ABSTRACT

Title of Dissertation: ESSAYS IN GREENHOUSE/NURSERY ECONOMICS

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This dissertation focuses on the greenhouse and nursery industry in the United States. Two major issues are explored: irrigation and plant disease. The first two essays examine wireless soil-moisture sensor networks, an emerging technology that measures soil moisture and optimizes irrigation levels in real time. The first essay describes a study in which a nationwide survey of commercial growers was administered to generate estimates of grower demand and willingness to pay for sensor networks. We find that adoption rates for a base system and demand for expansion components are decreasing in price, as expected. The price elasticity of the probability of adoption suggests that sensor networks are likely to diffuse at a rate somewhat greater than that of drip irrigation. In the second essay, yields, time-to-harvest, and plant quality were analyzed to measure sensor network profitability. Sensor-based irrigation was found to increase revenue by 62% and profit by 65% per year. The third essay investigates greenhouse nursery growers' response to a quarantine imposed on the west coast of the United States from 2002 to present for the plant pathogen that causes Sudden Oak Death. I investigate whether growers choose to 1) improve their sanitation practices, which reduces the underlying risk of disease without increasing the difficulty of detecting the pathogen, 2) increase fungicide use, which also prevents disease but makes existing infections much harder to detect, or 3) change their crop composition towards more resistant species. First, a theoretical model is derived to formalize hypotheses on grower responses to the quarantine, and then these predictions are empirically tested using several public data sources. I do not find evidence that growers improve their sanitation practices in response to the quarantine. I do, however, find evidence that growers heavily increase their fungicide use in response to a quarantine policy that requires visual (as opposed to laboratory) inspection for the disease before every crop shipment, suggesting that the quarantine may have the adverse effect of making the pathogen harder to identify. I also do find evidence that growers shift away from susceptible crops and towards resistant crops.

ESSAYS IN GREENHOUSE/NURSERY ECONOMICS

by

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Dissertation submitted to the Faculty of the Graduate School of the
University of Maryland, College Park, in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
2016

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Acknowledgements

I am deeply grateful for the vast web of support extended to me by the entire AREC community. First and foremost I would like to thank Professor Erik Lichtenberg for his patient guidance throughout graduate school. Without his generous provision of encouragement, advice and many different opportunities, this dissertation would not have been possible.

Throughout my graduate school experience, my fellow graduate students have been tremendously supportive both academically and otherwise and I am very grateful for their friendship and their collaborative spirits. I would especially like to thank Magda Tsaneva, my first year "graduate student mentor" who warmly welcomed me to the program and continued to provide both technical and moral support throughout. I also thank Katherine Faulkner for her persistent helpfulness.

The first two papers in this dissertation are part of the SCRI-MINDS project, and I thank the many people whose hard work made SCRI-MINDS possible, in particular Professor John Lea-Cox for managing research efforts at the University of Maryland. I also thank Professor Lea-Cox for discussing relevant plant science with me to motivate my research, along with Professors Cassandra Swett, Yilmaz Balci, Jack Rogers, and John Majsztrik. John Majsztrik and Ian Page both worked closely with Professor Lichtenberg and me on several papers, and I also thank them for their hard work and for their useful insights during those projects.

I thank Professor Erik Lichtenberg, Professors Jorge Holzer, Professor Lori Lynch, Professor Lars Olson, and Professor John Lea-Cox for giving me invaluable comments on my research and for taking the time to serve on my dissertation committee.

Finally, I thank my parents and siblings for their love, support, and encouragement. I also thank my husband Joshua and my daughter Sol for being constant sources of inspiration, sanity, joy, and love in my dissertation writing process and in my life.

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Introduction

This dissertation focuses on issues relating to greenhouse nurseries, a multibillion dollar agricultural industry which primarily produces ornamental crops. Analyses of greenhouse nurseries is complicated by several factors largely driven by heterogeneity of crop composition. The three essays of this dissertation focus on two major issues affecting greenhouse nurseries: water shortages and plant disease.

The greenhouse nursery industry produces ornamental plants (trees, shrubs, and flowers for landscaping and household use) as well as any plants grown under cover. The official NAICS code provides the following definition for greenhouse nurseries:

> This industry group comprises establishments primarily engaged in growing crops of any kind under cover and/or growing nursery stock and flowers. "Under cover" is generally defined as greenhouses, cold frames, cloth houses, and lath houses. The crops grown are removed at various stages of maturity and have annual and perennial life cycles. The nursery stock includes short rotation woody crops that have growth cycles of 10 years or less.

Unlike major commodity crops such as wheat, corn, and soybeans that are usually produced in a monoculture environment, a typical greenhouse nursery grows a wide variety of species. While a mono-cultural commodity farm may have thousands of acres devoted to a single species, a typical 40 acre greenhouse nursery may have upwards of 500 species (Parke and Grunwald 2012). This heterogeneity makes a number of management decisions more complex than they would be in other agricultural settings. The heterogeneity of crops also adds a level of complexity to researching the forces behind trends in the industry, partly because changes in the industry size cannot be explained by the overall number of crops sold.

According to the United States Department of Agriculture (USDA) 2012 Census of Agriculture, the market value of the industry was $14.5 billion, with 52,751 operations, accounting for 2.5 percent of all farms and 3.7 percent of all agricultural sales in the US. This is comparable to vegetables, melons, potatoes, and sweet potatoes ($17 billion) and fruit and tree nuts ($22 billion).

Plant diseases are highly prevalent and difficult to manage in greenhouse nurseries (Parke and Grunwald, 2012). According to the University of Georgia Extension 2013 Plant Disease Loss Estimates, disease losses account for a 9.1 percent reduction in total crop value for ornamental plants in Georgia on average, which was higher than the estimates for wheat (1.6 percent) and soybeans (4.4 percent), but lower than the losses in corn (19.8 percent) and cotton (19.6 percent). Disease reduction efforts can be costly for growers. According to the USDA Census of Horticultural Specialties, growers spend 2 percent of their budget on agricultural chemicals alone, which does not include the labors costs of applying those chemicals nor the cost of sanitation and management practices such as cleaning equipment between uses and inspecting for infected plants.

In many of the major greenhouse nursery producing states, such as Texas, California, and Oregon, water demand is rapidly outpacing available supply. The horticultural industry uses 222.6 billion gallons of water per year, accounting for 5.6 percent of all water use in agriculture (Farm and Ranch Irrigation Survey, 2013). Since agriculture accounts for more than 80 percent of total water use in western states, and ornamental crops can be water intensive, allocating water effectively within an operation is a critically important task. Among horticultural operations, 57 percent of water use is from ground water, which is being extracted much faster than it is being replenished in much of the country. (Farm and Ranch Irrigation Survey, 2013; Gleick, 2010)

Disease management and irrigation management are closely related. Over or under watering can stress the plants, making them more susceptible to disease. Grower management practices influence the amount of water used and plant health. Precision irrigation technologies are designed to reduce the amount of over or under watering by delivering the amount of water needed by the plant. A variety of factors influence the adoption of efficient irrigation technologies, include stable water prices, land ownership, and grower education level (Schoengold and Sunding, 2014; Daberkow and McBride, 2003). Grower behavior also influences plant health and the probability of disease through the adoption of best management practices. The factors with the biggest influence on best management practices include access to and quality of information, financial capacity, and being connected to agency or local networks of farmers or watershed groups (Baumgart-Getz, Prokopy, and Floress, 2012). This dissertation investigates the likelihood and factors that influence adoption and willingness to pay of both precision irrigation technologies and of farm management practices.

The three essays in this dissertation examine the management decisions and their payoffs for greenhouse nursery growers as they relate to disease control and irrigation. The first two essays focus primarily on irrigation. In particular, they focus on an emerging technology called wireless soil moisture sensor networks. These irrigation technologies measure the amount of moisture in the soil and send the information to a computer which automatically adjusts the amount of water sent to plants in real time. The first essay, co-authored with Professors Erik Lichtenberg and John Majsztrik, uses data from an original survey of greenhouse nursery growers to estimate growers' willingness to pay for the sensor networks. The second essay, co-authored with Erik Lichtenberg, John Lea-Cox, John Majsztrik and Bruk Belayneh, uses data from an operation that implemented these sensor networks to determine the effect of the networks on the operation's profitability. The third essay investigates growers' response to a quarantine imposed on the west coast of the United States from 2002 to present for the plant pathogen that causes Sudden Oak Death (*Phytophthora ramorum*). It investigates whether growers choose to 1) improve their sanitation practices, which reduces the underlying risk of disease without increasing the difficulty of detecting the pathogen, 2) increase fungicide use, which also prevents disease but makes existing infections much harder to detect, allowing growers to evade quarantine restrictions on sales of infected plants or 3) change their crop composition towards more resistant species.

Chapter 1: Grower Demand for Sensor-Controlled Irrigation

Erik Lichtenberg; John Majsztrik; Monica Saavoss

Abstract

Water scarcity is likely to increase in the coming years, making improvements in irrigation efficiency increasingly important. An emerging technology that promises to increase irrigation efficiency substantially are wireless irrigation sensor networks, which upload sensor data into irrigation management software, creating an integrated system that allows real-time monitoring and control of moisture status. This has been shown to reduce irrigation costs, lower plant loss rates, shorten production times, decrease pesticide application, increasing yields, quality, and profit. We use an original survey to investigate likely initial acceptance, ceiling adoption rates, and profitability of this new sensor network technology in the nursery and greenhouse industry. We find that adoption rates for a base system and demand for expansion components are decreasing in price, as expected. The price elasticity of the probability of adoption suggests that sensor networks are likely to diffuse at a rate somewhat greater than that of drip irrigation. Adoption rates for a base system and demand for expansion components are increasing in specialization in ornamental production: Growers earning greater shares of revenue from greenhouse and nursery operations are willing to pay more for a base system and are willing to purchase larger numbers of expansion components at any given price. We estimate that growers who are willing to purchase a sensor network expect investment in this technology to generate significant profit, consistent with findings from experimental studies.

Introduction

Current trends on water supply and demand indicate that the importance of greater water use efficiency is likely to grow, especially for agricultural uses, which account for 70 percent or more of consumptive use worldwide and over 90 percent in some locations (Sauer et al.; 2010; Schaible and Aillery, 2012). Population growth is increasing water demand for urban uses and for energy production (Sauer et al., 2010; Schaible and Aillery, 2012; Gleick, 2013). Expansion of irrigated acreage has intensified competition among agricultural users, between agricultural and other users, and between states and nations (Evans and Sadler, 2008; Sauer et al., 2010; Gleick, 2013; Kuwayama and Brozovic, 2013). Climate change is expected to shrink available freshwater supplies throughout much of the world (Evans and Sadler, 2008; Mote et al., 2005).

Growing water scarcity can be mitigated by increases in irrigation efficiency by combining more precise application equipment and decision support systems (Evans and Sadler, 2008). Automated wireless sensor networks, an emerging technology on the verge of commercial introduction, offer this kind of decision support. These systems upload data wirelessly into irrigation management software, allowing irrigation managers to monitor moisture status and match water application with plant uptake needs in real time. This technology differs from moisture sensors currently on the market in its integration of user-friendly software and control capabilities that permit real time information access and automated irrigation control. Research studies conducted in actual production environments indicate that these systems can reduce irrigation costs—including labor and energy in addition to water—substantially (Belayneh et al., 2013). Other documented benefits include lower plant loss rates, shorter production times, less need for pesticide application, and higher yield and quality (Lichtenberg et al., 2013). These research studies all indicate that adoption can be extremely profitable.

This paper uses an original survey of nursery and greenhouse farmers nation-wide to investigate likely initial acceptance, diffusion rates, and ultimate ceiling adoption rates of this new sensor network technology. We focus on the greenhouse, nursery, and floriculture industry, a large and growing segment of US agriculture. Sales of this sector totaled almost $17 billion in 2007, more than vegetables ($15 billion), wheat ($11 billion), cotton ($5 billion), and almost as much as fruits, nuts, and berries ($19 billion) or soybeans ($20 billion) (US Department of Agriculture, 2009). The value of each acre-foot of water used for greenhouse and nursery products is 2-3 orders of magnitude greater than other crops (Ackerman and Stanton, 2011). States in the water-scarce Pacific, Mountain, and South Central regions account for 37 percent of greenhouse and nursery sales, suggesting that water savings are likely extremely important for this industry (Hall, Hodges and Palma, 2011). The high market value of ornamental crops combined with their large footprint in water-scarce, high water cost regions makes them a likely market for sensor networks.

We investigate two dimensions of demand for these sensor networks with an eye toward gauging likely initial grower acceptance of this technology, how rapidly it is likely to disseminate, and the ultimate size of market for wireless sensor networks. We begin by estimating willingness to pay for a base system consisting of 5 sensors connected to a single transmission node plus software. We use the willingness to pay estimates to discuss characteristics of likely base system adopters and to explore likely effects of changes in system prices and grower perceptions of system benefits on the speed at which this technology is likely to diffuse. We then investigate potential system scale by estimating demand for additional transmission nodes, with each node holding up to 5 sensors. We use this estimated demand relationship to investigate characteristics associated with demand for additional nodes.

Briefly, the estimated coefficients of the base system willingness to purchase model indicate that as many one-fifth of nursery and greenhouse operators might purchase a base system when it becomes commercially available while about 30% are unlikely to purchase a base system at any price. The estimated price elasticity of demand for a base system suggests that this technology is likely to diffuse more rapidly than drip irrigation. Our estimates of base system willingness to pay combined with our estimates of demand for additional nodes, indicate an average expected profit from adoption of about $11,000 annually, with substantial variation around that figure.

We proceed as follows: We begin with a review of the literature on adoption of irrigation technologies. We then describe our survey of nursery and greenhouse operators and the data obtained from that survey. The subsequent section discusses the specification and estimation of models of willingness to pay for a base system and demand for additional nodes. We then discuss estimation results, followed by a discussion of implications for the initial adoption and subsequent diffusion of this technology. A final section concludes.

Economics of Precision Irrigation Adoption

Traditional gravity-fed irrigation systems rely on soils to hold a reservoir of water in the root zone, which is available for plant uptake. The efficiency of these systems is limited: Some of the water applied is lost via surface runoff, some percolates through the root zone into groundwater, and some groundwater drains into nearby streams and ditches. Improving uniformity of application by land leveling can reduce—but not eliminate—these losses (Feinerman et al., 1983).

Sprinkler and drip systems increase irrigation efficiency by substituting capital and energy for soil water holding capacity as well as by improving timing of application (Caswell and Zilberman, 1986; Lichtenberg, 1989; Shani et al., 2009). Farmers cultivating lower quality soils or land with greater slope are thus more likely to adopt more precise irrigation technologies than farmers cultivating better soils on level land, where the gains from increasing irrigation precision are lower (Lichtenberg, 1989; Dinar and Yaron, 1990; Negri and Brooks, 1990; Shrestha and Gopalakrishnan, 1993; Green et al., 1996; Green and Sunding, 1997; Moreno and Sunding, 2005; Koundouri et al., 2006; Schoengold et al., 2006). Larger farm operations, which presumably have greater capacity to finance investment in irrigation equipment, are also more likely to adopt drip and sprinkler systems (Dinar et al., 1992; Shrestha and Gopalakrishnan, 1993; Green et al., 1996). The gains from increasing irrigation precision—and thus the likelihood of adoption of more efficient irrigation technologies—have also been shown to be greater when water is more expensive (Dinar and Yaron, 1990; Green et al., 1996; Pfeiffer and Lin, 2014) and when the marginal value of water is greater (Caswell and Zilberman, 1985; Lichtenberg, 1989; Dinar et al., 1992; Shrestha and Gopalakrishnan, 1993; Schoengold et al., 2006).

As noted above, irrigation efficiency is lower—and thus investments in more efficient irrigation equipment are more profitable—on farms whose soils vary more in terms of soil permeability, slope, and similar factors (Feinerman et al., 1983). The same holds for investments in precision agriculture technologies more generally. For instance, variable rate fertilizer application is more profitable on fields whose soils vary more in terms of natural fertility (Babcock and Pautsch, 1998; Pautsch et al., 1999; Griffin et al., 2000; Oriade and Popp, 2000; Bullock et al., 2005) and correspondingly less profitable on farms with more uniform soils (Hudson and Hite, 2003).

The key advantage of sensor networks is that they provide more accurate information about substrate moisture status in real time, allowing growers to make timely adjustments to irrigation water applications. Sensor nodes collect data on environmental conditions, soil moisture, electrical conductivity, etc. from sensors and transmit those data to a base station connected to a personal computer. Those data are fed into software which graphically displays the sensor information from each node. The software can also be used to automate irrigation by transmitting instructions to nodes attached to latching solenoids that autonomously control irrigation (e.g., the node automatically turns the irrigation valve on and off when soil moisture reaches predetermined set points; see Belayneh, et al. (2013) for a more detailed description). The potential value of more accurate information about the production environment has been demonstrated for variable rate fertilizer application (Pautsch et al., 1999; Bullock et al., 2005) as well as for sensor networks (Belayneh et al., 2013; Lichtenberg et al., 2013).

Data

We investigated potential willingness to pay for sensor networks using data from an original survey of greenhouse and nursery operations conducted from January 2012 through March 2013. The survey was administered in person to growers at the Mid-Atlantic Nursery Trade Show and the Georgia Green Industry Association annual meeting and online via invitations circulated through extension networks. Incomplete surveys were followed-up with phone calls or emails. Growers attending the Mid-Atlantic Nursery Trade Show and Georgia Green Industry Association annual meeting numbered 541 and 80, respectively. The extension networks through which invitations were circulated have a potential reach of about 9,100 commercial greenhouse and nursery operations. A total of 268 surveys were completed, 35% of which were filled out at trade shows and 65% of which were completed online. The sample was more representative of commercial operations—and thus likely purchasers of the wireless sensor systems we studied—than of the greenhouse and nursery industry as a whole. For example, the revenue distribution of the respondents in our sample was skewed towards operations with high gross revenues compared with the national revenue distribution of the nursery and greenhouse growers as reported in the U.S. Census of Agriculture (Table 1). The 47% of operations surveyed by the Census of Agriculture that gross less than $25,000 per year are unlikely to profit from wireless sensor networks since their profit margins are unlikely to justify the cost of system purchase and maintenance. The sample is also skewed towards larger operations in terms of acreage (Table 1). Operations in Appalachia and the Southeast were over-represented relative to the share of operations reported by the Census of Agriculture while operations located in the Midwest were under-represented (Table 1).

The survey focused on general characteristics of the operation and the respondent, as well as questions that were directed specifically towards water use practices such as water sources. Questions concerning general characteristics of the operation included income, total costs, size, zip code, and revenue sources. Respondents were also asked to list the percent of total water used from surface water, deep wells, shallow wells, recycled water, rain, municipal water, and other water sources. Questions concerning characteristics of the respondent included age, education level, and position in the company.

Information about growers' willingness to pay for a base system and for additional nodes was elicited in the following series of steps. First, respondents were given the following background information:

> "As part of this project, we are developing and testing sensor networks that can monitor root zone moisture, weather and many

other variables for precision irrigation and nutrient management. These more advanced sensor networks can automatically turn irrigation on and off as needed, reducing or eliminating the need for manual irrigation control. The sensors decide when, where, and how much to irrigate based on set-points you determine. Answering the questions below will help us to better understand the extent of technology adoption in the nursery and greenhouse industry."

Respondents were then asked for their perceptions of potential benefits and limitations of sensor networks (Table 2). Next, respondents were asked to look at a schematic of a base sensor network system (Figure 1) and asked the following question:

> "A basic sensor system contains a base station, software, and a single node (with up to 5 sensors), which monitors and controls irrigation in a single production area/irrigation zone. Would you purchase a basic sensor system if the price was $X?"

The system price X was randomized across participants with values of $500, $1,000, $2,000, $3,000, $4,000, or $5,000."[1] Every offered price had nearly the same number of growers assigned to it (Table 3).

To determine how large a sensor network respondents might be willing to purchase, respondents were again shown the sensor network schematic in Figure 1 and asked the following question:

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[1]An earlier version of the survey also included a $1,500 bin, and there is one response with that price level. That observation is treated like the other price levels in the probit model.

> “A basic sensor system is expandable, so you could buy additional nodes (5 sensors), and use the same base station and software package. Suppose you already purchased the basic system, how many additional nodes would you be willing to purchase for your operation if EACH node cost $X?”

The price of an additional node X was randomized with values of $500, $1,000, $1,500 or $2,000. Respondents were to select the number of additional nodes from the following list: 0, 1, 2, 3, 4, 5, 6-7, 8-10, 11-15, 16-20, and 21 or more. Prices were assigned close to evenly (Table 3). Note that the additional nodes question tells the respondent to assume they already owns the base system, allowing them to report a willingness to buy additional nodes even if they were not willing to buy a base system at the price offered (and thus accommodating the possibility that they may have been willing to purchase a base system at a price lower than the one offered). This framing allows us to use the entire sample to estimate demand for additional nodes.

Thirty-seven percent of the growers included in the sample said they would be willing to buy a base system. Assuming that they had already purchased a base system, growers were willing to purchase an average of 3.5 additional nodes at the expected price of $500 per node. The desired scale of a wireless sensor network varied substantially: Some growers were not willing to purchase any additional nodes while others were willing to purchase more than 20. Both the share of growers willing to purchase a base system and the average number of additional nodes purchased generally decreases with increasing price, albeit not monotonically (Table 3). Differences in size of operation are the most likely source of this non-monotonicity: Growers who were quoted a price of $3000 for a base system and $1500 for each additional node are substantially smaller on average than growers quoted prices of $2000 or $4000 for a base system and $1000 or $2000 for each additional node.

Descriptive statistics of the variables used in the econometric analysis are shown in Table 4. The growers in the sample vary substantially in size as measured by both revenue and spatial extent of the operation. Most respondents specialized heavily in greenhouse and nursery production. About half of these growers had formal education at least through a bachelor's degree. Most growers had very positive perceptions of the capabilities of wireless sensor networks. Cost was the most frequently cited concern about the technology, followed by reliability.

Specification and Estimation

As is standard with referendum format questions, which have dichotomous (yes/no) answers, a probit model was used to estimate the willingness to purchase the base system. A tobit model was used to estimate demand for additional nodes since large shares of respondents were unwilling to buy any additional nodes at each price offered.

Estimating Willingness to Pay for a Base System

Growers presumably answer the question of whether they are willing to buy the sensor system affirmatively if and only if they expect that using a sensor network to control irrigation would increase profit relative to their current irrigation methods. The expected increase in profit from investing in a sensor network $\Delta\pi^*$ was not observed; instead, we observe the binary response of whether or not the grower would buy the system at the price quoted. We assume that growers would buy the system if they expect the investment to be profitable:

$$\Delta\pi^* = \alpha X + Z'\beta + \varepsilon$$

$$y = 1 \; if \; \Delta\pi^* > 0$$

$$y = 0 \; if \; \Delta\pi^* \leq 0$$

Here X is the randomized price assigned to each respondent, **Z** is a vector of controls and ε is a mean zero random error capturing the influence of all unobserved factors that enter into the grower's adoption decision. The probability that a grower would buy a base system is thus:

$$\Pr(Y = 1|X \quad, Z) = \Phi(\alpha X + \boldsymbol{Z}'\boldsymbol{\beta})$$

where Y =1 if the respondent answers affirmatively and Y=0 otherwise and $\Phi(\cdot)$denotes the cumulative distribution of ε. We assume that ε is distributed normally and thus estimate the parameters α and β using probit.

The set of characteristics **Z** used in the probit model include measures of operation size, the share of ornamental production in the firm's total revenue, the grower's education level, the grower's perception of the benefits and limitations of wireless sensor systems, and indicators for the operation's water sources and the region in which the operation is located.

There are three main types of ornamental production environments: greenhouse, container, and field. Greenhouse production is labor and energy intensive but has the highest profit per area. Typical operation size ranges are 0.1 to 10 acres of production area. Container production is less intensive, and can be more easily managed on a larger scale, with typical sizes of 0.5 to 50 acres of production area. Field operations tend to be the least intensive, with operation sizes typically in the range of 5 to 500 acres. Operations often have more than one production method being used at the same time (e.g., greenhouse and container production).

