The Economics of Decision-Making for Crop Disease Control[1]

Christine L. Carroll
Colin A. Carter
Rachael E. Goodhue
C.-Y. Cynthia Lin Lawell

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Abstract

When faced with a crop disease that requires long-term investments in order to control, short- and long-term decision-makers may choose to manage the disease differently. We develop and estimate a dynamic structural econometric model of grower decision-making that enables us to analyze how differences in decisions relate to differences in decision-making time horizons as well as to alternative channels, and apply our model to Verticillium wilt management for lettuce crops in Monterey County, California. We find that an intertemporal externality arises with short-term decision-making by renters, who may be less likely to incur costs or forego profit to invest in control options, even though doing so would benefit future renters and the landowner.

Keywords: dynamic decision-making, dynamic structural econometric model, intertemporal externality, agricultural economics

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[1]Carroll: California State University at Chico; clcarroll@csuchico.edu. Carter: University of California at Davis; colin@primal.ucdavis.edu. Goodhue: University of California at Davis; goodhue@primal.ucdavis.edu. Lin Lawell: Cornell University; clinlawell@cornell.edu. We thank Krishna V. Subbarao, Julian Alston, John Asker, Andre Boik, Colin Cameron, Estelle Cantillon, Miguel Gómez, Ali Hortacsu, Erich Muehlegger, Kevin Novan, Peter Orazem, John Rust, Wolfram Schlenker, Paul Scott, Margaret Slade, Dan Sumner, Christopher Taber, Sofia Villas-Boas, Marca Weinberg, Jim Wilen, and Jinhua Zhao for invaluable discussions and comments. We also received helpful comments from seminar participants at the University of California at Davis, California State University at Chico, and Cornell University, and from conference participants at the NBER Understanding Productivity Growth in Agriculture Research Conference, the Heartland Environmental and Resource Economics Workshop, the Association of Environmental and Resource Economists (AERE) Summer Conference, the American Agricultural Economics Association (AAEA) Annual Meeting, the Giannini Agricultural and Resource Economics Student Conference, and the Interdisciplinary Graduate and Professional Student (IGPS) Symposium. We received funding from USDA NIFA (grants # 2010-51181-21069 and 2019-67019-30122). We also benefited from valuable discussions with Tom Bengard, Bengard Ranch; Kent Bradford, Seed Biotechnology Center UC-Davis; Leslie Crowl, Monterey County Agricultural Commissioner's Office; Rich DeMoura, UC-Davis Cooperative Extension; Gerard Denny, INCOTEC; Lindsey du Toit, Washington State University; Thomas Flewell, Flewell Consulting; Hank Hill, Seed Dynamics, Inc.; Steve Koike, Cooperative Extension Monterey County; Dale Krolikowski, Germains Seed Technology; Chester Kurowski, Monsanto; Donald W. McMoran, WSU Extension; Marc Meyer, Monsanto; Chris Miller, Rijk Zwaan; Augustin Ramos, APHIS; Scott Redlin, APHIS; Richard Smith, Cooperative Extension Monterey County; Laura Tourte, UC Cooperative Extension Santa Cruz County; Bill Waycott, Monsanto; and Mary Zischke, California Leafy Greens Research Program. Carter and Goodhue are members and Lin Lawell is a former member of the Giannini Foundation of Agricultural Economics. Lin Lawell is a Faculty Fellow at the Atkinson Center for a Sustainable Future. All errors are our own.

1 Introduction

Invasive plant pathogens, including fungi, cause an estimated $21 billion in crop losses each year in the United States (Rossman, 2009). *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 (V. wilt). Lettuce is an important crop in California, and the majority of the 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).

Much of California's lettuce crop is grown in Monterey County, where lettuce production value is 27% of the 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.

V. wilt can be prevented or controlled by the grower by fumigating with methyl bromide, planting broccoli (a low-return crop), or not planting spinach. Each of these control options entails incurring costs or foregoing profit in the current period for future benefit.[2] Because the options for controlling V. wilt require long-term investments for future gain, an intertemporal externality arises with short-term growers (whom we call 'renters'), who might not reap the future benefits from investing in control options. Moreover, a renter planting spinach will be long gone before microsclerotia builds up to a level that will affect lettuce. Renters, therefore, might not make the long-term investments needed to control V. wilt. As a consequence, future renters and the landowner may suffer from decisions of previous renters.

In this paper, we analyze factors that affect crop choice and fumigation decisions made by growers and examine how the decisions of long-term growers (whom we call 'owners') differ from those of short-term growers (whom we call 'renters'). Renters and owners differ in their time horizon, but may differ in other ways as well. For example, renters and owners may face different conditions and work on land of differing quality and differing microsclerotia levels. Alternatively, renters, whose incentives may be governed in part by renter contracts, may face different incentives from owners. We seek to understand how differences in decisions relate to differences in decision-making time horizons as well as to alternative channels. Since there

[2] Some of these actions may also generate benefits in the current period. For example, 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. On net, however, and as verified by our empirical analysis, these control options generally require incurring net costs or foregoing profit in the current period.

is no observable variable picking up 'time horizon', estimating its effect requires a structural model that explicitly accounts for the time horizon as well as alternative channels.

Thus, in order to compare the long-term decision-making of owners with the short-term decision-making of renters, 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. We then use the parameter estimates to simulate counterfactual scenarios to analyze how differences in grower decisions relate to differences in time horizons, differences in state variables (which capture differences in conditions such as soil microsclerotia levels, output prices, revenues, and previous control option use), and differences in payoff parameters (which reflect differences in incentives, including those that arise from marketing contracts, shipper contracts, and renter contracts).

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. Second, because crop and fumigation decisions are irreversible (as is the damage from V. wilt) and have uncertain future payoffs, and because growers have leeway over the timing of crop and fumigation decisions, 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.

There are several advantages to using a dynamic structural model for the crop and fumigation decisions of owners and renters. First, a dynamic structural model best enables us to understand how differences in decisions relate to differences in decision-making time horizons as well as to alternative channels. Since there is no observable variable picking up 'time horizon', estimating its effect requires a structural model that explicitly accounts for the time horizon as well as alternative channels. Second, unlike reduced-form models, a structural approach explicitly models the dynamics of crop and fumigation decisions by incorporating continuation values that explicitly model how expectations about the future affect current decisions. Since we structurally model how the continuation values relate to the payoffs from the crop and fumigation choices, we are able to estimate parameters in the payoffs from different crop and fumigation choices. A third advantage of our structural model is that we can use the parameter estimates from our structural model to simulate various counterfactual scenarios. To analyze and address the possibility that owners and renters may differ in their characteristics, in the conditions they face, and/or in the quality of their fields, we run counterfactual simulations in which we use our structural model to simulate owners on renter fields and renters on owner fields.

The balance of this paper proceeds as follows. Section 2 provides background on V. wilt, options to control the disease, and the intertemporal externality. Section 3 is a brief review of the relevant literature. Section 4 describes our dynamic structural econometric model. Section 5 describes our data. We present our results in Section 6 and our counterfactual simulations in Section 7. Section 8 concludes.

2 Background

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 allow the fungus to remain in the soil even without a host plant (Short et al., 2015b). When a susceptible host is planted, microsclerotia attack through the roots, enter the water conducting tissue, and interfere with water uptake and transport through the plant. If the density of microsclerotia in the soil exceeds a threshold, a disease known as V. wilt occurs.

V. wilt was first documented on lettuce in 1995, after it killed a lettuce (*Lactuca sativa* L.) crop in California's Santa Cruz County in the previous year. Prior to 1995, lettuce was believed to be immune. Since then, the disease has spread rapidly through Monterey County, the prime lettuce production region of California, where it was first observed on lettuce in 1999. By 2010, more than 150 fields were infected with V. wilt (Atallah, Hayes, and Subbarao, 2011), amounting to more than 4,000 acres (Krishna Subbarao, personal communication, 2013).[3] 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, although it does not spread locally from field to field on its own, V. wilt can be introduced from another field via contaminated boots or equipment. Local spread is a relatively minor contributor, however, and can be mitigated by growers by cleaning equipment before moving between fields. Second, V. wilt is introduced to the soil via infested lettuce seeds. Lettuce seeds are also a relatively minor contributor. 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%, and therefore lower than the incidence of

[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 was actually even higher, numbering over 175 fields (Krishna Subbarao, personal communication, 2013). 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.

infection required for the high disease levels currently seen (Atallah, Hayes, and Subbarao, 2011).[4]

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., 2015a); 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). Infected spinach seeds carry an average of 200 to 300 microsclerotia per seed (Maruthachalam 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). Recent conclusive evidence has proven that planting infected spinach seeds causes V. wilt on lettuce (Short et al., 2015a).

One method for controlling V. wilt is to fumigate with methyl bromide. As methyl bromide is an ozone depleting substance, the Montreal Protocol phased out methyl bromide use for fumigation of vegetable crops such as lettuce in 2005; nevertheless, certain crops such as strawberries have received critical-use exemptions through 2016[5] (California Department of Pesticide Regulation, 2010; United States Environmental Protection Agency, 2020), and the residual effects from strawberry fumigation may provide protection for one or two seasons of lettuce before microsclerotia densities rise (Atallah, Hayes, and Subbarao, 2011). The long-term availability of this solution is limited and uncertain.

A second method for controlling V. wilt is to plant broccoli. Broccoli is not susceptible to V. wilt and also reduces the levels of microsclerotia in the soil (Subbarao and Hubbard, 1996; Subbarao, Hubbard, and Koike, 1999; Shetty et al., 2000). Owing to the relatively low returns from broccoli in the region, growers who plant this control crop must forgo the higher profits they would have received if they had planted a higher return crop instead.

A third method for controlling V. wilt is to not plant spinach, since spinach seeds are the vector of pathogen introduction (du Toit, Derie, and Hernandez-Perez, 2005). Growers who use this third control method of not planting spinach must forgo any relative profits they may have received if they had planted spinach instead of another crop.

[4]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).

[5]Critical-use exemption requests through 2014 specify that up to one third of the California strawberry crop may be fumigated with methyl bromide, but actual use was much lower. The remainder of the crop is treated with alternatives such as chloropicrin or 1,3-Dichloropropene (1,3-D) (United States Environmental Protection Agency, 2012). These alternatives (unless combined with methyl bromide) tend to be less effective for V. wilt, however (Atallah, Hayes, and Subbarao, 2011). Field trials of other chemical fumigants either have not been widely used due to township caps or are not yet registered and approved.

V. wilt can therefore be prevented or controlled by the grower by fumigating with methyl bromide, planting broccoli (a low-return crop), or not planting spinach. Because the options for controlling V. wilt require long-term investments for future gain, an intertemporal externality arises with renters, who might not make the long-term investments needed to control V. wilt. As a consequence, future renters and the landowner may suffer from decisions of previous renters.

Anecdotal evidence suggests that land values can drop as much as 25% when it is discovered that acreage is contaminated with *Verticillium dahliae*. Landowners have also reported renters asking for reduced rent because of *Verticillium dahliae* contamination (personal communication, Krishna Subbarao, 2013).

Contracting can sometimes internalize an externality that would otherwise be present (Coase, 1960). Contracts would seem to be the ideal solution: usually only two parties are involved in the rental agreement (the landowner and the renter) and a contract is likely already in place. Adding stipulations to control V. wilt would seem logical and simple. For example, contracts may include penalties for crop choice or fumigation decisions that do not conform to the contract. In addition, pesticide applications must be reported to the Monterey County Agricultural Commissioner, including the date, time, location, chemicals applied, and application method. In principle, these methods could allow landowners to monitor renters, should they choose to do so.

Nevertheless, the existing contracts may be inefficient or unenforced, and enforcing effort may not be possible. For example, it would be difficult for the landowner to tell if spinach had been planted until after it sprouted, by which time it would be too late for preventative action. Similarly, the level of sanitation effort a renter exerts to wash their boots and equipment every time they come to the field from elsewhere may not be observable or verifiable. Moreover, even if the renter could be subject to penalties resulting from the contract, the exact damages may be difficult to determine.

It may likewise be difficult for existing contracts to fully internalize the intertemporal externality by penalizing renters if a lettuce crop is afflicted with V. wilt. The delayed nature of the disease, wherein it may take several years for microsclerotia to build up in the soil to damaging levels, means that it may be difficult for landowners to observe when a field was contaminated and who is responsible. If a lettuce crop is afflicted with V. wilt, the contamination would likely have been the result of the actions of one or more previous renters rather the current renter currently renting the land under the current renter contract. It may be difficult to exact and enforce penalties on previous renters no longer working on the field for the contamination of a future crop years later. Moreover, even if would be possible for a landowner to exact and enforce penalties on previous renters from many years ago, it would be difficult for landowners to ascertain whether and how much each of the previous renters contributed to the contamination.

When it is costly for the renter to prevent V. wilt, and costly for the landowner to observe the renter's actions, a contract may not suffice to internalize the intertemporal externality and induce an efficient outcome. Furthermore, if contracts that include stipulations to control V. wilt are not the norm in the area, highly restrictive contracts – such as a contract that requires renters to plant broccoli, a low-return crop, in lieu of a more profitable crop – may be less desirable and receive lower rents. In addition, if such highly restrictive, less desirable contracts would only be accepted by lower quality renters, who may be even less likely to make long-term investments in land and soil quality than higher quality renters are, then issues of adverse selection and possible market unraveling (Akerlof, 1970) may arise as well.

Although we do not have data on contracts themselves, it is an empirical question whether existing renter contracts internalize the intertemporal externality imposed by renters on future renters and the landowner. To examine whether contracts internalize the intertemporal externality, we compare the results from renters with those from owners. Moreover, since V. wilt was first documented on lettuce in 1995 and first observed on lettuce in Monterey County in 1999, and the likely sources of the disease were not known until years later, it is possible that renter contracts may have evolved over time to better internalize the intertemporal externality as awareness and knowledge of V. wilt and its control options increased over time. We therefore also compare the renter results from the early time period (1993 to 2000) with those from the later time period (2001 to 2011).

3 Literature Review

The first 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 second 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. The seminal dynamic structural econometric model developed by Rust (1987, 1988) 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), durable goods (Gowrisankaran and Rysman, 2012; Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2020), copper mining decisions (Aguirregabiria and Luengo, 2016), supply chain externalities (Carroll et al., 2021), environmental regulations (Blundell, Gowrisankaran, and Langer, 2020), technology adoption (Oliva et al., 2020), the adoption of rooftop solar photovoltaics (Feger, Pavanini, and Radulescu, 2020; Langer and Lemoine, 2018), vehicle scrappage programs (Li and Wei, 2013), agricultural productivity (Carroll et al., 2019), organ transplant decisions (Agarwal et al., 2021), consumer stockpiling (Ching and Osborne, 2020), pest management (Yeh, Gómez, and Lin Lawell, 2021), urban travel demand (Donna, 2019), hotel pricing (Cho et al., 2018), forests (Araujo, Costa, and Sant'Anna, 2020), and vehicle ownership and usage (Gillingham et al., 2016).

There exists an extensive literature on contract choice in agriculture in both developed and developing country contexts (Allen and Lueck, 1992; Burchardi et al., 2019; At and Thomas, 2019). Dubois (2002) analyzes contracts and land fertility in the Philippines using a model that incorporates the dynamics of soil fertility: the tenant's actions in a given season affect future production because land fertility is a function of both the previous period's fertility and the tenant's actions.

4 Dynamic Structural Econometric Model

4.1 Model

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 – lettuce, spinach, broccoli, susceptible (other than lettuce), or resistant – combined with the choice to fumigate with methyl bromide. To focus on the crops most relevant to this problem, we include each of the crops most relevant to V. wilt – lettuce, spinach, and broccoli – as a separate crop; and we group the crops resistant to V. wilt together and the crops (other than lettuce) susceptible to V. wilt together. 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. The length of the season varies among crops, from as short as one month for spinach (Koike et al., 2011), to twelve months long for strawberries (SeeCalifornia, 2020). Moreover, growers who choose to fumigate a crop vary in how often they fumigate, and do not necessarily fumigate every month. 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.

Growers consider multiple factors when making their crop and fumigation decisions, including crop prices, yield, revenue, costs, non-monetary benefits, non-monetary costs, as well as the costs of microsclerotia building up in the soil over time and potentially impacting future crops. 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. Unfortunately, data on individual growers' actual price, quantity, costs, and level of microsclerotia are not available. Instead, we account for the important factors in a grower's payoff-maximizing crop and fumigation decisions by including in their monthly payoff function state variables that affect price, yield, revenue, costs, non-monetary benefits, non-monetary costs, miscrosclerotia levels, and/or the spread of V. wilt. 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. Monthly costs common to all crops are captured by the constant. The largest cost difference among crops is due to fumigation, so we include a dummy for methyl bromide fumigation to account for the 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 discretized crop prices for each crop ($price_{it}(d_{it})$), dummy variables for each crop that indicate whether this month is a harvest month for that crop ($harvest\ month\ dummy_{it}(d_{it})$), dummy variables for each crop that indicate 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 broccoli control option was used in the past ($broccoli\ history_{it}$), and a variable measuring whether and how much the methyl bromide control option was used in the past ($methyl\ bromide\ history_{it}$). There is a choice-specific shock $\epsilon_{it}(d_{it})$ associated with each possible action $d_{it} \in D$. The vector of choice-specific shocks $\epsilon_{it} \equiv \{\epsilon_{it}(d_{it}) | d_{it} \in D\}$ 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:

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

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

$$\begin{aligned}
\pi(d_{it}, &\mathbf{s_{it}}, \theta) = \\
&+ \theta_1 \cdot \text{lettuce dummy}_{it} \\
&+ \theta_2 \cdot \text{spinach dummy}_{it} \\
&+ \theta_3 \cdot \text{broccoli dummy}_{it} \\
&+ \theta_4 \cdot \text{methyl bromide dummy}_{it} \\
&+ \theta_5 \cdot (\text{lettuce dummy}_{it} * \text{broccoli history}_{it}) \\
&+ \theta_6 \cdot (\text{spinach dummy}_{it} * \text{broccoli history}_{it}) \\
&+ \theta_7 \cdot (\text{lettuce dummy}_{it} * \text{methyl bromide history}_{it}) \\
&+ \theta_8 \cdot (\text{spinach dummy}_{it} * \text{methyl bromide history}_{it}) \\
&+ \theta_9 \cdot (\text{last crop dummy}_{it}(d_{it}) * \text{susceptible dummy}_{it}) \\
&+ \theta_{10} \cdot (\text{last crop dummy}_{it}(d_{it}) * (1 - \text{susceptible dummy}_{it}) \\
&+ \theta_{11} \cdot (\text{price}_{it}(d_{it}) * \text{harvest month dummy}_{it}(d_{it}))) \\
&+ \theta_{12},
\end{aligned} \tag{1}$$

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

Since we include a separate term for the price of the crop being planted if it is a harvest month for that crop, and since monthly input and growing costs common to all crops are captured by the constant θ_{12}, the coefficients on the dummies for lettuce, spinach, and broccoli capture any additional monthly costs (monetary and otherwise) of the respective crops beyond the monthly costs common to all crops captured by the constant, as well as any additional benefits (monetary or otherwise) to planting these respective crops that are not internalized in their respective crop prices during their respective times of harvest. Because price is the discretized marketing average price of lettuce per acre, the price measures revenue per acre, and therefore incorporates yield as well. Thus, the coefficients on the dummies for lettuce, spinach, and broccoli capture any additional benefits or costs, monetary or otherwise, that are not fully captured by the price, yield, or revenue per acre for that crop; or by costs common to all crops.

In particular, the coefficient θ_1 on the lettuce dummy captures additional monthly costs of planting and growing lettuce beyond the monthly costs common to all crops captured by the constant; as well as any additional net benefits of lettuce that are not internalized in the lettuce price, including any additional benefits that may explain why growers continue to plant lettuce even though it is susceptible to V. wilt. Similarly, since planting spinach will tend to increase microsclerotia, the coefficient θ_2 on the spinach dummy captures the effects of spinach on payoffs that are not internalized in the spinach price, including the monthly costs of planting and growing spinach beyond the monthly costs common to all crops captured by the constant; as well as the microsclerotia costs (monetary and otherwise) of planting spinach. Likewise, the coefficient θ_3 on the broccoli dummy captures the effects of broccoli on payoffs that are not internalized in the broccoli price, including the monthly costs of planting and growing broccoli beyond the common monthly crop costs captured in the constant.

Especially in more recent years, methyl bromide fumigation is very expensive and raises input costs dramatically. Fumigation is the largest cost difference among crops. The coefficient θ_4 on the dummy for methyl bromide fumigation accounts for the costs of fumigation and absorbs the cost differences among crops.[6]

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 broccoli history within the last twelve months and the fu-

[6]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. On net, however, 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.

migation history with methyl bromide within the last twelve months. We expect broccoli history and methyl bromide fumigation history to be closely linked to the presence of microsclerotia in a field. 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. Broccoli history interacted with planting lettuce today would have a positive coefficient θ_5 if having planted broccoli is an effective control option. Similarly, methyl bromide fumigation history interacted with planting lettuce today would have a positive coefficient θ_7 if having fumigated with methyl bromide 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 broccoli history and methyl bromide 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 broccoli history and/or methyl bromide history.[7]

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. To separate out the two effects, we estimate the last crop dummy separately for susceptible crops (which include strawberries, artichoke, and cabbage) and for all other crops (including lettuce, spinach, broccoli, and resistant crops), since susceptible crops have a longer harvest season length. In our data set, the average harvest season length for susceptible crops is 2.6 months, while the average harvest season length for all other crops is 1.7 months. Thus, the coefficient θ_9 on the last crop dummy interacted with a dummy for susceptible crops captures the requirement to grow a particular crop over multiple months, while the coefficient θ_{10} on the last crop dummy interacted with a dummy for all other crops captures the tendency for a grower to choose to replant the same crop over and over again, perhaps harvest after harvest.

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

[7]We do not include spinach history in the per-period payoff for several reasons. First, as seen in Section 6, when we include spinach history in an alternative specification, the spinach history variable does not have a significant effect over the entire period, in the early period, or in the later period. Second, *Verticillium dahliae* takes several years to build up in the soil, and once present, persists for many years. The fungus can survive in the soil for fourteen years as microsclerotia (Short et al., 2015b). The appropriate length of time for spinach history is therefore likely to be quite long and at least as long as the time period of our data set. We unfortunately do not have enough years of data in order to control for the long-term spinach history in a relevant manner. Even if we did, growers may not necessarily base their decisions on long-term spinach history, since they may not know or recall the entire spinach history over many years. We hope in future work to acquire enough long-term data to enable us to include long-term spinach history.

to one during the harvest season for each crop to capture the fact that although growers may plant the same crop for multiple months, they only receive revenue during the months of the harvest season for that crop.[8] In particular, the expected gross revenue to harvesting a crop during non-harvest season months (e.g., during the winter) is 0.[9] Thus, by incorporating the expected gross return in the payoff function and by modeling the dynamic decision-making of growers choosing 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 profit-maximizing growers are unlikely to pull out the crop before it is ready to harvest (and therefore before they would receive the expected return), barring problems such as V. wilt or other issues that meant that crop was unhealthy.

We assume the state variables evolve as a finite state 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 crop price variable we use is the discretized annual county average, we assume that the crop and fumigation decisions of any one grower would not have a large enough effect to influence crop prices, and therefore that the distribution of discretized county-level crop prices next period does not depend on any single grower's decisions this period; we therefore model crop prices as evolving exogenously. We estimate the transition density for each crop price conditional on the crop prices for all crops nonparametrically using our data on the discretized annual county-level crop prices over the entire time period of our data set. In particular, we use empirical probabilities to estimate a grower's expectation of future values of the discretized crop prices for each crop conditional on the current values of the discretized 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.

We make the following conditional independence assumption on the transition density:

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

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

A standard assumption in many dynamic structural models, our conditional indepen-

[8]As explained in detail in Section 6, we also run an alternative specification to examine whether the results are robust to the possibility that some growers may plant the same crop for multiple months in a harvest season. As seen in the robustness checks in Section 6, 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.

[9]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. Monthly input and growing costs common to all crops are captured by the constant, which we expect to be negative.

dence assumption implies that, conditional on the current state variables $\mathbf{s}_{it}$ and the current action d_{it} chosen by the grower, the evolution of the observed state variables $\mathbf{s}_{it}$ does not depend on the particular realization of the idiosyncratic shocks ϵ_{it} to the payoffs of individual growers from each possible crop and fumigation action choice. For broccoli history and methyl bromide history, the conditional independence assumption makes sense since these state variables evolve deterministically as a function of this period's value of these state variables and this period's action. Similarly, for the last crop dummy, the conditional independence assumption makes sense since the last crop dummy for next period is a deterministic function of this period's action. For the crop prices, which evolve stochastically, since there are many growers in the county and no grower has a significant market share, it is reasonable to assume that shocks to any particular individual grower are unlikely to affect how discretized county-level crop prices evolve at the aggregate level for all growers.

