Title

Farm Size Distribution and Specialization and Their Impacts on Pesticide Use in Conventional and Organic Agriculture

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Farm Size Distribution and Specialization
and Their Impacts on Pesticide Use in Conventional and Organic Agriculture

By

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DISSERTATION

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To Xi and William.

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Abstract

Organic agriculture has grown tremendously over the past two decades. The large-scale production emerging with consolidation could undermine the positive perception of organic food. Pesticide use and cropland consolidation have become two rising concerns regarding the development of organic agriculture. More evidence is needed to quantify the benefit of pesticide use in organic agriculture relative to its use in conventional agriculture and to evaluate how it is affected by the growth of organic agriculture and by the consolidation of an increasing share of organic acres into large farms. My dissertation research considers the environmental impacts of pesticide use, in both conventional and organic crop production, the consolidation process, and the interaction between farm size and pesticide use. My dissertation includes three essays.

In essay 1, I examine the environmental impacts of pesticide use in fields treated with conventional and organic pesticide programs using the California Pesticide Use Report (PUR) database. The PUR database provides a detailed record of all commercial pesticide use in California since 1990. I find that pesticides used in organic production had smaller negative environmental impacts on surface water, groundwater, soil, air, and

pollinators compared to pesticides used in conventional production, which has a higher yield per acre and a lower pest-management cost.

However, the difference in the environmental impacts of pesticide use between the two production systems has declined in multiple dimensions. The environmental benefit from adopting organic production systems may be less than is commonly perceived. Two additional regression results find implications of total farm acreage and experience for environmental impacts of pesticide programs. Farms with more acreage are associated with the use of pesticides that have larger environmental impacts. More experienced farmers are associated with the use of pesticides that have greater impacts on surface water and groundwater, and less impact on soil, air, and pollinators. The environmental impacts of pesticide use in conventional agriculture remained stable in the study period regardless of changes in regulations and the use of active ingredients such as methyl bromide.

The change in pesticide use in organic agriculture is partially driven by the consolidation process. In essay 2, I identify individual organic fields in the PUR database, which allows me to document the occurrence of cropland consolidation, and assess the effect of consolidation on pesticide use in organic agriculture. Organic agriculture is increasingly characterized by the consolidation of production into the hands of larger operations. I leverage the PUR database to identify the organic field, and compare the impacts of organic and conventional pesticide programs and several dimensions of environmental quality.

Further analysis of the data reveals that pesticide use patterns are significantly correlated with the consolidation of organic cropland from 1995 to 2017. Although the number of organic farms increased, the acreage share of large farms increased, which is a clear sign of consolidation. Farms with larger organic acreage, holding other variables constant, applied sulfur and fixed copper pesticides more frequently than those with smaller acreage. As a result, they had greater impacts on surface water and smaller impacts on soil and air because those ingredients are more toxic to fish and algae, less toxic to earthworms, and have lower Volatile Organic Compound (VOC) emissions than other ingredients used in organic fields. The change in crop composition is another factor contributing to the change in the environmental impacts because the relationship between consolidation and pesticide use varies across crops. The results of this essay show how the environmental impacts of organic agriculture could continue to change as the sector grows.

The consolidation of acreage and value of production into a smaller number of larger operations has characterized U.S. agriculture for decades. Consolidation interacts with specialization, which is measured by a decline in the number of commodities produced per farm. In essay 3, I adapt and extend the endogenous growth model introduced in Lucas (2009) to explain changes in the size distribution of farms over time. Farmers have knowledge regarding the production of each crop, and this knowledge grows through learning from others. Increased knowledge increases the profitability of producing a specific crop. Knowledge regarding other crops also helps, to various degrees. As specialized knowledge accumulates, the opportunity cost of producing crops that farmers know less about increases, which reduces the number of crops produced by each farmer. The farm size distribution is an equilibrium outcome. As such, it effectively is a transformation of the underlying distribution of knowledge. Simulation results demonstrate how model parameters including learning rate, budget share, and elasticity of substitution alter the distribution of farm size and specialization.

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My Ph.D. journey started on Feb 1st, 2016 when I received a call from Dr. C.-Y. Cynthia Lin Lawell who congratulated me on my acceptance to the program. In early March, I visited the department on a rainy day (the first of many to come) and had a great dinner at Dr. Steve Boucher's house. Before that, my perception of the program came from two Davis graduates, Dr. David Bessler and Dr. Fujin Yi. I knew the program is one of the best Agricultural Economics programs in the world and everyone has a bike. At that time, I had no idea how this program would shape the way I look at agriculture.

The person I would like to thank the most is Dr. Rachael Goodhue, who is also the chair of my dissertation committee. I started to work as a graduate student researcher with her in the fall of 2017. We worked on various topics at the beginning and focused on pesticide regulations later. Initially, I was interested in California agriculture but not the pesticide use in particular and I did not know the existence of the Pesticide Use Report, a field-level panel database for all crop production in California since the 1990s, which ends up being the foundation of my dissertation and future research. In my oral exam, she invited Dr. Minghua Zhang, who provided insightful advice to my job market paper at an

early stage. Rachael also encouraged me to share my work with researchers from other disciplines. I presented my research on organic agriculture to the Pesticide Use Report Analysis Workgroup and received innovative feedback. My schedule became tighter after my son was born. Rachael rearranged the workflow and rescheduled meetings to adjust for my availability. When I sent emails during weekends or at night, she is still able to respondin time. In short, Rachael is amazing.

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Introduction

Modern agriculture faces environmental concerns about the use of pesticides. Organic agriculture is an alternative production method that limits the use of synthetic pesticides and fertilizers. The literature has documented that organic crop production does has a lower environmental impact per unit of land than conventional agriculture (Reganold and Wachter, 2016, Muller et al., 2017,Tuomisto et al., 2012).

However, previous studies often concentrate on a small geographic or crop variety scoop. In essay 1, I use the California Pesticide Use Report (PUR) database to examine the environmental impacts in conventional and organic crop production at a full scale. It includes all pesticide use in commercial production. I examine the period 1995 to 2015 and find that pesticides used in organic production had smaller negative environmental impacts on surface water, groundwater, soil, air, and pollinators than pesticides used in conventional production. Over time, this difference has declined. I also investigate how farm size and farming experience are correlated with pesticide use. I find that farmers with more acreage use pesticides that have larger environmental impacts. Specifically, more experienced farmers use pesticides that have greater impact on surface water and groundwater, and less impact on soil, air, and pollinators.

The environmental impacts of pesticide use in organic agriculture increased over my study period, which is an interesting observations that requires further investigation. In essay 2, I focus on organic crop production and try to quantify the change in pesticide use. I find that the pesticide portfolio has changed dramatically for organic crop growers, as illustrated by the decline in sulfur use and the increase in spinosad use. Pesticide use is correlated with farm size. The consolidation of organic cropland is another trend documented in essay 2. Historically, consolidation in agriculture as a whole has manifested as an decrease in the number of farms while the total cropland remains stable (MacDonald et al., 2018). In the organic sector, in contrast, both the number of farms and acreage have grown significantly for the last two decades. Nonetheless, consolidation has occurred because the share of large farms in total acreage had increased. In 2015, 56% of organic cropland was operated by growers with at least 500 acres of organic cropland, up from 15% in 1995. At the other end of the spectrum, growers with 10-50 acres accounted for 18% of organic cropland in 1995, which dropped to 8% in 2015. The average organic farm size increased from 46 acres in 1995 to 103 acres in 2015. The median organic farm size increased from 15 to 17 from 1995 to 2015.

Farms with larger organic acreage, holding other variables constant, applied sulfur and fixed copper pesticides more frequently than those with smaller acreage. As a result, they had greater impacts on surface water and smaller impacts on soil and air because those ingredients are more toxic to fish and algae, and less toxic to earthworms and have lower Volatile Organic Compound (VOC) emissions than other ingredients used in organic fields. The composition of organic crop has changed in California with the acreage share of vegetables increasing from 30% in 1995 to 50% in 2015. However, pesticide use patterns and the correlation with farm size do not differ between vegetables and other crops.

The consolidation of cropland has not been limited to the organic sector. MacDonald et al. (2018) documented that the consolidation of acreage and value of production into a smaller number of larger operations has characterized U.S. agriculture for decades. In essay 3, I adapt and extent the endogenous growth model introduced in Lucas (2009) to explain changes in the size distribution of farms and specialization over time. In the theoretical model, farmers have knowledge regarding the production of each crop, and this knowledge grows only through learning from other farmers. Increased knowledge increases the profitability and knowledge can be apply across crops to various degrees.

In my modeling framework, the opportunity cost of producing crops that farmers know less about increases as specialized knowledge accumulates, which reduces the number of crops produced by each farmer. The evolution of the farm size distribution in equilibrium and simulation results are presented to demonstrate how model parameters including learning rate, budget share, and elasticity of substitution alter the distribution of farm size and specialization.

Essay 1

The Environmental Impacts of Pesticide Use in California's Conventional and Organic Agriculture

1.1 Introduction

The food system has faced concerns about its use of pesticides since even before Rachel Carson published *Silent Spring* (Carson, 1962). Today, concerns about environmental impacts from pesticide applications continue to grow (Tang et al., 2018; Chen et al., 2018). In this context, organic agriculture is proposed as an alternative farming system as it prohibits the use of most synthetic substances (Reganold and Wachter, 2016, Muller et al., 2017). With strict modeling assumptions, Muller et al. (2017) presents simulation results that support organic agriculture as an alternative production system capable of providing food for the world population by 2050. Consumers' perception that organic agriculture is more environmentally friendly has facilitated its growth (Batte et al., 2007). According to the Organic Trade Association, U.S. organic food commodity sales reached $39 billion in 2015 in real terms, up from $4 billion in 1997, the base year. The share of organic food sales in total food commodity sales increased from less than 1% to 5% during the same time period (OTA, 2016).

In 2002, the National Organic Program (NOP) was launched. It established national standards for organic certification and took enforcement actions if there were violations of the standards. Organic growers are prohibited from using certain production practices that have significant negative environmental impacts. However, the regulation of organic agriculture is process-based, not outcome-based, and the regulatory agency does not monitor or enforce standards on environmental outcomes such as biodiversity and soil fertility (Seufert et al., 2017). Another source of concern comes from the way organic farming practices may change as the sector grows. As pointed out by Läpple and Van Rensburg (2011), late adopters of organic agriculture are more likely to be profit-driven and care less about the environment than early adopters. And, the prices of organic products remained at least 20% higher than their conventional counterparts in 2010 (Carlson, 2016), which could encourage additional entry. Therefore, unintended consequences might emerge and organic agriculture could be less environmentally friendly than commonly perceived.

There is some evidence of this in the scientific literature. Organic agriculture has been reported to have higher nitrogen leaching and larger nitrous oxide emissions per unit of output than conventional agriculture (Tuomisto et al., 2012). Certain pesticide active ingredients (AIs) used in organic agriculture have been found to be more toxic than conventional AIs in laboratory environments and field experiments (Biondi et al., 2012; Bahlai et al., 2010). For example, Racke (2007) reviewed the discovery and development of spinosad, a natural substance used to control a wide variety of pests, and observed that spinosad was approved based on its low mammalian toxicity. However, Biondi et al. (2012) found that spinosad is more harmful to natural predators than pesticides used commonly in conventional agriculture. As the case of spinosad demonstrates, pesticide use in organic agriculture could impose more environmental impact than conventional agriculture in one or more dimensions. Therefore more evidence is needed to evaluate the environmental impact of organic farming practices and its determinants.

In this essay, I provide novel evidence regarding the impact of pesticide use in organic and conventional agriculture on different dimensions of environmental quality, and quantify the difference between the environmental impacts of pesticide use in the two production systems in California. In addition, I examine the relationships between farmers' pesticide-use decisions and their experience and farm size.

California is the leading state for organic agriculture in the U.S., accounting for 12% of certified organic cropland and 51% of certified organic crop value nationally in 2016 (NASS USDA, 2017). The number of certified operations and cropland acreage in California doubled between 2002 and 2016. State organic crop sales increased almost tenfold at the farm level, in real terms, during the same time period (Klonsky and Richter, 2005a; Klonsky and Richter, 2011a; Klonsky and Healy, 2013a; Wei et al., 2020a).

This essay uses field-level pesticide application records and a fixed-effects model to analyze changes in the environmental impacts of pesticide use for both organic and conventional fields over 21 years. The database covers all registered agricultural pesticide applications in California, and contains over 48 million pesticide application records for over 64,000 growers and 781,000 fields from 1995 to 2015. In total, data from more than 55,000 organic fields and 11,000 growers who operated organic fields are analyzed in this essay. The Pesticide Use Risk Evaluation (PURE) model is used to assess the environmental impacts of pesticide use (Zhan & Zhang, 2012).

The results show that the environmental impact of pesticide use per acre is lower in organic fields across all of the environmental dimensions for which PURE indexes are defined: surface water, groundwater, soil, air, and pollinators. The difference in the impact on air is the smallest because natural pesticides are not systematically different from synthetic pesticides in terms of volatile organic compound (VOC) emissions. The estimated impacts on all five environmental dimensions are positively correlated with farm acreage. The measure of farmer experience is positively correlated with estimated impacts per acre on surface water and groundwater, and negatively correlated with estimated impacts on soil, air, and pollinators but the difference associated with variation experience are smaller than the estimated effect of whether the field is organic or not by orders of magnitude. Environmental impacts and the difference between organic and conventional production vary by crop. Four major California crops, lettuce, strawberries, processing tomatoes, and wine grapes, are examined in detail.

The benefit from organic agriculture is partially paid by consumers through a price premium for organic products (Gil et al., 2000; Krystallis and Chryssohoidis, 2005; Batte et al., 2007; Janssen and Hamm, 2012). Whether organic production is the most cost-effective way to reduce the environmental impacts of agriculture is not the focus of this essay. However, readers can gain some insight into the performance of organic agriculture by comparing the cost of alternative tools and their effects on environmental quality.

The contribution of this essay is threefold. First, it links the environmental impacts of organic crop production directly to pesticide applications. To the best of my knowledge, no other studies have examined this relationship. Previous literature provided abundant evidence on the environmental impact of organic agriculture as a system but failed to quantify the impact of specific farming practices (Gomiero et al., 2011; Hartmann et al., 2015; Pimentel et al., 2005; Tuomisto et al., 2012). Here, AIs and their contributions to environmental impacts are identified individually, which enhances the understanding of the differences in pesticide use between organic and conventional agriculture and how they vary across crops.

Second, this essay uses the PURE model to assess the environmental impacts of pesticide use (Zhan & Zhang, 2012). Compared to the risk quotient approach, which is another common method in the literature (Nelson and Bullock, 2003; Kovach et al., 1992), the PURE model provides a more salient measure of environmental impacts by incorporating additional environmental information, such as the distance from the pesticide application to the nearest surface water. The PURE model calculates risk indices for five environmental dimensions: surface water, groundwater, soil, air, and pollinators.

Third, by using the Pesticide Use Report (PUR) database, this essay's findings are based on the population of pesticide application data. Prior works include meta-analyses that cover numerous field experiments (Pimentel et al., 2005) and commercial operations (Tuomisto et al., 2012) examined for a crop or a small geographic area over a limited period of time. California's agriculture is characterized by many crops and diverse climate and soil conditions. The comprehensive coverage of the PUR database eliminates any sample selection issue.

The rest of the essay is organized as follows: section 2 introduces the PUR database and PURE model and presents summary statistics of historical pesticide use, section 3 provides the identification strategy to tackle grower heterogeneity, section 4 presents industry-level and crop-specific estimation results, and section 5 concludes.

1.2 Data and Descriptive Statistics

The Pesticide Use Reports (PUR) database, created and maintained by the California Department of Pesticide Regulation, is the largest and most complete database on pesticide and herbicide use in the world. Growers in California have reported information about every pesticide application since 1990. In this essay, pesticide uses prior to 1995 are not evaluated due to data quality issues identified previously (Wilhoit et al., 2001; Wei et al., 2020b). More than 3 million applications are reported annually. Reports include information on time, location, grower id, crop, pesticide product, AIs, quantity of product applied, treated acreage and other information, for every agricultural pesticide application. A "field" is defined as a combination of $grower\_id$ and $site\_location\_id$, which is a value assigned to each parcel by its grower.

To obtain the USDA organic certification, growers must meet requirements on several aspects of production: pesticide use, fertilizer use, and seed treatment. The requirement on pesticide use is burdensome because pesticides approved in organic agriculture are expensive and have less efficacy. Pesticide and fertilizer AIs used in organic agriculture undergo a sunset review by the National Organic Standards Board (NOSB) every five years and the main criterion is whether the ingredient is synthetic or not. In general, it is not reasonable for growers to use those pesticides exclusively but not apply for the organic certification, given higher price and lower efficacy of those pesticides. Therefore, growers who comply with the NOP's requirement on pesticide use can be viewed as equivalent to certified organic growers for the data sorting purpose. In Wei et al. (2020b), authors located individual organic fields using this approach. Namely, any field without a prohibited pesticide applied for the past three years is considered organic. Their paper compared organic crop acreage from PUR to other data sources and showed that pesticide use records alone can be used to identify organic crop production.

Environmental conditions for each field and toxicity values for each chemical are used to calculate the value of the PURE index developed by Zhan and Zhang (2012). The PURE index has been used in previous studies to represent environmental impacts of pesticide use (Lybbert et al., 2016a; Wang et al., 2016; Fermaud et al., 2016). The PURE index indexes environmental impacts of pesticide use in five dimensions: surface water, groundwater, soil, air, and pollinators. For each dimension, the PURE index is calculated on a per acre basis and it varies from 0 to 100, where 0 indicates trivial impact and 100 represents the maximum impact. Excluding air, the PURE index is the ratio of the predicted environmental concentration (PEC) to toxicity to the end organisms. The PEC estimates the effect of the pesticide application on the concentration level for chemicals in the environmental sample. The toxicity values cover both acute measures, such as LD50, and long-term measures, such as No Observed Effect Concentration and acceptable daily intake for humans. End organisms are fish, algae, and water fleas for surface water, humans for groundwater, earthworms for soil, and honeybees for pollinators. The PURE index for air is calculated based on potential VOC emissions, which is a common measure of airborne pollutants emitted from agriculture production (CEPA, 2019). The emission of VOCs is defined as the percentage of mass loss of the pesticide sample when heated. Unlike toxicity, VOC emissions do not have a strong link to whether the AIs are synthetic or natural. For example, the herbicide Roundup®, which contains glyphosate, has zero VOC emissions because there is no evaporation or sublimation. Meanwhile, sulfur products, which are widely used in organic agriculture, also have zero VOC emissions. The PURE index only captures impact from active ingredients in pesticides. Inert ingredients, which are not covered in this essay, are also found to have negative impacts on the environment (Krogh et al., 2003; Cox and Surgan, 2006) and on pollinators in particular (Durant et al., 2020).

1.2.1 Pesticides Used in Conventional and Organic Agriculture

Conventional and organic growers adopt different pest management practices. As specified by the NOP, organic growers shall use pesticides only when biological, cultural, and mechanical/physical practices are insufficient. Chemical options remain essential for organic pest management programs. Currently over 7,500 pesticide products are allowed for use in organic crop and livestock production, processing, and handling.

In Figure 1.1, the acreage treated with different types of pesticides is shown on the left y-axis for both conventional and organic fields. Treated acreage is divided evenly among types for AIs that belong to multiple pesticide types, such as sulfur, which is both a fungicide and an insecticide. The average number of pesticide applications per acre, which is defined as the total treated acreage divided by the total planted acreage, is plotted against the right y-axis in both panels. This is a common measure of pesticide uses that controls for differences in application rate among pesticide products (Kniss, 2017). If multiple AIs are used in a single application, the treated acreage is counted separately for each AI.

Planted acreage remained stable for conventional agriculture over the study period, so changes in the average number of applications per acre were due to changes in treated acreage. Organic planted acreage grew dramatically, but treated acreage increased even more. The number of applications per organic acre rose from 2 to 7. Figure 1.1 provides a highly aggregated view of pesticide use as different pesticide products with different AIs and application rates are used in conventional and organic fields.

