Supply Chain Externalities and Agricultural Disease[1]

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July 12, 2021

Abstract

Verticillium dahliae is a soil borne fungus that is introduced to the soil via infested spinach seeds and that causes subsequent lettuce crops to be afflicted with Verticillium wilt. Due to Verticillium wilt, a supply chain externality arises between companies selling spinach seed and growers who may grow lettuce. We analyze the externality between growers and seed companies. We estimate the grower's benefits from and the spinach seed company's cost to testing and cleaning spinach seeds in order to reduce the level of microsclerotia. To estimate a grower's benefits from testing and cleaning spinach seeds, we develop and estimate a dynamic structural econometric model of farmers' dynamic crop choice and fumigation decisions. We use our estimates of the grower's benefits from and spinach seed company's costs to testing and cleaning spinach seeds to determine the welfare-maximizing level of seed testing and cleaning. Our model enables us to compare the status quo, in which growers and seed companies are independent, to a vertically integrated industry, in which one company produces spinach seeds, as well as spinach, lettuce, and other crops. The vertically integrated industry would internalize the externality between growers and seed companies, and would choose the welfare-maximizing level of seed testing and cleaning. We find that significant welfare gains arise only when the seed company tests and cleans the spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price. Our work regarding the seed company and grower externality sheds light on how treatment of spinach seeds could potentially reduce externalities between seed companies and growers.

Keywords: agricultural economics, externalities

JEL codes: Q10, Q00, L23

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1 Introduction

Invasive plant pathogens, including fungi, cause an estimated $21 billion in crop losses each year in the United States (Rossman, 2009). California, a major agricultural producer and global trader, sustains significant economic damage from such pathogens. Fungi damage a wide variety of California crops resulting in yield and quality related losses, reduced exportability, and increased fungicide expenditures (Palm, 2001).

This paper focuses on *Verticillium dahliae*, a soil borne fungus that is introduced to the soil via infested spinach seeds and that causes subsequent lettuce crops to be afflicted with Verticillium wilt (V. wilt). Scientists believe that contaminated spinach seeds imported into California are responsible for the epidemic levels of the disease in lettuce.

Due to V. wilt, a supply chain externality arises between companies selling spinach seed and growers who may grow lettuce. Spinach seed companies may not have an incentive to test or clean spinach seeds, as they do not internalize the costs that infected spinach seeds impose on growers. Thus, decisions made by seed companies regarding whether and how much to test or clean spinach seeds impose an externality on growers. In this paper, we analyze the externality between growers and seed companies.

To estimate a grower's benefits from testing and cleaning spinach seeds, we develop and estimate a dynamic structural econometric model of growers' dynamic crop choice and fumigation decisions. The structural model generates parameter estimates with direct economic interpretations, and enables us to calculate grower welfare. We use our structural model to simulate grower decisions and welfare under counterfactual levels of testing and cleaning spinach seeds, which we then use to calculate the grower's benefits from testing and cleaning spinach seeds.

We use a dynamic model for several reasons. First, the control options (fumigation, planting broccoli, and not planting spinach) require incurring costs or foregoing profit in the current period for possible future benefit, and are thus are best modeled with a dynamic model.[2] Second, because cropping and fumigation decisions are irreversible (as is the damage from V. wilt), there is uncertainty over the reward from cropping and fumigation decisions, and growers have leeway over the timing of cropping and fumigation decisions. Thus, there is an option value to waiting which requires a dynamic model (Dixit and Pindyck, 1994). Third, *Verticillium dahliae* takes time to build up in the soil, and once present, persists for many years.

[2]Some of these actions may also generate benefits in the current period for the current crop. For example, in addition to being an investment in protecting potential future lettuce crops from V. wilt, methyl bromide is beneficial to the current crop of strawberries. However, on net, these control options generally require incurring net costs or foregoing profit in the current period.

We then estimate the spinach seed company's cost to testing and cleaning spinach seeds in order to reduce the level of microsclerotia, and compare the spinach seed company's cost to the grower's benefits. We use our estimates of the grower's benefits from and spinach seed company's costs to testing and cleaning spinach seeds to determine the welfare-maximizing level of seed testing and cleaning.

Our model enables us to compare the status quo, in which growers and seed companies are independent, to a vertically integrated industry, in which one company produces spinach seeds, as well as spinach, lettuce, and other crops. The vertically integrated industry would internalize the externality between growers and seed companies, and would choose the welfare-maximizing level of seed testing and cleaning.

Our work regarding the seed company and grower externality sheds light on how treatment of spinach seeds could potentially reduce externalities between seed companies and growers.

In the remainder of this paper, Section 2 provides background on the externality and why vertical integration may be a possible solution. Section 3 is a brief review of the relevant literature. In Section 4, we develop and estimate a dynamic structural econometric model to estimate a grower's benefits from testing and cleaning spinach seeds. In Section 5, we model the externality between seed companies and growers. Section 6 concludes.

2 Background

Lettuce is an important crop in California, and the majority of lettuce production in the United States occurs in California. The value of California's lettuce crop was $1.7 billion in 2013 (National Agricultural Statistics Service, 2015). Measured by value, lettuce ranks in the top ten agricultural commodities produced in California (National Agricultural Statistics Service, 2015). Lettuce production value is 27% of Monterey County's agricultural production value (Monterey County Agricultural Commissioner, 2015). Approximately ten to fifteen thousand acres are planted to lettuce in Monterey County each season (spring, summer, and fall). Spinach, broccoli, and strawberries are also important crops in the region.

Verticillium dahliae is a soil borne fungus that causes subsequent lettuce crops to be afflicted with V. wilt. No effective treatment exists once plants are infected by the fungus (Xiao and Subbarao, 1998; Fradin and Thomma, 2006). The fungus can survive in the soil for fourteen years as microsclerotia, which are resting structures that are produced as the pathogen colonizes a plant. This allows the fungus to remain in the soil even without a host plant. When a susceptible host is planted, microsclerotia attack through the roots, enter the water conducting tissue, and interfere with the water uptake and transport through the plant. If the density of microsclerotia in the soil passes a threshold, a disease known as V. wilt occurs.

V. wilt first killed a lettuce (*Lactuca sativa* L.) crop in California's Parajo Valley in 1995. Prior to this, lettuce was believed to be immune. Since then, the disease has spread rapidly through the Salinas Valley, the prime lettuce production region of California. By 2010, more than 150 fields were infected with V. wilt (Atallah, Hayes, and Subbarao, 2011),[3] amounting to more than 4,000 acres (Krishna Subbarao, personal communication, 2013).[4] Although growers have resisted reporting the extent of the disease since 2010, it is likely that the number of affected acres has increased since then (Krishna Subbarao, personal communication, 2013).

Verticillium dahliae is introduced to the soil in three possible ways. First, V. wilt can be spread locally from field to field by workers or equipment. Local spread is a relatively minor contributor, however, and growers have taken steps to mitigate this themselves, for example by cleaning equipment before moving between fields.

Second, V. wilt is introduced to the soil via infested lettuce seeds. However, studies of commercial lettuce seed lots from around the world show that fewer than 18% tested positive for *Verticillium dahliae* and, of those, the maximum incidence of infection was less than 5% (Atallah, Hayes, and Subbarao, 2011). These relatively low levels do not cause V. wilt in lettuce at an epidemic level. Models of the disease suggest that it would be necessary for lettuce seed to have an incidence of infection of at least 5% and be planted back to back for three to five seasons in order for the disease to appear, with at least five subsequent seasons required for the high disease levels currently seen (Atallah, Hayes, and Subbarao, 2011).

Third, V. wilt is introduced to the soil via infested spinach seeds. Spinach seeds have been shown to be the main source of the disease (du Toit, Derie, and Hernandez-Perez, 2005; Short et al., 2015); 89% of spinach seed samples are infected, with an incidence of infected seeds per sample of mean 18.51% and range 0.3% to 84.8% (du Toit, Derie, and Hernandez-Perez, 2005). The precise impact of planting infected spinach seeds on V. wilt of lettuce was recently assessed and proven to be the cause of the disease on lettuce (Short et al., 2015). The pathogen isolated from infected lettuce plants is genetically identical to the pathogen carried on spinach seeds (Atallah et al., 2010).

Infected spinach seeds carry an average of 200 to 300 microsclerotia per seed (Maruthacha-

[3]As not all the fields that were infected by 2010 were known at the time Atallah, Hayes, and Subbarao (2011) was published, the number of fields affected by 2010 fields was actually even higher, numbering over 175 fields (Krishna Subbarao, personal communication, 2013).

[4]Krishna Subbarao is a Professor of Plant Pathology and Cooperative Extension Specialist at the University of California at Davis. He has studied V. wilt for many years.

lam et al., 2013). As spinach crops are seeded at up to nine million seeds per hectare for baby leaf spinach, even a small proportion of infected seeds can introduce many microsclerotia (du Toit and Hernandez-Perez, 2005).

Testing or cleaning seeds is an important option for preventing *Verticillium dahliae* from being introduced into a field, but can be uncertain and potentially costly. Although *Verticillium dahliae* cannot be completely eliminated by seed cleaning, incidence levels in spinach seed can be significantly reduced (du Toit and Hernandez-Perez, 2005). Very recent developments in testing procedures suggest that testing spinach seed for *Verticillium dahliae* might soon be feasible on a commercial basis. Moreover, a very recent innovation speeds up testing spinach seeds. Previously, testing for *Verticillium dahliae* in spinach seeds took approximately two weeks and could not accurately distinguish between pathogenic and non-pathogenic species (Duressa et al., 2012). This new method takes only one day to complete, is highly sensitive (as it is able to detect one infected seed out of 100), and can distinguish among species (Duressa et al., 2012).

In addition to testing and cleaning spinach seeds, V. wilt can also be controlled by restricting the imports of spinach seeds infested with *Verticillium dahliae*, but doing so would have trade implications. Currently, the United States has no phytosanitary restrictions on spinach seed imports, but Mexico prohibits the importation of seeds if more than 10% are infected (IPC, 2003). V. wilt can also be prevented or controlled by the grower by fumigating with methyl bromide, planting broccoli (a low-return crop), or not planting spinach. These control options require long-term investment for future gain (Carroll et al., 2021).

Although testing or cleaning seeds may prevent *Verticillium dahliae* from being introduced into a field, spinach seed companies may not have an incentive to test or clean spinach seeds, as they do not internalize the costs that infected spinach seeds impose on growers. Thus, decisions made by seed companies regarding whether and how much to test or clean spinach seeds impose a supply chain externality on growers.

There are several reasons why the supply chain externality exists between spinach seed companies and growers. First, testing and cleaning spinach seeds is uncertain and potentially costly, and although testing or cleaning seeds may prevent *Verticillium dahliae* from being introduced into a field, spinach seed companies may not have an incentive to test or clean spinach seeds, as they do not internalize the costs that infected spinach seeds impose on growers.

A second reason a supply chain externality exists between spinach seed companies and growers is that, owing to asymmetric information, the price signal for tested and cleaned spinach seed versus contaminated seed is weak. Growers buying spinach seeds with the intention of planting lettuce in the following season may be willing to pay a very high price for clean seed after accounting for their potential loss in harvest revenue for lettuce and penalties for breaking contracts with lettuce shippers if their lettuce is afflicted with V. wilt. However, if a seed company has infected seed that it cannot otherwise sell, the seed company may be willing to pay a high price to clean the seed without passing on the cost if the seed company wishes to maintain market share (Dale Krowlikowski, Head of Operations and Research, Germains Technology Group, personal communication, 2015). Thus, owing to asymmetric information, there is no direct price signal between seed companies and growers, and, as a consequence, seed companies impose an externality on growers that they do not internalize.

A third reason a supply chain externality exists between spinach seed companies and growers is that V. wilt in lettuce is an example of a market failure in which transaction costs between seed companies and lettuce growers prevent them from reaching a potentially more efficient equilibrium solution. Transaction costs increase with the number of agents. There are a large number of growers attempting to bargain with a relatively small number of seed companies. Even large growers have relatively little bargaining power with respect to the seed companies, making negotiation and contracting difficult. Because microsclerotia are carried mainly on spinach seeds rather than lettuce seeds directly, lettuce growers have little bargaining power. In addition, growers have different incentives and priorities, rendering collective action ineffective. Up to 30% of spinach is now organic, so cleaning methods that are desirable to some growers are not acceptable to others. Due to the small number of seed companies, some growers are hesitant to resort to legal means, such as working toward a seed testing or cleaning requirement from the County Agricultural Commissioner, lest seed companies decide to leave the market. Such transactions costs may also impede other possible solutions such as third party testing.

Thus, owing to the lack of incentives for spinach seed companies to test or clean spinach seeds, asymmetric information, and transaction costs, spinach seed companies are unwilling to test or clean spinach seeds, especially as spinach producers are not affected by this disease. Thus, decisions made by seed companies regarding whether and how much to test or clean spinach seeds impose a supply chain externality on growers.

We consider vertical integration of the industry as a solution to the supply chain externality problem. Williamson (1971) describes some of the cases in which vertical integration is an appropriate tool to mitigate an externality, via "substituting internal organization for market exchange". While in some cases vertical integration would capture a positive externality (Brewin et al., 2014), vertical integration would address Verticillim wilt by eliminating a negative externality.

3 Literature Review

Our paper relates to several strands of literature. The first strand of literature to which our paper relates is on import controls and cleaning technology. As invasive species introductions have increased with greater levels of trade, economic analyses have become increasingly important for pest prevention and management (Levine and D'Antonio, 2003). Countries protect their citizens, animals, and plants from invasive species. Members of the World Trade Organization (WTO) are bound by the Agreement on the Application of Sanitary and Phytosanitary Measures (SPS Agreement), which states that in protecting human, plant, and animal health, a country must use the least trade restricting policy possible to achieve the desired level of protection. This agreement corrects externalities and market inefficiencies caused by invasive species (Olson, 2006). Policy options include tariffs, quarantines, and export certifications.

Most of the research regarding trade, trade policy, and invasive species damage focuses on calculating the expected marginal damage from invasive species and using tariffs to internalize the related externalities (Springborn, Romagosa, and Keller, 2011). Mérel and Carter (2008) discuss the optimal two-part tariff to cover the cost of inspections and the cost of damages from contaminated goods. An alternative to tariffs is quarantine, as in James and Anderson (1998). Brennan et al. (2004) provide an example of the impacts of a quarantine, in which growers lose access to the wheat seed export market as a result of a Karnal bunt outbreak. Batabyal and Beladi (2007) consider the incentives of the firm, and whether export certification can encourage firms to comply with quality requirements. Each of these papers focuses on the interaction between the government and importing firms.

Because the production of spinach seeds requires long, cool days, spinach seeds are not grown in California but produced in the Pacific Northwest or imported from other countries. Thus, trade policies are important. The SPS Agreement provides a legal basis for preventing the importation of contaminated seeds; however, only Mexico has taken this step with regard to spinach seeds. All of the methods described above, including tariffs, quarantines, and export certifications, require that the product can be tested. Only recently have quick, efficient tests been developed to detect *Verticillium dahliae* in spinach seed. Further, the method described by Mérel and Carter (2008) requires that contaminated seeds be cleaned. Du Toit and Hernandez-Perez (2005) test hot water and chlorine for their potential to eliminate or reduce the effect of *Verticillium dahliae* and other pathogens on spinach. Further work in this area could lead to significant reductions in the amount of *Verticillium dahliae* carried by seeds.