4.2 Value Functions, Continuation Values, and Choice Probabilities

To estimate the unknown parameters $\theta = (\theta_1, ..., \theta_{12})$, we build on the nested fixed point maximum likelihood estimation technique developed by Rust (1987, 1988). We assume that the observed choices coincide with the optimal decision rule that solves the grower's dynamic optimization problem. The differences in time horizons between long-term and short-term growers result in slightly different value functions and therefore slightly different techniques for solving for continuation values and choice probabilities, which we describe below.

4.2.1 Long-Term Growers ('Owners')

A long-term grower ('owner') faces an infinite horizon dynamic programming problem. Under the assumptions that the state variables and the choice-specific shocks ϵ_{it} are conditionally independent and that the choice-specific shocks ϵ_{it} are distributed multivariate extreme value, 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 infinite-horizon Bellman equation:

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

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:

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

and where β is the monthly discount factor. The choice probability for a long-term grower is given by:

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

After obtaining the model predictions for the choice probabilities as functions of the state variables and the unknown parameters θ, we estimate the parameters θ using the nested fixed point maximum likelihood estimation technique developed by Rust (1987, 1988). The likelihood function is a function of the choice probabilities, and therefore a function of the continuation value $V^c(\cdot)$. For each guess of the parameters θ, we solve for the continuation value $V^c(\cdot)$ by solving for a fixed point, and use the continuation value to solve for the choice probabilities, which we then plug into the likelihood function. From Blackwell's Theorem, the fixed point is unique.

4.2.2 Short-Term Growers ('Renters')

In contrast to long-term growers, who face an infinite horizon problem, short-term growers face a finite horizon dynamic programming problem with a finite horizon of $T = 12$ months. Under the assumptions that the state variables and the choice-specific shocks ϵ_{it} are conditionally independent and that the choice-specific shocks ϵ_{it} are distributed multivariate extreme value, the value function for a short-term grower for each period t, which gives the present discounted value of the grower's entire stream of per-period payoffs from time t forward at the optimum, is given by the following finite-horizon Bellman equation:

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

where $V_t^c(\cdot)$ is the continuation value at time t, which is the expected value of the value function at time $t+1$ conditional on the state variables and action at time t:

$$V_t^c(\mathbf{s}, d, \theta) = \int V_{t+1}(\mathbf{s}', \epsilon'; \theta) d \Pr(\mathbf{s}', \epsilon' | \mathbf{s}, \epsilon, d, \theta).$$

The continuation value $V_t^c(\cdot)$ for each time t is solved for via backwards iteration from the terminal condition that the final period continuation value V_T^c at month $T = 12$ is equal to zero. The choice probability for a short-term grower for each period t is given by:

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

After obtaining the model predictions for the choice probabilities for each period t as functions of the state variables and the unknown parameters θ, we estimate the parameters θ using maximum likelihood estimation. The likelihood function is a function of the choice probabilities, and therefore a function of the continuation values $V_t^c(\cdot)$. For each guess of the parameters θ, we solve for the continuation values $V_t^c(\cdot)$ for each period t by backwards iteration, and use the continuation values to solve for the choice probabilities for each period, which we then plug into the likelihood function.

4.3 Econometric Estimation

As explained above, the differences in time horizons between long-term and short-term growers lead to slightly different techniques for econometric estimation. For owners, who have an infinite horizon, an inner fixed point algorithm to compute the continuation value $V^c(\cdot)$ is nested within an outer optimization algorithm to find the maximizing value of the parameters θ via maximum likelihood estimation (MLE). For renters, who have a finite horizon, an inner algorithm to compute the continuation value $V_t^c(\cdot)$ for each period t using backwards iteration is nested within an outer optimization algorithm to find the maximizing value of the parameters θ via maximum likelihood estimation (MLE).

In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons. Thus, in our base-case specification, we pool owners (who have an infinite horizon) and renters (who have a finite horizon) together and estimate the same parameters θ for both owners and renters. Using the same per-period payoff function and parameters for owners and renters enables us to make welfare comparisons between owners and renters.

Although we use the same per-period payoff functions for long-term and short-term growers in our base-case specification, owing to the intertemporal externality, we expect short-term growers to be less concerned about the impact of their actions on the level of microsclerotia in the soil in the future. As a consequence, short-term growers may be less likely to incur costs or forego profit to fumigate or plant broccoli if they will not see the future benefit of engaging in these control options.

We also try an alternative specification for owners and renters in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons for their dynamic decision-making (i.e., long- vs. short-term), but also have different parameters θ in their per-period payoff functions as well. The parameters θ in the payoff functions measure how different actions and state variables affect their per-period payoff. Differences in parameter values between owners and renters may arise if there are differences in incentives faced by renters versus owners – including differences in monetary benefits, monetary costs, non-monetary benefits, non-monetary costs, marketing contracts, shipper contracts, and/or renter contracts – that lead to differences between owners and renters in how different actions and state variables affect their per-period payoffs.

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; and which in finite horizon dynamic discrete choice models are identified when the discount factor β, the distribution of the choice-specific shocks ϵ_{it}, and the final period continuation value V_T^c are fixed (Abbring, 2010; Magnac and Thesmar, 2002; Rust, 1994). We set our monthly discount factor to $\beta = 0.999$.[10] The parameters θ 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 lettuce dummy is identified in the difference between the per-period payoff from choosing to plant lettuce and the per-period payoff from any action choice d_{it} that does not involve planting lettuce. To identify the constant θ_{12}, we normalize the deterministic component $\pi(\cdot)$ of the per-period payoff from choosing the outside option 'other' to 0.

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 owner fields and the same number of renter 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.

5 Data

We use Pesticide Use Reporting (PUR) data from the California Department of Pesticide Regulation.[11] Our data set is composed of all fields in Monterey County on which any

[10]A monthly discount factor of $\beta = 0.999$ corresponds to a real annual interest rate of 1.2%. Rust (1987) uses a monthly discount factor of $\beta = 0.9999$, which corresponds to a real annual interest rate of 0.1%.

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

regulated pesticide was applied in the years 1993 to 2011, inclusive.[12] Additional data on prices, yields, and acreage come from the Monterey Agricultural Commissioner's Office. We collapse the data set into monthly observations.[13]

We group the crops into five categories: lettuce, spinach, broccoli, susceptible (which includes strawberries, artichoke, and cabbage; but excludes lettuce), and resistant (cauliflower and celery). From these, we form nine action choices: susceptible, susceptible with methyl bromide fumigation, resistant, broccoli, broccoli with methyl bromide fumigation, lettuce, lettuce with methyl bromide fumigation, spinach, and other.[14]

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.

Our data point to a variety of different types of growers. The vast majority (94%) of fields have only one grower over the entire time period. Of these, we call long-term growers ('owners') those who appear on the same field every year from 1994 to 2010, and we model their decision-making as an infinite horizon problem. Some long-term growers are associated with a large number of fields which they plant repeatedly and consecutively; other long-term growers have only a few fields.

The other 6% of the Pesticide Use Data fields have multiple growers who appear during the observed time period.[15] Of these, we want to consider growers who are most likely to

[12] 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.).

[13] 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; if there is no registered pesticide applied in one of those months, however, 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. We compared the distribution of these months between short-term and long-term growers and find that they are similar distributions. 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.

[14] 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. The outside option of 'other' includes various agricultural land uses that are rarely chosen in Monterey County, including livestock and nursery products.

[15] For a very small number of fields (191 out of more than 130,000, or less than 0.15%), the field identification appears to be either miscoded or reused such that a field is not uniquely identified. On these fields, there are more than five different growers per field. In some cases, there are overlaps related to collapsing the data set into monthly observations, i.e., one grower harvests a crop early in the month and another grower

be renters who have not invested in the land or soil quality. Due to the limited nature of the Pesticide Use Reporting (PUR) data, we adopt a conservative approach to identifying possible renters. In particular, we call short-term growers (‘renters’) those who appear on a field for only one year and never repeat, and who grow on a field on which other different short-term growers appear at different times over the course of the data set.[16] Although other growers may also have a short-term time horizon, we focus on this particular group in order to look at the maximum difference between the short-term and long-term growers. Of the short-term growers, only 37% do not appear on any other fields in any other year. To have a sufficient sample size, we use both growers who appear to rent on only one field as well as those who appear to rent on multiple fields.

Our data set for long-term growers (’owners’) consists of 615 growers, each appearing on his or her own field over seventeen years. Our data set for short-term growers (’renters’) consists of 3,409 growers who appear for one year each; the same field may be rented by different short-term growers (’renters’) in different years.

We use a marketing year average price for each crop[17] 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. The Monterey County Agricultural Commissioner’s Office publishes annual crop reports including prices, yields, 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 A.3 in Appendix A.[18]

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plants a different crop near the end of the month; but other cases are less clear, where different growers are recorded fumigating different crops on different size plots during the same time period. We do not include these fields in either the owner or renter data set.

[16]It is possible that the limited nature of the Pesticide Use Reporting data (encoded by grower identification number and field identification number) may be obscuring growers who have long-term interests at heart, even though they appear in a limited capacity. For example, rentals within a family, or a pest control advisor applying pesticide on behalf of an owner, may appear in what we are calling the renter data set. In a sense, the family bond may serve to reduce contract enforcement costs and, assuming the family members want to remain on good terms, may result in a type of repeated game rather than a single interaction. If anything, this issue should skew our results in favor of renters acting like owners, which would act against our finding any differences between owners and renters. In this case, our results would be a lower bound on the differences between owners and renters, and on the intertemporal externality.

[17]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.

[18]The cutoff values for the first 5 price bins are the 5 quintiles for marketing year average price, as calculated using the distribution of pooled prices over all time periods. Since the marketing year average price for susceptible crops (which include strawberries) is always in the highest quintile in every year of our

As seen in Figure A.3 in Appendix A, the marketing year price for broccoli is relatively low, almost always lower than the marketing year price for lettuce, and generally the lowest among the 5 crops, affirming that broccoli is a low-return crop, and therefore that planting broccoli to control V. wilt involves forgoing profit in the current period for future benefit. In addition, the marketing year price for spinach is sometimes higher than the marketing year price for lettuce, affirming that not planting spinach as a means of controlling V. wilt also involves forgoing profit in the current period for future benefit.

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).[19] 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.[20]

As data on growers' actual costs are unfortunately not available,[21] costs are captured

data set, and since the highest quintile spans a wide range of prices, we further divide the highest quintile into 2 bins, using the median marketing year average price for susceptible crops as the cutoff value. By splitting the highest quintile into 2 bins based on the median susceptible crop price, we allow the discretized marketing year average price for susceptible crops to vary over time, rather than always being in the same bin every single year of the data set. We do not use sextiles to delineate bins because the marketing year average price for susceptible crop is in the highest sextile in all except 3 years of our data set, and therefore would still almost always be in the highest bin; and also because the top sextile would span an even wider range of prices than our highest bin does. State space constraints, along with sample size considerations for our nonparametric estimation of the transition density for crop prices, preclude us from using more than 6 bins for price.

[19]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.

[20]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. For robustness, we also run the model using lagged prices instead of current prices, which assumes that the growers' best guess for this year's price is last year's price. As seen in our robustness results below, the results are robust to whether we assume growers have rational expectations about prices or whether we assume instead that growers use last year's price as the best guess for this year's price.

[21]Cost estimates for Monterey County from the University of California 'Cost and Return Studies' (University of California Agricultural Issues Center, 2020a,b) are not available for any of the 19 years of our analysis (1993-2011) for several of the key crops in our model; are only available for very few of the 19 years of our analysis for other crops in our model; and are not available for any of the crops in our model for any year in the early period (1993-2000). Spinach cost estimates for Monterey County are not available for any of the 19 years of our analysis; the latest year of spinach cost estimates for Monterey County prior to the time period of our data set is 1986, and the earliest year of spinach cost estimates for Monterey County after the time period of data set is 2015. Similarly, there are no cost estimates for resistant crops for any of the 19 years of our data set; the latest cost estimate for celery for Monterey County is for 1986, and the latest cost estimate for cauliflower for Monterey County is for 1986. The only cost estimate for resistant crops during the 19 years of our data set is the cost estimate for cauliflower for the entire Central Coast

by our crop-fumigation dummies and our constant. Monthly costs common to all crops are captured by the constant. Cost differences among crops are mainly driven by methyl bromide fumigation, which is explicitly included in the model. We expect the crop-fumigation dummies to at least partially capture the cost differences among the different crops.

Figure 1 plots the actual fraction of grower-months in each action type for owners and renters for the entire time period of our data set from 1993 to 2011 ('all'), the early period of the data from 1993 to 2000 ('early'), and the later period of the data from 2001 to 2011 ('late'). Figures A.1 and A.2 in Appendix A plot the actual fraction of grower-months in each action type by year for owners and renters, respectively. Summary statistics for the action and state variables for owners and renters are presented in Tables A.1 and A.2, respectively, in Appendix A.[22]

As seen in these figures and summary statistics tables, lettuce accounts for over 60% of the grower-months for owners. For renters, the two most frequent action choices are lettuce and other susceptible crops: lettuce accounts for over 40% of the grower-months in the early period and almost 30% of the grower-months in the later period, while other susceptible crops (which include strawberries, artichoke, and cabbage) account for over 20% of the grower-months in the early period and approximately 50% of the grower-months in the later period.

Also as seen in the figures and summary statistics tables, renters in the early period plant spinach more frequently than owners do and more frequently than renters in the late period do. Renters also plant broccoli less frequently than owners do, and are even less likely to plant broccoli in the late period compared to the early period. Relatedly, renters

region in 2001. Among susceptible crops, the latest cost estimate for artichoke in Monterey County is in 1981, prior to the time period of our data set; the only cost estimate for cabbage in the Central Coast region is for Santa Cruz in 1972, prior to the time period of our data set; and cost estimates for strawberries in Monterey County are only available for five out of the 19 years of our analysis, all of which are in the later time period (2001, 2003, 2006, 2010, and 2011), with only one other year of strawberry cost estimates for the entire Central Coast region in 1990. Cost estimates for broccoli in Monterey County are only available for two out of the 19 years of our analysis, both in the later time period (2001 and 2004); the latest year of broccoli cost estimates for Monterey County prior to the time period of our data set is 1986; the earliest year of broccoli cost estimates for Monterey County after the time period of our data set is 2017; and the earliest year of broccoli cost estimates for any part of the Central Coast region after the time period of our data set is 2012 for San Luis Obispo. Cost estimates for lettuce in Monterey County are only available for three out of the 19 years of our analysis, all in the later time period (2001, 2009, and 2010); the latest year of lettuce cost estimates for Monterey County prior to the time period of our data set is 1992; and the earliest year of lettuce cost estimates for Monterey County after the time period of our data set is 2015 (University of California Agricultural Issues Center, 2020a,b).

[22]To get a sense of how the grower-fields in our owner data set and our renter data set compare with all the grower-fields in the entire data set, Table A.3 in Appendix A compares the summary statistics for the discretized state variables for the owners and renters over the entire time period with those of all the grower-fields in the entire data set over the entire time period.

worked on land that had lower broccoli history than owners did. These statistics suggest that, by planting spinach and by not planting broccoli, renters impose an intertemporal externality on future renters and landowners, thereby causing the land used by renters to have lower broccoli history and potentially higher microsclerotia levels. These statistics therefore provide suggestive evidence that existing renter contracts do not fully internalize the intertemporal externality imposed by renters on future renters and the landowner.

In terms of using methyl bromide, however, renters were more likely to fumigate with methyl bromide than owners were; and moreover, while the methyl bromide use of owners declined over time between the early and late period, the methyl bromide use of renters increased over time. Relatedly, renters worked on land that had higher methyl bromide history than owners did.

Figure A.4 in Appendix A presents a map of the owners in our data set by township range. Each township range is approximately 6 miles by 6 miles.[23] Figures A.5-A.7 in Appendix A present maps of the renters in our data set over the entire time period, the early period, and the late period, respectively, by township range. Comparing the map for the owners with the maps for the renters, the spatial distributions of owners and of renters are roughly similar, which provides evidence that owners and renters faced similar agricultural and environmental conditions. To further examine whether the differences in crop and fumigation decisions of owners and renters in our data set may have resulted from differences in their characteristics, in the conditions they faced, and/or in the quality of their fields, we run counterfactual simulations in which we use the results of our structural model to simulate owners on renter fields and renters on owner fields, as we explain in detail in Section 7.

6 Results

6.1 Base-Case Specification

The base-case results are presented in Table 1. Since V. wilt first killed a lettuce crop in 1994, was first documented as having done so in 1995, and was first observed on lettuce in Monterey County in 1999, and since the likely sources of the disease were not known until years later, we run our model using data from 3 different time periods: the entire time period of our data set from 1993 to 2011 ('all'), the early period of the data from 1993 to

[23]The larger, more irregularly shaped areas are areas along the Highway 101 corridor, in the populated areas at the North end of the county, and in the hot springs area in the Southwest part of the county that were at some point rezoned to other types of land.

2000 (‘early’), and the later period of the data from 2001 to 2011 (‘late’). We report our estimates of 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 base-case results in Table 1, the lettuce dummy has a significant positive coefficient, which means that growers derive additional net benefits from planting lettuce for reasons that are not fully captured by its price and by the common crop costs subsumed in the constant.[24] One possible benefit beyond price that growers may derive from planting lettuce is that planting lettuce enables them to meet shipper contract requirements.[25] The lettuce dummy has a significant and positive total average effect as well. Thus, it is desirable for growers to control V. wilt, since they benefit from planting lettuce.

The coefficient on the spinach dummy is significant and negative, which suggests that the costs (monetary and otherwise) of planting and growing spinach are even higher than the common crop costs captured in the constant, and therefore that planting spinach is undesirable for reasons that are not fully captured by its price and by the common crop costs subsumed in the constant.[26] This coefficient provides evidence that V. wilt is a problem, since it is likely due to the fact that spinach is associated with V. wilt that planting spinach is undesirable and imposes costs on growers, monetary and otherwise, beyond the costs common to all crops.[27]

The broccoli dummy coefficient is significant and negative, which suggests that the monthly costs of planting and growing broccoli are even higher than the common monthly crop costs captured in the constant. Thus, broccoli is not only a low-return crop with a

[24]Because lettuce price is the discretized marketing average price of lettuce per acre, the lettuce price measures revenue per acre, and therefore incorporates yield as well. Monthly costs common to all crops are captured by the constant. Thus, the significant positive coefficient on the lettuce dummy suggests that lettuce is desirable to plant for reasons that are not fully captured by its price, yield, or revenue per acre; or by costs common to all crops.

[25]Although contracts can and do specify prices, the price we use in the model is the discretized county-level marketing average price, which we expect to be exogenous to individual contracting decisions.

[26]Because price is the discretized marketing average price of spinach per acre, the price measures revenue per acre, and therefore incorporates yield as well. The constant captures monthly costs common to all crops. 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; or by common crop costs.

[27]One may worry that the negative coefficient on the spinach dummy may possibly result from spinach having a shorter, one-month harvest season and therefore being potentially less appealing than crops with longer harvest seasons. Even when crop prices are divided by the length of the respective harvest season, however, the returns to spinach versus other crops still follow the same relative rank order, which suggests that the harvest season length is not the driving factor behind the negative coefficient on the spinach dummy. We confirm in robustness checks below that the significant negative coefficient on the spinach dummy is robust to whether we divide prices by harvest season length.

relatively low marketing year price (Figure A.3 in Appendix A), but it is also a relatively high-cost crop as well. In contrast, lettuce has a higher marketing year price than broccoli, as well as relatively low monthly net costs that are lower than the common monthly crop costs subsumed in the constant (since the lettuce dummy has a significant positive coefficient). Thus, broccoli is not a highly profitable crop, and less desirable to plant than lettuce, but planting broccoli may yield future benefits for lettuce growers. Planting broccoli is therefore a control option that requires incurring costs or forgoing profit in the current period for future benefit.

The coefficient on methyl bromide in the current period is significant and negative, which means that growers incur costs to fumigate with methyl bromide, even if doing so may yield future benefit to either the current crop or a future crop. The coefficient is more negative in the later period, likely because the Montreal Protocol started to limit the legal availability of methyl bromide during the later period (California Department of Pesticide Regulation, 2010; United States Environmental Protection Agency, 2020),[28] and also possibly because increased demand for methyl bromide in the later period when V. wilt became more of a problem may have resulted in higher costs to buying and using methyl bromide.

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 benefits of lettuce are enhanced in the presence of control options such as broccoli history. Moreover, for the entire time period and in the later period, the coefficient on the spinach dummy and broccoli history interaction term is significant and positive, and the point estimate is larger in magnitude than the spinach dummy, which suggests that the undesirability of planting spinach is offset by broccoli history, thereby providing further evidence that planting broccoli is an effective control option, especially in the later time period. Broccoli history has a significant positive total average effect on a grower's per-period payoff.

Our results show that methyl bromide does not appear to be as effective a control option as planting broccoli. The coefficient on the interaction term between lettuce and methyl bromide history is significant and negative over the entire time period and in the early time period, but is not statistically significant at a 5% level in the later time period. Similarly, the coefficient on the spinach dummy and methyl bromide history interaction term is significant and negative over the entire time period and in the later time period.

[28]As explained in more detail in Section 2, the Montreal Protocol phased out methyl bromide use for fumigation of vegetable crops such as lettuce in 2005; nevertheless, certain crops such as strawberries have received critical-use exemptions through 2016 (California Department of Pesticide Regulation, 2010; United States Environmental Protection Agency, 2020), and the residual effects from strawberry fumigation may provide protection for one or two seasons of lettuce before microsclerotia densities rise (Atallah, Hayes, and Subbarao, 2011).

The significant negative coefficients on the terms interacting methyl bromide history with lettuce and with spinach may indicate that methyl bromide may not have been an effective control option in the early period. The significant negative coefficient on the interaction term between lettuce and methyl bromide history in the early period may also indicate that in the early period, when growers and landowners were less aware of V. wilt, growers would only fumigate with methyl bromide if they already suffered from V. wilt; as a consequence, if growers on fields with methyl bromide history planted lettuce, their lettuce crop would be more likely to succumb to V. wilt. The significant negative coefficients on the terms interacting methyl bromide history with lettuce and with spinach may also indicate that lettuce is not as valuable if the soil has been recently fumigated, for example, because it is not organic. Methyl bromide history has a significant negative total average effect, which suggests that methyl bromide is neither an effective or desirable control option.

The last crop dummy interacted with a dummy for susceptible crops (which include strawberries, artichoke, and cabbage), which captures the requirement to grow a particular crop over multiple months, is significant and positive. Thus, as expected, growers growing crops that need to be grown over multiple months do grow these crops over multiple months.

The last crop dummy interacted with a dummy for all other crops (including lettuce, spinach, broccoli, and resistant crops), which captures the tendency for a grower to choose to replant the same crop over and over again, perhaps harvest after harvest, is significant and positive as well, and is larger in magnitude than the last crop dummy interacted with a dummy for susceptible crops.[29] The significant positive coefficient on the last crop dummy interacted with a dummy for all other crops suggests that growers tend to replant the same crop over and over again, perhaps harvest after harvest, and are less likely to switch crops. For example, growers or landowners may have connections and contracts that tie them to certain crops. They may have expertise or risk profiles that better suit certain crops. Growers may view the cost of switching to other crops to be 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.

[29] For the early time period, as seen in Table B.1 in Appendix B, we are unable to separately identify the last crop dummy for susceptible crops (other than lettuce) and for all other crops; we thus estimate one last crop dummy for all crops, which we find to be significant and positive. Results for the specification using one last crop dummy for all crops for the entire time period and the late time period as well are in Table B.2 in Appendix B. As seen in Table B.2 in Appendix B, results of likelihood ratio tests show that, for owners and renters over the entire period, owners in the early period, and owners and renters in the late period, the data does not reject the constrained model constraining the last crop dummy to be the same for susceptible crops and for all other crops, since the unconstrained model allowing the last crop dummy to differ for susceptible crops and for all other crops does not produce a statistically significant improvement in the ability of the model to fit data at a 5% level.

