Effort level | (2) Habitual forming | (3) Confidence level (acceptable items) | (4) Confidence level (nonacceptable items) |
|---|---|---|---|---|
| Education | 0.39** | 0.33*** | 0.37*** | 0.19** |
| | (0.17) | (0.09) | (0.11) | (0.08) |
| City: St. Louis Park | -0.09 | 0.13 | 0.08 | 0.37*** |
| | (0.17) | (0.09) | (0.11) | (0.08) |
| Education*City | 0.08 | -0.23* | -0.05 | -0.20* |
| | (0.22) | (0.13) | (0.15) | (0.10) |
| N | 2616 | 2616 | 2616 | 2616 |

Control variables include demographic characteristics ( e.g., age, education level, gender, race, and household income), household size, the number of children, changes in their sense of connection to the group of people living in their home street, neighborhood, and city, and years of experience engaging in organics recycling. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.26: Number of completed weekly surveys by study groups

| | Research Groups | Edina | St. Louis Park |
|---|---|---|---|
| **Week 1** | | | |
| | **T 1** | 57 | 83 |
| | **T 2** | 68 | 82 |
| | **C** | 63 | 94 |
| **Week 2** | | | |
| | **T 1** | 56 | 88 |
| | **T 2** | 67 | 84 |
| | **C** | 65 | 98 |
| **Week 3** | | | |
| | **T 1** | 59 | 88 |
| | **T 2** | 67 | 83 |
| | **C** | 66 | 102 |
| **Week 4** | | | |
| | **T 1** | 59 | 87 |
| | **T 2** | 69 | 84 |
| | **C** | 66 | 101 |
| **Week 5** | | | |
| | **T 1** | 60 | 90 |
| | **T 2** | 69 | 81 |
| | **C** | 66 | 102 |
| **Week 6** | | | |
| | **T 1** | 59 | 87 |
| | **T 2** | 70 | 83 |
| | **C** | 66 | 100 |
| **Baseline** | | 197 | 276 |
| **Endline** | | 197 | 276 |
| **Participants** | | 473 | |

Note: T1 is the educational treatment group, T2 is the social influence treatment group, and C is the control group. The final sample of 473 participants included in this research analysis.

Table A.27: YouTube links for different weekly video clips viewed by study groups in Edina and St. Louis Park

| Experiment Weeks | Video subject | Experiment group | Participants' City |
|---|---|---|---|
| Video Link Week1 | Fruits and vegetables | Educational Treatment | Edina and St. Louis Park |
| Video Link Week2 | Meat and dairy | Educational Treatment | Edina and St. Louis Park |
| Video Link Week3 | Miscellaneous household material | Educational Treatment | Edina and St. Louis Park |
| Video Link Week4 | Paper products | Educational Treatment | Edina and St. Louis Park |
| Video Link Week5 | Certified compostable items | Educational Treatment | Edina and St. Louis Park |
| Video Link Week6 | Preparing material for collection | Educational Treatment | Edina and St. Louis Park |
| Video Link Week1 | Why I do organics recycling | Social Influence Treatment | Edina |
| Video Link Week2 | How I do organics recycling | Social Influence Treatment | Edina |
| Video Link Week3 | How I tie bags/set them out | Social Influence Treatment | Edina |
| Video Link Week4 | How I store carts | Social Influence Treatment | Edina |
| Video Link Week5 | How others contribute/frequent items put in | Social Influence Treatment | Edina |
| Video Link Week6 | How I encourage others to participate | Social Influence Treatment | Edina |
| Video Link Week1 | Why I do organics recycling | Social Influence Treatment | St. Louis Park |
| Video Link Week2 | How I do organics recycling | Social Influence Treatment | St. Louis Park |
| Video Link Week3 | How I tie bags/set them out | Social Influence Treatment | St. Louis Park |
| Video Link Week4 | How I store carts | Social Influence Treatment | St. Louis Park |
| Video Link Week5 | How others contribute/frequent items put in | Social Influence Treatment | St. Louis Park |
| Video Link Week6 | How I encourage others to participate | Social Influence Treatment | St. Louis Park |
| Video Link Week1 | Virtual Farm Tour | Control Group | Edina and St. Louis Park |
| Video Link Week2 | Food and Farmers | Control Group | Edina and St. Louis Park |
| Video Link Week3 | Sustainable Agriculture | Control Group | Edina and St. Louis Park |
| Video Link Week4 | Urban Trees | Control Group | Edina and St. Louis Park |
| Video Link Week5 | Agricultural Safety | Control Group | Edina and St. Louis Park |
| Video Link Week6 | Bugs, bugs! | Control Group | Edina and St. Louis Park |