We use two measures of size, gross income and acreage in ornamental production. Gross income of the operation was included to account for differences in available funds to purchase any given technology. Higher grossing operations are also more likely to hire labor that specializes in managing their irrigation systems, so sensor networks may provide a relatively larger labor cost savings for them. Size in acres was included to measure the ability of a firm to take advantage of economies of scale in sensor placement. Similarly, larger operations of any given type tend to have more irrigation zones, which make the irrigation systems more complex and therefore costly to manage. Since the sensor systems simplify irrigation systems by enabling automation of irrigation management, larger firms may expect to experience greater increases in profit than smaller firms. We expect that both the gross income and size in acres will be positively correlated with a respondent's willingness to buy a sensor network.

The percent of all revenue from ornamental production was included because ornamental crops typically irrigate more frequently than agronomic producers, and therefore operations with high portions of their revenues coming from ornamental crops may see the benefits of investing in sensor networks more quickly, particularly for greenhouse and container production. Operations that specialize more in ornamental production may also be more aware of new technological developments. For example, producers specializing in ornamentals are likely to have more involvement in industry-specific information networks through trade-shows and targeted advertising. A sharper focus on the greenhouse and nursery industry also likely translates to more inputs focused on greenhouse and nursery production, including water, labor, and disease control measures. Sensor networks may reduce the cost of all these inputs, so we expect that willingness to buy a sensor network will increase with the percentage of revenue from greenhouse and nursery operations.

Growers with more formal education levels likely have both greater human capital and greater technological sophistication. Thus, higher educational attainment is likely correlated with both greater expected productivity increases and lower expected transition costs. Previous studies have indicated that individuals with higher levels of education are more willing to adopt new agricultural technologies (Feder et al., 1985; Dinar and Yaron, 1990; Koundouri et al., 2006). We expect that higher levels of education will correlate with a higher willingness to buy a sensor network.

Previous studies also indicate that older growers are less likely to adopt new technologies, suggesting that willingness to adopt a sensor network should decrease as the age of the operator increases, a finding that has been attributed to a shorter time horizon and higher transition costs (Feder et al., 1985). Research to date suggests that the payback period for investments in sensor networks is quite short (Belayneh et al., 2013; Lichtenberg et al., 2013) suggesting that a shorter time horizon should not be an impediment to adoption. Once technological sophistication is taken into account (by controlling for education level, for instance), transition costs may not correlate with age. There are thus reasons to believe that age may not be a factor in growers' willingness to buy sensor networks. We include it in our base specification regardless, in keeping with previous literature on this topic.

We expect willingness to buy a sensor network to be greater for growers who express positive views of their benefits and lower for growers who express concerns about their cost, effectiveness, or reliability. We thus include indicators of whether respondents expressed beliefs about each potential advantage and limitation of wireless sensor networks.

Water sources differ in terms of cost, quantity available, and quality. We thus include indicators of whether growers obtained water from shallow wells, deep wells, surface sources, municipal water systems, or gray water as well as whether growers reused runoff water. These sources are not mutually exclusive, as growers may use water from more than one source. All else equal, water from deep wells and municipal sources tends to be more expensive than water from other sources. Growers using water from these sources are likely to obtain greater reductions in water expenditures than growers using water from cheaper sources; we thus expect growers getting water from deep wells or municipal sources to be willing to pay more for a sensor network. Operations using surface water, recycled water, or gray water face a higher risk of growth reduction or plant death due to disease, phytotoxicity, etc. Since sensor networks have been shown to reduce disease losses (Lichtenberg et al., 2013), we expect growers using these water sources to be willing to pay more for a sensor network. Conversely, operations that rely solely on rain water for irrigation stand to gain very little from using sensor networks, so we expect growers using rainfall to be willing to pay less for a sensor network.

Finally, we include regional dummy variables to control for unobserved factors such as climate conditions, information networks, and water scarcity. We expect growers located in regions with higher levels of water scarcity (e.g., the Pacific, and South Central regions) to be willing to pay more for a wireless sensor network compared to growers located in regions where water is less scarce (e.g., the Northeast).

Estimating Demand for Additional Nodes

A single node gives information about substrate moisture status for a limited area. Growers with more extensive operations or those growing a larger number of plant species with different water requirements would likely need to use a larger number of nodes in order to benefit from greater irrigation precision. We estimate demand for additional nodes—contingent on prior acquisition of a base system—in order to gauge variations in the scale at which sensor networks are likely to be used and in order to investigate operation characteristics correlated with those variations. We use a double censored tobit model to estimate the demand for additional nodes. Responses are censored at 0, while the number of additional nodes to be purchased are top coded at 21 or more. Choices of the number of additional nodes greater than 5 were presented as ranges: 6-7, 8-10, 11-15, and 16-20. We use the midpoint of each range (6.5, 9, 13, and 18) as the observed number of additional nodes y_i in our tobit model. We observe the latent demand for additional nodes by grower i, y_i*, only if it lies between 0 and 21, i.e., observed demand y_i is:

$$y_i = 21 \; if \; y_i * \geq 21$$

$$y_i = y_i * \; if \; 0 < y_i * < 21$$

$$y_i = 0 \; if \; y_i * \leq 0$$

$$y_i * = \gamma W + \boldsymbol{V}'\boldsymbol{\delta} + \eta$$

where W is the randomized price, **V** is a vector of operation and grower characteristics, and η is a random error capturing the influences of all unobserved factors affecting a grower's demand for additional nodes (which we assume to be distributed normally with mean zero).

We expect that the same factors that influence willingness to pay for a base system to affect demand for additional nodes. Those factors include size, share of income derived from ornamental production, water source, education, and perceptions of benefits and limitations of sensor networks.

Operations that are larger in terms of acreage are likely to have more irrigation zones, and thus have a higher demand for additional nodes. Larger grossing operations may also have more funds available and may thus experience fewer financial constraints in deciding how extensive a sensor network system to purchase.

Operations that earn a greater percentage of revenue from ornamental crops typically grow a wider variety of plant species and are thus also likely to have a larger number of irrigation zones. For that reason, we expect the share of revenue from nursery and greenhouse operations to be positively correlated with the number of nodes demanded.

We also expect that growers using more costly water sources such as deep wells and municipal water systems to be willing to buy more extensive sensor network systems, since their potential gains from irrigation cost savings are likely to be greater. The same reasoning leads us to expect that operations in more water scarce regions such as the Pacific and the Southeast, where the costs of water are higher due to constraints on availability as well as direct acquisition expenses, will be willing to purchase larger numbers of nodes than growers in less water scarce regions such as the Northeast.

We investigate the effect of human capital on sensor network system scale by including grower education levels in the additional node demand equation.

The literature suggests that one mechanism for addressing uncertainty about the performance of a new agricultural technology is to experiment with it on a portion of the farm operation. Experience with the technology reduces uncertainty about its potential; if the technology is truly more profitable, the share of the operation on which it is used should expand over time (Feder, Just, and Zilberman 1985). We investigate the effects of uncertainty about performance by including indicator variables for whether a grower believed sensor networks to have the advantages and limitations presented in Table 1. Belief in each potential advantage may indicate less uncertainty about potential benefits; if so, it should be correlated with a larger number of additional nodes demanded. Belief in each potential limitation may indicate greater uncertainty about potential benefits and may thus be correlated with a smaller number of additional nodes demanded.

<u>*Estimation Results*</u>

Willingness to Purchase a Base System

We simplified our model for willingness to purchase a base system in two ways. First, we aggregated education into two levels: (i) high school and some college and (ii) a post-secondary degree (including associate, bachelors, masters, and doctoral degrees). Wald tests indicated that the coefficients of the post-secondary degree categories ($p = 0.549$) were jointly not significantly different from zero and that none of the post-secondary degree categories were significantly different from each other ($p = 0.082$). Aggregation of education levels had little or no effect on the remaining estimated coefficients. Second, Wald tests indicated that the perceptions of benefits were jointly significant ($p = 0.017$) but that perceptions of limitations ($p = 0.707$), water source ($p = 0.944$), age category ($p = 0.251$), and region ($p = 0.738$) were not. We thus dropped these sets of indicators from the main model. As a robustness check, we report estimated coefficients and marginal effects of the variables included in our main model from models including the complete set of regressors (Table 5).

The coefficients of the variables included in the probit model, used to determine willingness to pay for a base system model, all have signs consistent with our expectations (Table 5). They are also robust with respect to the inclusion of the additional control variables.

The coefficient of price is negative and significantly different from zero, consistent with downward sloping demand. The base system demand is not very sensitive to changes in price: A $100 reduction in price would increase the share of respondents willing to purchase a base system by only about 0.007 percentage points, on average (Table 6).

The coefficient of the percentage of revenue from ornamental production is positive and significantly different from zero, consistent with our hypothesis that growers who rely on nursery and greenhouse crops more heavily are likely to benefit more from using sensor networks and are likely to be more aware of potential benefits of sensor networks as well. Base system demand is more sensitive to the degree of specialization in greenhouse and nursery crops than to price: A one percentage point increase in the percentage of revenue from ornamental production is associated with 0.5 percentage point in increase in the share of respondents willing to purchase a base system, on average.

The coefficient of no post-secondary degree is negative and significantly different from zero, consistent with the hypothesis that farmers with more formal education are more likely to adopt new agricultural technologies. The effect of formal schooling on willingness to purchase a base system is substantial: Respondents without a post-secondary degree are 23 percentage points less likely to be willing to purchase a base system than those with a post-secondary degree.

The estimated coefficients of size in terms of acres and in terms of revenue are both positive but neither is significantly different from zero and both are quite small in magnitude, indicating a lack of scale effects influencing likely adoption of a base system. The average semi-elasticity of the likelihood of purchasing a base system with respect to income is significantly different from zero. But it too, is quite small: on average, an increase in income of $100,000 is associated with only a 0.05 percentage point increase in the probability of a respondent being willing to purchase a base system.

Willingness to purchase a base system was associated with some, but not all perceived benefits of sensor networks. Growers who believe that sensor networks can increase irrigation efficiency, reduce irrigation management costs, and improve product quality are more likely to be willing to buy a sensor network at the quoted price than those who did not. These beliefs are associated with substantial differences in base system demand. Those who believe that sensor networks can increase irrigation efficiency, reduce irrigation management costs, and improve quality are 12-15 percentage points more likely to be willing to purchase a base system. The coefficients of believing that sensor networks can reduce monitoring costs and lower product losses were both positive, as expected, but not significantly different from zero. Somewhat surprisingly though, growers who believe that sensor networks can reduce disease are 15 percentage points less likely to be willing to buy a sensor network at the quoted price. The coefficient of believing that sensor networks can increase ability to manage growth rates was also negative but was not significantly different from zero.

Estimated Demand for Additional Nodes

As with the probit model of willingness to purchase a base system, we simplified the tobit model of demand for additional nodes by dropping variables that were not significantly different from zero. Wald tests indicated that education levels (p = 0.636), age category (p = 0.994), perceptions of potential benefits of sensor networks (p = 0.418), and perceptions of potential drawbacks of sensor networks (p = 0.122) were not significantly different from zero. We thus removed these sets of indicators from the main model. As a robustness check, we report estimated coefficients and marginal effects of the variables included in our main model from models including them as additional controls (Table 7).

The coefficients of the variables included in the main model of demand for additional nodes all have signs consistent with our expectations (Table 7). They are also robust with respect to the inclusion of the additional control variables.

The coefficient of price is negative, consistent with downward sloping demand. It is significantly different from zero when additional controls are included but not otherwise. The effect of price on demand for additional nodes is quite small: a one percent increase in price decreases the unconditional expectation of the number of additional nodes demanded by 0.3

percent (Table 8). The effect of a change in price is split fairly evenly between reductions in the number of nodes demanded by those purchasing a positive amount (as indicated by an elasticity of 0.1) and reductions in the probability that a grower is willing to purchase any additional nodes (as indicated by a semi-elasticity of 0.09).

The coefficient of the percentage of revenue from ornamental production is positive and significantly different from zero, consistent with our hypothesis that growers who rely on nursery and greenhouse crops more heavily are likely to have a greater diversity of plant varieties and irrigation zones and thus need more nodes to obtain adequate coverage. Demand for additional nodes is quite inelastic with respect to the degree of specialization in greenhouse and nursery crops. A one percentage point increase in the share of income from ornamental production is associated with a 0.02 percent increase in the unconditional expectation of the number of additional nodes demanded. As with price, the effects of specialization in greenhouse and nursery crops are split fairly evenly between the extensive and intensive margins. A one percentage point increase in the share of income from ornamental crops is associated with a 0.6 percentage point increase in the probability that a grower is willing to purchase at least one additional node, compared to a 0.7 percent increase in the expected number of additional nodes demanded by growers willing to purchase at least one.

The estimated coefficients of size in terms of acres and in terms of revenue are both positive, as expected. The coefficient of income is significantly different from zero while the coefficient of size in acres is not, suggesting that cash flow may constrain the size of system demanded.

Growers obtaining water from deep wells and surface waters and those using gray water are willing to buy a larger number of nodes at any given price. As noted earlier, water from deep wells is more expensive to pump, so that growers using this source stand to save more in expenditures on energy for irrigation. Growers using surface water may face limits on their ability to expand their operations or to respond to drought; the positive coefficient of the surface water indicator is consistent with water having a higher implicit cost due to such constraints.

Growers in the Appalachian region are willing to buy fewer nodes at any given price than growers in other regions. Possible explanations include less plant and irrigation zone diversity and less water scarcity among growers in this region.

Implications for Initial Adoption and Diffusion of Sensor Network Technology

The estimated coefficients of the probit model can be used to draw inferences about likely initial adoption and subsequent diffusion of sensor network technology in the greenhouse and nursery industry. As is standard, we assume that growers whose willingness to pay for a base system is at least as great as the current price of a system will adopt the technology while those with a willingness to pay less than the current price will not. We thus use estimates of willingness to pay to estimate the share of nursery and greenhouse operators likely to adopt this technology initially. Growers who did not adopt the technology initially may do so later on, if the cost of the technology falls, as often occurs as producers of the technology benefit from economies of scale or from learning from experience in producing the technology. Alternatively, growers who did not adopt the technology initially may do so later on as the benefits of the technology become better known and as uncertainty about the technology shrinks (Feder et al., 1985). We examine the effects of changes in price and perceptions about benefits and drawbacks of sensor networks by estimating their effects on the share of growers with a willingness to pay for a base system greater than or equal to the price of system.

Initial Adoption

Predicted willingness to pay for each respondent is equal to max$\{0, \frac{Z\prime\beta}{\alpha}\}$. On average, respondents were willing to pay $1905 for a base system, substantially less than the projected initial price of $3500. There is substantial variability in willingness to pay for a base system, however, as indicated by a standard deviation slightly larger than the mean at $2015. Examination of the cumulative distribution of willingness to pay estimates (Figure 1) indicates that almost one fifth of our respondents were willing to pay at least the projected initial price of $3500. That estimate suggests that initial adoption of sensor networks could be high relative to many other new agricultural technologies generally and irrigation technologies in particular. For example, only 5.8% of irrigated farms used drip irrigation in 1978, the first year drip irrigation—introduced in the US in the late 1960s—was reported by the Farm and Ranch Irrigation Survey (Census of Agriculture, 1979).

At the other end of the spectrum, roughly 30% of our respondents were not willing to pay anything for a base system. Respondents unwilling to pay anything for a base system differed from those with a positive willingness to pay in terms of size and reliance on nursery operations. The average income of those with an estimated willingness to pay of zero was lower than that of those with a positive willingness to pay ($p = 0.103$). The average share of income from greenhouse and nursery operations of those with an estimated willingness to pay of zero was similarly lower than that of those with a positive willingness to pay ($p = 0.009$). These differences are consistent with the notion that larger operations that specialize more in ornamental production are more likely to adopt sensor network technology.

Impact of Changes in Network Price

As noted above, one factor that often drives diffusion of new technologies is falling prices that render the technology affordable to larger and larger numbers of potential buyers. While we cannot predict the rate of change in the price of the sensor networks, we can use the experience of similar types of products to estimate the range of rates at which sensor network costs might change over time. For example, a comparison of the price index for farm durable equipment as estimated by the Economic Research Service of the US Department of Agriculture with the GDP deflator for the period 1990-2011 indicates that real prices of farm durable equipment fell at an average annual rate of about 1.2%, while a comparison of the Producer Price Indexes for communications equipment during 2006-2013 and for wireless telecommunications services during 2009-2013 with the Consumer Price Index for the corresponding periods of time indicates that prices of these goods and services fell at respective annual average rates of 1.4% and 4.4% in real terms. The estimated coefficients of the probit model indicate that a 1% decrease in price results in an average 0.2 percentage point increase in the share of growers willing to purchase a base system (Table 6). If sensor network prices decrease at comparable rates, one would expect the share of growers willing to purchase a base system to increase at rates of 0.3-0.8 percentage points a year. This estimated rate of diffusion is comparable to that of drip irrigation, another precision irrigation technology: In 2008, 17.4% of irrigated farms used drip or trickle systems compared to 5.8% in 1978, corresponding to an average annual rate of increase of about 0.3%.

Impact of Changes in Grower Perceptions

Another factor known to drive diffusion of new technologies is the spread of information that increases expectations about profitability and reduces uncertainty about performance. The example of drip irrigation—which, like sensor-controlled irrigation, is a form of precision technology—provides a case in point. Adoption rates were initially relatively low due to design problems (clogged emitters, installation problems, etc.), lack of information, and the need for growers to change irrigation practices. Technological improvements by manufacturers (reductions in clogging, pressure-compensated emitters that increased application uniformity, designs for use with hard water and for frost protection, anti-siphon designs, etc.), combined with research that demonstrated increases in yields and quality in a number of crops, helped to change grower's perceptions (Camp, 1998; Ayars et al, 1999). The combination of technical improvements and greater information about performance increased growers' confidence and helped promote diffusion of drip technology.

Learning-by-doing derived from experience will likely lead to similar technical improvements in wireless sensor networks. Current generations of sensors are connected to nodes by wire; conversion to wireless transmission of data from sensors should improve reliability by eliminating cut or disconnected wires. Current configurations for fully automated irrigation require a node that is wired to a solenoid valve. A more distributed system where each solenoid had its own actuator that could be controlled wirelessly would be beneficial in many situations. Elimination of wiring would increase ease of installation, increase reliability, and remove limits on distance from sensors to nodes (currently 5 meters). For greenhouse and nursery uses, sensors that measure moisture in smaller volumes of substrate (currently about 350 ml) would increase usability. These technical improvements, combined with information about performance and reliability from experiments and commercial experience (e.g., Belayneh et al;, 2013; Lichtenberg et al., 2013) should help increase expectations about profitability and reduce uncertainty about performance.

To gauge the magnitude of the effect of information diffusion on rates of adoption of sensor networks, we conduct a set of simulations using the coefficients of current perceptions of the potential benefits of sensor networks. We focus on diffusion of beliefs that sensor networks increase irrigation efficiency and reduce irrigation management costs, since our analysis indicates that these two beliefs have a statistically significant effect on the probability that a grower would purchase a base system.

We model changes in adoption over time due to the spread of positive perceptions about sensor network performance as follows. Let P_{jt} be the number of growers who believe that sensor networks have benefits of type j in period t. Assume that each grower who does not believe that sensor networks have benefits of type j in period t changes that perception with probability **Ω**, so that the number of growers whose perception of sensor network benefits changes from negative to positive is $\Omega(1-P_{jt})$. We draw from our set of respondents without replacement, so that growers change their beliefs about sensor network performance from negative to positive but not vice versa. In period T, we compare the adoption rate for every positive perception and several information dispersion rates **Ω**. We compare diffusion rates for **Ω** =0.01, 0.1, and 0.2. We run 1000 trials for each value of **Ω** over a period of 200 years and report average adoption rates at the expected base system price of $2,500 for each period.

Our simulations indicate that diffusion of information about these benefits of sensor networks would have a very limited effect on rates of sensor network technology adoption (Table 9). Even after 50 years, of the 20% of non-adopters changing their beliefs about sensor network performance from negative to positive, the share of growers willing to purchase a base system increases by only 1-4 percentage points. The main reason is that a majority of growers already believe that sensor networks have these benefits: Over four-fifths believe that sensor networks can increase irrigation efficiency and almost three-fifths believe that sensor networks can reduce irrigation management costs (Table 4). These positive perceptions of sensor network performance result in relatively high likely initial adoption rates coupled with relatively small effects of information diffusion on subsequent adoption rates.

Sensor Network Profitability

The estimated coefficients of the probit and tobit models can also be used to draw inferences about current grower perceptions of the respective profitability of investing in a sensor network and additional nodes. Investing in a base system is profitable if the annual return on that investment is at least as great as the cost of system. Thus, the estimated willingness to pay for a base system is a conservative estimate of the expected annual profit from investing in a sensor network. The profit from a base station equals the difference between the grower's estimated willingness to pay and the expected market price of $2500, if positive, and zero if expected willingness to pay is less than $2500. If a grower's willingness to pay is less than the expected market price, we assume she would not buy additional nodes and set total profit equal to zero. For growers whose willingness to pay exceeds $2500, we add the profit from the purchase of a base station to the profit from the purchase of additional nodes. The profit from additional nodes equals the consumer surplus under a grower's demand curve for additional nodes (Just et al., 1984). The estimated number of nodes that respondent *i* would purchase at price W is $\widehat{N}_i(W) = \max\{0, \gamma W + \boldsymbol{V}_{\boldsymbol{i}}'\boldsymbol{\delta}\}$. We calculate consumer surplus assuming that demand is linear between the choke price for each respondent, $-\frac{\boldsymbol{V}_{\boldsymbol{i}}\boldsymbol{'\delta}}{\gamma}$, and the expected market price of $500 per node. Growers whose choke price is less than $500 would not buy any additional nodes and thus have consumer surplus from additional node purchases of zero, so that consumer surplus for each grower is $\max\left\{0, \frac{\left(\frac{v_i{}'\delta}{\gamma}-500\right)*\widehat{N_\iota(500)}}{2}\right\}$, where $\widehat{N}_\iota(500)$ is the expected number of nodes purchased by grower *i* at the price of \$500.

At the initial estimated price of \$2500 for a base system and \$500 per additional node, 30% of the respondents have positive consumer surplus from the purchase of a base system together with additional nodes; an additional 7% would purchase a base system but no additional nodes. The average consumer surplus for growers who would purchase a base system is \$16,343. There is considerable variability in estimated total consumer surplus from the purchase of additional nodes, as indicated by a standard deviation of \$36,902 and a range of \$0 to \$215,024.

The increase in estimated profit for growers whose expected benefits exceeded the cost of a base system plus any additional nodes purchased averaged 5.2% of annual revenue. For 40% of these growers, estimated profit from investing in a sensor network amounted to 0.5% or less of annual revenue (Figure 3). The estimated increase in profit was between 0.5% and 1% of annual revenue for 22% of these growers and between 1% and 5% of annual revenue for an additional 25% of these growers. A few growers had estimated profits amounting to larger shares of revenue (Figure 3). Since profit usually also amounts to a small share of revenue, these calculations suggest that investing in this technology can increase profit substantially, consistent with findings from experimental studies (Belayneh et al., 2013; Lichtenberg et al., 2013).

Conclusion

Water scarcity is likely to grow in the coming years, making improvements in irrigation efficiency increasingly important. An emerging technology that promises to increase irrigation efficiency substantially is a network that uploads soil moisture and other sensor data into irrigation management software, creating an integrated system that allows real-time monitoring and control of moisture status. This technology, which is on the verge of commercial introduction, has been shown in experimental settings to reduce irrigation costs, lower plant loss rates, shorten production times, decrease pesticide application, and increase yield, quality, and profit (Lichtenberg et al., 2013).