The coefficient on price at the time of harvest is not statistically significant at a 5% level. Thus, after controlling for crop and fumigation dummies for lettuce, spinach, broccoli, and methyl bromide, and after controlling for the requirement to grow a particular crop over multiple months and for the tendency for a grower to choose to replant the same crop over and over again, growers do not additionally respond to price. For example, although strawberries have a much higher revenue per acre than any of the vegetable crops, most owners concentrate on either strawberry crops or vegetable crops, so there are very few cases in the data of owners switching to strawberries from vegetable crops, even though that behavior is what one might expect based on price alone. As seen in the significant positive coefficient on the last crop dummy interacted with a dummy for all other crops, growers tend to replant the same crop over and over again, perhaps harvest after harvest, and therefore may not respond to price. For example, some owners may consider themselves vegetable growers and the cost of switching to strawberries is too high. Moreover, strawberry growers in California tend to rely heavily on methyl bromide (Hayden-Smith, 2016), and methyl bromide fumigation has high costs monetary and otherwise (as evidenced by our significant negative coefficient on the methyl bromide dummy), which may offset the high strawberry crop price. Indeed, strawberry costs are generally an order of magnitude higher than for the vegetable crops, in part due to fumigation cost (Richard Smith, Farm Advisor for Vegetable Crop Production & Weed Science with the University of California Cooperative Extension in Monterey County, personal communication, 2014).[30] Owners managing their land for long-term use may be particularly averse to fumigating with methyl bromide, for example because it renders their crops no longer organic, and therefore may be averse to planting crops such as strawberries that may necessitate methyl bromide fumigation. 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 (Mohapatra et al., 2010; Guthman, 2017).

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 costs of fumigation and to absorb cost differences among crops. As expected, the constant, which captures monthly costs that are common to all crops, is significant and negative. Also as expected, the coefficient on methyl bromide

[30] We also tried including a dummy for susceptible crops (which include strawberries) in our per-period payoff, but were unable to separately identify its coefficient from the coefficient on the methyl bromide dummy owing to collinearity; we therefore do not include the susceptible crop dummy in our base-case specification.

fumigation is significant and negative as well.

We use the parameter estimates to calculate the normalized average grower welfare per grower per month for owners and for renters over the entire time period ('all'), the early time period ('early'), and the later time period ('late'). The welfare is calculated as the present discounted value of the entire stream of payoffs to growers evaluated at the parameter values, summed over all growers in the relevant data set, then divided by the number of grower-months in the relevant data set. For each set of parameters ('all', 'early', and 'late'), the average grower welfare per grower per month is normalized so that the average welfare per grower per month for owners using that set of parameters is 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.

In the absence of an intertemporal externality, and if owners and renters faced the same state variables, we do not necessarily expect the renters to have a lower average welfare per grower-month. Indeed, over a short enough time period, in the absence of an intertemporal externality, and if owners and renters faced the same state variables, it is possible that renters, who optimize over a short time horizon, may have a higher average welfare per grower-month than owners, who optimize over a long time horizon and are therefore more willing to incur costs and forego profits in the short term in order to increase their future profits. Nevertheless, according to our welfare results in Table B.3 in Appendix B, average welfare per grower-month is higher for owners than for renters over the entire period, in the early time period, and in the later time period. Thus, owners who optimize over an infinite horizon instead of a finite horizon and who internalize the intertemporal externality are able to earn a higher discounted payoff per grower-month. We simulate counterfactual scenarios to analyze potential explanations for these results in Section 7.

6.2 Robustness Checks

We run two alternative specifications as robustness checks. In the first robustness check, we estimate our dynamic structural econometric model using lagged crop prices rather than current crop prices. In contrast to our base-case specification, which assumes rational expectations about crop price, this alternative specification assumes that growers' best guess for this year's crop price is last year's crop price. Table B.4 in Appendix B presents the results. The results are robust to whether we use lagged prices or current prices.

In our second robustness check, we examine whether the results are robust to the possibility that some growers may plant the same crop for multiple months in a harvest season. In our base-case specification, growers receive the average price each month during the harvest season. We run our second robustness check to address concerns related to double counting the revenues received by growers who grow crops with multi-month harvest seasons versus crops that grow in potentially only one-month harvest seasons (namely spinach).

In particular, we examine whether 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. Thus, in our second robustness check, we divide the marketing year average price for each crop by its average harvest season length in the data set, so that the grower receives the marketing year average price over the course of the harvest season, rather than the marketing year average price each month during the harvest season.

For each crop, we calculate the average number of months that crop is grown during the harvest season for that crop. 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.

For each crop and year, we divide the revenue by the average number of months for that crop and rebin the revenue values. This method better accounts for concerns about crops with a long growing season (e.g., strawberries) artificially having a higher value for revenue than crops with a short growing season (e.g., spinach).[31]

The results of the robustness check in which we divide the marketing year average price for each crop by its average harvest season length are presented in Table B.5 in Appendix B. Once again, the results are robust to whether we divide the marketing year average price for each crop by its average harvest season length.

In addition to our two robustness checks, we also try a third alternative specification

[31]We choose not to model growers as only receiving the revenue for their crop the first month of the harvest season, as this method 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 growers receive more revenue if they stay in the harvest season longer. For similar reasons, we choose not to model growers as only receiving the revenue for their crop the last month of the harvest season.

in which we drop the terms interacting the spinach dummy with broccoli history and with methyl bromide history, and include a spinach history variable instead. As seen in the results in Table B.6 in Appendix B, the spinach history variable does not have a significant effect in the entire period, in the early period, or in the later period. We therefore do not include spinach history in our base-case specification.

6.3 Alternative Specifications for Owners vs. Renters

In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons. Thus, in our base-case specifications, we pool owners (who have an infinite horizon) and renters (who have a finite horizon) together and estimate the same parameters θ for both owners and renters.

We also try several alternative specifications for owners vs. renters. In the first alternative specification for owners vs. renters, we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons for their dynamic decision-making (i.e., long- vs. short-term), but also have different parameters θ in their per-period payoff functions as well. The parameters θ in the payoff functions measure how different actions and state variables affect their per-period payoff. Differences in parameter values between owners and renters may arise if there are differences in incentives faced by renters versus owners – including differences in monetary benefits, monetary costs, non-monetary benefits, non-monetary costs, marketing contracts, shipper contracts, and/or renter contracts – that lead to differences between owners and renters in how different actions and state variables affect their per-period payoffs. We conduct a likelihood ratio test of the model allowing owners and renters to have different parameters versus the analogous base-case model constraining owners and renters to have the same parameters to see if owners and renters have different parameters.

The results of the first alternative specification for owners vs. renters, in which we allow owners and renters to not only have different time horizons for their dynamic decision-making, but also have different parameters θ, are reported in Table 2 for owners and Table 3 for renters.[32] As seen in the results of the likelihood ratio tests, the data rejects the constrained base-case model constraining owners and renters to have the same parameters, since the unconstrained model allowing owners and renters to have different parameters produces a statistically significant improvement in the ability of the model to fit the data at a 0.1% level for both owners (Table 2) and renters (Table 3).

We obtain similar results when we allow the last crop dummy to differ for susceptible

[32]Standard errors are reported in Table B.7 for owners and Table B.8 for renters in Appendix B.

crops and all other crops in Table B.9 for owners and Table B.10 for renters in Appendix B. Once again, as seen in the results of the likelihood ratio tests, the data rejects the constrained base-case model constraining owners and renters to have the same parameters, since the unconstrained model allowing owners and renters to have different parameters produces a statistically significant improvement in the ability of the model to fit the data at a 0.1% level for both owners (Table B.9) and renters (Table B.10).[33]

In the second alternative specification for owners vs. renters, we allow owners and renters to have not only the same parameters θ in their per-period payoff functions, but also the same infinite time horizon for their dynamic decision-making. Thus, this second alternative specification for owners vs. renters assumes that even though renters are short-term growers who only grow on the field for a short period of time, existing renter contracts internalize the intertemporal externality imposed by renters on future renters and the landowner, and thus induce renters to make the dynamically optimal decision as if they had an infinite time horizon rather than a finite time horizon. The results are reported in Table B.11.

We then conduct a likelihood ratio test of the first alternative specification for owners vs. renters – in which we allow owners and renters to not only have different time horizons for their dynamic decision-making, but also have different parameters – versus the second alternative specification for owners vs. renters – in which we constrain owners and renters to have the same parameters and the same infinite time horizon – to see if owners and renters have different parameters and different time horizons. As seen in the results of the likelihood ratio tests, the data rejects the constrained model constraining owners and renters to have the same parameters and same infinite time horizon, since the unconstrained model allowing owners and renters to have different parameters and different time horizons produces a statistically significant improvement in the ability of the model to fit the data at a 0.1% level for both owners (Table 2) and renters (Table 3). We obtain similar results when we allow the last crop dummy to differ for susceptible crops and all other crops in Table B.12.[34]

[33]For owners (Table B.9), we are unable to separately identify the last crop dummy for susceptible crops (other than lettuce) and for all other crops. For both owners (Table B.9) and renters (Table B.10), results of likelihood ratio tests show that the data does not reject the constrained model constraining the last crop dummy to be the same for susceptible crops and for all other crops, since the unconstrained model allowing the last crop dummy to differ for susceptible crops and for all other crops does not produce a statistically significant improvement in the ability of the model to fit data at a 5% level. Thus, for the first alternative specification for owners vs. renters, wherein owners and renters have different time horizons and different parameters, the specification in which we estimate the same last crop dummy for all crops, as reported in Table 2 for owners and Table 3 for renters, is a better fit to the data.

[34]We also conduct a likelihood ratio test of the base-case model allowing owners and renters to have the same parameters but different time horizons versus the model constraining owners and renters to have the same parameters and the same infinite time horizon. As seen in the results of the likelihood ratio tests, the data does not reject the constrained model constraining owners and renters to have the same parameters and same infinite time horizon, since the unconstrained model allowing owners and renters to have the same

Since the likelihood ratio tests show that allowing owners and renters to have different parameters as well as different time horizons produces a statistically significant improvement in the ability of the model to fit the data, we also run the base-case specification and the second alternative specification for owners vs. renters using two alternative specifications for the per-period payoff in which owners and renters have some of the same parameters θ in their per-period payoff, while some other parameters θ are allowed to vary either by owner vs. renter or by time period. In these alternative specifications of the per-period payoff, we use the same per-period payoff function for owners and renters, but we allow those parameters that appear to differ between owners and renters in Tables 2 and 3 to differ between owners and renters, and allow parameters that appear to differ between early and late periods in Tables 1, 2, and/or 3 to differ between the early and late periods. In particular, in both alternative specifications for the per-period payoff, the coefficient on the spinach dummy is allowed to differ by time period (early vs. late); and the coefficients on broccoli dummy, methyl bromide dummy, and price at the time of harvest are allowed to differ between owners and renters. In addition, in the second alternative specification for the per-period payoff, the coefficient on the last crop dummy no longer differs between susceptible crops and all other crops, but is instead allowed to differ between owners and renters. All other parameters are the same for owners and renters and for the entire time period.

Table B.13 presents the results for both alternative specifications for the per-period payoff when owners and renters have some of the same parameters θ in their per-period payoff functions, but differ in their time horizons. As seen in the results of the likelihood ratio tests, the data rejects the constrained model constraining owners and renters to have some of the same parameters, since the unconstrained model allowing owners and renters to have different parameters and different time horizons produces a statistically significant improvement in the ability of the model to fit data at a 0.1% level for both owners and renters.

Table B.14 presents the results for both alternative specifications for the per-period payoff when owners and renters have not only some of the same parameters θ in their per-period payoff functions, but also the same infinite time horizon for their dynamic decision-making. As seen in the results of the likelihood ratio tests, the data rejects the constrained model constraining owners and renters to have some of the same parameters and same infinite

parameters but different time horizons does not produce a statistically significant improvement in the ability of the model to fit the data at a 5% level. Nevertheless, the first alternative specification for owners vs. renters – in which we allow owners and renters to not only have different time horizons for their dynamic decision-making, but also have different parameters – better fits the data than both the base-case model and the model constraining owners and renters to have the same parameters and the same infinite time horizon. We obtain similar results when we allow the last crop dummy to differ for susceptible crops and all other crops in Table B.12.

time horizon, since the unconstrained model allowing owners and renters to have different parameters and different time horizons produces a statistically significant improvement in the ability of the model to fit data at a 0.1% level for both owners and renters.

Thus, the best-fit model for both owners and renters is the model allowing owners and renters to have different parameters and different time horizons, as reported in Table 2 for owners and Table 3 for renters.[35] When owners and renters are allowed to have different parameters in their per-period payoff, there are several main differences between the payoff parameters of owners and renters. First, in the early period, the coefficient on the spinach dummy is less negative for renters than for owners. Thus, existing contracts did not penalize renters for planting spinach in the early period. Second, in the late period, the coefficient on the lettuce dummy is less positive for renters than for owners, suggesting that renters benefited less from planting lettuce in the late period than owners did, perhaps because V. wilt was more of a problem for renters in the late period because the previous renters working on these fields in the early period had not been penalized for planting spinach. Third, the broccoli dummy has a significant positive total average effect for owners, but its total average effect is not significant at a 5% level for renters. Thus, existing contracts did not incentivize renters to plant broccoli despite its effectiveness as a control option and despite the future benefits it provides for future renters and the landowner. Fourth, the coefficient on the methyl bromide dummy is less negative for renters than for owners, suggesting that renters face lower costs (monetary and otherwise) than owners do for fumigating with methyl bromide. Owners managing their land for long-term use may be particularly averse to fumigating with methyl bromide, for example because it renders their crops no longer organic. As strawberry growers in California tend to rely heavily on methyl bromide (Hayden-Smith, 2016), the lower costs (monetary and otherwise) of methyl bromide fumigation for renters may explain in part why renters are more likely to plant susceptible crops (including strawberries) than owners are.

7 Counterfactual Simulations

There are several possible explanations for why the crop and fumigation decisions differ between owners and renters, and why the crop and fumigation decisions of renters differ in the earlier and later periods. One possible explanation is that renters faced different conditions such as different soil microsclerotia levels, output prices, revenues, soil quality, land quality, and previous control option use in the earlier period than in the later period; and similarly that owners had different characteristics, faced different conditions, and had

[35]Standard errors are reported in Table B.7 for owners and Table B.8 for renters in Appendix B.

different fields than renters did. Differences in conditions faced by owners and renters, and by renters in the early and late periods, are captured in part by differences in the data (or state variables) they faced. For example, as seen in the summary statistics in Tables A.1 and A.2 in Appendix A, one difference in the land and soil conditions between renters and owners is that renters worked on land that had lower broccoli history than owners did.

A second possible explanation for the differences in crop and fumigation decisions is that owners optimize over an infinite horizon, while renters optimize over a finite horizon. The differences in time horizons may explain differences in crop and fumigation decisions between owners and renters. The differences in time horizons may also explain why the crop and fumigation decisions change over time for renters but not for owners: the intertemporal externality that renters impose on future renters may cause conditions faced by renters to change and possibly deteriorate over time, leading to different crop and fumigation decisions by renters in the earlier and later periods.

A third possible explanation for the differences in crop and fumigation decisions between owners and renters, and between renters in the earlier periods and renters in the later periods, is that the parameters in the growers' payoff functions, which measure how different actions and state variables affect their per-period payoff, are different between owners and renters, and between renters in the earlier periods and renters in the later periods. Differences in parameter values between owners and renters may arise if there are differences in incentives faced by renters versus owners – for example due to differences in monetary benefits, non-monetary benefits, monetary costs, non-monetary costs, marketing contracts, shipper contracts, and/or renter contracts – that lead to differences between owners and renters in how different actions and state variables affect their per-period payoffs. Similarly, differences in parameter values between renters in the earlier periods and renters in the later periods may reflect in part differences over time in incentives faced by renters – reflecting differences over time in the severity of V. wilt, the effectiveness of control options, and renter contracts – that lead to differences over time in how different actions and state variables affect the per-period payoffs of renters.

To distinguish among the different explanations for differences in crop and fumigation decisions between owners and renters, and between renters in the earlier periods and renters in the later periods, we simulate counterfactual scenarios to analyze how differences in grower crop and fumigation decisions relate to differences in the data, differences in time horizons, and differences in parameter estimates. In particular, we simulate counterfactual scenarios that vary the data type (owner or renter), data time period (all, early, or late), time horizon (infinite or finite), parameter type (owner or renter), and/or parameter time period (all, early, or late). By using the results of our structural model to simulate owners on renter fields and renters on owner fields, our counterfactual simulations also enable us to address any concerns that the owners and renters in our data set may have differed in their characteristics, in the conditions they faced, and/or in the quality of their fields.

For each counterfactual scenario, we run twenty-five simulations.[36] In each simulation, we start with the state variables in the relevant data set from the first year of the relevant time period, and we simulate the actions and state variables for all relevant growers for all relevant time periods of the relevant time horizon. For each time period of the simulation, we take a draw from the choice probabilities evaluated at the state variables to simulate the action choice for each grower. We also take a draw from the transition density for the exogenous state variables (crop prices) to determine the values of the exogenous state variables next period.[37] We then calculate next period's values of the endogenous state variables (methyl bromide fumigation history, broccoli history, and last crop dummy), which evolve deterministically as a function of this period's action. Once the next period's state variables are determined, we draw the action for the next period from the choice probabilities evaluated at next period's state variables. We continue simulating actions and state variables for the length of the time horizon. For each simulation, we calculate the number of grower-months in each action type and the average welfare per grower-month.[38] For each counterfactual scenario, our estimates for the number of grower-months in each action type are calculated by taking the average of the number of grower-months in each action type over all twenty-five simulations for that scenario.

Standard errors are calculated using a nonparametric bootstrap. In particular, for each counterfactual scenario, we calculate the standard errors 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. For each counterfactual scenario, the standard error of the simulation statistics (e.g., mean fraction) for that scenario is the standard deviation of the respective statistic over all twenty-five bootstrap samples.[39]

[36] Constraints on computational time, particularly for the standard error calculations below, which require running twenty-five simulations using the parameter estimates from each of the twenty-five bootstrap samples, preclude us from running more than twenty-five simulations per scenario.

[37] As explained in more detail in Section 4, since the price variable we use is the annual 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.

[38] If a grower-month is missing in the actual data, we do not use that grower-month in the simulated data in calculating the number of grower-months in each action type and the average welfare per grower-month.

[39] Constraints on computational time preclude us from running the twenty-five simulations per bootstrap sample per scenario for more than twenty-five bootstrap samples per scenario. When we calculated the standard errors of the simulation statistics using 100 bootstrap samples instead of twenty-five bootstrap

To examine whether the owners in our data set would have made different crop and fumigation decisions in different periods of time if in one period (e.g., the early period) they faced the conditions (owner data) and/or parameters from a different period (e.g., the later period), we run counterfactual scenarios in which we simulate the decision-making of owners using owner data and owner infinite horizon under various different combinations of time periods for parameters and owner data. Figure C.1 in Appendix C presents the simulation results of the mean fraction of grower-months in each action for nine different counterfactual scenarios using owner data and owner infinite horizon using the structural parameters from the base-case specification in which owners and renters have the same parameters in Table 1. Each of the nine graphs presents the results from a different counterfactual scenario using owner data from one of three time periods (all, early, or late) and using parameter estimates from one of three time periods (all, early, or late). Across the different combinations of time periods for parameters and owner data, results show that the majority of grower-months are planted to lettuce. These crop-fumigation profiles resemble the actual choices of owners in the data in Figure 1. We also obtain similar results in Figure C.2 in Appendix C, which presents the simulation results of the mean fraction of grower-months in each action for the scenarios using owner data, owner infinite horizon, and the structural parameters for owners from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2.[40] When examining the fraction of grower-months in each action type by year for the simulations using the owner parameters, data, and infinite horizon (Figures C.3-C.5) in Appendix C, we similarly find that the crop mix is similar to the actual owner choices. Thus, the simulation results using owner data and owner (infinite) horizon appear to replicate the actual owner decisions relatively well.

To examine whether the owners in our data set would have made different crop and fumigation decisions if they had optimized over a finite horizon rather than an infinite horizon, and therefore whether differences in owner and renter crop and fumigation decisions are a result of differences in decision-making time horizon, we run counterfactual scenarios in which we simulate the decision-making of growers who are faced with the conditions (or state variables) faced by the owners in our data set (owner data) but who optimize over a finite horizon (renter horizon) instead of an infinite horizon. Figure 2 presents the simulation results of the mean fraction of grower-months in each action for nine different counterfactual scenarios using owner data and renter finite horizon using the structural parameters from the

samples for the first counterfactual scenario we ran – the counterfactual scenario using owner parameters for the entire period, owner data for the entire period, and an owner infinite horizon – the values of the standard errors calculated using 100 bootstrap samples were similar to those calculated using twenty-five bootstrap samples.

[40] Standard errors for the owner parameters are reported in Table B.7 in Appendix B.

base-case specification in Table 1. Across the different time periods for both the data and the parameters, results of our counterfactual scenarios using a finite horizon show that when growers face a short-term planning horizon rather than a long-term one, they are less likely to engage in control options such as planting broccoli or fumigating with methyl bromide that require incurring current costs for future gain.

To examine whether the owners in our data set would have made different crop and fumigation decisions if they had faced the same conditions and values of the state variables that the renters faced (renter data) rather than their actual conditions and state variables (owner data), and therefore whether the differences in crop and fumigation decisions between owners and renters are due to differences in data, which reflect differences in the conditions faced by renters and owners, we run counterfactual scenarios in which we simulate the decision-making of growers who optimize over an infinite horizon (owner horizon), but who are faced with the conditions (or state variables) faced by the renters in our data set (renter data). Figure 3 presents the simulation results of the mean fraction of grower-months in each action for nine different counterfactual scenarios using renter data and owner infinite horizon using the structural parameters from the base-case specification in Table 1. The results are similar across the parameter times, but differ across the data times. Using the early renter data results in lettuce being the most frequent crop choice, followed by susceptible crops; while using the late renter data results in susceptible crops being the most frequent crop choice, followed by lettuce. These crop-fumigation profiles resemble the actual renter decisions observed in the data in Figure 1. We also obtain similar results in Figure C.6 in Appendix C, which presents the simulation results of the mean fraction of grower-months in each action for nine different counterfactual scenarios using renter data, owner infinite horizon, and the structural parameters for owners from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2.[41] These results suggest that the differences in crop-fumigation choices between renters and owners may be due in part to differences in data, which capture differences in state variables and therefore differences in the conditions faced by growers.

The counterfactual scenarios in Figure 3 and Figure C.6 in Appendix C also enable us to examine whether differences in renter crop and fumigation decisions between the early and late period were due to differences in the conditions and values of the state variables that the renters had faced in the early and late period, as captured by differences in the renter data in different time periods. Irrespective of the parameter time, using the early renter data results in crop-fumigation profiles that begin to resemble the actual renter decisions in the early period in Figure 1, with lettuce being the most frequent crop choice, followed by susceptible

[41] Standard errors for the owner parameters are reported in Table B.7 in Appendix B.

crops. Similarly, irrespective of the parameter time, using the late renter data results in crop-fumigation profiles that begin to resemble the actual renter decisions in the late period in Figure 1, with susceptible crops being the most frequent crop choice, followed by lettuce. This pattern seems to suggest that the differences in crop-fumigation choices between renters in the early and late period may be due in part to differences in data faced by renters in the early and late period, which capture differences in state variables and therefore differences in the conditions faced by renters in the early and late period.

To examine whether the owners in our data set would have made different crop and fumigation decisions if they had made decisions based on the parameters faced by renters (renter parameters) rather than their actual (owner) parameters, and therefore whether the differences in crop and fumigation decisions between owners and renters are due to differences in parameter estimates – which reflect differences in incentives, monetary benefits, non-monetary benefits, monetary costs, non-monetary costs, marketing contracts, shipper contracts, and/or renter contracts – Figure 4 presents the simulation results of the mean fraction of grower-months in each action for nine different counterfactual scenarios using owner data, owner infinite horizon, and the structural parameters for renters (renter parameters) from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 3.[42] Results show that, when using the renter parameters, planting susceptible crops (other than lettuce) is the most frequently chosen action choice, and there is very little if any planting of broccoli or fumigation with methyl bromide. Certain cases, such as the middle column of Figure 4, which uses the renter parameters from the early period, and which therefore reflects renter contracts in the early period, closely approximate the actual decisions made by renters in the data. When examining the fraction of grower-months in each action type by year in Figures C.7-C.9 in Appendix C, we find that there is very little if any planting of broccoli or fumigating with methyl bromide, except in the very first years of the simulations with an infinite horizon. In the first years of the simulation, the crop mix is split between lettuce and other susceptible crops. As the years progress in the simulation, a larger and larger portion of the grower-months is planted to susceptible crops (other than lettuce). In the actual observed choices of renters over time in Figure A.2 in Appendix A, there is also a gradual switch from lettuce to other susceptible crops, but it is not as dramatic as in the simulations. Thus, when using the renter parameters, which reflect the incentives faced by renters due in part to renter contracts, growers are less likely to engage in control options such as planting broccoli that require incurring current costs for future gain.