A second strand of literature to which our paper relates is on vertical integration.

Vertical integration theory dates back to Coase (1937), who argued that firms exist to reduce transaction costs in markets. The theory was advanced by Williamson (1971), among others. The size and scope of a firm ought to depend on whether and how they offer a transaction cost advantage. Vertical integration, as opposed to sourcing inputs or selling outputs, should reflect advantages regarding transaction costs. To define such an advantage requires an explanation for why market transactions are inefficient and why those inefficiencies cannot be mitigated using contracts or pricing.

By nature, contracts are incomplete and cannot account for every possible contingency. This is especially true when complexity and uncertainty make defining safeguards difficult. For example, Williamson (1971) gives the example of a dispute within a firm compared to one between separate firms. In the first case, a senior manager can resolve the issue; in the second case, the firms must resort to (costly) negotiation or litigation.

Empirical testing of transaction cost theory and vertical integration has proved difficult (Bresnahan and Levin, 2012). Rarely are there counterfactuals to show what would have happened had firms not vertically integrated or vice versa, all else being constant. Many studies report statistically significant correlation between integration decisions, and theoretically-relevant transaction characteristics (Bresnahan and Levin, 2012).

De Fontenay and Gans (2014) provide a theoretical model of bilateral bargaining with externalities. They consider possible outcomes when agents bargain bilaterally with one another and negotiation outcomes produce externalities. We adapt this framework to consider the externality generated by spinach seeds on lettuce production. Brewin et al. (2014) analyze an empirical example in which specialized farming is compared to integrated enterprises. They consider hog and forage operations that operate separately and those that operate as a joint farm. Hog operations produce large amounts of manure that is costly to dispose of. Forage operations require fertilizers. In integrated operations, manure from the hogs can be used as fertilizer for forage, benefiting the forage portion of the farm and eliminating the externality inherent in the hog farm. The non-integrated operations suffer because price signals are not complete in the market. In an area with a large population of livestock, manure has a very low or zero price for hog growers and is external to their profit maximization. Integration captures this positive externality.

A third strand of literature to which our paper relates is on the economics of pest management (Hueth and Regev, 1974; Carlson and Main, 1976; Wu, 2001; Noailly, 2008; McKee et al., 2009), which focuses on pests for which treatment is available after crops are affected. In contrast, V. wilt cannot be treated once crops are affected. Existing work on crop disease, such as Johansson et al. (2006) and Gómez, Nunez, and Onal (2009) on soybean rust, and Atallah et al. (2015) on grapevine leafroll disease, focuses on spatial issues regarding the spread of the disease. In contrast, V. wilt has only a limited geographic impact, and thus dynamic considerations are more important than spatial ones for V. wilt.

A fourth strand of literature to which our paper relates is on dynamic models in agricultural management. As *Verticillium dahliae* persists in the soil for many years, a static model such as that proposed by Moffitt, Hall, and Osteen (1984) will not properly account for the future benefits of reducing microsclerotia in the soil. The dynamics of V. wilt more closely fit the seed bank management model by Wu (2001).

Dynamic models have been used in agricultural management to analyze many problems. Weisensel and van Kooten (1990) use a dynamic model of growers' choices to plant wheat, or to use tillage fallow versus chemicals to store moisture. In a related paper, van Kooten, Weisensel, and Chinthammit (1990) use a dynamic model that explicitly includes soil quality in the grower's utility function and the trade-off between soil quality (which may decline due to erosion) and net returns.

Our paper builds on the literature on dynamic structural econometric modeling. Rust's (1987; 1988) seminal papers develop a dynamic structural econometric model using nested fixed point maximum likelihood estimation. This model has been adapted for many applications, including bus engine replacement (Rust, 1987), nuclear power plant shutdown (Rothwell and Rust, 1997), water management (Timmins, 2002), agriculture (De Pinto and Nelson, 2009; Scott, 2013), air conditioner purchases (Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2020), and copper mining decisions (Aguirregabiria and Luengo, 2016), short- versus long-term decision-making for disease control (Carroll et al., 2021), vehicle scrappage programs (Li and Wei, 2013), the adoption of rooftop solar photovoltaics (Feger, Pavanini, and Radulescu, 2020; Langer and Lemoine, 2018), organ transplant decisions (Agarwal et al., 2021), vehicle ownership and usage (Gillingham et al., 2016), and agricultural productivity (Carroll et al., 2019).

4 Estimating Grower Benefits

To estimate a grower's benefits from testing and cleaning spinach seeds, we develop and estimate a dynamic structural econometric model of growers' dynamic crop choice and fumigation decisions. The structural model generates parameter estimates with direct economic interpretations.

4.1 Data

We use Pesticide Use Reporting (PUR) data from the California Department of Pesticide Regulation.[5] Our data set is composed of all fields in Monterey County on which any regulated pesticide was applied in the years 1993 to 2011, inclusive.[6] Additional data on prices, yields, and acreage come from the Monterey Agricultural Commissioner's Office. We collapse the data set into monthly observations.

We group the crops into six categories: susceptible (which includes artichoke, strawberries, and cabbage, but excludes lettuce which we represent separately), resistant (cauliflower and celery), lettuce, spinach, broccoli, and other.[7] From these, we form nine action choices: susceptible, susceptible with recent fumigation, resistant, broccoli, broccoli with recent fumigation, lettuce, lettuce with recent fumigation, spinach, and other.[8]

For control options, we use recent histories for broccoli and methyl bromide because their effects on microsclerotia are relatively short-lived. Microsclerotia levels rebound within one to two seasons, or approximately one year. Thus, broccoli history is the number of months broccoli was planted in the last 12 months, and methyl bromide history is the number of months methyl bromide was used in the last 12 months.

The vast majority of fields (94% of observations) in our data set have only one grower over the entire time period. Of these, we analyze those long-term growers who appear in the data on from 1994 to 2010, and we model their decision-making as an infinite horizon problem. This data set on long-term growers consists of 615 fields, each over seventeen years.

[5] For more information see: `http://www.cdpr.ca.gov/docs/pur/purmain.htm`.

[6] We use the field identifier as as well as the section, township, and range data from the PUR data set to match fields across time. We delete a small number of observations that are non-agricultural uses (golf courses, freeway sidings, etc.).

[7] To make the model manageable, we include only the most common crops in Monterey County and those that are most often grown in rotation with lettuce. The crops explicitly included in our model account for nearly 90% of the observations. We account for the many rarely planted crops by including an "other" option, which includes various herbs, berries, nursery products, nuts, wine grapes, livestock, and many others.

[8] The data contain the crop planted in each field for each recorded pesticide application. Although the focus of our research is on methyl bromide, the other pesticides provide observations regarding which crops are in the ground at which times. Due to the nature of the data, sometimes we do not observe the entire production cycle of a crop. For example, strawberries are often in the ground for a year or more; however, if there is no registered pesticide applied in one of those months, a gap in the production cycle may appear in our data. We account for this issue in several ways. As long as the missing data are missing for exogenous reasons, missing data will not bias the results. Since there are no pesticide treatments for V. wilt once crops are in the ground, we have reason to believe that missing months mid-production cycle due to no pesticide application in that month are exogenous to the impact of V. wilt on crop and methyl bromide fumigation choice. We compared the distribution of these months between short-term and long-term growers and find that they are similar distributions. Finally, in the simulations, we simulate all months in the time period, but only count grower-months that are present in the actual data when calculating welfare and other statistics for comparison purposes.

We use a marketing year average price for each crop[9] to represent growers' expectations about prices for each year. The marketing year average price is in units of dollars per acre, and therefore measures revenue per acre and incorporates yield.[10] Using the current year's marketing year average price assumes that growers have rational expectations about what the average marketing year price will be that year.[11] The Monterey County Agricultural Commissioner's Office publishes annual crop reports including prices, yields harvest, and acreages for major crops in the county. Monterey County is a major producer of many of the crops included in our model. For most crops, these prices are highly correlated with California-wide price data published by the National Agricultural Statistics Service. We discretize the marketing year average price into 6 bins; the marketing year average price bins are shown in Figure 1.

We combine the marketing year average price data with data on the timing of harvests for various crops in Monterey. For each crop, the harvest month dummy variable for that crop is equal to one in months during which that crop may be harvested, and zero in months during which that crop is not harvested (i.e., winter months for most crops).[12] For all crops, we have observations during the winter months, including crops that have just been planted and are not yet ready for harvest, and crops such as strawberries that overwinter for harvest in the coming year.

Summary statistics for the state variables for long-term growers are in Table 1. The mean discretized price for broccoli is relatively low, affirming that broccoli is a low-return crop, and therefore that planting broccoli to control V. wilt involves forgoing profit in the

[9]For lettuce, we use a weighted average of the prices for head and leaf lettuce. In the early years of the data set, romaine and other types of lettuce were not broken out separately, so gross revenue numbers vary based on this reporting, but do not affect the discretized value of the price.

[10]We look at gross revenue rather than net revenue due to data limitations. Costs are captured by our crop-fumigation dummies and our constant. Estimating net revenue did not improve the overall model, and cost differences among crops are mainly driven by methyl bromide fumigation, which is explicitly included in the model, and/or the difference between strawberry costs compared to other crops. Strawberry costs are generally an order of magnitude higher than for the vegetable crops, in part due to fumigation cost according to Richard Smith, Farm Advisor for Vegetable Crop Production & Weed Science with the University of California Cooperative Extension in Monterey County. We also attempted to incorporate this effect by including dummy variables for the different crop choices and fumigation, with resistant crops as the baseline. Unsurprisingly, the susceptible dummy variables (which includes strawberries) was collinear with the methyl bromide fumigation variable; we therefore do not include the susceptible crop dummy variable in our model. We expect the crop-fumigation dummies to at least partially capture the cost differences among the different crops.

[11]Instead of rational expectations about price, another possible assumption is that growers' best guess for this year's price is last year's price. The results are robust to whether we use lagged prices rather than current prices (Carroll et al., 2021).

[12]There is a separate harvest month dummy variable for each crop-month. These data come from Richard Smith, Farm Advisor for Vegetable Crop Production & Weed Science with the University of California Cooperative Extension in Monterey County.

current period for future benefit. Spinach is a relatively small portion of the acreage grown in Monterey County, approximately a tenth of the size of the acreage planted to lettuce according to the most recent Monterey County Crop Report.

Figure 2 plots the actual fraction of grower-months in each action type for the long-term growers. As seen in Figure 2, lettuce accounts for over 60% of the grower-months for these long-term growers. Figure 3 plots the actual fraction of grower-months in each action by month of year. The actual fraction of grower-months in each action varies by the month of the year, with lettuce predominant in the spring and summer months and other and susceptible crops having the highest proportion in the winter months. Figure 4 plots the actual fraction of grower-months in each action type over the years. The proportions are relatively constant across years.

4.2 Econometric Model

To estimate a grower's benefits from testing and cleaning spinach seeds, we develop and estimate a single-agent dynamic structural econometric model using the econometric methods developed by Rust (1987). Each month t, each grower i chooses an action $d_{it} \in D$. The possible actions for each grower for each month include one of five crops (resistant, susceptible (other than lettuce), lettuce, spinach, and broccoli), combined with the choice to fumigate with methyl bromide. To focus on the crops most relevant to this problem, we group the crops resistant to V. wilt together and the crops (other than lettuce) susceptible to V. wilt together. Lettuce, spinach, and broccoli are included separately as these crops are most relevant to V. wilt. Susceptible crops include strawberries, artichoke, and cabbage. Resistant crops include cauliflower and celery.

Although the raw data are observations on the day and time any fumigant is applied on a field, we aggregate to monthly observations. Growers are generally only making one crop-fumigation decision each season. The length of the season varies among crops, and can be as short as one month for spinach and more than a year for strawberries. For this reason, we choose a month as the time period for each crop-fumigation decision. To cover the case of multi-month seasons, we include a dummy variable for whether the grower continues with the same crop chosen in the previous month. Moreover, because not all crops are harvested in all months, we also include dummy variables for each crop-month indicating whether a particular month is a harvest month for a particular crop. For example, although Monterey County grows crops during a large portion of the year, few crops are harvested in the winter months.

To estimate growers' losses from V. wilt, it would be ideal to observe actual prices, quantities, costs, and level of microsclerotia for both growers facing losses from V. wilt and those who are not. In theory, profit maximizing growers make optimal planting and fumigating decisions factoring in planting and input costs, as well as the costs of microsclerotia building up in the soil over time and potentially impacting future crops. Unfortunately, data on growers' actual price, quantity, costs, and level of microsclerotia are not available.[13]

We account for the important factors in a grower's profit maximizing decision by including in the payoff function state variables that affect revenue; state variables that affect costs; state variables that affect both revenue and costs; and state variables that affect either revenue or cost by affecting the microsclerotia and the spread of V. wilt. The different state variables we include may have effects on price, yield, input costs, or microsclerotia levels. Costs are accounted for by the crop-fumigation dummies and the constant in our model, and we allow these costs to differ between the early and later periods of our data set. The largest cost difference among crops is due to fumigation, so we include a dummy for methyl bromide fumigation to account for the net costs of fumigation and to absorb cost differences among crops.

The per-period payoff to a grower from choosing action d_{it} at time t depends on the values of the state variables $\mathbf{s_{it}}$ at time t as well as the choice-specific shock $\epsilon_{it}(d_{it})$ at time t. The state variables $\mathbf{s_{it}}$ at time t include crop prices for each crop ($price_{it}(d_{it})$), dummy variables for each crop indicating whether this month is a harvest month for that crop ($harvest\ month\ dummy_{it}(d_{it})$), dummy variables for each crop indicating whether that crop is the same as the crop chosen in the previous month ($last\ crop\ dummy_{it}(d_{it})$), a variable measuring whether and how much the methyl bromide control option was used in the past ($methyl\ bromide\ history_{it}$), and a variable measuring whether and how much the broccoli control option was used in the past ($broccoli\ history_{it}$).

There is a choice-specific shock $\epsilon_{it}(d_{it})$ associated with each possible action $d_{it} \in D$. Let ϵ_{it} denote the vector of choice-specific shocks faced by grower i at time t: $\epsilon_{it} \equiv \{\epsilon_{it}(d_{it}) | d_{it} \in D\}$. The vector of choice-specific shocks ϵ_{it} is observed by grower i at time t, before grower i makes his time-t action choice, but is never observed by the econometrician.

The per-period payoff to a grower from choosing action d_{it} at time t is given by:[14]

[13]The University of California at Davis "Cost and Return Studies" have a limited number of estimates for revenue and costs, but estimates are not available for all the crops and years in our model.