This paper uses an original survey to investigate likely initial acceptance, ceiling adoption rates, and profitability of this new sensor network technology in the nursery and greenhouse industry. We find that adoption rates for a base system and demand for expansion components are decreasing in price, as expected. The price elasticity of the probability of adoption suggests that sensor networks are likely to diffuse at a rate comparable to or possibly greater than that of drip irrigation. Adoption rates for a base system and demand for expansion components are also increasing in specialization in ornamental production: Growers earning greater shares of revenue from greenhouse and nursery operations are willing to pay more for a base system and willing to purchase larger numbers of expansion components at any given price. Consistent with previous literature on adoption of new agricultural technologies, willingness to pay for a base system increases with education level and perceived benefits of sensor networks, notably increased irrigation efficiency, reduced irrigation management costs, and improved quality. We estimate that growers who are willing to purchase a sensor network expect investment in this technology to earn significant profit, consistent with findings from experimental studies.

While our study focuses on ornamental production, the lessons drawn from it are likely applicable more broadly. The most obvious extension is to production of vegetables and small fruits, both in greenhouses and in field production. Like ornamentals, these are high value crops whose growers have been shown to be more likely to adopt technologically sophisticated irrigation methods. Many growers of these crops already use some form of precision irrigation equipment, so adoption of wireless sensor technology would require less wholesale change in irrigation practices. Like ornamentals, these crops are labor-intensive, making savings in irrigation labor from automation of irrigation especially valuable. Like ornamentals, vegetables and small fruits are typically grown on smaller acreages than grains and oilseeds, making installation and maintenance less expensive and obviating potential problems with wireless data transmission. Additionally, much is known about optimal water management for these crops, making it feasible to automate irrigation control. Finally, these crops are grown worldwide under irrigation in areas where water scarcity is already a pressing concern, making the water saving potential of this technology especially valuable. These considerations suggest that wireless sensor technology could contribute substantially to alleviating conflicts between production of high quality foods and competing uses of water, demand for both of which tend to increase with income and thus economic growth.

Our estimates are based on responses to hypothetical choice questions for a technology that is not yet on the market. They suggest that a relatively large share of nursery and greenhouse operators could be early adopters and that diffusion of this technology could be at least as rapid than other precision irrigation technologies (or precision agricultural technologies more generally). Once this technology has been on the market for a few years, it would be interesting to compare actual adoption rates to the predictions made here.

Acknowledgements

This research was supported by US Department of Agriculture Specialty Crop Research Initiative Grant 2009-51181-05768 to the University of Maryland. We thank Anna Alberini, Ted McConnell, and John Lea-Cox for their comments and suggestions. Responsibility for all errors is, of course, that of the authors. The data used in this study are available from Erik Lichtenberg.

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Table 1. Comparison of Sample with National Statistics on Nursery and Greenhouse Operations

Category	Percentage of Growers in Category	
	Census of Agriculture 2007	Survey Sample
Revenue		
$1,000,000 or more	6.56	35.26
$500,000 to $999,999	4.69	16.84
$250,000 to $499,999	6.29	14.21
$100,000 to $249,999	12.86	11.58
$50,000 to $99,999	10.16	5.79
$25,000 to $49,999	12.56	5.79
$10,000 to $24,999	17.91	7.89
$5,000 to $9,999	11.49	2.11
$2,500 to $4,999	8.78	0.00
$1,000 to $2,499	6.24	0.53
Less than $1,000	2.47	0.00
Acreage		
1 to 9	38.29	32.17
10 to 49	36.03	27.71
50 to 69	6.01	5.1
70 to 99	5.4	3.18
100 to 139	4.18	5.41
140 to 179	2.36	3.18
180 to 219	1.51	3.18
220 to 259	1.06	2.55
260 to 499	2.71	6.37
500 to 999	1.55	6.05
1000 to 1999	0.56	2.55
2000 or more	0.34	2.55
Region		
Pacific	18.81	21.31
North East	21.19	19.34
South East	14.41	20.98
Appalachia	12.26	19.34
Midwest	20.58	10.49
Great Plains	1.66	3.28
South Central	7.16	3.61
Mountain	3.72	1.64

Table 2. Potential Benefits and Drawbacks of Sensor Networks

Potential Benefits	Increase efficiency
	Reduce monitoring time/costs
	Reduce irrigation management costs
	Increase ability to manage growth rates
	Increase quality
	Reduce disease occurrence
Potential Drawbacks	The sensors would not control irrigation correctly
	The cost would be too high
	The sensors would not be reliable
	There would be too much maintenance involved
	The sensors would not be as efficient as our current system

Table 3. Distribution of Responses by Offered Price

Price Level for	**Number of Responses**	
Base System		***Number Who Would Buy a Base System***
$1000	59	32
$2000	50	19
$3000	52	26
$4000	58	15
$5000	49	14
Additional Node		***Average Number of Additional Nodes Purchased***
$ 500	62	4.5
$1000	52	3.9
$1500	57	2.0
$2000	56	3.8

Table 4. Descriptive Statistics of Variables Used in the Probit and Tobit Models

Variable	Mean	Standard Deviation	Minimum	Maximum
Farm Operation				
Operation Size (Acres)	222.8773	610.8162	0	6000
Annual Income ($1000)	2252.068	11279.64	0	150000
Percent of Income from Greenhouse and Nursery Crops	83.97398	33.51402	0	100
Located in Appalachian Region	0.197026	0.398494	0	1
Located in Midwest	0.096654	0.296037	0	1
Located in Northeast	0.193309	0.395629	0	1
Located in Pacific Region	0.230483	0.421927	0	1
Located in Southeast	0.189591	0.392708	0	1
Located in South Central Region	0.037175	0.189542	0	1
Use Water from Shallow Well	0.29368	0.456296	0	1
Use Water from Deep Well	0.460967	0.499403	0	1
Use Surface Water	0.301115	0.459598	0	1
Use Recycled Water	0.215613	0.412014	0	1
Use Rain Water	0.182156	0.386693	0	1
Use Municipal Water	0.193309	0.395629	0	1
Use Gray Water	0.048327	0.214856	0	1
Use Water from Other Sources	0.04461	0.20683	0	1
Farm Operator				
High School Graduate	0.063197	0.243771	0	1
Some College	0.107807	0.310714	0	1
Associate Degree	0.078067	0.268777	0	1
Bachelor’s Degree	0.360595	0.481068	0	1
Post-Graduate Degree	0.122677	0.328677	0	1
Age 20-29	0.033457	0.180163	0	1
Age 30-39	0.118959	0.324344	0	1
Age 40-49	0.197026	0.398494	0	1
Age 50-59	0.260223	0.439574	0	1
Age 60+	0.122677	0.328677	0	1
Perceptions of Wireless Sensor Networks				
Sensor Networks Can Reduce Product Loss	0.609665	0.488735	0	1
Sensor Networks Can Improve Increase Quality	0.70632	0.456296	0	1
Sensor Networks Can Improve Irrigation Efficiency	0.825279	0.380436	0	1
Sensor Networks Can Reduce Disease	0.572491	0.495639	0	1

Sensor Networks Can Reduce Irrigation Management Cost	0.587361	0.493227	0	1
Sensor Networks Can Increase Ability to Manage Growth Rates	0.550186	0.498402	0	1
Sensor Networks Can Reduce Monitoring Cost	0.505576	0.500901	0	1
Sensor Cost Would Be Too High	0.825279	0.380436	0	1
Sensors Would Not Control Irrigation Correctly	0.431227	0.496171	0	1
Sensors Would Not Be Reliable	0.516729	0.500652	0	1
Sensors Would Require Too Much Maintenance	0.330855	0.471398	0	1
Sensors Would Not Be as Efficient as Current System	0.148699	0.356455	0	1

Table 5. Estimated Coefficients of the Probit Willingness to Purchase Base System Model

Variable	Base Model	Model with Additional Controls
Base System Price	-0.000204*** (0.001)	-0.000211*** (0.002)
Operation Size (Acres)	0.000206 (0.198)	0.000165 (0.386)
Operation Size Missing (0/1)	0.548 (0.579)	0.772 (0.538)
Annual Income ($1000)	0.0000155 (0.167)	0.0000145 (0.178)
Annual Income Missing (0/1)	-0.490 (0.101)	-0.637** (0.047)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.0160** (0.035)	0.0150* (0.080)
Percent of Income from Greenhouse and Nursery Crops Missing (0/1)	1.427* (0.079)	1.341 (0.144)
High School Diploma/Some College (0/1)	-0.714*** (0.005)	-0.781*** (0.006)
Education Level Missing (0/1)	0.290 (0.332)	0.435 (0.366)
Sensor Networks Can Reduce Product Loss (0/1)	0.152 (0.477)	0.171 (0.447)
Sensor Networks Can Improve/Increase Quality (0/1)	0.405* (0.069)	0.398* (0.093)
Sensor Networks Can Improve Irrigation Efficiency (0/1)	0.448* (0.098)	0.493 (0.114)
Sensor Networks Can Reduce Disease (0/1)	-0.435** (0.033)	-0.381* (0.089)
Sensor Networks Can Reduce Irrigation Management Cost (0/1)	0.385** (0.049)	0.408* (0.059)
Sensor Networks Can Increase Ability to Manage Growth Rates (0/1)	-0.142 (0.488)	-0.187 (0.406)
Sensor Networks Can Reduce Monitoring Cost (0/1)	0.119 (0.552)	0.172 (0.428)
Constant	-1.847** (0.018)	-1.951** (0.048)
Number of Observations	268	268

p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively. Additional controls include region indicators, indicators of beliefs about drawbacks of sensor networks, water source indicators, and age.

Table 6. Average Partial Effects of Independent Variables on the Probability of Purchasing a Base System

Independent Variable	Change in Probability of Purchasing a Base System due to	
	One unit increase in independent variable	One percent increase in independent variable
Base System Price	-0.0000665*** (0.000)	-0.190*** (0.000)
High School Diploma/Some College (0/1)	-0.232*** (0.004)	
Operation Size (Acres)	0.0000671 (0.195)	0.0147 (0.205)
Annual Income ($1000)	0.00000503 (0.163)	0.00842*** (0.003)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.00521** (0.031)	
Sensor Networks Can Reduce Product Loss (0/1)	0.0494 (0.475)	
Sensor Networks Can Improve/Increase Quality (0/1)	0.132* (0.064)	
Sensor Networks Can Improve Irrigation Efficiency (0/1)	0.146* (0.094)	
Sensor Networks Can Reduce Disease (0/1)	-0.142** (0.029)	
Sensor Networks Can Reduce Irrigation Management Cost (0/1)	0.125** (0.044)	
Sensor Networks Can Increase Ability to Manage Growth Rates (0/1)	-0.0463 (0.487)	
Sensor Networks Can Reduce Monitoring Cost (0/1)	0.0387 (0.551)	
Observations	268	268
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively.		

Table 7. Estimated Coefficients of the Two-Limit Tobit Additional Node Demand Model

Variable	Base Model	Model with Additional Controls
Additional Node Price	-0.00159 (0.113)	-0.00174* (0.083)
Operation Size (Acres)	0.00109 (0.294)	0.00111 (0.302)
Operation Size Missing (0/1)	-6.212 (0.308)	-8.589 (0.164)
Annual Income ($1000)	0.000138*** (0.003)	0.000152*** (0.002)
Annual Income Missing (0/1)	-2.791** (0.046)	-2.468 (0.181)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.122** (0.013)	0.120** (0.014)
Percent of Income from Greenhouse and Nursery Crops Missing (0/1)	12.20** (0.024)	11.56** (0.034)
Located in Appalachian Region (0/1)	-4.900** (0.030)	-5.284** (0.023)
Located in Midwest (0/1)	0.872 (0.716)	0.568 (0.815)
Located in Northeast (0/1)	-3.498 (0.117)	-3.273 (0.160)
Located in Pacific Region (0/1)	-0.208 (0.921)	-0.716 (0.740)
Located in Southeast (0/1)	-2.372 (0.274)	-2.746 (0.209)
Use Water from Shallow Well (0/1)	0.561 (0.701)	0.400 (0.791)
Use Water from Deep Well (0/1)	3.262** (0.025)	2.741* (0.065)
Use Surface Water (0/1)	2.509* (0.071)	2.773** (0.046)
Use Recycled Water (0/1)	0.771 (0.568)	0.183 (0.891)
Use Rain Water (0/1)	0.888 (0.554)	-0.212 (0.890)
Use Municipal Water (0/1)	1.170 (0.492)	0.986 (0.559)
Use Gray Water (0/1)	9.105*** (0.001)	8.117*** (0.002)

Use Water from Other Sources (0/1)	-0.238 (0.932)	-1.339 (0.647)
Constant	-9.575* (0.063)	-7.977 (0.167)
Sigma	7.432*** (0.000)	6.991*** (0.000)
Number of Observations	233	233
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively. Additional controls include indicators of education level, indicators of beliefs about benefits of sensor networks, indicators of beliefs about drawbacks of sensor networks, and age.		

Table 8. Average Partial Effects of Independent Variables on the Demand for Additional Nodes

Independent variable	**Expected number of additional nodes demanded**			**Expected number of additional nodes demanded conditional on positive demand**			**Probability of positive demand**	
	Average absolute change due to a one unit increase	*Average percent change due to a one percent increase*	*Average percent change due to a one unit increase*	*Average absolute change due to a one unit increase*	*Average percent change due to a one percent increase*	*Average percent change due to a one unit increase*	*Average absolute change due to a one unit increase*	*Average absolute change due to a one percent increase*
Additional Node Price	-0.000855 (0.110)	-0.320 (0.121)		-0.000572 (0.110)	-0.109 (0.111)		-0.0000748 (0.107)	-0.0919 (0.109)
Operation Size (Acres)	0.000586 (0.292)	0.0354 (0.260)		0.000392 (0.292)	0.0131 (0.283)		0.0000513 (0.291)	0.00968 (0.280)
Annual Income ($1000)	0.0000742*** (0.002)	0.0265*** (0.000)		0.0000496*** (0.002)	0.0135*** (0.000)		0.00000650*** (0.003)	0.00693*** (0.000)
Percent of Income from Greenhouse and Nursery Crops (0-100)	0.0655** (0.012)		0.0194** (0.014)	0.0438** (0.012)		0.00685** (0.012)	0.00574*** (0.010)	
Located in Appalachian Region (0/1)	-2.630** (0.029)		-0.777** (0.031)	-1.759** (0.029)		-0.275** (0.030)	-0.230** (0.026)	
Located in Midwest (0/1)	0.468 (0.715)		0.138 (0.715)	0.313 (0.715)		0.0490 (0.715)	0.0410 (0.715)	
Located in Northeast (0/1)	-1.877 (0.115)		-0.555 (0.117)	-1.256 (0.115)		-0.196 (0.116)	-0.164 (0.112)	
Located in Pacific Region (0/1)	-0.112 (0.921)		-0.0330 (0.921)	-0.0747 (0.921)		-0.0117 (0.921)	-0.00978 (0.921)	

Located in Southeast (0/1)	-1.273 (0.273)		-0.376 (0.274)	-0.852 (0.274)		-0.133 (0.274)	-0.112 (0.271)	
Use Water from Shallow Well (0/1)	0.301 (0.700)		0.0890 (0.700)	0.201 (0.700)		0.0315 (0.700)	0.0264 (0.700)	
Use Water from Deep Well (0/1)	1.751** (0.023)		0.517** (0.025)	1.171** (0.023)		0.183** (0.024)	0.153** (0.022)	
Use Surface Water (0/1)	1.347* (0.068)		0.398* (0.071)	0.901* (0.069)		0.141* (0.070)	0.118* (0.067)	
Use Recycled Water (0/1)	0.414 (0.568)		0.122 (0.568)	0.277 (0.568)		0.0433 (0.568)	0.0363 (0.568)	
Use Rain Water (0/1)	0.477 (0.553)		0.141 (0.553)	0.319 (0.553)		0.0499 (0.553)	0.0417 (0.553)	
Use Municipal Water (0/1)	0.628 (0.491)		0.186 (0.492)	0.420 (0.491)		0.0657 (0.492)	0.0550 (0.491)	
Use Gray Water (0/1)	4.886*** (0.000)		1.444*** (0.001)	3.268*** (0.001)		0.511*** (0.001)	0.428*** (0.000)	
Use Water from Other Sources (0/1)	-0.128 (0.932)		-0.0377 (0.932)	-0.0854 (0.932)		-0.0134 (0.932)	-0.0112 (0.932)	
N	233	233	233	233	233	233	233	233
p-values in parentheses. ***, **, * denote significantly different from zero at 1%, 5%, and 10% levels, respectively.								

Table 9. Effects of Information Diffusion on the Share of Growers Willing to Purchase a Sensor Network at the Current Price

Year	Sensors Can Increase Irrigation Efficiency			Sensors Can Reduce Irrigation Management Cost		
	Annual Rate of Information Diffusion (Ω)			Annual Rate of Information Diffusion (Ω)		
	1%	**10%**	**20%**	**1%**	**10%**	**20%**
0	0.369	0.369	0.369	0.369	0.369	0.369
1	0.370	0.373	0.377	0.370	0.372	0.375
2	0.370	0.376	0.384	0.370	0.374	0.379
3	0.371	0.380	0.389	0.370	0.376	0.382
4	0.371	0.383	0.393	0.370	0.378	0.385
5	0.372	0.386	0.396	0.370	0.379	0.387
6	0.372	0.388	0.399	0.371	0.381	0.389
7	0.373	0.391	0.401	0.371	0.382	0.390
8	0.373	0.393	0.403	0.371	0.384	0.391
9	0.373	0.395	0.405	0.371	0.385	0.392
10	0.374	0.397	0.406	0.371	0.386	0.393
20	0.377	0.405	0.410	0.374	0.392	0.395
30	0.380	0.409	0.410	0.376	0.394	0.396
40	0.383	0.410	0.410	0.378	0.395	0.396
50	0.385	0.410	0.410	0.380	0.395	0.396

Chapter 2: Yield, Quality and Profitability of Sensor-Controlled Irrigation: A Case Study of Snapdragon (*Anthirinum majus L.*) Production

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Abstract

Advanced wireless irrigation sensor networks that can monitor and control irrigation are only recently commercially available, but on-farm research has found a number of advantages compared with current irrigation practices including reduced water application, disease incidence, production time and labor together with increased profitability. We examined the effects of wireless sensor networks to control irrigation in greenhouse production of snapdragons (*Antirrhinum majus*) using grower data on production, expenditures and sales which included three years of data before and after implementation of sensor irrigation networks. We calculated changes in yield, production time, quality, cost, revenue and profit. Sensor-based irrigation was found to increase revenue by 62% ($65,173) and profit by 65% ($35,327) per year. Sensor-based irrigation was also found to increase quality and the number of stems harvested per crop. The time to first harvest and time to last harvest were reduced for all cultivar groups, indicating that the plants grew faster using sensor networks. Production time per crop was decreased, allowing 2.5 additional production rows per year. Electricity usage was also reduced, likely due to less frequent irrigation using sensor networks. These results are in line with other benefits we have seen by installing sensor networks in other types of ornamental operations.

The Authors gratefully acknowledge funding support for this project from USDA–NIFA Specialty Crops Research Initiative; Award #2009-51181-05768. We thank Charles and Richard Bauer for their assistance with conducting this experiment and providing historical production, sales and expenditure data.

Introduction

Population expansion, economic growth, global climate change and depletion of groundwater reserves are putting increasing pressure on ground and surface water supplies (Sauer et al., 2010; Evans et al., 2013; Gleick, 2013). That pressure is likely to have an especially large effect on agriculture; in the United States, for instance, agriculture accounts for 80 percent of consumptive water use nationally and up to 90 percent or more in many western states (Schaible and Aillery, 2012). Irrigated agriculture is more productive than dryland farming, so shrinking water supplies could have a disproportionately large effect on food and fiber production (Evans et al., 2013).

The potential for droughts, changing rainfall patterns and increasing pressure on freshwater resources makes it vital to improve irrigation efficiency. There are a number of ways that irrigation can be improved, for example by switching from overhead to drip irrigation and by properly designing and maintaining an irrigation system. Irrigation can be further made more efficient by better matching water application rates with crop uptake in real time, which can be accomplished by combining equipment that monitors moisture status and weather conditions with decision support systems that apply water as needed (Evans et al., 2013). While precision irrigation equipment has become available, adoption rates remain low, due in part to a lack of decision support systems that can help growers make sense of data to determine optimal irrigation timing and application rates (Evans et al., 2013).

Recent developments in sensor technology and associated software offer a means to overcome these barriers. New wireless sensor systems upload sensor data on moisture status, humidity, solar radiation and other environmental data into irrigation management software, giving irrigation managers real-time information on plant moisture demand, which are also able to automate irrigation application. Research conducted in ornamental production environments indicates that these systems can reduce irrigation water application substantially, along with labor and energy used for irrigation (Belayneh et al., 2013). These systems have also been shown to lower plant loss rates, shorten production times and reduce pesticide applications (Chappell et al., 2013; Lichtenberg et al., 2013). As a result, adoption can be extremely profitable.

This paper examines the yield, quality and profitability effects of using a wireless sensor network to control irrigation in continuous greenhouse production of snapdragons (*Antirrhinum majus L.*). The greenhouse, nursery and floriculture industry is a large and growing segment of United States agriculture, with sales totaling almost $17 billion in 2007, comparable to the sales of vegetables ($15 billion) and soybeans ($20 billion) (U.S. Department of Agriculture, 2009). This industry is especially large in Western states, which continue to face growing water scarcity (Hall et al., 2011). Although greenhouses and nurseries typically occupy much less land than agronomic crops, their consumptive water use is relatively high (Beeson, 2004). Moreover, the value of water used for greenhouse and nursery products is substantially higher than agronomic crops (Ackerman and Stanton, 2011).

Irrigation management in greenhouse production of ornamental plants is in many ways more challenging than in agronomic crops. Crops are often grown year-round, with crop mixes changing seasonally. Moisture demand typically varies daily due to changing weather conditions. Container-grown plants lack the water storage capacity that soils provide for field-grown crops. Also, qualitative grower observation of soil surface or plant growth and development gives very imprecise measures of water availability in the root zone. Growers tend to avoid under-irrigation, which can stress plants and slow growth. But over-irrigation can also have adverse effects, including nutrient leaching (Cabrera et al. 1993, Chen et al. 2001, Ross et al. 2002, Ristvey et al. 2004), slowed growth (Beeson and Haydu 1995, Lichtenberg et al. 2013), higher denitrification rates (Myrold and Tiedje 1985), lower root zone oxygen levels (Groffman and Tiedje 1991, Daum and Schenk 1996) and increased risk of disease (Parke and Grunwald 2012, Lichtenberg et al. 2013). To take one example, Brennan (2007) found that the negative economic consequences of overwatering lettuce were large enough to offset costly investments in uniform sprinkler systems.

We examined the effects of greater irrigation precision achieved through the use of wireless sensor networks to control irrigation in greenhouse production of snapdragons. We used data on production, expenditures and sales before and after implementation of sensor-based irrigation from a commercial growing operation to estimate changes in yield, production time, quality, cost, revenue and profit.

Materials and Methods

Snapdragon production

In order to understand the impact of sensor networks on yield, quality and profitability, we used production and sales records from a commercial greenhouse which focuses primarily on year-round production of snapdragon (*Antirrhinum majus*) for fresh-cut flowers. Production records were kept beginning in 2000. Sales and expenditure records were available from 2007-2012. The greenhouse is located in Jarrettsville, MD, USA (39° 36' N, 76° 28' W) and had 0.15 ha under continuous production. Plants were grown using hydroponic production methods following standard operation practices for all aspects of production except irrigation.