Table A.28: Timeline of study weeks for each organics recycling collection day over the study period.

| Participant's organics recycling collection day | First day of Week | Last day of Week |
|---|---|---|
| **Study Week 1:** | | |
| Tuesday, June 1, 2021 | Tuesday, June 1, 2021 | Sunday, June 6, 2021 |
| Wednesday, June 2, 2021 | Wednesday, June 2, 2021 | Monday, June 7, 2021 |
| Thursday, June 3, 2021 | Thursday, June 3, 2021 | Tuesday, June 8, 2021 |
| Friday, June 4, 2021 | Friday, June 4, 2021 | Wednesday, June 9, 2021 |
| Saturday, June 5, 2021 | Saturday, June 5, 2021 | Thursday, June 10, 2021 |
| **Study Week 2:** | | |
| Monday, June 7, 2021 | Monday, June 7, 2021 | Sunday, June 13, 2021 |
| Tuesday, June 8, 2021 | Tuesday, June 8, 2021 | Monday, June 14, 2021 |
| Wednesday, June 9, 2021 | Wednesday, June 9, 2021 | Tuesday, June 15, 2021 |
| Thursday, June 10, 2021 | Thursday, June 10, 2021 | Wednesday, June 16, 2021 |
| Friday, June 11, 2021 | Friday, June 11, 2021 | Thursday, June 17, 2021 |
| **Study Week 3:** | | |
| Monday, June 14, 2021 | Monday, June 14, 2021 | Sunday, June 20, 2021 |
| Tuesday, June 15, 2021 | Tuesday, June 15, 2021 | Monday, June 21, 2021 |
| Wednesday, June 16, 2021 | Wednesday, June 16, 2021 | Tuesday, June 22, 2021 |
| Thursday, June 17, 2021 | Thursday, June 17, 2021 | Wednesday, June 23, 2021 |
| Friday, June 18, 2021 | Friday, June 18, 2021 | Thursday, June 24, 2021 |
| **Study Week 4:** | | |
| Monday, June 21, 2021 | Monday, June 21, 2021 | Sunday, June 27, 2021 |
| Tuesday, June 22, 2021 | Tuesday, June 22, 2021 | Monday, June 28, 2021 |
| Wednesday, June 23, 2021 | Wednesday, June 23, 2021 | Tuesday, June 29, 2021 |
| Thursday, June 24, 2021 | Thursday, June 24, 2021 | Wednesday, June 30, 2021 |
| Friday, June 25, 2021 | Friday, June 25, 2021 | Thursday, July 1, 2021 |
| **Study Week 5:** | | |
| Monday, June 28, 2021 | Monday, June 28, 2021 | Sunday, July 4, 2021 |
| Tuesday, June 29, 2021 | Tuesday, June 29, 2021 | Monday, July 5, 2021 |
| Wednesday, June 30, 2021 | Wednesday, June 30, 2021 | Tuesday, July 6, 2021 |
| Thursday, July 1, 2021 | Thursday, July 1, 2021 | Wednesday, July 7, 2021 |
| Friday, July 2, 2021 | Friday, July 2, 2021 | Thursday, July 8, 2021 |
| **Study Week 6:** | | |
| Tuesday, July 6, 2021 | Tuesday, July 6, 2021 | Sunday, July 11, 2021 |
| Wednesday, July 7, 2021 | Wednesday, July 7, 2021 | Monday, July 12, 2021 |
| Thursday, July 8, 2021 | Thursday, July 8, 2021 | Tuesday, July 13, 2021 |
| Friday, July 9, 2021 | Friday, July 9, 2021 | Wednesday, July 14, 2021 |
| Saturday, July 10, 2021 | Saturday, July 10, 2021 | Thursday, July 15, 2021 |

Figure A.1: Agreement ranking with statements about the environment at the endline of the study (Total respondents:473)