[14]Because the model requires discrete data, we bin the action and state variables. This means that there are no meaningful units associated with the variables, payoffs, or value functions; and the payoff and value functions described in the model do not explicitly measure revenue or profit. However, the payoff function does include action and state variables that affect revenue (such as price); costs (such as the methyl bromide dummy); both revenue and costs; and either revenue and/or costs through their effect on microsclerotia and the spread of V. wilt.

$$U(d_{it}, \mathbf{s_{it}}, \epsilon_{it}, \theta) = \pi(d_{it}, \mathbf{s_{it}}, \theta) + \epsilon_{it}(d_{it}),$$

where the deterministic component $\pi(\cdot)$ of the per-period payoff is given by:

$$\begin{aligned}
\pi(d_{it}, \mathbf{s_{it}}, \theta) = {} & \theta_1 \cdot \text{spinach dummy}_{it} \\
& + \theta_2 \cdot \text{methyl bromide dummy}_{it} \\
& + \theta_3 \cdot \text{broccoli dummy}_{it} \\
& + \theta_4 \cdot (\text{lettuce dummy}_{it} \text{* methyl bromide history}_{it}) \\
& + \theta_5 \cdot (\text{lettuce dummy}_{it} \text{ * broccoli history}_{it}) \\
& + \theta_6 \cdot (\text{spinach dummy}_{it} \text{*methyl bromide history}_{it}) \qquad (1) \\
& + \theta_7 \cdot (\text{spinach dummy}_{it} \text{*broccoli history}_{it}) \\
& + \theta_8 \cdot \text{lettuce dummy}_{it} \\
& + \theta_9 \cdot (\text{price}_{it}(d_{it})\text{* harvest month dummy}_{it}(d_{it})) \\
& + \theta_{10} \cdot \text{last crop dummy}_{it}(d_{it}) \\
& + \theta_{11},
\end{aligned}$$

where *spinach dummy*$_{it}$, *methyl bromide dummy*$_{it}$, *broccoli dummy*$_{it}$, and *lettuce dummy*$_{it}$ are among the possible actions $d_{it} \in D$.

Spinach will tend to increase microsclerotia, thus decreasing the quantity harvested, increasing microsclerotia costs, and potentially increasing input costs as growers need to fumigate more. The coefficient θ_1 on the spinach dummy captures the effects of spinach on payoffs that are not internalized in the spinach price.[15]

Especially in more recent years, methyl bromide fumigation is very expensive and raises input costs dramatically. Fumigation is the largest cost difference among crops. Thus, methyl bromide fumigation is a control option that requires incurring costs or forgoing profit in the current period for future benefit. The coefficient θ_2 on the dummy for methyl bromide fumigation accounts for the costs of fumigation and absorbs the cost differences among

[15] We do not include spinach history in addition to the spinach dummy in the per-period payoff for several reasons. First, when we include spinach history within the last twelve months, the coefficients on spinach history are not significant. Second, owing to state space constraints, including spinach history would necessitate dropping other state variables, many of which are significant. Third, *Verticillium dahliae* takes several years to build up in the soil, and once present, persists for many years. The appropriate length of time for spinach history is therefore likely to be at least as long as the time period of our data set. We therefore unfortunately do not have enough years of data in order to control for spinach history in a relevant manner. Fourth, since *Verticillium dahliae* takes several years to build up in the soil, and once present, persists for many years, growers may not necessarily base their decisions on spinach history, since they may not know or recall the entire spinach history over many years.

crops.[16]

Broccoli is not highly profitable, but may yield future benefits for lettuce growers. Thus, planting broccoli is a control option that requires incurring costs or forgoing profit in the current period for future benefit. The coefficient θ_3 on the broccoli dummy captures the effects of broccoli on payoffs that are not internalized in the broccoli price.

Since the control options require incurring costs or forgoing profit in the current period for future benefit, previous use of control options may affect current payoffs. We therefore include variables indicating the fumigation history with methyl bromide within the last twelve months and the broccoli history within the last twelve months. We expect methyl bromide fumigation history and broccoli history to be closely linked to the presence of microsclerotia in a field. Methyl bromide fumigation history and broccoli history will tend to decrease microsclerotia levels in the soil, leading to increased harvest for susceptible crops, lower microsclerotia costs, and lower input costs.

We interact the variables measuring previous use of control options with a dummy variable for lettuce being planted in the current period because lettuce is the primary susceptible crop. Methyl bromide fumigation history interacted with planting lettuce today would have a positive coefficient θ_4 if having fumigated with methyl bromide is an effective control option. Similarly, broccoli history interacted with planting lettuce today would have a positive coefficient θ_5 if having planted broccoli is an effective control option. These two parameters therefore enable us to assess the effectiveness of these two respective control options.

We also interact the methyl bromide history and broccoli history variables with the dummy variable for spinach being planted in the current period, to capture whether the undesirability of spinach is mitigated by having methyl bromide history and/or broccoli history.

Growers continue to plant lettuce even though it is susceptible, and the coefficient θ_8 on the lettuce dummy captures any additional benefit of lettuce beyond its price.

Growers base decisions in part on the price or gross return they expect to receive for their harvested crops (Scott, 2013). We interact price with a dummy variable that is equal to one during the harvest season for each crop to capture the fact that although a grower may plant the same crop for multiple months, he only receives revenue during the months of the

[16] In addition to being an investment in protecting potential future lettuce crops from V. wilt, methyl bromide can also be beneficial to the current crop of strawberries. However, on net, methyl bromide fumigation generally requires incurring net costs or foregoing profit in the current period. A negative sign on the coefficient on the dummy for methyl bromide fumigation would indicate a net cost to methyl bromide fumigation.

harvest season for that crop.[17] In particular, the expected gross revenue to harvesting a crop during non-harvest season months (e.g., during the winter) is 0.[18] Thus, by incorporating the expected gross return in the payoff of function and by modeling the dynamic decision-making of growers of when and what to plant, and whether and when to fumigate, our model accounts for the biological reality of how long a crop needs to be in the ground, because a profit maximizing grower is unlikely to pull out the crop before it is ready to harvest (and therefore before he would receive the expected return), barring problems such as V. wilt or other issues that meant that crop was unhealthy.

The last crop dummy variable is equal to one if the crop chosen this month is the same as the crop planted in the previous month. The last crop dummy captures both the requirement to grow a particular crop over multiple months, as well as any tendency for a grower to choose to replant the same crop over and over again, perhaps harvest after harvest.

The value function for a long-term grower, which gives the present discounted value of the grower's entire stream of per-period payoffs at the optimum, is given by the following Bellman equation:

$$V(\mathbf{s}, \epsilon, \theta) = \max_{d \in D}(\pi(d, \mathbf{s}, \theta) + \epsilon(d) + \beta \int V(\mathbf{s}', \epsilon'; \theta) d \Pr(\mathbf{s}', \epsilon' | \mathbf{s}, \epsilon, d, \theta)), \tag{2}$$

where β is the discount factor. We set our monthly discount factor to $\beta = 0.999$.

To estimate the unknown parameters $\theta = (\theta_1, ..., \theta_{11})$, we use a nested fixed point maximum likelihood estimation technique developed by Rust (1987, 1988). We assume the observed choices are the result of the optimal decision rule $d_t = \gamma(\mathbf{s}_t, \epsilon_t)$ that solves the Bellman equation.

We assume the state variables evolve as a first-order Markov process, with a transition density given by $\Pr(\mathbf{s}_{t+1}, \epsilon_{t+1} | \mathbf{s}_t, d_t, \epsilon_t, \theta)$. Since the price variable we use is the annual

[17] On average, the length of the harvest season is less than 2 months in our data set, and equal to about 1.5 months on average for most crops. The exception are susceptible crops, which include strawberries, and which have an average harvest season length of 2.59 months. In the case of strawberries, however, strawberries are an ongoing harvest crop and therefore the more months in the harvest season it is grown, the more product can be harvested, so it is reasonable to assume that a grower may receive revenue each harvest month during which strawberries are grown. We choose not to model the grower as only receiving the revenue for his crop the first month of the harvest season, as this would not explain why growers may plant the same crop for multiple months in the harvest season. Staying in the harvest season longer sometimes yields higher revenue because it enables the grower to harvest more product or replant the crop for more harvest, both of which are better captured by having the grower receive more revenue if he stays in the harvest season longer. For similar reasons, we choose not to model the grower as only receiving the revenue for his crop the last month of the harvest season. As seen in Carroll et al. (2021), we find that the results are robust to whether we divide the marketing year average price for each crop by its average harvest season length, and therefore to whether we assume growers who plant the same crop for multiple months receive more revenue than those who plant that crop for only one month.

[18] The costs of inputs are included in the constant, which we expect to be negative.

county average, we assume that the choice of any one grower would not have a large enough effect to influence prices, and therefore that the distribution of price next period does not depend on any single grower's decisions this period; we therefore model crop prices as evolving exogenously. In particular, we estimate the transition density for each crop price as a nonparametric function of lagged values of the crop prices for all crops. The endogenous state variables (methyl bromide fumigation history, broccoli history, and last crop dummy) evolve deterministically as a function of this period's action.

As is standard in many dynamic structural models, we make the following conditional independence assumption on the transition density:

$$\Pr(\mathbf{s}_{t+1}, \epsilon_{t+1} | \mathbf{s}_t, d_t, \epsilon_t, \theta) = \Pr(\mathbf{s}_{t+1} | \mathbf{s}_t, d_t, \theta) \Pr(\epsilon_{t+1} | \theta).$$

We also assume that the choice-specific shocks are distributed multivariate extreme value.

Under these assumptions, the value function for a long-term grower given in Equation (2) can be rewritten as:

$$V(\mathbf{s}, \epsilon, \theta) = \max_{d \in D(\mathbf{s})} (\pi(d, \mathbf{s}, \theta) + \epsilon(d) + \beta V^c(\mathbf{s}, d, \theta)),$$

where $V^c(\cdot)$ is the continuation value, which is the expected value of the value function next period conditional on the state variables and action this period:

$$V^c(\mathbf{s}, d, \theta) = \int V(\mathbf{s}', \epsilon'; \theta) d \Pr(\mathbf{s}', \epsilon' | \mathbf{s}, \epsilon, d, \theta). \tag{3}$$

The choice probability for a long-term grower is given by:

$$\Pr(d | \mathbf{s}, \theta) = \frac{\exp(\pi(d, \mathbf{s}, \theta) + \beta V^c(\mathbf{s}, d, \theta))}{\sum_{\tilde{d} \in D(\mathbf{s})} \exp(\pi(\tilde{d}, \mathbf{s}, \theta) + \beta V^c(\mathbf{s}, \tilde{d}, \theta))}.$$

After obtaining the model predictions for the choice probabilities as functions of the state variables and the unknown parameters θ, the parameters θ can then be estimated using maximum likelihood. The likelihood function is a function of the choice probabilities, and therefore a function of the continuation value $V^c(\cdot)$. Solving for the parameters θ via maximum likelihood thus requires an inner fixed point algorithm to compute the continuation value $V^c(\cdot)$ as rapidly as possible and an outer optimization algorithm to find the maximizing value of the parameters θ, i.e., a fixed point calculation is nested within a maximum likelihood estimation (MLE). From Blackwell's Theorem, the fixed point is unique.

Identification of the parameters θ comes from the differences between per-period payoffs across different action choices, which in infinite horizon dynamic discrete choice models are identified when the discount factor β and the distribution of the choice-specific shocks ϵ_{it} are fixed (Abbring, 2010; Magnac and Thesmar, 2002; Rust, 1994). In particular, the parameters in our model are identified because each term in the deterministic component $\pi(\cdot)$ of the per-period payoff given in Equation (1) depends on the action d_{it} being taken at time t, and therefore varies based on the action taken; as a consequence, the parameters do not cancel out in the differences between per-period payoffs across different action choices and are therefore identified. For example, the coefficient θ_1 on the spinach dummy is identified in the difference between the per-period payoff from choosing to plant spinach and the per-period payoff from any action choice d_{it} that does not involve planting spinach.[19]

Standard errors are formed by a nonparametric bootstrap. Fields are randomly drawn from the data set with replacement to generate 100 independent panels each with the same number of fields as in the original data set. The structural model is run on each of the new panels. The standard errors are then formed by taking the standard deviation of the parameter estimates from each of the panels.

4.3 Results

The results for the long-term growers are presented in Table 2. We report our estimates for the parameters in the per-period payoff function in Equation (1). The payoffs do not have units because price is discretized and therefore no longer in dollars. Since we do not have units for payoffs, we can compare only relative payoffs and welfare.

According to the results in Table 2, the coefficient θ_1 on the spinach dummy is significant and negative, suggesting that planting spinach is undesirable for reasons that are not fully captured by its price.[20] This provides evidence that V. wilt is a problem, since it is likely due to the fact that spinach is associated with V. wilt that spinach is undesirable.[21]

The coefficient on methyl bromide in the current period is significant and negative,

[19]To identify the constant θ_{11}, we normalize the deterministic component $\pi(\cdot)$ of the per-period payoff from choosing "other" to 0.

[20]Because price is the discretized marketing average price of spinach per acre, the price measures revenue per acre, and therefore incorporates yield as well. Thus, the significant negative coefficient on the spinach dummy suggests that spinach is not desirable to plant for reasons that are not fully captured by its price, yield, or revenue per acre.

[21]One may worry that the negative coefficient on the spinach dummy is possibly also consistent with a problem in modeling where the other crops with longer crop cycles would potentially be more appealing than spinach. However, even when returns are divided by the length of season, the returns to spinach versus other crops still follow the same order. This suggests that the season length is not the driving factor behind this coefficient. We confirm in Carroll et al. (2021) that the significant negative coefficient on the spinach dummy is robust to whether we divide returns by season length.

which means there is a cost to methyl bromide that may yield future benefit to either the current crop or a future crop. The broccoli dummy coefficient is negative, which, though not significant, suggests that planting broccoli is not as desirable as planting lettuce (since the lettuce dummy has a significant positive coefficient) and requires foregoing current benefits (or incurring current costs) for future gain. The coefficient on the interaction term between lettuce and broccoli history is significant and positive, which suggests that planting broccoli is an effective control option.

The lettuce dummy has a significant positive coefficient, which means that long-term growers derive benefits from planting lettuce beyond its price, such as meeting shipper contract requirements.[22] Thus, it is desirable for growers to control V. wilt, since they benefit from planting lettuce.

The coefficient on price at the time of harvest is negative. At first blush this may appear counterintuitive, as economic theory predicts that price will have a positive effect on return. After looking further into the data, however, the reason for this result becomes more clear. Strawberries have a much higher revenue per acre than any of the vegetable crops included in this data set, on the order of $70,000 for strawberries versus $20,000 or less for some vegetable crops. Most growers concentrate on either strawberry crops or vegetable crops, so there are very few cases in the data of growers switching to strawberries from vegetable crops, even though this is what one would expect based on price alone. When strawberries are removed as an action choice in the analysis, the coefficient for price is then positive. In addition, some strawberry growers are switching to contracts in which the price plays very little role in determining their profit. They are paid a baseline amount for growing the crop and may make more money in a particularly good year, but do not bear the downside risk in a poor year.

