Organic Farming, Soil Health, and Farmer Perceptions: A Dynamic Structural Econometric Model

Michael A. Meneses, Miguel I. Gómez, David R. Just,
Ravi Kanbur, David R. Lee, and C.-Y. Cynthia Lin Lawell

Abstract

New insights from soil science show that the use of pesticides can be harmful to beneficial soil microbes that improve agricultural yields. Farmers may not be fully aware of soil microbiomes, however, and as a consequence, may not be making optimal decisions about pesticide use and organic farming adoption. In this paper, we develop and estimate a dynamic structural econometric model to examine whether farmers are aware of and account for soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields when making their decisions about pesticide use and organic farming adoption. Empirical results show that farmers are acting as if the clean soil stock has very little effect on crop yields, when in fact it increases yields. Our structural estimates allow us to simulate a number of key outcomes of interest, including pesticide use and farmer welfare under counterfactual scenarios in which farmers' beliefs about soil-microbe based ecosystem services are brought in line with findings from plant and soil sciences. We find that informing farmers about soil microbiomes decreases pesticide use, increases organic adoption, and increases mean farmer welfare in both the short and long run.

Keywords: organic farming, dynamic structural econometric model, perceptions, soil health
***JEL* Codes:** Q12, Q57, Q24
This draft: November 13, 2024

---

*Meneses: Cornell University; mam789@cornell.edu. Gómez: Cornell University; mig7@cornell.edu. Just: Cornell University; drj3@cornell.edu. Kanbur: Cornell University; sk145@cornell.edu. Lee: Cornell University; drl5@cornell.edu. Lin Lawell: Cornell University; clinlawell@cornell.edu. We thank Shadi Atallah, Nano Barahona, Marc Bellemare, Peter Blair Henry, Apurva Borar, Jacob Bradt, Dylan Brewer, Stephanie Brockmann, Vincenzina Caputo, Clare Casteel, Bingyan Dai, Will Davis, Eric Denemark, Avanti Dey, Victor Simoes Dornelas, Yurou He, Alan Hinds, John Hubbard, Jenny Ifft, Becca Jablonski, Kelsey Jack, Ted Jaenicke, Jerzy Jaromczyk, Kaleb Javier, Melanie Khamis, Joseph Kuvshinikov, Shanjun Li, Tongzhe Li, Francesco Lissoni, Tong Liu, Trevon Logan, Khyati Malik, Conrad Miller, Rosina Moreno, José Nuño-Ledesma, Matthew Oliver, Yu Qin, Jess Rudder, Todd Schmit, Michelle Segovia, Robert Stavins, Michael Toman, Harold van Es, Joakim Weill, Lawrence White, Casey Wichman, and Hongyu Zhao for detailed and helpful comments and discussions. We benefited from seminar participants at Cornell University and Georgia Institute of Technology; and from conference participants at the Ph.D. Excellence Initiative Summer Research Workshop at New York University; an Association of Environmental and Resource Economists (AERE) Session at the Eastern Economics Association (EEA) Annual Conference (AERE@EEA); the Heartland Environmental and Resource Economics Workshop; the Institute for Operations Research and the Management Sciences (INFORMS) Annual Meeting; the American Economic Association (AEA) Summer Mentoring Pipeline Conference (SMPC); the Northeastern Agricultural and Resource Economics Association (NAREA) Annual Meeting; the Agricultural and Applied Economics Association (AAEA) Annual Meeting; the California Department of Pesticide Regulation (DPR) Pesticide Use Report (PUR) Analysis Workgroup; the Southern Economic Association (SEA) Annual Meeting; the Southeastern Workshop on Energy & Environmental Economics & Policy (SWEEEP); the Interdisciplinary PhD Workshop in Sustainable Development (IPWSD) at Columbia University; the United States Society for Ecological Economics (USSEE) Conference; the International Business Analytics Conference (IBAC); the Economics of Science and Innovation Summer School at the University of Barcelona; the Ph.D. Applied Macroeconomics guest lecture at Cornell University; and the Voices of Quebec Labrador Foundation panel 'The Rise of Young Professionals'. We received funding from the U.S. Department of Agriculture (USDA) National Institute of Food and Agriculture (NIFA), Cornell Graduate School Conference Travel Grants, Cornell TREESPEAR Research Grants, and the Cornell DEEP-GREEN-RADAR Khaled H. Kheiravar Memorial Scholarship. Gómez, Just, Kanbur, Lee, and Lin Lawell are Faculty Fellows at the Cornell Atkinson Center for Sustainability. All errors are our own.

1 Introduction

Soil microbes benefit agricultural production and improve agricultural yields by enhancing crop nutrient use, stress tolerance, and pest resistance (Singh et al., 2016; Lori et al., 2017; Yadav et al., 2017; Yibeltie and Sahile, 2018; Blundell et al., 2020; Kalam et al., 2020; Verma et al., 2020; Righini et al., 2022; Thiebaut et al., 2022). New insights from soil science show that the use of synthetic pesticides and fertilizers can be harmful to these beneficial soil microbes (Li et al., 2022; Blundell et al., 2020; Dash et al., 2017; Lori et al., 2017; Newman et al., 2016; Kalia and Gosal, 2011; Lo, 2010; Hussain et al., 2009). Thus, while using pesticides and fertilizers may have the initial effect of increasing crop yields, over time these synthetic compounds exert an indirect negative effect on crop yields through their negative effects on soil health. In contrast, organic farming and other production regimes like regenerative agriculture that reduce dependence on synthetic compounds enhance microbial health and, thus, may lead to higher yields in the long run. These insights have important implications for a farmer's optimal strategy regarding synthetic compound use and organic farming adoption (Meneses et al., 2024).

Farmers may not be fully aware of soil microbiomes and the feedback between synthetic compounds, soil health, pest resistance, and crop yields, however, and as a consequence, may not be making optimal decisions about synthetic compound use and organic farming adoption. Previous theoretical research by Meneses et al. (2024) has shown that not being informed about soil bacteria could change behavior in a way that leads farmers to adopt sub-optimal, and even detrimental management practices. Previous experimental analysis by Murphy et al. (2020) has shown that farmers in developing countries usually do not have sufficient information about their soil nutrient levels to make profit-maximizing decisions about fertilizer usage; and that there can be potentially large net benefits to providing farmers with soil information.

In this paper, we develop and estimate a dynamic structural econometric model to examine whether farmers are aware of and account for soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields when making their decisions about pesticide use and organic farming adoption. To do so, we first empirically document the insights from soil science that the use of pesticides may increase contemporaneous yields; and also that, over time, not using pesticides increases yields.

Next, in order to understand the beliefs and perceptions of rice farmers that underlie and rationalize their pesticide use decisions, we develop and estimate a dynamic structural econometric model. The structural parameters we estimate include parameters measuring any misperceptions farmers may have about how enhancing microbial health may affect yields. Our structural parameter estimates therefore enable us to infer farmers' current understanding of the interrelations between soil microbes, pesticides, and crop yields.

Our structural estimates also allow us to simulate a number of key outcomes of interest, including pesticide use and farmer welfare under counterfactual scenarios in which farmers' beliefs about soil-microbe based ecosystem services are brought in line with findings from plant and soil sciences. In particular, we run counterfactual simulations to compare a base simulation of actual behavior under farmer misperception, with a counterfactual simulation of optimal behavior under full information.

Empirical results show that farmers are acting as if the clean soil stock has very little effect on crop yields, when in fact it increases yields. Results of counterfactual simulations show that informing farmers about soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields will decrease pesticide use and increase organic adoption, will increase farmers' net present value (PDV of the entire stream of per-period profits) in the long run, and increases increase farmers' net present value on average in the short run.

2 Literature Review

Our paper builds on several strands of literature. First, our paper builds on the literature on the relationship between pesticide use and farm production and profit. Chambers, Karagiannis, and Tzouvelekas (2010) shows pesticide use as increasing returns to quasi-fixed factors of production like capital and land. In contrast, Jacquet, Butault, and Guichard (2011) use a mathematical programming model to determine whether pesticide use can be reduced without affecting farmer income and find that a up to a 30 percent reduction is possible.

Second, our paper builds on the literature on soil health. Sexton, Lei, and Zilberman (2007) acknowledge the effect that pesticide use can have on soil health through its impact on soil microbiomes. Kalia and Gosal (2011) also document the damaging effects that the application of pesticides in conventional farming has on soil microorganisms that benefit plant productivity. Jaenicke and Lengnick (1999) estimate a soil-quality index consistent with the notion of technical efficiency. 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. Meneses et al. (2024) develop a dynamic bioeconomic model of a farmer's decisions regarding the use of synthetic compounds (e.g., synthetic fertilizers and pesticides) and the transition from conventional to organic management, accounting for the interrelationships among synthetic compound use, soil health, and crop yields.

Our paper also 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), agricultural land use (Scott, 2013), agricultural disease control (Carroll et al., 2024a), durable goods (Gowrisankaran and Rysman, 2012; Rapson, 2014), wind turbine shutdowns and upgrades (Cook and Lin Lawell, 2020), copper mining (Aguirregabiria and Luengo, 2016), supply chain externalities (Carroll et al., 2024b), environmental regulations (Blundell, Gowrisankaran, and Langer, 2020), technology adoption (Oliva et al., 2020), agricultural groundwater management (Sears, Lin Lawell, and Walter, 2024; Sears et al., 2024b,a), the adoption of rooftop solar photovoltaics (Feger, Pavanini, and Radulescu, 2020; Langer and Lemoine, 2018), vehicle scrappage programs (Li, Liu, and Wei, 2022), 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, 2024), forests (Araujo, Costa, and Sant'Anna, 2020; Wu et al., 2024), grapes (Sambucci, Lin Lawell, and Lybbert, 2024), and vehicle ownership and usage (Gillingham et al., 2021).