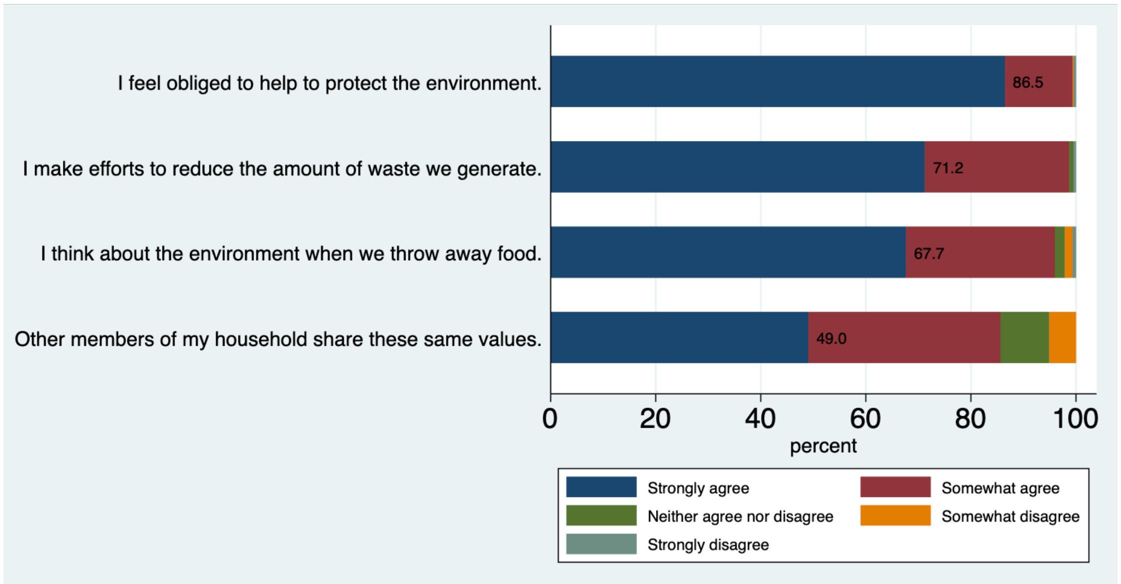
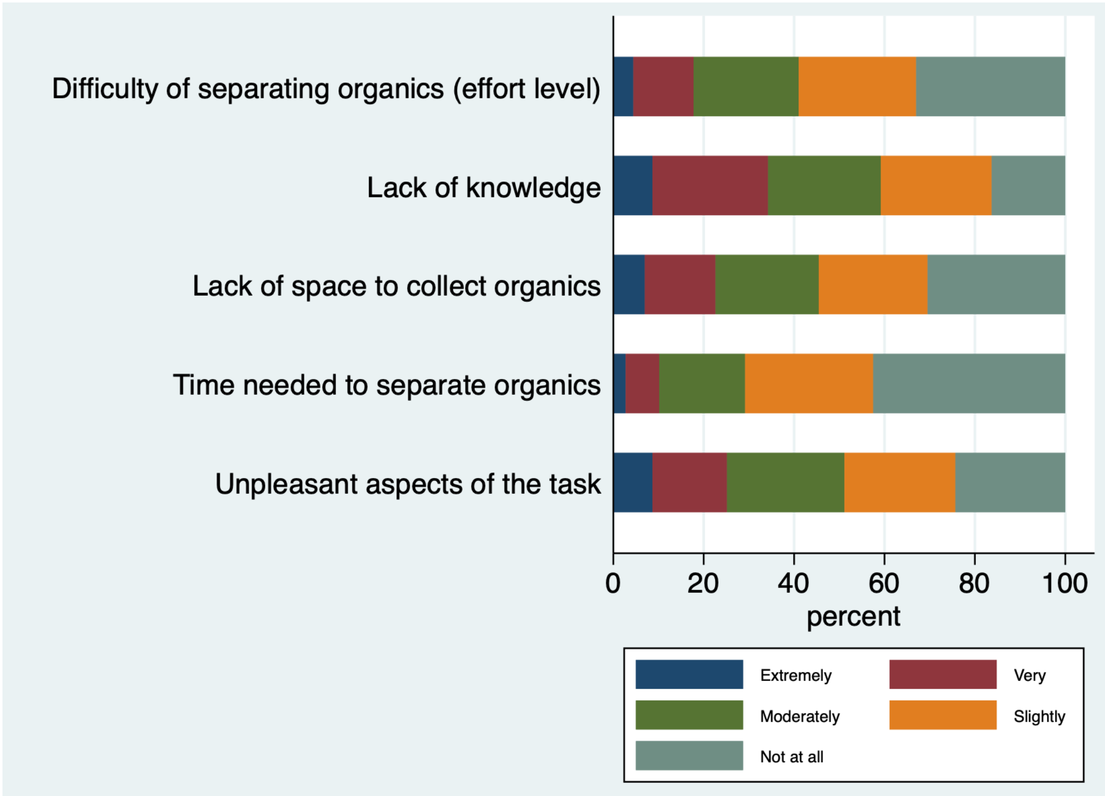