The negative coefficient on price at the time of harvest therefore suggests that growers may be committed to previous crops and therefore do not respond to price. For example, growers may have connections and contracts that tie them to certain crops. They may have expertise or risk profiles that better suit certain crops. Perhaps some growers consider themselves vegetable growers and the cost of switching to strawberries is too high. Uncertainty related to the future of methyl bromide and its lack of suitable replacements for treating V. wilt could also play a role. Factors that may make growers less likely to switch crops are at least partially captured in our model by the last crop dummy. We hope to explore these issues further in future work.

The coefficient on the last crop dummy is significant and positive, which suggests that

[22]In the model, returns are estimated at the county level, so although contracts can and do specify prices, we expect the return used in the model to be exogenous to contracting decisions.

growers are committed to previous crops, which is also consistent with the hypothesis that growers do not switch crops often and therefore are less responsive to price.

The total average effects of the variables that appear in more than one term of the per-period payoff function are reported at the bottom of Table 2. The spinach dummy has a total average effect that is significant and negative on net, which provides evidence that V. wilt is a problem, even if the undesirability of spinach is mitigated by having methyl bromide history and/or broccoli history.

The lettuce dummy has a significant and positive total average effect, which means that long-term growers derive benefits from planting lettuce beyond its price, and that the benefits of lettuce are enhanced in the presence of control options such as methyl bromide history and/or broccoli history.

Methyl bromide history has a positive total average effect, which, though not significant, suggests that methyl bromide may be an effective control option. Similarly, broccoli history has a significant and positive total average effect, suggesting that planting broccoli is an effective control option.

In using a marketing year average price for each crop to represent growers' expectations about prices for each year, we assume that growers have rational expectations about the price. Instead of rational expectations about price, another possible assumption is that growers' best guess for this year's price is last year's price. The results are robust to whether we use lagged prices rather than current prices (Carroll et al., 2021).

We choose not to model the grower as only receiving the revenue for his crop the first month of the harvest season, as this would not explain why growers may plant the same crop for multiple months in the harvest season. Staying in the harvest season longer sometimes yields higher revenue because it enables the grower to harvest more product or replant the crop for more harvest, both of which are better captured by having the grower receive more revenue if he stays in the harvest season longer. For similar reasons, we choose not to model the grower as only receiving the revenue for his crop the last month of the harvest season. As seen in Carroll et al. (2021), we find that the results are robust to whether we divide the marketing year average price for each crop by its average harvest season length, and therefore to whether we assume growers who plant the same crop for multiple months in a harvest season receive more revenue than those who plant that crop for only one month in the harvest season.

We use our parameter estimates to calculate the normalized average welfare per grower per month. The welfare is calculated as the present discounted value of the entire stream of payoffs evaluated at the parameter values, summed over all long-term growers, then divided by the number of grower-months. The average welfare per grower per month is then normalized to 100.

The standard errors for the welfare values are calculated using the parameter estimates from each of 100 bootstrap samples. For each of the 100 bootstrap samples, we calculate the average welfare per grower per month using the parameter estimates from that bootstrap sample, and normalize it. The standard error of the normalized welfare is the standard deviation of the normalized welfare over all 100 bootstrap samples.

The welfare results are presented at the bottom of Table 2.

5 Evaluating the Externality

We now consider the externality between spinach seed companies and lettuce growers. Seed companies maximize profits subject to international export and import regulations as well as local seed testing and cleaning requirements. The seed companies impose an externality on growers if they sell contaminated seed into the region. To analyze the externality between spinach seed companies and lettuce growers, we introduce a representative seed company who can choose whether and how much to test and clean spinach seeds to reduce the level of microsclerotia.

For this paper, we define integration as the incorporation of a seed company and one or more growers. This is vertical integration because the seed companies supply inputs to the growers. [23] Owing to asymmetric information, the price signal for tested and cleaned seed versus contaminated seed is weak. Since cleaning seed is costly, profit-maximizing seed companies will not clean or test seeds, resulting in an externality. In a perfect market, price signals would be clearer, transaction costs lower, and contracting more complete, all of which would eliminate the externality. However, as we described above, this is not currently happening in Monterey County. To simulate the effects of internalizing this externality, we adapt the methodology of Brewin et al. (2014).

Ideally, we would be able to use the profit and cost functions for seed companies to estimate the model. Unfortunately, such data are proprietary and unavailable to us. As a proxy, we estimate different types of cost functions for seed cleaning based on discussions with people in the industry.

The connection between growers and the seed company comes through the coefficient θ_1 on the spinach dummy in the per-period payoff in our dynamic structural model of growers' decisions. The spinach dummy coefficient captures the effects of spinach on payoffs that are

[23] We defer considerations of horizontal integration and market power to future work.

not internalized in spinach price. We assume the seed company controls the spinach dummy coefficient, since its actions affect the contamination level of spinach seeds and therefore how spinach affects microsclerotia, which in turn affects lettuce growers. The cleaner the spinach seeds, the less negative the spinach dummy coefficient, and the higher the benefits to the grower. However, the seed company incurs costs in order to test and clean the spinach seeds and make the spinach dummy coefficient less negative. Since the seed company's choice of spinach dummy coefficient affects the grower's choices and payoffs, there is an externality between seed companies and growers.

We use the estimated parameters from our dynamic structural model in Section 4 to simulate how different values of the spinach dummy coefficient that the seed company can choose will affect the choices and payoffs of growers. According to the results of the dynamic structural model for growers in Table 2, the coefficient θ_1 on the spinach dummy in the owner all parameters in -1.1311.

We consider the set of twenty-one evenly spaced values of the spinach dummy coefficient θ_1 between -2.00 and 0.00. A spinach dummy coefficient θ_1 of -2.00 represents an even greater negative effect from spinach seeds (and therefore microsclerotia) on grower payoffs. A spinach dummy coefficient θ_1 equal to 0.00 implies that the effect of spinach on grower payoffs (aside from price effects) is neutral and not economically significant. In other words, the seed company has tested and cleaned seed to the point where V. wilt is no longer an economically damaging disease for lettuce.

For each possible value of the spinach dummy coefficient θ_1, we run 100 simulations of the choices and payoffs that would arise if the spinach dummy coefficient were equal that values. For each of the 100 simulations, we calculate the average grower welfare per month, which is the total welfare divided by the number of grower-months. Then, for each possible value of the spinach dummy coefficient, we average the grower welfare per month over the 100 simulations using that value of the spinach dummy coefficient. We then calculate the average additional benefits to the grower for each value of the spinach dummy coefficient by subtracting the average grower welfare per month when the spinach dummy coefficient θ_1 is -2.00 from the average grower welfare per month at that value of the spinach dummy coefficient. In other words, we normalize the average grower welfare per month when the spinach dummy coefficient θ_1 is -2.00 to 0.

Standard errors are calculated using a nonparametric bootstrap. In particular, we calculate the standard errors of the (additional) grower benefits using the parameter estimates from each of twenty-five bootstrap samples. For each of the twenty-five bootstrap samples, we run twenty-five simulations using the parameter estimates from that bootstrap sample.[24] The standard error of the (additional) grower benefits is the standard deviation of the respective statistic over all twenty-five bootstrap samples.

Figure 5 plots the (additional) benefits to a grower per month, averaged over 100 simulations as a function of the coefficient θ_1 on the spinach dummy. As expected, the additional benefits to the growers are the highest when the coefficient on spinach is equal to zero. As the coefficient on spinach becomes more negative, the additional benefits to growers decline.

For the seed company model, we need a measure of the cost that the seed company incurs per unit change in the spinach dummy coefficient θ_1 per grower-month, i.e., how much it costs the seed company to reduce microsclerotia by any given amount for one grower-month. We spoke with several seed company representatives and others knowledgeable about the spinach seed industry. Opinions varied regarding the functional form of the cost function. Costs may increase exponentially (i.e., eliminating most of the microsclerotia is relatively cheap, but cleaning all of the microsclerotia is very expensive or impossible). For example, with hot water treatments, hotter water and longer exposure are more effective for treating microsclerotia, but also increase the risk that seeds will not germinate (du Toit, 2005; Subbarao, personal communication, 2014). The functional form of the cost function depends on a complicated set of factors.

Gerard Denny at Incotec stated that as a general statement about physical disinfection, cost is relatively flat across different levels of infestation. The process cost for chemical treatment is also flat, but chemical treatment rates and regulation compliance may cause increasing treatment costs. Mary Zischke of the California Leafy Greens Research Program also mentions that up to 30% of spinach grown now is organic, which further complicates seed treatment and cleaning.

Due to the potential differences in the functional form for the seed company costs, we consider two different models: an exponentially increasing cost function:

$$C(\theta_1) = c_0(\exp(c_1\theta_1) - \exp(-c_1 2)), \tag{4}$$

where $c_0 = \{1, 2, 3\}$ and $c_1 = \{0.01, 0.03, 0.05\}$; and a log cost function:

$$C(\theta_1) = c_2 \log(c_3(2 + \theta_1) + 1), \tag{5}$$

[24] Constraints on computational time preclude us from running the twenty-five simulations per bootstrap sample for more than twenty-five bootstrap samples per scenario. When we calculated the standard error for welfare for scenario 1 using 100 bootstrap samples instead of twenty-five bootstrap samples, the value of the standard errors were similar using both twenty-five bootstrap samples and 100 bootstrap samples.

where $c_2 = \{1, 2, 3\}$ and $c_3 = \{0.03, 0.05, 0.07\}$.

The exponential cost function represents the idea that cleaning seeds partially may be relatively cheap, but ensuring that they are entirely free of microsclerotia is extremely costly to impossible. Hot water treatment effectively removes microsclerotia from the seed coat, but may not remove microsclerotia from the interior of the seed, especially without affecting germination rates. Likewise, for any chemical seed treatment, removing additional microsclerotia would require a higher chemical concentration, thus increasing costs.

By contrast, the log function represents a case in which seed cleaning and testing costs are relatively flat. If low levels of microsclerotia are not a concern, then cleaning seeds to an acceptable level may be relatively inexpensive on the margin.

For each of the two types of cost function, we run nine versions with different parameters for c_0, c_1, c_2, and c_3, respectively. For each, we simulate the model across the twenty-one different possible coefficients on the spinach dummy variable. The cost to the seed company is normalized to zero when the coefficient is equal to -2.00, which represents seed that is even more contaminated than the current status quo.

We estimate the spinach seed company's cost to testing and cleaning spinach seeds in order to reduce the level of microsclerotia, and compare the spinach seed company's cost to the grower's benefits. We use our estimates of the grower's benefits from and spinach seed company's costs to testing and cleaning spinach seeds to determine the welfare-maximizing level of seed testing and cleaning, where welfare is defined as the additional benefits to the grower minus the costs to the seed company.

Figure 6 graphs the cost equations for the nine different combinations of c_0 and c_1 for the exponential cost function in Equation (4). Without detailed cost data from individual seed companies, it is difficult to conclude which cost estimates are most realistic. If seed treatment costs are quite high, as is the case when $c_0 = 3$ and $c_1 = 0.05$, then costs always exceed benefits and the seed company, even if vertically integrated with a set of growers, has no incentive to clean seeds and would in fact be willing to sell seeds that are even more contaminated than in the current status quo. In other cases, when the cost function slope is less steep, benefits to the integrated firm are highest when the spinach coefficient is equal to zero and microsclerotia are economically unimportant. If this is the case, high transaction costs may be what is currently preventing an efficient outcome.

Likewise, Figure 7 graphs the cost equations for the nine different combinations of c_2 and c_3 for the log cost function in Equation (5). As in the previous figure, if costs are more realistically represented by the high cost functions shown here, then the status quo is an efficient equilibrium, unfortunately for lettuce growers. Otherwise, if seed cleaning is less costly, these simulations show that it is possible for seed companies and growers to reach a more economically optimal equilibrium, barring transaction costs.

We compare the status quo, in which growers and seed companies are independent, to a vertically integrated industry, in which one company produces spinach seeds, as well as spinach, lettuce, and other crops. The vertically integrated industry would internalize the externality between growers and seed companies, and would choose the welfare-maximizing level of seed testing and cleaning.

For each type of cost function, we find the value of the coefficient θ_1 on the spinach dummy (among the twenty-one possible evenly spaced values of the spinach dummy coefficient θ_1 between -2.00 and 0.00) that maximizes welfare, which we define as the additional benefits to growers minus cost to the seed company. The welfare-maximizing value of the coefficient θ_1 on the spinach dummy is the socially optimal value of the coefficient on the spinach dummy, and reflects the socially optimal amount of testing and cleaning by the seed company if the externality is internalized.

The socially optimal value of the coefficient on the spinach dummy, which reflects the socially optimal amount of testing and cleaning by the seed company if the externality is internalized, represents the scenario in which a seed company and one or more growers are integrated as one firm. As one profit maximizing unit, the integrated firm will choose a set of actions (crop and fumigation decisions) as well as the spinach dummy parameter to maximize welfare, defined as the additional benefits to growers minus the cost of testing and cleaning seeds.

Tables 3 and 4 show the socially optimal value of the spinach coefficient θ_1, as well as the (additional) benefits to growers, costs to the seed company, and welfare that arise under the socially optimal value of the spinach coefficient, for each set of cost parameters for the two different cost functions. In more than half of the cases, the socially optimal spinach dummy coefficient is greater than (i.e., less negative than) the actual coefficient of -1.1311, which means that the socially optimal amount of spinach seed testing and cleaning is more than what arises when the externality is not internalized (the status quo).

In many cases, the socially optimal spinach dummy coefficient is 0.00 and not significant, which means that at the social optimum, after controlling for spinach price, planting spinach should not have any significant negative effect on grower payoffs. In these cases, it is socially optimal for the seed company to test and clean spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price. When the socially optimal spinach dummy coefficient is 0.00 and not significant, welfare is significant and positive, which means that testing and cleaning spinach seeds this thoroughly not only maximizes welfare, but also that the welfare gains acheived from doing so are significant and positive.

Another case in which the socially optimal amount of spinach seed testing and cleaning is more than what arises under the status quo is when the socially optimum spinach dummy coefficient is -1.00 and significant. In this case, both benefits and costs are significant and positive, but welfare is not significant. Thus, even though a socially optimum spinach dummy coefficient of -1.00 requires more testing and cleaning than the status quo, there is no significant welfare gain.

In other cases, we find that vertical integration would not lead to more testing and cleaning of seeds than arises in the status quo. When the socially optimal spinach dummy coefficient is significant and requires less testing and cleaning than the status quo, welfare is not significant, which means that there is no significant welfare gain in instances when the social optimum requires less cleaning than the status quo.

Thus, we find that in more than half of the cases, the socially optimal amount of spinach seed testing and cleaning is more than what arises when the externality is not internalized (the status quo). Significant welfare gains arise only when the seed company tests and cleans the spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price. In other cases, even though it maximizes welfare, the socially optimal amount of spinach seed testing and cleaning does not yield any welfare gains.