3 Empirical Application

3.1 Rice Farmers in California

For the empirical application, we wanted to consider a crop for which a farmer who was fully informed about soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields would plausibly adopt a pesticide use and organic adoption strategy that greatly differs from that of farmer who was unaware of soil microbes.

We found documentation suggesting that a pesticide commonly used by rice growers, thiobencarb (a pre-emergence herbicide used to control grasses, sedge, and broadleaf weeds around rice crops) may be fairly harmful to certain nitrogen-fixing cyanobacteria that help maintain soil fertility and support crop yields (Dash et al., 2017).

As consequence, a rice farmer who is knowledgeable about soil microbes and the interactions between pesticide use, soil health, and crop yields may invest in and maintain a non-zero amount of clean soil stock, while one who is unaware of soil microbes may not.

We focus in particular on rice farmers in California. California is the second largest rice-producing state behind Arkansas, producing about $900 million in production value per year (Smith, 2023). Most California rice is medium-grain japonica rice, which is used in Asian and Mediterranean dishes such as sushi, paella, and risotto (Smith, 2023), and the majority of California rice is grown in the Sacramento Valley, where hot days, cool nights, and clay soil that retains moisture create ideal conditions for growing japonica rice (USA Rice, 2020).

3.2 National Organic Program

In the United States, the National Organic Program (NOP), which is directed by the U.S. Department of Agriculture (USDA) Agricultural Marketing Service (AMS) and became effective on February 20, 2001, oversees and enforces the integrity of the rigorous USDA organic standards and the accreditation of organic certifiers (USDA Agricultural Marketing Service, 2000b; Organic Produce Network, 2022). Organic is one of the most heavily regulated and closely monitored food systems in the U.S. Any product labeled as organic must be USDA certified (Organic Produce Network, 2022). The National Organic Program establishes national standards for the production and handling of organically produced products, including a National List of substances approved for and prohibited from use in organic production and handling; as well as requirements for labeling products as organic and containing organic ingredients (USDA Agricultural Marketing Service, 2000b).

The organic production and handling requirements of the National Organic Program include the requirement that the field or farm parcel must have had no prohibited substances applied to it for a period of 3 years immediately preceding harvest of the crop (USDA Agricultural Marketing Service, 2000a).

3.3 Data

We use farmer-field-level pesticide use data from the California Department of Pesticide Regulation (DPR) Pesticide Use Reporting (PUR) database (California Department of Pesticide Regulation [CA DPR], 2024). This data includes information about whether unapproved (or prohibited) pesticides were applied on a given farmer-field in a given year. Thus, in this paper we use the terms 'unapproved pesticide', 'synthetic pesticide', and 'pesticide' synonymously.

For crop yield data, we use county-level rice yield data from the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Quick Stats (U.S. Department of Agriculture [USDA], 2024).

For price data, we obtain data on conventional and organic rice prices from the USDA NASS Organic Production Survey (U.S. Department of Agriculture [USDA], 2007, 2012, 2017), the USDA NASS Certified Organic Survey (U.S. Department of Agriculture [USDA], 2023), the University of California Rice Research and Information Center (UC Rice Research and Information Center, 2023), and the University of California at Davis Cost and Return Studies (Espino et al., 2021). From these sources, we obtain annual data on conventional and organic rice prices for 10 years (2005, 2008-2012, 2014-2016, and 2019). We convert prices to real prices in 2010 USD using the consumer price index from the Federal Reserve Bank of Minneapolis (Federal Reserve Bank of Minneapolis, 2024). Figure 1 plots the annual real conventional rice price. Figure 2 plots the real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$, as calculated using the real conventional price P_{con} and the real organic price P_{org}.[1]

We focus on farmer-fields in the CA DPR PUR data set that plant rice at least once during the 10 years for which we have conventional and organic rice price data. There are 17,695 such farmer-fields that plant rice, comprising 2,101 farmers[2] and spanning 15 counties. These 15 counties are: Butte, Colusa, Fresno, Glenn, Lassen, Merced, Placer, Sacramento, San Joaquin, Solano, Stanislaus, Sutter, Tehama, Yolo, and Yuba. In the annual farmer-field-level panel data set we use for our dynamic structural econometric model, which spans the 10 years for which we have conventional and organic

[1] As explained in more detail in Section 6, the horizontal grey lines in the figures indicate the cutoffs used to discretize our price variables for use in our dynamic structural econometric model.

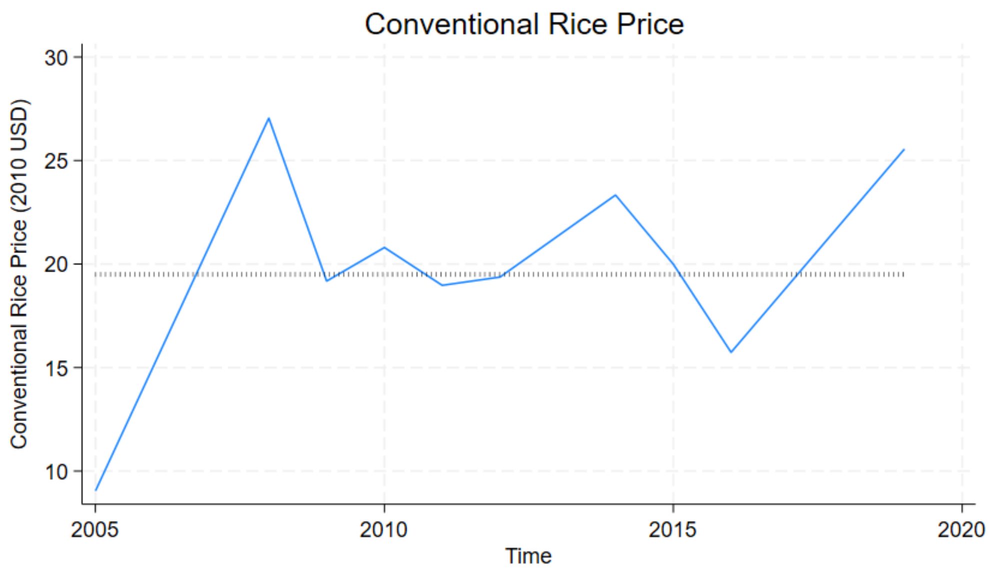
[2] There are 2,101 unique grower ID's. This grower ID variable is as close as we can get to observing the unique farmers, though the identifier is not perfect. The California Department of Pesticide Regulation (DPR) does not guarantee that 2,101 unique grower IDs means that 2,101 unique farmers appear in the data. This is because farmers can be assigned new ID's if a county ag commissioner decides to do so, or loses track of old ID numbers, and old ID numbers can in theory be reassigned to new farmers once the previous farmer retires. In the conversations we have had with employees at California's county commissioners offices though, they indicated that cases like this are rare, and not the norm.

rice prices (2005, 2008-2012, 2014-2016, and 2019), there are 67,230 farmer-field-year observations.

Among the farmer-fields that plant rice at least once during the 10 years of the annual farmer-field-level panel data set we use for our dynamic structural econometric model, in any given year that farmer-field may or may not plant rice, and may or may not use an (unapproved) pesticide. Thus, the possible actions a_{it} for each rice farmer-field in each year are: (1) plant rice and use pesticide (a_{it} = RC), (2) plant rice and do not use pesticide that year (a_{it} = RN), (3) do not plant rice that year and use pesticide that year (a_{it} = OC), and (4) do not plant rice and do not use pesticide that year (a_{it} = ON). Table 1 presents the distribution of a_{it} in the data.

We also include as a state variable the clean soil stock k_{it} as measured by the number of previous consecutive years the farmer has not used any (unapproved) pesticide. In particular, the clean soil stock k_{it} is equal to 0 if the rice farmer used an unapproved synthetic pesticide the previous year, 1 if the rice farmer did not use an unapproved synthetic pesticide the previous year but used an unapproved synthetic pesticide two years ago, 2 if the rice farmer did not use an unapproved synthetic pesticide the previous two years but used an unapproved synthetic pesticide three years ago, and 3 if the rice farmer did not use an unapproved synthetic pesticide for the previous three years but used an unapproved synthetic pesticide four years ago, and so on. Table 2 presents summary statistics for the clean soil stock k_{it} in the data; Table 3 presents the distribution of the clean soil stock k_{it} in the data.

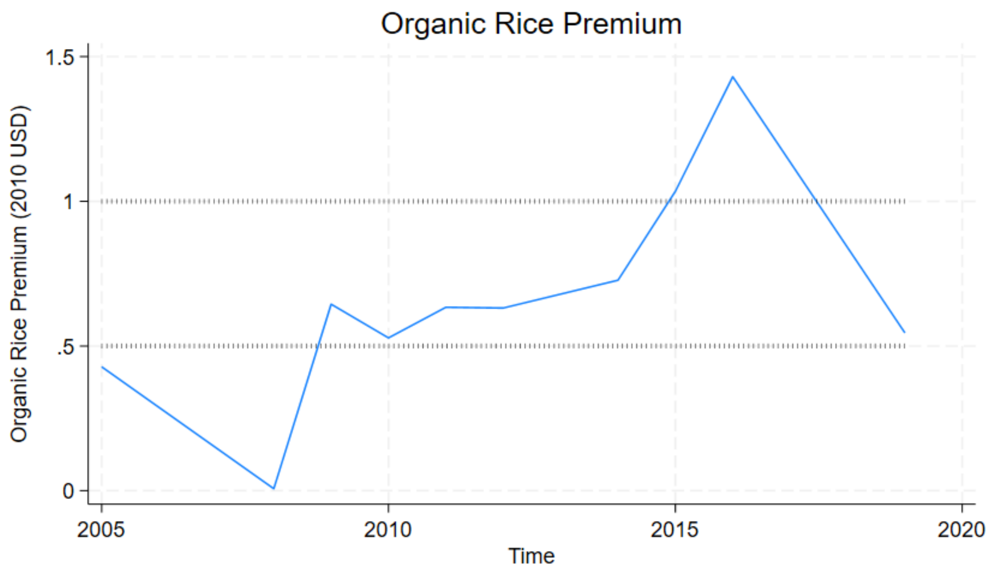
Figure 1: Real Conventional Rice Price



Note: Horizontal dashed grey line indicates cutoff used to discretize real conventional rice price.