Typical practices for the grower were as follows. Seedlings were germinated and grown in open 25.4 cm x 50.8 cm trays (Landmark Plastic Corp., Akron, OH) with Pro-Mix Flex media

(Premier Tech, Quebec, Canada) for 2-5 weeks depending on the season. Plastic bags that are 25 cm (diameter) by 1.8 meter (length) were filled completely with perlite and placed on rolling benches. Nine rectangular holes of size 6.3 cm by 13.3 cm were cut, evenly spaced, into the top and running along the middle of the bag. Bags were planted with six plants per hole, when the seedlings reached approximately 7-8 cm in height. Eighteen bags were placed end to end in a row, with six/seven rows of bags per bench. Benches were 190 cm wide and 33 m long, with a planting density of 5832 or 6804 plants per bench.[2] Plants were irrigated using one Chapin BTF drip tape per bag with 1.33 gallons per minute flow per 100 foot length and 15 cm emitter spacing (Jain Irrigation, Inc., Fresno, CA). The drip tape was treaded through the holes and placed in direct contact with the perlite substrate. Irrigation water is pumped from a nutrient tank, with fresh water added from a perennial spring as needed. Irrigation varied depending on the season and conditions, but was typically applied 3-12 times per day using a QCOM controller (QCOM Controls, Lake Forest, CA). Plastic bags drained freely through holes made at the bottom of the bag into troughs to increase substrate aeration and reduce disease incidence. All runoff was collected into a small lined pit, particulates were filtered and water was pumped back into the irrigation tank (recirculated). Water quality parameters (pH, EC) were adjusted automatically using Hanna pH and EC sensors (Hanna Instruments, Woonsocket, RI) connected to a Crop King controller (Crop King, Inc., Lodi, OH). Nutrients were adjusted based on tissue analysis, as per typical grower practice. The typical production time, from sowing seeds to harvesting the first flowers, ranged from 16 to 40 weeks depending on the season (mainly due to differences in photosynthetically active radiation).

[2] The grower briefly varied plant density to increase yields, but discontinued changes in density after they did not appreciably increase marketable yield.

Starting in 2009 and continuing through 2010, a sensor network composed of ten CMU (Carnegie Mellon University, Pittsburg, PA) and Em50R (Decagon Devices Inc., Pullman, WA) data loggers was installed in the greenhouse. EC5 sensors (Decagon Devices Inc., Pullman, WA) were used to indicate substrate water status over the growing period across the greenhouse. Five EC5 sensors were connected to each data logger, which transmitted data to a base station (Carnegie Mellon University, Pittsburgh, PA) connected to the grower's computer. The data was visualized and displayed using a prototype Sensorweb program (Carnegie Mellon University, Pittsburgh, PA). During this period, the sensor network allowed the grower to have an effective way to monitor substrate water status in the greenhouse based on raw outputs of the EC5 capacitance soil moisture sensors. Starting in 2011, the sensor network implemented in the greenhouse was used to control duration and frequency of irrigation. An improved version of the Sensorweb program, in addition to providing improved functions (for example irrigation scheduling) allowed researchers to access the site remotely over the internet. Prototype nR5 control nodes (Decagon Devices, Pullman, WA) allowed the grower and researchers to program the nodes via Sensorweb to open and close solenoid valves based on VWC set-points and automate irrigation.

The VWC set-points were selected based on a substrate-specific calibration done for the perlite substrate and the EC5 capacitance sensors and ranged between 0.29-0.33 $m^3 \bullet m^{-3}$ (29-33%) depending on the plant growth stage. A lower set-point was used when seedlings were transplanted and the set-point was generally increased to provide more irrigation water as the plant development and water uptake increased.

Since benches in the greenhouse had a 2% slope, EC5 sensors were installed at the higher/upper side of the benches to measure VWC in the direst section of the benches. Five EC5 sensors were distributed across rows on a bench in order to get a precise VWC reading. These readings were averaged on 15-minute basis and compared to the set-points used by the grower in Sensorweb. When the averaged VWC reading dropped below the set-point VWC, irrigation was applied for a duration specified by the grower.

As the greenhouse pump capacity was limited, 8-12 staggered irrigation periods of 10 minute length were set for each bench in the greenhouse per day. When a set-point VWC has been reached, the nR5 nodes would turn on solenoids and apply irrigation for 3-3.5 minutes. As the irrigation function was implemented on a 5-minute basis in Sensorweb, an additional irrigation event would be triggered after a wait period of 1.5-2 minutes when the VWC set-point has not been reached. When the set-point VWC was reached after an irrigation period set for a bench, irrigation was applied at the next irrigation period available for the bench.

Since all VWC data was logged at 15 minute intervals by the nodes, the wireless sensor network installed at the greenhouse allowed a continuous monitoring of the VWC to capture temporal variation in the benches. The precision of VWC readings was also increased by installing multiple sensors that were averaged and compared to a set-point to trigger irrigation events. Sensorweb allowed the grower to program times when irrigation could and could not be applied, set the irrigation length and prioritize which blocks were irrigated first. During irrigation events, the nR5 nodes could turn on solenoids and apply irrigation for a specified amount of time, which can be as short as few seconds. Irrigation events could also be micro-pulsed such that there is a set amount of wait time between consecutive pulses. The Sensorweb program could also determine if an additional irrigation event would be triggered based on the VWC set-point. The ability to apply micro-pulses with the drip irrigation system was particularly useful, allowing the applied water time to diffuse through the substrate. Two benches were controlled using nR5 nodes in 2011 and 2012, with the remaining areas controlled by the grower.

Different snapdragon cultivars are grown in different seasons. Varieties are grouped according to photoperiod (daylength), heat tolerance and other factors: Group 1/2 is grown in the fall (September 1-November 30), Group 2 in the late summer and early winter (August 8-25, December 1-15), Group 2/3 in mid-summer and mid-winter (July 20-August 7, December 20-January 7) and Group 3 in mid-summer and mid-winter (July 7-20, January 7-25) and Group 3/4 from late winter through early summer (January 25-July 7).

Except for irrigation, production was conducted using the grower's standard practices. Production records maintained by the grower for each crop include information on the sow date, transplant date, each of the multiple dates on which stems were harvested and the number of stems harvested on each date. The grower's sales records reported the number of stems of each quality grade sold by date and historical records of labor and energy costs for the period 2007-2012. The years 2007-2008 correspond to the period prior to the installation of the wireless sensor network. The years 2011-2012 correspond to the period when irrigation was controlled by the wireless sensor network. The intermediate years 2009-2010 constitute a transition period during which the sensor network was initially installed and calibrated and substrate moisture was monitored in preparation for automated control by the network.

The average number of stems harvested per crop, the average number of days to first and last harvest of each crop, the shares of crops from each cultivar group and the share of crops grown when irrigation was managed using sensor-based information are shown in Table 1. Time series plots of the number of days to first harvest, number of days to last harvest and number of stems harvested for each crop of snapdragons are shown in Figures 1-3, respectively.

Statistical Methods

Sensor networks can affect profit by altering yield, quality and production costs of an operation. This section presents the methods used to estimate each of these effects. We then discuss the methods used to estimate the impact of adopting a sensor network on profitability.

<u>Yield</u>

Wireless sensor networks can affect annual yield in two ways: (1) by altering yield per crop and (2) by changing the number of crops harvested per year. Annual yield is the product of these two. We estimate them separately, using a different method for each.

We used ordinary least squares regression (equivalent in this case to analysis of variance) to determine the effect of sensor networks on the number of stems harvested per crop **j**. Specifically, we regressed the number of stems per crop on an indicator for cultivar group **m**, an indicator for whether the sensor system was in use and interactions between the cultivar group and the sensor indicator:

$$\text{Stems}_j = a_0 + \sum_m b_m \text{ Cultivar}_{mj} + c_0 \text{ 1[Sensor = 1]} + \sum_m d_m \text{ Cultivar}_{mj}\text{*1[Sensor=1]} + e_j \quad (1)$$

We dropped data from the transition years 2009-2010 in order to obtain a clean comparison between pre- and post-sensor irrigation control.

We then used the estimated coefficients of equation (1) to calculate the average number of stems harvested for each cultivar group before and after installation of the sensor network.

Stems per Crop from Cultivar Group m without Sensors = $a_0 + b_m$ (2)

Stems per Crop from Cultivar Group m with Sensors = $a_0 + b_m + c_0 + d_m$ (3)

The effect of using a wireless sensor network on the number of crops harvested per year was investigated in two ways. We first used ordinary least squares regression to verify the effect of sensor networks on production time. Specifically, we regressed the number of days elapsed between the sow date and the first and last harvest dates for each crop j on the cultivar group m, an indicator for whether the sensor system was in use and interactions between the cultivar group and the sensor indicator:

$$Days_j = f_0 + \sum_m g_m\ Cultivar_{mj} + h_0\ 1[Sensor = 1] + \sum_m i_m\ Cultivar_{mj}*1[Sensor=1] + u_j \qquad (4)$$

As with the yield regression, we dropped data from the transition years 2009-2010 in order to obtain a clean comparison between pre- and post-sensor irrigation control.

We then used the estimated coefficients to compare time to initial and final harvest for each cultivar group before and after the installation of the sensor network:

Days to Initial/Final Harvest of a Crop from Cultivar Group m without Sensors = $f_0 + g_m$ (5)

Days to Initial/Final of a Crop from Cultivar Group m with Sensors = $f_0 + g_m + h_0 + i_m$ (6)

To calculate profitability with and without the sensor network, we used the average number of crops of each cultivar group harvested during the three years prior to and succeeding installation of the wireless sensor network, 2007-2008 and 2011-2012, respectively.

Crop Quality

Snapdragon quality is determined by two features: length of the flower spike and straightness of the stem. Stems are divided into three grades. Those with flower spikes equal to 20 cm or longer are the highest quality, grade 1. Those with flower spikes of 15 – 20 cm long are classified as grade 2. Snapdragon plants with flower spikes less than 15 cm long or with stems that are crooked rather than straight are classified as the lowest quality, grade 3. Grade 1 stems command the highest price, followed by grades 2 and 3 respectively.

We used ordinary least square regression to evaluate the effect of the sensor networks on the distribution of stem quality. Unfortunately, the sales records that reported flower grade were not matched to the cultivar that produced them, so we were not able to directly link cultivars to sales. We therefore aggregated sales into the number of stems in each grade classification per week. Stems sold were linked to cultivar groups using data on days to first harvest and days to last harvest and, in cases where harvest data were lacking, the date at which each crop was removed from the bench (the "cutout date"). Only one crop of cultivar Group 3 was grown during 2011-2012, so we merged cultivar Group 3 into Group 2/3, which is typically grown right before or right after Group 3.

For each grade k and week t, we calculated the share of weekly sales in that grade and regressed it on the share of each cultivar group m harvested in that week plus interaction terms between the share of the cultivar group and the share of the plants produced using sensors[3]:

$$\text{Share of Grade}_{kt} = \sum_m w_{km}\ \text{Share of Cultivar}_{kmt} + \sum_m x_{km}\ \text{Share of Cultivar}_{kmt} * \text{Share of Harvest Using Sensors}_{kmt} + v_t \qquad (7)$$

As with the yield and time to harvest regressions, we dropped data from the transition years 2009-2010 in order to obtain a clean comparison between pre- and post-sensor irrigation control.

We combined the regression coefficients with information obtained from the grower about the average price received for each grade to calculate the average price received for a stem from each cultivar group m before and after installation of the sensor network:

$$\text{Average Pre-sensor Price per Stem of Cultivar m} = \sum_k w_{km} * \text{price}_k \qquad (8)$$

$$\text{Average Post-sensor Price per Stem of Cultivar m} = \sum_k (w_{km} + x_{km}) * \text{price}_k \qquad (9)$$

<u>Production Costs</u>

Major production costs are labor, electricity and the costs of the sensor system. Labor and electricity costs L_t and E_t were taken directly from the grower's historical records and

[3] There were three weeks in which harvests contained both plants that used sensors and plants that did not. For all other weeks, the sensor variable is binary.

measured by the average annual amount spent on the category before and after the sensor systems were installed (the periods 2007-2009 and 2010-2012, respectively). The annual cost of the sensor network K was estimated from equipment list prices and annualized assuming equipment lifetimes of 3 years and an interest rate of 6% (Table 2).

Profitability

The yield, quality and production costs measurements were combined to assess the average annual profit before the sensor systems were installed and after the sensor systems were installed. The average number of stems and price per cultivar group were estimated using regression coefficients. Annual labor and electricity costs and the number of crops harvested from each cultivar annually were averaged for the two years before and after the sensor control of irrigation was implemented (the periods 2007-2008 and 2011-2012, respectively). Profit was calculated as follows:

Pre-Sensor Profit=$\sum_m$ Average Number of Crops of Cultivar Group m * Stems per Crop of Cultivar Group m * Average Price of Cultivar Group m - L_t - E_t (10)

Post-Sensor Profit=$\sum_m$ Average Number of Crops of Cultivar Group m * Stems per Crop of Cultivar Group m * Average Price of Cultivar Group m - L_t - E_t – K (11)

Results

Use of the sensor network to control irrigation increased yield per crop, reduced production time (and thus increased the number of crops harvested per year), increased quality, reduced electricity usage and increased profitability. Expenditures on labor increased due to increased harvesting.

Yield

The estimated coefficients of the yield regression (equation (1)) indicate that the sensor network increased the number of stems harvested from each cultivar group (Table 3 and Figure 1). The largest increase was experienced by cultivar Group 1/2, whose average yield per crop rose by 80%. The smallest increase occurred in Group 3/4, whose yield rose by 10%. Sensor controlled irrigation increased average yields of Groups 2, 2/3 and 3 between 25 and 40%.

Group 1/2 also experienced the greatest acceleration of production, as sensor-controlled irrigation reduced the time to first harvest by almost 25% and time to final harvest by 15% (Table 3 and Figures 2 and 3). Group 2/3 experienced the greatest compression of the harvest period overall, as sensor-controlled irrigation reduced the time to first harvest by 30% and the time to final harvest by 20%. Sensor-controlled irrigation had the smallest effect on production time of cultivar Group 3, whose time to first and final harvests fell only by 1 and 9%, respectively. Time to first harvest of Group 2 fell by 23% while time to final harvest fell by 24% and time to first and last harvests of Group 3/4 each fell by 12% and 10%, respectively.

These reductions in production time led to changes in the crop mix (due to altered timing of production) as well as to an increase the number of crops grown annually (Table 4). Overall, sensor-controlled irrigation allowed the grower to harvest 2.5 extra crops per year, an increase of 7%.

Increases in yield per crop and the number of crops per year combined with these changes in crop mix resulted in an increase in annual average output of 47% (Table 4).

Quality

Sensor-controlled irrigation improved snapdragon quality for all cultivar groups (Tables 5 and 6). The share of grade 1 stems harvested increased substantially for cultivar Groups 2 and 3/4, less substantially for cultivar Group 1/2 and remained roughly the same for cultivar Group

2/3. The increases in the shares of grade 1 stems in Groups 1/2 and 2/3 were due to decreases in the shares of grade 3 stems, as the shares of grade 2 stems increased in both groups. The average price received for a crop of Group 2 snapdragons increased by almost 17%, while the average price received for a crop of Group 3/4 snapdragons increased by almost 14%. Overall quality rose for Group 1/2 as well, due to increases in the shares of both grade 1 and grade 2 stems and a corresponding decrease in grade 3 stems, resulting in an increase in average price of 7%. The average price received for a crop of Group 2/3 snapdragons increased by almost 4% due to a lower share of grade 3 stems and higher shares of grade 1 and 2 stems.

Production Costs

After implementation of sensor controlled irrigation, average electricity costs fell by an average of $300 per year, a decrease of 8%, while labor costs rose by $3986, or 27%. The annualized cost of the sensor network was estimated at $7147 (Table 7).

Profitability

Estimates of yield and quality derived using equations (11) and (12) were combined with estimates of the average number of crops of each cultivar group per year, average expenditures on labor and electricity and the cost of the sensor network to determine annual revenue, cost and profit with and without the sensor network (Table 7). Use of the sensor network to control irrigation increased revenue by 62% annually due to both greater yield and higher average price (increased quality). Annual costs were higher (58%) since the cost of the sensor network and labor costs outweighed reductions in electricity expenditures. Annual profit increased by 65% as the increase in revenue outweighed the increase in cost.

Discussion

Using sensor networks to control irrigation increased profit by increasing yield per crop (Figure 6), reducing production time (Figures 4 and 5) thus increasing the number of crops harvested per year (Table 4) and reducing electricity use (Table 7). These effects are in line with previous studies of sensor networks. Shortening production time is extremely valuable in continuous production systems like greenhouse crops, since it frees up space for additional crops that could not otherwise be produced. In a study using sensor networks to control irrigation in Gardenia (*Gardenia augusta*), production time was cut roughly in half, which more than doubled annual profit (Chappell et al., 2013; Lichtenberg et al., 2013). The impact of sensor controlled irrigation was perhaps not as dramatic in our case but was nevertheless quite sizeable: an additional crop per year, combined with changes in the mix of cultivars grown, increased output by two-fifths and profit by almost two-thirds.

Sensor networks have also been shown to reduce irrigation water application in gardenia (van Iersel et al. 2009) and ornamental tree production (Belayneh et al., 2013). For this operation, water was pumped from a perpetual spring and fertigation water recirculated continuously, so water savings were not as important for the grower compared with municipal or well sources that are not reused. However, pumping water through the greenhouse likely accounts for a large share of electricity usage at the operation and reductions in pumping volume likely account for most of the differences in electricity use pre- and post-sensor implementation (Table 7). Thus, our finding of a reduction in electricity use is an indication of water savings. Although water savings did not increase profitability substantially, this is mainly due to the water being unpriced and the irrigation system being efficient. Even with a low cost of water, profitability was increased through improvements in flower quality and reductions in growing period. Water savings on the order of those indicated by the reduction in electricity usage here could however, increase profit more substantially for more water-intensive crops or for crops grown in locations with higher water prices. In open production systems (greenhouse, container and field), lower application rates of both water and nutrients, would also reduce leaching, providing environmental benefits through reduced water withdrawals and reduced nutrient leaching to surface and groundwater (Lichtenberg et al. 2013).

The average annual stem output was increased from 106,173 stems per year before sensors to 156,320 stems per year after sensors (Table 4). This increase per crop and increase in the total number of crops adds to the growers profit (Table 7). Sensor networks have also been shown to increase harvested yields per crop in gardenia by reducing losses, likely through reductions in disease incidence (Lichtenberg et al., 2013).

Higher yields should also lead to higher labor costs due to increased harvesting activity, as was found in the case of gardenia production (Lichtenberg et al., 2013) as well as in this analysis. In both cases, the increase in revenue from greater productivity outweighed the increase in labor cost, as one would expect from any crop that is profitable to grow.

One effect of sensor controlled irrigation not previously documented is a change in product quality. Based on grower records, quality effects were mixed. Sensor controlled irrigation improved quality for all cultivar groups and (Tables 5 and 6 and Figure 7). It is interesting to note that sensors increased quality the most for Groups 2 and 3/4, which are grown during summer, when high heat and humidity at the operation make it difficult to grow snapdragons. This highlights the precision aspect of sensor networks for controlling irrigation. Overall average quality, as measured by the production-weighted average price received, increased using sensor networks. It proved feasible to increase overall average quality even more by altering timing of production, specifically, growing more crops of the cultivar groups for which quality increased at the expense of cultivar groups experiencing less marked improvements in quality. In actuality, the grower reduced the number of crops of one cultivar group whose quality increased modestly while increasing the number of crops whose quality increased the most.

Conclusion

As climate change, population growth and unsustainable extraction of groundwater exacerbate water shortages in large portions of the United States and abroad, policymakers face challenges allocating increasingly scarce water resources efficiently. With over 80 percent of all consumptive water uses going to agriculture, on-farm irrigation technologies may prove to be an important tool in addressing water scarcity. Wireless sensor networks are an emerging technology that has been shown to reduce water usage, while maintaining growth and quality. They have also been shown to provide a number of other benefits, including reduced production time, reduced product loss and reduced leaching.

This study used wireless sensor networks to control irrigation in continuous hydroponic snapdragon cut flower production and found that sensor controlled irrigation increased profit by reducing growing time (thereby allowing production of an additional crop per year), increasing yield per crop, improving cut flower quality and reducing electricity costs. The increase in profit was substantial, more than one-third greater than pre-sensor levels even after subtracting sensor system costs. Similar benefits have been observed under a variety of ornamental production situations, suggesting that sensor controlled irrigation can increase profitability while saving water under a variety of growing conditions. Increases in irrigation efficiency achieved by the use of sensor networks have important environmental benefits as well, such as reducing pressure on water supplies, reducing greenhouse gas emissions by reducing energy and fertilizer use and reducing nutrient leaching into waterways. Benefits in terms of grower profitability and reductions in environmental impacts are likely to be greater in crops that require higher water inputs and in areas with water quality or quantity concerns. For that reason, additional research on the use of sensor networks to control irrigation in fruits, vegetables and other crops should be of great interest.

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Table 1. Descriptive statistics of production data for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. Both pre- and post-sensor data are averaged.

Variable	Mean	Standard Deviation	Minimum	Maximum
Stems Harvested Per Crop	3196	1789	60	11,740
Number of Days to First Harvest	113	46	42	361
Number of Days to Last Harvest	149	80	67	536
Share of Crops When Sensor System in Use	0.33	NA	NA	NA
Share of Crops from Cultivar Group ½	0.28	NA	NA	NA
Share of Crops from Cultivar Group 2	0.15	NA	NA	NA
Share of Crops from Cultivar Group 2/3	0.12	NA	NA	NA
Share of Crops from Cultivar Group 3	0.05	NA	NA	NA
Share of Crops from Cultivar Group ¾	0.38	NA	NA	NA

Table 2. Configuration and cost of a wireless sensor network that controlled irrigation at a greenhouse operation growing snapdragons (*Antirrhinum majus*) in continuous hydroponic production.

	Number	Price	Total	Lifetime (years)	Annualized Cost @ 6% Interest
Nodes	15	$ 675	$10,125	3	$ 3,688
Soil Moisture Sensors	50	$ 70	$3,500	3	$ 1,275
Additional Sensors	25	$ 150	$3,750	3	$ 1,366
Sensorweb Base Station plus Computer	1	$ 600	$600	3	$ 219
4G Internet Access	1	$ 600	$600	1	$ 600
Annual Total			$18,575		$ 7,147

Table 3. Estimated coefficient of regression analyses for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. This system was used to compare pre- and post-sensor data collected by the grower to determine the impact of wireless sensor networks on plant growth, quality, yield and profitability. Standard errors clustered by crop year are in parentheses.

Regressor	Dependent Variable				
	Number of Days Until				Number of Stems Harvested
	First Harvest	First Harvest	Last Harvest	Last Harvest	
Sensor System in Use (1 = Yes)	-50.05*** (9.009)	-28.05*** (5.371)	-36.73** (17.43)	-32.44*** (7.772)	2005*** (417.2)
Cultivar Group 2	-34.19*** (10.11)	-24.97** (8.373)	18.16 (19.55)	13.286 (16.45)	-16.31 (468.1)
Cultivar Group 2/3	-49.95*** (9.825)	-38.05*** (9.388)	22.02 (19.00)	15.91 (24.31)	474.2 (454.9)
Cultivar Group 3	-46.80*** (12.71)	-34.57*** (12.18)	-41.71* (24.58)	-38.07** (15.12)	270.2 (588.4)
Cultivar Group 3/4	-79.34*** (7.599)	-64.46*** (7.663)	-73.68*** (14.70)	-65.93*** (8.362)	629.4* (351.9)
Sensor System in Use*Cultivar Group 2	20.07 (15.42)		-12.12 (29.39)		-970.0 (713.8)
Sensor System in Use*Cultivar Group 2/3	31.07 (19.21)		-34.68 (37.15)		-1,235 (889.46)
Sensor System in Use*Cultivar Group 3	48.41 (39.68)		24.55 (76.76)		-1,211 (1838)
Sensor System in Use*Cultivar Group 3/4	39.67*** (12.52)		25.40 (24.21)		-1,7041*** (575.7)
Constant	167.4*** (6.083)	156.0*** (12.81)	184.9*** (11.77)	182.9*** (8.059)	2506*** (281.7)
Observations	236	236	236	236	236
R-squared	0.386	0.357	0.229	0.216	0.119
*** p <0.01, ** p < 0.05, * p < 0.1					

Table 4. Number of crops harvested and estimated yield by cultivar, pre- and post-sensor for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system and a wireless sensor network.