[42]Standard errors for the renter parameters are reported in Table B.8 in Appendix B.

8 Conclusion

In this paper we analyze and compare short- versus long-term decision-making for crop disease control by developing and estimating a dynamic structural econometric model of V. wilt management over the period 1993 to 2011. Results show that although planting broccoli can be an effective control option, growers with a short time horizon are less likely to incur costs and forego profits in the current period for future benefit by planting this low-return, high-cost control crop. Renters plant broccoli less frequently than owners do, and are even less likely to plant broccoli in the late period (2001 to 2011) compared to the early period (1993 to 2000). In addition, renters in the early period plant spinach more frequently than owners do. By planting spinach and not planting broccoli, renters impose an intertemporal externality on future renters and landowners, thereby raising the microsclerotia levels and lowering the land quality of the land used by future renters. As a consequence, renters work on land that has lower broccoli history, higher microsclerotia levels, and lower quality than owners do. These differences in the conditions faced by renters and owners, and in conditions faced by renters in the early and late period, further contribute to differences in the crop and fumigation choices being made by renters and owners, and by renters in the early and late period.

Although contracts can be a potential method for internalizing an externality between different parties, our empirical results show that existing renter contracts do not fully internalize the intertemporal externality imposed by renters on future renters and the landowner. Differences in payoff parameter estimates between renters and owners, which reflect differences in incentives faced by owners and renters that lead to differences in how different actions and state variables affect their per-period payoffs, suggest that existing contracts did not penalize renters for planting spinach in the early period; and moreover that existing contracts did not incentivize renters to plant broccoli despite its effectiveness as a control option and despite the future benefits it provides for future renters and the landowner. In counterfactual simulations using the renter payoff parameters, which reflect renter contracts and incentives faced by renters, growers are less likely to engage in control options such as planting broccoli that require incurring current costs for future gain.

There are several possible reasons why existing renter contracts do not fully internalize the intertemporal externality imposed by renters on future renters and the landowner, including the relatively recent development of the disease and knowledge of its causes, more restrictive contracts not being the norm, the possibility of land unknowingly being contaminated before rental, difficulty in enforcing or monitoring aspects of the contract such as whether boots and equipment are washed between fields, difficulty in enforcing penalties on previous renters no longer working on the field for the contamination of a future crop years later, and/or difficulty in ascertaining how much each of the previous renters contributed to the contamination once it is discovered. V. wilt was not documented on lettuce until 1995 and was not observed on lettuce in Monterey County until 1999, and the likely sources of the disease were not known until years later. If contracts that include stipulations to control V. wilt are not the norm in the area, highly restrictive contracts – such as a contract that requires or incentivizes renters to plant broccoli, a low-return crop, in lieu of a more profitable crop – may be less desirable and receive lower rents. In addition, if such highly restrictive, less desirable contracts would only be accepted by lower quality renters, who may be even less likely to make long-term investments in land and soil quality than higher quality renters are, then issues of adverse selection and possible market unraveling (Akerlof, 1970) may arise as well, and further explain why renter contracts do not fully internalize the intertemporal externality imposed by renters on future renters and the landowner.

Our results point to several potential avenues for future research. First, in order to best examine and illustrate the differences in long-term and short-term decision-making for crop disease control, and the intertemporal externalities that arise with the latter, we have focused on extreme and clearly defined cases of long- and short-term growers, and we have defined 'owners' and 'renters' in such a way that precludes the possibility that a grower might switch from one status to the other during the time period of our data set. In future work, we hope to consider growers with different lengths of history on a field, and also to add an option for owners to rent land to short-term users. Second, when we consider growers with different lengths of history on a field in future work, unobserved heterogeneity may become more important. In our best-fit specification, which allows the parameters to differ for owners and renters, we allow for unobserved heterogeneity between owners and renters by estimating the dynamic structural econometric model separately for owners and for renters. We hope in future work to further capture unobserved heterogeneity using methods developed by Arcidiacono and Miller (2011), Scott (2013), and Connault (2016). Third, although costs are accounted for by the crop-fumigation dummies and the constant in our model, although we allow these costs to differ between the early and later periods of our data set, although the costs we capture include monthly input and growing costs that are incurred even during months prior to harvest, and although the costs we capture include both monetary and non-monetary costs, we do not explicitly model changes in crop and fumigation costs over time, as time series data on growers' crop and fumigation costs are not available.[43] In future

[43]As explained in detail in Section 5, cost estimates for Monterey County from the University of California 'Cost and Return Studies' are not available for either spinach or any resistant crop for any of the 19 years of our analysis; are not available for any of the crops in our model for any year in the early period; are only available for broccoli for two out of the 19 years of our analysis; and are only available for lettuce for three

work we hope to develop methods and/or acquire data to enable us to further capture and estimate crop and fumigation costs and changes in these costs over time.

out of the 19 years of our analysis (University of California Agricultural Issues Center, 2020a,b).

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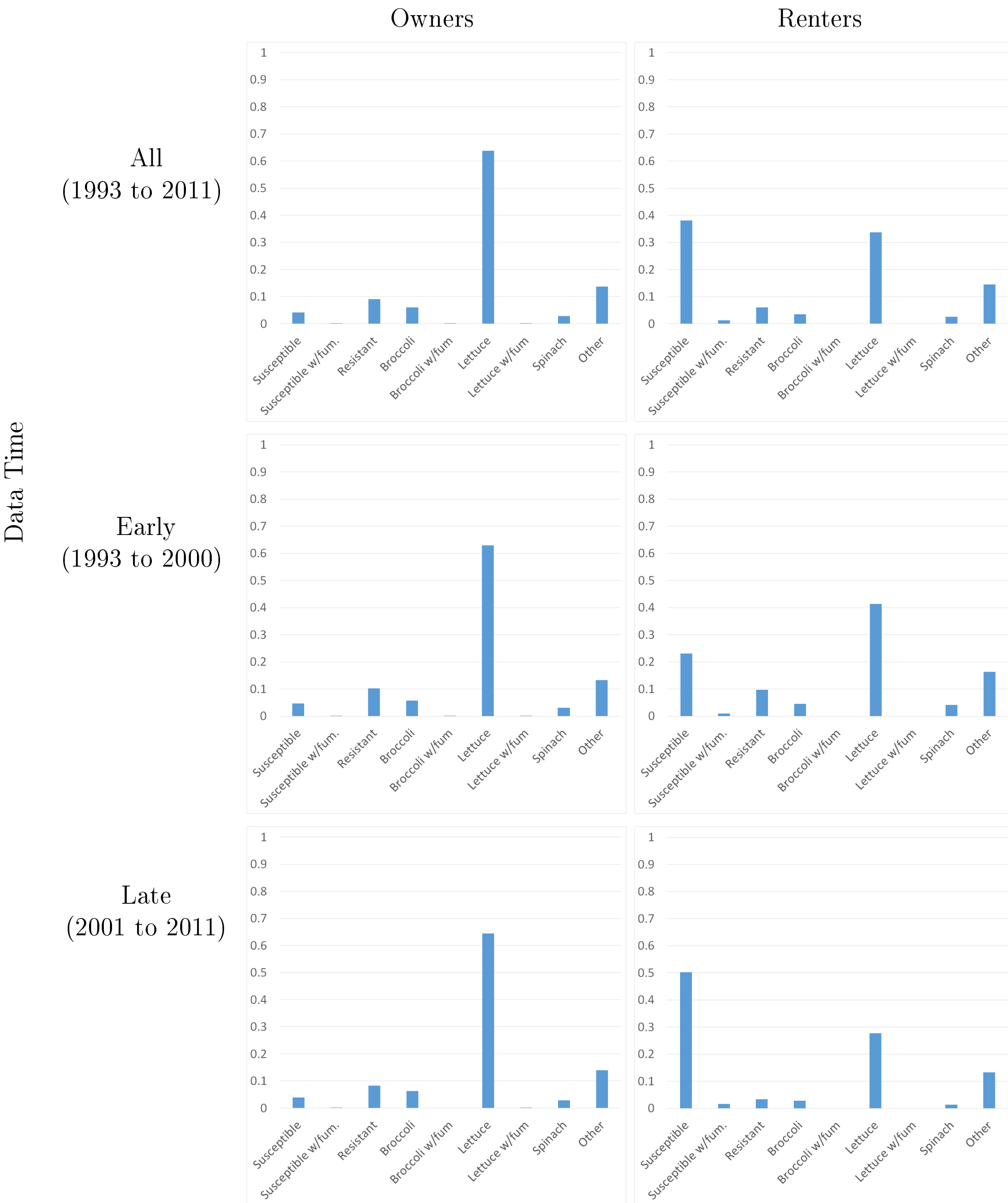
Figure 1
Actual fraction of grower-months in each action



Notes: Figures present the actual mean fraction of grower-months in each action for owners and renters, as calculated from the actual data for owners and renters from the entire time period from 1993 to 2011 ('all'), the early period from 1993 to 2000 ('early'), and the later period from 2001 to 2011 ('late').

Table 1
Structural parameter estimates: Base-case specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.3687***	1.3916***	1.3486***
	(0.0142)	(0.054)	(0.0268)
Spinach dummy	−1.0234***	−0.7893***	−1.3114***
	(0.0077)	(0.0978)	(0.0049)
Broccoli dummy	−0.7452***	−0.9193***	−0.6099***
	(0.0082)	(0.1033)	(0.0246)
Methyl bromide dummy	−5.0341***	−5.0627***	−5.0226***
	(0.0022)	(0.3354)	(0.0066)
Lettuce dummy*Broccoli history	0.2819***	0.2815***	0.2893***
	(0.0078)	(0.0220)	(0.0130)
Spinach dummy*Broccoli history	0.1327***	0.0987	0.1960***
	(0.0100)	(0.0987)	(0.0209)
Lettuce dummy*Methyl bromide history	−0.1526***	−0.2640**	−0.0428
	(0.0280)	(0.0817)	(0.0481)
Spinach dummy*Methyl bromide history	−0.2777***	−0.3192	−0.4895***
	(0.0026)	(0.3044)	(0.0019)
Last crop dummy*Susceptible	9.3716***		8.9883***
	(0.0012)		(0.0068)
Last crop dummy*(1-Susceptible)	13.3819***		13.4399***
	(0.0001)		(0.0007)
Last crop dummy		13.5478***	
		(1.1456)	
Price*Harvest month dummy	−0.0254	−0.0371	−0.0100
	(0.0157)	(0.0207)	(0.0144)
Constant	−1.2615***	−1.2139***	−1.3245***
	(0.0166)	(0.1587)	(0.0428)
Total average effects on per-period payoff of:			
Lettuce dummy	1.3775***	1.4002***	1.3575***
	(0.0142)	(0.0540)	(0.0268)
Spinach dummy	−1.0195***	−0.7868***	−1.3056***
	(0.0077)	(0.0978)	(0.0049)
Broccoli history	0.1611***	0.1635***	0.1638***
	(0.0044)	(0.0127)	(0.0072)
Methyl bromide history	−0.0930***	−0.1610***	−0.0352
	(0.0156)	(0.0476)	(0.0265)
Number of growers	4,024	2,329	2,537
Number of observations	34,570	14,855	19,715

Notes: In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Table reports results from estimating the base-case model using data from the entire time period from 1993 to 2011 ('all'), the early period from 1993 to 2000 ('early'), and the later period from 2001 to 2011 ('late'). For the early time period, as seen in Table B.1 in Appendix B, we are unable to separately identify the last crop dummy for susceptible crops (other than lettuce) and for all other crops; we thus estimate one last crop dummy for all crops. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table 2

Structural parameter estimates for owners: Different parameters for owners and renters specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.4346***	1.3844***	1.4691***
Spinach dummy	−1.1311***	−1.1905***	−1.0703***
Broccoli dummy	−0.3320	−0.5953	−0.1615
Methyl bromide dummy	−6.0705***	−5.6993***	−6.3633***
Lettuce dummy*Broccoli history	0.3682***	0.3674***	0.3707***
Spinach dummy*Broccoli history	0.2643	0.2665	0.2573
Lettuce dummy*Methyl bromide history	0.3717	0.1992	0.8501*
Spinach dummy*Methyl bromide history	0.0260	0.0787	0.2734
Last crop dummy	21.2161***	24.2249***	20.0534***
Price*Harvest month dummy	−0.1585***	−0.1558***	−0.16***
Constant	−1.1482***	−1.0881***	−1.1906***
Total average effects on per-period payoff of:			
Lettuce dummy	1.4498***	1.4003***	1.4838***
Spinach dummy	−1.1206***	−1.1791***	−1.0603***
Broccoli history	0.2424***	0.2390***	0.2460***
Methyl bromide history	0.2378	0.1276	0.5554*
Likelihood ratio test to compare with model constraining owners and renters to have the same parameters:			
HO: Owners and renters have the same parameters			
LR Test statistic D for owners	544.0***	170.6***	403.2***
Likelihood ratio test to compare with model constraining owners and renters to have same parameters and same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for owners	384.0***	115.6***	310.4***
Number of growers	615	615	615
Number of observations	25,761	10,833	14,928

Notes: Table presents owner parameter estimates for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well. Table reports results from estimating the model using data from the entire time period from 1993 to 2011 ('all'), the early period from 1993 to 2000 ('early'), and the later period from 2001 to 2011 ('late'). Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

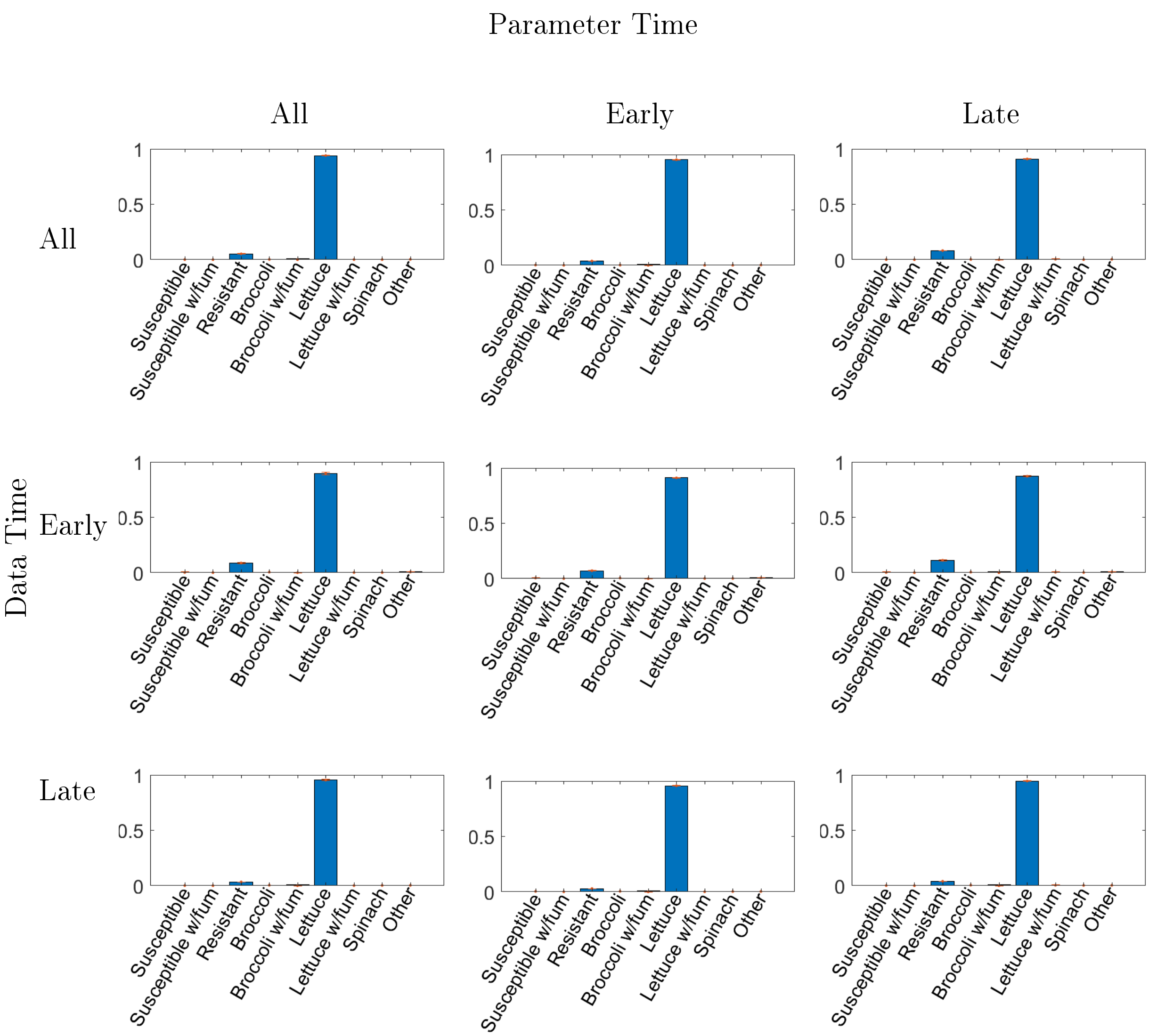
Table 3

Structural parameter estimates for renters: Different parameters for owners and renters specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.1418***	1.3062***	0.9446***
Spinach dummy	−0.9102***	−0.4113***	−1.6942***
Broccoli dummy	−0.7869*	−0.7347***	−0.8572***
Methyl bromide dummy	−3.4359***	−3.2691***	−3.4927***
Lettuce dummy*Broccoli history	0.0900	0.0865	0.1188
Spinach dummy*Broccoli history	0.0685	−0.0602	0.2835
Lettuce dummy*Methyl bromide history	−0.7858	−1.2257**	−0.5477
Spinach dummy*Methyl bromide history	−0.6607***	−0.5787***	−1.8690***
Last crop dummy	6.2960***	6.5520***	6.0021***
Price*Harvest month dummy	0.1689***	0.1091***	0.2249***
Constant	−1.4824***	−1.3666***	−1.6426***
Total average effects on per-period payoff of:			
Lettuce dummy	1.1421***	1.3049***	0.9458***
Spinach dummy	−0.9100***	−0.4129***	−1.6914***
Broccoli history	0.0322	0.0331	0.0367
Methyl bromide history	−0.2830	−0.5310**	−0.1763
Likelihood ratio test to compare with model constraining owners and renters to have the same parameters:			
HO: Owners and renters have the same parameters			
LR Test statistic D for renters	723.4***	215.2***	592.0***
Likelihood ratio test to compare with model constraining owners and renters to have same parameters and same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for renters	597.0***	188.2***	468.2***
Number of growers	3,409	1,714	1,922
Number of observations	9,306	4,144	5,162

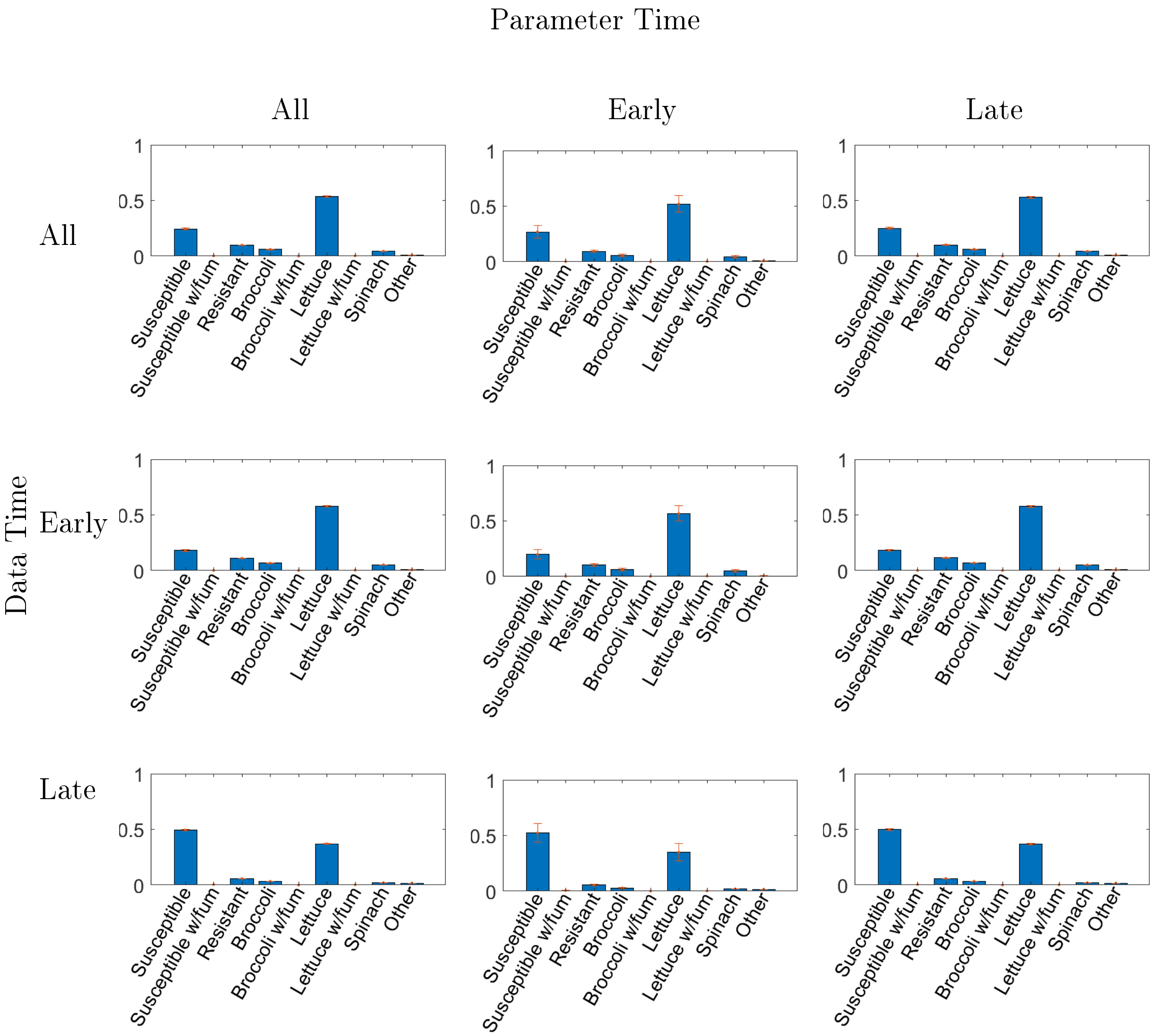
Notes: Table presents renter parameter estimates for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well. Table reports results from estimating the model using data from the entire time period from 1993 to 2011 ('all'), the early period from 1993 to 2000 ('early'), and the later period from 2001 to 2011 ('late'). Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Figure 2
Counterfactual fraction of grower-months in each action:
Simulations using owner data and renter horizon



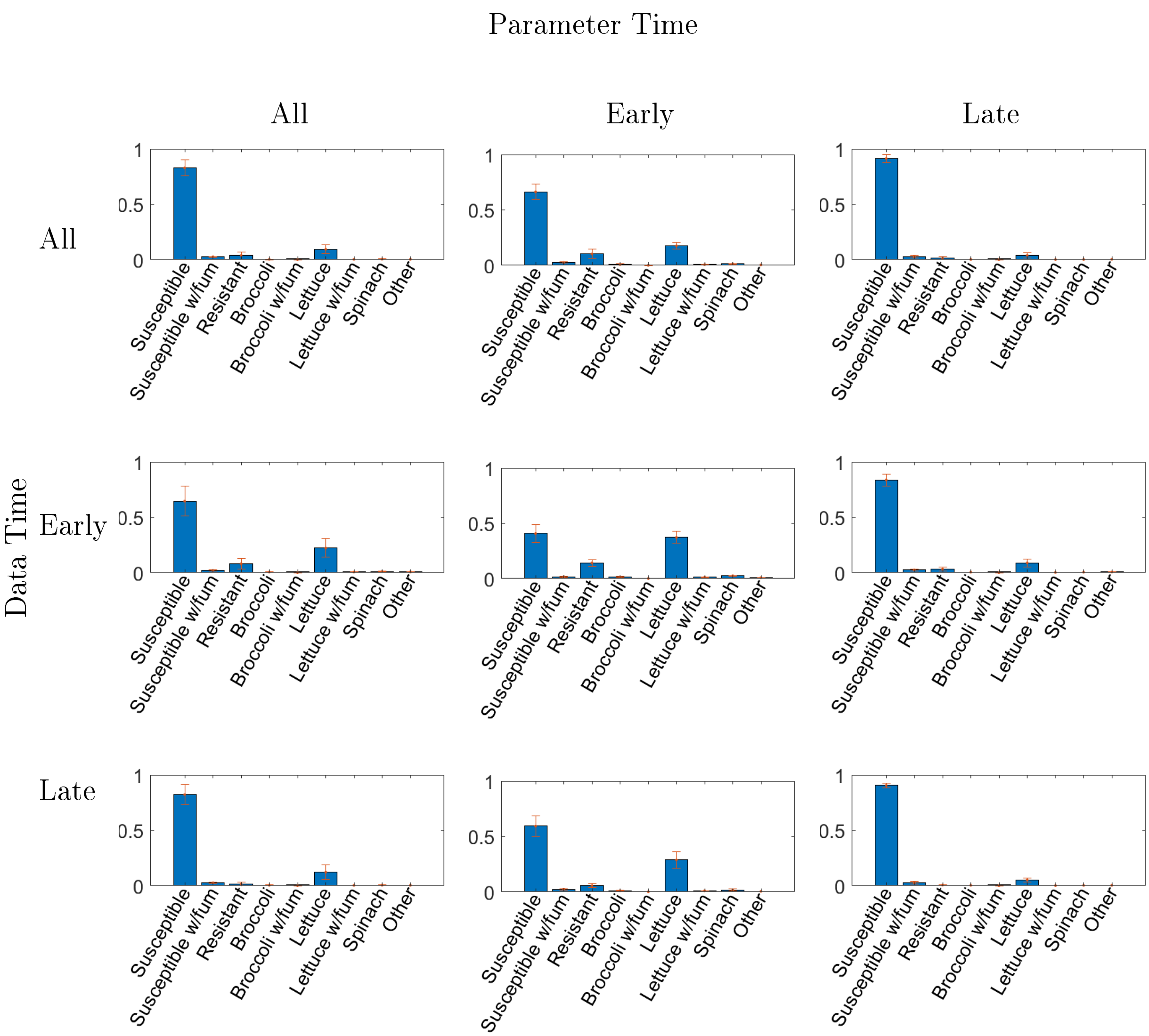
Notes: Figures present the counterfactual results for mean fraction of grower-months in each action from 9 different counterfactual scenarios using parameter estimates from our base-case specification in Table 1 applied to owner data and a renter finite horizon. In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using owner data from one of 3 time periods (all, early, or late) and using parameter estimates from one of 3 time periods (all, early, or late). For each of the 9 counterfactual scenarios, 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 3
Counterfactual fraction of grower-months in each action:
Simulations using renter data and owner horizon



Notes: Figures present the counterfactual results for mean fraction of grower-months in each action from 9 different counterfactual scenarios using parameter estimates from our base-case specification in Table 1 applied to renter data and an owner infinite horizon. In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using renter data from one of 3 time periods (all, early, or late) and using parameter estimates from one of 3 time periods (all, early, or late). For each of the 9 counterfactual scenarios, 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 4
Counterfactual fraction of grower-months in each action:
Simulations using renter parameters, owner data, and owner horizon



Notes: Figures present the counterfactual results for mean fraction of grower-months in each action from 9 different counterfactual scenarios using the structural parameters for renters from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 3 (standard errors in Table B.8 in Appendix B) applied to owner data and an owner infinite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using owner data from one of 3 time periods (all, early, or late) and using renter parameter estimates from one of 3 time periods (all, early, or late). For each scenario, 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.