Data Sources: USDA NASS Organic Production Survey (U.S. Department of Agriculture [USDA], 2007, 2012, 2017), USDA NASS Certified Organic Survey (U.S. Department of Agriculture [USDA], 2023), University of California Rice Research and Information Center (UC Rice Research and Information Center, 2023), and University of California at Davis Cost and Return Studies (Espino et al., 2021). We convert prices to real prices in 2010 USD using the consumer price index from the Federal Reserve Bank of Minneapolis (Federal Reserve Bank of Minneapolis, 2024).

Figure 2: Real Organic Rice Price Premium



Notes: The real organic price premium is given by $\frac{P_{org}-P_{con}}{P_{org}}$, where P_{con} is the real conventional price and P_{org} is the real organic price. Horizontal dashed grey lines indicate cutoffs used to discretize real organic rice price premium.

Data Sources: USDA NASS Organic Production Survey (U.S. Department of Agriculture [USDA], 2007, 2012, 2017), USDA NASS Certified Organic Survey (U.S. Department of Agriculture [USDA], 2023), University of California Rice Research and Information Center (UC Rice Research and Information Center, 2023), and University of California at Davis Cost and Return Studies (Espino et al., 2021). We convert prices to real prices in 2010 USD using the consumer price index from the Federal Reserve Bank of Minneapolis (Federal Reserve Bank of Minneapolis, 2024).

Table 1: Distribution of Action a_{it}

Action a_{it}		**Frequency**	**Percent**
$a_{it} = \mathrm{RC}$	Plant rice and use pesticide that year	61,890	92.06
$a_{it} = \mathrm{RN}$	Plant rice and do not use pesticide that year	1,355	2.02
$a_{it} = \mathrm{OC}$	Do not plant rice that year and use pesticide that year	3,931	5.85
$a_{it} = \mathrm{ON}$	Do not plant rice and do not use pesticide that year	54	0.08

Notes: Each observation is a farmer-field-year. There are 67,230 farmer-field-year observations. There are 17,695 farmer-fields in the data set, comprising 2,101 farmers and spanning 15 counties. By 'pesticide', we mean 'unapproved synthetic pesticide'.

Data Source: CA DPR PUR (California Department of Pesticide Regulation [CA DPR], 2024).

Table 2: Summary Statistics for Clean Soil Stock k_{it}

	Mean	**Std. Dev.**	**Min**	**Max**	**# Obs**
# Previous consecutive years no pesticide was used	0.3619	1.3736	0	26	67,230

Notes: Each observation is a farmer-field-year. There are 67,230 farmer-field-year observations. There are 17,695 farmer-fields in the data set, comprising 2,101 farmers and spanning 15 counties. By 'pesticide', we mean 'unapproved synthetic pesticide'.

Data Source: CA DPR PUR (California Department of Pesticide Regulation [CA DPR], 2024).

Table 3: Distribution of Clean Soil Stock k_{it}

Clean Soil Stock k_{it}	**Frequency**	**Percent**
0	55,973	83.26
1	7,452	11.08
2	1,508	2.24
3	912	1.36
4	317	0.47
5	204	0.30
6	152	0.23
7	125	0.19
8	97	0.14
9	80	0.12
10	67	0.10
11	62	0.09
12	63	0.09
13	48	0.07
14	42	0.06
15	34	0.05
16	23	0.03
17	16	0.02
18	19	0.02
19	11	0.02
20	9	0.01
21	5	0.01
22	5	0.01
23	4	0.01
24	1	0.00
25	0	0.00
26	1	0.00

Notes: Clean soil stock k_{it} is measured by the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide. Each observation is a farmer-field-year. There are 67,230 farmer-field-year observations. There are 17,695 farmer-fields in the data set, comprising 2,101 farmers and spanning 15 counties.

Data Source: CA DPR PUR (California Department of Pesticide Regulation [CA DPR], 2024).

4 Production Function

We first estimate a production function in order to empirically assess whether soil microbes do indeed matter for rice. Our production function also serves as an input into our dynamic structural model.

The production function ln_q($\cdot$) for the log of rice yield y_{it} is given by:

$$\ln y_{it} = \ln q(c_{it}, k_{it}; \alpha) = \alpha_0 + \alpha_c c_{it} + \alpha_k k_{it}, \tag{1}$$

where y_{it} is the rice yield in hundredweights (CWT); c_{it} is a dummy variable for farmer i using an unapproved synthetic pesticide in year t; and k_{it} is the clean soil stock as measured by the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide. In particular, the clean soil stock k_{it} is equal to 0 if the rice farmer used an unapproved synthetic pesticide the previous year, 1 if the rice farmer did not use an unapproved synthetic pesticide the previous year but used an unapproved synthetic pesticide two years ago, 2 if the rice farmer did not use an unapproved synthetic pesticide the previous two years but used an unapproved synthetic pesticide three years ago, and 3 if the rice farmer did not use an unapproved synthetic pesticide for the previous three years but used an unapproved synthetic pesticide four years ago, and so on.

Since yield data is only available at the county level, not the farmer-field level, we estimate the production function using county averages, where each observation is a county-year in which data on rice yield per farmer-yield growing rice data is available. In particular, we regress log rice yield per farmer-field growing rice in a county-year on the fraction of farmer-fields growing rice in a county-year who applied an unapproved synthetic pesticide that year and the average over farmer-fields growing rice in a county-year of the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide. Because the variables in the regression reflect means rather than individual observations, the appropriate method of estimation is analytically weighted least squares (Davidson and MacKinnon, 2004), where the weight is the number of farmer-fields in the county-year. We therefore use inverse variance weights that weight counties with more farmers more heavily.

We estimate two types of specifications of our production function. 'Misperception' specifications do not account for soil microbes, and therefore do not include any regressor relating to the clean soil stock k_{it}. 'Full Information' specifications account for soil microbes, and therefore include a regressor relating the clean soil stock k_{it}, the average over farmer-fields growing rice in a county-year of the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide.

Summary statistics for the annual county-level variables we use to estimate our production function are presented in Table 5. We use data from 1990-2019. We start in 1990 since reporting was not mandatory in 1989. There are 15 counties with data for at least one year over 1990-2019. The county-level yield variable reports rice yields in hundredweights (CWT). In North America, 1 hundredweight equals 100 pounds (U.S. Department of Agriculture [USDA], 1992).

Results for our true 'Full Information' production function estimation are in Table 5. As expected, α_c is significant and positive in the 'Full Information' specifications, which means that, in actuality, when accounting for soil microbes, the contemporaneous use of an unapproved synthetic pesticide has a positive effect on yield that year. In addition, consistent with recent insights from soil science that show the important of soil microbes and a clean soil stock, α_k is significant and positive in the 'Full Information' specifications, which means that yields are higher the more previous consecutive years the farmer has not used any unapproved synthetic pesticide.

Results for our 'Misperception' production function estimation are in Table 6. As expected, in the 'Misperception' specifications, α_c is significant and positive, which means that farmers who do not account for soil microbes perceive that using an unapproved synthetic pesticide that year has a positive effect on yield.

Table 4: Summary Statistics for Production Function Estimation, 1990-2019

	Mean	**Std. Dev.**	**Min**	**Max**	**# Obs**
Number of farmer-fields growing rice in county-year	553.50	591.91	1	2,522	325
Rice yield (CWT) per farmer-field growing rice in county-year	6,731	3,661	1,145	53,000	325
Fraction of farmer-fields growing rice in county-year who applied pesticide that year	0.9580	0.1269	0	1	325
Average over farmer-fields growing rice in county-year of # previous consecutive years no pesticide was used	0.3116	0.9024	0	10.2500	325

Notes: Each observation is a county-year. We use data from 1990-2019. There are 15 counties with data for at least one year over 1990-2019. In North America, 1 hundredweight equals 100 pounds (U.S. Department of Agriculture [USDA], 1992). By 'pesticide', we mean 'unapproved synthetic pesticide'.

Data Sources: CA DPR PUR (California Department of Pesticide Regulation [CA DPR], 2024), USDA NASS Quick Stats (U.S. Department of Agriculture [USDA], 2024).