Cultivar Group	**Number of crops**[a]	**Stems per crop**[b]	**Total stem output**[c]
Pre-Sensor-Controlled			
Group 1/2	26	2,506	65,156
Group 2	4	2,490	9,959
Group 2/3	11	2,980	32,782
Group 3	6	2,776	16,657
Group 3/4	28	3,135	87,791
Annual Average	37.5		106,173
Post-Sensor-Controlled			
Group 1/2	32	4,511	144,352
Group 2	15	3,525	52.870
Group 2/3	6	3,750	22,501
Group 3	1	3,570	3,570
Group 3/4	26	3,436	89,346
Annual Average	40		156,320

[a] Totals for 2007-2008 (pre-sensor) and 2011-2102 (post-sensor).
[b] Estimated from regression coefficients reported in Table 2.
[c] Calculated as number of crops times estimated yield per crop.

Table 5. OLS regression of weekly grade shares for snapdragon (*Antirrhinum majus*) production. This system was used to compare pre- and post-sensor data collected by the grower to determine the impact of wireless sensor networks on plant growth, quality, yield and profitability.

Regressor	Share of Grade 1	Share of Grade 2	Share of Group 3
Share of Group 1/2	0.701*** (0.037)	0.134*** (0.031)	0.165*** (0.024)
Share of Group 2	0.358*** (0.123)	0.451** (0.116)	0.0191*** (0.053)
Share of Group 2/3	0.655*** (0.036)	0.202** (0.028)	0.143*** (0.023)
Share of Group 3	0.528*** (0.046)	0.248*** (0.031)	0.225*** (0.031)
Share of Group 3/4	0.090* (0.046)	0.037 (0.039)	-0.128*** (0.025)
Sensor System in Use*Cultivar Group 1/2	0.460*** (0.127)	-0.345*** (0.119)	-0.115** (0.055)
Sensor System in Use*Cultivar Group 2	0.013 (0.076)	0.077 (0.071)	-0.090*** (0.026)
Sensor System in Use*Cultivar Group 2/3	0.246*** (0.055)	-0.065 (0.044)	-0.181*** (0.033)
Sensor System in Use*Cultivar Group 3	174	174	174
Sensor System in Use*Cultivar Group 3/4	0.701*** (0.037)	0.134*** (0.031)	0.165*** (0.024)
Observations	0.358*** (0.123)	0.451** (0.116)	0.0191*** (0.053)
Standard errors in parentheses * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$			

Table 6. Impact of wireless sensor network controlled irrigation on the distribution of quality and average price received per stem by cultivar type for snapdragon (*Antirrhinum majus*), grown using a recirculating hydroponic production system. Results are estimated from regression coefficients reported in Table 4.

	Grade 1	Grade 2	Grade 3	Average Price
Price per Stem	\$0.665	\$0.535	\$0.300	
Pre-Sensor-Controlled				
Group 1/2	70%	13%	17%	\$0.587
Group 2	36%	45%	19%	\$0.537
Group 2/3	65%	20%	14%	\$0.586
Group 3	53%	25%	22%	\$0.551
Group 3/4	Post-*Sensor-Controlled*			
Post-*Sensor-Controlled*				
Group 1/2	82%	11%	8%	\$0.624
Group 2	67%	28%	5%	\$0.609
Group 2/3	77%	18%	4%	\$0.625
Group 3	70%	13%	17%	\$0.587
Group 3/4	36%	45%	19%	\$0.537

Table 7. Comparison of profitability pre- and post-sensor for a wireless soil moisture sensor network for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. Average yearly values are reported.

	Pre-Sensor-Controlled	Post-Sensor-Controlled
Revenue	$40,316.86	$65,173.00
Labor Cost	$14,975.83	$18,961.33
Electricity Cost	$3,837.98	$3,538.02
Sensor System Cost		$7,147.09
Annual Profit	$21,503.06	$35,526.58

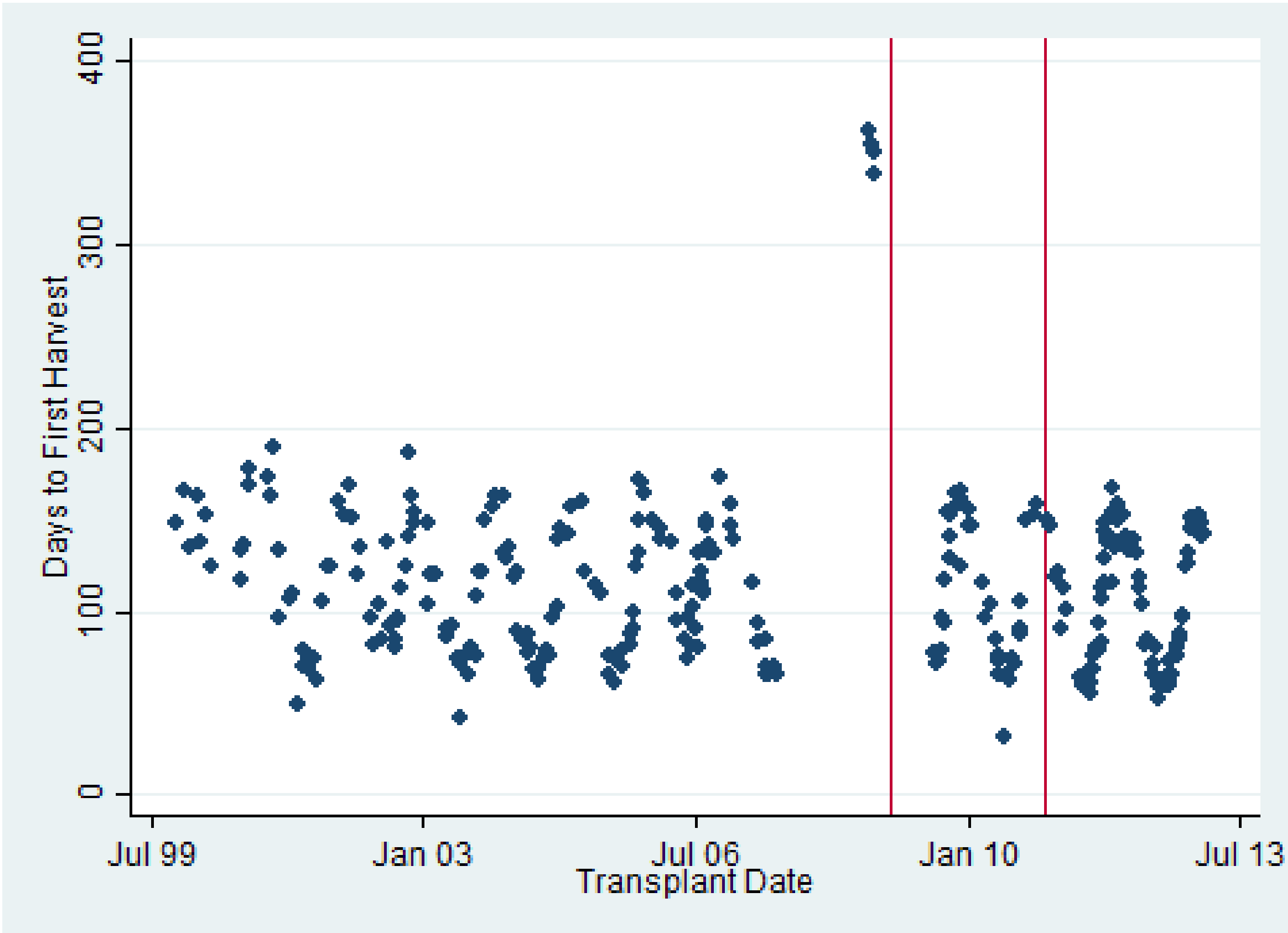

Figure 1. Length of time from planting to first harvest for each crop of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. Red lines demarcate the initial installation of a wireless irrigation sensor network and the initiation of sensor-controlled irrigation.

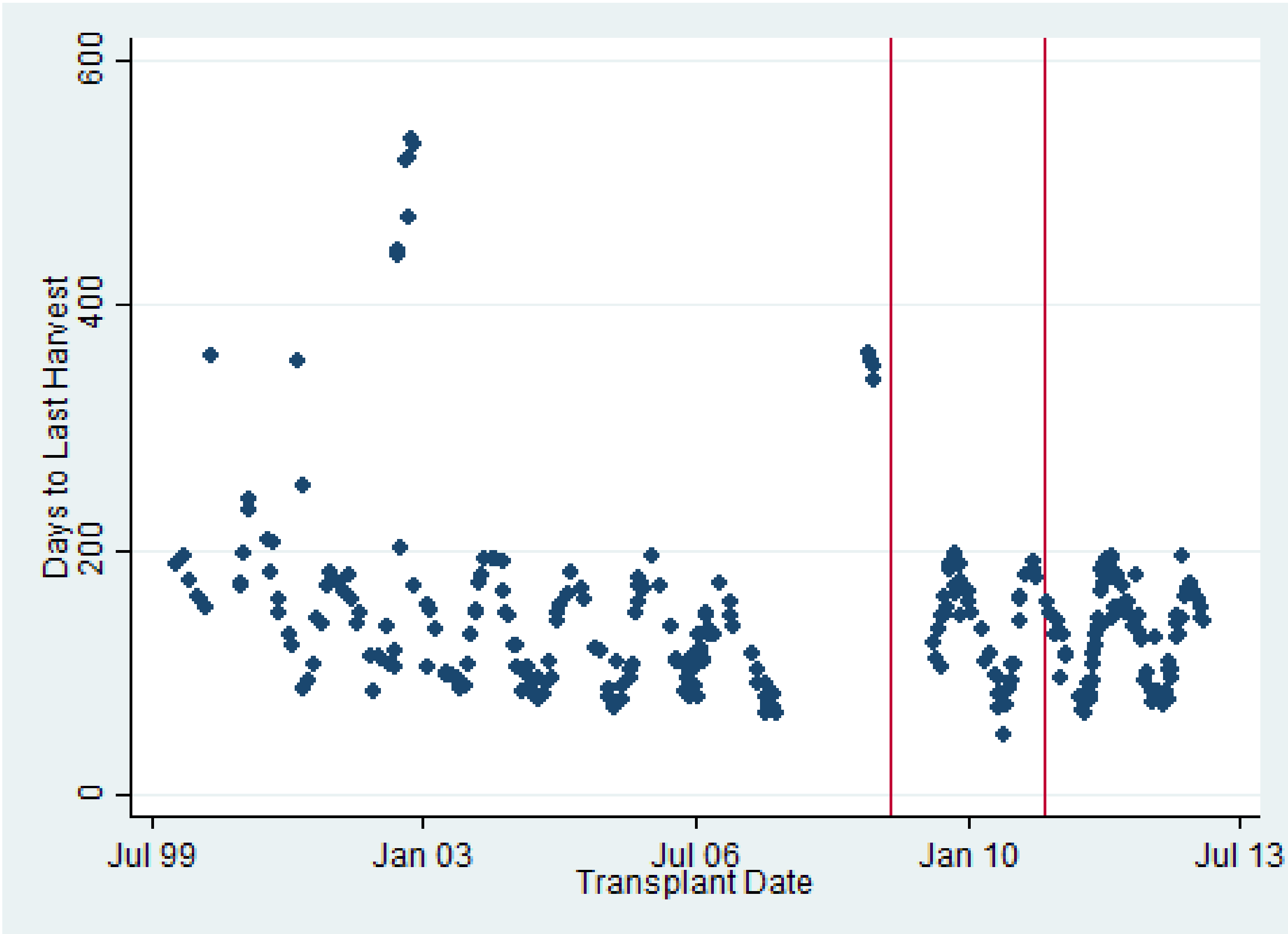

Figure 2. Length of time from planting to last harvest for each crop of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. Red lines demarcate the initial installation of a wireless irrigation sensor network and the initiation of sensor-controlled irrigation.

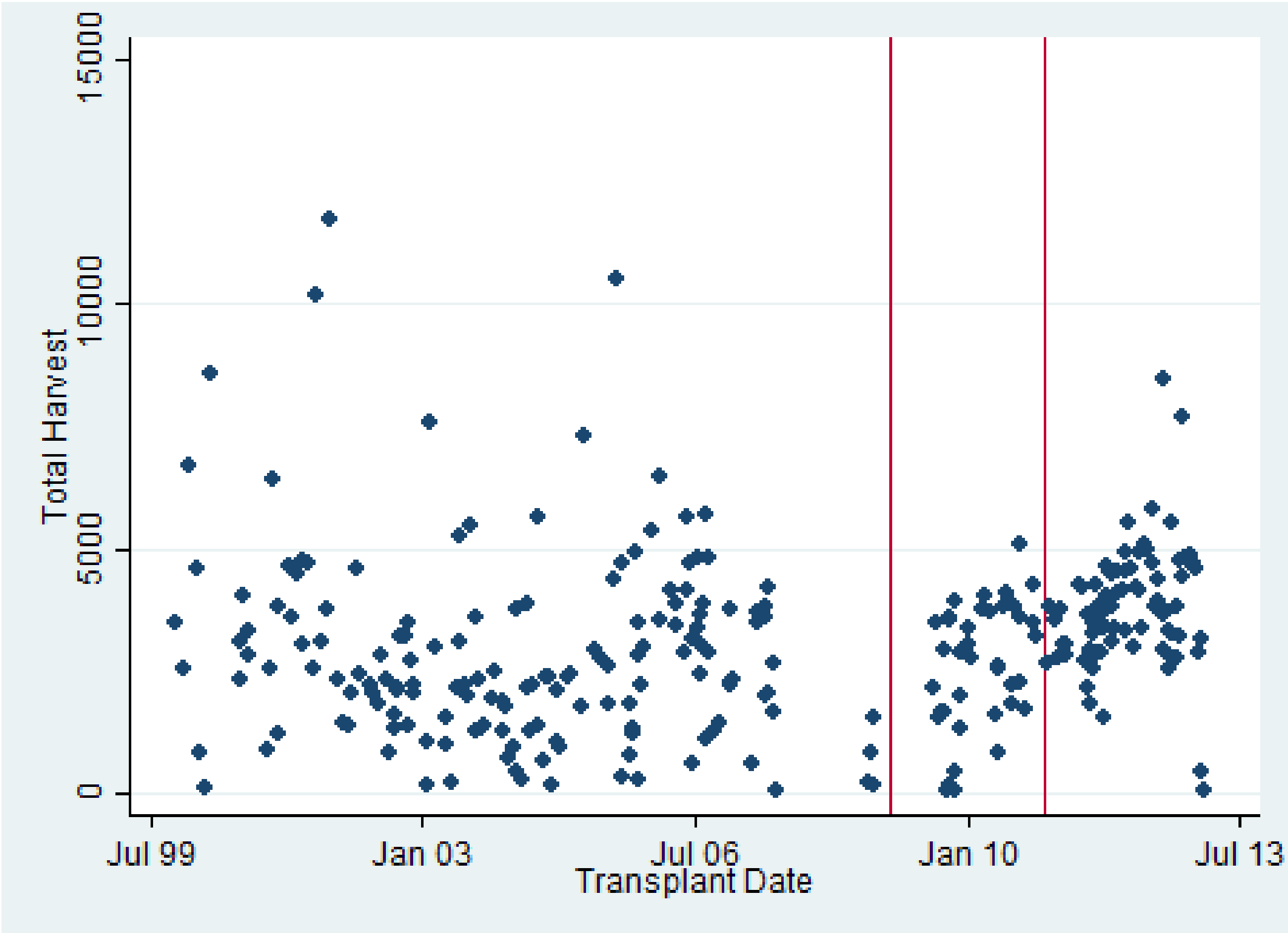

Figure 3. Number of stems harvested for each crop of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. Red lines demarcate the initial installation of a wireless irrigation sensor network and the initiation of sensor-controlled irrigation.

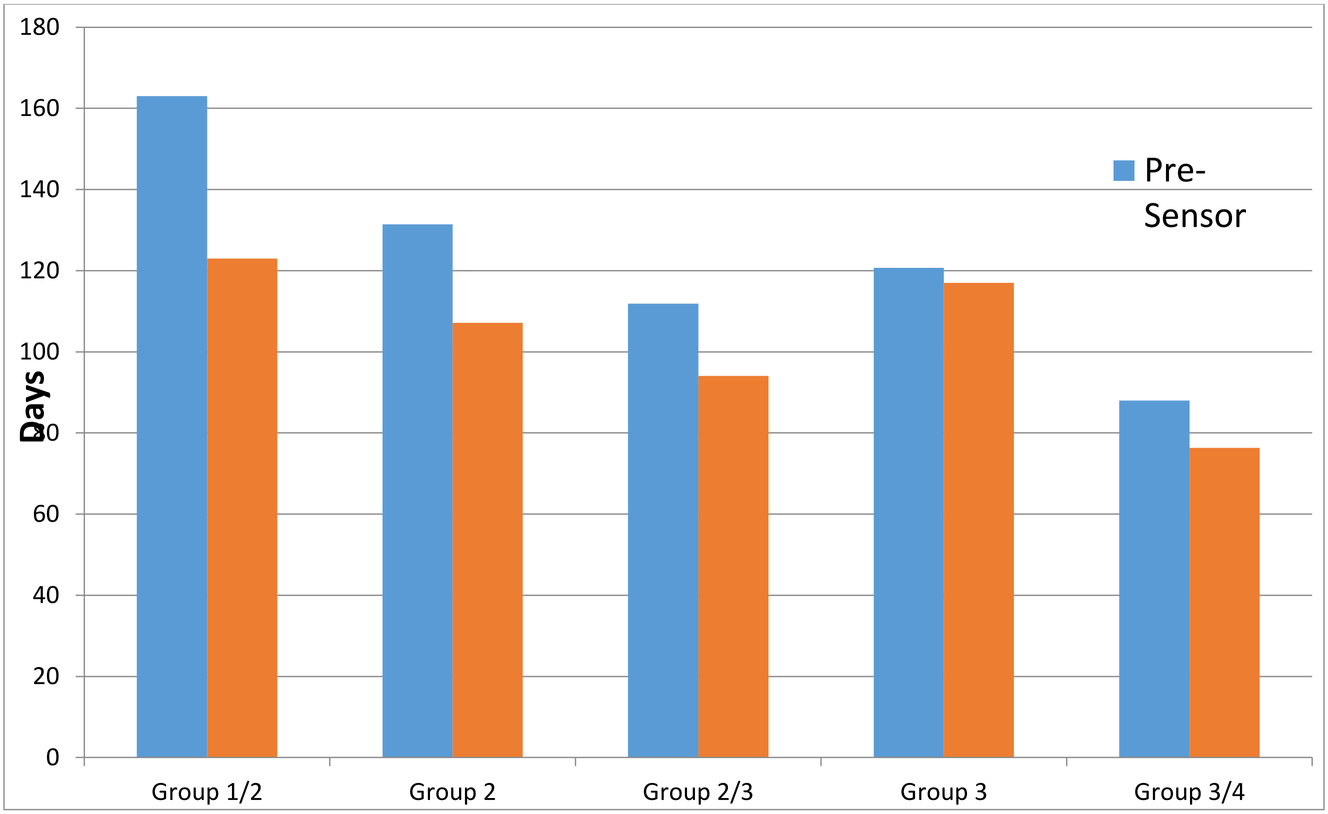

Figure 4. Length of time from planting to first harvest for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. This system was used to determine the impact of wireless irrigation sensor networks on plant growth, quality, yield and profitability.

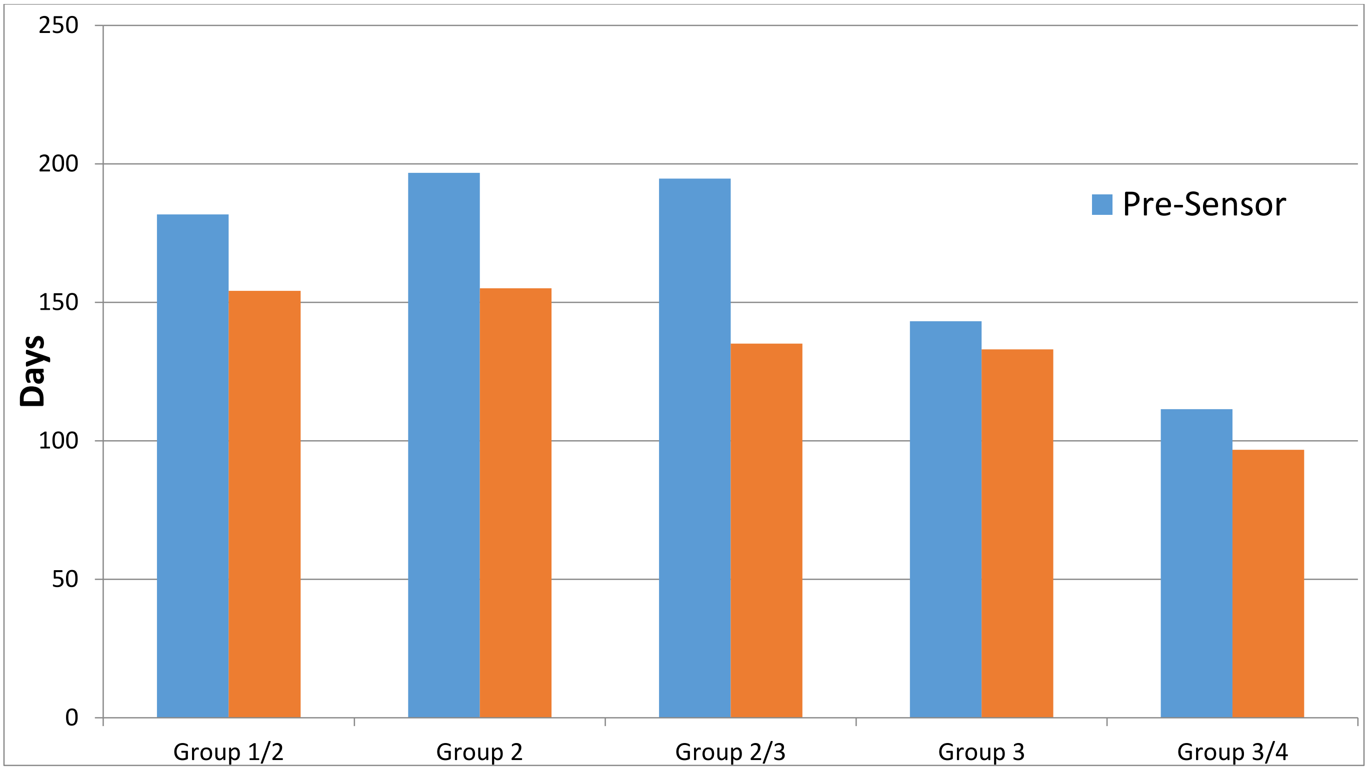

Figure 5. Length of time from planting to final harvest for hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. This system was used to determine the impact of wireless irrigation sensor networks on plant growth, quality, yield and profitability.