Figure A.2: Importance rankings for factors affecting sorting food waste at the beginning of organics recycling (Total respondents:473)



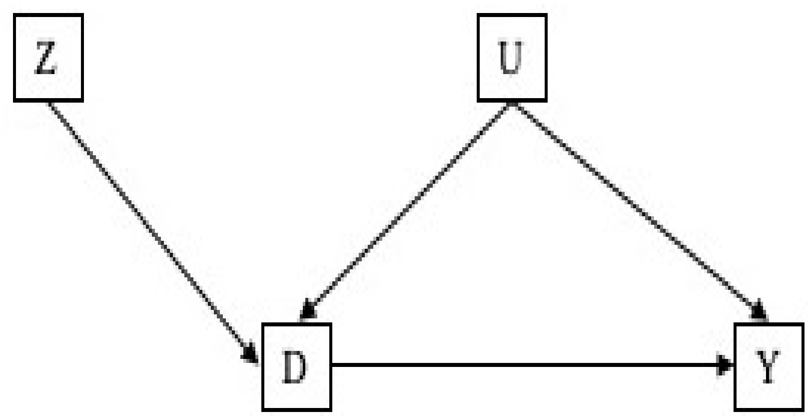
# Appendix B

## Supplementary Materials to Chapter 3

Two different instrumental variables are used in the estimations of this study: the concern of a farmer about insecticide resistance, measured through self-reported survey responses, and the proximity of the farm operation to reported counties with confirmed cases of insecticide resistant aphid, constructed independently of the survey. Tables B.1 and B.2 present the joint regression analysis of all outcome variables with change in management due to insecticide resistance concerns as the endogenous variable and with insecticide resistance concerns and average distance as instrumental variables, respectively. The purpose of this analysis is to evaluate whether the instrumental variable has a direct effect on the outcome variable, independent of the causal variable. Columns 1 and 2 of Panel A and columns 1 and 3 of Panel B of Table B.1 show that there is no significant association between instrument variable and foliar_5years, insecticide treated seed, pyrethroid use, and field scouting frequency as outcome variables by control for endogenous variable; indicating that there is no net association between an instrumental variable and outcome variables when also conditioning on change management (endogenous variable). However, there are significant associations between insecticide resistance concern and scouting and organophosphate use when controlling the endogenous variable raising questions about the validity of the exclusion assumption for the instrumental variable.

Some researchers believe that by evaluating the joint regression of all outcome variables and the instrumental variable, the exclusion assumption of the instrumental variable can be empirically tested. However, Morgan and Winship (2015) argue that such a test of the exclusion assumption is flawed. More specifically, they argue that the assumption that the instrumental variable Z has no net association with the outcome variable Y, except for the directed path Z $\rightarrow$ D $\rightarrow$ Y, is a strong and untestable assumption.

Figure B.1: Graph with a valid IV for an unblocked back-door path.




According to the figure above, a simple causal graph where there is an unblocked backdoor path between D and Y due to an unobserved common cause U, and Z is a valid instrumental variable for the causal effect of D on Y. In this scenario, conditioning on D is believed to block the indirect relationship between Z and Y through D. If there is no association between Z and Y after conditioning on D, it may be concluded that the instrumental variable assumption is true. Morgan and Winship (2015) argued that even when the instrumental variable assumption is valid, conditioning on D creates dependence between Z and U because D is a collider that is mutually caused by both Z and U (i.e., Z $\rightarrow$ D $\leftarrow$ U $\rightarrow$ Y). They argue conditioning on variables along back-door paths can effectively identify a causal effect. If all back-door paths between the causal variable and the outcome variable are blocked after conditioning, they won't influence the association between the causal variable and the outcome. However, it's essential to be cautious when conditioning on a collider or a descendant of a collider because such conditioning can unblock previously blocked back-door paths. Therefore, each back-door path must be carefully assessed when evaluating a conditioning strategy, as a variable can act as a colider on one path but not on another (Morgan and Winship, 2015). This dependence between Z and U leads to an association between Z and Y within at least one stratum of D, regardless of the validity of the instrumental variable. Therefore, the faulty test yields an association between Z and Y when conditioning on D, irrespective of the validity of the instrumental variable assumption.