Table 5: True 'Full Information' Production Function

		Dependent variable is: Log of rice yield (CWT)	
Parameter	Regressor	(1)	(2)
α_c	Use pesticide	3.757***	4.032***
		(0.503)	(0.444)
α_k	# Previous consecutive years no pesticide was used	0.400***	0.367***
		(0.0675)	(0.0541)
α_0	Constant	4.983***	4.280***
		(0.496)	(0.469)
County Fixed Effects		N	Y
# Observations		325	325
# Counties		15	15
R-squared		0.185	0.521

Notes: Standard errors in parentheses. Each observation is a county-year. We use data from 1990-2019. Inverse variance weights that weight counties with more farmers more heavily are used. By 'pesticide', we mean 'unapproved synthetic pesticide'. Since yield data is only available at the county level, not the farmer-field level, we estimate the production function using county averages, where each observation is a county-year in which data on rice yield per farmer-yield growing rice data is available. In particular, we regress log rice yield per farmer-field growing rice in a county-year on the fraction of farmer-fields growing rice in a county-year who applied an unapproved synthetic pesticide that year and the average over farmer-fields growing rice in a county-year of the number of previous consecutive years no unapproved synthetic pesticide was used. 'Full Information' specifications account for soil microbes, and therefore include as a regressor the average over farmer-fields growing rice in a county-year of the number of previous consecutive years no unapproved synthetic pesticide was used. In North America, 1 hundredweight equals 100 pounds (U.S. Department of Agriculture [USDA], 1992). Significance codes: *** p<0.001, ** p<0.01, * p<0.05

Table 6: 'Misperception' Production Function

		Dependent variable is: Log of rice yield (CWT)	
Parameter	Regressor	(1)	(2)
α_c	Use pesticide	3.012^{***}	3.473^{***}
		(0.513)	(0.467)
α_0	Constant	5.789^{***}	4.885^{***}
		(0.502)	(0.493)
County Fixed Effects		N	Y
# Observations		325	325
# Counties		15	15
R-squared		0.097	0.449

Notes: Standard errors in parentheses. Each observation is a county-year. We use data from 1990-2019. Inverse variance weights that weight counties with more farmers more heavily are used. By 'pesticide', we mean 'unapproved synthetic pesticide'. Since yield data is only available at the county level, not the farmer-field level, we estimate the production function using county averages, where each observation is a county-year in which data on rice yield per farmer-yield growing rice data is available. In particular, for the 'Misperception' specifications, which do not account for soil microbes, we regress log rice yield per farmer-field growing rice in a county-year on the fraction of farmer-fields growing rice in a county-year who applied an unapproved synthetic pesticide that year. In North America, 1 hundredweight equals 100 pounds (U.S. Department of Agriculture [USDA], 1992). Significance codes: *** p<0.001, ** p<0.01, * p<0.05

5 Dynamic Structural Model

To understand the beliefs and perceptions of rice farmers that underlie and rationalize their pesticide use decisions as revealed in the data, we develop and estimate a dynamic structural econometric model.

The vector of structural parameters θ we estimate include parameters that measure any farmer misperception of how the use of pesticides and the stock of clean soil affect yield; and parameters in the cost function. Our structural parameter estimates therefore enable us to infer California rice farmers' current understanding of the interrelations between soil microbes, pesticides, and crop yields.

Each year t, each rice farmer i chooses an action $a_{it} \in A$. The possible actions for each rice farmer in each year are (1) planting rice and using pesticide (a_{it} = RC), (2) planting rice and not using pesticide that year (a_{it} = RN), (3) not planting rice that year and using pesticide that year (a_{it} = OC), and (4) not planting rice and not using pesticide that year (a_{it} = ON). Table 1 presents the distribution of a_{it} in the data.

The per-period payoff $u(\cdot)$ to a farmer from choosing action a_{it} at time t depends on the values of the state variables $\mathbf{s_{it}}$ at time t. The state variables $\mathbf{s_{it}}$ at time t include the (discretized) conventional rice price $P_{con,t}$, the (discretized) organic rice price $P_{org,t}$, and the clean soil stock k_{it} as measured by the number of previous consecutive years the farmer has not used pesticide.

In particular, the clean soil stock k_{it} is equal to 0 if the rice farmer used pesticide the previous year, 1 if the rice farmer did not use pesticide the previous year but used pesticide two years ago, 2 if the rice farmer did not use pesticide the previous two years but used pesticide three years ago, and 3 if the rice farmer did not use pesticide for the previous three years but used pesticide four years ago, and so on. Table 2 presents summary statistics for the clean soil stock k_{it} in the data; Table 3 presents the distribution of the clean soil stock k_{it} in the data. For the structural model, we cap k_{it} at 15. In other words, if the rice farmer did not use pesticide for the previous 15 years or more, then $k_{it} = 15$. When $c_{it} = 0$, the yield as given by the first-stage production function in Specification (1) from Table 5 when $k_{it} = 14$ and $k_{it} = 15$ is 39,458.31 CWT and 58,864.88 CWT, respectively, which is below and above the maximum yield in the data of 53,000 CWT (Table). Thus, we cap k_{it} at $k_{it} = 15$ so that when a farmer choose not to use pesticide for many years, the yield does not continue to increase indefinitely far beyond the range of yield in the data.

The farmer's perceived yield (or quantity) $\breve{q}(c_{it}, \mathbf{s_{it}}; \theta)$ from planting rice is given by:

$$\breve{q}(c_{it}, \mathbf{s_{it}}; \theta) = \exp\left(\ln q(c_{it}, k_{it}; \hat{\alpha}) + \gamma_c c_{it} + \gamma_k k_{it}\right), \tag{2}$$

where c_{it} is a dummy variable for farmer i using pesticide in year t, k_{it} is the clean soil stock defined above, $q(c_{it}, k_{it}; \hat{\alpha})$ is the estimated yield as given from the production function estimated in the first stage (given by Specification (1) from Table 5), and $\hat{\alpha}$ are the production function parameter estimates from the first-stage production function estimation in Specification (1) from Table 5. For our structural model, yield (or quantity) and perceived yield are in units of 1 million pounds.[3]

The structural parameters θ to be estimated include γ_c, which measures any misperception of how the use of pesticide c_{it} affects log yield; and γ_k, which measures any misperception of how the clean soil stock k_{it} affects log yield.

We use the term 'misperception in yield' to describe the difference between the perceived yield (or quantity) $\breve{q}(\cdot)$ that rationalizes the data and the estimated 'true' yield $q(\cdot)$. This 'misperception in yield' can encapsulate any of a number of reasons why the yield $\breve{q}(\cdot)$ that rationalizes the decisions made by farmers as revealed in the data may differ from the estimated 'true' yield $q(\cdot)$, including farmers not being fully aware of soil microbes and their interactions with pesticide use and yields, farmers being uncertain about soil microbes and their interactions, and farmers behaving suboptimally. Our structural parameters γ_c and γ_k capture the portion of this 'misperception in yield' that can be explained by the use of pesticide c_{it} and the clean soil stock k_{it}, respectively. Thus, the 'misperceptions' that the structural parameters $\gamma = (\gamma_c, \gamma_k)$ measure broadly encompasses a broad set of possible phenonema, including misperception, misunderstanding, lack of information, and uncertainty.

The structural parameters γ_c and γ_k are identified from variation in the use of pesticide c_{it}, the clean soil stock k_{it}, and organic adoption among farmers who plant rice, and variation in the use of pesticide c_{it} and the clean soil stock k_{it} between farmers who do and do not plant rice.

We assume the cost of planting rice is given by the following rice production cost function $\text{cost}(c, q; \theta)$:

$$\text{cost}(c_{it}, \breve{q}_{it}; \theta) = \kappa_c c_{it} + \kappa_1 \breve{q}_{it} + \kappa_{cq} c_{it} \breve{q}_{it} + \kappa_2 \breve{q}_{it}^2 + \kappa_{cq2} c_{it} \breve{q}_{it}^2, \tag{3}$$

where the cost parameters $\kappa = (\kappa_c, \kappa_1, \kappa_{cq}, \kappa_2, \kappa_{cq2})$ are among the structural parameters to be estimated.

If farmer i plants rice and uses pesticide in year t ($a_{it} = \text{RC}$), then that farmer is necessarily a conventional farmer and his deterministic payoff is given by:

$$u_0(a_{it} = \text{RC}, \mathbf{s_{it}}; \theta) = P_{con,t} \cdot \breve{q}(c_{it}, \mathbf{s_{it}}; \theta) - \text{cost}(c_{it}, \breve{q}(c_{it}, \mathbf{s_{it}}; \theta); \theta). \tag{4}$$

If farmer i plants rice and does not use pesticide in year t ($a_{it} = \text{RN}$), then that farmer might be either a conventional or organic farmer, depending on whether the farmer also did not use an unapproved chemical input in any of the previous three years, and his deterministic payoff is given by:

[3] While our county-level yield data and the yield that is logged for the dependent variable in our production function estimation both have yield in hundredweights (CWT), or 100 pounds;(U.S. Department of Agriculture [USDA], 1992), for our dynamic structural model, we divide yield and perceived yield by 10,000 in our structural model. Thus, for our dynamic structural model, yield (or quantity) is in units of 1 million pounds.

$$u_0(a_{it} = \text{RN}, \mathbf{s_{it}}; \theta) = (1-\mathbf{1}\{k_{it} \geq 3\}) \cdot P_{con,t}\breve{q}(c_{it}, \mathbf{s_{it}}; \theta) + \mathbf{1}\{k_{it} \geq 3\} \cdot P_{org,t}\breve{q}(c_{it}, \mathbf{s_{it}}; \theta) - \text{cost}(c_{it}, \breve{q}(c_{it}, \mathbf{s_{it}}; \theta); \theta), \tag{5}$$

where $\mathbf{1}\{k_{it} \geq 3\}$ is a dummy variable for the farmer not using pesticide in any of the previous three years.

So that we can identify the parameters in the per-period payoff, we normalize the deterministic payoff for a farmer who does not planting rice and uses pesticide ($a_{it} = \text{OC}$) to be 0:

$$u_0(a_{it} = \text{OC}, \mathbf{s_{it}}, \theta) = 0. \tag{6}$$

To allow the per-period payoff to possibly differ when the farmer did not plant rice and also did not use pesticide, the deterministic per-period payoff for not planting rice that year and not using pesticide ($a_{it} = \text{ON}$) is set equal to a parameter ν to be estimated:

$$u_0(a_{it} = \text{ON}, \mathbf{s_{it}}, \theta) = \nu. \tag{7}$$

In addition to the state variables $\mathbf{s_{it}}$, the per-period payoff $u(\cdot)$ to a farmer from choosing action a_{it} at time t also depends on the choice-specific shock $\epsilon_{it}(a_{it})$ at time t. There is a choice-specific shock $\epsilon_{it}(a_{it})$ associated with each possible action $a_{it} \in A$. The vector of choice-specific shocks $\epsilon_{it} \equiv \{\epsilon_{it}(a_{it}) | a_{it} \in A\}$ is observed by farmer i at time t, before farmer i makes his time-t action choice, but is never observed by the econometrician.