Between Tables 3 and 4, depending on the type of cost function and the parameters of the cost function, there are two socially optimal coefficients on the spinach dummy that are greater than (i.e., less negative than) the actual coefficient of -1.1311, meaning that the socially optimal amount of spinach seed testing and cleaning is more than what arises when the externality is not internalized (the status quo): 0.00 and -1.00. We use these two socially optimal spinach dummy coefficients to simulate the crop choices of long-term growers when the spinach seed company engages in the socially optimal amount of spinach seed testing and cleaning.

Standard errors and 95% confidence intervals are calculated using a nonparametric bootstrap. In particular, we calculate the standard errors of the simulation statistics (e.g., mean fraction of grower-months in each action) using the parameter estimates from each of twenty-five bootstrap samples. For each of the twenty-five bootstrap samples, we run twenty-five simulations using the parameter estimates from that bootstrap sample.[25] The standard

[25]Constraints on computational time preclude us from running the twenty-five simulations per bootstrap sample for more than twenty-five bootstrap samples per scenario. When we calculated the standard error for welfare for scenario 1 using 100 bootstrap samples instead of twenty-five bootstrap samples, the value of

error of the simulation statistics (e.g., mean fraction of grower-months in each action) is the standard deviation of the respective statistic over all twenty-five bootstrap samples.

Figures 8-9 simulate growers crop choices for each of the two socially optimal spinach dummy coefficients that require more spinach seed testing and cleaning than the status quo. The fraction of grower-months planted to lettuce is higher under the socially optimal spinach dummy coefficients of 0.00 and -1.00 than they are in the actual data in Figure 2. Thus, when the spinach seed company internalizes the externality and engages in the socially optimal amount of seed testing and cleaning, growers plant more lettuce, likely because V. wilt then becomes less of a problem.

Figures 10-11 show the fraction of grower-months in each action type by month of year. Compared to Figure 3, which shows the actual data, the simulations under the socially optimal spinach dummy coefficients of 0.00 and -1.00 show more grower-months planted to lettuce, especially in the last months of the year when the actual data consists more of susceptible and other crops. Figures 12-13 show the fraction of grower months in each action type by year. Compared to Figure 4, which shows the actual data, the simulations under the socially optimal spinach dummy coefficients of 0.00 and -1.00 show more grower-months planted to lettuce and fewer grower-months planted to other crops. Thus, when the spinach seed company internalizes the externality and engages in the socially optimal amount of seed testing and cleaning, growers plant more lettuce, likely because V. wilt then becomes less of a problem.

6 Conclusion

Due to V. wilt, a supply chain externality arises between companies selling spinach seed and growers growing lettuce. Although testing or cleaning seeds may prevent *Verticillium dahliae* from being introduced into a field, spinach seed companies may not have an incentive to test or clean spinach seeds, as they do not internalize the costs that infected spinach seeds impose on growers. In the absence of integration, seed companies and lettuce growers are unable to achieve a potentially more efficient equilibrium solution on their own, as contracting and price signals do not adequately internalize the externality, and as growers lack bargaining power in negotiating with seed companies.

In this paper, we analyze the externality between growers and seed companies. In our model, the seed company controls the spinach dummy coefficient, which captures the effects of spinach on the grower's per-period payoffs that are not internalized in spinach price, since

the standard errors were similar using both twenty-five bootstrap samples and 100 bootstrap samples.

the seed company's actions affect the contamination level of spinach seeds and therefore how spinach affects microsclerotia, which in turn affects lettuce growers.

We calculate the benefits to growers from testing and cleaning spinach seed by simulating growers' optimal decisions and welfare using different values for the spinach dummy coefficient. As expected, we find that benefits to growers are the highest when the spinach dummy coefficient is equal to zero (i.e., the seed company tests and cleans the spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price) and decrease as the spinach dummy coefficient increases in absolute value (i.e., as less testing and cleaning is done).

We then estimate the spinach seed company's cost to testing and cleaning spinach seeds in order to reduce the level of microsclerotia, and compare the spinach seed company's cost to the grower's benefits. Because seed cleaning cost data are not available, we use several functional forms and parameters to estimate potential cost functions. We also determine the welfare-maximizing level of seed testing and cleaning.

We compare the status quo, in which growers and seed companies are independent, to a vertically integrated industry, in which one company produces spinach seeds, as well as spinach, lettuce, and other crops. The vertically integrated industry would internalize the supply chain externality between growers and seed companies, and would choose the welfare-maximizing level of seed testing and cleaning.

We find that in more than half of the cases, the socially optimal amount of spinach seed testing and cleaning is more than what arises when the externality is not internalized (the status quo). Significant welfare gains arise only when the seed company tests and cleans the spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price. In other cases, even though it maximizes welfare, the socially optimal amount of spinach seed testing and cleaning does not yield any welfare gains.

Thus, depending on the functional form and parameters used to estimate seed company cost, the vertically integrated firm may choose not to test and clean seeds at all, may partially test and clean the seeds, or may test and clean seeds fully. In some cases, we find that vertical integration would not lead to more testing and cleaning of seeds than arises in the status quo. In most cases, however, vertical integration does lead to more testing and cleaning of seeds.

In the cases in which the social optimum would require more spinach seed testing and cleaning than the status quo, when the spinach seed company internalizes the externality and engages in the socially optimal amount of seed testing and cleaning, growers plant more lettuce, likely because V. wilt then becomes less of a problem.

We find that a cooperative solution would increase welfare, and in most cases, a cooperative solution would require that the spinach seed company engage in more spinach seed testing and cleaning than in the status quo. In particular, significant welfare gains arise only when the seed company tests and cleans the spinach seeds so thoroughly that planting spinach does not have any significant negative effect on grower payoffs after controlling for spinach price. Determining who pays for cleaning and testing the seed, or for future advances such as resistant varieties or replacement fumigants for methyl bromide, and determining how to divide the joint surplus are still complicated issues, but, nevertheless, cooperation among the different players can increase social welfare.

Our work regarding the seed company and grower externality sheds light on how treatment of spinach seeds could potentially reduce externalities between seed companies and growers.

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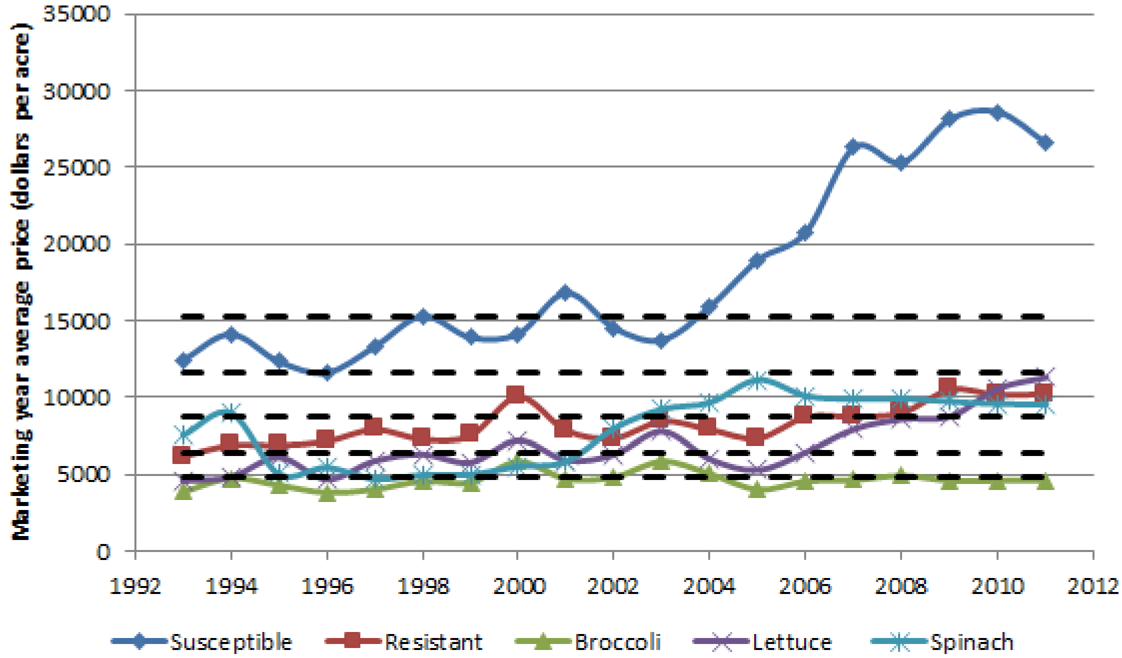
Figure 1

Marketing year average prices per acre



Note: Black dashed lines delineate the bins used to discretize the marketing year average price.

Table 1
Summary statistics for state variables

	Mean	Std. Dev.	Minimum	Maximum
Spinach dummy	0.0285	0.1665	0	1
Methyl bromide today dummy	0.0033	0.0577	0	1
Broccoli dummy	0.0606	0.2385	0	1
Lettuce *Methyl bromide history	0.0229	0.1602	0	3
Lettuce *Broccoli history	1.1709	1.8277	0	12
Spinach *Methyl bromide history	0.0015	0.0431	0	2
Spinach *Broccoli history	0.0397	0.3701	0	10
Lettuce today dummy	0.6379	0.4806	0	1
Susceptible price*Susceptible harvest	5.0660	1.4914	0	6
Resistant price*Resistant harvest	1.8748	1.6125	0	4
Broccoli price*Broccoli harvest	1.1742	0.5082	0	2
Lettuce price*Lettuce harvest	1.9552	1.1004	0	4
Spinach price*Spinach harvest	2.5268	1.4709	0	4

Notes: Number of observations: 25,789. For each crop, the harvest month dummy variable for that crop is equal to one in months during which that crop may be harvested, and zero in months during which that crop is not harvested (i.e., winter months for most crops).