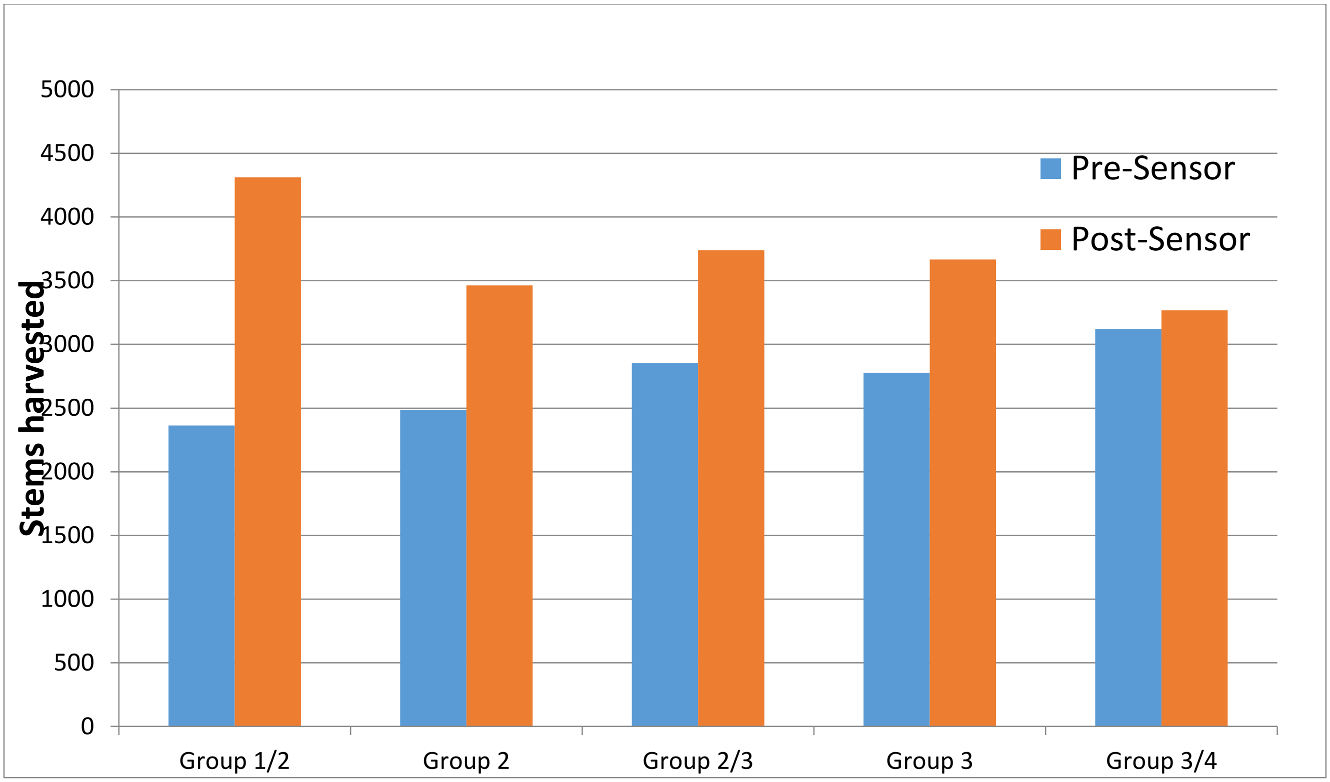

Figure 6. Total number of stems harvested per crop during continuous hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. This system was used to determine the impact of wireless irrigation sensor networks on plant growth, quality, yield and profitability.

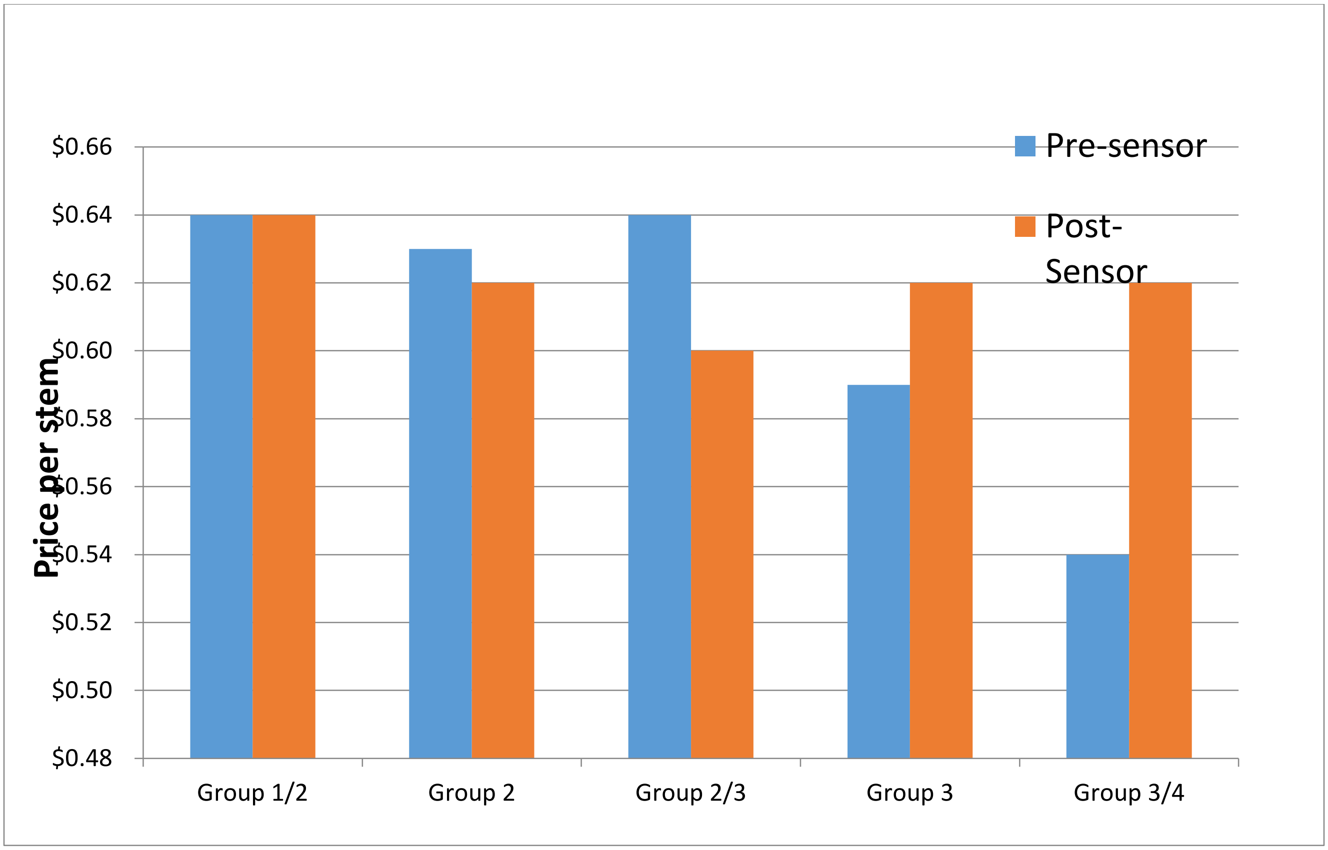

Figure 7. Quality-adjusted average price per stem by group for continuous hydroponic production of greenhouse grown snapdragon (*Antirrhinum majus*) using a recirculating fertigation system. This system was used to determine the impact of wireless irrigation sensor networks on plant growth, quality, yield and profitability.

Chapter 3: Quarantines Evasion and Plant Disease Control: The Case of Sudden Oak Death

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Abstract

Governments frequently use quarantines to limit the spread of an infectious disease. However, such policies may incentivize agents to expend resources towards hiding disease status rather than preventing disease. This paper investigates greenhouse nursery growers' response to a quarantine imposed on the west coast of the United States from 2002 to present for the plant pathogen that causes Sudden Oak Death. I investigate whether growers choose to 1) improve their sanitation practices, which reduces the underlying risk of disease without increasing the difficulty of detecting the pathogen, 2) increase fungicide use, which also prevents disease but makes existing infections much harder to detect, or 3) change their crop composition towards more resistant species. To test whether growers respond in any of these three ways, I use fixed-effects panel data regression models and data from the USDA-NASS Floriculture and Chemical Use Survey, the California Department of Agriculture Pesticide Use Reporting data, the USDA-NASS Floriculture Survey, and the USDA-NASS Census of Horticultural Specialties. I do not find evidence that growers improve their sanitation practices in response to the quarantine. I do, however, find evidence that growers heavily increase their fungicide use in response to a quarantine policy that requires visual (as opposed to laboratory) inspection for the disease before every crop shipment, suggesting that the quarantine may have the adverse effect of making the pathogen harder to identify. I also do find evidence that growers shift away from susceptible crops and towards resistant crops. These findings suggest that policymakers should consider incentives to hide disease that result from quarantines. In the case of Sudden Oak Death, the

findings suggest that policymakers should use laboratory rather than visual inspections for plant pathogens, or at least randomize between the two methods.

Introduction

During a disease outbreak, governments can control the spread of infection by imposing a quarantine, which restricts the movement of infected individuals. In order for quarantines to be effective, it must be possible to identify infected individuals so that compliance with the restrictions on the movement can be assured. However, the effectiveness of quarantines can be undermined if infected individuals avoid detection. This same dynamic has been observed in human disease and livestock disease. For instance, incentives to avoid screening hinders progress on a wide range of contagious diseases including SARS (Samaan et al. 2004), Tuberculosis (Paralkar 2008), and HIV (Chesney 1999; Kalichman and Simbayi 2003; Ti et al. 2013).

This essay examines the case of a quarantine imposed by to control the spread of a plant disease caused by the pathogen *Phytophthora ramorum*. The quarantine is an example of a policy that risks a potentially harmful behavioral response. *P. ramorum* is currently killing trees in tanoak, redwood, and coastal evergreen forests in the West Coast of the United States. The economic impact of this disease has been estimated to range between $100 and $300 million per year in the ornamental crops industry alone (Kliejunas 2010). The quarantine imposes export restrictions and other negative consequences on greenhouse nurseries infested with *P. ramorum*. While these policies likely contain the disease among growers correctly identified as being infested, they may also encourage growers to preemptively take actions to obscure disease status. In particular, growers may use agricultural chemicals in a manner that makes detection of the disease less likely. This behavior could partially or completely offset benefits from the quarantine, by complicating disease monitoring efforts.

In this paper, I assess how the risk of *P. ramorum* and associated government restrictions affect grower behavior through increased chemical use, sanitation practices, and market composition of host and non-host plants. I first present a theoretical model that explores grower choice of fungicide use and crop composition in response to the inspection regime. Next, I empirically investigate whether growers alter chemical use and management practices in response to the quarantine using the California Department of Agriculture Pesticide Use Reporting data Nursery. I then estimate the degree to which farmers change their sanitation practices in response to the inspection regime using data from the Floriculture Chemical Use Survey. Finally, I empirically examine how growers respond in terms of their crop composition using data from The USDA Census of Horticultural Specialties and the USDA-NASS Floriculture Survey.

This paper proceeds as follows. Section 2 provides background information on *P. ramorum*, section 3 reviews evidence of similar behavior from the literature, section 4 presents a theoretical model, section 5 explains the available data, section 6 presents empirical models, section 7 presents the empirical results, and section 8 concludes.

Phytophthora ramorum *Background*

Phytophthora ramorum was first documented in Marin County, California in April 1995 when homeowners reported an unusual die off of tanoak trees (Svihra 1999, 2001). As tanoak trees were initially considered a weed, the pathogen was not seriously investigated until it began infecting higher valued coast live oak trees in 1998 (Frankel 2008). By then, the pathogen was established in six counties on the central coast of California. Shortly after, the pathogen was discovered to infect a wide range of hosts, including oak, rhododendrons, camellias, and Douglas firs. The pathogen is now established in fourteen counties on the central California coast.

P. ramorum was originally introduced to the United States through greenhouse nurseries in western California during the late 1990s (Parke and Grunwald, 2012; Davidson and Shaw 2003). Genetic microsatellite mapping has provided very strong evidence that Sudden Oak Death in the United States not only originated from nurseries, but also that nurseries continue to be a contributing factor in its spread (Croucher, Mascheretti, and Garbelotto 2013). Several other studies have traced the origins of *p. ramorum* in several areas of the United States to a single nursery (Frankel 2008, Garbelotto and Rizzo 2005, Stokstad 2004).

P. ramorum generally spreads through water transmission. Usually, rain moves infected sporangia from nearby plants. Other mechanisms for dispersal are irrigation splashing, plant-to-plant contact, the movement of infested debris (through wind or other means), and water runoff (Kliejunas 2010).

In an attempt to halt the spread of this disease, state and federal agencies enacted a number of restrictions on the movement of plants. The state governments has authority to restrict movement of plants within the state and the federal government is allowed to restrict movement of plants between states. However, the only state to restrict intra-state movement of plants was California, and the restricted area aligned exactly with the federal government's restriction on out-of-state movement. Thus, all counties either face both intra-states shipping restrictions and out-of-state shipping restriction or neither level of restriction. The USDA Animal and Plant Inspection Service (APHIS) certifies inspectors that can perform inspections for both state and federal regulations.

In 2001, the agencies established two regulatory areas with varying requirements for exporting nursery products out of the area. The first regulatory area is referred to as the quarantined area and originally consisted of nine coastal counties in California (Santa Clara, Marin, Sonoma, Napa, Santa Cruz, San Mateo, Monterey, Solano, and Alameda). Additional coastal counties in California were added in 2001 (Mendocino), 2004 (Humboldt and Contra Costa), and 2005 (Lake and San Francisco). The second regulatory area is referred to as the restricted area and consists of the portions of Oregon, Washington, and California that are not quarantined. Since 2001, three different policies were imposed to regulated areas, with the more stringent inspection requirements in the quarantined area and the less stringent inspection requirements in the restricted area. The least stringent policy required that all nurseries be visually inspected annually to make any shipments. All inventory are visually inspected by an APHIS-certified inspector. If any inventory appear symptomatic, they are sent to a laboratory for testing. If more than 40 plants appear symptomatic, then 40 plants are selected and sent to a laboratory for testing. This policy was implemented in the restricted area in 2004. The second least stringent policy required that all nurseries selling host and associated products be inspected annually in a laboratory in order to make any shipments. Under this policy, all plants are first visually inspected. A sample of 40 plants are sent to a laboratory for testing. The inspector first selects for plants with visual symptoms. If there are fewer than 40 symptomatic plants, then the inspector selects the remaining plants at random. This policy was implemented in the quarantined counties from 2001 to present day and in the restricted area from 2005 to 2007.[4] The most stringent policy required that all nurseries selling host and associated products be visually

[4] The initial export restriction was issued by the California Department of Food and Agriculture (Frankel 2008). All subsequent regulations were issued by the USDA Animal and Plant Health Inspection Service (APHIS).

inspected before every shipment and was implemented in the quarantined counties in 2005. The timeline on page 34 provides additional details on these policies.

Most operations obtain the vast majority of their revenue through wholesale shipments of inventory (National Nursery Survey, 2013). In the Pacific region, which includes Washington, Oregon, California, Alaska, and Hawaii, 11 percent of the inventory in the horticultural inventory is sold outside the region (National Nursery Survey, 2013). When an operation tests positive for *p. ramorum* in an inspection, the operation must stop all shipments from that operation, including local shipments. Operations are not allowed to begin shipments again until an inspector declares the operation free of *p. ramorum*. Doing so often requirement burning the entire inventory and soil in the operation. The operation is then subject to more frequent inspections following a positive *p. ramorum* screening.

The quarantine and regulations surrounding *p. ramorum* may introduce incentives for growers to evade detection through the use of fungicides. Most fungicides generally do not kill the targeted pathogen in an infected plant. Rather, the fungicide creates an environment where the pathogen does not thrive but remains present at low inoculum levels. As a result, the growth of the disease slows and symptoms are reduced even though the pathogen is still present. The pathogen can later spread and cause symptoms to manifest once fungicide use ends. Growers use fungicides to prevent the disease, but fungicide use may also be a mechanism for hiding the disease from buyers and inspectors. (Shishkoff 2005, 2010, 2014; Chastagner et al. 2010).

The supply chain of the greenhouse nursery industry begins with growers. Growers sell wholesale quantities of plants to either large market vendors such as chain store retailers or landscaping companies. Over recent decades, the consolidation of retail vendors such as Home Depot and Lowes has driven the consolidation of growers towards larger operations. The retailer or landscaper then delivers the product directly to the consumer. If a retailer finds a diseased batch of plants, it is able to send it back to the grower for a refund. However, plants are generally in a retail setting for a short period of time, so if a disease manifests, it often will not do so until the consumer has purchased it from the retailer. (Hall et al. 2005; Parke and Grunwald, 2012)

Consumers are typically unaware of which growers or retailers use fungicides in excess and which do not. For this reason, the buyer generally does not know whether minimizing the risk of a dormant disease manifesting requires routine fungicide application. In addition to the lack of information, the probability of their particular tree being diseased is low, property owners may lack the economies of scale that make applications cost-effective, and homeowners may have health and environmental concerns about excess fungicide application. The social costs of a diseased tree also do not fall on the owner alone—they fall on the owner's neighbors, so the owner may not be properly incentivized to control plant disease on her property. Thus the consumer typically does not apply enough fungicide and when a disease is present, symptoms develop.

If plants with undetectable disease continue to be sold, information asymmetry could eventually lead to a market break down analogous to the market for lemons in the used car industry. Even if buyers were well informed about the risks of the disease, the knowledge that some growers use fungicides heavily can create increased uncertainty about the disease status of an individual plant. An alternative to a quarantine is a mandatory label for all host plants, but that policy could also cause a market breakdown or reduction in demand because individual homeowners may not want to treat plants preventatively. Since the costs of purchasing a diseased plant and having it spread are high, buyers may be wary to invest in potential host plants at all.

This potential breakdown serves as a justification for the government interventions that followed the outbreak.

Effective alternatives to fungicide use are available. Growers use a Hazard Analysis of Critical Control Points (HACCP) system to identify areas that may grow or spread disease and directly address the sanitation of these areas. In the context of nursery production, critical control points include direct contact between containers and contaminated ground, movement of contaminated soil by tools and equipment, and contamination of plants by use of infested irrigation water. To prevent infestation at these critical control points, growers can use best management practices such as raising containers off the ground, sanitizing equipment, and treating irrigation water before applying it. While HACCP is most effective when applied in its entirety, nursery growers can benefit from adopting only some of the best management practices that are recommended. Although it is not known how many U.S. nursery growers have adopted the practice, HACCP is widely used in food processing industries in the U.S. and in the horticultural industry in Australia. (Parke and Grunwald, 2012). Absent a third party certification system that effectively differentiates operations with good sanitation practices from those without good sanitation, a HACCP system may not benefit the farmer enough to justify the costs. For this reason, growers may still rely on the use of fungicide to prevent disease and hide diseases when they do occur.

Evidence from the Literature

Growers have used agricultural chemicals to strategically evade other regulations. For instance, Lichtenberg et al. (1993) modeled growers' incentives to use pesticides in response to restrictions on the period after application in which workers are allowed to re-enter the field. Although the re-entry time restrictions were intended to reduce workers' exposure to agricultural chemicals, the authors showed that they actually incentivized an increase in total pesticide application. Sunding and Zivin (2000) also examined the incentives for farmers under re-entry restrictions, but explicitly modeled insect growth and allowed the amount of pesticide applied to vary. Using this approach, they concluded that re-entry restrictions have an ambiguous effect on farm worker health, but may increase the total pesticide amount applied in some cases. This precedent demonstrates a willingness among growers to bypass regulatory intent through adaptive behavior.

Some recent examples of hiding infection status in response to quarantines and similar negative consequences such as stigmatization in the case of human disease include tuberculosis, HIV, and meningococcal disease. Paralkar (2008) notes that social stigmatization associated with tuberculosis in India frequently delays treatment by months, causing the disease to spread. CDC (2000) notes that stigma serves as a similar barrier to screening for individuals with HIV. Governments have been documented under-reporting human disease incidence for fear of sanctions, despite receiving medical aid in response to reporting. For example, every year millions of Muslims travel to Mecca, Saudi Arabia as part of their religious practice. Malani and Laxminarayan (2011) documented strong evidence that many countries with high Muslim populations systematically under-reported the incidence of meningococcal disease when Saudi Arabia barred travelers from countries with high rates of the disease.

Disease detection avoidance occurs both in the form of under-reporting and in actively attempting circumvent the test among animal diseases as well. Gramig et al (2005), for example, outline how under-reporting of disease occurs in livestock operations and makes disease eradication more difficult. Cattle farmers in the United States during the bovine tuberculosis outbreak responded to cattle testing even more deceptively than under-reporters during a government eradication program in 1917. Cattle could develop resistance to the tuberculosis testing chemical, Tuberculin, for several weeks. Some farmers intentionally injected their cattle with Tuberculin prior to inspection in order to pass inspection regardless of infection status. The practice became known as "plugging the test" and became a major impediment for eradicating the disease (Olmstead and Rhode 2004).

Model

This section presents a theoretical model that formalizes predictions about how the testing regime affects fungicide use and crop composition. The testing regime in the model reflects the restrictions in place in infested counties in California. Affected greenhouse nurseries can largely still operate provided that they submit to regular inspections for *P. ramorum*.

Consider a grower with capacity to grow K individual plants, N of which consist of species susceptible to a disease and the rest of which are species resistant to the disease. The grower can choose the distribution of resistant and susceptible plants to grow, with exogenous prices for susceptible plants p. The marginal profit from each resistant plant is constant at π_r, with the total profit from all sales of resistant plants equal to $\pi_r \cdot (K-N)$.

The grower faces an *ex ante* disease risk R, with a higher value of R indicating a higher level of risk. Risk levels are determined by the climate, density of host species, and existence of a likely entry path of the disease, all of which are treated as exogenous. The grower can then choose the amount of fungicide F to apply and the composition of the crop in terms of susceptible plants N and resistant plants K-N.

The probability that an individual plant will show symptoms and thus test positive for the disease, $\mu(F, R, N)$, is decreasing in fungicide use due to decreased symptoms and decreased disease such that $\frac{\partial \mu}{\partial F} < 0$. Fungicide use exhibits diminishing returns so that that $\frac{\partial^2 \mu}{\partial F^2} > 0$. The probability of testing positive for the disease μ(F, R,N) is increasing in the risk level R due to higher incidence of disease and increasing in the number of susceptible plants N due to susceptible plants serving as host for other susceptible plants, i.e., $\frac{\partial \mu}{\partial N} > 0$ and $\frac{\partial \mu}{\partial R} > 0$. I assume that the number of susceptible plants has an increasing effect on the probability of failing inspection such that $\frac{\partial^2 \mu}{\partial N^2} > 0$: As the number of susceptible plants rises, space between them becomes smaller, making disease transmission more likely. I further assume that the cross partial $\frac{\partial^2 \mu}{\partial F \partial N}$ is equal to zero because the fungicide use level F relates to the amount used per individual suceptible plant N. Also, fungicide effectiveness does not vary based on the number of plants that it is applied to, as evidenced by the constant dosage reccomendations on fungicide labels. Thus, there is no reason to think that its effectiveness would change as N changes. Since I assume the disease is the only source of losses, no losses are possible when there are no susceptible plants such that μ(F,R,0) = 0.

Inspectors test a random sample of λ plants where a higher λ is indicative of a stricter inspection regime. A policy regime with no inspections is characterized by λ = 0. If a plant shows symptoms, I assume it will test positive for the disease, but otherwise will not. Symptomatic plants cannot be sold regardless of whether they are diseased because symptoms are generally unaesthetic and indicate some kind of underlying poor health of the plant. Once the inspector chooses the sample to test in a lab, I also assume that the test is perfectly accurate. Both the number of susceptible plants planted N and the level of fungicide use F are chosen prior to inspection.

Inspection results are publicized, and failing an inspection can damage the reputation of an operation. Several operations which failed inspection in California went out of business shortly after (Palmieri et al. 2010). Given these regulations, I assume that failed operations are not able to sell any plants. The grower takes the per plant price p as given and chooses how many plants to grow, how much fungicide to apply at per unit cost c, and how much of other inputs to apply at unit cost w to maximize profit. The expected number of plants from the susceptible species which are asymptomatic is $(1-\mu(F,R,N))N$. In the absence of an inspection regime, the grower can earns a revenue of $(1-\mu(F,R,N))Np$. The probability of passing inspection is $(1-\mu(F,R))^{\lambda}$. Growers that fail inspection will not be able to sell any plants of susceptible species and will thus earn no revenue from susceptible plants. The total expected revenue from sales of susceptible plants is thus $pN(1-\mu(F,R,N))^{\lambda+1}$.

Profit for the grower π is equal to the expected value of sales susceptible crop sales net of production costs plus the profit from sales of the resistant crop. I assume that the marginal profit from the resistant crops π_r is such that $p(1-\mu(F^*,R, K))^{\lambda}+1-w-cF^*<\pi_r< p-w-cF^*$, where F^* is the profit-maximizing level of fungicide used.