Table B.1: Joint regression (OLS) of outcome variables, instrumental variable (Insecticide resistance concern), and endogenous variable (Change management due to insecticide resistance concern).

| **Panel A: Total Sample** | (1) Foliar_5Years | (2) Insecticide Treated Seed | (3) Scouting |
|---|---|---|---|
| Change Management | 0.13* | 0.25*** | -0.10 |
| | (0.07) | (0.07) | (0.07) |
| Insecticide Resistance Concern | 0.00 | -0.02 | 0.05*** |
| | (0.02) | (0.02) | (0.02) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 366 | 369 | 369 |
| R-squared | 0.089 | 0.070 | 0.116 |
| **Panel B: Subsample of farmers used foliar insecticide in the past 5 years** | Pyrethroid Use | Organophosphates Use | Times a Year Fields Were Scouted |
| Change Management | 0.12 | 0.18** | -0.09 |
| | (0.08) | (0.08) | (0.14) |
| Insecticide Resistance Concern | 0.00 | 0.05*** | 0.01 |
| | (0.02) | (0.02) | (0.04) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 271 | 271 | 271 |
| R-squared | 0.143 | 0.162 | 0.051 |

Table B.2: Joint regression (OLS) of outcome variables, instrumental variable (Farm operation's proximity to reported counties with confirmed cases of insecticide resistance aphid) and endogenous variable (Change management due to insecticide resistance concern).

| **Panel A: Total Sample** | (1)<br>Foliar_5Years | (2)<br>Insecticide Treated Seed | (3)<br>Scouting |
|---|---|---|---|
| Change Management | 0.08 | 0.21*** | -0.07 |
| | (0.06) | (0.07) | (0.07) |
| Average Distance | -0.00*** | -0.00 | -0.00** |
| | (0.00) | (0.00) | (0.00) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 367 | 370 | 370 |
| R-squared | 0.164 | 0.065 | 0.091 |
| **Panel B: Subsample of farmers used foliar insecticide in the past 5 years** | Pyrethroid Use | Organophosphates Use | Times a Year Fields Were Scouted |
| Change Management | 0.15** | 0.22** | -0.10 |
| | (0.07) | (0.08) | (0.15) |
| Average Distance | 0.00*** | -0.00** | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 272 | 272 | 272 |
| R-squared | 0.188 | 0.172 | 0.056 |

Table B.3: Joint regression (Probit regression) of outcome variables, instrumental variable (Insecticide resistance concern) and endogenous variable (Change management due to insecticide resistance concern).

| **Panel A: Total Sample** | (1) Foliar_5Years | (2) Insecticide Treated Seed | (3) Scouting |
|---|---|---|---|
| Change Management | 0.40* | 0.70*** | -0.33* |
| | (0.22) | (0.21) | (0.19) |
| Insecticide Resistance Concern | 0.00 | -0.05 | 0.14*** |
| | (0.05) | (0.05) | (0.05) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 366 | 369 | 369 |
| **Panel B: Subsample of farmers used foliar insecticide in the past 5 years** | Pyrethroid Use | Organophosphates Use | Times a Year Fields Were Scouted |
| Change Management | 0.39 | 0.50** | -0.12 |
| | (0.29) | (0.22) | (0.19) |
| Insecticide Resistance Concern | 0.01 | 0.15*** | 0.01 |
| | (0.06) | (0.05) | (0.05) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 271 | 271 | 271 |

Table B.4: Joint regression (Probit regression) of outcome variables, instrumental variable (Average distance), and endogenous variable (Change management due to insecticide resistance concern).