The per-period payoff to a farmer from choosing action a_{it} at time t is given by:

$$u(a_{it}, \mathbf{s_{it}}, \epsilon_{it}, \theta) = u_0(a_{it}, \mathbf{s_{it}}, \theta) + \epsilon_{it}(a_{it}), \tag{8}$$

where $u_0(\cdot)$ is the deterministic component of the per-period payoff.

The structural parameters to be estimated are $\theta = (\gamma, \kappa, \nu)$, where γ are misperception parameters, κ are cost parameters, and ν is the deterministic payoff when a farmer does not plant rice and does not use pesticide (this is relative to a deterministic payoff of 0 when a farmer does not plant rice and uses pesticide).

We assume the state variables evolve as a finite state first-order Markov process, with a transition density given by $\Pr(\mathbf{s}_{t+1}, \epsilon_{t+1} | \mathbf{s}_t, a_t, \epsilon_t, \theta)$. Since the conventional and organic rice price variables we use are discretized annual averages, we assume that the crop and pesticide use decisions of any one farmer would not have a large enough effect to influence crop prices, and therefore that the distribution of discretized annual conventional and organic rice prices next period does not depend on any single grower's decisions this period; we therefore model rice prices as evolving exogenously. For the clean soil stock k_{it} as measured by the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide, the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide evolves deterministically as a function of this period's value of the clean soil stock k_{it} and this period's pesticide use decision.

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

$$\Pr(\mathbf{s}_{t+1}, \epsilon_{t+1}|\mathbf{s}_t, a_t, \epsilon_t, \theta) = \Pr(\epsilon_{t+1}|\mathbf{s}_{t+1}, \theta)\Pr(\mathbf{s}_{t+1}|\mathbf{s}_t, a_t, \theta). \tag{9}$$

We also assume that the choice-specific shocks are distributed multivariate extreme value. A standard assumption in many dynamic structural models, our conditional independence assumption implies that, conditional on the current state variables $\mathbf{s}_{it}$ and the current action a_{it} chosen by the farmer, 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 farmers from each possible crop and pesticide use choice. For the clean soil stock k_{it} as measured by the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide, the conditional independence assumption makes sense since the number of previous consecutive years the farmer has not used any unapproved synthetic pesticide evolves deterministically as a function of this period's value of the clean soil stock k_{it} and this period's action. For the conventional and organic rice prices, which are stochastic, since there are many growers in California and no grower has a significant market share, it is reasonable to assume that shocks to any particular individual grower are unlikely to affect what the discretized annual rice prices are at the aggregate level for all growers.

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 farmer's value function, 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:

$$V(\mathbf{s_{it}}, \epsilon_{it}, \theta) = \max_{a_{it}\in A} u_0(a_{it}, \mathbf{s_{it}}, \theta) + \epsilon_{it}(a_{it}) + \beta V^c(\mathbf{s_{it}}, a_{it}, \theta), \tag{10}$$

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:

$$V^c(\mathbf{s_{it}}, a_{it}, \theta) = E[V(\mathbf{s_{it}}, \epsilon_{it}, \theta)|s_{it}, a_{it}] \tag{11}$$

and where β is the annual discount factor. The choice probability is given by:

$$\Pr(a_{it}|\mathbf{s_{it}}, \theta) = \frac{\exp\left(u_0(a_{it}, \mathbf{s_{it}}, \theta) + \beta V^c(\mathbf{s_{it}}, a_{it}, \theta)\right)}{\sum_{\tilde{a}_{it}\in A}\exp\left(u_0(\tilde{a}_{it}, \mathbf{s_{it}}, \theta) + \beta V^c(\mathbf{s_{it}}, \tilde{a}_{it}, \theta)\right)}. \tag{12}$$

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. 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).

Identification of the parameters θ comes from the differences between per-period payoffs across different action choices, which in infinite horizon dynamic discrete choice models are identified when the discount factor β and the distribution of the choice-specific shocks ϵ_{it} are fixed (Abbring, 2010; Magnac and Thesmar, 2002; Rust, 1994). We set our annual discount factor to $\beta = 0.9$. In particular, the parameters θ in our model are identified because we normalize the deterministic payoff $u_0(a_{it} = \mathrm{OC}, \mathbf{s_{it}}, \theta)$ for a farmer who does not planting rice and uses unapproved chemical input to be 0; as a consequence, the parameters do not cancel out in the differences between per-period payoffs across different action choices and are therefore identified.

Standard errors are formed by a nonparametric bootstrap. Farmer-fields are randomly drawn from the data set with replacement to generate 100 independent panels each with the same number of farmer-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.

6 Transition Density for Prices

We use two state variables for price: the real conventional price P_{con}; and the real organic price premium $\frac{P_{org} - P_{con}}{P_{org}}$.

Since the conventional and organic rice price variables we use are discretized annual averages, we assume that the crop and pesticide use decisions of any one farmer would not have a large enough effect to influence crop prices, and therefore that the distribution of the discretized annual conventional rice price and organic rcie price premium next period does not depend on any single grower's decisions this period; we therefore model rice prices as evolving exogenously. Moreover, we assume that the real conventional price and the real organic price premium are each independent and identically distributed with no serial correlation. Furthermore, since we are now using the real organic price premium instead of the real organic price, we assume that the real conventional price and the real organic price premium are distributed independently of one another. We assume no serial correlation for the real conventional price and the real organic price premium both because it appears to be a reasonable approximation given the time series behavior of these variables (see Figures 1 and 2), and also due to data limitations: our annual price data only provides a very limited amount of consecutive observations to credibly estimate a first-order Markov transition matrix for prices.[4]

[4] Since we only have price data for 10 years of data (2005, 2008-2012, 2014-2016, 2019), we only have 10 observations for estimating the transition density for prices. Since we do not have price data for 2006-2007, if we try to estimate a first-order Markov transition density for prices, we cannot really use information from the 2005 prices either, so any first-order Markov transition density we estimate essentially does not include any information for prices for the years 2005-2007. Similarly, since we do not have price data for 2017-2018, if we try to estimate a first-order Markov transition

When discretizing our price variables, we choose the bins for the variables so that we do not have any price tuples that we do not observe in the data. Having tuples we do not observe in the data leads to issues including losing variation/information, which impedes our ability to identify parameters.

We bin our prices such that we do not have any price-bin tuples that we do not observe in the data. Having tuples we do not observe in the data leads to issues including losing variation/information, which impedes our ability to identify parameters .

We discretize the real conventional price P_{con} into 2 bins, 'low' and 'high', where a real conventional price less than \$19.50 is in the 'low' bin, and a real conventional price greater than or equal to \$19.50 is in the 'high' bin. Figure 1 plots the annual real conventional rice price, along with a horizontal dashed grey line indicating the cutoff for the bins. For each discretized bin for conventional prices, we use the average over all annual real conventional price values that fall in that bin for the value of the real conventional price to use for that bin. In particular, real conventional prices in the 'low' bin are assigned a real conventional price value of \$16.4604, and real conventional prices in the 'high' bin are assigned a real conventional price value of \$23.3469.

For the distribution for the discretized real conventional price, we use the empirical distribution of the discretized real conventional price. In other words, for each bin, we assume that the probability that the real conventional price in any given year is in that bin is the fraction of years with real price data that have real conventional price in that bin. The empirical distribution of discretized real conventional price has $\Pr(P_{con} = \text{low}) = 0.5$ and $\Pr(P_{con} = \text{high}) = 0.5$.

We discretize the real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$ into 3 bins: 'low', 'med', and 'high', where a real organic price premium less than \$0.50 is in the 'low' bin; a real organic price premium greater than or equal to \$1 is in the 'high' bin; and real organic price premia in between the 2 cutoffs are in the 'med' bin. Figure 2 plots the real organic price premium $\frac{P_{org}-P_{con}}{P_{org}}$, along with horizontal dashed grey lines indicating the cutoffs for the bins. For each discretized bin for the real organic price premium, we use the average over all annual the real organic price premium values that fall in that bin for the value of th real organic price premium to use for that bin. In particular, real organic price premia in the 'low' bin are assigned a real organic price premium value of \$0.2178; real organic price premia in the 'med' bin are assigned a real organic price premium value of \$0.6186; and real organic price premia in the 'high' bin are assigned a real organic price premium value of \$1.2326.

For the distribution for the discretized real organic price premium, we use the empirical distribution of the discretized real organic price premium. In other words, for each bin, we assume that the probability that the real organic price premium in any given year is in that bin is the fraction of years with real price data that have the real organic price premium in that bin. The empirical distribution

density for prices, we cannot really use information from the 2019 prices either, so any first-order Markov transition density we estimate essentially does not include any information for prices for the years 2017-2019 either. Thus, if we try to estimate a first-order Markov transition density for prices, we are essentially only using data and information from the years 2008-2016 and not using the data and information we have for 2005 and 2019. We are also missing price data for 2013, which further limits the amount of consecutive information we have to credibly estimate a first-order Markov transition matrix for prices. Nevertheless, based on the time series plots for real conventional price and real organic price premium, the assumption of no serial correlation seems reasonable.

of discretized real organic price premium has $\Pr(\frac{P_{org}-P_{con}}{P_{org}} = \text{low}) = 0.2$, $\Pr(\frac{P_{org}-P_{con}}{P_{org}} = \text{med}) = 0.6$, and $\Pr(\frac{P_{org}-P_{con}}{P_{org}} = \text{high}) = 0.2$.

7 Results

The structural parameter estimates are presented in Table 7.