Appendix A.
Supplementary Figures and Tables Describing Data

Figure A.1
Actual fraction of grower-months for each action by year: Owners

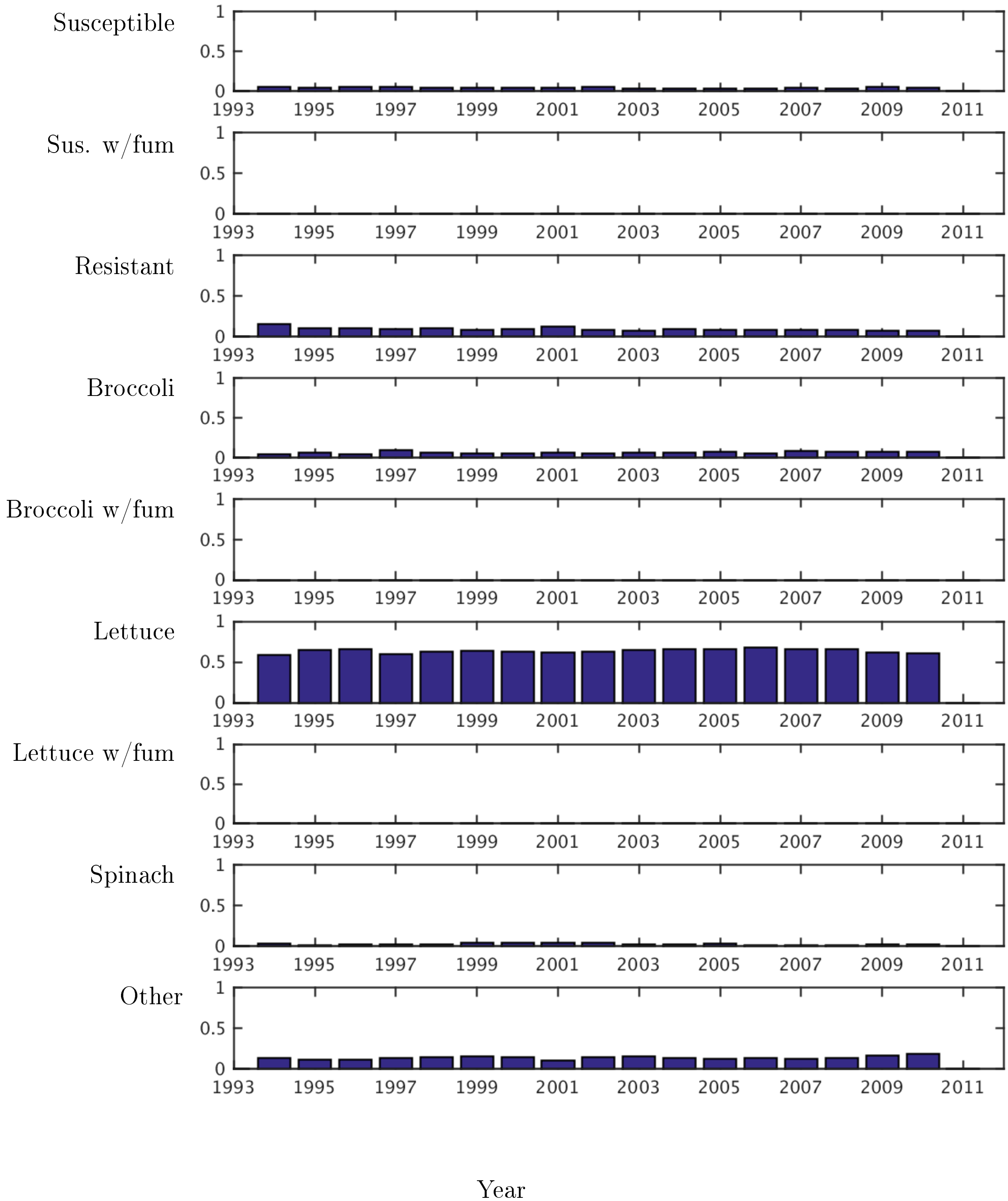


Figure A.2
Actual fraction of grower-months for each action by year: Renters

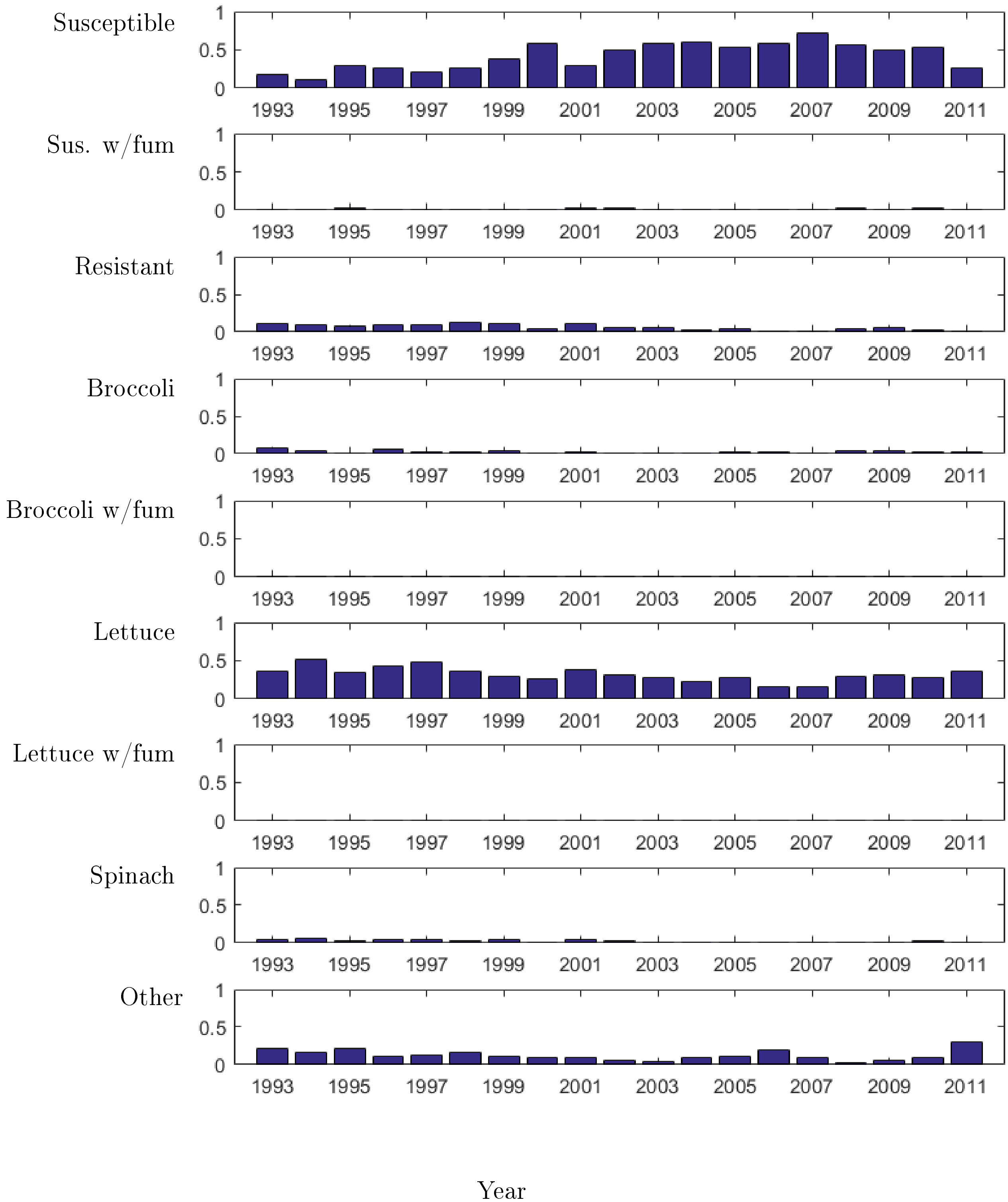
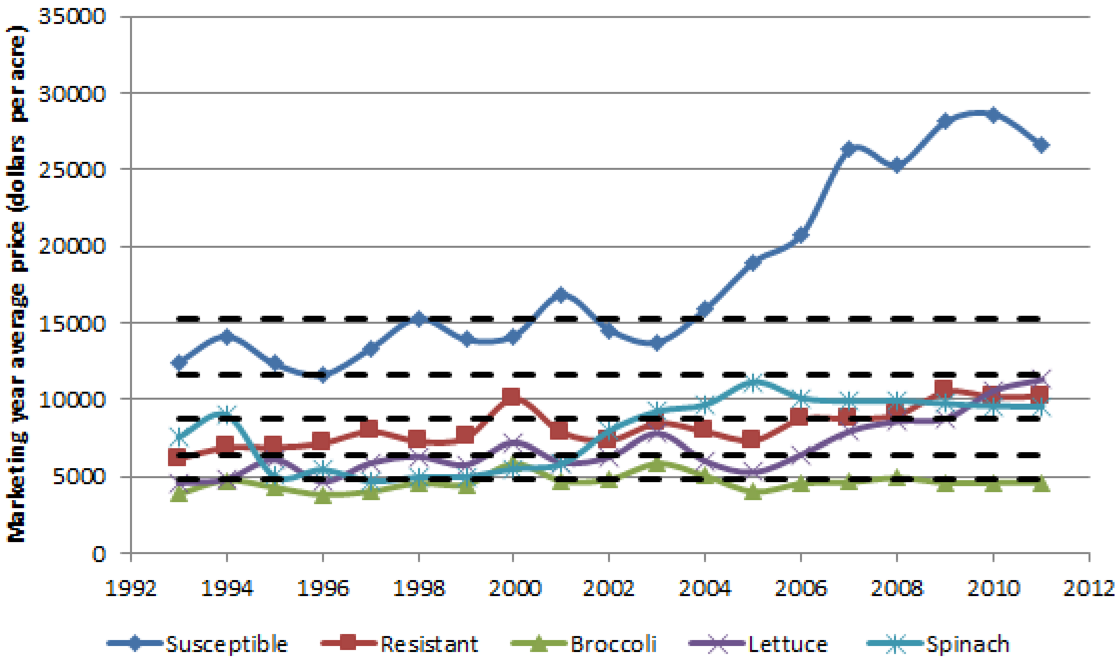


Figure A.3
Marketing year average prices per acre



Notes: The marketing year average price is in units of dollars per acre, and therefore measures revenue per acre and incorporates yield. The Monterey County Agricultural Commissioner's Office publishes annual crop reports including prices, yields, 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. Black dashed lines delineate the bins used to discretize the marketing year average price. The cutoff values for the first 5 price bins are the 5 quintiles for marketing year average price. Since the marketing year average price for susceptible crops (which include strawberries) is always in the highest quintile in every year of our data set, and since the highest quintile spans a wide range of prices, we further divide the highest quintile into 2 bins, using the median marketing year average price for susceptible crops as the cutoff value.

Table A.1
Summary statistics: Owners

	Owner all	Owner early	Owner late
Lettuce dummy	0.6379	0.6288	0.6444
	(0.4806)	(0.4831)	(0.4787)
Spinach dummy	0.0285	0.0299	0.0276
	(0.1665)	(0.1703)	(0.1637)
Broccoli dummy	0.0606	0.0566	0.0634
	(0.2385)	(0.2312)	(0.2438)
Methyl bromide dummy	0.0033	0.0051	0.0021
	(0.0577)	(0.0709)	(0.0455)
Broccoli history	1.5821	1.3330	1.7639
	(1.9597)	(1.9818)	(1.9232)
Lettuce dummy * Broccoli history	1.1709	0.9565	1.3273
	(1.8277)	(1.7727)	(1.8513)
Spinach dummy * Broccoli history	0.0397	0.0418	0.0382
	(0.3701)	(0.3795)	(0.3630)
Methyl bromide history	0.0567	0.0791	0.0404
	(0.3424)	(0.3639)	(0.3249)
Lettuce dummy * Methyl bromide history	0.0229	0.0364	0.0131
	(0.1602)	(0.1945)	(0.1286)
Spinach dummy * Methyl bromide history	0.0015	0.0027	0.0006
	(0.0431)	(0.0598)	(0.0246)
Lettuce price * Lettuce harvest month dummy	1.9552	1.5739	2.2333
	(1.1004)	(0.9202)	(1.1371)
Spinach price * Spinach harvest month dummy	2.5268	1.7349	3.1043
	(1.4709)	(1.0454)	(1.4676)
Broccoli price * Broccoli harvest month dummy	1.1742	1.0828	1.2409
	(0.5082)	(0.4455)	(0.5398)
Susceptible price * Susceptible harvest month dummy	5.0660	4.6038	5.4032
	(1.4914)	(0.4831)	(1.4988)
Resistant price * Resistant harvest month dummy	1.8748	1.8736	1.8757
	(1.6125)	(1.5703)	(1.6427)
Number of observations	25,789	10,877	14,912

Notes: Means are presented for owners over the entire time period from 1993 to 2011 ('all'), owners over the early period from 1993 to 2000 ('early'), and owners over the later period from 2001 to 2011 ('late'). Standard deviations are in parentheses. 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).

Table A.2
Summary statistics: Renters

	Renter all	Renter early	Renter late
Lettuce dummy	0.3380	0.4129	0.2776
	(0.4730)	(0.4924)	(0.4479)
Spinach dummy	0.0264	0.0431	0.0130
	(0.1604)	(0.2031)	(0.1132)
Broccoli dummy	0.0349	0.0445	0.0271
	(0.1835)	(0.2063)	(0.1625)
Methyl bromide dummy	0.0134	0.0101	0.0161
	(0.1151)	(0.1001)	(0.1258)
Broccoli history	0.3348	0.2874	0.3730
	(1.0003)	(1.0009)	(0.9982)
Lettuce dummy * Broccoli history	0.1402	0.1355	0.1440
	(0.6573)	(0.6455)	(0.6667)
Spinach dummy * Broccoli history	0.0098	0.0096	0.0099
	(0.1906)	(0.1452)	(0.2204)
Methyl bromide history	0.1450	0.1117	0.1718
	(0.5813)	(0.5048)	(0.6351)
Lettuce dummy * Methyl bromide history	0.0081	0.0053	0.0103
	(0.1559)	(0.1074)	(0.1860)
Spinach dummy * Methyl bromide history	0.0007	0.0017	0.0000
	(0.0274)	(0.0410)	(0.0000)
Lettuce price * Lettuce harvest month dummy	2.0509	1.3110	2.6468
	(1.2716)	(0.7618)	(1.2869)
Spinach price * Spinach harvest month dummy	2.9083	2.3483	3.3592
	(1.4310)	(1.2836)	(1.3835)
Broccoli price * Broccoli harvest month dummy	1.0841	1.0176	1.1377
	(0.4188)	(0.3269)	(0.4735)
Susceptible price * Susceptible harvest month dummy	5.1649	4.7183	5.5246
	(1.3913)	(1.1529)	(1.4609)
Resistant price * Resistant harvest month dummy	1.9244	1.7260	2.0841
	(1.6409)	(1.4392)	(1.7709)
Number of observations	9,312	4,154	5,158

Notes: Means are presented for renters over the entire time period from 1993 to 2011 ('all'), renters over the early period from 1993 to 2000 ('early'), and renters over the later period from 2001 to 2011 ('late'). Standard deviations are in parentheses. 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).

Table A.3
Summary statistics: All grower-fields

	Owner all	Renter all	All grower-fields
Lettuce dummy	0.6379	0.3380	0.4746
	(0.4806)	(0.4730)	(0.4994)
Spinach dummy	0.0285	0.0264	0.0516
	(0.1665)	(0.1604)	(0.2212)
Broccoli dummy	0.0606	0.0349	0.1222
	(0.2385)	(0.1835)	(0.3275)
Methyl bromide dummy	0.0033	0.0134	0.0060
	(0.0577)	(0.1151)	(0.0770)
Broccoli history	1.5821	0.3348	0.8693
	(1.9597)	(1.0003)	(1.6892)
Lettuce dummy * Broccoli history	1.1709	0.1402	0.4341
	(1.8277)	(0.6573)	(1.2114)
Spinach dummy * Broccoli history	0.0397	0.0098	0.0259
	(0.3701)	(0.1906)	(0.3138)
Methyl bromide history	0.0567	0.1450	0.0465
	(0.3424)	(0.5813)	(0.3247)
Lettuce dummy * Methyl bromide history	0.0229	0.0081	0.0069
	(0.1602)	(0.1559)	(0.0982)
Spinach dummy * Methyl bromide history	0.0015	0.0007	0.0006
	(0.0431)	(0.0274)	(0.0272)
Lettuce price * Lettuce harvest month dummy	1.9552	2.0509	1.9387
	(1.1004)	(1.2716)	(1.2289)
Spinach price * Spinach harvest month dummy	2.5268	2.9083	2.5978
	(1.4709)	(1.4310)	(1.4904)
Broccoli price * Broccoli harvest month dummy	1.1742	1.0841	1.1357
	(0.5082)	(0.4188)	(0.5046)
Susceptible price * Susceptible harvest month dummy	5.0660	5.1649	4.8486
	(1.4914)	(1.3913)	(1.8276)
Resistant price * Resistant harvest month dummy	1.8748	1.9244	1.9542
	(1.6125)	(1.6409)	(1.6296)
Number of observations	25,789	9,312	1,033,964

Notes: Means are presented for owners over the entire time period from 1993 to 2011, renters over the entire time period from 1993 to 2011, and for all grower-fields in the entire data set over the entire time period from 1993 to 2011. Standard deviations are in parentheses. 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 A.4
Map of owners