Examining the Figure 1.1 , insecticide is the most used pesticide type, accounting for 36% and 44% of total treated acreage in conventional and organic agriculture respectively in 2015. Herbicide is the second most used type of pesticide in conventional fields. In contrast, organic growers' use of herbicides is limited. Fungicide is another major pesticide type, and sulfur is the most used fungicide AI in both conventional and organic fields. Sulfur is an important plant nutrient, fungicide, and acaricide in agriculture. The pesticide

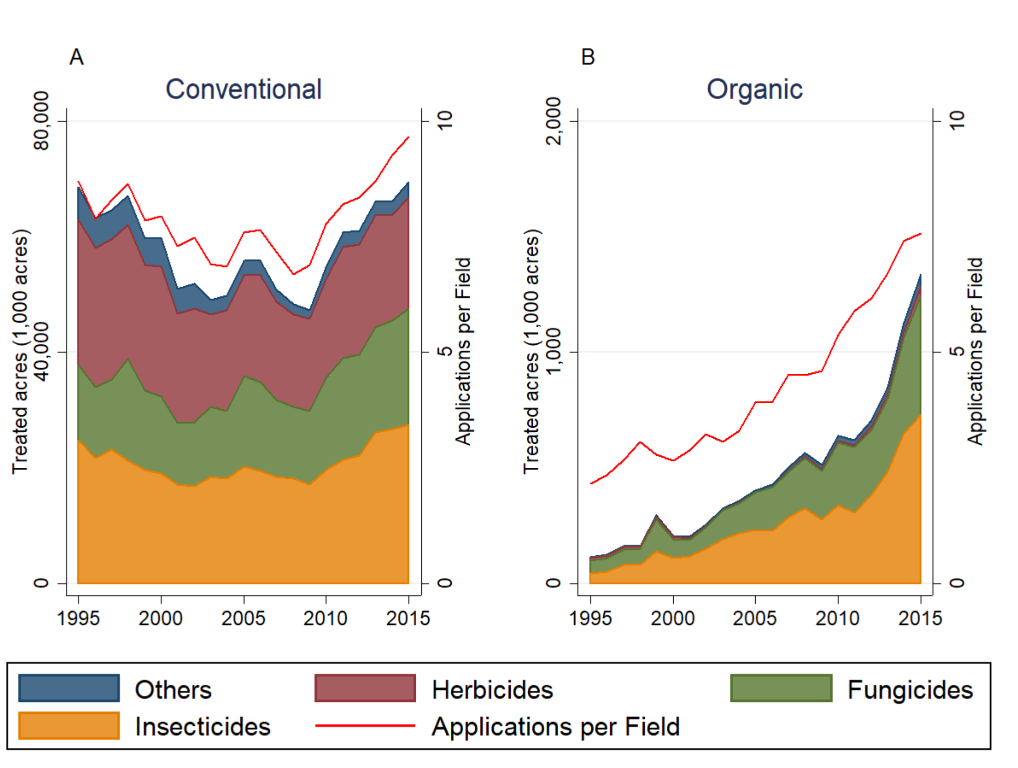


Figure 1.1: Treated Acreage by Major Pesticide Types and the Number of Applications per Field (A: Conventional and B: Organic): 1995 - 2015

group "others" primarily includes plant growth regulators and pheromones.

Disaggregating insecticide use provides more detailed insight into the nature of the difference between conventional and organic production. Figure 1.2 plots the insecticide-treated acreage by physiological functions affected (IRAC, 2020). Only three groups of insecticides are available to organic growers, while six are available to conventional growers. In conventional agriculture, 67% of treated acreage in 2015 was treated with insecticides that targeted nerves or muscles, which include organophosphates, pyrethroids, and neonicotinoids. For organic growers, two AIs, spinosad and pyrethrins, are available to target those physiological functions. The "unknown" category, which is mostly sulfur, accounted for a significant portion of treated acreage in organic agriculture. Insecticides that target the midgut, which includes *Bacillus thuringiensis* (Bt) and several granulosis viruses, are widely applied in organic fields. Conventional growers rarely use them due to the high cost. In 2015, acreage treated with midgut targeted insecticides was 1% of total treated acreage in conventional agriculture and 24% in organic agriculture. A detailed discussion of insecticide and fungicide use by mode of action in conventional and organic production is in the appendix.

1.2.2 PURE Indices for Conventional and Organic Agriculture

Insecticides and fungicides in the two pest management programs have different modes of action and pose different levels of environmental impact. Simply comparing treated acreage or the amount of pesticide products used does not identify the differences in environmental impacts. In this context, the PURE index serves as a consistent measure

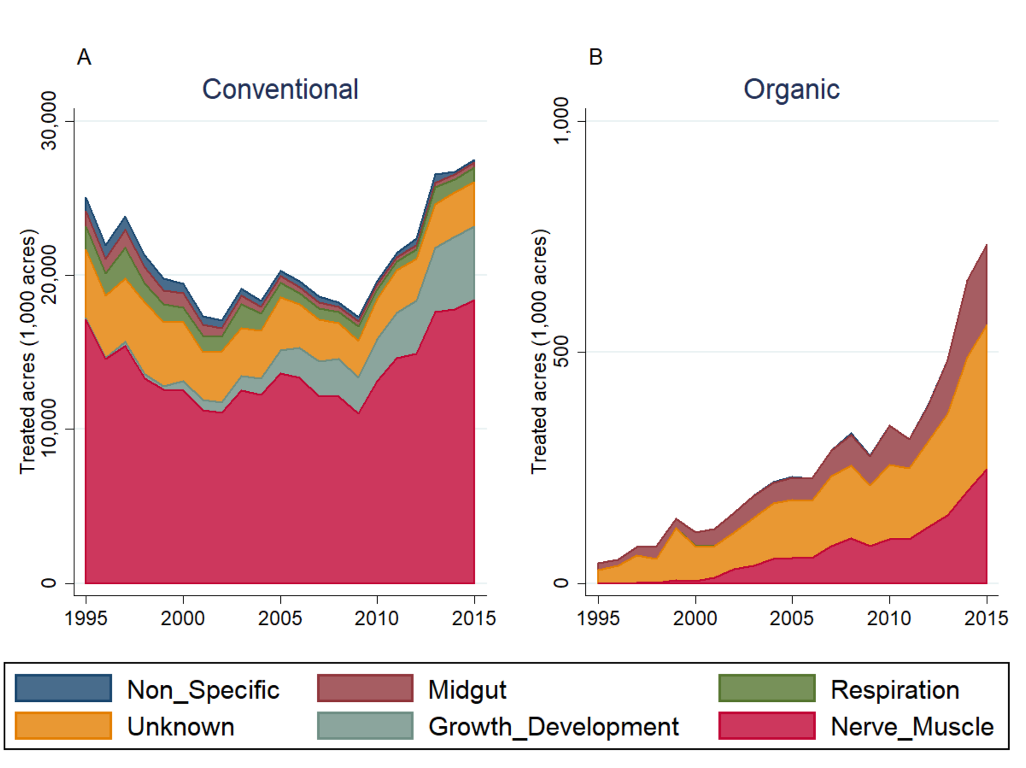


Figure 1.2: Treated Acreage of Insecticides by Physiological Targets (A: Conventional and B: Organic): 1995 - 2015

across farming systems.

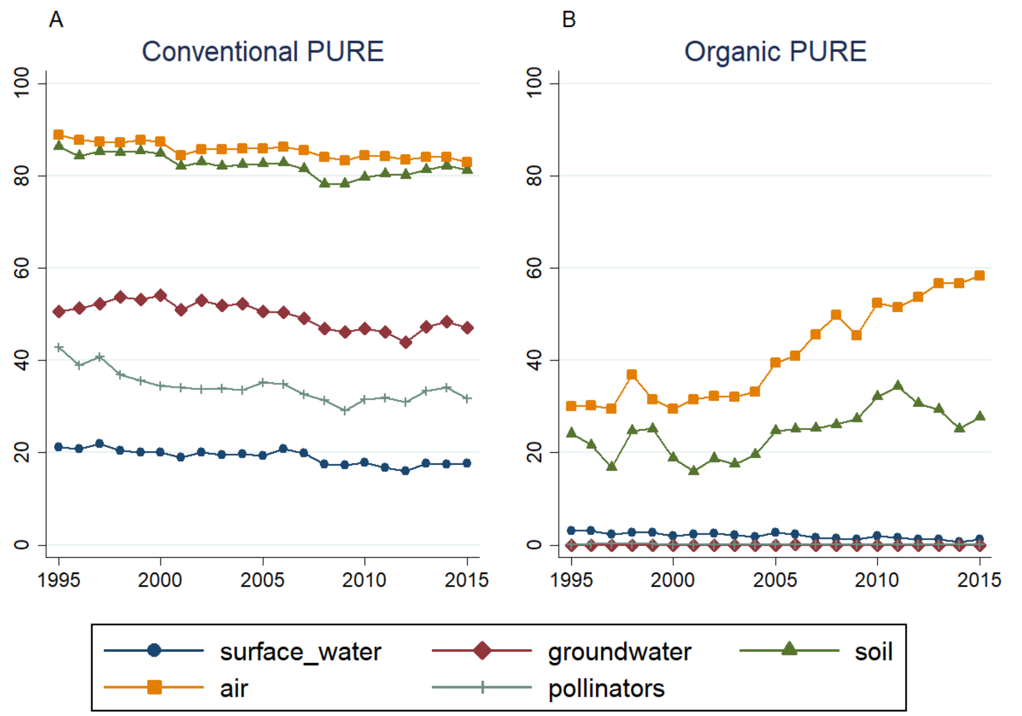


Figure 1.3: PURE Index Weighted by Acres per Field (A: Conventional and B: Organic): 1995 - 2015

Figure 1.3 plots PURE indices for conventional and organic fields by year. Index values for air and soil are significantly higher than those for the other environmental dimensions in both farming systems, which means that pesticide use in general has greater impacts on air and soil quality than groundwater, pollinators, and surface water. Risk indices of conventional fields (figure 1.3A) are relatively stable from 1995 to 2015, with no obvious overall changes for air or soil, despite the many changes that have occurred during this 20-year period in regulations and grower portfolios. While PURE indices decreased 16% for surface water, 26% for pollinators, and 7% for groundwater over the same time period, these three were much less impacted by pesticides in 1995, the beginning of the study period. Despite the numerous regulatory actions designed to reduce environmental impacts over this 20-year period, such as the methyl bromide phase-out, large-scale substitution of pyrethroids for organophosphates, and regulations to reduce VOC emissions from nonfumigant products, the overall environmental impacts of conventional pesticide use show only limited reductions when aggregated across all crops.

PURE indices for organic fields (figure 1.3B) are similar to conventional fields in that the air and soil have significantly higher index vales than the others. However, the aggregate risk indices in all five dimensions are much lower in organic fields. Compared to conventional agriculture, organic agriculture has dramatically lower PURE indices for surface water (90%), groundwater (99%), air (51%), soil (70%), and pollinators (99%). The reduction for air varies greatly across major California crops. Large reductions in the PURE index for air are observed for table grapes (64%), wine grapes (63%), and processing tomatoes (63%), while others had relatively small ones such as leaf lettuce (19%) and almonds (28%). The reduction in the PURE index for soil varies across crops as well, ranging from leaf lettuce (86%) to carrots (33%). For surface water, groundwater, and pollinators, the differences between the PURE index in organic and conventional fields are similar across crops. A noticeable spike in PURE indices appeared in 1998 for organic agriculture caused by a single application of copper sulfate with an application rate of 150 lb/acre, which is ten times larger than the average application rate and clearly a data abnormality.

The PURE index is a measure of environmental impacts on the per acre basis.

One could use the yield difference between conventional and organic agriculture to adjust values in Figure 1.3 and transfer them to a measure of impacts per unit of output. Organic agriculture is found to have 10%-20% lower yields than conventional agriculture (Stanhill, 1990; De Ponti et al., 2012; Seufert et al., 2012; Reganold and Wachter, 2016). If we use the 15% yield loss as an average to adjust the results for all crops, organic agriculture reduced the PURE index for surface water (88%), groundwater (99%), air (42%), soil (65%), and pollinators (99%). The impact of organic practices on pesticide use is crop-specific. This aggregate result is derived based on current crop mix in California.

Each crop is susceptible to a different spectrum of pests, which are managed by a distinct pesticide portfolio as part of a broader pest management program. Comparing PURE indices for individual crops shows the benefit from pesticide use in organic agriculture varies significantly. Based on value, production region, and the acreage share of organic production, four crops are selected to illustrate this point: lettuce, strawberries, wine grapes, and processing tomatoes. Lettuce, strawberries, and wine grapes are the three highest-valued organic crops in California, with organic sales values of $241, $231, and $114 million in 2016 respectively (NASS USDA, 2017). Production of strawberries and lettuce is concentrated in the Central Coast region. Processing tomatoes are an important crop in the Central Valley. Wine grape production occurs in a number of regions across the state. In 2015, the acreage shares of organic production are 8% (lettuce), 9% (strawberries), 4% (processing tomatoes), and 2% (wine grapes) for the selected crops.

Table 1.1: Field-Year Summary Statistics for Selected Crops

Variable	Conventional					Organic				
	All Crops	Lettuce	Strawberries	Wine Grapes	Processing Tomatoes	All Crops	Lettuce	Strawberries	Wine Grapes	Processing Tomatoes
Farm acreage (acre)	45.3	14.1	29.1	54.4	81.4	18.4	8.9	16.1	30.4	68.9
PUR Experience (year)	8.9	7.8	6.9	9.1*	9.7	7.2	5.6	5.4	10.1	8.1
PURE surface water	19.2	16.9	49.3	14.0	14.9	1.9	0.1	0.0	0.9	0.5
PURE groundwater	47.2	44.8	32.0	51.5	55.4	0.0	0.0	0.0	0.0	0.1
PURE soil	82.3	86.9	92.9	86.3	92.5	21.6	9.8	5.1	25.7	24.6
PURE air	81.9	74.1	89.7	77.5	91.4	48.8	45.3	71.9	35.4	36.3
PURE pollinators	36.7	59.2	57.2	19.4	34.9	0.1	0.0	0.1	0.3	0.0
N	3,396,625	332,620	34,757	210,058	73,464	114,952	17,851	1,888	7,741	1,998

Note: * The conventional mean is less than the organic mean at the 1% level.

For my analysis, the unit of observation is a field-year, defined as a field with one or more pesticide applications in a given calendar year. In total, more than 3 million field-year observations are included in the PUR database from 1995 to 2015. Table 1.1 provides field-year summary statistics for key variables by crop. Overall, 3% of them applied only pesticides approved in organic agriculture. For all crops, conventional farms are significantly larger in size and have higher PURE indices. The average farm size in PUR is smaller than the average number in the USDA Census (USDA NASS, 2017). One potential explanation is that one farm could have fields in different counties and apply for multiple pesticide application permits within in each county, which classifies it as multiple "farms" in the PUR.

For all crops, lettuce, strawberries, and processing tomatoes, growers who operate conventional farms have significantly more experience, measured by years they are observed in the PUR. For wine grapes, conventional growers have less experience than organic growers. Ideally, farming experience is measured directly or researchers use age as a proxy. However, the PUR database does not contain any demographic information, which limited my ability to measure experience. The PUR experience is smaller than the farming experience reported in the Census, which has many reasons. (USDA NASS, 2017). First, the PUR database I use started in 1995. Any farming experience before 1995 is not recorded. The Census is conducted every 5 years. Farms that entered and exited within the 5 year gap are included in the PUR database but not the Census, which reduce the average experience.

Conventional strawberries have significantly greater impact on surface water and less impact on groundwater, measured by the PURE indices, comparing to other conventional crops. Organic strawberries, on the other hand, had a higher PURE index for air and a lower PURE index for soil than other organic crops. Pesticides used in conventional production of wine grapes have less impact on pollinators than pesticides used in other conventional crops.

1.3 Empirical Framework

To identify the effect of organic agriculture on pesticide uses and associated environmental impacts, I must address the issues of selection bias at both the grower and the field levels. Compared to growers who utilize conventional practices, growers who adopt organic ones may have different underlying characteristics, such as attitudes toward environmental issues, which can also affect their pesticide use decisions directly. If grower characteristics are time-invariant, an unbiased estimation could be achieved by including a grower fixed effect in the regression. There is also time-variant heterogeneity that is associated with individual growers, due to factors such as farm size and experience, that simultaneously influences the adoption of organic production and pesticide use decisions. The identification concern here is that growers with more farming experience or larger farms, including both conventional and organic acreage, are more likely to operate organic fields and use less pesticides (Bravo-Monroy et al., 2016; Genius et al., 2006). Therefore it is not reasonable to compare environmental impacts of pesticide use for growers without considering these characteristics. For each grower, annual total acreage and experience serve as measures of time-variant heterogeneity. Acreage and experience may alter the environmental impact of growers' pesticide programs. As shown in Table 1.1, there is a significant difference for these two variables between conventional and organic growers.

There could be field-level heterogeneity as well, due to pest or disease pressure, that undermines my identification strategy. Fields with less pest or disease pressure need less pesticides and are more likely to be converted into organic production at the same time. Including field fixed effects in the estimation is one approach to address these issues. Organic fields tend to be concentrated spatially to avoid pesticide drift from nearby conventional fields (Parker and Munroe, 2007a; Tolhurst et al., 2017). Spatial relationships are not considered here because the PUR database does not have information on the distance between fields. The effect of organic status on environmental impacts of pesticide use can be estimated by the following regression:

$$\begin{aligned} y_{it} = &\beta_0 + \beta_1 \mathit{Organic}_{it} + \beta_2 \mathit{Organic}_{it} \times \mathit{Year}_t + \beta_3 \mathit{Year}_t + \beta_4 \mathit{Acreage}_{g[i]t} + \beta_5 \mathit{PUR\_Exp}_{g[i]t} \\ &+ \lambda_{g[i]} + \sigma_i + \theta_t + \phi_{c[i]} + e_{it} \end{aligned} \tag{1.1}$$

The dependent variable y_{it} is the PURE index for one of the five environmental dimensions in field i in year t. Grower $g[i]$ who grows crop $c[i]$ on field i in year t adopts either organic or conventional pest management practices, which is denoted by the binary variable $\mathit{Organic}_{it}$ (the notation follows Perry and Moschini (2020)). The variable $\mathit{Acreage}_{g[i]t}$ represents the total farm acreage, organic plus conventional, measured in 1,000 acres, for grower $g[i]$ who operated field i in year t. $\mathit{PUR\_Exp}_{g[i]t}$ measures the number of years grower $g[i]$ was observed in PUR. The time value $Year_t$ ranges from 1 to 21, which matches year 1995 to 2015. The grower fixed effect $\lambda_{g[i]}$ represents time-invariant grower heterogeneity. σ_i is the field fixed effect, which covers the time-invariant field heterogeneity. The fixed effect θ_t captures year to year variations. Pest management practices vary across crops, which alter the environmental impact of pesticide uses. The crop fixed effect $\phi_{c[i]}$ captures such variation.

Pesticide use in conventional and organic agriculture varies across crops as shown previously. Therefore, equation 1 is estimated for a subset of crops including, lettuce, strawberries, processing tomatoes, and wine grapes, to examine determinants of these differences. For lettuce, in particular, the environmental impacts from pesticide use do not have a linear time trend for the entire time period because the pesticide portfolio for conventional growers changed dramatically. After 2005, organophosphorus insecticides were gradually replaced by pyrethroid and neonicotinoid insecticides, which are less toxic in general. To capture this trend more precisely, a dummy variable that splits the study period in half is included to interact with the organic status variable in equation 1. The regression equation for lettuce is as follows:

$$\begin{aligned} y_{it} = &\beta_0 + \beta_1 \mathit{Organic}_{it} + \beta_2 \mathit{Organic}_{it} \times \mathit{06\_15}_t + \beta_3 \mathit{Organic}_{it} \times \mathit{Year}_t + \beta_4 \mathit{Year}_t \\ &+ \beta_5 \mathit{Acreage}_{g[i]t} + \beta_6 \mathit{PUR\_Exp}_{g[i]t} + \lambda_{g[i]} + \sigma_i + \theta_t + \phi_{c[i]} + e_{it} \end{aligned} \tag{1.2}$$

where $\mathit{06\_15}_t$ is a dummy variable, which equals 1 for observations in years 2006 to 2015. The coefficient of $\mathit{Organic}_{it} \times \mathit{06\_15}_t$ captures the change of the difference between two systems in the second half of the study period. It is expected to be positive because conventional growers switched to less toxic pesticides, which reduce the difference between the environmental impacts of conventional and organic pesticide use.