Figure 2
Actual fraction of grower-months in each action

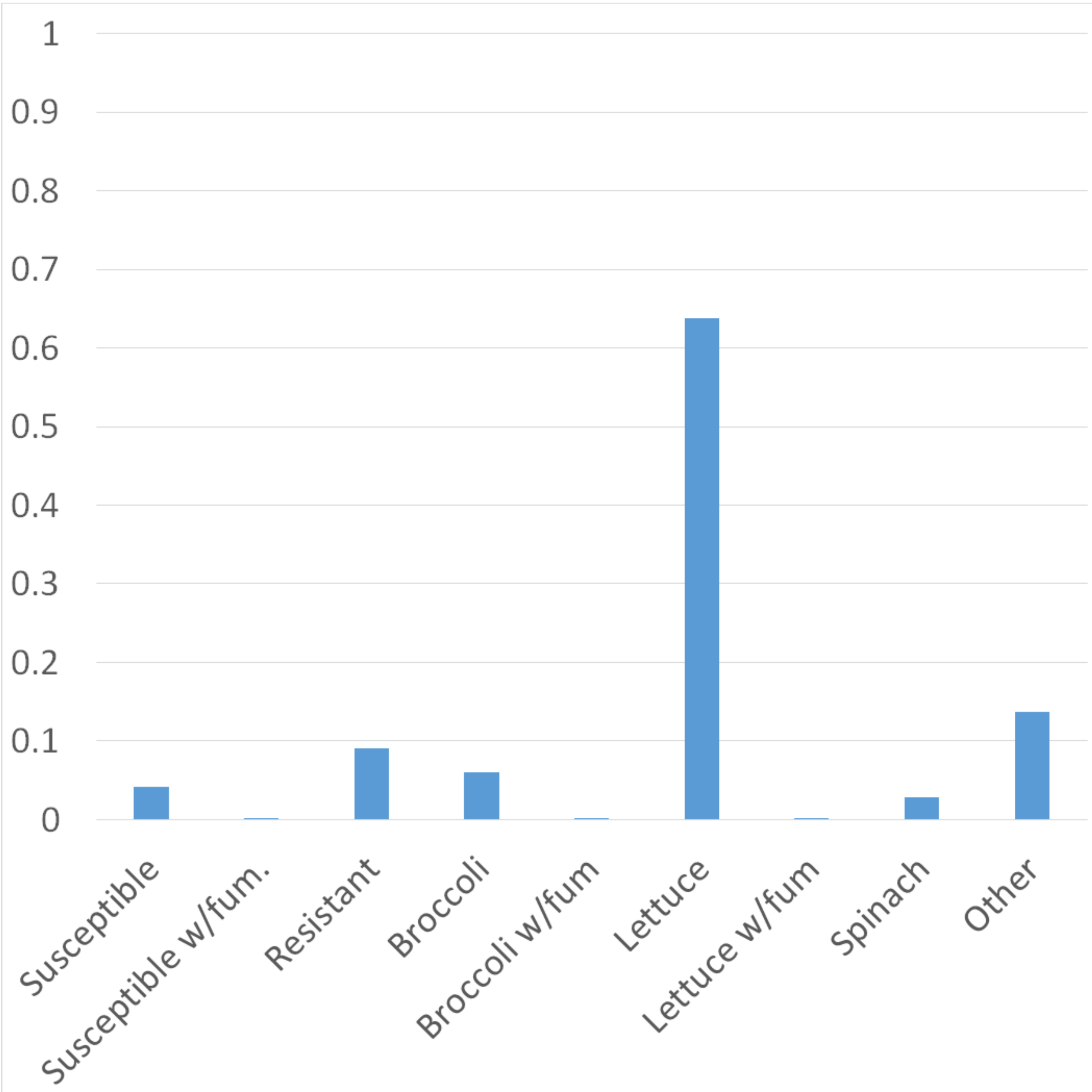


Figure 3
Fraction of grower-months in each action type by month of year

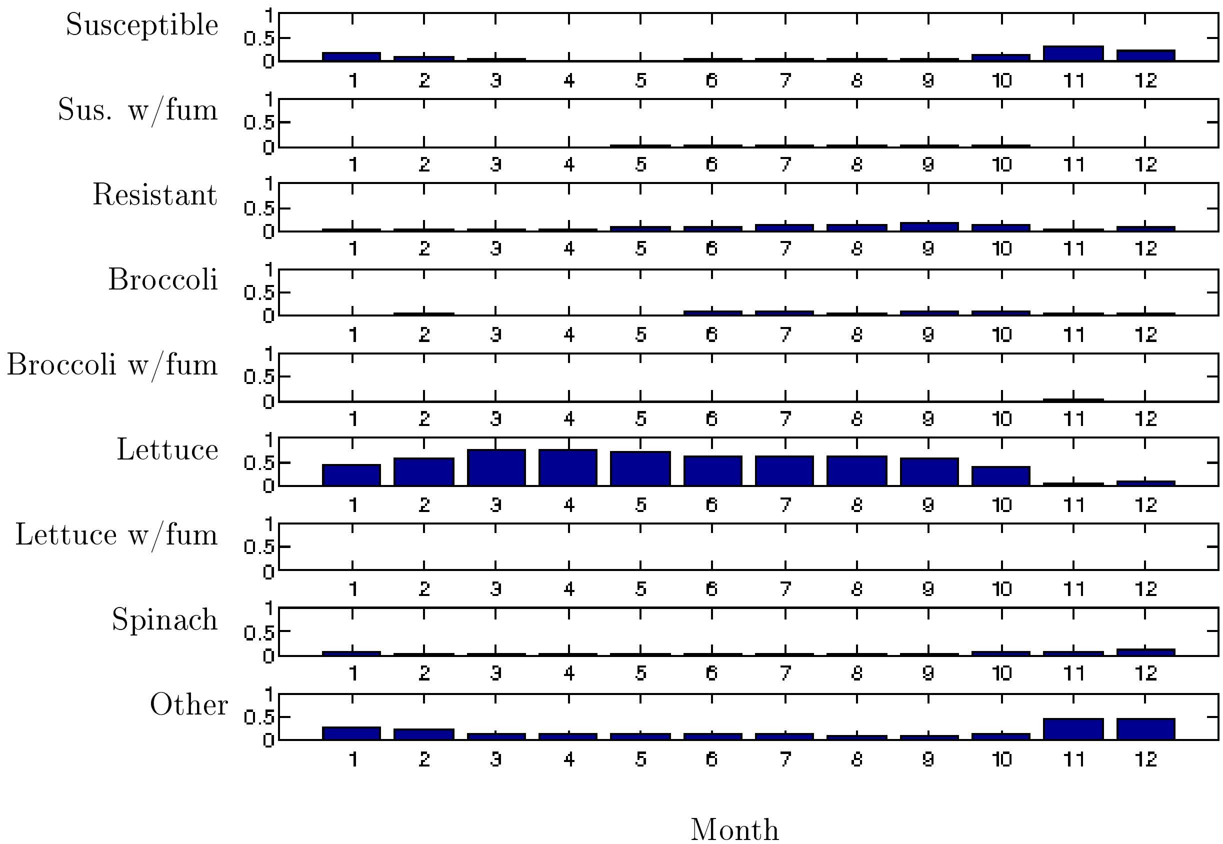


Figure 4
Actual fraction of grower-months for each action type by year

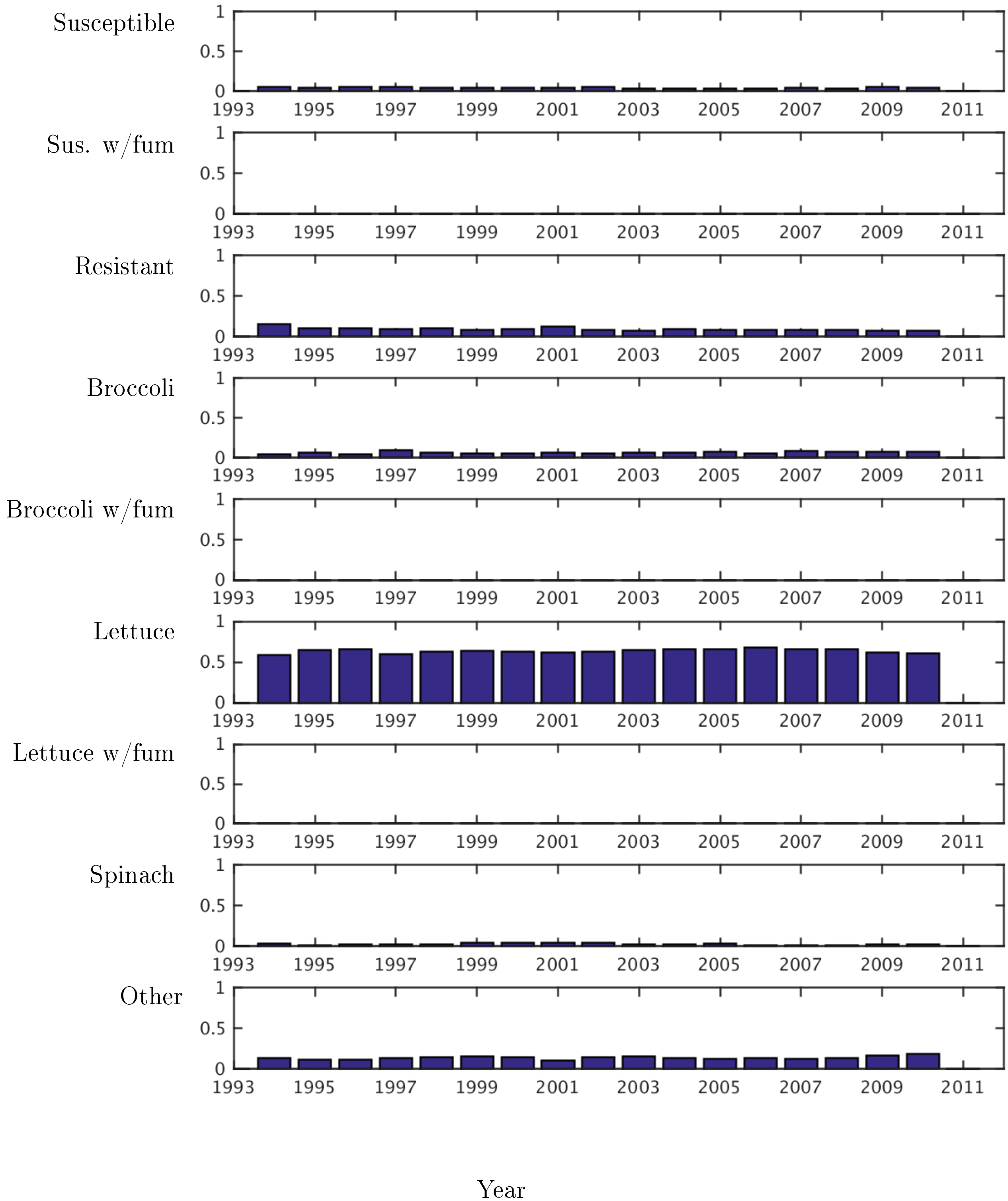
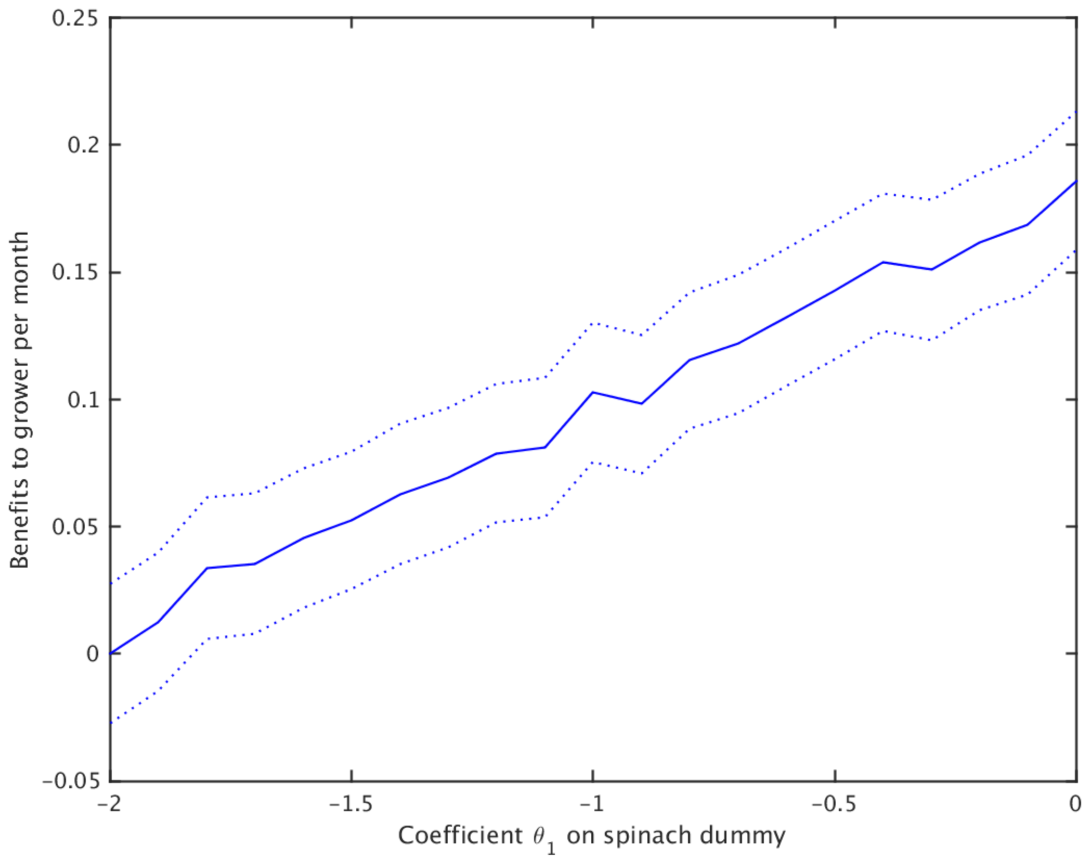


Table 2
Results for long-term growers

	(1)
Coefficients in the per-period payoff function on:	
Spinach dummy	-1.1311^{***}
	(0.2981)
Methyl bromide dummy	-6.0705^{***}
	(0.064)
Broccoli dummy	-0.332
	(0.2035)
Lettuce dummy*Methyl bromide history	0.3717
	(0.4648)
Lettuce dummy*Broccoli history	0.3682^{***}
	(0.0605)
Spinach dummy*Methyl bromide history	0.026
	(0.1956)
Spinach dummy*Broccoli history	0.2643
	(0.4769)
Lettuce dummy	1.4346^{***}
	(0.1817)
Price*Harvest month dummy	-0.1585^{***}
	(0.0414)
Last crop dummy	21.2161^{***}
	(1.0463)
Constant	-1.1482^{***}
	(0.3027)
Total average effects on per-period payoff of:	
Spinach dummy	-1.1206^{***}
	(0.2987)
Lettuce dummy	1.4498^{***}
	(0.1817)
Methyl bromide history	0.2378
	(0.2968)
Broccoli history	0.2424^{***}
	(0.0409)
Grower welfare (per grower-month)	100^{***}
	(5.0957)
Number of observations	25,761

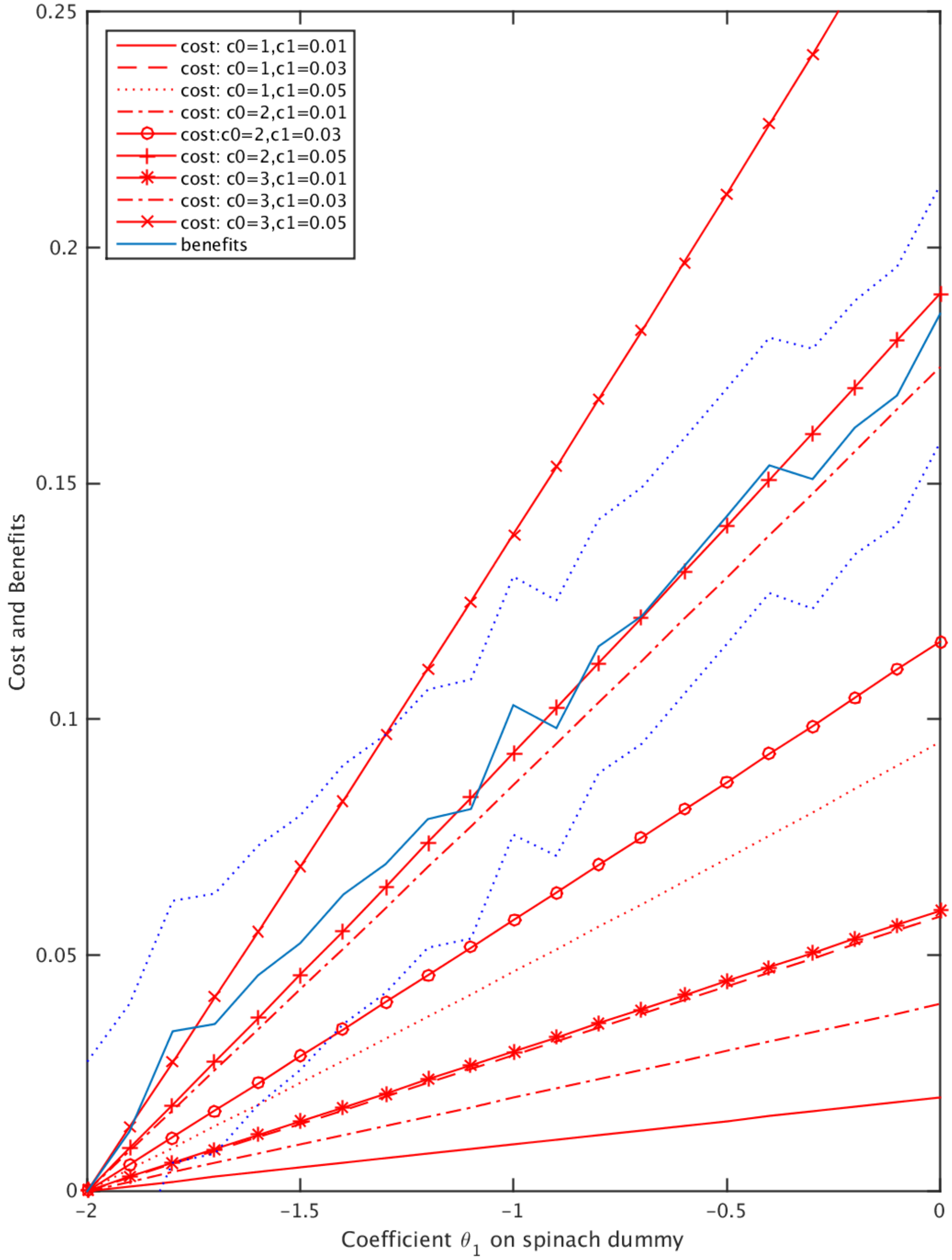
Notes: Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level, † 10% level.