Across all specifications, γ_k, which measures any misperception of how log yield is affected by the clean soil stock k_{it}, the number of previous consecutive years (up to 15 years) no unapproved synthetic pesticide was used, is negative. Thus, farmers underestimate how the clean soil stock k_{it}, as me8asured by the number of previous consecutive years no unapproved synthetic pesticide was used, affects yield. The net perceived effect of clean soil stock k_{it} on log yield is given by the sum of γ_k and the coefficient $\hat{\alpha}_k$ on the clean soil stock k_{it} from our production function estimation. Given $\hat{\alpha}_k = 0.400$ from Specification (1) in Table 5 and $\gamma_k = -0.285$ across all specifications in Table 7, the net perceived effect on log yield of the clean soil stock k_{it}, the number of previous consecutive years (up to 15 years) no unapproved synthetic pesticide was used, is 0.115, which is less than 30% of the actual effect. In other words, farmers are acting as if the clean soil stock k_{it} has very little effect on rice crop yields, when in fact it increases yields.

Across all specifications in Table 7, γ_c, which measures any misperception of how the use of an unapproved synthetic pesticide c_{it} affects log yield, is negative. The net perceived effect of the use of an unapproved synthetic pesticide c_{it} on log yield is given by the sum of γ_c and the coefficient $\hat{\alpha}_c$ on the use of an unapproved synthetic pesticide c_{it} from our production function estimation. Given $\hat{\alpha}_c = 3.757$ from Specification (1) in Table 5 and γ_c ranges from -0.839 to -0.836 in Table 7, the net perceived effect of the use of an unapproved synthetic pesticide c_{it} on log yield ranges from 2.918 to 2.921. This is roughly similar to the coefficient on the use of an unapproved synthetic pesticide c_{it} in the 'Misperception' specification of our production function in Specification (1) of Table 6, which was 3.011.

Table 7: Dynamic Structural Parameter Estimates

		(1)	(2)	(3)
Parameters in the perceived yield $\breve{q}(\cdot)$				
γ_c	Misperception of how log yield is affected by pesticide use c_{it}	-0.839***	-0.836***	-0.836***
		(0.0118)	(0.0139)	(0.0136)
γ_k	Misperception of how log yield is affected by clean soil stock k_{it}	-0.285***	-0.285***	-0.285***
		(0.0042)	(0.0043)	(0.0043)
Coefficients in rice production cost on:				
κ_c	Use pesticide c_{it}	-0.025***	-0.042***	-0.048***
		(0.0007)	(0.0012)	(0.0015)
κ_1	Perceived yield $\breve{q}_{it}$	0.070***	0.065***	0.063***
		(0.0024)	(0.0024)	(0.0026)
κ_{cq}	Perceived yield $\breve{q}_{it}$ X Use pesticide c_{it}		0.069***	0.067***
			(0.0022)	(0.0023)
κ_2	Perceived yield squared $\breve{q}_{it}^2$	0.0863***	0.0846***	0.08543***
		(0.0011)	(0.0012)	(0.0014)
κ_{cq2}	Perceived yield squared $\breve{q}_{it}^2$ X Use pesticide c_{it}			0.08535***
				(0.0014)
Other parameters				
ν	Deterministic payoff when farmer does not plant rice and does not use pesticide	-10.00***	-10.00***	-10.00***
		(0.00000)	(0.00000)	(0.00001)
# Observations		67,230	67,230	67,230
# Farmer-fields		17,695	17,695	17,695
# Counties		15	15	15

Notes: Standard errors in parentheses. Each observation is a farmer-field-year. Clean soil stock k_{it} is measured by the number of previous consecutive years (up to 15 years) no unapproved synthetic pesticide was used. Significance codes: *** p<0.001, ** p<0.01, * p<0.05

8 Counterfactual Simulations

Our structural estimates allow us to simulate a number of key outcomes of interest, including pesticide use and farmer welfare under counterfactual scenarios in which farmers' beliefs about soil-microbe based ecosystem services are brought in line with findings from plant and soil sciences. In particular, we use the estimated parameters from our dynamic structural econometric model in Table 7 to compare a base simulation of actual behavior under farmer misperception, with a counterfactual simulation of optimal behavior under full information.

We first run a base simulation of actual behavior ('Misperception'), which uses the parameter estimates from our dynamic structural econometric model in Table 7 for all the parameters. For each farmer-field, we start from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, and then forward simulate actions and states for each year from that year onwards to the final year of our data set ('short run') and also to 10 years past the the final year of our data set ('long run'). In particular, for each year of our simulation, we draw the action a_{it} for that year from the choice probabilities $\Pr(a_{it}|\mathbf{s_{it}}, \theta)$ evaluated at the state for that year and at the estimated parameters $\hat{\theta}$. Based on that year's action a_{it} and clean soil stock k_{it}, we determine the clean soil stock $k_{i,t+1}$ for next year. For the next year's real conventional price and real organic price premium, we draw from their respective distributions. After one simulation for all farmer-years, we tabulate the actions a_{it} and calculate summary statistics for clean soil stock k_{it}, the number of organic farmers, the mean of the true yield, the mean of the perceived yield, and the PDV of the entire stream of true per-period payoffs (calculated using the true yield). We repeat the simulation 100 times, and average over 100 simulations.

We next run a counterfactual simulation of optimal behavior ('Full Information'), in which we set the misperception parameters γ_k and γ_c both to 0, and then use the parameter estimates from our dynamic structural econometric model in Table 7 for all the remaining parameters. For each farmer-field, we start from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, and then forward simulate actions and states for each year from that year onwards to the final year of our data set ('short run') and also to 10 years past the the final year of our data set ('long run'). In particular, for each year of our simulation, we draw the action a_{it} for that year from the choice probabilities $\Pr(a_{it}|\mathbf{s_{it}}, \theta)$ evaluated at the state for that year, $\gamma_k = 0$, $\gamma_c = 0$, and at the estimated parameters $\hat{\theta}$ for the remaining parameters. Based on that year's action a_{it} and clean soil stock k_{it}, we determine the clean soil stock $k_{i,t+1}$ for next year. For the next year's real conventional price and real organic price premium, we draw from their respective distributions. After one simulation for all farmer-years, we tabulate the actions a_{it} and calculate summary statistics for clean soil stock k_{it}, the number of organic farmers, the mean of the true yield, and the PDV of the entire stream of true per-period payoffs (calculated using the true yield). We repeat the simulation 100 times, and average over 100 simulations.

The results for the short run are presented in Tables 8 and the results for the long run are presented in Table 9. In these tables, Specifications (1), (2), and (3) use parameter estimates from Specifications (1), (2), and (3), respectively, of Table 7. We find that the PDV of the entire stream of per-period payoffs is higher under full information than under misperception, both in the short run and the long run, and the margin widens as we move into the long run. The negative value that we get for the PDV of the entire stream of per-period payoffs under misperception is relative to the outside option when the farmer does not plant rice but still uses synthetic pesticide, and is presumably therefore planting another crop. This negative value therefore tells us that under misperception, they would have been better off taking the outside option of not planting rice but still uses synthetic pesticide than growing rice. Under full information, pesticide use is lower and organic adoption is higher, and this difference is more pronounced in the long run. Under farmer misperception, less than 0.1 percent of farmer-field-years produce organically in both the short and long run. In contrast, under full information, 55 to 58 percent of farmer-field-years produce organically in the short run, and 58 to 62 percent produce organically in the long run. The minimum, mean, 75th percentile, 95th percentile, and maximum PDV of the entire stream of per-period payoffs is higher under full information than under misperception in both the short run and the long run. While the 5th percentile, 25th percentile, and median (50th percentile) PDV of the entire stream of per-period payoffs are lower under full information than under misperception in the short run, they are all higher under full information than under misperception in the long run.

Table 8: Counterfactual Simulations: Short Run

		Misperception			**Full Information**		
		(1)	(2)	(3)	(1)	(2)	(3)
Distribution of a_{it} (% of farmer-field-years)							
a_{it} = RC	Plant rice and use pesticide that year	97.73	97.76	97.76	5.70	6.16	4.74
a_{it} = RN	Plant rice and do not use pesticide that year	1.61	1.59	1.59	94.31	93.84	95.26
a_{it} = OC	Do not plant rice that year and use pesticide that year	0.66	0.65	0.65	0.0000	0.0000	0.0000
a_{it} = ON	Do not plant rice and do not use pesticide that year	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Organic production (% of farmer-field-years)		0.06	0.06	0.06	56.11	54.57	58.14
Mean over farmer-field-years							
k_{it}	Clean soil stock	0.049	0.049	0.049	4.149	3.845	4.365
q_{it}	Yield (million lbs)	0.80	0.80	0.80	1.65	2.34	1.62
$\breve{q}_{it}$	Perceived yield (million lbs)	0.27	0.27	0.27			
PDV of entire stream of per-period payoffs							
Mean over farmer-fields ($)		73	73	50	144	128	136
(Std. Dev. in parentheses)		(89)	(89)	(321)	(231)	(172)	(234)
Min over farmer-fields ($)		-1,322	-1,234	-6,708	-2	-3	-3
5th %-ile over farmer-fields ($)		17	17	14	1	1	1
25th %-ile over farmer-fields ($)		52	52	52	7	7	8
50th %-ile over farmer-fields ($)		72	72	71	19	19	19
75th %-ile over farmer-fields ($)		86	86	85	207	207	191
95th %-ile over farmer-fields ($)		100	99	99	329	322	350
Max over farmer-fields ($)		1,608	1,622	851	1,708	1,716	1,739
Total PDV of entire stream of per-period payoffs (million $)		1.84	1.85	1.28	3.63	3.25	3.44

Notes: Table presents averages over 100 simulations. The 'short run' simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to the final year of our data set, year 2019. The 'Misperception' scenario is a base simulation of actual behavior, and uses the parameter estimates from our dynamic structural econometric model in Table 7 for all the parameters; Specifications (1), (2), and (3) use parameter estimates from Specifications (1), (2), and (3), respectively, of Table 7. The 'Full Information' scenario is a counterfactual simulation of optimal behavior, in which we set the misperception parameters γ_k and γ_c both to 0, and then use the parameter estimates from our dynamic structural econometric model in Table 7 for all the remaining parameters; Specifications (1), (2), and (3) use parameter estimates from Specifications (1), (2), and (3), respectively, of Table 7. The PDV of entire stream of per-period payoffs is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year (a_{it} = OC), which is normalized to 0.