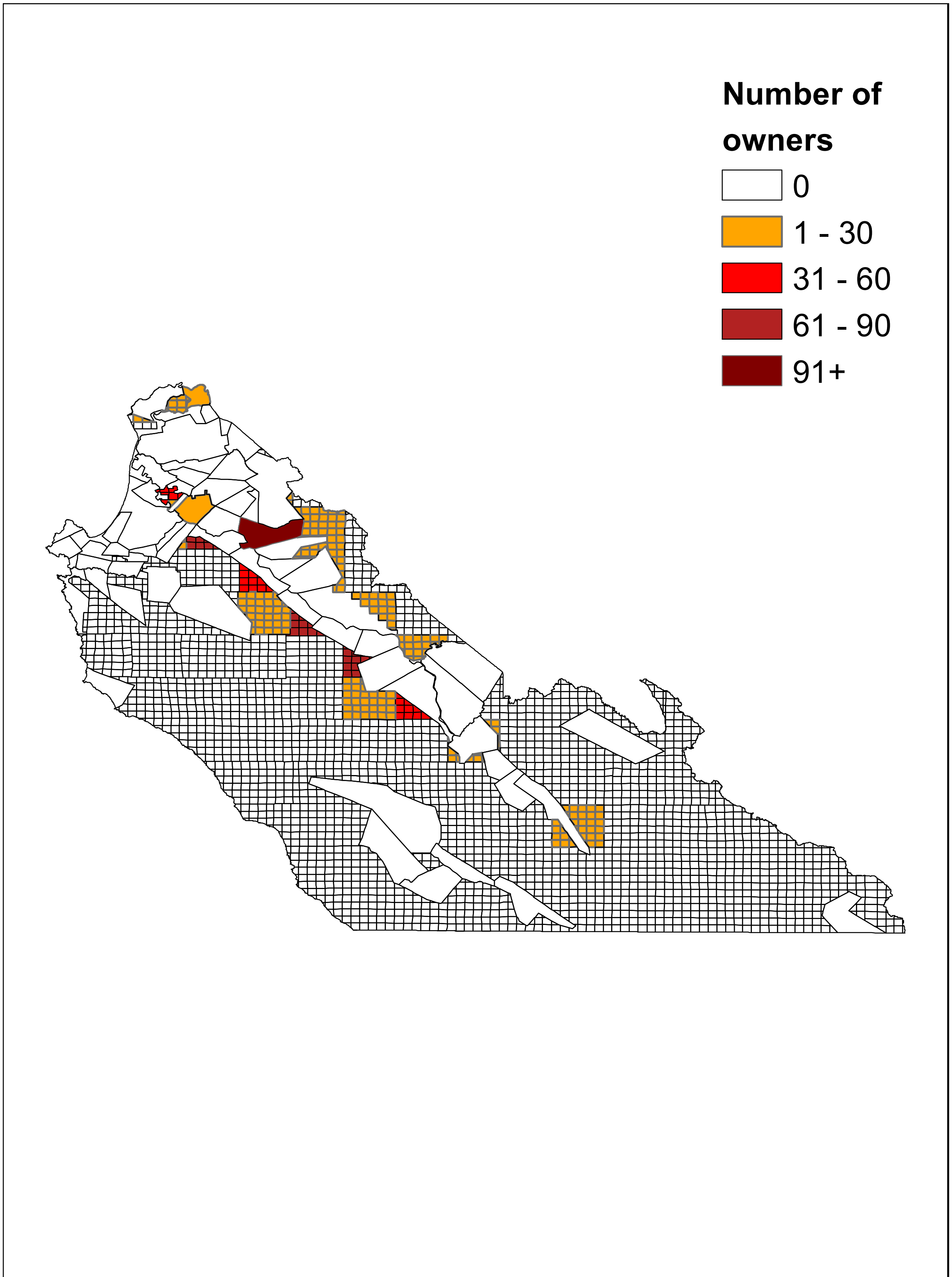


Figure A.5
Map of renters over the entire time period

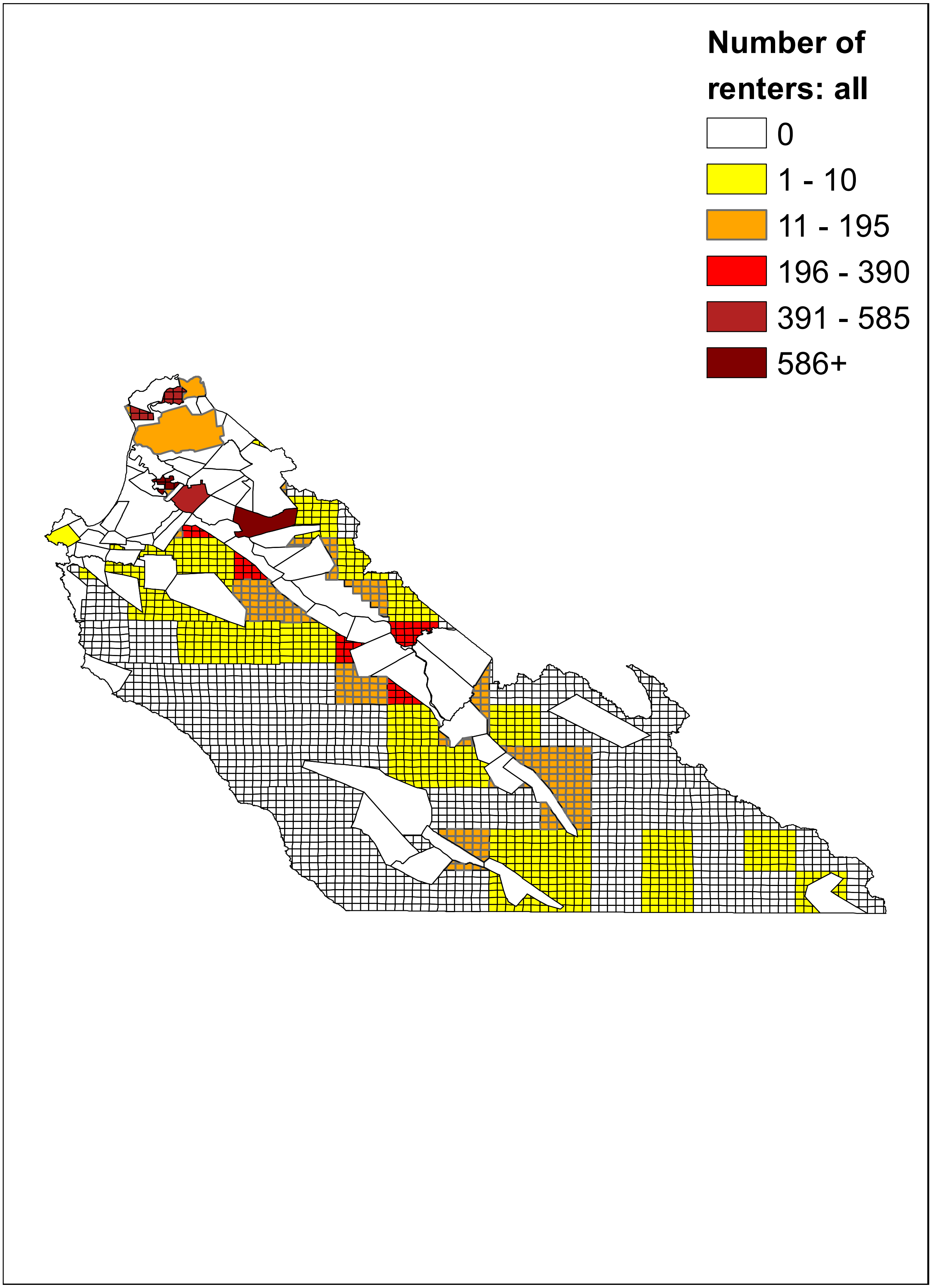


Figure A.6
Map of renters in the early time period

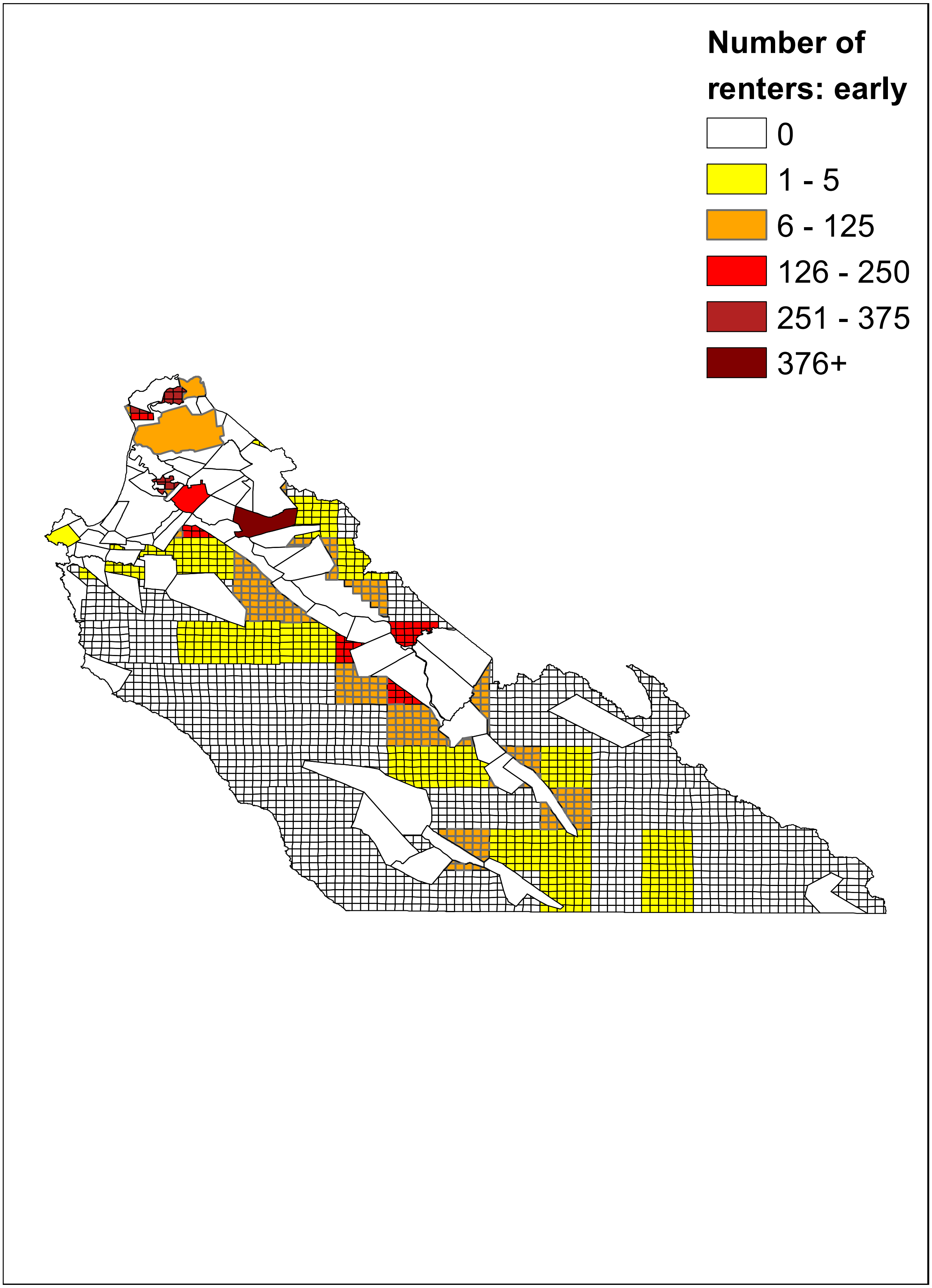
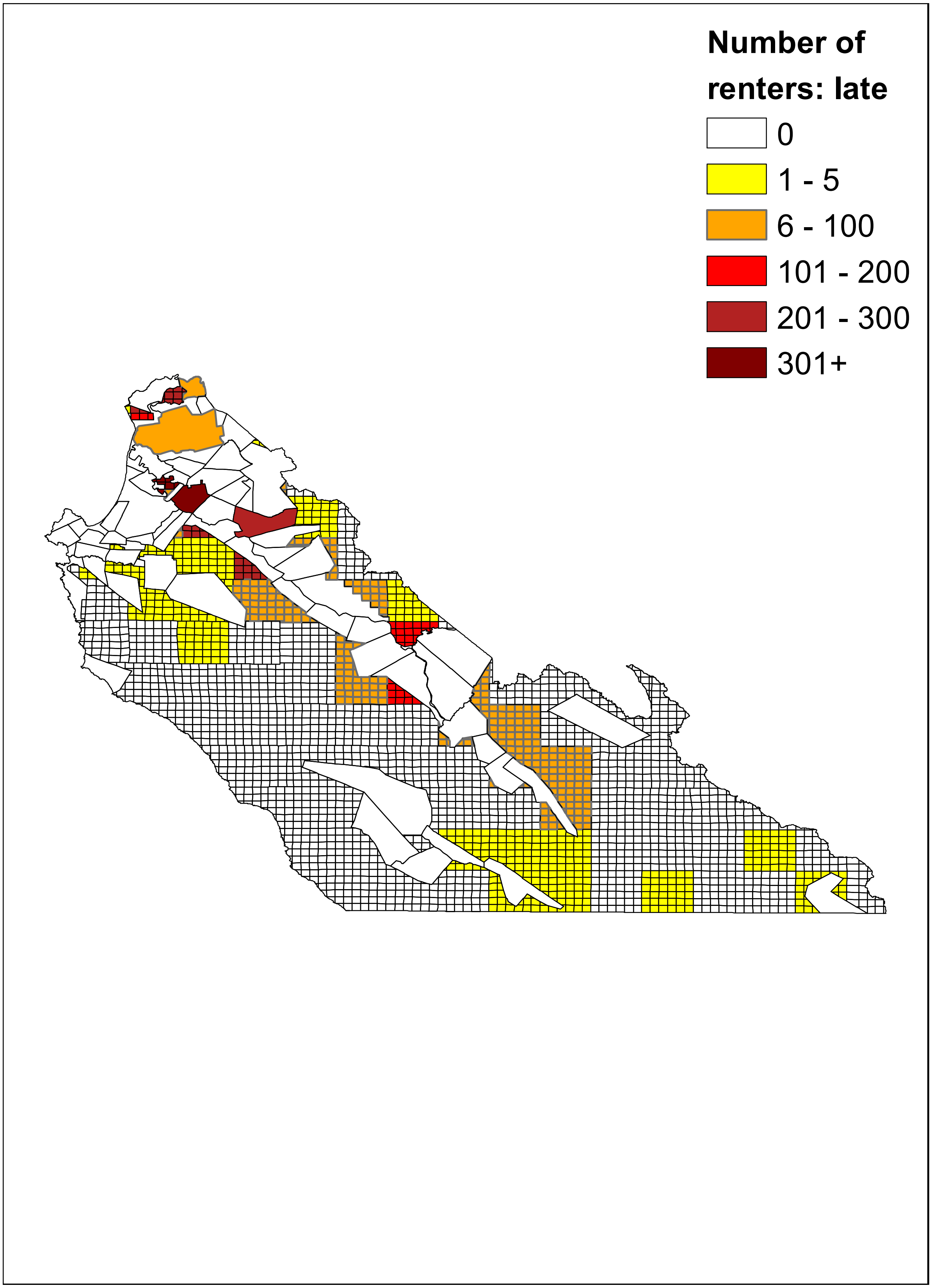


Figure A.7
Map of renters in the late time period



Appendix B.
Robustness Checks

Table B.1
Different last crop dummy for susceptible crops and all other crops specification

	All (Base)	Early	Late (Base)
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.3687***	1.3917***	1.3486***
Spinach dummy	−1.0234***	−0.7889***	−1.3114***
Broccoli dummy	−0.7452***	−0.919***	−0.6099***
Methyl bromide dummy	−5.0341***	−5.0627***	−5.0226***
Lettuce dummy*Broccoli history	0.2819***	0.2814***	0.2893***
Spinach dummy*Broccoli history	0.1327***	0.0985*	0.1960***
Lettuce dummy*Methyl bromide history	−0.1526***	−0.2641***	−0.0428
Spinach dummy*Methyl bromide history	−0.2777***	−0.3191***	−0.4895***
Last crop dummy*Susceptible	9.3716***	24.2170***	8.9883***
Last crop dummy*(1-Susceptible)	13.3819***	24.2170***	13.4399***
Price*Harvest month dummy	−0.0254	−0.0371*	−0.0100
Constant	−1.2615***	−1.2139***	−1.3245***
Total average effects on per-period payoff of:			
Lettuce dummy	1.3775***	1.4003***	1.3575***
Spinach dummy	−1.0195***	−0.7864***	−1.3056***
Broccoli history	0.1611***	0.1635***	0.1638***
Methyl bromide history	−0.0930***	−0.1610***	−0.0352
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the specification in which owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons (owners have an infinite horizon and renters have a finite horizon); and in which we estimate the last crop dummy separately for susceptible crops (which include strawberries, artichoke, and cabbage) and for all other crops (including lettuce, spinach, broccoli, and resistant crops). We use this specification as our base-case specification for the entire time period ('all') and for the later time period ('late') in Table 1. For the early time period, however, we are unable to separately identify the last crop dummy for susceptible crops (other than lettuce) and for all other crops. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.2
Same last crop dummy for all crops specification

	All	Early (Base)	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.3698***	1.3916***	1.3499***
Spinach dummy	−1.0215***	−0.7893***	−1.3084***
Broccoli dummy	−0.7429***	−0.9193***	−0.6076***
Methyl bromide dummy	−5.0336***	−5.0627***	−5.0232***
Lettuce dummy*Broccoli history	0.2816***	0.2815***	0.2889***
Spinach dummy*Broccoli history	0.1324*	0.0987	0.1954***
Lettuce dummy*Methyl bromide history	−0.1526**	−0.2640**	−0.0415
Spinach dummy*Methyl bromide history	−0.2873***	−0.3192	−0.4864***
Last crop dummy	10.5370***	13.5478***	9.9679***
Price*Harvest month dummy	−0.0256	−0.0371	−0.0104
Constant	−1.2619***	−1.2139***	−1.3244***
Total average effects on per-period payoff of:			
Lettuce dummy	1.3786***	1.4002***	1.3588***
Spinach dummy	−1.0177***	−0.7868***	−1.3026***
Broccoli history	0.1609***	0.1635***	0.1636***
Methyl bromide history	−0.0932**	−0.1610***	−0.0344
Likelihood ratio test to compare with model that does not constrain last crop dummy to be the same for all crops:			
HO: Last crop dummies are the same for susceptible crops and all other crops			
LR Test statistic D for owners	2.0	0.0	1.2
LR Test statistic D for renters	−9.4	10.0**	−4.2
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the specification in which owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons (owners have an infinite horizon and renters have a finite horizon); and in which we estimate one last crop dummy for all crops. For the early time period, as seen in Table B.1 in Appendix B, we are unable to separately identify the last crop dummy for susceptible crops (other than lettuce) and for all other crops; we therefore use this specification, which estimates one last crop dummy for all crops, as our base-case specification for the early time period ('early') in Table 1. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.3
Normalized average present discounted grower welfare per grower-month

	All	Early	Late
Owner Welfare (per grower-month)	**100**	**100**	**100**
	(0.62)	(8.81)	(0.69)
Renter Welfare (per grower-month)	74.05	78.44	74.17
	(0.89)	(7.56)	(1.03)

Notes: Table presents the results for the normalized average present discounted grower welfare per grower-month using parameter estimates from our base-case specification in Table 1. In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. For each set of parameters ('all', 'early', and 'late'), the average grower welfare per grower per month is normalized so that the average welfare per grower per month for owners using that set of parameters is 100. Standard errors in parentheses. The standard errors for the welfare values are calculated using the parameter estimates from each of 100 bootstrap samples. All welfare values are significant at a 0.1% level.

Table B.4
Robustness 1: Lagged price specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.7493***	1.3791***	1.4046***
	(0.0355)	(0.0361)	(0.0785)
Spinach dummy	−0.8753***	−0.8100***	−1.2646***
	(0.0573)	(0.1007)	(0.1295)
Broccoli dummy	−0.6736***	−0.9819***	−0.5769***
	(0.0588)	(0.0835)	(0.1215)
Methyl bromide dummy	−4.8272***	−5.0042***	−5.0278***
	(0.0303)	(0.0944)	(0.5451)
Lettuce dummy*Broccoli history	0.2732***	0.265***	0.2794***
	(0.0183)	(0.0178)	(0.0207)
Spinach dummy*Broccoli history	0.1112**	0.0951	0.1882***
	(0.0384)	(0.0638)	(0.044)
Lettuce dummy*Methyl bromide history	−0.5608***	−0.2819**	−0.0092
	(0.0702)	(0.0857)	(0.1006)
Spinach dummy*Methyl bromide history	−0.4572***	−0.3671***	−0.5362***
	(0.0213)	(0.0227)	(0.0321)
Last crop dummy	1.7816***	15.4141***	20.0112***
	(0.0737)	(0.0032)	(0.0055)
Price*Harvest month dummy	−0.0601***	−0.0776***	0.0069
	(0.0106)	(0.0150)	(0.0208)
Constant	−0.738***	−1.1003***	−1.3785***
	(0.1095)	(0.1200)	(0.1977)
Total average effects on per-period payoff of:			
Lettuce dummy	1.7573***	1.3871***	1.4132***
	(0.0355)	(0.0361)	(0.0785)
Spinach dummy	−0.8724***	−0.8078***	−1.2590***
	(0.0573)	(0.1007)	(0.1295)
Broccoli history	0.1556***	0.1540***	0.1582***
	(0.0203)	(0.0104)	(0.0114)
Methyl bromide history	−0.3259***	−0.1728***	−0.0178
	(0.0392)	(0.0488)	(0.0544)
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the alternative specification in which we use lagged crop prices rather than current crop prices for *Price*. Standard errors are in parentheses. As in our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.5
Robustness 2: Price divided by harvest season specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.4112***	1.4584***	1.3825***
	(0.1106)	(0.043)	(0.0966)
Spinach dummy	−1.0011***	−0.7456***	−1.2972***
	(0.1132)	(0.0949)	(0.0946)
Broccoli dummy	−0.6758***	−0.8328***	−0.5479***
	(0.1759)	(0.0763)	(0.1475)
Methyl bromide dummy	−5.0377***	−5.0667***	−5.0249***
	(0.1556)	(0.1719)	(0.3949)
Lettuce dummy*Broccoli history	0.2822***	0.2821***	0.2899***
	(0.0189)	(0.0218)	(0.0216)
Spinach dummy*Broccoli history	0.1340*	0.1040	0.1957**
	(0.0648)	(0.0604)	(0.0538)
Lettuce dummy*Methyl bromide history	−0.1507**	−0.2646**	−0.0422
	(0.0476)	(0.0830)	(0.0851)
Spinach dummy*Methyl bromide history	−0.2753***	−0.3280***	−0.4648***
	(0.0183)	(0.0391)	(0.0340)
Last crop dummy	10.5161***	24.2158***	9.9676***
	(0.0381)	(0.0105)	(0.2279)
Price*Harvest month dummy	0.0037	0.0039	0.0138
	(0.0238)	(0.0168)	(0.0192)
Constant	−1.3585***	−1.3385***	−1.4130***
	(0.1618)	(0.1365)	(0.1777)
Total average effects on per-period payoff of:			
Lettuce dummy	1.4200***	1.4670***	1.3914***
	(0.1106)	(0.0430)	(0.0966)
Spinach dummy	−0.9972***	−0.7429***	−1.2914***
	(0.1132)	(0.0949)	(0.0946)
Broccoli history	0.1613***	0.1641***	0.1642***
	(0.0107)	(0.0126)	(0.0120)
Methyl bromide history	−0.0918***	−0.1616***	−0.0343
	(0.0266)	(0.0473)	(0.0468)
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the alternative specification in which *Price* is the marketing year average price for each crop by its average harvest season length in the data set, so that the grower receives the marketing year average price over the course of the harvest season, rather than the marketing year average price each month during the harvest season. As in our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.6
Spinach history specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Spinach history	0.1509	0.1694	0.1491
	(11.0300)	(1.6888)	(5.1846)
Lettuce dummy	1.3659	1.3806	1.3535
	(5.8202)	(1.9822)	(1.4321)
Spinach dummy	−1.1311	−1.0287	−1.2726***
	(2.1952)	(2.9695)	(0.3272)
Broccoli dummy	−0.7140	−0.8970	−0.5656
	(3.9122)	(2.8765)	(0.9259)
Methyl bromide dummy	−5.0433***	−5.0742***	−5.0367***
	(0.3957)	(0.2990)	(0.6697)
Lettuce dummy*Broccoli history	0.2742	0.2750	0.2815
	(1.2886)	(0.9935)	(1.3728)
Lettuce dummy*Methyl bromide history	−0.1313	−0.2518	−0.0202
	(3.1238)	(0.7852)	(0.4219)
Last crop dummy	10.5808***	40.3207***	9.9888***
	(2.1192)	(3.4052)	(1.9682)
Price*Harvest month dummy	−0.0304	−0.0448	−0.0106
	(1.2317)	(0.6217)	(0.6791)
Constant	−1.3479	−1.2508	−1.4644
	(4.1856)	(2.4994)	(1.6673)
Total average effects on per-period payoff of:			
Lettuce dummy	1.5247	1.6188	1.3919
	(12.4286)	(3.0294)	(1.7665)
Spinach dummy	−1.1311	−1.0287	−1.2726***
	(2.1952)	(2.9695)	(0.3272)
Broccoli history	0.1531	0.1565	0.1549
	(0.7194)	(0.5655)	(0.7553)
Methyl bromide history	−0.0733	−0.1433	−0.0111
	(1.7440)	(0.4469)	(0.2321)
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the alternative specification in which we drop the interactions between the spinach dummy and broccoli history and between the spinach dummy and methyl bromide history, and include a spinach history variable instead. Standard errors are in parentheses. As in our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.7
Different parameters for owners and renters specification: Results for owners

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.4346***	1.3844***	1.4691***
	(0.1817)	(0.1874)	(0.1782)
Spinach dummy	−1.1311***	−1.1905***	−1.0703***
	(0.2981)	(0.3297)	(0.2419)
Broccoli dummy	−0.3320	−0.5953	−0.1615
	(0.2035)	(0.4956)	(0.1800)
Methyl bromide dummy	−6.0705***	−5.6993***	−6.3633***
	(0.0640)	(0.1077)	(0.0630)
Lettuce dummy*Broccoli history	0.3682***	0.3674***	0.3707***
	(0.0605)	(0.0632)	(0.0558)
Spinach dummy*Broccoli history	0.2643	0.2665	0.2573
	(0.4769)	(0.2598)	(0.6341)
Lettuce dummy*Methyl bromide history	0.3717	0.1992	0.8501*
	(0.4648)	(0.4174)	(0.3797)
Spinach dummy*Methyl bromide history	0.0260	0.0787	0.2734
	(0.1956)	(0.3034)	(0.1949)
Last crop dummy	21.2161***	24.2249***	20.0534***
	(1.0463)	(3.8795)	(0.7860)
Price*Harvest month dummy	−0.1585***	−0.1558***	−0.1600***
	(0.0414)	(0.0458)	(0.0399)
Constant	−1.1482***	−1.0881***	−1.1906***
	(0.3027)	(0.2381)	(0.2592)
Total average effects on per-period payoff of:			
Lettuce dummy	1.4498***	1.4003***	1.4838***
	(0.1817)	(0.1874)	(0.1782)
Spinach dummy	−1.1206***	−1.1791***	−1.0603***
	(0.2987)	(0.3299)	(0.2431)
Broccoli history	0.2424***	0.2390***	0.2460***
	(0.0409)	(0.0405)	(0.0400)
Methyl bromide history	0.2378	0.1276	0.5554*
	(0.2968)	(0.2630)	(0.2450)
Number of observations	25,761	10,833	14,928

Notes: Table presents owner parameter estimates and standard errors for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level. Parameter estimates are also reported in the paper in Table 2.