(1) $\Pi=pN(1-\mu(F,R, N))^{\lambda+1}-wN-cFN+\pi_r(K-N)$

Optimization Conditions

The grower chooses fungicide use F such that the marginal benefits of fungicide use are equal to the marginal cost of fungicide use c in the case of an interior solution or less than the marginal costs of fungicide use in the corner solution where no fungicide is applied. The marginal benefit of fungicide use is the product of the price per plant p, the marginal increase in sales from passing inspections$(\lambda+1)\left(1-\ \mu(\mathrm{F,R,N})\right)^{\lambda}$, and the reduction in the probability that a plant shows symptoms due to fungicide use $\frac{\partial\mu}{\partial \mathrm{F}}$:

$$(2)\ -\mathrm{p}(\lambda+1)\left(1-\ \mu(\mathrm{F,R,N})\right)^{\lambda}\frac{\partial\mu}{\partial \mathrm{F}}-c\leq 0$$

Similarly, the grower sets the number of susceptible plants N such that the marginal benefit of an additional susceptible plant is equal to or less than the marginal cost of an additional susceptible species plant. The marginal benefit of a susceptible plant include the marginal revenue from sales of the susceptible plants $\mathrm{p}\left(1-\mu(\mathrm{F,R,N})\right)^{\lambda+1}$minus the marginal revenue lost from susceptible plants through the increased risk of getting caught, due to having a larger number of susceptible species plants, $\mathrm{pN}(\lambda+1)\left(1-\mu(\mathrm{F,R,N})\right)^{\lambda}\frac{\partial\mu}{\partial \mathrm{N}}$. The marginal costs of a susceptible species plant include the non-fungicide cost of growing it w, the fungicide-related costs cF, and the marginal opportunity costs of growing a resistant plant π_r.

$$(3)\ -\mathrm{pN}(\lambda+1)\left(1-\mu(\mathrm{F,R,N})\right)^{\lambda}\frac{\partial\mu}{\partial \mathrm{N}}+\ \mathrm{p}\left(1-\mu(\mathrm{F,R,N})\right)^{\lambda+1}-w-cF-\pi_r\leq 0$$

The second order conditions for (2) and (3) to be determine a maximum are listed in inequalities (1.1), (1.2), and (1.3) in the appendix.

Imposition of a quarantine can be represented as a shift from having no inspection requirement at all (λ = 0) to requiring some positive number of plants inspected (λ > 0). In the model, this means that I am most interested in the directional change in the variables of interest due to a change in λ from an initial value of 0. When λ = 0 and the first order conditions hold with equality, (1.1), (1.2), and (1.3) simplify to

$$(4)\ -\frac{\partial^2\mu}{\partial F^2}p\leq 0$$

(5) $p\left[-2\frac{\partial\mu}{\partial N}-N\frac{\partial^2\mu}{\partial N^2}\right]\leq 0$

(6) $-\frac{\partial^2\mu}{\partial F^2}p^2N\left[-2\frac{\partial\mu}{\partial N}-N\frac{\partial^2\mu}{\partial N^2}\right]\geq 0$

In this case, the necessary conditions for an interior solution are also sufficient.

Impact of Quarantine Imposition on Fungicide Use

The model implies that a profit maximizing grower responds to imposition of a quarantine regime by increasing fungicide applications per plant in an attempt to reduce detectable disease symptoms. Let Ω denote the determinate of the Hessian matrix defined by (6). When $\lambda = 0$ and the first order conditions hold with equality, $\frac{\partial F}{\partial\lambda}$ simplifies[5] to:

(7)

$$\frac{\partial F}{\partial\lambda}=\frac{-\left[\frac{\partial\mu}{\partial F}+l\,n\big(1-\ \mu(F,R,N)\big)\right]}{\frac{\partial^2\mu}{\partial F^2}}$$

The right hand side of equation (7) is unambiguously positive, indicating that fungicide use increases when a quarantine regime is imposed on a previously unregulated operation. Intuitively, fungicide use increases because the costs of displaying symptoms of an infection increases the likelihood of getting caught, so growers are willing to spend more on avoiding displaying symptoms. The increase in the fungicide application rate is greater when fungicides are more effective in suppressing symptoms ($\frac{\partial\mu}{\partial F}$ is larger in absolute value). It is also greater when the *ex ante* risk level R is large, since the gains from the reduction in risk are greater.

Impact of Quarantine Imposition on Crop Diversification

[5] The general form of equation (7) can be found in equation (1.4) in the appendix

When a quarantine is imposed on unregulated growers, growers may respond by shifting production towards a resistant crop that does not risk failing inspections. To verify this, I am interested in the sign of $\frac{\partial N}{\partial \lambda}$.

When λ=0, and the first order conditions hold with equality, $\frac{\partial N}{\partial \lambda}$ simplifies[6] to:

(8)

$$\frac{\partial N}{\partial \lambda} = \frac{-p^2 N^2 \frac{\partial^2 \mu}{\partial F^2}\left[\frac{\partial \mu}{\partial N} - ln\big(1 - \mu(F,R,N)\big)\left[1 - \frac{\big(1 - \mu(F,R,N)\big)}{N}\right]\right]}{\Omega}$$

Under a non-inspection regime, $\frac{\partial N}{\partial \lambda}$ is negative. Under such conditions, an implementation of a quarantine regime will incentivize farmers to reduce the number of susceptible plants that they grow, and increase the number of resistant plants.

Summary: Hypotheses for Empirical Investigation

The model has produced two hypotheses, namely that when a testing regime is imposed, growers will: (1) increase fungicide use; and (2) shift their crop composition away from susceptible plant species towards resistant species. I test these hypotheses empirically in the subsequent sections.

<u>Data</u>

I use several data sources on the chemical use, management practices, composition, and costs of crop sales in the greenhouse nursery industry. Sources include California Department of Agriculture Pesticide Use Reporting data, the Pacific Northwest Plant Disease Management

[6] The general form of equation (8) can be found in equation (1.5) in the appendix

Handbook, the Western Regional Climate Center database, the USDA-NASS Nursery and Floriculture Chemical Use Survey, the USDA-NASS Floriculture Survey, and the USDA Census of Horticultural Specialties.

The California Department of Agriculture Pesticide Use Reporting data provides application level data for all greenhouse nurseries in the state of California between 1991 and 2012. Data include grower IDs, acres planted, date of chemical application, pounds of active ingredient, chemical name, chemical code, location by county and zip code, and broad crop categories. Crop categories include nursery greenhouse flowers, nursery greenhouse plants in containers, nursery greenhouse transplants, nursery outdoor flowers, nursery outdoor plants in containers, and nursery outdoor transplants. Within each nursery and greenhouse category are subcategories that specify the genus or species to which the fungicide is being applied.

The California Department of Agriculture Pesticide Use Reporting data report on hundreds of different chemicals. To categorize these chemicals in a systematic manner, I use the Pacific Northwest Plant Disease Management Handbook, which discusses the use for nearly all agricultural chemicals used in California. Only oomycete-specific fungicides are effective at targeting *P. ramorum,* so I use the Pacific Northwest Plant Disease Management Handbook's fungicide use descriptions to categorize fungicides as oomycete-specific or not. The handbook also reports the active ingredients as well as the brand name of each chemical. . See Table 1 for fungicide use summary statistics.

To control for weather related factors that influence the risk of disease, I use the Western Regional Climate Center Database, which reports daily precipitation, temperature minimums, temperature maximum, and growing degree days for monitoring stations in all fifty-eight counties in California.

The USDA NASS Agriculture Chemical Usage- Nursery and Floriculture Program surveyed greenhouse nurseries in the states of Michigan, Florida, Pennsylvania, Texas, California, and Oregon in each of the years 2000, 2003, 2006, and 2009 about pest management practices. The survey reports the percent of operations stating that they engage in each pest management practice by state and year. The survey asks whether the participant engages in fourteen specific sanitation practices that would be relevant to the prevention of *P. ramorum.* These management practices cover proper sanitation of equipment, proper spacing of host plants from the ground and other host plants, and management of greenhouse humidity and temperature.[7] Proper sanitation reduces disease pressure by killing pathogens before they are able to infect the plants. Proper spacing isolates infected plants before the grower knows that the plant is infected, so that the infection does not spread. Proper management of greenhouse humidity and temperature reduce disease pressure by ensuring that plants are not stressed. See Table 2 for summary statistics for management practices.

The last two data sets relate to crop composition of nursery sales and production in the United States. The USDA Census of Horticultural Specialties, conducted most recently in 1998 and 2009, contains sales by total revenue and number of plants sold by genus and state and number of stems sold by genus and state. It also includes expenditures of horticultural operation by state and category of expense (e.g. utilities, chemical use, and containers). The USDA-NASS Floriculture Survey publishes the sales in terms of dollars and number of plants by state and

[7] The full list of management practices is: Plant density adjusted; row spacing or row directions adjusted; sterilized growing media used; diagnostic laboratory services used for pest detection via plant tissue analysis; Diagnostic Laboratory Services Used for Pest Detection Via Soil Analysis; Benches or Other Platform Devices Sanitized Between Uses; Containers Sanitized Between Uses; Ground Covers Sanitized Between Uses; Incoming Stock Inspected; Infected Plants or Plant Parts Removed or Pruned; Water Management Practices Used; Greenhouse Relative Humidity Modified; Greenhouse Temperature Modified; and Greenhouse Ventilated.

genus for common cut and potted flowers by state for fifteen participating states annually. The three affected states—Washington, California, and Oregon—are all included in this survey. Azaleas are the only host genus included in the survey. Descriptive statics for the two crop composition surveys are in Table 3.

Empirical Strategy

I use several empirical models to test the hypotheses derived from the theoretical analysis. I use data from the California Pesticide Use Reporting System and the Pacific Northwest Plant Disease Management Handbook to examine the effects of quarantine restrictions on fungicide use in California. I use four different measures of fungicide use: (1) the share of total pounds of active ingredients applied that could target *P. ramorum*, (2) the per acre application rate of active ingredient, (3) the absolute number of pounds of active ingredients in fungicides that could target *P. ramorum* applied, and (4) the number of fungicide acre-treatments per acre for host species using. I repeat all the regressions with only non-host species (which are unaffected by quarantine restrictions) as a falsification test. Next, I use data from the USDA-NASS Nursery and Floriculture Chemical Use Survey to test whether quarantine restrictions affect broader sanitation efforts using a difference-in-difference model of the percentage of growers using number of different sanitation practices before and after quarantine imposition. Finally, I use state-level data from the USDA Floriculture Survey and the Census of Horticultural Specialties to test the effects of quarantines on crop composition in terms of number of plants sold, dollar value of plants sold, and destination of plants sold .

Fungicide Use across Growers in California

The theoretical model predicts that under a shift from a non-quarantine regime to a quarantine regime will increase fungicide use and decrease the number of susceptible plants grown relative to the resistant plants. Pesticide use data are from the California Department of Agriculture.

Only oomycete-specific fungicides work on *P. ramorum*, which makes them uniquely relevant when studying the effect of policies relating to *P. ramorum.* I consider fungicides to be oomycete-specific if the Pacific Northwest Plant Disease Management Handbook lists oomycetes in the description of the fungicide's targeted pathogens. I use four different metrics of the level of oomycete-specific fungicide use. Let W_{gt} indicate the metric of fungicide use that will vary across regressions where W_{cgt} will represent:

- the share of all fungicides applied which are oomycete-targeting in terms of pounds of active ingredient in month t by grower g;
- the absolute amount of oomycete-specific fungicides applied for each grower in month t by grower g in terms of pounds of active ingredient;
- the rate of oomycete-specific fungicides applied in terms of pounds of active ingredient per acre treated in month t by grower g; and
- the number of treatments per acre applied by grower g in month t.

Each metric of oomycete-specific fungicide has different advantages. The portion of total fungicide use that is oomycete-specific in terms of pounds of active ingredients is useful because it reveals whether absolute changes in fungicide use are the result of an increase of total fungicide use or a shift in composition of fungicides. The absolute number of pounds of oomycete-specific fungicides applied provides information about whether growers actually apply more fungicide in total, or just adjust the composition of chemicals used. The rate of oomycete-specific fungicide applications provides information on the intensity of use, rather than the amount so that the estimation coefficients can help distinguish whether growers are applying fungicides in different doses or whether they are applying fungicides at different intervals at the same doses. Finally, treatments per acre measures the fungicide application while adjusting for the variation in typical concentration between different types of fungicides. Since some active ingredients are typically applied in much greater quantities than others, this metric allows for a more consistent comparison.

Treatments per acre are ideally calculated by dividing the rate of fungicide used by the recommended dose as provided by the manufacturer, adding the number of doses within a grower, and dividing by the total number of acres grown by the grower. The California Pesticide Use Reporting Data do not contain the actual recommended dose amount per acre, and the official label recommendations vary across brands, partially depending on interactions with other chemicals. To substitute for the recommended maximum doses, I calculate the number of acre-treatments per acre by normalizing each chemical code by the maximum rate observed in the data for that chemical code excluding unrealistic rates as flagged by the California Department of Food and Agriculture (CDFA). The California Pesticide Use Reporting flags outliers based on a survey of scientists who consider the distribution of reported application rates as well as other factors. The documentation for the data reports that it would ideally use the maximum label rates to flag outliers but the label rates were not available. Their outlier flagging may therefore serve as a reasonable proxy for maximum label rates.

The USDA and the CDFA have imposed several different types of restrictions on nursery growers relating to *P. ramorum* since 2002 (See the California policy timeline). The policies represented in the sample were:

- Nurseries selling host and associated products[8] must be inspected annually in a laboratory to ship interstate or intrastate, which affected restricted counties starting in 2001
- All nurseries must be visually inspected annually to ship interstate, which affected restricted counties starting in 2006 and all California counties starting in 2007
- All nurseries selling host and associated products must be visually inspected before every shipment to ship interstate, which affected restricted counties starting in 2005

Since the different restrictions may induce different responses by the growers, I include each separately in the California county regressions.

I include several control variables that may influence the use of fungicides. The dummy variable R_{ct} corresponds to R in the theoretical model because it is an indicator that the area is at high risk for *P. ramorum*. The variable R_{ct} is equal to 1 if the most recent United States Forest Service *P. ramorum* risk maps label any part of the county c as having a medium or high risk of *P. ramorum* as of time t. The theoretical model hypothesis indicates that the coefficient of R_{ct} will be positive. The average rainfall amount, the minimum temperature, the maximum temperature, and the average number of growing degree days both increase the overall risk for fungal plant diseases (as opposed to the risk of *P. ramorum* specifically). For this reason, the sign of both variables is ambiguous, but their inclusion will serve to isolate the risk of *P.*

[8] The USDA classifies host plants as plants that have been fully documented to pass Koch's postulates *for P. ramorum*. Associated products are suspected of being host plants on the basis that *P. ramorum* has been detected using PCR (Polymerase Chain Reaction), but Koch's postulates for *P. ramorum* have not yet been fully documented.

ramorum. The number of acres planted directly affects fungicide use because growers who plant more acres generally have higher volumes of plants that they need to protect against disease. I expect that higher number of acres planted is associated with higher levels of fungicide applications. The increase in fungicide use could occur through growers increasing the absolute amount of fungicides used, increasing the application rate, or increasing the number of acre-treatments per acre.

For fungicides for grower g in county c and time t, each fungicide use equation is specified as:

$$W_{cgt}=\alpha_0 + \alpha_1 GDD40_{ct} + \alpha_2 GDD50_{ct} + \alpha_3 P_{ct} + \alpha_4 R_{ct} + \alpha_5 AP_g + \sum_{p=1}^{7} \gamma_p Q_{ct} + \eta_g + \varepsilon_{cgt},$$

where W_{cg} is the metric fungicide use as specified above; the variable $GDD40_{ct}$ represents the number of growing degree days in county c and month t with a base line of forty degrees Fahrenheit and the variable $GDD50_{ct}$ represents the number of growing degree days in county c and month t with a base line of fifty degrees Fahrenheit; P_{ct} represents the precipitation in inches in county c and time t; R_{ct} is a dummy variable for whether any area in the county is considered at an elevated risk for *P. ramorum* at time according to the forest service risk maps. AP_{gc} is the number of acres planted by grower g in month t. γ_p are a series of dummy variables for whether each of the three policy restrictions listed in the California policy timeline are in place in county c and time t. η_g are grower fixed effects and ε_{cgt} is the error term.

If the hypothesis that the quarantine increased the fungicide use, particularly within susceptible species, is correct, then I would expect the coefficients on the dummy variables γ_p in the above equation to be large and positive. In particular, I would expect the dummy variables for the more stringent policies, such as the requirement that nurseries must be visually inspected before every interstate shipment, to have the largest magnitude. I would also expect policies that involve visual inspection to have a larger effect than those that involve laboratory testing because fungicides are more effective in hiding the visual symptoms of disease than influencing laboratory testing.

Management Practices

Growers in quarantined counties might use more fungicides to reduce losses of unsaleable (symptomatic) plants or to decrease the chance of failing inspection. Controlling for disease risk levels partially separates these two reasons. Further, if the underlying disease risk is driving fungicide use, then growers would not use more fungicide for annual visual inspections than they would for annual laboratory inspections. Policymakers are not likely to systematically implement laboratory inspections over visual inspections for lower risk areas. Fungicides, however, are more effective at masking the visual symptoms of disease than they are at stopping the disease from being detected in a laboratory. Finally, if growers are primarily motivated by stopping disease spread rather than avoiding failing an inspection, they would likely implement other best management practices for preventing disease such as good sanitation practices.

Let S_{st} represent the percent of operations in each state that use each of fourteen sanitation practices. I test the effect of inspections on sanitary practices with the following specification:

$$S_{st=} \beta_0 + \beta_1 Q_s Q_t + \tau_s + \eta_t + \varepsilon_{st},$$

where Q_sQ_t is a dummy for a quarantine state and quarantine year, which equals one if the state is California and the year is after 2001 or if the state Oregon and the year is after 2004. It equals zero otherwise. τ_s are the sate fixed effects, η_t are the year fixed effects, and ε_{st} is the error term.

If states prioritize preventing disease itself over preventing failing an inspection, I expect the coefficient on the interaction term β_1 to be positive and large.

Crop Composition

The theoretical model predicts that as the intensity of inspections increase, growers shift to more resistant crops. I use data from the USDA-NASS Floriculture Survey and the USDA Census of Horticultural Specialties to examine how the quarantine has affected crop composition in terms of both the absolute number of host plants sold and the of sales of host plants in dollars, and the percent of all sales that are of host rather than resistant species.

The specification for assessing the quarantine on crop composition is as follows:

$A_{st}=\delta_0+ \delta_1 Q_s Q_t + \delta_2 P_{st}+\tau_s+\eta_t+ \varepsilon_{st},$

where A_{st} represents the sales of azaleas in state s and year t, in terms of both dollars and number of plants in two separate regressions; Q_sQ is a dummy for a quarantine state and quarantine year, which equals one if the state is California and the year is after 2001 or if the state Oregon and the year is after 2004 and equals zero otherwise; P_{st} represents the average price of the azaleas in states and the year t; τ_s are state fixed effects; η_t are year fixed effects; and ε_{st} is the error term. If the quarantine is driving sales of host plants down in quarantined states, I would expect δ_1 to be large and negative.

The Census of Horticultural Specialties crop categories that have at least one genus which has only host species are Christmas trees, broad leaf evergreens, and deciduous shrubs. Within each category, I regress the difference in the portion of plants sold and dollars sold that are hosts between 2009 and 1998 on whether or not the state was affected. The genera contain both host and non-host species were excluded entirely from the model:

$\Delta H_{st}=\theta_0+ \theta_2 Q_{s,}$

where ΔH_{st} is the difference in portion of plants sold that are hosts between 1998 and 2009 (such that $\Delta H_{st} = \frac{\text{Host Plants Sold in 2009}}{\text{Total Plants Sold in 2009}} - \frac{\text{Host Plants Sold in 1998}}{\text{Total Plants Sold in 1998}}$) and Q is a dummy for a quarantine state, which equals one if the state is Oregon or California or Washington and zero otherwise.

If the quarantine does incentivize growers to switch to more resistant crops, then Q_s will be negative.

Results

Growers appear to have changed their behavior in terms of fungicide use and crop composition in response to the quarantine, but not in terms of their management practices Tables 4-8). The estimated coefficients suggest that growers do apply more oomycete-specific fungicides to host plants in response to policy changes both as a percentage of total fungicide use and in terms of absolute pounds of active ingredient applied, but they do not increase fungicide use on non-host plants (see Table 4 and Table 5). Growers achieve this higher level of fungicide use by applying oomycete-specific fungicides more often rather than increasing application rates. I did not find evidence that growers increase the use sanitation measures such as cleaning containers between uses (Table 6). However, growers have shifted production from host species to resistant species in the affected states (Tables 7 and 8).

Fungicide Use across Growers in California

The estimated coefficients support the hypothesis that growers do use fungicides to evade quarantine restrictions: Visual inspections are associated with greater use of more oomycete-specific fungicides, while laboratory inspections are not. This finding is consistent with the fact that fungicides are more capable of reducing visual symptoms than they are of evading laboratory tests. Falsification tests using only fungicide application on non-host plants do not show any effect of quarantine policies on fungicide use, supporting the hypothesis that the results are in fact driven by the *p. ramorum* quarantine policies rather than other unobserved changes.

The requirement that all host and associated nursery products be visually inspected before every interstate shipment, with follow-up laboratory tests for symptomatic plants, is associated with a 28 percentage point increase in the portion of total fungicide use that is oomycete-specific on host plants. The effect of visual rather than laboratory inspections on fungicide use may be because fungicides are more likely to mask visual symptoms than to prevent *P. ramorum* from detection in laboratory tests, so fungicides would be useful for growers to evade detection under such a policy. The effect is also likely large because the requirement pertains to individual shipments rather than a single annual requirement.

In the regression model for the portion of fungicide use that in oomycete-specific, the coefficient for the policy variable requiring annual visual inspection of host plants is -0.000001 and the coefficient for the policy variable requiring annual laboratory inspection of host plants is 0.01. The small magnitude and lack of statistical significance of both coefficients indicates that annual inspections of any kind do not appear to affect the portion of fungicide use that is oomycete-specific. The fact that inspections on every shipment have a much larger influence on the amount of fungicide used than annual inspections do is consistent with the model prediction that fewer inspections will lead to less fungicide use. No policy has either a large or a statistically significant on the portion of fungicides applied that are oomycete-specific on non-hosts plants (Table 5).

None of the policies included in the regression have either a large or a statistically significant effect on the average rate at which oomycete-specific fungicides are applied on either the host plants or the non-host plants. This implies that growers tend to respond to inspection with an increased frequency of fungicide use rather than an increase in intensity per usage.

There is a large increase in the absolute number of pounds of the active ingredient in oomycete-specific fungicides under the policy requiring visual inspections before each shipment in host products. Although the coefficient is not statistically significant, the magnitude is quite large. On average, there is a 1.02 pounds of active ingredient per grower per month estimated increase under the policy for host plants, when the average number of pounds of active ingredient per grower per month for the whole sample of host plants was 4.65 pounds per month, or a 22 percent increase. In contrast, the estimated coefficient for the same policy for non-host plants is zero and the average number of oomycete-specific pounds of active ingredient applied to non-hosts is 2.16 per grower per month.

The requirement that nurseries be visually inspected before every shipment is associated with a positive and statistically significant at the .1 level effect on the acre-treatments per acre. No policy has either a large or statistically significant effect on the acre-treatments per acre for non-host plants (Table 5).

The hypotheses that growers rely primarily on fungicides to mask symptoms and avoid detection where possible is supported by the estimated impact of quarantine status on sanitation practices that reduce disease incidence but not symptoms of affected plants (Table 6). Difference-in-difference regressions do not yield a positive interaction term for the quarantine state and year for any of fourteen best management practices included in the USDA-NASS Floriculture Survey. Although the negative coefficients on the interaction terms are unlikely to be responsible for the disproportionate decrease in best management practices in quarantine states, there is no indication that growers have improved such practices.