In the fixed effect model, the identification of β_1 requires the observation of a significant number of fields before and after the adoption of organic practices in the PUR database. Although certified organic cropland was only 5% of total cropland in California (NASS USDA, 2017), in the PUR database there are more than 53,000 fields using only pesticides approved for organic agriculture, which are operated by more than 10,000 growers. The coefficient of interest, β_1, is identified by comparing fields under conventional and organic management without regard for what their organic status may have been in the past or will be in the future.

By including field and grower fixed effects would introduce more noise than signal and amplify any potential measurement error. Comparing fields with similar attributes could serve as an alternative to address field heterogeneity. Therefore, I also propose to use a sub-sample containing only fields where both conventional and organic practices were observed for the same crop. The direction of the transition between systems should not matter, though transition from organic to conventional is rarely observed. The regression equation is as follows:

$$
\begin{aligned}
y_{it} =& \beta_0 + \beta_1 \textit{Organic}_{it} + \beta_2 \textit{Organic}_{it} \times \textit{Year}_t + \beta_3 \textit{Year}_t + \beta_4 \textit{Acreage}_{g[i]t} + \beta_5 \textit{PUR\_Exp}_{g[i]t} \\
& + \lambda_{g[i]} + \theta_t + \phi_{c[i]} + e_{it}
\end{aligned} \tag{1.3}
$$

The hypothesis is that the intercept in equation 3 is smaller than that in equation 1 because fields that are continuously operated under the conventional method are not included and more pesticides are typically applied to them. However, fields that stay in organic production are also excluded, so the difference between two systems is not necessarily smaller in this sub-sample than the full sample estimation.

For the same reason, the model is established for another sub-sample containing growers who operated both conventional and organic fields as an alternative to including grower fixed effects. The estimated intercept for this sub-sample is expected to be smaller than that for the the full sample because growers who did not engage in organic production and their fields are excluded. The regression equation is as follows:

$$
\begin{aligned}
y_{it} =& \beta_0 + \beta_1 \textit{Organic}_{it} + \beta_2 \textit{Organic}_{it} \times \textit{Year}_t + \beta_3 \textit{Year}_t + \beta_4 \textit{Acreage}_{g[i]t} + \beta_5 \textit{PUR\_Exp}_{g[i]t} \\
& + \sigma_i + \theta_t + \phi_{c[i]} + e_{it}
\end{aligned} \tag{1.4}
$$

The evolution of the organic industry is another interesting direction to explore. In particular, does organic agriculture become less environmentally friendly when more profit-driven growers enter, as suggested in Läpple and Van Rensburg (2011)? This question is partially answered by including the interaction term $Organic_{it} \times Year_t$. The hypothesis is that the coefficient is positive because more profit-driven growers, with less concern for the environment, entered over time and chose pesticide portfolios with greater environmental impacts. Other unobserved changes, such as the growth of pest population due to weather shocks or the development of pesticide resistance, could lead to an increase in pesticide use in organic fields. But, much of those variations are captured by the time fix effects and the year trend.

1.4 Results

The results from the full sample and sub-sample fixed effect model are reported first, followed by the results for four selected crops.

1.4.1 Results for Full Sample and Sub-Sample Estimation

Observations within the three-year transitional period are considered as conventional fields. This underestimates the environmental impacts of conventional pesticide use and therefore the benefit from organic agriculture. Excluding those observation does not alter the results since they only account for 1% of the fields.

The results from the full sample estimation are reported in Table 1.2. Each column shows the impact of pesticide use on different environmental dimensions measured by PURE indices. For example in column 1, the intercept represents the impact on surface water when other variables are set to zero, which is 17.51. The impact is decreasing by

0.62 each year, shown by the coefficient of t. If the grower adopted organic practices, the impact on surface water would reduce by 15.04 but increase by 0.37 every year as indicated by the coefficient of $Organic$ and $Organic \times t$. Farm acreage and experience are related to the environmental impact as well.

Table 1.2: Effect of Organic Pesticide Use on PURE Index Values: All Crops

Variable	Surface water	Groundwater	Soil	Air	Pollinators
Organic	-15.04***	-36.06***	-53.59***	-42.51***	-29.60***
	(0.25)	(0.31)	(0.45)	(0.43)	(0.27)
Organic × *Year*	0.37***	0.81***	1.07***	1.37***	0.65***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
Year	-0.62***	-0.53***	0.12**	0.12**	-0.07
	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)
Acreage	0.10***	0.41***	0.18***	0.15***	0.09***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
PUR_Exp	0.19***	0.16**	-0.28***	-0.44***	-0.28***
	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)
β_0	17.51***	38.84***	89.19***	79.92***	38.74***
	(1.51)	(1.38)	(1.48)	(1.44)	(1.26)
N	3,195,150	3,195,150	3,195,150	3,195,150	3,195,150
R^2	0.59	0.48	0.57	0.47	0.52

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1.
Grower, field, year, and crop fixed effects are included in all models.

For all five PURE dimensions, pesticides used in organic agriculture reduced environmental impact. The reduction, captures by the variable $Organic$, is significant at the 1% level for five environmental dimensions. Relative to the intercept, organic practices reduced environmental impacts for surface water by 86%, for groundwater by 93%, for soil by 60%, for air by 53%, and for pollinators by 76% on a per acre basis holding other variables fixed. The relatively small impact on air is linked to the facts that natural AIs do not have less VOC emissions in general. Regulations regarding high VOC-emitting pesticide AIs also contribute to this result partially because they do no affect two systems evenly. In 2015, the sale and use of 48 pesticide products were restricted due to their VOC emissions, which accounted for 5% of treated acreage in conventional agriculture and 1% of treated acreage in organic agriculture. Although reductions in PURE index values do not translate directly into dollar values or health outcomes, results from Table 1.2 suggest that pesticide use in organic fields substantially reduced environmental impacts.

The coefficient for *Organic* $\times$ t represents the change of the difference between two farming systems over time and is positive for all environmental dimensions, which supports the hypothesis that, comparing with conventional agriculture, the environmental impacts associated with pesticide use in organic agriculture have grown over time. Air has the largest coefficient among the five environmental dimensions, which is consistent with previous figures that environmental impacts increased the most for air across all crops. The variable t is the common time trend for all conventional fields and t is negative for surface water and groundwater, which means the environmental impacts from pesticide use decreased in conventional agriculture on those dimensions. The environmental impact on soil and air increased. The combination of variables t and *Organic* $\times$ t shows the time trend for organic fields alone, which is upward sloping for groundwater, soil, air, and pollinators, and downward sloping for surface water.

Two variables *Acreage* and *Exp*, capture time-invariant grower heterogeneity. Although the variable *Organic* dominates the overall effect, coefficients for both *Acreage* and *Exp* influence the environmental impact associated with crop production. For the same grower-crop combination, a larger farm size is associated with pesticide application programs that pose more negative impacts for all five environmental dimensions. Meanwhile, more experience is correlated with the environmental impacts on soil, air, and pollinators. The PURE indices for surface water and groundwater are positively correlated with experience. This is partially due to the fact that experienced farmers use less organophosphate insecticide per acre, which are more toxic to earthworms and honeybees than alternative AIs.

Table 1.3: Effect of Organic Pesticide Use on PURE Index Values: Sub-Sample Estimation without the Field Fixed Effect

Variable	Surface water		Groundwater		Soil		Air		Pollinators	
	Coef.	z-test	Coef.	z-test	Coef.	z-test	Coef.	z-test	Coef.	z-test
Organic	-16.94***	-5.16	-37.77***	-3.72	-55.51***	-2.95	-42.77***	-0.41	-32.05***	-6.18
	(-0.27)		(-0.34)		(-0.47)		(-0.46)		-(0.29)	
Organic × *Year*	0.50***	4.60	0.84***	0.83	1.16***	1.80	1.47***	2.36	0.73***	2.83
	(-0.02)		(-0.03)		(-0.04)		(-0.03)		(-0.02)	
Year	-0.60***	0.23	-0.62***	-0.74	0.18	0.47	-0.20	-2.73	0.31***	4.25
	(-0.08)		(-0.11)		(-0.12)		(-0.11)		(-0.08)	
Acreage	-0.24***	-4.67	-0.05	-4.99	0.15	-0.37	0.27***	1.46	-0.04	-1.58
	(-0.07)		(-0.09)		(-0.08)		(-0.08)		(-0.08)	
PUR_Exp	0.05	-1.64	0.15	-0.08	-0.26*	0.15	-0.23*	1.79	-0.63***	-3.55
	(-0.08)		(-0.11)		(-0.13)		(-0.11)		(-0.09)	
β_0	10.33***	-2.86	29.94***	-3.88	73.27***	-5.91	78.34***	-0.61	27.55***	-5.43
	(-2.01)		(-1.83)		(-2.25)		(-2.15)		(-1.63)	
N	194,763		194,763		194,763		194,763		194,763	
R^2	0.40		0.38		0.50		0.41		0.45	

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Year and crop fixed effects are included in all models. z test is conducted for each coefficient to show the difference between the full sample and sub-sample results.

Table 1.4: Effect of Organic Pesticide Use on PURE Index Values: Sub-Sample Estimation without the Grower Fixed Effect

Variable	Surface water		Groundwater		Soil		Air		Pollinators	
	Coef.	z-test	Coef.	z-test	Coef.	z-test	Coef.	z-test	Coef.	z-test
Organic	-15.25***	-0.57	-36.49***	-0.93	-54.40***	-1.22	-43.96***	-2.28	-30.48***	-2.22
	(-0.27)		(-0.34)		(-0.49)		(-0.47)		(-0.29)	
Organic × *Year*	0.39***	0.71	0.83***	0.71	1.14***	1.40	1.51***	3.30	0.72***	2.47
	(-0.02)		(-0.02)		(-0.04)		(-0.03)		(-0.02)	
Year	-0.91***	-3.81	-0.67***	-1.25	0.30**	1.67	0.23*	1.12	0.29***	4.02
	(-0.07)		(-0.10)		(-0.10)		(-0.09)		(-0.08)	
Acreage	0.07***	-1.06	0.41***	0.00	0.18***	0.00	0.12***	-1.06	0.14***	1.77
	(-0.02)		(-0.03)		(-0.02)		(-0.02)		(-0.02)	
PUR_Exp	0.48***	3.81	0.29**	1.16	-0.50***	-2.04	-0.66***	-2.23	-0.65***	-4.14
	(-0.07)		(-0.10)		(-0.10)		(-0.09)		(-0.08)	
β_0	16.41***	-0.47	32.50***	-2.94	84.81***	-1.84	79.36***	-0.24	38.46***	-0.14
	(-1.82)		(-1.66)		(-1.86)		(-1.83)		(-1.51)	
N	2,007,597		2,007,597		2,007,597		2,007,597		2,007,597	
R^2	0.59		0.52		0.61		0.55		0.56	

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Year and crop fixed effects are included in all models. z test is conducted for each coefficient to show the difference between the full sample and sub-sample results.

The sub-sample estimation yields similar results (Table 1.3 and Table 1.4). Namely, (1) in conventional agriculture, the environmental impacts on surface water and groundwater associated with pesticide use decreased over time, (2) pesticides used in organic agriculture significantly reduced the environmental impacts measured by the PURE index, (3) the difference between conventional and organic pesticide use decreased.The intercept is smaller than the coefficient of *Organic* occasionally because the crop and time fixed effects are oftentimes positive and significant and the impacts on those dimensions in organic fields are small.

For the sub-sample with fields that have transitioned between production systems, total farm acreage is no longer significantly associated with impacts on groundwater, soil, and pollinators and the environmental impact on surface water is negatively correlated with farm acreage. The main reason for this seemingly dramatic difference, comparing to the full sample estimation, is that there are more wine grape vineyards and fewer almond orchards and alfalfa fields in the sub-sample. Although the organic price premium is limited for wine grapes, the organic farming practices are associated with high quality of grapes, which encourage growers to adopt organic production (Iordachescu et al., 2010; Rojas-Méndez et al., 2015; Ogbeide, 2015). The price premium is significant for almond and alfalfa (Brodt et al., 2009; Evers III, 2011). However, organic almonds suffer from an average 20% of yield loss, which hinders the transition (Holtz et al.). For alfalfa, the price depends on the organic status as well as quality, which is hard to control for organic growers due to weed and pest pressures (Brodt et al., 2009).

The z-test results in Table 1.3 and Table 1.4 show that the coefficients of *Organic* are similar to or larger, in absolute value, than those in the full sample estimation, which implies that the difference between two production systems are larger in the sub-sample than full sample.

1.4.2 Results for Selected Crops

Differences in environmental impacts between organic and conventional production vary across crops. The full-sample regression is estimated for selected crops individually, except for lettuce where an additional time dummy is added to split the sample in half, to highlight important patterns of pesticide use in conventional and organic production. The specifications without grower or field fixed effects provide similar results and therefore results are not presented here for individual crops.

The PURE index values are plotted for conventional and organic lettuce fields in Figure 1.4. The risk index from pesticides used in conventional lettuce fields decreased since growers have gradually transitioned from organophosphates to pyrethroid and neonicotinoid insecticides over the past twenty years and organophosphate insecticides are more toxic than their pyrethroid and neonicotinoid alternatives (PPDB, 2020).

Prior to 2005, diazinon (an organophosphate) was the most used insecticide in conventional lettuce production while the usage of lambda-cyhalothrin (a pyrethroid), was limited in lettuce. However, by 2015, lambda-cyhalothrin was the most used insecticide in conventional lettuce fields while fewer than 30 acres of lettuce were treated with diazinon. Consistent with these changes, in Table 1.5, the coefficients for *Organic* × *06_15* are significant and positive showing that the difference in the environmental impacts from pes-

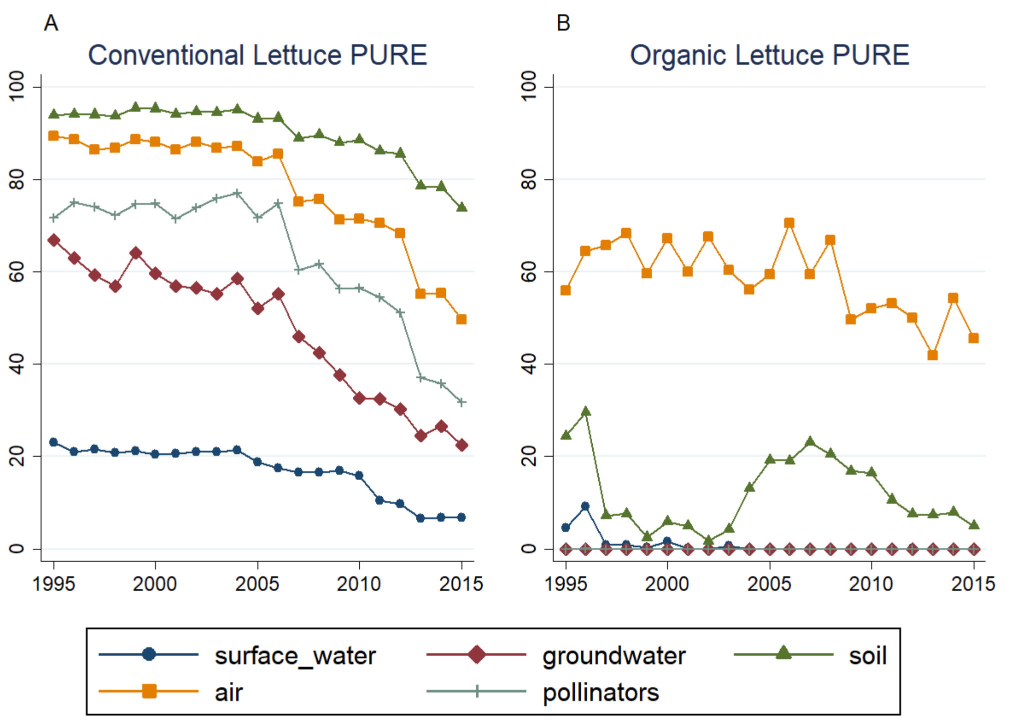


Figure 1.4: PURE Index for Lettuce Fields Weighted by Acres per Field (A: Conventional and B: Organic): 1995 - 2015

Table 1.5: Effect of Organic Pesticide Use on PURE Index Values: Lettuce

Variable	Surface water	Groundwater	Soil	Air	Pollinators
Organic	-19.31***	-49.20***	-67.41***	-39.60***	-64.40***
	(1.07)	(1.52)	(2.02)	(2.30)	(1.53)
Organic $\times$ *06_15*	1.10**	1.41*	8.82***	7.47***	6.98***
	(0.38)	(0.59)	(1.15)	(1.54)	(0.61)
Organic $\times$ *Year*	0.80***	1.91***	0.40*	0.63**	1.82***
	(0.08)	(0.11)	(0.17)	(0.21)	(0.11)
Year	0.93	-0.53	-2.28*	-2.38	-1.34
	(0.85)	(1.24)	(0.92)	(1.30)	(1.02)
Acreage	0.66***	0.81***	0.51***	0.81***	1.10***
	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)
PUR_Exp	-1.92*	-1.42	1.56	1.12	-0.28
	(0.85)	(1.24)	(0.92)	(1.30)	(1.02)
β_0	18.61***	59.16***	95.21***	87.56***	66.93***
	(2.49)	(3.62)	(2.67)	(3.77)	(2.97)
N	270,688	270,688	270,688	270,688	270,688
R^2	0.54	0.57	0.61	0.57	0.58

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1.
Grower, field, year, and crop fixed effects are included in all models.

ticides use between conventional and organic lettuce production decreased in the second half of the study period.

In Table 1.6, differences in environmental impacts between conventional and organic strawberries are largely driven by the environmental impacts of pre-plant soil fumigation, which is used by conventional but not organic strawberry growers. Soil fumigation is a common practice for managing pathogens, nematodes, and weeds in conventional strawberry fields. While soil fumigants are most commonly regulated because of their negative effects on human health via the impact on air quality and ozone layer, most soil fumigants are also highly toxic to earthworms (PPDB, 2020). Accordingly, the PURE

Table 1.6: Effect of Organic Pesticide Use on PURE Index Values: Strawberries

Variable	Surface water	Groundwater	Soil	Air	Pollinators
Organic	-49.52***	-15.51***	-77.08***	-52.59***	-52.50***
	(4.51)	(4.12)	(4.85)	(5.66)	(4.02)
Organic $\times$ *Year*	0.86**	-1.11***	1.19***	1.27**	0.86**
	(0.31)	(0.30)	(0.34)	(0.40)	(0.28)
Year	-1.58**	-1.38**	-1.40***	-0.32	-1.09**
	(0.53)	(0.51)	(0.32)	(0.32)	(0.36)
Acreage	-0.55	-1.92	-0.95	-0.76	-1.30
	(1.01)	(1.00)	(0.57)	(0.81)	(0.93)
PUR_Exp	0.81	2.82***	0.93**	-0.09	0.12
	(0.55)	(0.53)	(0.33)	(0.32)	(0.38)
β_0	62.44***	39.70***	101.14***	95.53***	70.52***
	(2.26)	(2.26)	(1.23)	(1.31)	(1.56)
N	28,071	28,071	28,071	28,071	28,071
R^2	0.57	0.55	0.68	0.51	0.59

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1.
Grower, field, year, and crop fixed effects are included in all models.

index for soil is large. Consequently organic strawberry production achieves a 78% reduction in the environmental impact on soil. Conventional strawberry production also poses higher impacts on surface water because several AIs are highly toxic to fish and aquatic invertebrates (PPDB, 2020), including abamectin for controlling spider mites (Dybas, 1989), malathion for whiteflies (Bi & Toscano, 2007), and pyraclostrobin for gray mold (Mercier et al., 2010). As a result, the coefficient of *Organic* for surface water is larger than average. The difference in the PURE index for air is smaller because azadirachtin and clarified neem oil, two primary AIs contributing to VOC emissions in the nonattainment area of Ventura (CDPR, 2020, Rosemary, 2008), a major strawberry producing county, together accounted for 18% of treated acreage for organic strawberries.