Table 9: Counterfactual Simulations: Long Run

		Misperception			Full Information		
		(1)	(2)	(3)	(1)	(2)	(3)
Distribution of a_{it} (% of farmer-field-years)							
$a_{it} = \text{RC}$	Plant rice and use pesticide that year	97.76	97.79	97.79	8.16	8.60	6.82
$a_{it} = \text{RN}$	Plant rice and do not use pesticide that year	1.58	1.56	1.56	91.84	91.40	93.18
$a_{it} = \text{OC}$	Do not plant rice that year and use pesticide that year	0.66	0.65	0.65	0.0000	0.0000	0.0000
$a_{it} = \text{ON}$	Do not plant rice and do not use pesticide that year	0.0000	0.0000	0.0000	0.0012	0.0013	0.0000
Organic production (% of farmer-field-years)		0.04	0.04	0.04	59.19	57.57	62.03
Mean over farmer-field-years							
k_{it}	Clean soil stock	0.037	0.037	0.037	4.768	4.404	5.102
q_{it}	Yield (million lbs)	0.74	0.74	0.74	2.48	2.92	2.40
$\breve{q}_{it}$	Perceived yield (million lbs)	0.27	0.27	0.27			
PDV of entire stream of per-period payoffs							
Mean over farmer-fields ($)		92	93	70	268	245	247
(Std. Dev. in parentheses)		(88)	(88)	(321)	(242)	(145)	(258)
Min over farmer-fields ($)		-1,280	-1,192	-6,668	16	15	16
5th %-ile over farmer-fields ($)		67	67	67	178	277	29
25th %-ile over farmer-fields ($)		75	75	75	188	188	187
50th %-ile over farmer-fields ($)		86	86	85	208	208	193
75th %-ile over farmer-fields ($)		100	99	99	266	266	253
95th %-ile over farmer-fields ($)		115	114	114	405	384	442
Max over farmer-fields ($)		1,629	1,643	876	1,909	1,783	1,913
Total PDV of entire stream of per-period payoffs (million $)		2.34	2.35	1.77	6.77	6.20	6.27

Notes: Table presents averages over 100 simulations. The 'long run' simulations simulate each farmer-field from the actual value of the state (clean soil stock k_{it} and prices) in the first year for which we have data for that farmer-field, to 10 years past the the final year of our data set (i.e., to year 2029). The 'Misperception' scenario is a base simulation of actual behavior, and uses the parameter estimates our dynamic structural econometric model in Table 7 for all the parameters; Specifications (1), (2), and (3) use parameter estimates from Specifications (1), (2), and (3), respectively, of Table 7. The 'Full Information' scenario is a counterfactual simulation of optimal behavior, in which we set the misperception parameters γ_k and γ_c both to 0, and then use the parameter estimates from our dynamic structural econometric model in Table 7 for all the remaining parameters; Specifications (1), (2), and (3) use parameter estimates from Specifications (1), (2), and (3), respectively, of Table 7. The PDV of entire stream of per-period payoffs is relative to the per-period payoff from the outside option of not planting rice and using pesticide that year ($a_{it} = \text{OC}$), which is normalized to 0.

9 Conclusion

We develop and estimate a dynamic structural econometric model to examine whether farmers are aware of and account for soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields when making their decisions about pesticide use and organic farming adoption.

We first empirically document the insights from soil science that the use of pesticides may increase contemporaneous yields; and also that, over time, not using pesticides increases yields. Next, in order to understand the beliefs and perceptions of rice farmers that underlie and rationalize their pesticide use decisions as revealed in the data, we develop and estimate a dynamic structural econometric model. The structural parameters we estimate include parameters measuring any misperceptions farmers may have about how enhancing microbial health may affect yields. Empirical results show that farmers are acting as if the clean soil stock has very little effect on rice crop yields, when in fact it increases yields.

Our structural estimates allow us to simulate a number of key outcomes of interest, including pesticide use and farmer welfare under counterfactual scenarios in which farmer's beliefs about soil-microbe based ecosystem services are brought in line with findings from plant and soil sciences. We find that informing farmers about soil microbiomes and the feedback between pesticides, soil health, pest resistance, and crop yields will decrease pesticide use and increase organic adoption, will increase farmers' net present value (PDV of the entire stream of per-period profits) in the long run, and increases increase farmers' net present value on average in the short run. These results have important implications regarding the possible effects and benefits of extension programs targeting farmers' understanding of soil microbes.

References

Abbring, J. 2010. "Identification of Dynamic Discrete Choice Models." *Annual Review of Economics* 2:367–394.

Agarwal, N., I. Ashlagi, M. Rees, P. Somaini, and D. Waldinger. 2021. "Equilibrium Allocations under Alternative Waitlist Designs: Evidence from Deceased Donor Kidneys." *Econometrica* 89:37–76.

Aguirregabiria, V., and A. Luengo. 2016. "A Microeconometric Dynamic Structural Model of Copper Mining Decisions." Working Paper, University of Toronto.

Araujo, R., F.J.M. Costa, and M. Sant'Anna. 2020. "Efficient Forestation in the Brazilian Amazon: Evidence from a Dynamic Model." Working paper, FGV EPGE and University of Delaware.

Blundell, R., J.E. Schmidt, A. Igwe, A.L. Cheung, R.L. Vannette, A.C. Gaudin, and C.L. Casteel. 2020. "Organic management promotes natural pest control through altered plant resistance to insects." *Nature Plants* 6:483–491.

Blundell, W., G. Gowrisankaran, and A. Langer. 2020. "Escalation of Scrutiny: The Gains from Dynamic Enforcement of Environmental Regulations." *American Economic Review* 110:2558–2585.

California Department of Pesticide Regulation [CA DPR]. 2024. "Pesticide Use Reporting (PUR) Archive." [Online]. Accessed 1 May 2023. URL: `https://files.cdpr.ca.gov/pub/outgoing/pur_archives/`.

Carroll, C.L., C.A. Carter, R.E. Goodhue, and C.Y.C. Lin Lawell. 2019. "Crop Disease and Agricultural Productivity: Evidence From a Dynamic Structural Model of Verticillium Wilt Management." In W. Schlenker, ed. *Agricultural Productivity and Producer Behavior*. Chicago: University of Chicago Press, pp. 217–249.

—. 2024a. "The economics of decision-making for crop disease control." Working paper, Cornell University.

—. 2024b. "Supply chain externalities and agricultural disease." Working paper, Cornell University.

Chambers, R.G., G. Karagiannis, and V. Tzouvelekas. 2010. "Another look at pesticide productivity and pest damage." *American Journal of Agricultural Economics* 92:1401–1419.

Ching, A.T., and M. Osborne. 2020. "Identification and Estimation of Forward-Looking Behavior: The Case of Consumer Stockpiling." *Marketing Science* 39:669–848.

Cook, J.A., and C.Y.C. Lin Lawell. 2020. "Wind Turbine Shutdowns and Upgrades in Denmark: Timing Decisions and the Impact of Government Policy." *Energy Journal* 41:81–118.

Dash, N.P., A. Kumar, M.S. Kaushik, G. Abraham, and P.K. Singh. 2017. "Agrochemicals influencing nitrogenase, biomass of N2-fixing cyanobacteria and yield of rice in wetland cultivation." *Biocatalysis and Agricultural Biotechnology* 9:28–34.

Davidson, R., and J.G. MacKinnon. 2004. *Econometric Theory and Methods*. New York: Oxford University Press.

Espino, L.A., W. Brim-DeForest, M. Leinfelder-Miles, B.A. Linquist, P. Buttner, J. Murdock, D. Stewart, and D.A. Sumner. 2021. "Sample costs to produce rice in the Sacramento Valley - 2021." University of California at Davis Cost and Return Studies. [Online]. Accessed 14 May 2023. URL: `https://coststudyfiles.ucdavis.edu/uploads/pub/2021/11/03/2021ricesacramentovalley.pdf`.

Federal Reserve Bank of Minneapolis. 2024. "Consumer price index, 1913-." [Online]. Accessed 12 Jan 2024. URL: `https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913`.

Feger, F., N. Pavanini, and D. Radulescu. 2020. "Welfare and Redistribution in Residential Electricity Markets with Solar Power." Working Paper.

Gillingham, K., F. Iskhakov, A. Munk-Nielsen, J. Rust, and B. Schjerning. 2021. "Equilibrium Trade in Automobiles." Working paper, Yale University, Australian National University, University of Copenhagen, and Georgetown University.

Gowrisankaran, G., and M. Rysman. 2012. "Dynamics of Consumer Demand for New Durable Goods." *Journal of Political Economy* 120:1173–1219.

Hussain, S., T. Siddique, M. Saleem, M. Arshad, and A. Khalid. 2009. "Chapter 5: Impact of Pesticides on Soil Microbial Diversity, Enzymes, and Biochemical Reactions." *Advances in Agronomy* 102:159–200.

Jacquet, F., J.P. Butault, and L. Guichard. 2011. "An economic analysis of the possibility of reducing pesticides in French field crops." *Ecological Economics* 70:1638–1648.

Jaenicke, E., and L. Lengnick. 1999. "A Soil-Quality Index and its Relationship to Efficiency and Productivity Growth Measures: Two Decompositions." *American Journal of Agricultural Economics* 81:881–893.