Table B.8
Different parameters for owners and renters specification: Results for renters

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.1418***	1.3062***	0.9446***
	(0.0515)	(0.1030)	(0.1746)
Spinach dummy	−0.9102***	−0.4113***	−1.6942***
	(0.0649)	(0.0991)	(0.2957)
Broccoli dummy	−0.7869*	−0.7347***	−0.8572***
	(0.3779)	(0.1953)	(0.2350)
Methyl bromide dummy	−3.4359***	−3.2691***	−3.4927***
	(0.1099)	(0.2273)	(0.3797)
Lettuce dummy*Broccoli history	0.0900	0.0865	0.1188
	(0.0890)	(0.0574)	(0.0659)
Spinach dummy*Broccoli history	0.0685	−0.0602	0.2835
	(0.4075)	(0.1735)	(0.5055)
Lettuce dummy*Methyl bromide history	−0.7858	−1.2257**	−0.5477
	(0.4823)	(0.4757)	(0.9411)
Spinach dummy*Methyl bromide history	−0.6607***	−0.5787***	−1.869***
	(0.0591)	(0.1674)	(0.0788)
Last crop dummy	6.2960***	6.5520***	6.0021***
	(0.7458)	(0.3843)	(0.7797)
Price*Harvest month dummy	0.1689***	0.1091***	0.2249***
	(0.0179)	(0.0242)	(0.0275)
Constant	−1.4824***	−1.3666***	−1.6426***
	(0.0824)	(0.1334)	(0.1894)
Total average effects on per-period payoff of:			
Lettuce dummy	1.1421***	1.3049***	0.9458***
	(0.0515)	(0.1030)	(0.1746)
Spinach dummy	−0.9100***	−0.4129***	−1.6914***
	(0.0650)	(0.0991)	(0.2957)
Broccoli history	0.0322	0.0331	0.0367
	(0.0319)	(0.0249)	(0.0194)
Methyl bromide history	−0.2830	−0.5310**	−0.1763
	(0.1631)	(0.1972)	(0.2613)
Number of observations	9,306	4,144	5,162

Notes: Table presents renter parameter estimates and standard errors for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level. Parameter estimates are also reported in the paper in Table 3.

Table B.9

Different parameters for owners and renters, and different last crop dummy for susceptible crops and all other crops specification: Results for owners

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.4339***	1.3862***	1.4734***
Spinach dummy	−1.1346***	−1.1974***	−1.0804***
Broccoli dummy	−0.3305***	−0.5902***	−0.1570***
Methyl bromide dummy	−5.9540***	−5.6621***	−6.2346***
Lettuce dummy*Broccoli history	0.3683***	0.3676***	0.3705***
Spinach dummy*Broccoli history	0.2636***	0.2690***	0.2604***
Lettuce dummy*Methyl bromide history	0.3612***	0.1950***	0.7924***
Spinach dummy*Methyl bromide history	0.0869***	0.0159***	0.2837***
Last crop dummy*Susceptible	21.2161***	24.2249***	20.0534***
Last crop dummy*(1-Susceptible)	21.2161***	24.2249***	20.0535***
Price*Harvest month dummy	−0.1588***	−0.1561***	−0.1589***
Constant	−1.1463***	−1.0891***	−1.1970***
Total average effects on per-period payoff of:			
Lettuce dummy	1.4461***	1.3981***	1.4875***
Spinach dummy	−1.1261***	−1.1888***	−1.0712***
Broccoli history	0.2130***	0.2128***	0.2196***
Methyl bromide history	0.2041***	0.1093***	0.4605***
Likelihood ratio test to compare with model constraining owners and renters to have the same parameters:			
HO: Owners and renters have the same parameters			
LR Test statistic D for owners	542.0***	170.8***	402.4***
Likelihood ratio test to compare with model that does not constrain last crop dummy to be the same for all crops:			
HO: Last crop dummies are the same for susceptible crops and all other crops			
LR Test statistic D for owners	0.0	0.2	0.4
Number of observations	25,534	10.779	14,755

Notes: Table presents owner parameter estimates for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well; and in which the last crop dummy is allowed to differ for susceptible crops (which include strawberries, artichoke, and cabbage) and all other crops (including lettuce, spinach, broccoli, and resistant crops). Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.10

Different parameters for owners and renters, and different last crop dummy for susceptible crops and all other crops specification: Results for renters

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.1468***	1.3081***	0.9604***
Spinach dummy	−0.9052***	−0.4095***	−1.6720***
Broccoli dummy	−0.7748***	−0.7260***	−0.8220***
Methyl bromide dummy	−3.4430***	−3.2756***	−3.4992***
Lettuce dummy*Broccoli history	0.08730**	0.0847	0.1123**
Spinach dummy*Broccoli history	0.0673***	−0.0624	0.2805***
Lettuce dummy*Methyl bromide history	−0.7743***	−1.2215***	−0.5296***
Spinach dummy*Methyl bromide history	−0.6512***	−0.5722***	−12.9356***
Last crop dummy*Susceptible	6.8455***	7.1930***	6.5727***
Last crop dummy*(1-Susceptible)	5.9026***	6.2993***	5.4360***
Price*Harvest month dummy	0.1660***	0.1071***	0.2216***
Constant	−1.4781***	−1.3644***	−1.6404***
Total average effects on per-period payoff of:			
Lettuce dummy	1.1478***	1.3102***	0.9636***
Spinach dummy	−0.9045***	−0.4117***	−1.6696***
Broccoli history	0.0519**	0.0451	0.0685**
Methyl bromide history	−0.4625***	−0.6857***	−0.5993***
Likelihood ratio test to compare with model constraining owners and renters to have the same parameters:			
HO: Owners and renters have the same parameters			
LR Test statistic D for renters	163.2***	1.6	239.6***
Likelihood ratio test to compare with model that does not constrain last crop dummy to be the same for all crops:			
HO: Last crop dummies are the same for susceptible crops and all other crops			
LR Test statistic D for renters	−569.6	−203.6	−356.6
Number of observations	9,036	4,076	4,960

Notes: Table presents renter parameter estimates for the specification in which we allow owners (who have an infinite horizon) and renters (who have a finite horizon) to not only have different time horizons, but also have different parameters θ in their per-period payoff functions as well; and in which the last crop dummy is allowed to differ for susceptible crops (which include strawberries, artichoke, and cabbage) and all other crops (including lettuce, spinach, broccoli, and resistant crops). Standard errors are in parentheses. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.11

Same infinite horizon for owners and renters specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.2846***	1.3334***	1.2426***
Spinach dummy	−1.0994***	−0.8412***	−1.4039***
Broccoli dummy	−0.4288**	−0.5787***	−0.2969
Methyl bromide dummy	−5.0993***	−5.1816***	−5.0448***
Lettuce dummy*Broccoli history	0.3709***	0.3624***	0.3862***
Spinach dummy*Broccoli history	0.2230***	0.1831***	0.2888***
Lettuce dummy*Methyl bromide history	−0.2041	−0.2673	−0.1486*
Spinach dummy*Methyl bromide history	−0.3649***	−0.3579**	−0.7843***
Last crop dummy	17.5703***	15.9081***	25.4309***
Price*Harvest month dummy	−0.0255	−0.0366*	−0.0079
Constant	−1.2613***	−1.2160***	−1.3313***
Total average effects on per-period payoff of:			
Lettuce dummy	1.2961***	1.3447***	1.2545***
Spinach dummy	−1.0928***	−0.8360***	−1.3954***
Broccoli history	0.2133***	0.2124***	0.2194***
Methyl bromide history	−0.1242	−0.1641	−0.1004*
Likelihood ratio test to compare with model that does not constrain owners and renters to have same parameters and same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for owners	384.0***	115.6***	310.4***
LR Test statistic D for renters	597.0***	188.2***	468.2***
Likelihood ratio test to compare with model that constrains owners and renters to have the same parameters but not the same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for owners	−160.0	−55.0	−92.8
LR Test statistic D for renters	−126.4	−27.0	−123.8
Number of observations	9,306	4,144	5,162

Notes: Table presents parameter estimates for the specification in which we allow owners and renters to not only have the same parameters θ in their per-period payoff functions, but also have the same infinite time horizon for their dynamic decision-making. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.12

Same infinite horizon for owners and renters, different last crop dummy for susceptible crops and all other crops specification

	All	Early	Late
Coefficients in the per-period payoff function on:			
Lettuce dummy	1.2847***	1.3333***	1.2426***
Spinach dummy	−1.0990***	−0.8410***	−1.4039***
Broccoli dummy	−0.4290***	−0.5788***	−0.2970***
Methyl bromide dummy	−5.0985***	−5.1813***	−5.0449***
Lettuce dummy*Broccoli history	0.3709***	0.3624***	0.3861***
Spinach dummy*Broccoli history	0.2229***	0.1832***	0.2888***
Lettuce dummy*Methyl bromide history	−0.2042***	−0.2673***	−0.1486***
Spinach dummy*Methyl bromide history	−0.3638***	−0.3662***	−0.7844***
Last crop dummy*Susceptible	21.2161***	24.2249***	25.4309***
Last crop dummy*(1-Susceptible)	21.2161***	24.2249***	25.4309***
Price*Harvest month dummy	−0.0255*	−0.0366*	−0.0078
Constant	−1.2613***	−1.216***	−1.3314***
Total average effects on per-period payoff of:			
Lettuce dummy	1.2962***	1.3446***	1.2545***
Spinach dummy	−1.0924***	−0.8359***	−1.3954***
Broccoli history	0.2133***	0.2124***	0.2193***
Methyl bromide history	−0.1242***	−0.1644***	−0.1004***
Likelihood ratio test to compare with model that does not constrain owners and renters to have same parameters and same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for owners	384.0***	115.8***	669.4***
LR Test statistic D for renters	27.4**	−15.2	111.4***
Likelihood ratio test to compare with model that constrains owners and renters to have the same parameters but not the same infinite horizon:			
HO: Owners and renters have the same parameters and same owner infinite horizon			
LR Test statistic D for owners	−158.0	−55.0	267.0***
LR Test statistic D for renters	−135.8	−16.8	−128.2
Number of observations	34,570	14,855	19,715

Notes: Table presents parameter estimates for the specification in which we allow owners and renters to not only have the same parameters θ in their per-period payoff functions, but also have the same infinite time horizon for their dynamic decision-making; and in which the last crop dummy is allowed to differ for susceptible crops (which include strawberries, artichoke, and cabbage) and for all other crops (including lettuce, spinach, broccoli, and resistant crops). Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

Table B.13
Some of the same parameters for owners and renters specification

	Different last crop dummy for:	
	susceptible crops and all other crops	owners and renters
Coefficients in the per-period payoff function on:		
Lettuce dummy	1.3293***	1.3298***
Spinach dummy*Early	−0.9160***	−0.9161***
Spinach dummy*Late	−1.2743***	−1.2744***
Broccoli dummy*Owner	−0.3483	−0.3482
Broccoli dummy*Renter	−1.7879*	−1.7831*
Methyl bromide dummy*Owner	−5.9354***	−5.9388***
Methyl bromide dummy*Renter	−3.6051***	−3.6057***
Lettuce dummy*Broccoli history	0.3691***	0.3688***
Spinach dummy*Broccoli history	0.2469***	0.2467***
Lettuce dummy*Methyl bromide history	−0.3830***	−0.3835***
Spinach dummy*Methyl bromide history	−0.5793***	−0.5687***
Last crop dummy*Susceptible	9.2901***	
Last crop dummy*(1-Susceptible)	13.3803***	
Last crop dummy*Owner		15.6340***
Last crop dummy*Renter		9.0505***
Price*Harvest month dummy*Owner	−0.1206***	−0.1207***
Price*Harvest month dummy*Renter	0.1379***	0.1380***
Constant	−1.2390***	−1.2390***
Total average effects on per-period payoff of:		
Lettuce dummy	1.3405***	1.3410***
Spinach dummy*Early	−0.9093***	−0.9093***
Spinach dummy*Late	−1.2670***	−1.2671***
Broccoli history	0.2130***	0.2128***
Methyl bromide history	−0.2300***	−0.2300***
Likelihood ratio test to compare with model that does not constrain owners and renters to have some of the same parameters:		
HO: Owners and renters have some of the same parameters		
LR Test statistic D for owners	154.0***	152.0***
LR Test statistic D for renters	1,298.0***	1,293.2***
Number of observations	34,570	34,570

Notes: Table presents the parameter estimates for the specifications in which owners and renters have some of the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

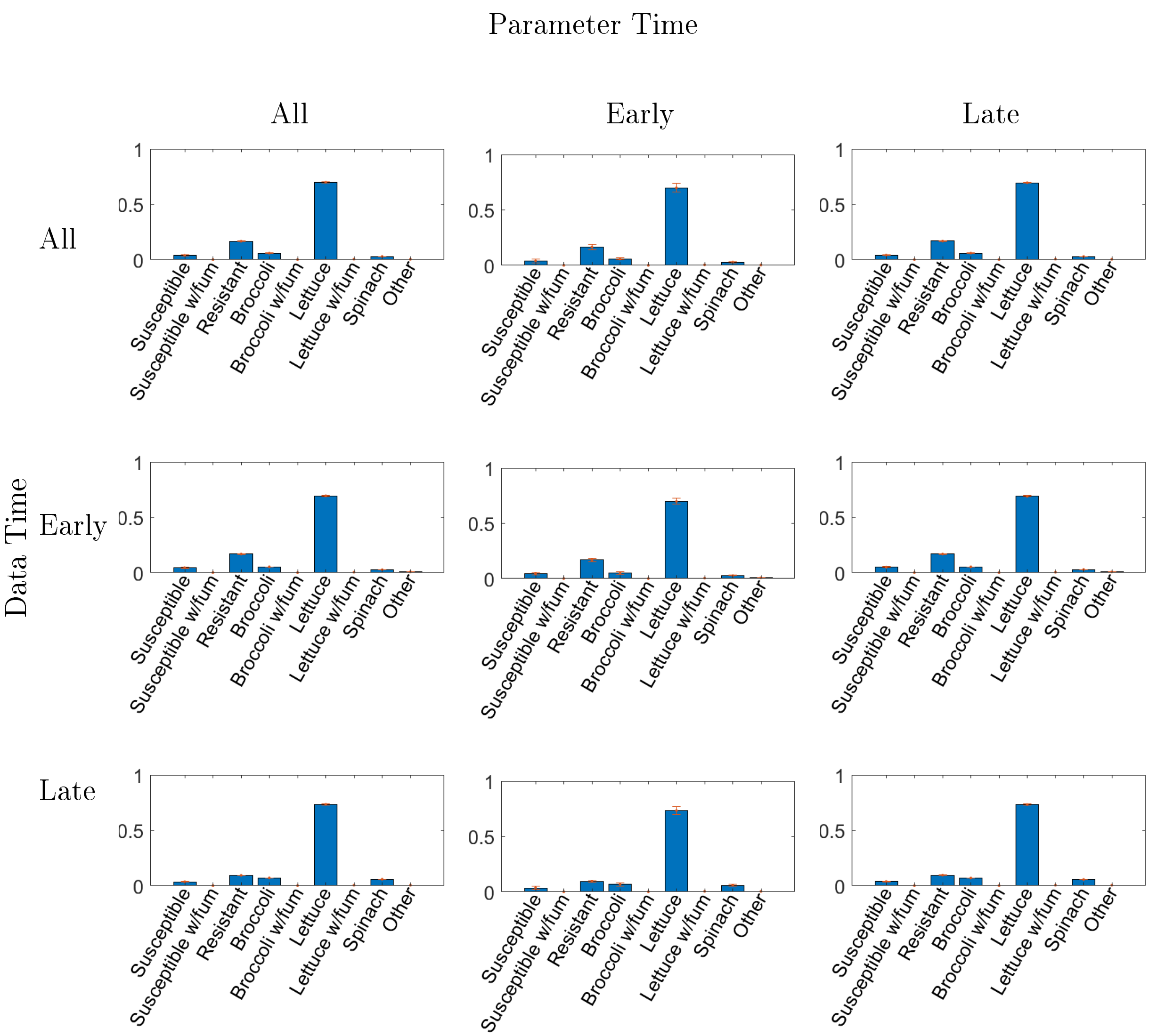
Table B.14
Some of the same parameters and same infinite horizon for owners and renters specification

	Different last crop dummy for: susceptible crops and all other crops	owners and renters
Coefficients in the per-period payoff function on:		
Lettuce dummy	1.3077***	1.3073***
Spinach dummy*Early	−0.9320***	−0.9339***
Spinach dummy*Late	−1.2923***	−1.2950***
Broccoli dummy*Owner	−0.3409***	−0.3412***
Broccoli dummy*Renter	−0.5931***	−0.5926***
Methyl bromide dummy*Owner	−5.9393***	−5.9465***
Methyl bromide dummy*Renter	−4.1643***	−4.1661***
Lettuce dummy*Broccoli history	0.3902***	0.3903***
Spinach dummy*Broccoli history	0.2673***	0.2677***
Lettuce dummy*Methyl bromide history	−0.2284***	−0.2260***
Spinach dummy*Methyl bromide history	−0.4682***	−0.4539***
Last crop dummy*Susceptible	21.2161***	
Last crop dummy*(1-Susceptible)	21.2161***	
Last crop dummy*Owner		21.2161***
Last crop dummy*Renter		21.2161***
Price*Harvest month dummy*Owner	−0.1214***	−0.1214***
Price*Harvest month dummy*Renter	0.1420***	0.1420***
Constant	−1.2442***	−1.2439***
Total average effects on per-period payoff of:		
Lettuce dummy	1.3200***	1.3196***
Spinach dummy*Early	−0.9243***	−0.9262***
Spinach dummy*Late	−1.2843***	−1.2869***
Broccoli history	0.2253***	0.2254***
Methyl bromide history	−0.1406***	−0.1389***
Likelihood ratio test to compare with model that does not constrain owners and renters to have some of the same parameters and same infinite horizon:		
HO: Owners and renters have some of the same parameters and same owner infinite horizon		
LR Test statistic D for owners	130.0***	130.0***
LR Test statistic D for renters	1,234.2***	1,235.6***
Number of observations	34,570	34,570

Notes: Table presents the parameter estimates for the specifications in which owners and renters to not only have some of the same parameters θ in their per-period payoff functions, but also have the same infinite time horizon for their dynamic decision-making. Standard errors are in parentheses. Significance codes: *** 0.1% level, ** 1% level, * 5% level.

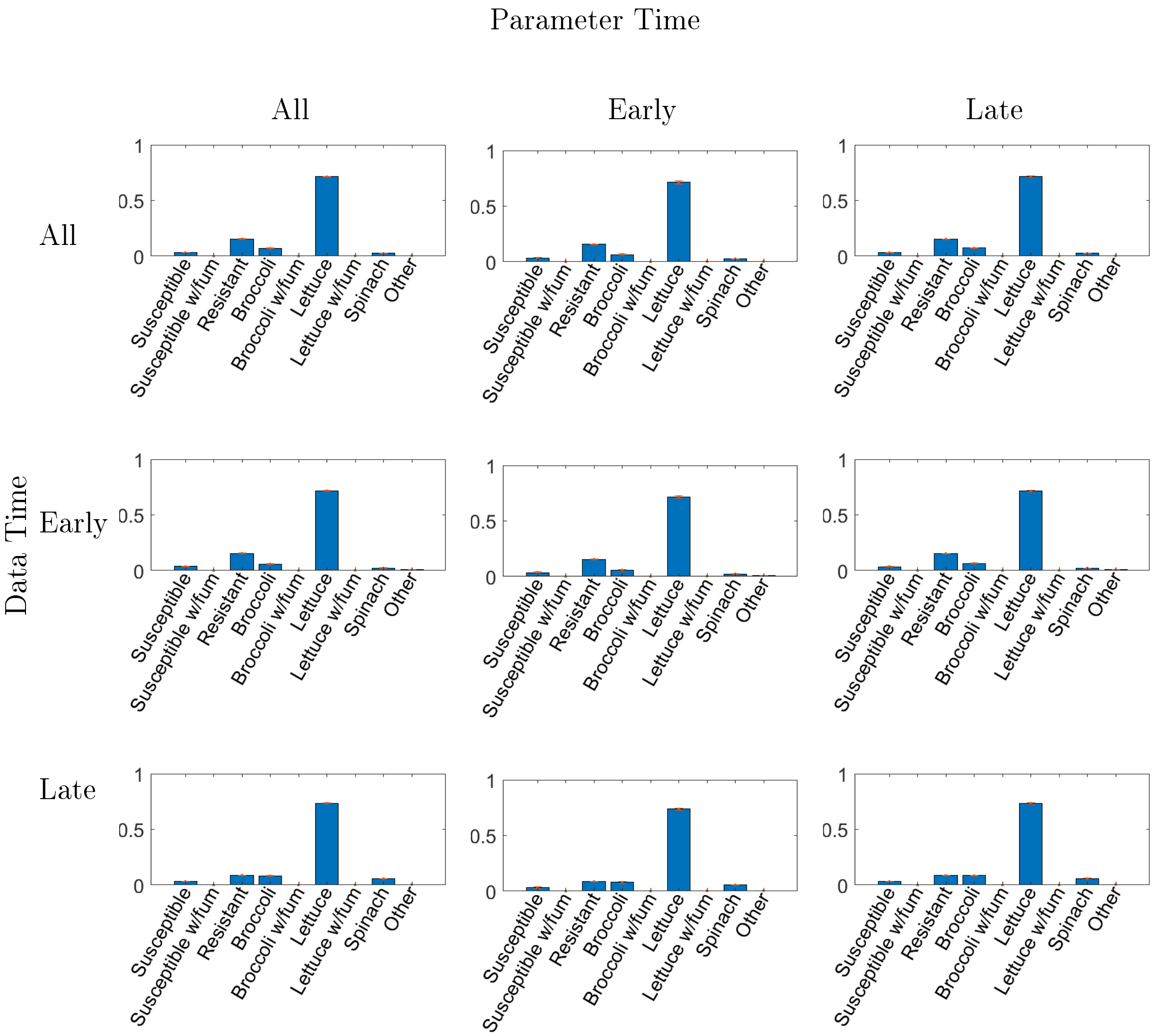
Appendix C.
Supplementary Counterfactual Simulation Results

Figure C.1
Counterfactual fraction of grower-months in each action:
Simulations using owner data and owner horizon



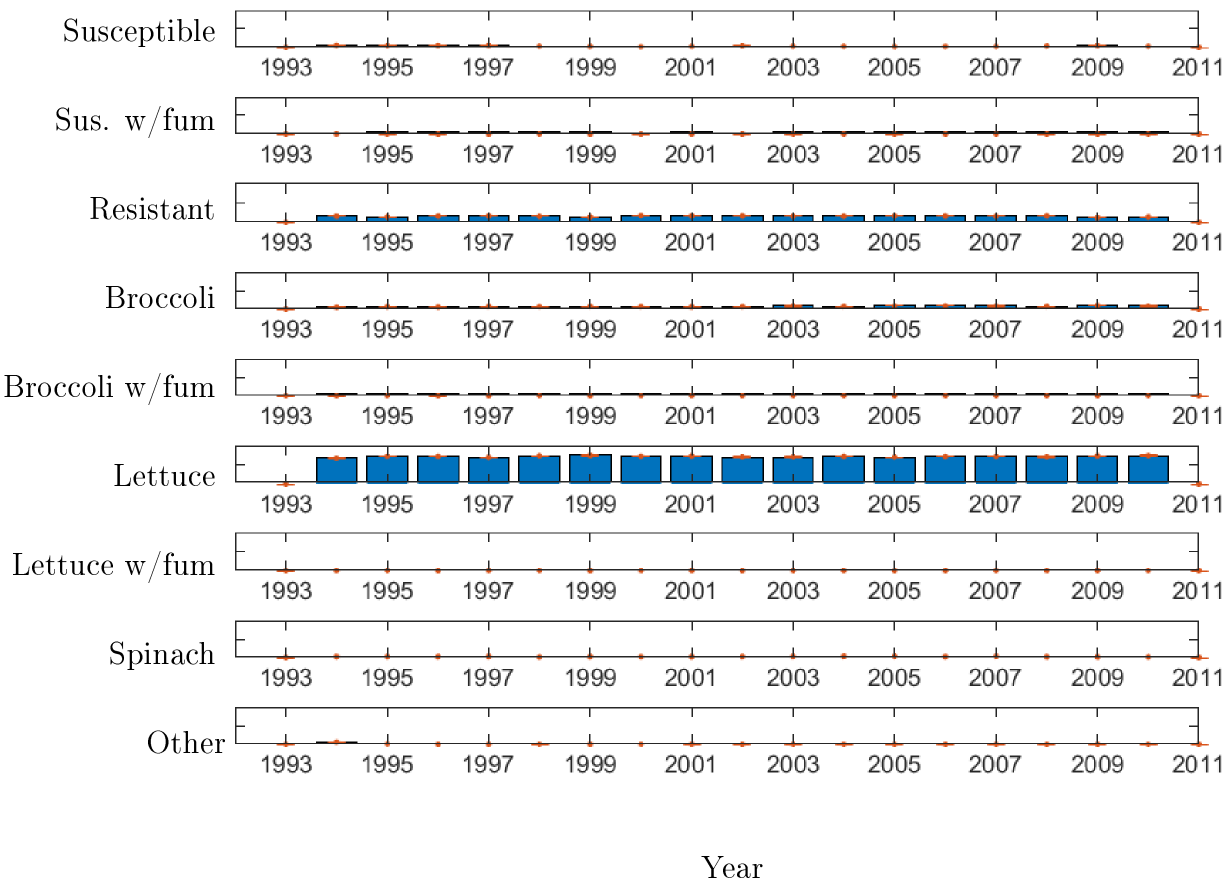
Notes: Figures present the counterfactual results for the mean fraction of grower-months in each action from 9 different counterfactual scenarios using parameter estimates from our base-case specification in Table 1 applied to owner data and an owner infinite horizon. In our base-case specification, owners and renters have the same parameters θ in their per-period payoff functions, but differ in their time horizons: owners have an infinite horizon and renters have a finite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using owner data from one of 3 time periods (all, early, or late) and using parameter estimates from one of 3 time periods (all, early, or late). For each of the 9 counterfactual scenarios, 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 C.2
Counterfactual fraction of grower-months in each action:
Simulations using owner parameters, owner data, and owner horizon