In column 2 for groundwater, the coefficient for *Organic* $\times$ t is negative, the opposite of the other environmental dimensions. The difference between conventional and organic production is expanding because pesticides used in conventional strawberry fields is having greater impact on groundwater over time due to the regulation on methyl bromide, a soil fumigant. Based on its ozone depletion effects, the use of methyl bromide was phased out in the U.S. and strawberry growers increased their usage of alternative fumigants, such as 1,3-D and chloropicrin (Ajwa et al., 2003, Fennimore et al., 2003). Those two alternatives are less likely to be retained by soil and therefore have greater impact on groundwater than methyl bromide (PPDB, 2020).

Table 1.7: Effect of Organic Pesticide Use on PURE Index Values: Processing Tomatoes

Variable	Surface water	Groundwater	Soil	Air	Pollinators
Organic	-10.65***	-43.97***	-73.94***	-88.65***	-12.92***
	(2.04)	(2.80)	(3.54)	(3.44)	(1.84)
Organic × *Year*	-0.41**	-0.25	0.03	2.38***	-1.02***
	(0.15)	(0.20)	(0.30)	(0.27)	(0.13)
Year	4.93**	6.50**	0.63	-0.66	-2.68
	(1.75)	(2.43)	(1.70)	(1.87)	(2.16)
Acreage	0.57***	1.34***	0.54***	0.67***	-0.12
	(0.09)	(0.13)	(0.09)	(0.09)	(0.13)
PUR_Exp	-4.31*	-5.72*	-0.46	0.85	4.12
	(1.75)	(2.43)	(1.70)	(1.87)	(2.16)
β_0	1.42	39.11***	89.55***	88.21***	31.70***
	(1.79)	(2.60)	(1.74)	(1.96)	(2.27)
N	55,106	55,106	55,106	55,106	55,106
R^2	0.70	0.59	0.51	0.42	0.48

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1.
Grower, field, year, and crop fixed effects are included in all models.

Comparing the results in Table 1.7 with other tables in this section, organic processing tomato production reduces the environmental impact on air by a larger percentage than all organic production on average. The key difference between processing tomatoes and other crops is that processing tomatoes are more threatened by diseases than by insects or nematodes (Flint, Klonsky, et al., 1985). The two most common diseases are powdery mildew and bacterial speck, which are treated with sulfur and copper hydroxide respectively in organic production (Zalom, 2007). In 2015, the acreage treated with these two AIs accounted for 42% of total acreage treated for organic processing tomatoes. In comparison, the share of sulfur-and copper hydroxide-treated acreage is below 10% for production of lettuce and strawberries and 25% for all organic crops. These two AIs have lower VOC emissions than other AIs used in organic production such as pyrethrins, azadirachtin, and clarified neem oil, which together accounted for nearly 30% of treated acreage for organic lettuce and strawberries, 18% for organic processing tomatoes, and 18% for all crops. However, the impact is increasing as indicated by the positive coefficient for the variable $\textit{Organic} \times \textit{Year}$.

Wine grape production occurs in many regions in California, and pest and disease pressures vary across production regions due to different climate and soil conditions. In the North Coast production region, which includes Napa and Sonoma counties among others, powdery mildew is a common disease because the fungus prefers a cooler temperatures, ideally around 21°C, to grow (Yarwood et al., 1954). Measured by treated acreage, 9 out of the 10 most used AIs are fungicides targeting powdery mildew in this area. In the San Joaquin Valley, in contrast, powdery mildew is rarely seen because of high temperatures. Due in part to the large number of frost-free days per growing season, insects are the primary concern (Ross, 2009). For wine grapes, the most used AIs beside sulfur are abamectin targeting spider mites, imidacloprid targeting vine mealybugs, and methoxyfenozide targeting lepidoptera (Varela et al., 2015). These insecticide AIs are

Table 1.8: Effect of Organic Pesticide Use on PURE Index Values: Wine Grapes

Region	Variable	Surface water	Groundwater	Soil	Air	Pollinators
State	*Organic*	-4.98***	-28.43***	-42.68***	-31.70***	-4.51***
		(0.45)	(0.88)	(1.23)	(1.22)	(0.41)
	Organic $\times$ *Year*	0.08**	0.69***	1.30***	1.36***	-0.20***
		(0.03)	(0.06)	(0.09)	(0.08)	(0.03)
	Year	-0.32***	-0.17	0.25	-0.67***	-0.32***
		(0.08)	(0.15)	(0.13)	(0.14)	(0.09)
	Acreage	-0.64***	-0.47***	-1.02***	-1.07***	-1.01***
		(0.04)	(0.06)	(0.06)	(0.07)	(0.06)
	PUR_Exp	0.24**	0.01	0.27*	0.63***	0.93***
		(0.09)	(0.16)	(0.14)	(0.14)	(0.10)
	β_0	17.01***	54.29***	81.65***	83.48***	15.84***
		(0.41)	(0.69)	(0.53)	(0.53)	(0.40)
	N	206,627	206,627	206,627	206,627	206,627
	R^2	0.50	0.52	0.53	0.52	0.44
Napa and Sonoma Counties	*Organic*	-3.86***	-24.54***	-41.67***	-29.63***	-5.48***
		(0.65)	(1.20)	(1.71)	(1.70)	(0.49)
	Organic $\times t$	-0.03	0.62***	1.47***	1.74***	0.14***
		(0.04)	(0.08)	(0.12)	(0.11)	(0.03)
	t	-0.70***	0.01	0.59**	0.01	0.24
		(0.14)	(0.23)	(0.18)	(0.19)	(0.13)
	Acreage	-1.98**	4.33***	0.90*	5.01***	0.15
		(0.69)	(0.84)	(0.45)	(0.56)	(0.60)
	Exp	0.74***	-0.11	-0.04	-0.37	-0.05
		(0.15)	(0.24)	(0.20)	(0.20)	(0.14)
	β_0	20.41***	49.86***	78.22***	78.03***	7.13***
		(0.75)	(1.10)	(0.79)	(0.78)	(0.58)
	N	68,819	68,819	68,819	68,819	68,819
	R^2	0.47	0.53	0.55	0.50	0.37
San Joaquin Valley[1]	*Organic*	-3.81***	-35.09***	-46.16***	-38.59***	-7.81***
		(1.08)	(2.45)	(3.53)	(3.16)	(1.27)
	Organic $\times t$	0.04	0.33	0.58*	0.25	-0.48***
		(0.08)	(0.18)	(0.26)	(0.24)	(0.09)
	t	-0.55**	-1.36*	0.31	-0.99*	-0.08
		(0.21)	(0.57)	(0.44)	(0.47)	(0.38)
	Acreage	-0.34*	0.45	0.29*	0.24	0.55
		(0.16)	(0.28)	(0.14)	(0.17)	(0.29)
	Exp	0.35	0.94	-0.05	1.01*	1.07**
		(0.22)	(0.57)	(0.44)	(0.47)	(0.39)
	β_0	14.58***	65.16***	86.10***	85.41***	16.81***
		(0.58)	(1.31)	(0.88)	(0.95)	(0.88)
	N	62,202	62,202	62,202	62,202	62,202
	R^2	0.57	0.44	0.43	0.48	0.39

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Grower, field, year, and crop fixed effects are included in all models. [1] The San Joaquin Valley includes Fresno, Kern, Kings, Madera, Merced, San Joaquin, Stanisalus, and Tulare counties.

more toxic for humans, earthworms, and honeybees and have larger VOC emissions than the fungicides used for powdery mildew (PPDB, 2020), so the estimated intercept in Table 1.8 is larger in the San Joaquin Valley than in Napa and Sonoma counties and the state as a whole for groundwater, soil air, and pollinators. Powdery mildews in grapes are often treated with sulfur (Jepsen et al., 2007). In 2015, table, wine, and raisin grapes accounted for 77% of acreage treated with sulfur among all crops. To control powdery mildew, organic growers also rely on bio-ingredients such as Bacillus pumilus and Bacillus subtilis, which have larger VOC emissions than sulfur and mineral oils. Thus, organic wine grapes growers in Napa and Sonoma counties only achieve a 38% reduction in the PURE index for air while the reduction in the San Joaquin Valley is 45%.

1.5 Conclusion

Using a consistent index, this essay quantifies the environmental impacts of pesticide use in conventional and organic fields and how they have changed over time. Information from this analysis could benefit organic crop production worldwide because California is an important production region with a diverse set of crops and environmental conditions. Previous studies rarely focused on the use of specific AIs or the change in the structure of pesticide use when evaluating the environmental impact of organic agriculture. To the best of my knowledge, the PUR database has never been used to compare pesticide use for conventional and organic production.

The U.S. organic agriculture sector has grown significantly over the past two decades, after the launch of the NOP in 2002. Organic farming has the potential to continue to expand in the future. Pesticides are essential for both conventional and organic crop production. However, pesticide use is not static. The pesticide portfolio changed dramatically for both farming systems in the study period. Based on field-level pesticide application information, this essay shows that the environmental impact of pesticide use on air increased in organic fields due to the adoption of new chemicals and the reduction in the use of sulfur, which has zero VOC emissions.

Pesticides used in organic agriculture had lower environmental impacts per acre on surface water, groundwater, soil, air, and pollinators depending on the pesticide portfolios for conventional and organic growers. However, the difference between two systems is decreasing over time for all five dimensions. Notably, they had almost the same level of VOC emissions in 2015. In both production systems, increases in growers' total acreage were associated with increases in the environmental impacts of pesticide use in all dimensions. Increases in grower experience were associated with increases in the environmental impacts of pesticide use to surface water and groundwater, and decreases in the impacts on soil, air, and pollinators. The magnitude of effects of these two variables is smaller than the effect of the organic status of the field.

Pesticide use in organic agriculture has evolved to have greater environmental impacts over time. This is consistent with findings in Läpple and Van Rensburg (2011), who showed that late adopters, those who adopted organic farming after the launch of government supporting program, are more likely to be profit-driven and less likely to be environmentally concerned than early adopters.

New policy instruments could alter the current situation. When reviewing pesticide and fertilizer AIs used in organic agriculture, the NOSB could focus on environmental criteria such as VOC emissions, which has not been considered previously. Such policy instruments could partially offset the negative environmental impacts of pesticide used in organic fields.

Whether organic farming is the most cost-effective way to reduce the environmental impacts of agriculture remains unclear because the changes in PURE index values does not directly translate to a one-dimensional environmental or food safety benefit that is comparable across commodities or farming methods. An alternative approach to reducing environmental impacts is to regulate pesticide use directly, which could have a significant cost. For example, the ban of methyl bromide was estimated to result in an annual revenue loss of $234 million (Carpenter et al., 2000) and a 10% revenue loss for the strawberry industry in California (Carter et al., 2005). However, as the result shows, the PURE air index for strawberry did not decrease in conventional production after the ban. In addition, the groundwater index value increased because alternatives to methyl bromide have a greater impact on groundwater.

A limitation of this essay is the lack of data regarding grower characteristics. In previous studies, demographic variables, such as gender and education, were shown to be determinants of the adoption of organic farming (Läpple and Van Rensburg, 2011, Mzoughi, 2011, Burton et al., 1999). Here, these characteristics are addressed by using time-invariant grower fixed effects. More information regarding the determinants of pesticide use decisions might be revealed if those characteristics data were available. Future research could focus on impacts on human health rather then the environment and calculate the monetary value of reduced mortality and morbidity of converting to organic production. And, estimating the value of improved environmental quality associated with organic agriculture, identified in this essay, is another research direction.

While pesticide use remains important for both farming systems, another caveat is that this essay does not investigate the environmental impacts of non-chemical pest management practices, such as biological, cultural, and mechanical/physical controls. However, if one were to pursue that direction by collecting data on non-chemical practices, the analysis would necessarily be done on a relatively small scale, unlike the comprehensive data used here.

Essay 2

Cropland Consolidation and the Environmental Impacts of Pesticide Use in California's Organic Agriculture

2.1 Introduction

Organic agriculture has been proposed as an essential part of sustainable food systems (Muller et al., 2017). In 2016, over 5 million acres of land were certified organic in the United States, which generated over $7.5 billion worth of agricultural products. California is the leading state as a producer of organic crops in the United States, accounting for 12% of organic cropland and 51% of crop sales value in 2016 (NASS USDA, 2017). According to Willer and Lernoud (2019), the United States is the largest market for organic products and accounted for 43% of global organic retail sales in 2017.

Organic land use data for California have been collected for a limited number of years by two government agencies, the United States Department of Agriculture (USDA) and the California Department of Food and Agriculture (CDFA) (NASS USDA, 2010; NASS USDA, 2016b; NASS USDA, 2016a; NASS USDA, 2017; Klonsky and Richter, 2005b; **klonsky0005statistical**; Klonsky and Richter, 2011b; Klonsky and Healy, 2013b; Wei et al., 2020a). Farm-level acreage and location information are not publicly available from either source. Detailed crop acreage data would facilitate further investigation of key topics such as the spatial distribution of organic fields, which previously could be studied only at a very small geographic scale using other data sources (Parker & Munroe, 2007b).

In this context, California's unique Pesticide Use Report (PUR) database serves as an alternative source of very detailed and long-term data, which allows the identification of individual organic fields based on their historical pesticide use records. The PUR database contains information on all commercial agricultural pesticide use in California since 1990, including information on the chemicals used, crops and acreages for millions of individual applications.

Pesticide use patterns for organic fields and their environmental impacts have not been studied previously. Existing studies often evaluate the environmental performance of organic agriculture as a system, rather than focusing on specific farming practices (Gomiero et al., 2011, Hartmann et al., 2015, Pimentel et al., 2005, Tuomisto et al., 2012). To the best of my knowledge, no study has quantitatively described pesticide use in organic agriculture or assessed its environmental impacts for ecosystems on a large scale across numerous crops and over a long time period (all crop production in California for twenty-two years). The pesticide products used in organic agriculture are generally less toxic, but their reduced efficacy could drive higher application rates, which makes the overall environmental impact of organic agriculture less obvious. In fact, certain pesticides used in organic agriculture have been found to be more toxic than conventional pesticides targeting the same pest (Biondi et al., 2012, Bahlai et al., 2010). In Läpple and Van Rensburg (2011), the authors found that farmers who entered organic production after the supporting policy was launched are more likely to be profit-driven and less environmentally concerned than farmers who began organic production before any supporting policy was in place. Therefore, studying pesticide use in organic agriculture and how it changes can expand the understanding of organic agriculture and its future.

The consolidation into larger operations is another important issue for organic agriculture because it could undermine the perception of organic agriculture as environmentally friendly. Although both the number of organic farms and total organic acreage has increased, consolidation still exists if large farms grow faster than small farms. Consumers used to associate organic agriculture with small farms and diverse crop production (Adams & Salois, 2010). Meanwhile, the consolidation process had been clearly documented for the organic food processing sector (Howard, 2009) and U.S. agriculture in general (MacDonald et al., 2018). Farm size, measured in acreage, was found to be positively correlated with pesticide use for staple crop productions in the previous literature for conventional agriculture (Wu et al., 2018). If this relationship also applies to organic agriculture, then cropland consolidation could have a negative impact on the environment, which means that organic agriculture could become less environmentally friendly than it used to be as the consolidation proceed. I find that the farm size is positively associated with use of sulfur and fixed copper pesticides in the organic crop production.

Organic agriculture in California has a diverse crop portfolio, which affects farm size and pesticide use simultaneously. Certain crops are produced in a large scale, measured in acreage, and require intensive pesticide use. How changes in the crop mix interact with the consolidation process is another issue investigated in this essay.

The objective of this essay is threefold: to identify organic fields in the PUR database using historical pesticide use records; to characterize the patterns and trends of production and pesticide use for those identified organic fields collectively by crop, crop acreage, year, farm size, and other attributes; to assess the environmental impacts of pesticide use in organic agriculture and the consolidation of organic cropland.

2.2 Data and Methods

In this section, we develop the method to identify organic fields and assess pesticide use in organic agriculture using the PUR database. Organic crop acreages identified from the PUR database are compared with data from other sources to validate of my method. The Pesticide Use Risk Evaluation (PURE) index is used to evaluate the environmental impacts of pesticide usage. The impact of cropland consolidation on the pesticide use patterns and the environmental impacts of organic agriculture are quantified using regression methods.

2.2.1 The Pesticide Use Report (PUR) Database

The main dataset used in this essay is the PUR database, which contains detailed information on location, timing, amount and name of product applied, application methods, acreage treated, and crop treated. Since 1990, all agricultural pesticide use information in California has been collected by the County Agricultural Commissioners (CAC), who in turn, report it to the California Department of Pesticide Regulation (CDPR), which publishes the PUR database annually. The PUR database is the largest and most complete dataset on pesticide use in the world and it contains more than 3 million application records for agricultural use each year. Numerous studies in environmental science, plant pathology, and agricultural economics have been conducted based on the PUR database (Reynolds et al., 2005; Larsen et al., 2017; Davidson, 2004; Lybbert et al., 2016b).

Non-chemical pest management practices, such as biological, cultural, and mechanical/physical controls, are not recorded in the PUR database. As a result, this essay focuses only on the potential impacts posed by pesticide usage in organic agriculture. The PUR database from 1995 to 2017 were used in this essay for two reasons. First, this time frame provides coverage before and after the launch of the National Organic Program (NOP) in 2001, which allows us to determine any effects of that policy change. Secondly, while the PUR database are available from 1990 onward, the data quality is known to be more variable in the early years (Wilhoit et al., 2001).

Pesticide use information in the PUR database is available at the field level. In this essay, a "field" is defined using two variables in the PUR database, "GROWER_ID" and "SITE_LOCATION_ID". "GROWER_ID" is a number assigned to a grower or operator by CAC on their pesticide permit, and it remains constant for the same grower over time. Operators within a farm could apply for the pesticide permit separately, which create difficulties for me to identify operations. However, it is costly to comply with all the requirements and therefore it does not happen often. "SITE_LOCATION_ID" is a code assigned by CAC on the pesticide permit which indicates a particular location (field) where an application may occur. For a given field, this code may change from year to year, as it was assigned by growers, which creates some uncertainties in identifying organic fields across years. This uncertainty is accounted for in the analyses, as described below.

For each agricultural pesticide application, the PUR database specifies the location of application in the variable "COMTRS", which stands for the county, meridian, township, range, and section as defined by the Public Lands Survey mapping system (PLSS). This information allows us to locate which section does the field belong and aggregate pesticide usage at the 1x1 mile PLSS section-level, which is the finest spatial scale reported in the PUR database. This detailed section-level analysis of the spatial distribution of organic fields in California and, how it has changed over time, is only possible using my method for identifying organic production fields in the PUR database.

In the PUR database, acreage information is recorded as both treated acreage and planted acreage. The former represents the acres physically treated in a pesticide application while the latter remains constant for the field within a year. However, researchers have demonstrated that planted acreage in the PUR database is not consistently reliable for annual crops (Steggall et al., 2018). So, in this essay, we use the maximum treated acreage in a given year as the acreage for each field for annual crops. This approach assumes that the entire field is treated with pesticide at least once per year. If this assumption is invalid, then the planted acreage will be undercounted. As presented below, the validity of this approach is supported by the consistency of state-scale crop acreages that are generated from the PUR database with those from other data sources.

One caveat of the PUR database for organic production is that since 2000, pesticide products deemed as having "minimum impacts" are no longer required to be registered with CDPR, which exempts them from the pesticide use reporting requirement. A detailed list of these pesticide ingredients can be found in the California Code of Regulations section 6147 (CDPR, 2000). Most ingredients exempted from registration are natural or naturally-derived products (e.g., garlic oil), which could presumably be used in organic agriculture and have impacts on the surrounding environment. However, these exempted ingredients are not widely applied, based on their minimal amounts of usage in the PUR database prior to 2000 when they were still required to be reported. Therefore, this issue is not likely to invalidate the results, especially because the number of fields where only such ingredients were applied before 2000 is small.