| **Panel A: Total Sample** | (1) Foliar_5Years | (2) Insecticide Treated Seed | (3) Scouting |
|---|---|---|---|
| Change Management | 0.26 | 0.60*** | -0.22 |
| | (0.22) | (0.20) | (0.19) |
| Average Distance | -0.01*** | -0.00 | -0.00*** |
| | (0.00) | (0.00) | (0.00) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 367 | 370 | 370 |
| **Panel B: Subsample of farmers used foliar insecticide in the past 5 years** | Pyrethroid Use | Organophosphates Use | Times a Year Fields Were Scouted |
| Change Management | 0.48* | 0.63*** | -0.13 |
| | (0.27) | (0.24) | (0.20) |
| Average Distance | 0.01*** | -0.01** | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| Farmer & Farm Characteristics | Yes | Yes | Yes |
| Observations | 272 | 272 | 272 |

Table B.5: Seemingly unrelated bivariate probit regression parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **TOTAL SAMPLE.**

| **Panel A:** **Resistance Concern Level as IV** | (1) First Stage | (2) IV Results | (3) IV Results | (4) IV Results |
|---|---|---|---|---|
| | Change Management | Foliar_5Years | Insecticide Treated Seed | Scouting |
| Change Management | | 0.15 | 0.25 | 1.27*** |
| | | (0.84) | (0.97) | (0.16) |
| Resistance Concern | 0.17*** | | | |
| | (0.04) | | | |
| Wald test $\chi^2(1)$ | | 0.10; P = 0.74 | 0.16; P = 0.68 | 12.77; P = 0.00 |
| Observations | 366 | 366 | 369 | 369 |
| **Panel B:** **Average Distance as IV** | | | | |
| Change Management | | 1.63*** | 2.07*** | 1.28*** |
| | | (0.18) | (0.14) | (0.19) |
| Average Distance | -0.01*** | | | |
| | (0.00) | | | |
| Wald test $\chi^2(1)$ | | 7.44; P = 0.00 | 4.62; P = 0.03 | 4.39; P = 0.03 |
| Observations | 367 | 367 | 370 | 370 |

Note Column (1) is the first stage estimation and columns (2), (3) and (4) are seemingly unrelated bivariate probit regression estimators.; All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience, and acre planting farm; All outcomes of interest are binary variables where it equals 1 if the farmer reported using the insect management practice and 0 otherwise; Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance. Standard errors in parentheses are robust to heteroskedasticity.

Table B.6: Seemingly unrelated bivariate probit regression parameter estimates for change management due to insecticide resistance concern (with two different instrumental variables)- Different management practices for **SUBSAMPLE**.

| **Panel A: Resistance Concern Level as IV** | (1) First Stage | (2) IV Results | (3) IV Results | (4) IV Results |
|---|---|---|---|---|
| | Change Management | Pyrethroid Use | Organophosphates Use | Frequency of Field Scouting |
| Change Management | | 0.37 | $1.86^{***}$ | |
| | | (0.69) | (0.21) | |
| Resistance Concern | $0.19^{***}$ | | | |
| | (0.05) | | | |
| Wald test $\chi^2(1)$ | | 0.002; P = 0.96 | 1.41; P = 0.23 | |
| Observations | 271 | 271 | 271 | |
| **Panel B: Average Distance as IV** | | | | |
| Change Management | | $-1.04^{***}$ | $1.88^{***}$ | |
| | | (0.37) | (0.19) | |
| Average Distance | $-0.01^{**}$ | | | |
| | (0.00) | | | |
| Wald test $\chi^2(1)$ | | 7.47; P = 0.00 | 4.97; P = 0.02 | |
| Observations | 272 | 272 | 272 | |

Note Column (1) is the first stage estimation and columns (2) and(3) are seemingly unrelated bivariate probit regression estimators; All regressions control for farmers and farm environment including farmer's education level, age, experience, risk aversion, patience, and acre planting farm; Pyrethroid and Organophosphate use are binary variables where it equals 1 if the farmer reported using them as foliar insecticide and 0 otherwise; Frequency of Field Scouting was not included into these analyses since it is ordered categorical variable; Resistance concern is the concern level of farmers about insecticide-resistant soybean aphids on a scale of 0 (Not at all concerned) to 10 (Very concerned) and average distance is the average farm operation's proximity to reported counties with confirmed cases of pesticide resistance. Standard errors in parentheses are robust to heteroskedasticity.