Several factors suggest that growers alter fungicide use in response to the threat posed by inspection rather than to an underlying risk of disease when altering their fungicide use regime. First, visual inspections tend to have a larger effect on fungicide use than laboratory inspections, consistent with the fact that fungicides tend to be more effective at masking the visual symptoms of disease than they are at decreasing the probability of a disease being detected in a laboratory (Table 4). Second, the dummy variable for elevated risk as reported by USDA forest service risk maps is very small and close to zero in all regressions (Table 4). Third, a wide variety of management practices reduce disease prevalence but do not affect the probability of avoiding detection once a disease arises (Table 6).

Crop Composition

The estimated coefficients of the crop composition models suggest that the imposition of quarantines does affect the crop composition chosen, consistent with the theoretical model (Table 7 and Table 8). Estimated coefficients using both the USDA-NASS Floriculture Survey and the USDA Census of Horticultural Specialties indicate that the market responded to the *P. ramorum* quarantine by producing fewer host plants. The USDA-NASS Floriculture Survey indicates that the absolute sales of azaleas, which is the only host product in the survey, have declined disproportionately in quarantine states during quarantine years. The coefficients from the regressions using the difference in the total of plants sold that are hosts from the Census of Horticultural Specialties indicate that for every host plant category, the estimated coefficients of the model indicate that there have been disproportionate declines in quarantine states during quarantine years in the share of crops that are potential *P. ramorum* hosts (Table 7). Both sources indicate that the price of host plants have disproportionately increased in quarantine states during the quarantine years.

The USDA-NASS Floriculture Survey separates sales of azaleas into small pots which are less than five inches in diameter and large pots which are more than five inches in diameter. The survey indicates that the sales of azaleas have disproportionately decreased by 437,900 small plants per year and by 581,900 large plants per year in quarantine states during quarantine years compared to twelve non-quarantine states (Table 8). These figures represent a 40 percent increase in average annual sales small azaleas and a 32 percent increase in the sales of large azaleas per state in the three affected states before the quarantine. The coefficient on the interaction term between quarantine year and quarantine state was statistically significant for both large and small azaleas. There was also a disproportionate decrease in sales of azaleas as a percent of total floriculture revenue in the quarantine states relative to the other states over the quarantine time period by more than 4 percent.

The coefficients from the regressions using the USDA Census of Horticultural Specialties is consistent with those of the Floriculture survey, but with a smaller magnitude. The USDA Census of Horticultural specialties had three categories of plants in which there were both genera that were composed of only host species and genera that were composed of only non-host species: broadleaf evergreens, deciduous shrubs, and Christmas trees. Within each category, genera that had both host and non-host species were excluded. The percent of plants sold that were hosts disproportionately decreased in quarantine states between 1998 and 2009 between 4 percent for deciduous shrubs and 10 percent for Christmas trees (Table 8).

Conclusion

Correctly assessing the infection status of individuals is important for containing the spread of any contagious disease. When negative consequences for harboring a disease are imposed, agents are frequently empowered and incentivized to take actions than reduce the probability of detection. In human and livestock disease, reducing the probability of detection can take the form of fever-reducing drugs or failure to report suspicious symptoms. In the case of certain plant diseases, growers can influence the probability of detection through their choice of chemical use.

In this paper, I investigate how growers respond to increased inspections and regulations in the context of the plant pathogen that causes Sudden Oak Death. I approach this question in three ways. First, I create a theoretical model to formally predict how greenhouse nursery operators change their fungicide use patterns and their crop composition in response to the implementation of mandatory disease inspections. My model predicts that when a testing regime is imposed, growers will increase their fungicide use and shift their production away from susceptible plant species towards resistant species. Second, I provide empirical evidence consistent with the hypothesis that growers increased their fungicide use targeting the disease in response to the inspections using data on the grower level for California. However, based on state-level data, I do not find evidence that growers improved their management practices in response to increased inspection or increased disease prevalence. Third, I provide empirical evidence consistent with the hypothesis that growers changed their crop composition in response to the inspection regime using state level data from the USDA Census of Horticultural Specialties and the USDA-NASS Floriculture Survey.

The estimated coefficients have two policy implications for the reduction of *P. ramorum*. First, since the findings support the hypothesis that growers respond with greater fungicide use to visual inspections but not to laboratory inspections, movement restrictions should be based on laboratory inspections only. Although fungicides may also affect the accuracy of laboratory inspections, the increased probability of avoiding detection is not as well documented. Second, since growers usually increase fungicide use by applying more frequently rather than increasing quantities per application, mandatory waiting periods between fungicide application and inspection may be an effective tool in improving detection rates. For a mandatory waiting period to be effective, further research must estimate optimal waiting times and proper enforcement must be available through laboratory testing.

The policy implications of this paper extend beyond the greenhouse nursery industry. Fungicides specifically are a major line of defense against major pathogens affecting coffee plants (*Hemileia vastatrix*), cocoa plants (*Moniliophthora perniciosa, Moniliophthora roreri, Oncobasidium theobroma*, *Phytophthora palmivora*, *Phytophthora megakarya and Phytophthora capsici*), rice (*Magnaporthe oryzae*), and wine grapes (*Botrytis cinerea*). Regulators typically address the spread of disease through some sort of testing regimen, but fungicides suppress the symptoms, so the effectiveness of such regulations is limited. In addition to other crops that are at risk of fungal disease, disease detection evasion is a serious concern among other agricultural industries, including livestock, and in the containment of human disease.

In the case of fungal plant diseases, policymakers can reduce their reliance on visual symptoms in favor of laboratory testing. Waiting periods, in which growers are required to temporarily suspend pesticide use immediately prior to testing, can improve disease detection accuracy. Waiting period compliance can be assessed through laboratory testing. Optimal duration of waiting periods should be informed through research on the magnitude of symptom masking potential across plants and specific fungicides.

To achieve the goal of accurately assessing disease status, policymakers can use a variety of tests to determine whether or not an operation is infested in order to minimize the effect of any one test. In the case of *P. ramorum*, this may mean using multiple laboratory testing procedures. If actors are able to evade detection in all available testing procedures, policymakers can either construct a uniform policy across an entire region that is deemed infested rather than on an individual basis.

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Policy Timeline for Quarantined California Counties

- May 2001: The counties of Santa Clara, Marin, Sonoma, Napa, Santa Cruz, San Mateo, and Monterey are declared to be “quarantined” and nurseries selling host and associated articles must be inspected visually annually to ship intrastate
- July 2001: Mendocino County is added to the list of quarantined counties
- February 2002: Solano, and Alameda are added to the list of quarantined counties and all quarantined nurseries in quarantined counties selling host and associated products must be inspected annually in a laboratory to ship interstate
- April 2004: Humboldt and Contra Costa Counties are added to the list of quarantined counties. The non-quarantined counties in California are declared “restricted” by a federal order and all nurseries selling host and associated products must be annually visually inspected to ship interstate
- January 2005: Lake and San Francisco Counties are added to the list of quarantined counties. All nurseries selling host and associated products in quarantined counties must be visually inspected before every shipment to ship interstate
- January 2006: : All nurseries in quarantine counties, regardless of whether they ship host and associated products, must be visually inspected annually to ship interstate
- January 2007: All nurseries in California, regardless of whether they ship host and associated products, must be visually inspected annually to ship interstate

Table 1: Summary Statistics for Fungicide Use

Host Plants					
	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Pounds of Active Ingredients that are Oomycete-Specific	14,358	4.65	42.20	0.00	2062.72
Pounds of Active Ingredients that are Not Oomycete-Specific	14,358	921.62	6698.76	0.00	283315.20
Oomycete-Specific Pounds of Active Ingredient per Acre	14,358	0.04	0.32	0.00	8.54
Oomycete-Specific Pounds of Active Ingredient per Acre	14,358	9.46	43.47	0.00	1055.89
Non-Host Plants					
	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Pounds of Active Ingredients that are Oomycete-Specific	19,534	2.16	29.06	0.00	1858.32
Pounds of Active Ingredients that are Not Oomycete-Specific	19,534	521.32	4443.31	0.00	167317.20
Oomycete-Specific Pounds of Active Ingredient per Acre	19,534	0.04	0.45	0.00	17.60
Oomycete-Specific Pounds of Active Ingredient per Acre	19,534	4.71	28.24	0.00	1055.89

Table 2: Summary Statistics for Management Practices

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Plant Density Adjusted	24	52.71	12.08	23	74
Row Spacing or Row Directions Adjusted	24	43.17	13.32	15	71
Sterilized Growing Media Used	24	55.25	16.74	14	81
Diagnostic Laboratory Services Used for Pest Detection via Plant Tissue Analysis	24	17.71	7.14	4	33
Diagnostic Laboratory Services Used for Pest Detection Via Soil Analysis	24	20.42	8.36	3	37
Benches or Other Platform Devices Sanitized Between Uses	24	56.75	16.85	16	83
Containers Sanitized Between Uses	24	47.00	12.94	15	65
Ground Covers Sanitized Between Uses	24	40.25	12.67	20	72
Incoming Stock Inspected	24	70.92	9.98	50	86
Infected Plants or Plant Parts Removed or Pruned	24	83.79	7.89	68	94
Water Management Practices Used	24	36.00	9.87	19	64
Greenhouse Relative Humidity Modified	24	51.54	14.28	23	74
Greenhouse Temperature Modified	24	51.83	15.63	22	79
Greenhouse Ventilated	24	67.00	15.29	37	86

Table 3: Summary Statistics for Host Plant Sales

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum	Source
Azaleas: 1000s of small plants sold	196	163.94	389.05	1.00	3137.00	USDA Floriculture Survey
Azaleas: 1000s of large plants sold	334	247.43	589.64	2.00	4475.00	USDA Floriculture Survey
Portion of total floriculture sales that are Azaleas	293	0.01	0.03	0.00	0.24	USDA Floriculture Survey
Broadleaf Evergreens: Portion of Sales that were Host Plants	91	0.57	0.32	0.00	1.00	USDA Census of Horticultural Specialties
Deciduous Shrubs: Portion of Sales that were Host Plants	98	0.09	0.08	0.00	0.32	USDA Census of Horticultural Specialties
Christmas Trees: Portion of Sales that were Host Plants	72	0.23	0.31	0.00	1.00	USDA Census of Horticultural Specialties

Table 4: Fungicide Use for Host and Associated Products

	(1)	(2)	(3)	(4)
	Hosts: Portion of Pounds that are Oomycete-Specific	Hosts: Oomycete-Specific Pounds/Acre	Hosts: Oomycete-Specific Pounds	Hosts: Oomycete-Specific Acre Treatments/Acre From Max
Elevated Risk	-0.0000221	-0.000174	0.00243	-0.0000181
	(-0.00)	(-0.00)	(0.00)	(-0.00)
Nurseries selling host and associated products must be inspected annually in a laboratory to ship interstate or intrastate	0.00988	0.0262	-1.585	-0.00326
	(0.73)	(0.74)	(-0.31)	(-0.28)
All nurseries must be visually inspected annually to ship interstate	-0.000000993	-0.00000783	0.000109	-0.000000814
	(-0.00)	(-0.00)	(0.00)	(-0.00)
All nurseries selling host and associated products must be visually inspected before every shipment to ship interstate	0.281***	-0.000764	1.015	0.160*
	(3.52)	(-0.00)	(0.03)	(2.29)
Acres Planted	-9.10e-08	-0.000000718***	0.0000100	-7.46e-08
	(-1.66)	(-5.01)	(0.48)	(-1.55)
Maximum Temperature	0.000755	0.00183	0.119	0.000345
	(1.89)	(1.75)	(0.77)	(0.98)
Minimum Temperature	-0.00134*	-0.00310*	-0.162	-0.000872
	(-2.44)	(-2.16)	(-0.77)	(-1.81)
Precipitation in Inches	0.00277***	0.00301	0.130	0.00167**
	(4.39)	(1.82)	(0.54)	(3.01)
Number of Growing Degree Days with a Base of 40	0.00198**	0.00205	0.0145	0.00139*
	(2.61)	(1.03)	(0.05)	(2.08)
Number of Growing Degree Days with a Base of 50	-0.000843*	-0.00156	-0.0262	-0.000378
	(-2.41)	(-1.70)	(-0.19)	(-1.23)
Precipitation Missing	0.0157	0.00409	-0.646	0.0217*
	(1.26)	(0.13)	(-0.13)	(1.98)
Temperature Missing	-0.00416	-0.0221	-1.795	-0.0155
	(-0.25)	(-0.51)	(-0.28)	(-1.06)

Constant	-0.0178	0.0679	5.607	0.00417
	(-0.36)	(0.52)	(0.30)	(0.10)
N	14367	14373	14373	14358
Grower fixed effects are included in all models. * p<0.05 ** p<0.0 *** p<0.001				

Table 5: Falsification Test for Fungicide Use in Non-Host and Associated Products

	(1)	(2)	(3)	(4)
	Non-Hosts: Portion of Pounds that are Oomycete-Specific	Non-Hosts: Oomycete-Specific Pounds/Acre	Non-Hosts: Oomycete-Specific Pounds	Non-Hosts: Oomycete-Specific Acre Treatments/ Acre From Max
Elevated Risk	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Nurseries selling host and associated products must be inspected annually in a laboratory to ship interstate or intrastate	-0.019**	-0.005	-2.439	-0.019*
	(-2.62)	(-0.15)	(-1.07)	(-2.48)
All nurseries must be visually inspected annually to ship interstate	-0.001	-0.010	-0.570	-0.002
	(-0.02)	(-0.04)	(-0.03)	(-0.04)
All nurseries selling host and associated products must be visually inspected before every shipment to ship interstate	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Acres Planted	-2.46e-08	-0.0000006***	0.000	-2.46e-08
	(-0.67)	(-3.87)	(1.66)	(-0.65)
Maximum Temperature	0.001***	0.005***	0.333***	0.0007*
	(3.53)	(4.17)	(4.01)	(2.42)
Minimum Temperature	-0.001**	-0.004**	-0.248*	-0.0008*
	(-3.21)	(-2.96)	(-2.29)	(-2.18)
Precipitation in Inches	0.001**	0.005**	0.360**	0.001**
	(3.04)	(2.88)	(2.64)	(2.61)
Number of Growing Degree Days with a Base of 40	0.001	0.003	0.109	0.001*
	(1.94)	(1.31)	(0.68)	(2.45)
Number of Growing Degree Days with a Base of 50	0.000	0.002	0.208**	-0.000
	(0.21)	(1.92)	(2.95)	(-0.19)
Precipitation Missing	0.015	0.042	3.733	0.014
	(1.75)	(1.15)	(1.44)	(1.63)

	0.0108	0.125**	10.16**	0.011
Temperature Missing	(1.01)	(2.68)	(3.03)	(0.99)
	-0.00723	-0.153	-14.53	-0.006
Constant	(-0.22)	(-1.07)	(-1.41)	(-0.17)
N	19547	19557	19557	19534
Grower fixed effects are included in all models. * p<0.05 ** p<0.01 *** p<0.001				

Table 6: Percent of Growers Using Best Management Practices by State

Dependent Variable: Percent of growers in state that use each practice	Quarantine State		Quarantine State x Quarantine Year		Constant		N
Plant Density Adjusted	-12.26	(-1.72)	-5.176	(-0.59)	56.42***	(11.51)	24
Row Spacing or Row Directions Adjusted	-5.574	(-0.67)	-11.88	(-1.17)	45.19***	(7.97)	24
Sterilized Growing Media Used	-8.721	(-0.87)	-13.65	(-1.11)	63.24***	(9.23)	24
Diagnostic Laboratory Services Used for Pest Detection via Plant Tissue Analysis	0.257	(0.06)	-0.912	(-0.18)	20.41***	(7.25)	24
Diagnostic Laboratory Services Used for Pest Detection Via Soil Analysis	2.316	(0.42)	-3.206	(-0.47)	23.89***	(6.31)	24
Benches or Other Platform Devices Sanitized Between Uses	-4.596	(-0.44)	-12.15	(-0.93)	64.70***	(8.95)	24
Containers Sanitized Between Uses	4.287	(0.57)	-9.559	(-1.03)	51.07***	(9.88)	24
Ground Covers Sanitized Between Uses	-4.632	(-0.66)	-16.59	(-1.90)	42.04***	(8.68)	24
Incoming Stock Inspected	-5.022	(-1.28)	-14.26**	(-2.95)	75.01***	(27.89)	24
Infected Plants or Plant Parts Removed or Pruned	-3.449	(-0.67)	-5.382	(-0.85)	86.65***	(24.53)	24
Water Management Practices Used	7.904	(1.19)	-11.15	(-1.36)	28.03***	(6.16)	24
Greenhouse Relative Humidity Modified	4.500	(0.43)	-13.00	(-1.00)	47.50***	(6.58)	24
Greenhouse Temperature Modified	-0.294	(-0.03)	-10.53	(-0.76)	53.43***	(6.94)	24
Greenhouse Ventilated	0.551	(0.05)	-17.38	(-1.37)	70.65***	(10.04)	24

Year fixed effects are included in all regressions
t statistics are in parentheses
* p<0.05   ** p<0.01   *** p<0.001

Table 7: Host Plant Sales by State and Year

	(1)	(2)	(3)
	Broadleaf Evergreens Difference in Total Portion Plants Sold that are Hosts	Deciduous Shrubs Difference in Total Portion Plants Sold that are Hosts	Christmas Trees Difference in Total Number of Host Plants Sold
Quarantine State	-0.0743	-0.0380	-0.101
	(-0.54)	(-0.30)	(-0.79)
Constant	-0.119**	-0.0805*	-0.0253
	(-3.15)	(-2.51)	(-0.66)
N	40	46	33

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 8: Azalea Sales by State and Year

	(1)	(2)	(3)
	Number of Small Plants Sold	Number of Large Plants Sold	Portion of Sales in Dollars
Quarantine State x Quarantine Year	-437.9***	-581.9***	-0.0413***
	(-6.69)	(-6.81)	(-9.43)
State Fixed Effects?	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes
Constant	0.307	66.31	0.00780*
	(0.00)	(0.85)	(2.17)
N	196	334	293
t statistics in parentheses			
* p<0.05 ** p<0.01 *** p<0.001			

Appendix

(1.1)

$$p\ (\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[\ \lambda\big(1-\ \mu(F,R,N)\big)^{-1}(\frac{\partial\mu}{\partial F})^{2}-\ \frac{\partial^{2}\mu}{\partial F^{2}}\right]\leq 0$$

(1.2)

$$p(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-2\frac{\partial\mu}{\partial N}+N\lambda\big(1-\mu(F,R,N)\big)^{-1}\ \left(\frac{\partial\mu}{\partial N}\right)^{2}-N\frac{\partial^{2}\mu}{\partial N^{2}}\right]\leq 0$$

(1.3)

$$pN\ (\lambda+1)\left[\ \lambda\big(1-\ \mu(F,R,N)\big)^{\lambda-1}\ \left(\frac{\partial\mu}{\partial F}\right)^{2}-\frac{\partial^{2}\mu}{\partial F^{2}}\big(1-\ \mu(F,R,N)\big)^{\ \lambda}\right]*$$

$$\left[p(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-2\frac{\partial\mu}{\partial N}+N\lambda\big(1-\mu(F,R,N)\big)^{-1}\ \left(\frac{\partial\mu}{\partial N}\right)^{2}-N\frac{\partial^{2}\mu}{\partial N^{2}}\right]\right]-$$

$$\left[p\ (\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-\frac{\partial\mu}{\partial F}+\ N\lambda\big(1-\ \mu(F,R,N)\big)^{-1}\frac{\partial\mu}{\partial N}\frac{\partial\mu}{\partial F}-N\frac{\partial\mu}{\partial F\partial N}\right]-c\right]^{2}\ \geq 0$$

(1.4)

$$\frac{\partial F}{\partial \lambda} = -\frac{\begin{array}{c} -pN\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[\frac{\partial \mu}{\partial F}+(\lambda+1)l\,n\left(1-\ \mu(F,R,N)\right)\right]* \\ \left[p(\lambda+1)\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[-2\frac{\partial \mu}{\partial N}+N\lambda\left(1-\mu(F,R,N)\right)^{-1}\ \left(\frac{\partial \mu}{\partial N}\right)^{2}-N\frac{\partial^{2}\mu}{\partial N^{2}}\right]\right]- \\ p\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[-N\frac{\partial \mu}{\partial N}-N(\lambda+1)\,ln\left(1-\ \mu(F,R,N)\right)+\left(1-\ \mu(F,R,N)\right)l\,n\left(1-\ \mu(F,R,N)\right)\right]* \\ \left[p\ (\lambda+1)\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[-\frac{\partial \mu}{\partial F}+\ N\lambda\left(1-\ \mu(F,R,N)\right)^{-1}\frac{\partial \mu}{\partial N}\frac{\partial \mu}{\partial F}-N\frac{\partial \mu}{\partial F\partial N}\right]-c\right] \end{array}}{\begin{array}{c} pN\ (\lambda+1)\left[\ \lambda\left(1-\ \mu(F,R,N)\right)^{\lambda-1}\ \left(\frac{\partial \mu}{\partial F}\right)^{2}-\frac{\partial^{2}\mu}{\partial F^{2}}\left(1-\ \mu(F,R,N)\right)^{\ \lambda}\right]* \\ \left[p(\lambda+1)\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[-2\frac{\partial \mu}{\partial N}+N\lambda\left(1-\mu(F,R,N)\right)^{-1}\ \left(\frac{\partial \mu}{\partial N}\right)^{2}-N\frac{\partial^{2}\mu}{\partial N^{2}}\right]\right]- \\ \left[p\ (\lambda+1)\left(1-\ \mu(F,R,N)\right)^{\lambda}\left[-\frac{\partial \mu}{\partial F}+\ N\lambda\left(1-\ \mu(F,R,N)\right)^{-1}\frac{\partial \mu}{\partial N}\frac{\partial \mu}{\partial F}-N\frac{\partial \mu}{\partial F\partial N}\right]-c\right]^{2} \end{array}}$$

(1.5)

$$\frac{\partial N}{\partial \lambda} = -\frac{\begin{array}{c} p^2 N\,(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{2\lambda}\left[\lambda\big(1-\ \mu(F,R,N)\big)^{-1}\ \left(\frac{\partial \mu}{\partial F}\right)^2 - \frac{\partial^2 \mu}{\partial F^2}\right] * \\ \left[-N\frac{\partial \mu}{\partial N} - N(\lambda+1)\,ln\big(1-\ \mu(F,R,N)\big) + \big(1-\ \mu(F,R,N)\big)l\,n\big(1-\ \mu(F,R,N)\big)\right] + \\ \left[p\,(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-\frac{\partial \mu}{\partial F} +\ N\lambda\big(1-\ \mu(F,R,N)\big)^{-1}\frac{\partial \mu}{\partial N}\frac{\partial \mu}{\partial F} - N\frac{\partial \mu}{\partial F \partial N}\right] - c\right] \\ * \, pN\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[\frac{\partial \mu}{\partial F} + (\lambda+1)l\,n\big(1-\ \mu(F,R,N)\big)\right] \end{array}}{\begin{array}{c} pN\,(\lambda+1)\left[\lambda\big(1-\ \mu(F,R,N)\big)^{\lambda-1}\ \left(\frac{\partial \mu}{\partial F}\right)^2 - \frac{\partial^2 \mu}{\partial F^2}\big(1-\ \mu(F,R,N)\big)^{\lambda}\right] * \\ \left[p(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-2\frac{\partial \mu}{\partial N} + N\lambda\big(1-\mu(F,R,N)\big)^{-1}\ \left(\frac{\partial \mu}{\partial N}\right)^2 - N\frac{\partial^2 \mu}{\partial N^2}\right]\right] - \\ \left[p\,(\lambda+1)\big(1-\ \mu(F,R,N)\big)^{\lambda}\left[-\frac{\partial \mu}{\partial F} +\ N\lambda\big(1-\ \mu(F,R,N)\big)^{-1}\frac{\partial \mu}{\partial N}\frac{\partial \mu}{\partial F} - N\frac{\partial \mu}{\partial F \partial N}\right] - c\right]^2 \end{array}}$$

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