For convenience, some chemically-related individual active ingredients (AIs) were grouped together, such as combining the many different strains of *Bacillus thuringiensis*, which target different insects and are each treated as a distinct AI in the PUR database, into a single "microbial" group. A detailed list of microbials is available in the appendix. The group of "Copper, fixed" includes the summation of copper, copper oxychloride, copper octanoate, copper oxide, and copper hydroxide; and the two forms of copper sulfate (basic copper sulfate and copper sulfate pentahydrate).

2.2.2 Identifying Organic Fields from the PUR Database

Organic growers are required to comply with a set of crop management standards, regarding seeds and planting stock practices, soil fertility and crop nutrient management, pest, weed, and disease management, and crop rotation among others (NOP, 2001). The most relevant requirement for this essay is that there is a 36-month transition period between the last application of any prohibited substance under organic regulations and officially recognized organic production. The field identification method relies on this requirement. First, we constructed a list of allowed and prohibited substances based on various sources (as described in the Appendix). Second, we checked each field in the PUR database, to see which AIs were applied over the previous three years. If there were no applications of any prohibited ingredients, then the field was considered organic as of that year. Organic growers who do not use any chemical tools at all to manage pests and weeds are missing from the PUR database entirely, and therefore not identified in this essay. However, based on acreage comparisons between the PUR database and other data sources, those growers appear to operate a very limited number of acres.

A field could comply with the pest, weed, and disease management standards of the NOP while violating other standards (such as applying synthetic fertilizers) and still not qualify for organic production. Because the PUR database only contains pesticide use information, my method cannot distinguish such fields from actual certified organic fields. On the other hand, growers could follow organic farming practices but choose not to certify their fields for various reasons. However, as mentioned above, the amounts of acreage in these categories must not be very substantial because the PUR-derived organic crop acreages agree with those from CAC compiled sources, suggesting that my method is valid.

One caveat of this method is the consistency of field information in the PUR database from year to year. As mentioned previously, the "SITE_LOCATION_ID" on pesticide permits, a number chosen by growers or assigned by county, indicate a physical field location, but the id number may change from year to year. When that ID does change, a new "field" appears in the PUR database for which we do not have information on its historical (i.e., over the previous three years) pesticide applications. In this situation, we assume for annual crops that the land was fallow before a new "SITE_LOCATION_ID" was assigned. This assumption could cause us to overestimate the total organic acreage somewhat, by including fields with a new "SITE_LOCATION_ID" which may have had prohibited substance applications in the past three years. Pasture and rangeland have unique pest management practices and enormous acreage, but they are not covered in this essay as they do not suit my primary purpose of evaluating the environmental impacts of pesticide use in organic crop fields.

2.2.3 Other Data Sources for Organic Acreage

To test the validity of my method for identifying organic fields, we compared organic acreages derived from the PUR database with those available in other data sources, primarily from CDFA and USDA. The acreage data in each source were collected using different approaches and therefore it is common to observe differences.

CDFA organic registration data: The California Organic Products Act requires an annual registration of all organic producers, handlers, and processors, regardless of their annual sales. Producers report acreage and total sales, expected or actual, for each crop they grow organically. Data for 1998 to 2016 have been summarized to the state-crop level in previous studies (Klonsky and Richter, 2005b; **klonsky0005statistical**; Klonsky and Richter, 2011b; Klonsky and Healy, 2013b; Wei et al., 2020a).

USDA certification and organic survey data: The USDA's Economic Research Service (ERS) collected acreage data for seven crops at the state level from USDA-accredited state and private organic certifiers between 2000 and 2011 (ERS, 2011). However, the data only cover seven crops/crop groups and certified organic growers (growers with less than $ 5,000 annual organic sales are exempted from certification). Meanwhile, USDA's National Agricultural Statistics Service (NASS) conducted five organic surveys between 1995 and 2017, which gathered organic crop acreage at the state level. However, responses to those surveys were voluntary and the average response rate for California was 69% (NASS USDA, 2010, NASS USDA, 2016b, NASS USDA, 2016a NASS USDA, 2017). Therefore, we used the NASS survey data only when the USDA ERS data series were not available to construct the crop acreage data series.

California Strawberry Commission (CSC) survey data. For strawberries, the CSC collects organic data through its annual survey (CSC, 2021). The CSC data provide other information in addition to acreage and total sales, such as strawberry varieties and harvest timing. The response rate for this survey is unknown, which limits the understanding of its data quality.

All three of these data sources were aggregated by crop (for the limited number of crops they include) or county, and individual field-level data are not available publicly. This limitation underscores the value of the PUR database and my method for providing unique information regarding organic crop production in California over space and time.

2.2.4 Assessing the Environmental Impacts of Pesticide Use

For pesticide applications on the identified organic fields in the PUR database, the PURE index was used to assess the potential environmental impacts for five environmental dimensions: surface water, groundwater, soil, air, and pollinator (Zhan & Zhang, 2012). The PURE index is calculated for five different environmental dimensions: surface water, groundwater, soil, air, and pollinators. For dimensions other than air, index values are calculated based on predicted environmental concentrations and standard toxicity values for relevant organisms. The algorithm used to calculate the predicted environmental concentrations includes the site-specific environmental conditions (e.g., soil properties and meteorological conditions), which is a major advantage over other indices for assessing the environmental impacts of pesticide use, such as the Environmental Impact Quotient (Kovach et al., 1992). The predicted environmental concentrations have been proven to align with monitoring data in a previous study (Zhan & Zhang, 2012). The index value for air is calculated using the predicted volatile organic compound (VOC) emissions of each pesticide product. Individual index values are normalized to range from 0 (negligible impact) to 100 (highest impact).

The PURE index values are calculated for each AI in each pesticide application for each field. These disaggregated index values are then summed at the field level to provide a general index value assessment for each field. To evaluate the overall impact for each crop, an acreage-weighted average across all relevant fields can be determined. This aggregation can be taken one step further, across all AIs, to show the potential impact for all pesticide use using the same aggregation process for organic and conventional fields.

2.2.5 Consolidation of Organic Cropland and the Pesticide Use

The consolidation of cropland into larger operations has been a persistent phenomenon in conventional agriculture since the 1930s (Gardner, 2009, Hart et al., 2003, MacDonald et al., 2018). Changes in farm size, at least measured in acreage, may create environmental concerns due to the differing production practices in larger and smaller operations. In this essay, consolidation is measured by the changes in the percentages of organic cropland operated by growers in each size class, similar to MacDonald et al. (2018). Acreage is endogenous and driven by several factors that also affect organic choice and pesticide use. Therefore, the relationship found in this essay is far from causality.

The correlation between farm acreage and pesticide use is identified using the following regression model with the grower, year, and crop fixed effects:

$$y_{ijt} = \beta_0 + \beta_1 \mathit{Acreage}_{g[i]t} + \beta_2 \mathit{Exp}_{g[i]t} + \lambda_{g[i]} + \theta_{t[i]} + \phi_{c[i]} + e_{it} \tag{2.1}$$

where y_{ijt} is the total pesticide used, the number of applications, and the application rate of AI/AI group j in field i at year t. The variable of focus is $\mathit{Acreage}_{g[i]t}$, which represents the total organic acreage, measured in units of 1,000 acres, operated by grower

g who manages field i at year t. The years of farming observed in the PUR database for grower g is $Exp_{g[i]t}$. There are three fixed effects in this model: grower fixed effect $\lambda_{g[i]}$, year fixed effect $\theta_{t[i]}$, and crop fixed effect $\phi_{c[i]}$. The application rate is defined as:

$$App\_rate_{ijt} = \frac{Total\_AI\_Used_{ijt}}{Total\_Acreage\_Treated_{ijt}} \tag{2.2}$$

where $Total\_AI\_Used_{ijt}$ is the pounds used of AI/AI group j at field i in year t and $Total\_Acreage\_Treated_{ijt}$ is the sum of treated acreage of each AI/AI group j for field i at year t.

The effects of farm acreage on the environmental impacts is identified using the following regression model:

$$y_{it} = \beta_0 + \beta_1 Acreage_{g[i]t} + \beta_2 Exp_{g[i]t} + \lambda_{g[i]} + \theta_{t[i]} + \phi_{c[i]} + e_{it} \tag{2.3}$$

where y_{it} is one of the PURE index values in field i at year t.

Including the fixed effects and the farming experience variable help to mitigate the bias caused by the existence of unobserved factors (and therefore omitted variables) that influence the outcomes of interest. For example, growers with more farming experience may be more likely to operate larger farms and use less pesticide on a per acre basis at the same time. If the experience variable is omitted from the regression, the estimation of β_1 will be biased by capturing the effects that are not within my research interest. The grower, crop, and year fixed effects serve the same purpose of helping to mitigate the omitted variables bias. Equation 1 and 2 are used in the aggregate analysis as well as crop-specific studies.

2.3 Results and Discussion

This section presents data on the organic fields identified from the PUR database along with acreage summary for the top organic crops. The comparisons of organic acreages reported in different data sources are made to examine the validity of my approach. The pesticide use patterns are summarized for organic crop production and its environmental impacts are assessed using the PURE index. Finally, the trend of cropland consolidation is presented and the effect of consolidation on pesticide use and the environmental impacts are quantified.

2.3.1 Organic Fields Identified in the PUR Database

Figure 2.1 maps organic fields identified from the PUR database for all crops. Each pixel represents a section with any organic acreage. They are color-coded based on the number of organic acres in that section. Organic fields were more widespread in 2017 (Figure 2B) than in 1995 (Figure 2A). The number of sections with organic cropland increased from 1,451 to 3,008. Also, there was a pronounced shift toward more organic acreage within sections. By definition, each section contains 640 acres of cropland at a maximum. In 1995, only 5% of sections had more than 100 acres of organic cropland, which increased to 18% in 2017. In particular, substantial growth was observed in Monterey, Fresno, and Imperial counties (outlined in red). Monterey County has the most organic acreage and the greatest number of sections with organic fields, increasing from 54 sections in 1995 to 202 sections in 2017. The top five organic crops in Monterey (leaf lettuce, spinach, broccoli, strawberry, and celery) accounted for 73% of total organic acreage in 2017. As the leading county, Monterey had 47% of the state's organic lettuce and 61% of California's organic strawberry acreage in 2017. Details on total organic acreage, average farm size, and number of organic farms for each county are available in the appendix.

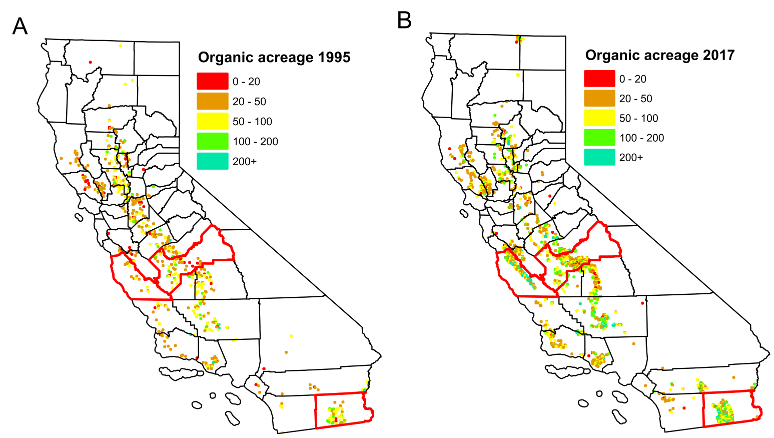


Figure 2.1: Spatial Distribution and Acreage of Organic Fields Identified Using the PUR Database (A: 1995 and B: 2017)

2.3.2 Organic Crop Acreage in the PUR Database

Table 2.1 shows organic acreage for the top 10 crops (ranked by organic acreage in 2015) during the 23-year period from 1995 to 2017 and the total crop acreage for both conventional and organic production in 2015 . Eight of the ten crops are fruits and vegetables. The remaining two are rice and almonds. Overall, the total organic acreage of these crops grew from 52,223 acres in 1995 to 176,657 acres in 2015—an increase of more than threefold. The first two columns show that organic acreage remained relatively stable in the five years before the NOP was established in 2001. Acreages of most of these crops grew dramatically in the subsequent years.

Table 2.1: Organic Acreage for Top 10 Crops in the PUR Databse: 1995-2015

Crop	Organic acreage by year					Total acreage[1]	Organic share
	1995	2000	2005	2010	2015	2015	2015
Carrots	1,773	3,352	3,842	8,697	22,492	63,000	36%
Grapes, wine	12,212	13,048	18,368	18,301	18,092	560,000	3%
Lettuce, leaf	384	2,633	8,609	9,579	15,368	38,500	40%
Grapes, table & raisin	9,798	9,492	15,233	17,866	15,345	112,000	14%
Tomatoes, processing	5,639	4,645	6,324	6,835	11,400	296,000	4%
Spinach	61	708	2,336	4,580	11,016	26,700	41%
Rice	1,420	4,852	4,958	6,818	10,457	421,000	2%
Almonds	1552	2,072	2,170	5,352	8,769	890,000	1%
Broccoli	375	1,754	2,528	2,988	7,563	115,000	7%
Tomatoes, fresh	419	1,724	435	1,388	5,080	28,600	18%
Other crops	34,034	42,916	45,523	50,232	79,500		
Total	67,667	87,196	110,326	132,636	205,082		

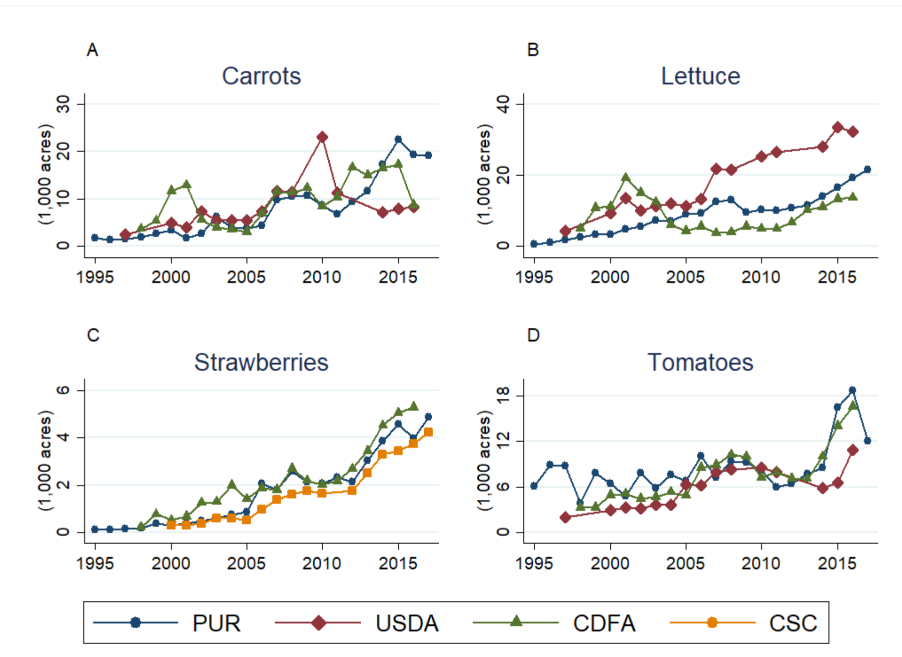
[1]Total acreage includes all acreage defined as either organic or conventional.

Total acreage can be less informative than the acreage share of organic production if one tries to infer the importance of organic production for various crops. The shares of organic acreage relative to total acreage, listed in the last column of Table 2.1, show a wide variation across crops. For wine grapes, processing tomatoes, rice, and almonds organic acreage accounted for less than 5% of total crop acreage, which aligns with the average value of 3.4% of cropland in California that is certified organic (NASS USDA, 2016a). Meanwhile, fresh fruits and vegetables have a much higher share of organic acreage. For carrots, leaf lettuce, and spinach, 36%, 40%, and 41% of acreage respectively was devoted to organic production (Table 2.1). Among crops not shown in Table 2.1, kale, blackberries, and blueberries also have large organic shares, where organic production accounted for 55%, 36%, and 25% of their total acreage, respectively, in 2015. This phenomenon can be explained by the economic motivations for organic growers. More acreage will be cultivated as organic if the price premium for organic products is substantial compared to the increase in costs, and fresh produce, such as salad mixes, has a higher organic price premium than other products (Carlson & Jaenicke, 2016).

2.3.3 Organic Acreage Comparisons

Measures of State-specific total organic acreage from different data sources are compared for all seven crops/crop groups available in the USDA organic certification and survey data (ERS, 2011) plus strawberries from the CSC survey data (CSC, 2021). Among these eight crops/crop groups, four of them are annual and the others are perennial crops. Their organic acreage is plotted in Figure 2.2 and Figure 2.3 below.

As mentioned previously, then data sources have different reporting requirements and discrepancies can be caused by a variety of reasons that apply to all crops. In the CDFA registration data, new organic growers report their expected acreage for the next year. If growers decide not to engage in that expected organic production, their registration records remain in the system, which could produce an inaccurate inflation in acreage data, especially for crops that went through a rapid growth of organic production. Growers with less than $5,000 annual organic sales are required to register their production with CDFA

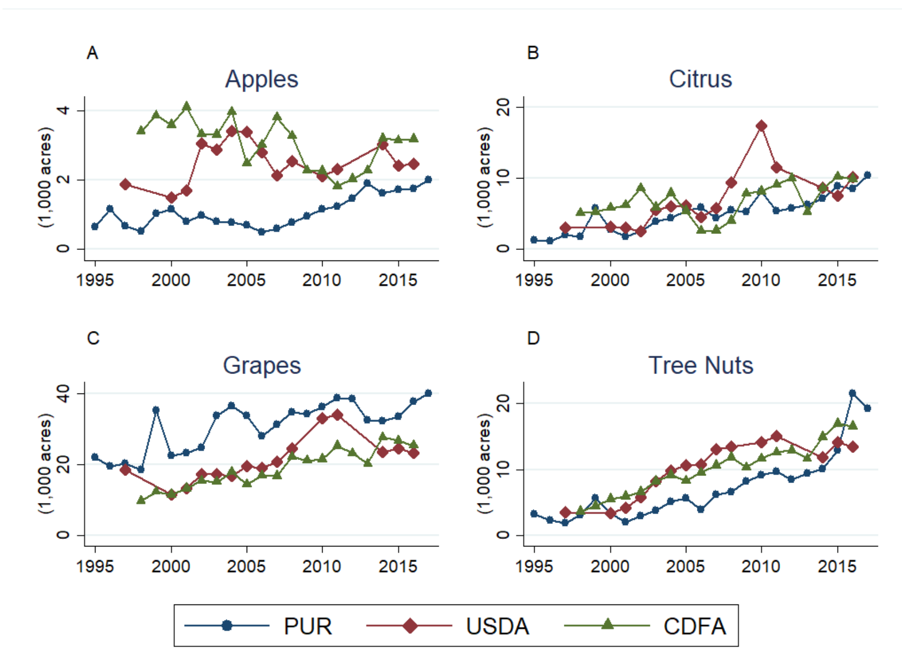


Source: PUR Database, CDFA Registration, USDA Organic Survey

Figure 2.2: Organic Acreage from Different Data Sources for Selected Crops (A: Carrots, B: Lettuce, C: Strawberries, and D: Tomatoes): 1995 - 2015

but do not have to apply for organic certification. So their acreage might not be counted in USDA data. Both USDA and CDFA data relies on a set of well-defined organic standards and restrictive regulations, which did not exist before 2001.

For perennial crops, new registrations with CDFA or new certifications with USDA must include the documentation of orchards before they are fully established (i.e., before pesticides would be used). Therefore, we observe new orchards and vineyards in the USDA and CDFA data before they enter the PUR database. If growers adopt the organic pest management program but do not market their products as organic, their acreage is only covered in the PUR database, not the others.