Figure 5
Normalized average per-month (per-period) additional benefits for a grower for differing spinach dummy coefficient values



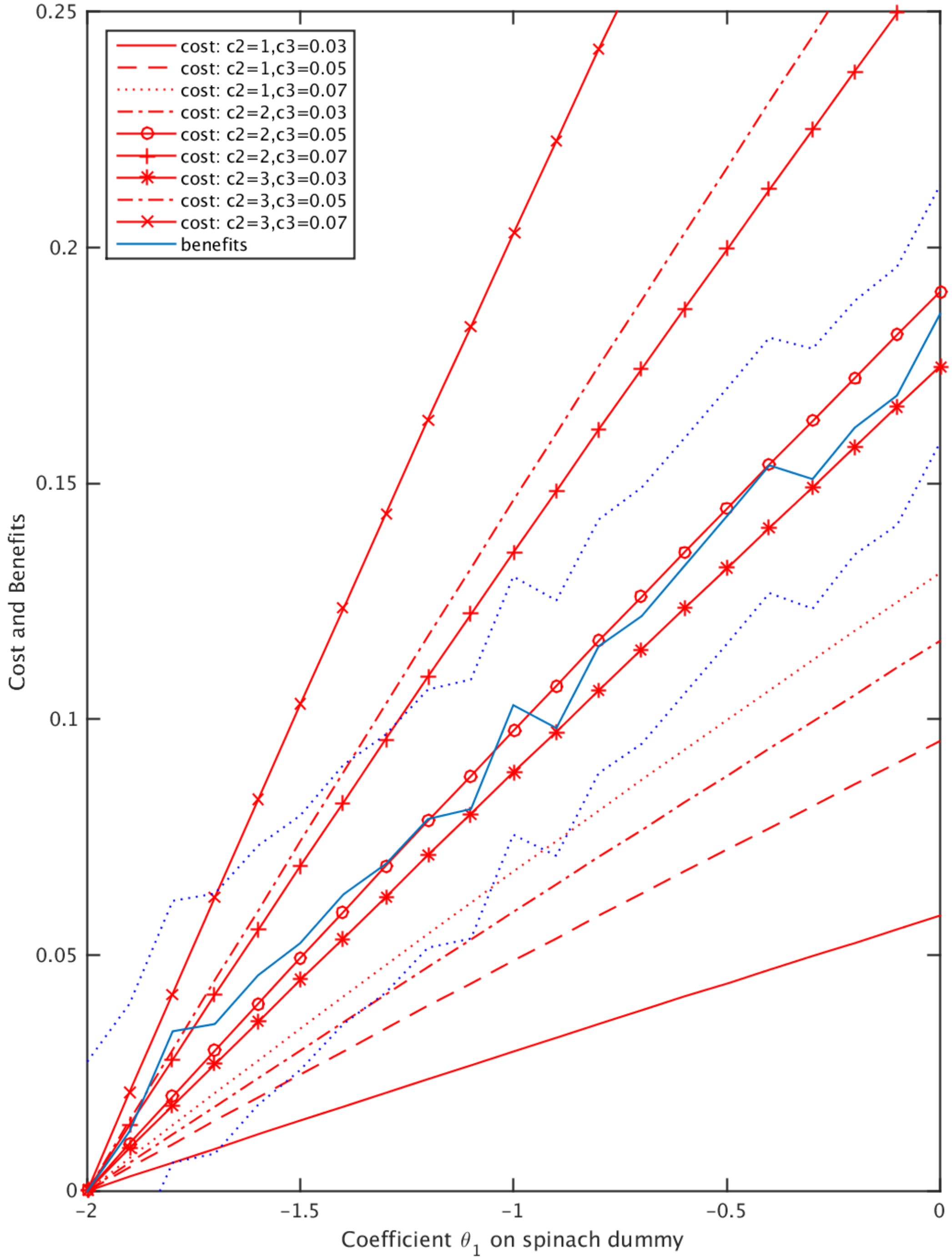
Notes: Benefits are averaged over 100 simulations. Dotted blue lines indicate the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 6
Exponential cost function and grower benefits: $C(\theta_1) = c_0(\exp(c_1\theta_1) - \exp(-c_1 2))$



Notes: Benefits are averaged over 100 simulations. Dotted blue lines indicate the 95% confidence interval for benefits, which is calculated using a nonparametric bootstrap.

Figure 7
Log cost function and grower benefits: $C(\theta_1) = c_2 \log(c_3(2 + \theta_1) + 1)$



Notes: Benefits are averaged over 100 simulations. Dotted blue lines indicate the 95% confidence interval for benefits, which is calculated using a nonparametric bootstrap.

Table 3
Optimal spinach dummy coefficient: Exponential cost function $C(\theta_1) = c_0(\exp(c_1\theta_1) - \exp(-c_1 2))$

c_0	c_1	Socially optimal coefficient θ_1 on spinach dummy	Benefits	Costs	Welfare
1	0.01	0.00	0.1859***	0.0198***	0.1661***
		(0.5188)	(0.0273)	(0.0036)	(0.0273)
1	0.03	0.00	0.1859***	0.0582***	0.1277***
		(0.5188)	(0.0273)	(0.0107)	(0.0273)
1	0.05	0.00	0.1859***	0.0953***	0.0907***
		(0.5188)	(0.0273)	(0.0178)	(0.0274)
2	0.01	0.00	0.1859***	0.0396***	0.1463***
		(0.5188)	(0.0273)	(0.0072)	(0.0273)
2	0.03	0.00	0.1859***	0.1165***	0.0694*
		(0.5188)	(0.0273)	(0.0214)	(0.0274)
2	0.05	-1.80***	0.0338	0.0182	0.0156
		(0.162)	(0.0278)	(0.0911)	(0.0274)
3	0.01	0.00	0.1859***	0.0594***	0.1265***
		(0.5188)	(0.0273)	(0.0107)	(0.0273)
3	0.03	-1.00*	0.1029***	0.0860*	0.0168
		(0.5188)	(0.0273)	(0.0438)	(0.0274)
3	0.05	-1.80***	0.0338	0.0273	0.0065
		(0.3697)	(0.0278)	(0.1366)	(0.0274)

Notes: Standard errors in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level, † 10% level.

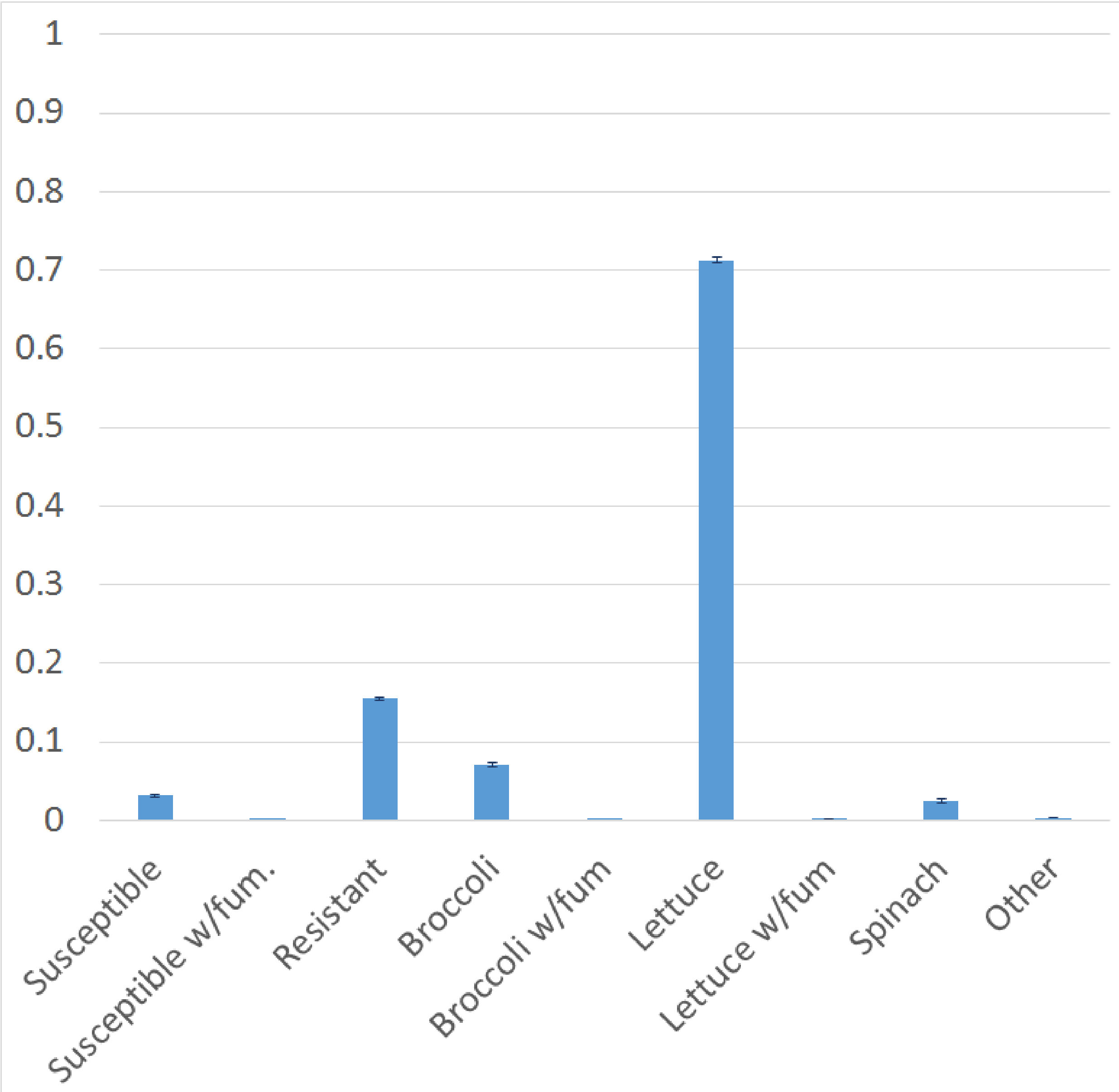
Table 4

Optimal spinach dummy coefficient: Log cost function $C(\theta_1) = c_2 \log(c_3(2 + \theta_1) + 1)$

c_2	c_3	Socially optimal coefficient θ_1 on spinach dummy	Benefits	Costs	Welfare
1	0.03	0.00	0.1859***	0.0583***	0.1276***
		(0.5188)	(0.0273)	(0.0035)	(0.0273)
1	0.05	0.00	0.1859***	0.0953***	0.0906***
		(0.5188)	(0.0273)	(0.0102)	(0.0274)
1	0.07	0.00	0.1859***	0.1310***	0.0549*
		(0.5188)	(0.0273)	(0.0164)	(0.0274)
2	0.03	0.00	0.1859***	0.1165***	0.0694*
		(0.5188)	(0.0273)	(0.0070)	(0.0274)
2	0.05	-1.80***	0.0338	0.0199	0.0139
		(0.3162)	(0.0278)	(0.0554)	(0.0274)
2	0.07	-1.80***	0.0338	0.0278	0.0059
		(0.3697)	(0.0278)	(0.0904)	(0.0274)
3	0.03	-1.80***	0.0338	0.0179	0.0158
		(0.5188)	(0.0278)	(0.0283)	(0.0274)
3	0.05	-1.80***	0.0338	0.0299	0.0039
		(0.3697)	(0.0278)	(0.0831)	(0.0274)
3	0.07	-2.00***	0.0000	0.0000	0.0000
		(0.1414)	(0.0275)	(0.1345)	(0.0274)

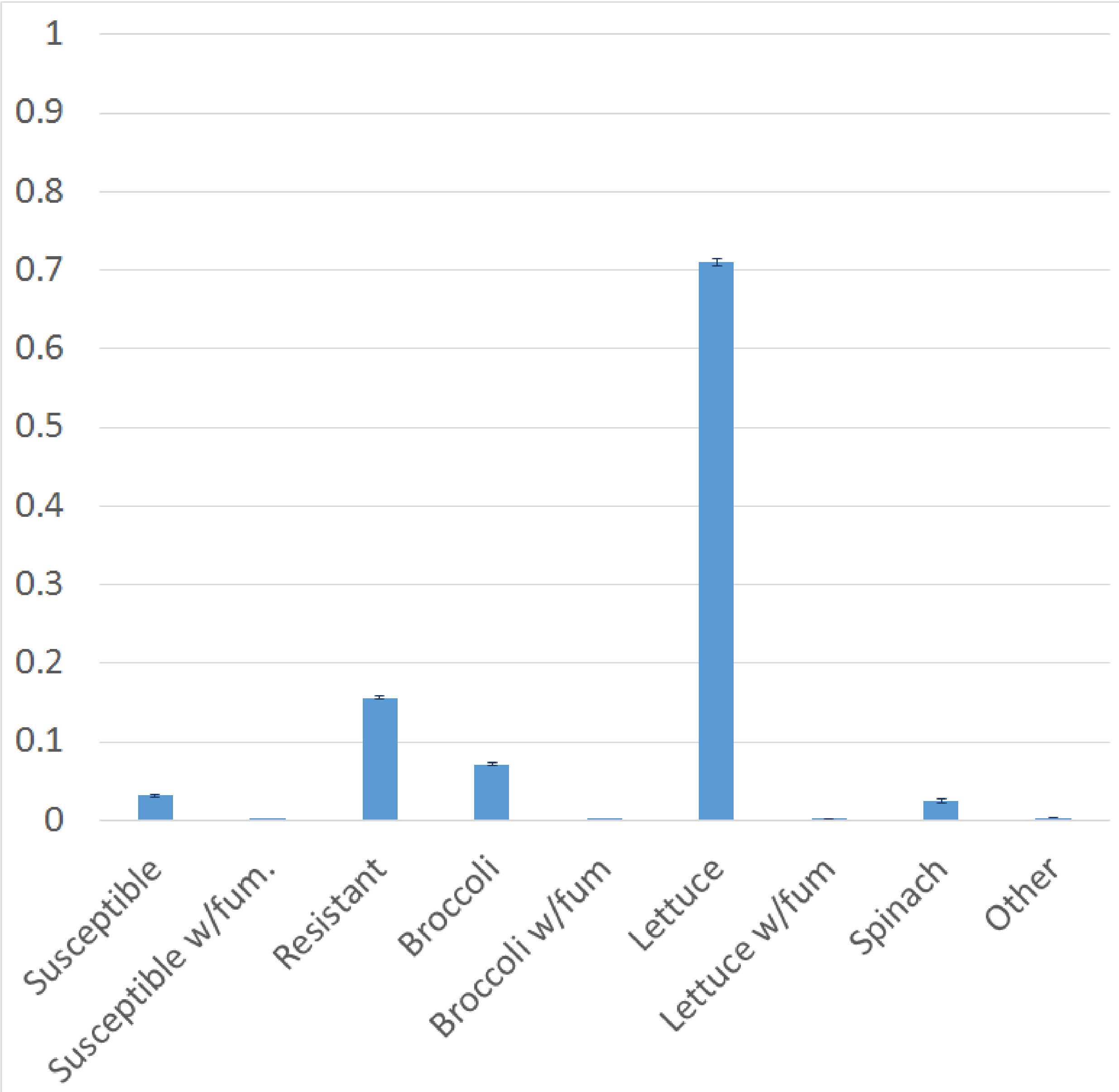
Notes: Standard errors in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level, † 10% level.