Table B.7: Survey response rate.

| | **Minnesota** | | | **North Dakota** | | | **Total** |
|---|---|---|---|---|---|---|---|
| | **Own** | **Own/Operate** | **Operate** | **Own** | **Own/Operate** | **Operate** | |
| **All Survey Mailed Out** | 763 | 1451 | 86 | 194 | 455 | 42 | 2991 |
| | | 2300 | | | 691 | | |
| All Returned Responses | 138 | 356 | 20 | 18 | 65 | 6 | 603 |
| | | 514 (22.3%) | | | 89 (12%) | | (20.1%) |
| Returned but Not Eligible | 82 | 78 | 2 | 13 | 26 | 3 | 204 |
| | | 162 (7.0%) | | | 42 (6%) | | (6.8%) |
| Crop Consultant/Agronomist | 1 | 1 | 0 | 0 | 0 | 0 | 2 |
| Rents Land | 34 | 16 | 0 | 4 | 1 | 0 | 55 |
| Retired Farmers | 34 | 28 | 1 | 7 | 9 | 3 | 82 |
| Refused | 0 | 3 | 0 | 0 | 0 | 0 | 3 |
| Not Farming Soybean | 13 | 30 | 1 | 2 | 16 | 0 | 62 |
| Returned and Eligible Responses | 56 | 278 | 18 | 5 | 39 | 3 | 399 |
| | | 352 (15.3%) | | | 47 (6.8%) | | (13.3%) |
| All Not Returned Responses | 618 | 1083 | 64 | 172 | 387 | 36 | 2360 |
| | | 1765 (76.7%) | | | 595 (86.1%) | | (78.9%) |
| Undeliverable Mails | 7 | 12 | 2 | 4 | 3 | 0 | 28 |
| | | 21 (0.9%) | | | 7 (1%) | | (0.93%) |
| Total – Undeliverable Mails | 756 | 1439 | 84 | 190 | 452 | 42 | 2963 (0.93%) |
| | | 2279 | | | 684 | | |
| Gross Response Rate | 18.2% | 24.7% | 23.8% | 9.4% | 14.3% | 14.2% | 20.3% |
| | | 22.5% | | | 13.01% | | |

Note: for the calculation of the gross response rate, we included all returned responses, both eligible and ineligible, in our calculations, and used the total number of surveys that were mailed out, excluding any that were not deliverable.

Table B.8: Farm operation characteristics for the total sample, Minnesota and North Dakota farmers.

| | Mean | Standard Deviation | Max | Min | Total Responses |
|---|---|---|---|---|---|
| **Total Sample** | | | | | |
| Total acres of all crops planted | 1,340 | 2,217 | 35,000 | 0 | 428 |
| Total soybean acres planted | 732 | 3,500 | 71,000 | 0 | 432 |
| Rented acres of all crops planted | 795 | 1,079 | 11,000 | 0 | 380 |
| Soybean Yield | 57 | 219 | 4340 | 0 | 387 |
| Livestock for commercial purpose (%) | 34% | | | | |
| **Minnesota** | | | | | |
| Total acres of all crops planted | 1,187 | 2,131 | 35,000 | 0 | 374 |
| Total soybean acres planted | 545 | 902 | 14,000 | 0 | 377 |
| Rented acres of all crops planted | 681 | 890 | 8,700 | 0 | 332 |
| Soybean Yield | 61 | 232 | 4340 | 0 | 344 |
| Livestock for commercial purpose (%) | 33% | | | | |
| **North Dakota** | | | | | |
| Total acres of all crops planted | 2,395 | 2,516 | 18,000 | 0 | 54 |
| Total soybean acres planted | 2,014 | 9,496 | 71,000 | 0 | 55 |
| Rented acres of all crops planted | 1,581 | 1,759 | 11,000 | 0 | 48 |
| Soybean Yield | 25 | 12 | 55 | 0 | 43 |
| Livestock for commercial purpose (%) | 40% | | | | |

Note: Soybean yield is the total average of harvested soybean bushels per acre. The total acres of all crops planted is the total acres of all different types of crops they planted in 2021. Rented acres are the total acres that farmers rented to plant all crops. Total soybean acres planted is the total acres of soybean they planted in 2021.

Figure B.2: Counties Location of surveyed farmers and dotted areas are the counties which reported on insecticide failure to control aphid on soybean farms from 2015 and 2021.