Source: PUR Database, CDFA Registration, USDA Organic Survey

Figure 2.3: Organic Acreage from Different Data Sources Selected Crops (A: Apples, B: Citrus, C: Grapes, and D: Tree Nuts): 1995 - 2015

Meanwhile, discrepancies in acreage are caused by crop specific reasons. For lettuce (Figure 2.2B), USDA has consistently reported higher acreage values since 2004. In 2016, the lettuce acreage from the USDA organic survey is more than double the acreage from the CDFA registration data (NASS USDA, 2017). One reason could be potential double or multiple cropping of lettuce in one calendar year. When growers harvested lettuce multiple times from the same field, USDA reported the sum of acres for each harvest while CDFA asked for the size of the field. My method accounts for this phenomenon by counting days between the first and last pesticide applications. Normally, both leaf and head lettuce require at most 130 days from planting to harvest in California (Smith et al., 2011, Turini et al., 2011). So if two pesticide applications occur more than 130 days apart for the same field, we assume that the lettuce was harvested twice and the acreage would be doubled. After this adjustment, the PUR database still falls short of the acreage documented in the USDA dataset but is in-between the other two sources since 2003. Before 2003, CDFA had more acreage than the other data series because the crop category "lettuce, salad mix", which contains arugula, red/green mustard, and other crops (which are listed separately in the PUR database and the USDA data), used to be reported as lettuce.

For strawberries (Figure 2.2C), the CSC data always show somewhat less acreage because their data are derived from surveys (rather than required reporting) and the survey response rate is not reported. For apples (Figure 2.3A), the organic acreage is small compared other perennial crops, which amplifies the potential measurement errors.

All types of grapes (table, wine, and raisins), are combined in Figure 2.3C. The PUR database reported more organic acreage consistently. Abraben et al. (2017) showed that organic labeling generates a meaningful price premium only for low-quality wine, while the price of high-quality wine is actually reduced by consumers' perception of the organic label. This marketing issue creates an incentive for growers to intentionally avoid certifying their organic production in higher-end wine grape production. Therefore, we observe more grape acreage following the organic farming practices than certifying as organic.

For tree nuts (almond, chestnut, pecan, pistachio, and walnut), the PUR database reported less organic acreage than the USDA and CDFA sources with a narrowing gap in recent years (Figure 2.3D). Tree nut acreage has gone through a tremendous growth phase in California during the past two decades, with almond acreage increasing from 595,000 in 2000 to 1,110,000 in 2015, the period when Figure 1D indicates that the PUR database is missing large portions of organic acreage (CDFA, 2000, CDFA, 2015). Normally pesticide applications are not required for the first two years in a nut orchard (Duncan et al., 2019, Brar et al., 2015, Grant et al., 2017), which makes the PUR database less reliable for capturing new organic tree nut acreage.

While organic fields without any pesticide applications in a given year are missing from the PUR database, this appears to be only a minor limitation because organic acreage from the PUR database is not consistently smaller than that from the other two sources for all crops. This minor limitation is compensated by the major advantages of the PUR database, i.e., its fine spatial scale and comprehensiveness in terms of all crops, years and counties being included.

2.3.4 Pesticides Used in California's Organic Fields

Due to the availability of information on the specific pesticides used, we are able to determine pesticide use patterns in organic agriculture in California. As discussed earlier, the lists from the Organic Materials Review Institute (OMRI) and the Washington State Department of Agriculture (WSDA) yielded 1,027 pesticide products and 216 AIs registered for use in organic production in California. Combined with entries from the National List, we are able to construct a list of 496 prohibited and 271 allowed AI substances for organic agriculture.

From 1995 to 2015, a total of 1,428 distinct DPR-registered products were identified as allowed for use in organic agriculture. This list includes 550 insecticides, 454 fungicides, 35 herbicides, and 563 other minor pesticide types, which collectively represent a total of 272 different manufacturers.

The top 15 AI/AI groups, ranked by acres treated in 2015, and their historical use from 1995 to 2015 are listed in Table 2.2. This Table reports "Acreage treated", which is different from actual field area, because a single plot of land is counted multiple times when pesticides within the same AI/AI group were applied multiple times on the same field.

Sulfur has been recognized as a soft chemical and it is the most widely-applied single AI in organic fields. Sulfur is an important plant nutrient, fungicide, and acaricide in organic agriculture (Paulsen, 2005). In 1995, organic growers treated 272,676 acres of land with pesticides and about 50% of them (137,266 acres) were treated with sulfur products.

Table 2.2: Top 15 Active Ingredient or Ingredient Groups Applied in Organic Fields

AI (group)	Acreage treated				
	1995	2000	2005	2010	2015
Microbials	14,890	35,160	84,819	173,246	351,671
Sulfur	137,266	157,300	248,312	276,767	327,563
Copper, fixed	30,515	31,990	56,186	72,070	163,640
Spinosad	0	5,665	39,856	66,550	154,598
Azadirachtin	456	11,580	22,467	30,949	109,546
Pyrethrins	83	263	18,586	34,882	105,775
Mineral oil	522	816	3,674	21,016	55,142
Neem oil, clarified	0	5,283	20,457	24,918	47,378
Reynoutria sachalinensis	0	0	0	16,025	43,548
Gibberellins	4,890	5,906	11,643	16,430	23,897
Potash soap	1,905	4,913	758	4,818	19,889
Copper sulfate	10,093	12,176	8,452	12,397	19,159
Potassium bicarbonate	0	2,321	12,301	11,490	14,498
Hydrogen peroxide	0	0	7	3,430	14,171
Neem oil	0	0	0	0	13,119
Total	272,676	344,156	561,923	817,593	1,545,877

However, in 2015, sulfur was no longer the most widely-applied AI based on acreage treated, and it only accounted for 21% of acreage treated for all crops (327,563 out of 1,545,877). The changes in sulfur use were mainly driven by grape production. Powdery mildews in grapes and pome fruits are often treated with sulfur in California (Jepsen et al., 2007). Together organic table, raisin, and wine grape growers treated 109,736 acres with sulfur products in 1995 and 226,317 acres in 2015, which accounted for 80% and 69% of total acres treated with sulfur, respectively.

In addition, during the study period the application rate of sulfur in organic grape fields decreased from over 15 lb/acre in 1995 to less than 9 lb/acre in 2015. One potential explanation is that growers may have reduced their sulfur application rate to avoid outbreaks of spider mites. Sulfur products are known to decimate predatory mites, as reported in field studies for hop yards and vineyards, which can lead to secondary spider mite outbreaks (Zhang et al., 2013, Prischmann et al., 2005, Gent et al., 2009). In addition, sulfur applications control powdery mildew, a food source for predatory mites, and can therefore lead to increases in the spider mite population (Asalf et al., 2012, Poncet et al., 2008). The rising usage of azadirachtin, clarified neem oil, and neem oil supports this theory, as all three of these AIs are recommended in the IPM guidelines to control spider mite in organic grape fields (Varela et al., 2019).

Two other AIs worth mentioning, spinosad and *Reynoutria sachalinensis*, show how the progress of technology has shaped the pesticide portfolio for organic growers. Spinosad was registered for use as a broad-spectrum insecticide by the US Environmental Protection Agency (EPA) in 1997, and was first used in cotton to manage pyrethroid-resistant caterpillars (Bret et al., 1997). It is also recommended for looper and leafminer treatments, and it was quickly adopted by organic growers, becoming the third most heavily used AI in organic fields in 2015. *Reynoutria sachalinensis* was first registered by EPA as a fungicide for greenhouse and non-food crop treatments in 2000. This ingredient, under the product name Regalia®, was first registered with OMRI for use in organic production in 2009, after which it became widely used by organic growers to manage powdery mildew. Changes in the pesticide portfolio will have consequences in the environmental performance of organic agriculture, especially as the sector grows.

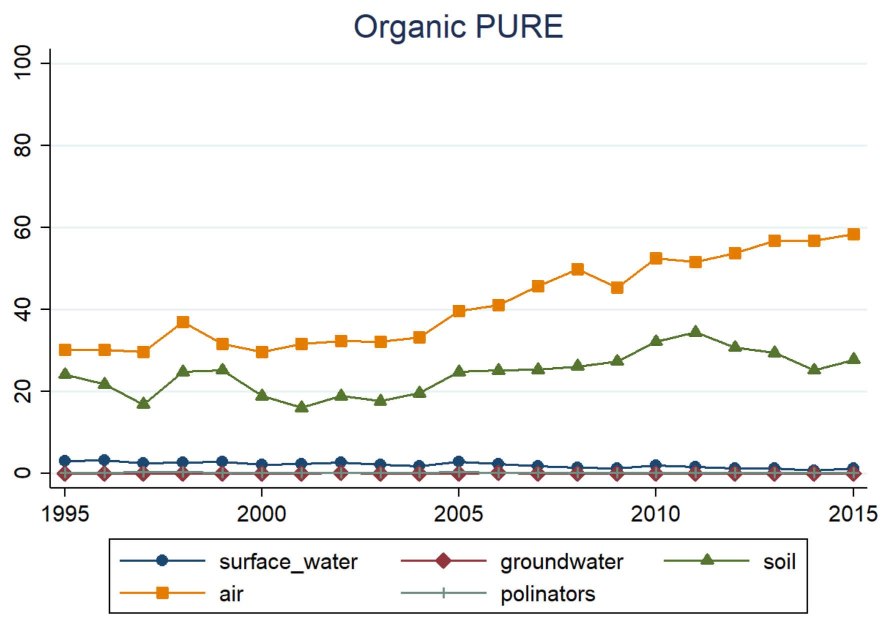


Figure 2.4: PURE Index Values for Organic Agriculture: 1995 - 2015

2.3.5 PURE Index Values

The PURE index values for organic fields are plotted in Figure 2.4. The noticeable increase in soil and air index values occurring in 1998 is due to a single application of copper sulfate in a rice field with an application rate of 150 lb/acre [1], which is ten times larger than the average application rate, so it is clearly a data anomaly.

The PURE index for air increased steadily from 1995 to 2015, at an average annual growth rate of 4%. Several factors probably contributed, related to overall application rates and the changes in the organic AI portfolio over the years. The PURE index for air is calculated by multiplying the AI application rate by its VOC emission potential, which is

[1] The average application rate is 12 lb/acre in 1997 and 13 lb/acre in 1999.

a physicochemical property related to its tendency to evaporate or sublimate into the surrounding air. During the study period, the average application rate across all pesticides for organic growers decreased from 9.1 lb/acre in 1995 to 2.9 lb/acre in 2015 in contrast to the increase in the value of the PURE air index. However, the pesticide portfolio changed significantly as organic growers diversified their pesticide AI options and relied less on sulfur products over time. Because dusting sulfur products have zero VOC emission, the increasing applications of virtually any other AIs would have contributed to a steady increase, as observed in the PURE index value for air.

However, the results in Figure 2.4 should be interpreted with caution. The PURE index values are calculated based on site-specific information, such as the pesticide application rate, soil characteristics, and distances to groundwater and surface water. Therefore, aggregated results may not apply to individual fields. For example, in fields with sandy soil, instead of remaining in the soil, pesticides are more likely to move to groundwater due to irrigation or rainfall, which would reduce the PURE index value for the soil and increase the index value for groundwater. Growers can achieve a better understanding of their own usage/impact considerations by combining aggregate results with site-specific information.

2.3.6 Consolidation of Organic Cropland

Management of organic cropland has shifted toward larger farm operations during the study period. The acreage share of each size class remained relatively stable until 2001 when NOP introduced a national standard for organic crop production and established the foundation of the organic price premium nation-wide by protecting the integrity of the "organic" distinction (Figure 2.5). However, in later years the share of organic acreage operated by farms in larger acreage classes rose. For example, in 2015, 56% of organic cropland was operated by growers with at least 500 acres of organic cropland, up from 15% in 1995. At the other end of the spectrum, growers with 10-50 acres accounted for 18% of organic cropland in 1995, which dropped to 8% in 2015.

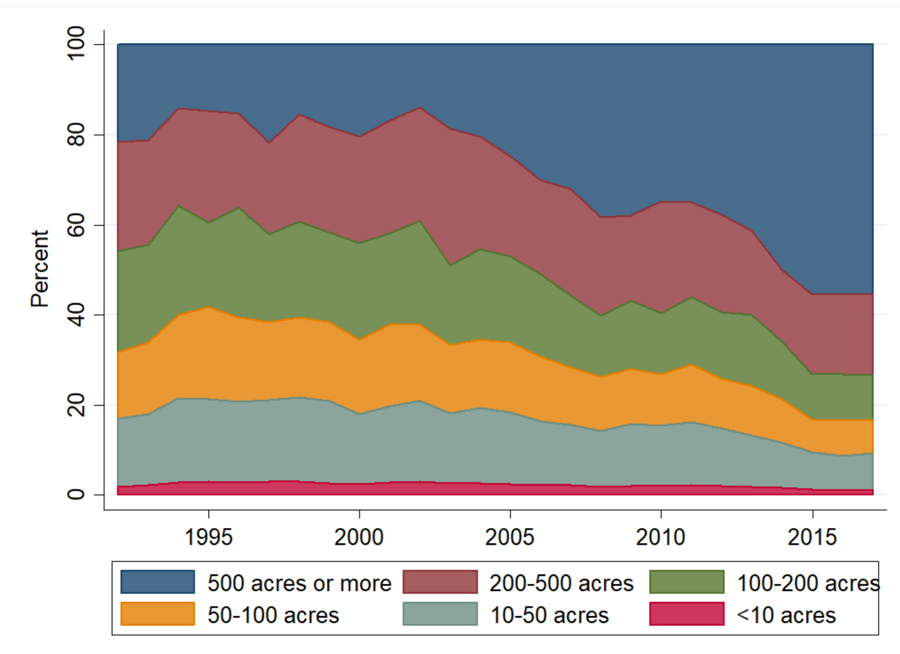


Figure 2.5: Shifts in Organic Cropland Percentages among Acreage Size Classes: 1995 - 2015

As mentioned previously, the observation that organic farms are getting larger could be driven by the change in crop mix instead of the consolidation process. To examine that, we plot the acreage share of each crop category in Figure 2.6. The acreage share of vegetables increased tremendously, from 30% in 1995 to 50% in 2015, while the acreage of grapes and field crops fell. Given that vegetables, such as lettuce and spinach, are produced at a smaller acreage scale than field crops, such as rice, the consolidation process in organic agriculture is profound as shown in the PUR database.

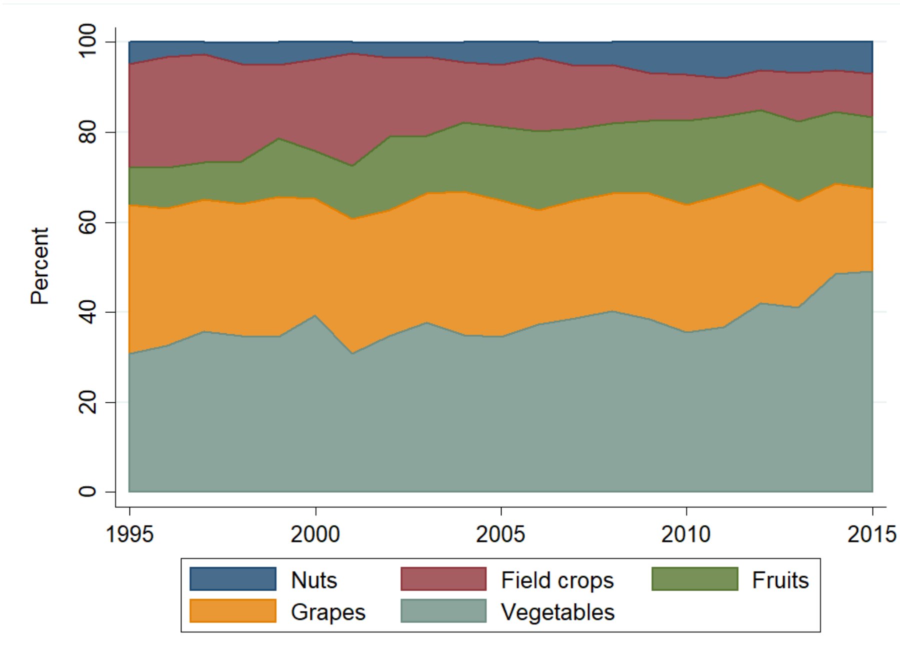


Figure 2.6: Shifts in Organic Cropland Percentages among Crop Categories: 1995 - 2015

Median crop acreage per grower is another common measure of farm size (MacDonald et al., 2018). By definition, half of growers operate less cropland than the median acreage value, while the other half operate more. Therefore, the median is a more meaningful statistic than the average because it not as sensitive to changes at the extremes. Acreages are not comparable across crops as the revenue per acre varies greatly. However, for any given crop, the change of median acreage over time reveals cropland shifts. Table 2.3 shows the median crop acreage per grower for the top 10 organic crops in 2015.

Table 2.3: Median Crop Acreage Per Grower for the Top 10 Organic Crops: 1995-2015

Crop	Year				
	1995	2000	2005	2010	2015
Carrot	38	69	80	50	33
Grape, wine	10	10	12	12	10
Lettuce, leaf	9	17	30	31	49
Grape, table & raisin	18	20	30	33	30
Tomato, processing	83	78	168	100	77
Spinach	4	10	23	49	38
Rice	149	78	84	113	93
Almond	28	40	37	62	43
Broccoli	6	20	21	24	18
Tomato, fresh	2	9	3	2	4
All crops	15	17	16	16	17

Although larger farms continued to add cropland during the study period overall, such consolidation is not a universal pattern for all crops. Table 2.3 shows that by 2015, three out of ten crops actually had a decrease in median acreage per grower compared to 1995. Spinach growers had the most growth in median acreage, from 4 to 38 acres. Leaf lettuce production also consolidated with the median farm size increasing by 40 acres. The last row of Table 2.3 reports the median of total organic acreage per farm.

For crops with a lower organic price premium, growers lack the incentive to expand production. Therefore, it is not surprising to see that median acreage decreased for the processed and staple crops in Table 2.3, particularly wine grape, rice, and processing tomato. Carrot has gone through the most significant growth of total organic acreage over the past two decades (Table 2.1). However, as small farms have continued to join in the production of organic carrot, the consolidation process (proportionally) seems to have lagged behind other crops.

2.3.7 Correlation between Consolidation and Pesticide Usage in Organic Fields

The effect of organic cropland consolidation on pesticide use is identified based on equation 1. Table 2.4 shows estimates for the number of pesticide applications and the use of three major AIs/AI groups.

Table 2.4: Correlation between Organic Acreage and Total Lbs of AI used, Number of Applications, and Application Rates of the Three Top AI/AI Groups in Organic Crop Production

Variable	Microbials			Sulfur			Copper, fixed		
	Total AI	App	App_rate	Total AI	App	App_rate	Total AI	App	App_rate
Acreage	0.01	-0.17***	0.02***	1.69***	0.13***	0.29***	0.14***	0.14***	0.20
	(0.07)	(0.04)	(0.01)	(0.24)	(0.04)	(0.07)	(0.04)	(0.04)	(0.24)
Exp	0.03***	0.01	0.00	-0.06	-0.01	-0.02	-0.01	-0.01	0.15
	(0.01)	(0.03)	(0.00)	(0.08)	(0.01)	(0.01)	(0.02)	(0.01)	(0.20)
β_0	1.36	2.63***	0.18***	25.78***	3.96***	110.88	3.77***	2.55***	2.30***
	(0.89)	(0.31)	(0.04)	(3.48)	(0.13)	(74.24)	(1.01)	(0.22)	(0.60)
N	51,206	51,206	51,206	28,322	28,322	28,322	24,217	24,217	24,217
R^2	0.24	0.32	0.28	0.65	0.61	0.50	0.42	0.40	0.13

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Year, crop, and grower fixed effect are included in all models.

Microbials are the most widely used pesticide category in organic agriculture (Table 2.2). The number of applications per field and the application rate are significantly correlated with organic acreage. Growers with more organic acreage applied microbials less frequently but used more products per acre in each application. Overall, the use of microbials did not vary across growers in different organic acreage size classes. The use of spinosad, azadirachtin, and pyrethrins is similar to that of microbials. Farms' organic acreage has a significant impact on the number of applications and application rate but in different directions, so the combined effect is not significant. For sulfur and fixed copper, the application rate is not correlated with my variable of interest. However, an increase in the organic acreage leads to an increase in the number of applications for those two AI/AI groups. Therefore, more sulfur and fixed copper products are used on farms with more organic acreage.