Figure 8
Simulated mean fraction of grower-months in each action when spinach dummy coefficient θ_1 equals 0



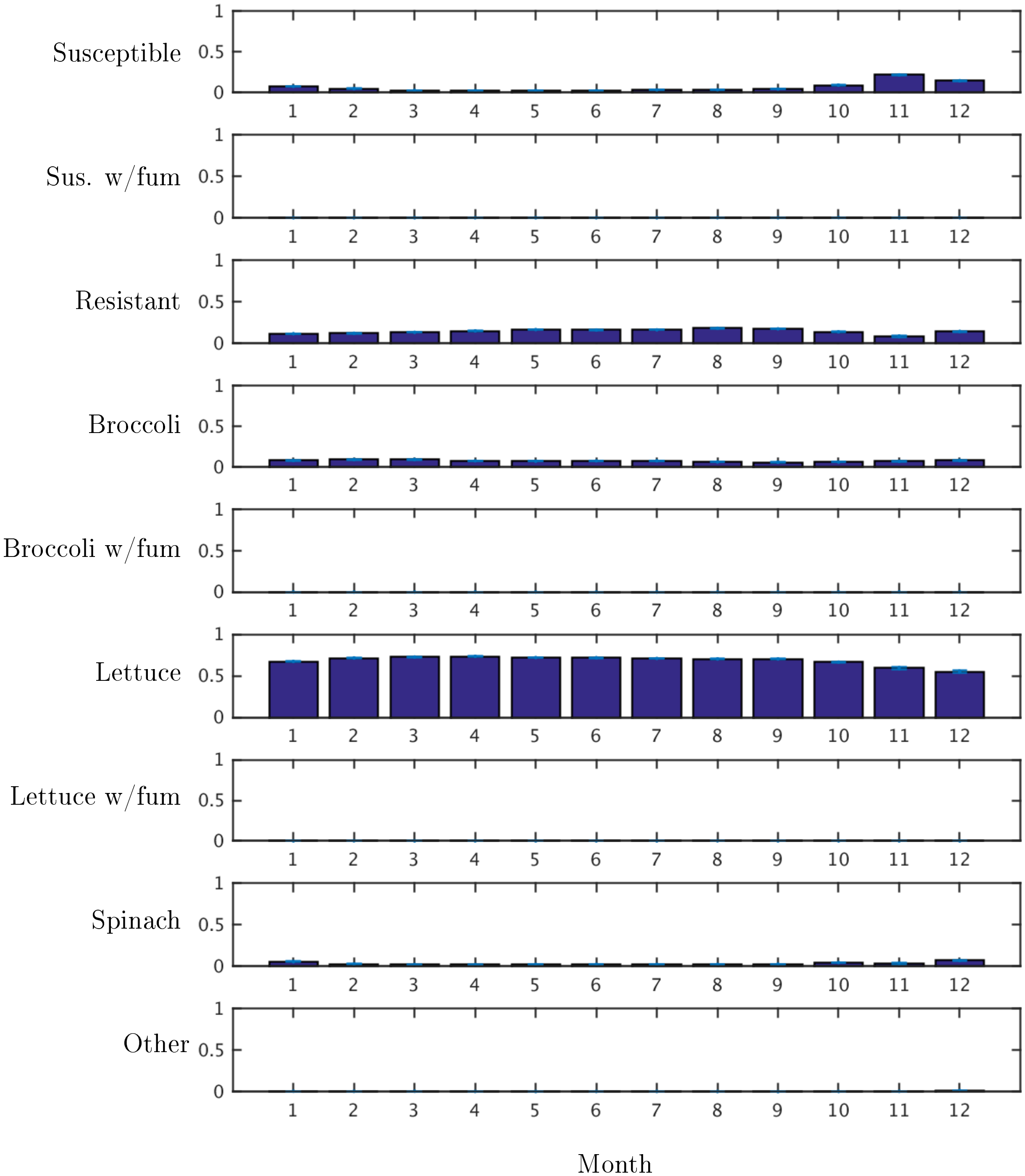
Notes: The fraction of grower-months in each action is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 9
Simulated mean fraction of grower-months in each action when spinach dummy coefficient θ_1 equals -1.00



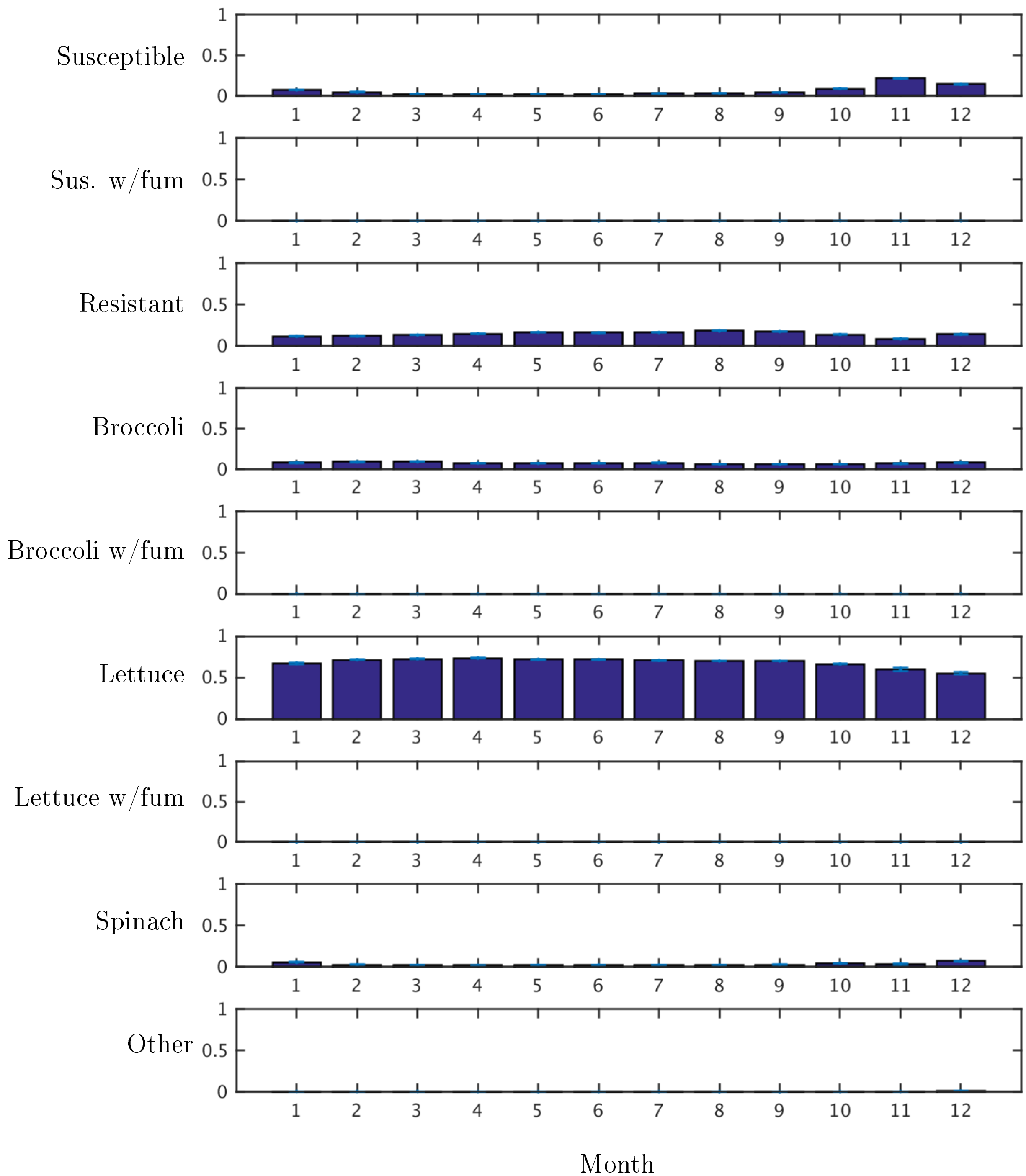
Notes: The fraction of grower-months in each action is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 10
Simulated fraction of grower-months in each action type by month of year when spinach dummy coefficient θ_1 equals 0



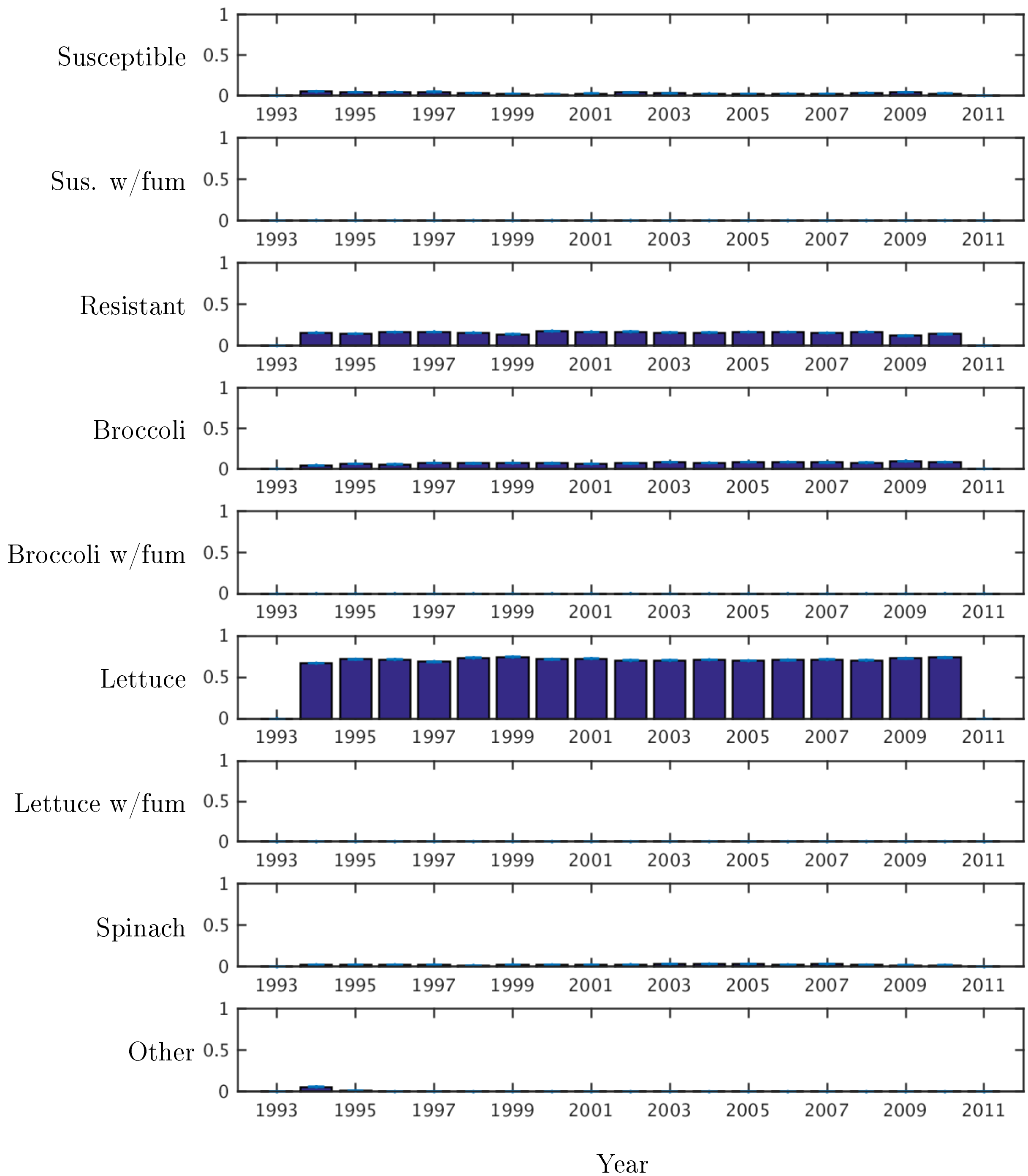
Notes: The fraction of grower-months in each action by month of year is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 11
Simulated fraction of grower-months in each action type by month of year when spinach dummy coefficient θ_1 equals -1.00



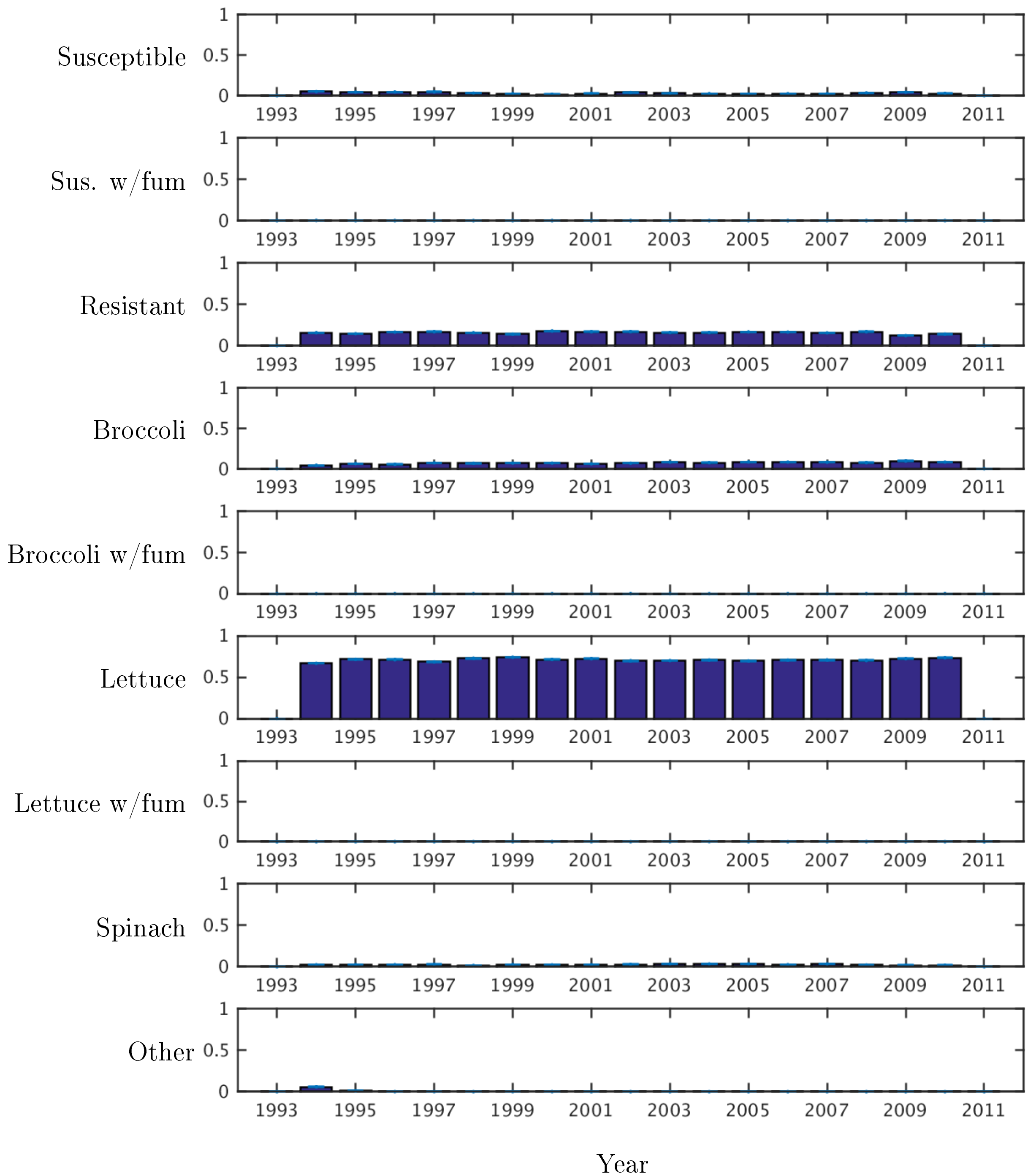
Notes: The fraction of grower-months in each action by month of year is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 12
Simulated fraction of grower-months in each action type by year when spinach dummy coefficient θ_1 equals 0



Notes: The fraction of grower-months in each action by year is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.

Figure 13
Simulated fraction of grower-months in each action type by year when spinach dummy coefficient θ_1 equals -1.00



Notes: The fraction of grower-months in each action by year is averaged over 25 simulations. Error bars represent the 95% confidence interval, which is calculated using a nonparametric bootstrap.