Kalam, S., A. Basu, I. Ahmad, R.Z. Sayyed, H.A. El-Enshasy, D.J. Dailin, and N.L. Suriani. 2020. "Recent Understanding of Soil Acidobacteria and Their Ecological Significance: A Critical Review." *Frontiers in Microbiology* 11.

Kalia, A., and S. Gosal. 2011. "Effect of pesticide application on soil microorganisms." *Archives of Agronomy and Soil Science* 57:569–596.

Langer, A., and D. Lemoine. 2018. "Designing Dynamic Subsidies to Spur Adoption of New Technologies." NBER Working Paper No. 24310.

Li, S., Y. Liu, and C. Wei. 2022. "The Cost of Greening Stimulus: A Dynamic Analysis of Vehicle Scrappage Programs." *International Economic Review* 63:1561–1594.

Li, X., B. Li, L. Chen, J. Liang, R. Huang, X. Tang, X. Zhang, and C. Wang. 2022. "Partial substitution of chemical fertilizer with organic fertilizer over seven years increases yields and restores soil bacterial community diversity in wheatârice rotation." *European Journal of Agronomy* 133:126445.

Lo, C.C. 2010. "Effect of pesticides on soil microbial community." *Journal of Environmental Science and Health Part B* 45:348–359.

Lori, M., S. Symnaczik, P. Mäder, G. De Deyn, and A. Gattinger. 2017. "Organic farming enhances soil microbial abundance and activity-A meta-analysis and meta-regression." *PLOS ONE* 12:e0180442.

Magnac, T., and D. Thesmar. 2002. "Identifying Dynamic Discrete Decision Processes." *Econometrica* 70:801–816.

Meneses, M.A., C.L. Casteel, M.I. Gómez, D.R. Just, R. Kanbur, D.R. Lee, and C.Y.C. Lin Lawell. 2024. "Organic Farming Transitions: A Dynamic Bioeconomic Model." Working paper, Cornell University.

Murphy, D.M., D. Roobroeck, D.R. Lee, and J. Thies. 2020. "Underground Knowledge: Estimating the Impacts of Soil Information Transfers Through Experimental Auctions." *American Journal of Agricultural Economics* 102:1468–1493.

Newman, M.M., N. Hoilett, N. Lorenz, R. Dick, M. Liles, C. Ramsier, and J. Kloepper. 2016. "Glyphosate effects on soil rhizosphere-associated bacterial communities." *Science of the Total Environment* 543:155–160.

Oliva, P., B.K. Jack, S. Bell, E. Mettetal, and C. Severen. 2020. "Technology Adoption Under Uncertainty: Take-Up and Subsequent Investment in Zambia." *Review of Economics and Statistics* 102:617–632.

Organic Produce Network. 2022. "Organic Certification Requirements." [Online]. Accessed 19 September 2022. URL: `https://www.organicproducenetwork.com/article-education/6/organic-certification-requirements-and-the-usda-organic-standards`.

Rapson, D. 2014. "Durable Goods and Long-run Electricity Demand: Evidence from Air Conditioner Purchase Behavior." *Journal of Environmental Economics and Management* 68:141–160.

Righini, H., O. Francioso, A. Martel Quintana, and R. Roberti. 2022. "Cyanobacteria: A Natural Source for Controlling Agricultural Plant Diseases Caused by Fungi and Oomycetes and Improving Plant Growth." *Horticulturae* 8.

Rothwell, G., and J. Rust. 1997. "On the Optimal Lifetime of Nuclear Power Plants." *Journal of Business & Economic Statistics* 15:195–208.

Rust, J. 1988. "Maximum Likelihood Estimation of Discrete Control Processes." *SIAM Journal on Control and Optimization* 26:1006–1024.

—. 1987. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher." *Econometrica: Journal of the Econometric Society* 55:999–1033.

—. 1994. "Structural Estimation of Markov Decision Processes." In R. Engle and D. McFadden, eds. *Handbook of Econometrics*. Amsterdam: North-Holland, vol. 4, pp. 3081–3143.

Sambucci, O., C.Y.C. Lin Lawell, and T.J. Lybbert. 2024. "Pesticide Spraying and Disease Forecasts: A Dynamic Structural Econometric Model of Grape Growers in California." Working paper, Cornell University.

Scott, P.T. 2013. "Dynamic Discrete Choice Estimation of Agricultural Land Use." Working Paper, Available ¡http://www.ptscott.com¿.

Sears, L., C.Y.C. Lin Lawell, G. Torres, and M.T. Walter. 2024a. "Adjudicated Groundwater Property Rights: A Structural Model of the Dynamic Game Among Groundwater Users in California." Working paper, Cornell University.

—. 2024b. "Moment-based Markov Equilibrium Estimation of High-Dimension Dynamic Games: An Application to Groundwater Management in California." Working paper, Cornell University.

Sears, L., C.Y.C. Lin Lawell, and M.T. Walter. 2024. "Groundwater under open access: A structural model of the dynamic common pool extraction game." Working paper, Cornell University.

Sexton, S.E., Z. Lei, and D. Zilberman. 2007. "The economics of pesticides and pest control." *International Review of Environmental and Resource Economics* 1:271–326.

Singh, J.S., A. Kumar, A.N. Rai, and D.P. Singh. 2016. "Cyanobacteria: A Precious Bio-resource in Agriculture, Ecosystem, and Environmental Sustainability." *Frontiers in Microbiology* 7.

Smith, A. 2023. "California Rice is Back." Ag Data News, 23 Aug 2023. URL: https://agdatanews.substack.com/p/california-rice-is-back.

Thiebaut, F., M. Urquiaga, A. Rosman, M. da Silva, and A. Hemerly. 2022. "The Impact of Non-Nodulating Diazotrophic Bacteria in Agriculture: Understanding the Molecular Mechanisms That Benefit Crops." *International Journal of Molecular Sciences* 23:11301.

Timmins, C. 2002. "Measuring the Dynamic Efficiency Costs of Regulators' Preferences: Municipal Water Utilities in the Arid West." *Econometrica* 70:603–629.

UC Rice Research and Information Center. 2023. "Rice." University of California at Davis. [Online]. Accessed 14 May 2023. URL: https://agronomy-rice.ucdavis.edu/.

U.S. Department of Agriculture [USDA]. 2023. "Certified organic survey." National Agricultural Statistics Service (NASS). [Online]. Accessed 14 May 2023. URL: https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Organic_Production/.

—. 2007. "Organic Production Survey." National Agricultural Statistics Service (NASS). [Online]. Accessed 14 May 2023. URL: https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Organic_Production/.

—. 2012. "Organic Production Survey." National Agricultural Statistics Service (NASS). [Online]. Accessed 14 May 2023. URL: https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Organic_Production/.

—. 2017. "Organic Production Survey." National Agricultural Statistics Service (NASS). [Online]. Accessed 14 May 2023. URL: https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Organic_Production/.

—. 2024. "Quick Stats." National Agricultural Statistics Service (NASS). [Online]. Accessed 3 June 2024. URL: https://www.nass.usda.gov/Data_and_Statistics/index.php.

—. 1992. "Weights, Measures, and Conversion Factors for Agricultural Commodities and Their Products." Economic Research Service in cooperation with the Agricultural Marketing Service, the Agricultural Research Service, and the National Agricultural Statistics Service, U.S. Department of Agriculture. Agricultural Handbook No. 697. URL: https://www.ers.usda.gov/webdocs/publications/41880/33132_ah697_002.pdf?v=0.

USA Rice. 2020. "Where Rice Grows: California." URL: https://www.usarice.com/thinkrice/discover-us-rice/where-rice-grows/state/california.

USDA Agricultural Marketing Service. 2000a. "National Organic Program." 7 CFR 205. 21 December 2000.A Rule by the Agriculture Department, and the Agricultural Marketing Service. URL: https://www.ecfr.gov/current/title-7/subtitle-B/chapter-I/subchapter-M/part-205.

—. 2000b. "National Organic Program: A Rule by the Agricultural Marketing Service on 12/21/2000." 65 FR 80637. 21 December 2000. URL: https://www.federalregister.gov/documents/2000/12/21/00-32257/national-organic-program.

van Kooten, G.C., W.P. Weisensel, and D. Chinthammit. 1990. "Valuing Tradeoffs between Net Returns and Stewardship Practices: The Case of Soil Conservation in Saskatchewan." *American Journal of Agricultural Economics* 72:104–113.

Verma, R., H. Annapragada, N. Katiyar, N. Shrutika, K. Das, and S. Murugesan. 2020. "Chapter 4 - Rhizobium." In N. Amaresan, M. Senthil Kumar, K. Annapurna, K. Kumar, and A. Sankaranarayanan, eds. *Beneficial Microbes in Agro-Ecology*. Academic Press, pp. 37–54.

Wu, T., D.R. Just, C.Y.C. Lin Lawell, J. Zhao, Z. Fei, A. Ortiz-Bobea, and Q. Wei. 2024. "Optimal forest management for interdependent products: A nested dynamic bioeconomic model and application to bamboo." Working paper, Cornell University.

Yadav, S., S. Rai, R. Rai, A. Shankar, S. Singh, and L.C. Rai. 2017. *Cyanobacteria: Role in Agriculture, Environmental Sustainability, Biotechnological Potential and Agroecological Impact*, Singapore: Springer Singapore. pp. 257–277.

Yeh, D.A., M.I. Gómez, and C.Y.C. Lin Lawell. 2024. "Sustainable pest management, beliefs, and behavior: A dynamic bioeconomic analysis." Working paper, Cornell University.

Yibeltie, G., and S. Sahile. 2018. "The Role of Cyanobacteria on Agriculture." *Journal of Natural Sciences Research* 8.