Sulfur serves as a protectant fungicide for powdery mildew. Fixed coppers are often used to treat plant diseases caused by the genus *Xanthomonas* such as bacterial leaf spot and leaf blight. Therefore, both of these AI/AI groups must be applied preventatively and regularly to be effective (Schwartz and Otto, 1998, Hanna et al., 1997). The observation that growers with more organic acreage used sulfur and fixed copper more frequently is one of the theoretical predictions in Zilberman et al. (1991) where growers use pesticides as a tool to mitigate uncertainty in production. Changes in sulfur and fixed copper use have environmental consequences because sulfur and fixed copper products are less toxic to earthworms and are more toxic to aquatic organisms than spinosad and pyrethrins. Using the PURE index values as the dependent variable in equation 1, we can identify the impact on the environment.

Table 2.5: Correlation between Organic Acreage and the PURE Index Value

Variable	Surface water	Groundwater	Soil	Air	Pollinator
Acreage	0.17***	0.00**	-1.51***	-1.85***	0.01**
	(0.02)	(0.00)	(0.21)	(0.20)	(0.00)
Exp	-0.07	-0.00	-0.66***	-1.46***	0.01
	(0.04)	(0.00)	(0.11)	(0.11)	(0.01)
β_0	3.34***	-0.01	24.11***	48.96***	0.30***
	(0.39)	(0.04)	(0.96)	(0.92)	(0.07)
N	127,735	127,735	127,735	127,735	127,735
R^2	0.47	0.67	0.53	0.53	0.45

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Year, crop, and grower fixed effect are included in all models.

The result of an increase in acreage on PURE index values is shown in Table 2.5. For surface water, the average index value is 4.35 and growers with more organic acreage have a greater impact. The major AIs/AI groups listed in Table 2.4 have varying toxicities to aquatic organisms. The toxicity is commonly measured by the half maximal effective concentration (EC_{50}), which is the dissolved concentration (mg/L) needed for a response halfway between the baseline and maximum lethality. A larger EC_{50} is associated with a less toxic chemical. For algae, the EC_{50} values are much larger for spinosad (6.1) and pyrethrins (320) than copper hydroxide (0.01), which is the most heavily applied AI in the fixed copper group (PPDB, 2020). The EC_{50} toxicity value of sulfur is 0.06 and it is known to be an artifact due to the fact that sulfur is almost completely insoluble in water. So the impact of sulfur use on surface water is minimal.

The PURE soil index value is estimated based specifically on the toxicity for earthworms, which is measured by the dose that is lethal to 50% of the test population (LC_{50}). Similar to the EC_{50}, the four AIs/AI groups impacted by the organic acreage per farm have different levels of toxicity. Sulfur and Copper hydroxide are less toxic to earthworms, with LC_{50} values of 2,000 and 677, respectively; spinosad and pyrethrins are moderately toxic to earthworm, with LC_{50} values of 458 and 24, respectively (PPDB, 2020). So larger operations have less impact on soil by using sulfur and copper products more frequently.

The PURE index value for air is determined by the level of VOC emissions. Sulfur products have zero VOC emissions as they do not sublimate or evaporate at ambient temperatures. The use of sulfur products reduces VOC emissions, which in turn leads to a decrease in the PURE air index value. For groundwater, the average index value is almost zero and there is not enough variation across fields to identify a significant impact of the acreage or experience variables. The impact on organic acreage on pollinators is significant but with a smaller magnitude for a similar reason.

Table 2.6: Correlation between Organic Acreage and Total Lbs of AI Used, Number of Applications, and Application Rates of the Three Top AI/AI Groups in Organic Vegetable Production

Variable	Total microbials		Total sulfur		Total copper, fixed	
	Coef.	z-test	Coef.	z-test	Coef.	z-test
Acreage	0.00	0.10	1.47***	0.56	0.08**	1.20
	(0.07)		(0.31)		(0.03)	
Exp	0.02	0.71	-0.05	-0.05	-0.15***	3.13
	0.01		(0.19)		(0.04)	
β_0	0.90***	0.49	18.44	0.63	5.11***	-0.85
	(0.29)		(11.08)		(1.22)	
N	38,133		7,720		11,034	
R^2	0.18		0.60		0.34	

Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.1. Year, crop, and grower fixed effect are included in all models.

As shown in the previous section, the crop composition has changed for organic agriculture in the past two decades. In particular, The acreage share of vegetables increased. Therefore, the same regression is estimated again to test whether more sulfur and copper pesticides were used in vegetable fields as the farm acreage increased. The results in Table 2.6 show that farm acreage is positively correlated with sulfur and copper pesticides usage, which is not different from the general pattern. In the sub-sample of vegetable fields, the coefficients of acreage are also not different from the those in the full sample. Therefore, the rise in the acreage share of vegetable production does not contribute to the change in pesticide use.

2.4 Conclusion

This essay identified organic fields from the PUR database using historical pesticide use records, analyzed pesticide use and associated environmental impacts in organic crop production, established the consolidation of organic cropland, and quantified the effect of acreage expansion on pesticide use and its environmental impacts.

Our approach provides the basis for future studies to use the PUR database for the analysis of many different aspects of organic agriculture in California. From a spatial perspective, organic fields in California have expanded into new production regions over the past two decades, and the growth of organic acreage for fresh fruits and vegetables has been profound. For example, organic acreage for kale exceeded conventional acreage in 2015.

Organic growers' pesticide portfolio has changed dramatically during the study period. New AIs, such as spinosad and azadirachtin, were quickly adopted once approved for organic use and the shares of usage for sulfur and fixed copper, which were widely applied in earlier years, fell accordingly. This essay applied the PURE index, based on pesticide use, to assess the environmental impacts of organic crop production. We showed that organic agriculture has greater impacts on air and soil than on surface water, groundwater, and pollinators. There have been upward trends in the index values, particularly for the air and soil, which indicates that the changes which have occurred in the portfolio have negative environmental consequences, and previous assessments might have been too optimistic in generalizing the environmental performance of organic agriculture as the sector has grown dramatically.

Using the PUR database, we found that large farm operations increased their share of total organic acreage, especially after the launch of the NOP in 2001. The NOP was designed to convey a reliable signal to consumers that distinguishes organic produce from conventional. Consumers are willing to pay more for organic products, so producers have more incentive to expand their organic production. However, not all crops have followed the consolidation trend. The number of organic farms increased as well as the organic acreage. The consolidation happens when the number of farms increased slower than the acreage.

The process of cropland consolidation resulted in shifts in the pesticide portfolio, which can alter the environmental impact of organic agriculture. Namely, growers with larger organic farm size applied more sulfur and fixed copper and less spinosad and pyrethrins per acre. These four major AIs/AI groups have different ecotoxicological properties. Compared to spinosad and pyrethrins, sulfur and copper hydroxide are less toxic to earthworms and copper hydroxide is more toxic to aquatic organisms. Therefore, the pesticide practices of larger organic operations have greater impacts on surface water and less on soil. The impact on air, measured by VOC emissions, was smaller for larger operations because the sulfur products they use heavily have zero VOC emissions. Changes in the crop composition are observed in organic agriculture in California. The acreage share of vegetables increased while the share of grapes and field crops decreased. However, the shift in crop mix does not alter the result that the consolidation affects pesticide use and environmental impacts because this pattern does not change significantly across crops.

Primarily due to the lack of field-level data, previous studies focused less on the variation within the organic agriculture sector. Instead, the average performance across numerous organic growers was compared with other farming systems to illustrate the benefit from organic farming practices. The recent trend of cropland consolidation into larger operations has raised the question of how large organic farms behave differently from small ones, and what impacts those differences might have. The results partially answer this question in terms of pesticide use and show that as organic cropland has increased, growers have changed their pesticide portfolios and associated environmental impacts. As observed in conventional agriculture (MacDonald et al., 2018), the consolidation of cropland is almost inevitable. Therefore, new policy tools might be necessary to address the usage of pesticides in organic agriculture. The change in farm size could also alter practices other than pest management, such as fertilizer use. Future studies are needed to deliver a comprehensive analysis on the effect of consolidation on the overall environmental performance of organic agriculture.

Essay 3

A Conceptual Framework of the Farm Size Distribution and Specialization in U.S. Agriculture

3.1 Introduction

Why do farms differ in size? Why are farms becoming more specialized? The consolidation of acreage and production has long characterized U.S agriculture (MacDonald et al., 2018). Meanwhile the number of very small farms has continued to grow over the last thirty years, in part because the definition of a farm has not been adjusted for inflation.[1] Another trend documented by MacDonald et al. (2018) is that as production shifts to large farms, specialization also occurs. In 1996, 37% of the value of corn production came from farms that grew fewer than 3 commodities.[2] This share increased to 57% by 2015. Similar patterns exist for other field crops as well as livestock. For example, 31% of the value of hog production occurred on farms without any crop harvested in 2015, up from 14% in 1996.

Farm size and specialization interact. On one hand, more specialized farms need less acreage to take advantage of economies of scale. On the other hand, large farms can purchase specialized equipment or acquire specialized knowledge, which decreases the cost of producing a small number of crops. In this essay, I will focus only on crop farms and argue that changes in either size or specialization can be explained by changes in the distribution of crop-based knowledge across farmers, which I will call the knowledge distribution from now on. Recent trends in size and specialization can be explained by a model with heterogeneous farm operators whose knowledge evolves over time.[3] Farm operators learn from others, and expand acreage of one crop, ceteris paribus, as their knowledge increases for that crop. The knowledge they learn is specialized to a certain crop production process and it cannot be perfectly transferred to produce other crops. As farmers' specialized knowledge accumulates, the opportunity cost of planting crops that they

[1]In the U.S., a farm is defined as "any place that sells, or normally could sell, at least $1,000 of agricultural commodities".

[2]There are 21 crop commodity categories in the Agricultural Resource Management Survey.

[3]In the model, I assume all farms have a single operator. Although the 2017 Census shows that about 54% of farms have more than one operator and different operators may have different expertise, as long as production decisions are made based on the knowledge of all operators, farms with multiple operators can be modeled as farms managed by a single operator with a knowledge that is a composite of the knowledge of all operators.

know less about increases, which results in specialization in a few crops for which they have the largest knowledge stock when everything else is equal.

In this essay, I present a multi-good model to study changes in farm size and specialization. For crop farms, size can be measured by acreage, quantity of output, value added, or revenue and in many other ways (Sumner, 2014). Although revenue is a widely used measurement when a farm grows multiple crops, it is affected by other factors beside production decisions. Demand shocks and inflation could alter farm "size" without farmers changing their practices. The same reasoning applies to quantity produced. Some inputs, such as weather, are not determined by farmers, which makes quantities an inaccurate measure of farmers' decisions. The value of production per acre varies across crops due to differences in cost and revenue across crops. When measuring size by total acreage, farms that grow different crops are not directly comparable. Albeit imperfect, acreage is the measurement of farm size in this essay.

In the model, acreage increases directly as knowledge accumulates. Farm operators have crop-based knowledge, which may increase after meeting and learning from other farmers. Knowledge and land are inputs in production, which makes land demand for each crop a function of knowledge. The more knowledge farmers have about one crop, the more acreage they will allocate to that crop. Total land supply is fixed but the acreage of a specific crop varies based on the evolution of knowledge. To simplify the model, the demand for goods is assumed to be exogenous. Equilibrium prices clear all commodity markets and the land market, thus determining the farm size for each producer given his knowledge level. In other words, the farm size distribution is a transformation of the underlying knowledge distribution, similar to the intuition in Lucas Jr (1978). Because the total land supply is fixed, the growth of farm size is accomplished by farmers exiting the crop sector. Although knowledge does not depreciate over time by assumption, knowledge evolves for everyone, which means individuals need to keep learning in order to maintain their current acreage.

This approach of modeling the evolution of knowledge is based on Lucas (2009) where agents have opportunities to increase their knowledge by learning from others. Learning comes from imitation. Agents meet randomly with others and copy their knowledge if it is better. The meeting process is modeled as taking draws from the knowledge distribution. The meeting and learning process are costless for agents, which means whether agents learn or not in each period is not correlated with their production.[4] Therefore agents who currently have no production can still increase their knowledge and start producing in the future. This implication of Lucas (2009) is consistent with observations of U.S. agriculture that show people enter the agricultural sector. The Census of Agriculture collects information about how long the principal operator has operated any farm. In 2017, beginning farmers, who are defined as principal operators with no more than ten years of experience on any farm, operated 25% of total farms which accounted for 16% of total farmland and 15% of total agricultural sales (USDA NASS, 2017).

The evidence of learning from other farmers is well documented in the economic literature. Foster and Rosenzweig (1995) first separated learning by doing and learning

[4]One might be concerned about the assumption that learning is free. Lucas and Moll (2014) showed that the equilibrium outcomes are not sensitive to the cost of learning. In their paper, agents allocate time between production and meeting which makes learning costly.

from others in agriculture. They found that farmers with experienced neighbors earn higher profits. Using data on farmers' communication network, Conley and Udry (2010) showed the significance of social learning in the diffusion of agricultural technology. Other studies have covered the role of learning in specific farming decisions in the U.S. (e.g., Alexander (2002); Kroma (2006); Schneider et al. (2009); Goodhue et al. (2010)).

Learning as modeled here only covers learning between farmers, which does not necessarily require farmers to meet in person. As long as the knowledge acquired by one farmer is generated by another farmer, the process can be modeled as meeting and learning between farmers. To extend this point, both public and private agencies have facilitated information diffusion among farmers in different ways. If the information they shared, both online and in print, is based on findings in a farmer's fields, learning from this piece of information can be viewed as learning from that farmer. Examination of the knowledge generated from other sources, such as extension agents or industry dealers, is left for future work.

Previous endogenous growth analyses focused on a one-good economy in which a composite good is produced and consumed (Melitz, 2003; Luttmer, 2007; Sampson, 2015). Therefore they cannot explain the trend of specialization observed in agriculture. This essay contributes to the endogenous growth literature by modeling the evolution of industry-based knowledge when there are multiple industries (crops). In agriculture, much production and marketing knowledge is crop-based. Some crop-based knowledge, such as the management of pests, can be applied to a large group of crops. Other knowledge, such as the timing of harvest, refers to a single crop or a small number of crops. Specialized knowledge required in farming can be very similar for plants with similar agronomic characteristics. Later in the essay, I model the evolution of crop-based knowledge and its application to other crops explicitly. New ideas generated from growing one crop benefit farm operators in producing other crops as well. The more crops have in common, the more benefit farmers obtain from applying knowledge across crops.

If knowledge evolves independently across crops, producers are less likely to master the production of a large number of crops. For example, if learning about almond production is independent of learning about strawberry production, the probability that a farmer is knowledgeable about both is small. So, learning will lead to specialization. Specialization can also be manifested as focusing on a subset of crops that are similar in agronomic characteristics because farmers can apply knowledge across these crops. Following the same reasoning, this model has implications for the number of farms. Assuming there is a minimum acreage required for each crop to establish production, farmers will exit production if their optimal land demand is smaller than the crop-specific threshold. A faster learning process results in a larger variation in productivity because farmers have a larger probability to increase their knowledge. If we consider the number of farms that produce a specific crop, a larger variation in productivity means that there are more farms exited from production due to lack of knowledge. If the demand of a crop is fixed or increases more slowly than the evolution of knowledge, more farms will exit and the number of farms will decrease.

The model and implications are presented in section 2. Numerical simulations illustrating the effect of demand- and supply-side factors on the equilibrium path of farm structure are included in section 3 and section 4 concludes.

3.2 Model

Consider a closed economy including an initial set of I farm operators and J crops. Time is discrete, infinite and indexed by t. Farm operators are endowed with stocks of knowledge and land, both of which may change over time. Knowledge is crop-based and land is homogeneous with a fixed total supply. Land cannot be purchased but the land rental market is perfect.

3.2.1 Demand

The demand system is characterized by an exogenous expenditure on agricultural commodities Y_t, the elasticity of substitution $\rho > 0$, and the budget share $a_j > 0$ for each crop j. The demand function for crop j at time t is

$$\bar{Q}^d_{jt} = \frac{a_j p_{jt}^{-\rho}}{\sum_{k=1}^{J} a_k p_{kt}^{1-\rho}} Y_t \tag{3.1}$$

where $\bar{Q}^d_{jt}$ is the quantity demanded and p_{jt} is the equilibrium price for crop j at time t. I also assume the budget share of all crops sums to one: $\sum_{j=1}^{J} a_j = 1$. The expenditure Y_t is assumed to grow at a fixed rate. The annual growth rate of U.S. food expenditure has been between 1% to 3% since 1997, so a fixed growth rate is appropriate (Okrent et al., 2018). The demand function is formed such that it can be rationalized by an utility function with a constant elasticity of substitution equal to ρ.

This setting deviates from the endogenous growth literature by assuming a predetermined total expenditure. However, it is convenience to use an exogenous demand system to study the evolution of farm size and specialization in the U.S.

3.2.2 Production

Farmer i has land L_i^e and crop-based knowledge $\theta_{ij0} \geq 0$ at time 0 for each crop j, which is independent across j. Following the notation in Lucas (2009), the distribution of knowledge θ_{ijt} is represented by the cumulative density function $G_j(x,t)$. All the knowledge associated with crop j exists at $t = 0$ and there is no other source of knowledge besides $G_j(x,t)$, which is

$$G_j(x,t) = \Pr\{\theta_{ijt} \leq x\}.$$

Knowledge θ_{ijt} and land L_{ijt} produce crop j with no uncertainty. The production function $q(\cdot)$ with L_{ijt} and θ_{ijt} as inputs is

$$q(\theta_{ijt}, L_{ijt}) = f(L_{ijt})\theta_{ijt}$$

where $f(\cdot)$ is a function with $f' > 0$ and $f'' < 0$. The production function in this model has land as its only input.

Knowledge is applicable across crops to an extent that varies based on crop pairs. This connection is defined as the knowledge substitution matrix S which measures the fraction of production knowledge that is common across pairs of crops. Within this matrix, element $s_{jk}, \in [0,1]$, is the multiplier if farm operators use knowledge θ_{ikt} to produce crop j. Land is homogeneous and equally productive for all crops. So, knowledge is the only factor influencing productivity. The output of crop j from using L_{ijt} and θ_{ikt} is as follows:

$$q(\theta_{ikt}, L_{ijt}) = f(L_{ijt})\theta_{ikt}s_{jk}.$$

Assume matrix S is symmetric with diagonal elements equal to 1, then the quantity produced Q_{ijt} can be expressed as the maximum of output using all knowledge stock. Formally,

$$\begin{aligned} Q_{ijt} &= f(L_{ijt}) \times \left[\max_{k=1\ldots J}\{\theta_{ikt}s_{kj}\}\right] \\ &= f(L_{ijt})(\theta^*_{ijt}) \end{aligned} \tag{3.2}$$

where $\theta^*_{ijt} = \max_{k=1\ldots J}\{\theta_{ikt}s_{kj}\}$, which represents the maximum knowledge available for farmer i to produce crop j. Because each θ_{ijt} follows the distribution with cumulative density function $G_j(x,t)$, the distribution of θ^*_{ijt} can be derived from the assumption that θ_{ijt} is distributed independently across j. The cumulative density function for the distribution of θ^*_{ijt} is

$$\begin{aligned} G^*_j(x,t) &= \Pr\{\theta^*_{ijt} \leq x\} \\ &= \Pi^J_{k=1} G_k(\frac{x}{s_{kj}}, t). \end{aligned} \tag{3.3}$$

By normalizing land rent to 1 and denoting relative price at time t as p_{jt} for crop j, we can define the profit function for farmer i as $\pi(L_{ijt}, \theta_{ijt}) = \sum_{j=1}^{J}(p_{jt}Q_{ijt} - L_{ijt}) + L_i^e$. Note that profits from each crop are additively separable, so any benefit from vertical integration is not considered in this essay.[5] Because land is the only input, the complementarity in terms of production cost across crops is also assumed away. With a known price sequence $\{p_{jt}\}_{t=0}^{\infty}$, the producer's problem can be solved in each period and the solution provides the sequence of optimal land demand vector $\{L_{ijt}^*\}_{t=0}^{\infty}$. Each L_{ijt}^* satisfies the condition that $f'(L_{ijt}^*) = \frac{1}{p_{jt}\theta_{ijt}^*}$.