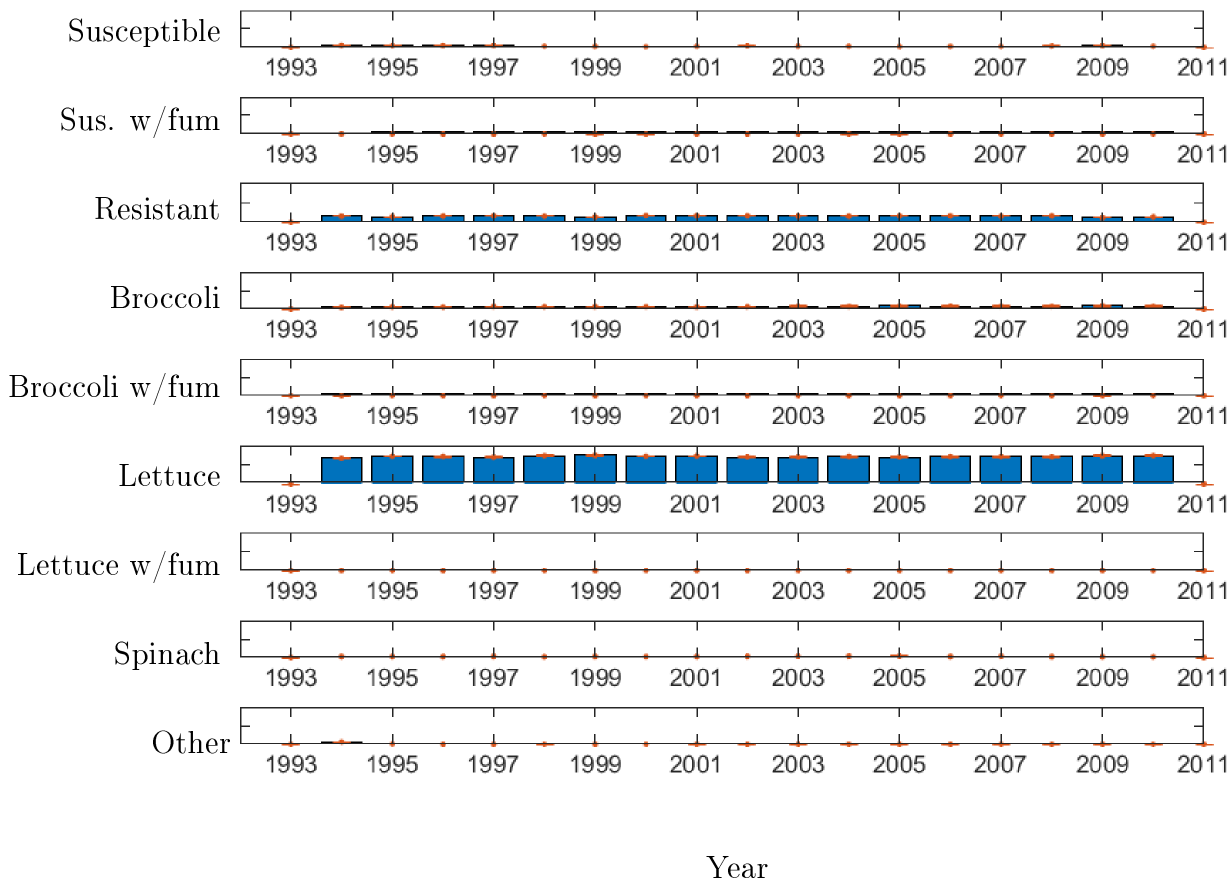
Notes: Figures present the counterfactual results for mean fraction of grower-months in each action from 9 different counterfactual scenarios using the structural parameters for owners from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2 (standard errors in Table B.7 in Appendix B) applied to owner data and an owner infinite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using owner data from one of 3 time periods (all, early, or late) and using owner parameter estimates from one of 3 time periods (all, early, or late). For each of the 9 counterfactual scenarios, 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 C.3
Counterfactual fraction of grower-months in each action by year:
Simulations using owner all parameters, owner all data, and owner horizon



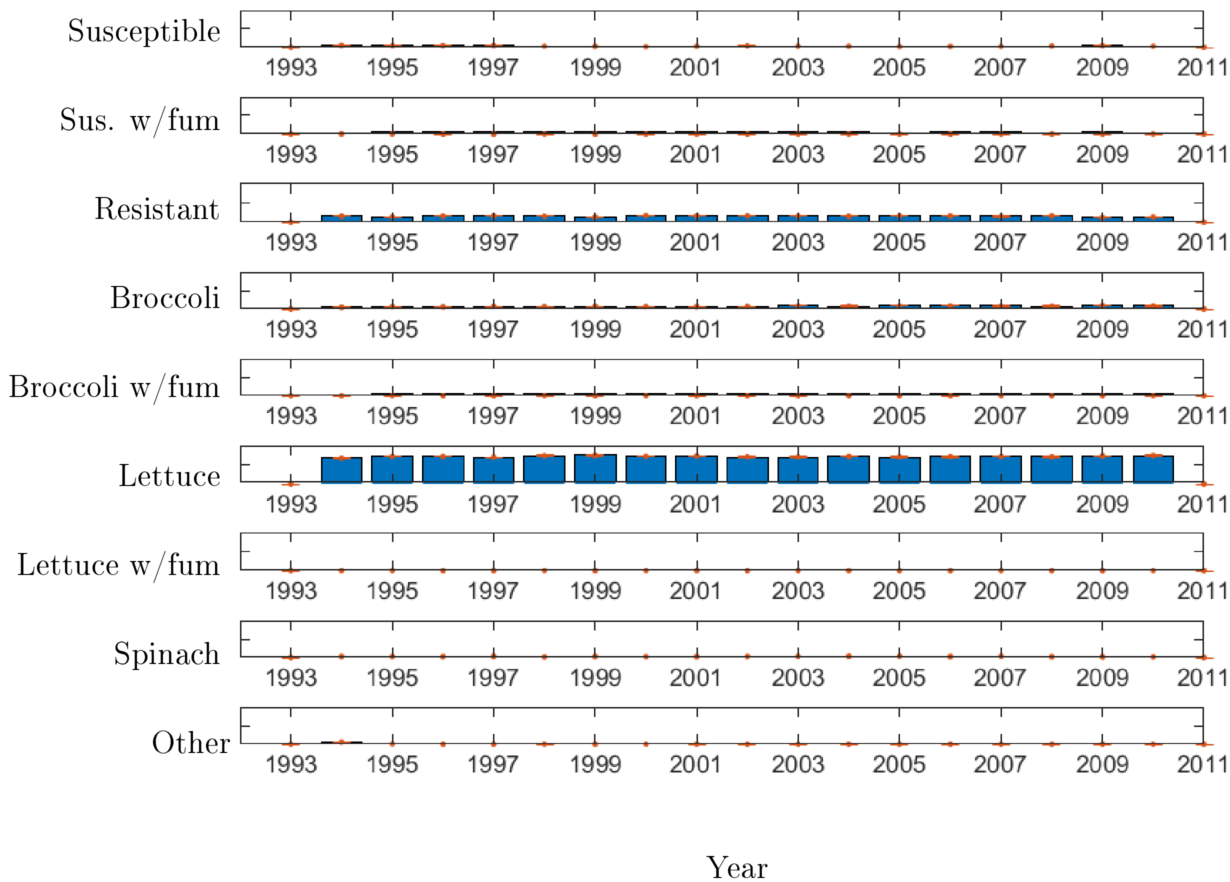
Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for owners over the entire time period ('all') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2 (standard errors in Table B.7 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon. 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 C.4
Counterfactual fraction of grower-months in each action by year:
Simulations using owner early parameters, owner all data, and owner horizon



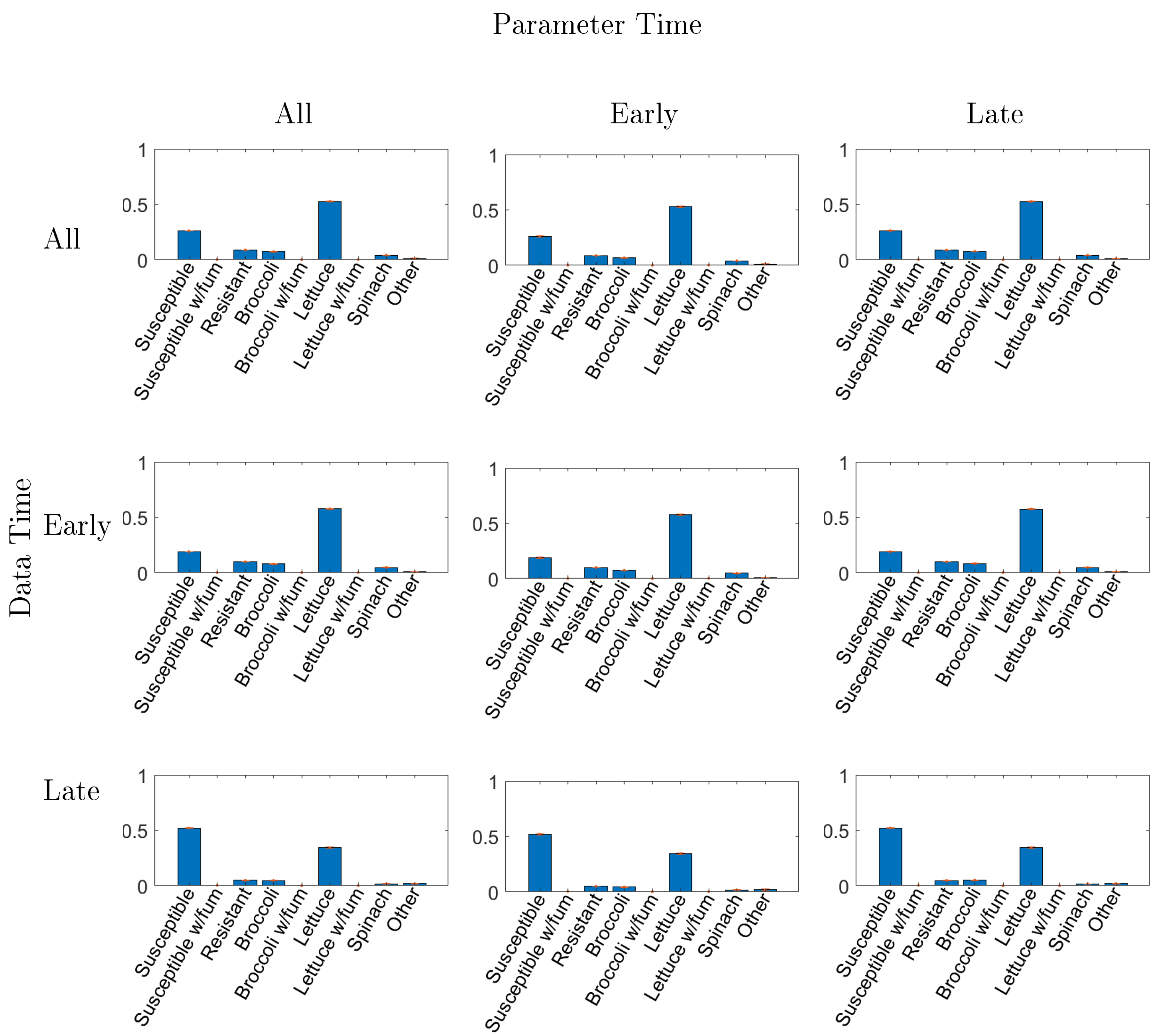
Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for owners in the early period ('early') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2 (standard errors in Table B.7 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon. 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 C.5
Counterfactual fraction of grower-months in each action by year:
Simulations using owner late parameters, owner all data, and owner horizon



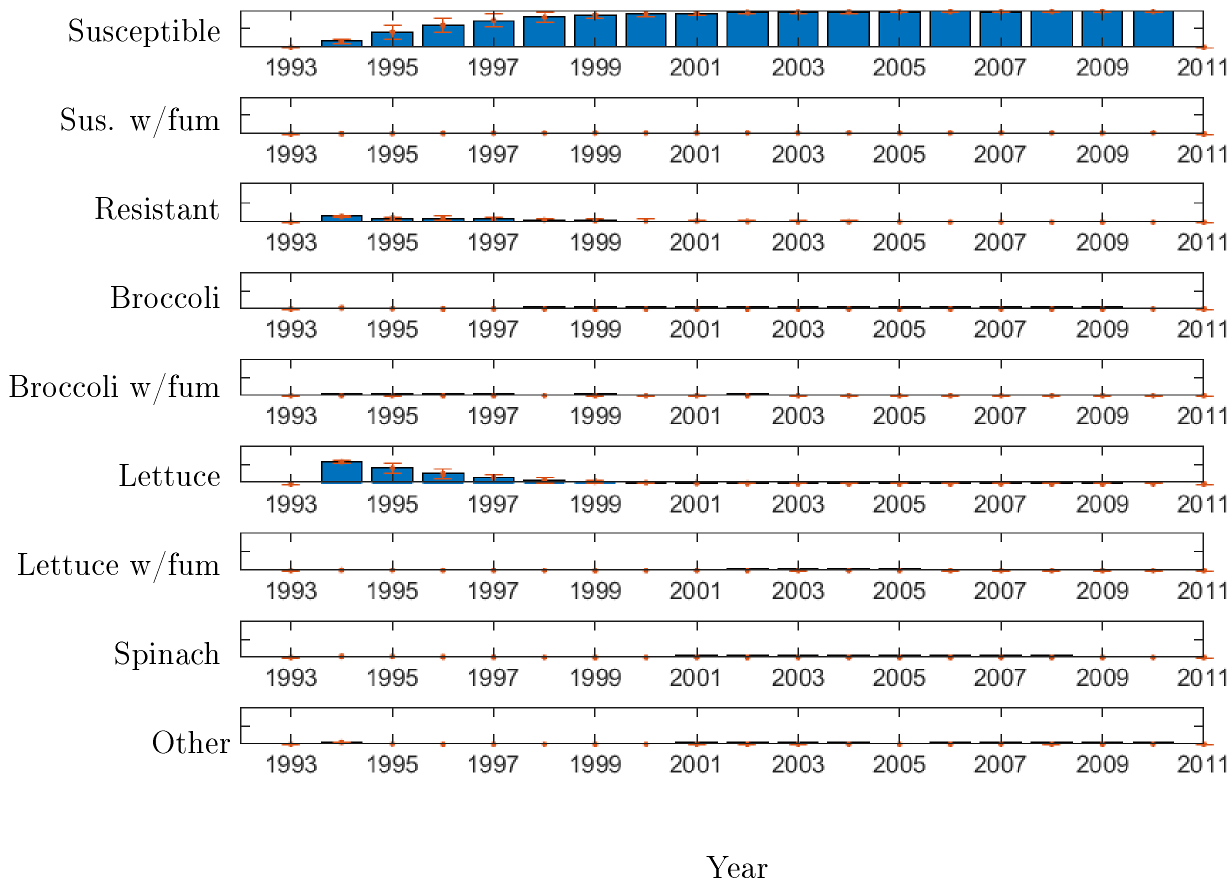
Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for owners in the late time period ('late') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2 (standard errors in Table B.7 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon.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 C.6
Counterfactual fraction of grower-months in each action:
Simulations using owner parameters, renter data, and owner horizon



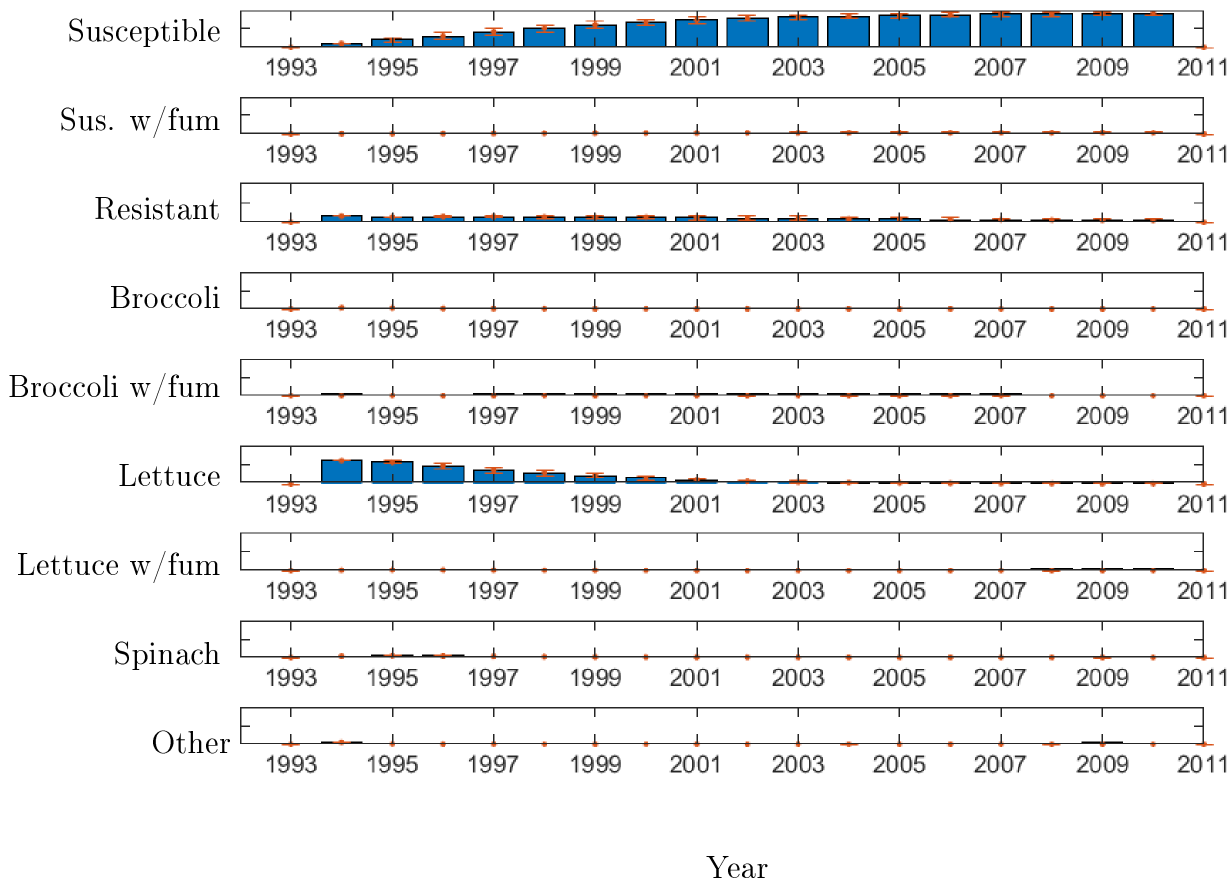
Notes: Figures present the counterfactual results for mean fraction of grower-months in each action from 9 different counterfactual scenarios using the structural parameters for owners from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 2 (standard errors in Table B.7 in Appendix B) applied to renter data and an owner infinite horizon. Each of the 9 figures presents the results from a different counterfactual scenario using renter data from one of 3 time periods (all, early, or late) and using owner parameter estimates from one of 3 time periods (all, early, or late). For each of the 9 counterfactual scenarios, 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 C.7
Counterfactual fraction of grower-months in each action by year:
Simulations using renter all parameters, owner all data, and owner horizon



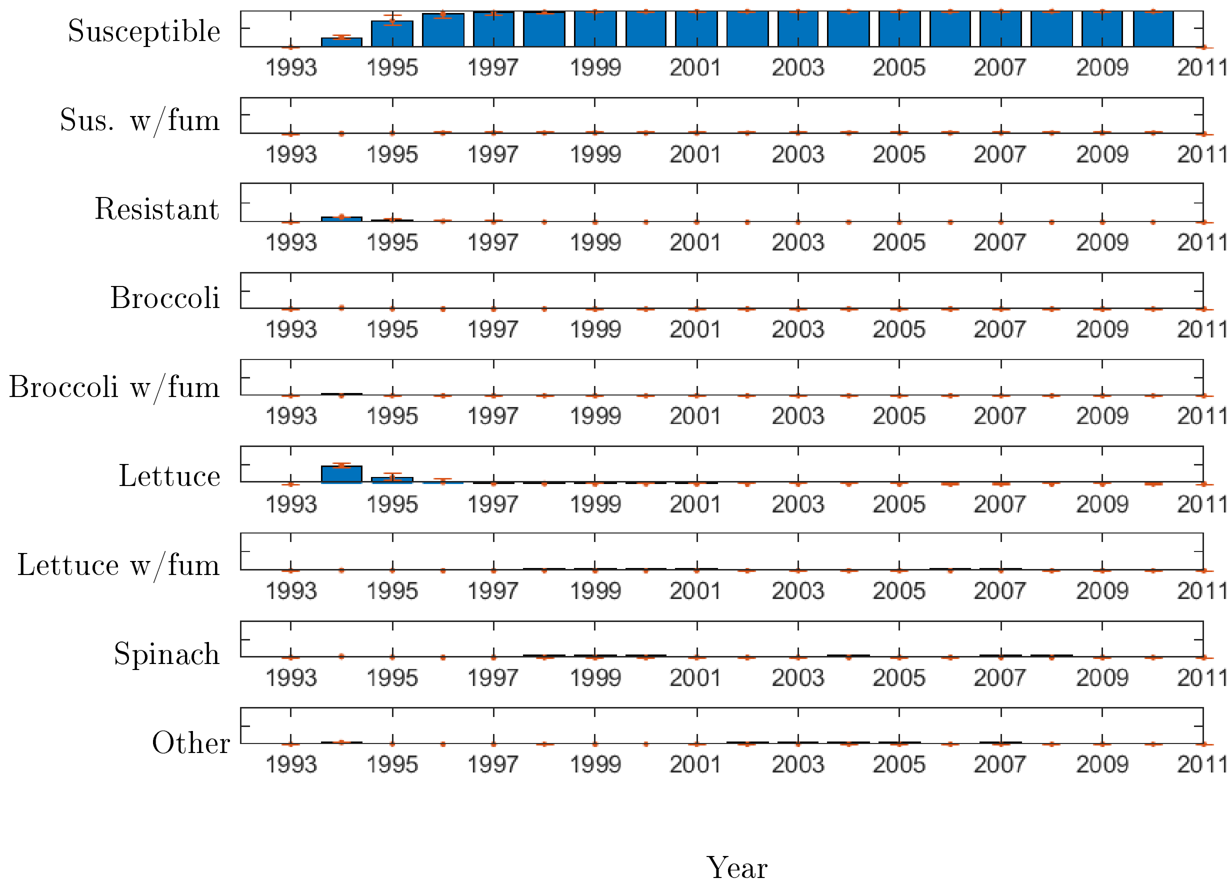
Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for renters over the entire time period ('all') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 3 (standard errors in Table B.8 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon. 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 C.8
Counterfactual fraction of grower-months in each action by year:
Simulations using renter early parameters, owner all data, and owner horizon



Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for renters in the early time period ('early') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 3 (standard errors in Table B.8 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon. 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 C.9
Counterfactual fraction of grower-months in each action by year:
Simulations using renter late parameters, owner all data, and owner horizon



Notes: Figure presents the counterfactual results for fraction of grower-months in each action from the counterfactual scenario using the structural parameters for renters in the late time period ('late') from the best-fit specification, wherein owners and renters are allowed to have different parameters, in Table 3 (standard errors in Table B.8 in Appendix B) applied to owner data over the entire period ('all') and an owner infinite horizon. 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.