3.2.3 Entry and Exit

The model enables farmers to enter and exit from the production of each crop. A minimum amount of land L_j^{min} is required to establish the production of j, similar to Luttmer (2007) where any existing firm has to maintain a certain number of labor.[6] The minimum knowledge required to operate L_j^{min} is $\theta_{jt}^{min} = \frac{1}{p_{jt}f'(L_j^{min})}$. Price p_{jt} is an equilibrium outcome which reflects the knowledge of all farmers for all crops at time t. Farmers do not have any constraint other than the knowledge requirement to produce multiple crops. Therefore farmer i will (and must) enter if $\theta_{ijt}^* > \theta_{jt}^{min}$. There is no fixed cost for entering and entry could happen in any t. After entry, farmer i decides to exit at time t if $\theta_{ijt}^* \leq \theta_{jt}^{min}$.

Even though an individual's knowledge does not depreciate, farmer i still could exit if θ_{jt}^{min} grows faster than θ_{ijt}^*. Recall that p_{jt} is the crop price divided by the land rent.

[5] Specifically, livestock production and further processing are not included in this essay

[6] An alternative approach is to follow Jovanovic (1982) and set a positive profit threshold below which farmers will exit.

So the growth of θ_{jt}^{min} comes from the decline in p_{jt} which is caused by crop prices falling and land rent rising over time. Exit is possible for every farmer because learning in each period is independent across farmers. If farmer i does not learn anything about any crop at time t, he will have the same knowledge level at time $t+1$, which is $\theta_{ijt}^* = \theta_{ijt+1}^*$. The equilibrium price of crop j will fall because other farmers increase their knowledge level, which makes $\theta_{jt+1}^{min} > \theta_{jt}^{min}$. If $\theta_{ijt+1}^* < \theta_{jt+1}^{min}$, farmer i will not produce crop j. If he continues to produce crop j at time $t+1$, it is still possible for him to not learn anything and θ_{jt+1}^{min} will rise again. If farmer i does not learn anything for multiple time periods, eventually he will exit from producing crop j. But whether a farmer learns or not is independent across time, which makes exiting less likely for farmers with higher knowledge θ_{ijt}^*.

The implication that θ_{jt}^{min} will fall is consistent with Lucas Jr (1978), who showed that the cut-off above which individuals will become entrepreneurs will always increase as the wage increases. Unlike Luttmer (2007), exit is not irreversible. Farmers continue to learn after exit from producing crop j and may re-enter if they gain enough knowledge to meet the minimum threshold θ_{jt}^{min}.

For each crop j, a proportion of farmers have $\theta_{ijt}^* \leq \theta_{jt}^{min}$ such that it is not optimal for them to produce crop j even at the minimum scale. I will denote this proportion as $\beta_j \in [0, 1]$. If knowledge evolves independently across crops, the proportion of farmers who decide not to produce anything is $\prod_j \beta_j$. For a finite number of crops, the proportion of farms that have positive production of at least one crop converges to a constant $1 - \prod_j \beta_j$.[7]

[7]An extension from this essay is adding a non-agricultural sector to study how farming responds to knowledge evolution outside agriculture.

3.2.4 Evolution of Knowledge

The evolution of knowledge is modeled the same way as in Alvarez et al. (2008). Farmers have opportunities to meet with other farmers and increase their knowledge, modeled as a deterministic process with arrival rate α_j for crop j, which I will call the learning rate from now on. This approach is considered deterministic because farmers will meet with others for certain. The interpretation of α_j is that in an time interval $(t, t + \Delta)$, each farmer will meet with $\alpha_j \Delta$ other farmers which is modeled as taking $\alpha_j \Delta$ draws from the knowledge distribution. Although it is certain they will meet others, it is still uncertain whether they will learn, which requires meeting with farmers who have a higher level of knowledge.[8] For example, if farmer i meets with farmer i' at time t to discuss crop j and $\theta_{ijt} > \theta_{i'jt}$, farmer i does not learn from i' and her knowledge θ_{ijt} remains the same after the meeting. An implication of this learning mechanism is that learning slows with knowledge stock. Farmers with higher knowledge level are less likely to learn.

Because farmers only learn from people who know more than they do, for a specific crop, the probability of farmer i holding the same knowledge of crop j after meetings equals to the probability of meeting with $\alpha_j \Delta$ people who all know less than θ_{ijt}, which is $G_j(\theta_{ijt}, t)^{\alpha_j \Delta}$. This learning rule results in the following law of motion for knowledge distribution across farmers, $G_j(x, t)$:

$$G_j(x, t + h) = G_j(x, t) \times G_j(\theta_{ijt}, t)^{\alpha_j \Delta}.$$

[8]An alternative way of modeling mentioned in Alvarez et al. (2008) is that meeting with others is not certain. Both approaches provide uncertainty at the individual level and a closed form solution at the aggregate level. Here I choose the deterministic approach to simplify formulas for knowledge evolution and application across crops.

The evolution path of knowledge is determined by the initial distribution $G_j(x, 0)$.

$$\ln(G_j(x,t)) = \ln(G_j(x,0))e^{\alpha_j t} \tag{3.4}$$

Notice that $\frac{\partial^2 G_j(x,t)}{\partial t^2} > 0$ for $t > \frac{1}{\alpha_j}\ln(-\frac{1}{\ln(G_j(x,0))})$. Because $G_j(x,t)$ represents the proportion of the population with knowledge less than x, the knowledge distribution continues to move rightward at a decreasing rate. This model implication aligns with the empirical findings in Alston et al. (2009), which showed that both global land and labor productivity grew at a slower pace from 1990 to 2005 than from 1961 to 1990.

I assume the initial distribution of θ_{ij0} follows a Fréchet distribution with a minimum of zero, which is commonly used to model a productivity distribution (e.g., Jones, 2005 and Lucas, 2009), in order to stay in the same distribution family at each time t. The support of the Fréchet distribution is from zero to positive infinity, ensuring that there is not a maximum level of knowledge $\bar{\theta}$ where $G_j(\bar{\theta}, t) = 1$. This is equivalent to saying that every farmer has the opportunity to learn at any time. From equation 3.4 we can see that if the initial distribution is defined as $\theta_{ij0} \overset{d}{\sim}$ Fréchet(μ, σ), then at time t the knowledge distribution for crop j is $\theta_{ijt} \overset{d}{\sim}$ Fréchet$(\mu, e^{\frac{\alpha_j t}{\mu}}\sigma)$. Combined with equation 3.3, the distribution of θ^*_{ijt} is also a Fréchet distribution with parameters μ and $\left(\sum_k e^{\alpha_k t} s^{\mu}_{kj}\right)^{\frac{1}{\mu}}\sigma$. If learning is modeled as a random process, the distribution of θ^*_{ijt} will not have a closed form solution in equilibrium. The two parameters μ and σ are the shape and scale of the Fréchet distribution. Figure 3.1 plots the Fréchet distribution with parameters (μ, σ) equal to $(1, 1)$, $(1, 2)$, $(2, 1)$, and $(2, 2)$. An increase in either μ or σ moves the peak of the distribution to the right. A larger σ makes the distribution flatter, while a larger μ is associated with a more concentrated distribution.

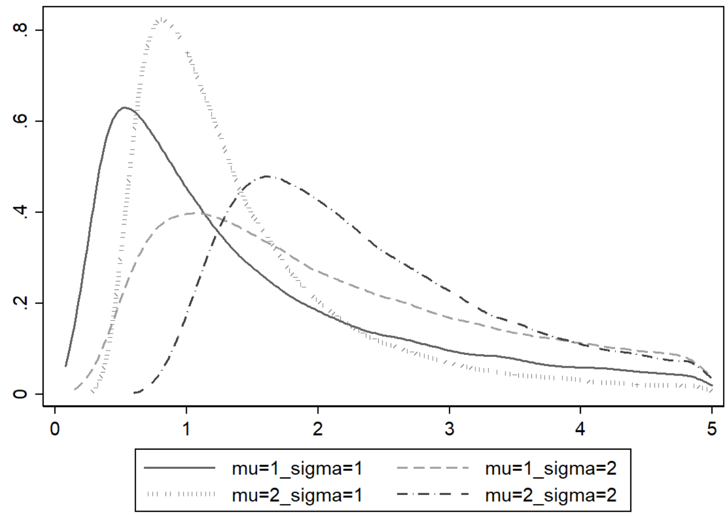


Figure 3.1: Fréchet Distribution with Different Values of μ and σ

3.2.5 Equilibrium

A competitive equilibrium across all crops characterized by the initial distribution $G_j(x, 0)$ for each crop j includes a sequence of crop prices $\{p_{jt}\}_{t=0}^{\infty}$, land demand for each crop $\{L^*_{ijt}\}_{t=0}^{\infty}$, and consumption $\{c^*_{ijt}\}_{t=0}^{\infty}$. To solve for the competitive equilibrium prices, the quantity supplied must equal the quantity demanded for all crops and land. I will have J crop clearing conditions and J equilibrium prices along with the land market clearing condition, $\bar{L}^d_t = \bar{L}^s_t$. With $J + 1$ equations at each t, we can solve for J unknown prices. The supply function is an integral over the knowledge distribution $G^*_j(x, t)$:

$$\bar{Q}^s_{jt} = I \Pr(\theta^*_{ijt} > \theta^{min}_{jt}) \int_{\theta^{min}_{jt}}^{\infty} f(L^*_{ijt}) g^*_j(x, t)\, dx$$

where $\bar{Q}^s_{jt}$ is the quantity supplied and $g^*_j(x,t)$ is the probability density function of $G^*_j(x,t)$. The land market clearing condition is more straightforward with $\bar{L}$ being the total land supply:

$$\bar{L} = \sum_{i=1}^{I} \sum_{j=1}^{J} L^*_{ijt} = \sum_{i=1}^{I} L^e_i.$$

The equilibrium defined above yields predictions regarding land demand and diversification. To simplify the result, I assume $f(L_{ijt}) = L^{\lambda}_{ijt}$ with $\lambda \in (0,1)$. The optimal land demand can be solved as $L^*_{ijt} = \left(p_{jt}\theta^*_{ijt}\lambda\right)^{\frac{1}{1-\lambda}}$. The supply function under this assumption is the following:

$$\begin{aligned}\bar{Q}^s_{jt} &= (p_{jt}\lambda)^{\frac{\lambda}{1-\lambda}} \sum_{i=1}^{I} \left({\theta^*_{ijt}}^{\frac{1}{1-\lambda}} \mathbb{1}\{\theta^*_{ijt} > \theta^{min}_{jt}\} \right) \\ &= (p_{jt}\lambda)^{\frac{\lambda}{1-\lambda}} h_{jt}(\mu, \sigma, \boldsymbol{\alpha}, S, t, L^{min}_j, p^*_{jt})\end{aligned}$$

where $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_J)$ is the vector of learning rates. Because θ^*_{ijt} follows a Fréchet distribution, $h_{jt}(\cdot)$ can be written as an incomplete gamma function and the condition $\frac{1}{1-\lambda} < \mu$ is sufficient for $h_{jt}(\cdot)$ to exist. The function $h_{jt}(\cdot)$ measures the average knowledge level for existing producers for crop j at time t. Price is negatively correlated with $h_{jt}(\cdot)$ because of self-selection. Farmers with lower knowledge levels will exit when the price decreases, which makes the remaining producers more knowledgeable on average than previously. The ratio of two equilibrium quantities can be expressed based on the supply and demand functions, which gives the relation between two equilibrium prices:

$$\frac{p_{jt}^*}{p_{kt}^*} = \left[\frac{a_j h_{kt}(\mu, \sigma, \boldsymbol{\alpha}, S, t, L_k^{min}, p_{kt}^*)}{a_k h_{jt}(\mu, \sigma, \boldsymbol{\alpha}, S, t, L_j^{min}, p_{jt}^*)}\right]^{\frac{1-\lambda}{\lambda+\rho-\lambda\rho}}. \tag{3.5}$$

The land market clearing condition also contains equilibrium prices:

$$\bar{L} = \lambda^{\frac{1}{1-\lambda}} \sum_{j=1}^{J} {p_{jt}^*}^{\frac{1}{1-\lambda}} h_{jt}(\mu, \sigma, \boldsymbol{\alpha}, S, t, L_j^{min}, p_{jt}^*). \tag{3.6}$$

After substituting p_{jt}^* for p_{kt}^* using equation 3.5, equation 3.6 can be rewritten as:

$$p_{jt}^* = \frac{1}{\lambda}\bar{L}^{1-\lambda}\left(\frac{a_j}{h_{jt}(\cdot)}\right)^{\frac{1-\lambda}{\lambda+\rho-\lambda\rho}}\left(\sum_{k=1}^{J} a_k^{\frac{1}{\lambda+\rho-\lambda\rho}} h_{kt}(\cdot)^{\frac{\lambda+\rho-\lambda\rho-1}{\lambda+\rho-\lambda\rho}}\right)^{\lambda-1} \tag{3.7}$$

As mentioned earlier, $h_{jt}(\cdot)$ is a function containing price p_{jt}; there is no closed-form solution for equilibrium prices. Prices will be solved numerically in the simulation section. Using equation 3.7, I can express land in each crop j and farm size for farmer i as a function of $h_{jt}(\cdot)$. Farm size L_{it}^* is defined as the total acreage per farm.

$$L_{ijt}^* = \bar{L}\left(\frac{a_j}{h_{jt}(\cdot)}\right)^{\frac{1}{\lambda+\rho-\lambda\rho}}\left(\sum_{k=1}^{J} a_k^{\frac{1}{\lambda+\rho-\lambda\rho}} h_{kt}(\cdot)^{\frac{\lambda+\rho-\lambda\rho-1}{\lambda+\rho-\lambda\rho}}\right)^{-1} {\theta_{ijt}^*}^{\frac{1}{1-\lambda}} \tag{3.8}$$

$$L_{it}^* = \bar{L}\left(\sum_{k=1}^{J} a_k^{\frac{1}{\lambda+\rho-\lambda\rho}} h_{kt}(\cdot)^{\frac{\lambda+\rho-\lambda\rho-1}{\lambda+\rho-\lambda\rho}}\right)^{-1} \sum_{j=1}^{J}\left[\left(\frac{a_j}{h_{jt}(\cdot)}\right)^{\frac{1}{\lambda+\rho-\lambda\rho}} {\theta_{ijt}^*}^{\frac{1}{1-\lambda}}\right] \tag{3.9}$$

Using equation 3.8, I define the specialization level as the acreage share of the biggest crop.

$$special\_land_{it} = \frac{\max_j\{L^*_{ijt}\}}{L^*_{it}}$$

If we denote the number of farms at time t by N_t, I can write N_t as the proportion of farmers that produce at least one crop. The number of farms that produce crop j, denoted N_{jt}, is expressed in the same way.

$$N_t = I \cdot \Pi_{k=1}^{J}[1 - \Pr(L^*_{ikt} > L_k^{min})]$$

$$N_{jt} = I \cdot [1 - \Pr(L^*_{ijt} > L_j^{min})]$$

3.3 Simulation

Both demand-side and supply-side factors influence the evolution of farm size and specialization. In each, I simplify one side of the market to focus on the workings of the other. In this section, two examples are presented. In the supply-side example, the growth of industry j is determined by the learning rate α_j and the knowledge substitution matrix $\boldsymbol{S}$, which measures how well farmers can apply knowledge between crops. Therefore, the example includes two pairs of crops to show how α_j and $\boldsymbol{s}_j$ matter in the example when the budget shares are assumed to be the same for all crops. In the demand-side example, the budget share parameter a_j and the elasticity of substitution parameter ρ govern the growth of industry j. Simulation results will provide support for arguments in the theoretical section.

3.3.1 A Supply-Side Example

By setting $a_j = a_{j'} \; \forall j, j' \in \{1, ..., J\}$, every crop has the same budget share and gross revenue. The expression for equilibrium price p^*_{jt} can be simplified accordingly:

$$p^*_{jt} = \frac{1}{\lambda} \bar{L}^{1-\lambda} h_{jt}(\cdot)^{\frac{\lambda-1}{\lambda+\rho-\lambda\rho}} \left(\sum_{k=1}^{J} h_{kt}(\cdot)^{\frac{\lambda+\rho-\lambda\rho-1}{\lambda+\rho-\lambda\rho}} \right)^{\lambda-1} . \tag{3.10}$$

The supply-side example is simulated using equation 3.10. Parameter values are listed in Table 3.1. The difference in learning rates across crops is that $\alpha_2 = \alpha_4 > \alpha_1 = \alpha_3$. The differences between crop pair (1,2) and (3,4) show how learning rate affects farm size and specialization. The interpretation of $\alpha_1 = 1$ is that, in each period, each farmer meets with one other farmer to discuss crop 1, as is also the case for crop 3. For crops 2 and 4, the learning rate is larger and each farmer meets with two other farmers in each period. The matrix $\boldsymbol{S}$ defines how knowledge can be applied across crops. $s_{12} = s_{21} = 0.8$ meaning that knowledge between crops 1 and 2 has 80% in common and farmers can use knowledge of crop 1 to produce crop 2 (and vice versa) and remain 80% productive. Knowledge between crops 3 and 4 only have 60% in common. Because crops 1 and 3 have the same learning rate, the comparison between them shows how applying knowledge across crops affects farm size and specialization. Same reasoning applies to crops 2 and 4. The minimum acreage of production is 0.2 for each crop.

The theory predicts that knowledge of crop 2 and 4 evolves faster than knowledge of crop 1 and 3. At the aggregate level, a higher knowledge rate results in a larger stock of knowledge, which leads to more production and smaller acreage for crop 2 and 4 because

Table 3.1: Parameters for the Supply-Side Example

Parameter	Definition	Value
$\boldsymbol{a}$	Budget share	(0.25,0.25,0.25,0.25)
$\boldsymbol{\alpha}$	Learning rate	(1,2,1,2)
$\boldsymbol{S}$	Knowledge substitution matrix	$\begin{pmatrix} 1 & 0.8 & 0 & 0 \\ 0.8 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0.6 \\ 0 & 0 & 0.6 & 1 \end{pmatrix}$

the budget shares are the same for all crops. At the individual level, each farmer also produces outputs using less acreage for crops 2 and 4 than crops 1 and 3. For crop pairs that have the same learning rate, the distribution of θ^*_{i1t} and θ^*_{i2t} will evolve faster than θ^*_{i3t} and θ^*_{i4t} respectively because farmers can cross-apply knowledge between crop 1 and 2 with less friction. Therefore the model predicts that crop 1 and 2 will have more output and less acreage than crop 3 and 4.

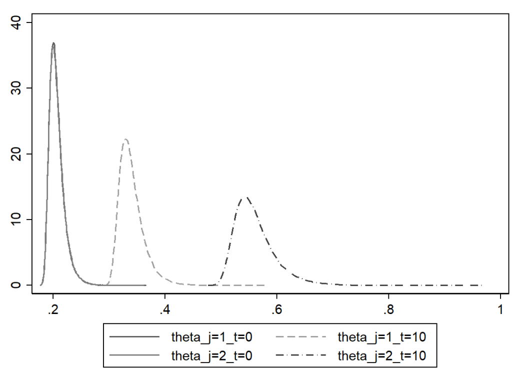


Figure 3.2: Distribution of Knowledge across Farmers for Crop 1 and 2 at $t = 0$ and $t = 10$

At $t = 0$, all crops has the same knowledge distribution, $\theta_{ij0} \overset{d}{\sim}$ Fréchet$(20, 0.2)$. Figure 3.2 shows that by $t = 10$, the knowledge distribution of crop 2 has evolved faster than crop 1. Both of them start from the same initial distribution plotted by the solid line on the left. By meeting with one extra farmer in each period, the difference between two distribution is significant after ten periods. A similar difference exists between crop 3 and 4.

Farmers could apply knowledge across crops 1 and 2 and still keep 80% of the knowledge. The difference between distribution of θ^*_{i1t} and θ^*_{i2t} (left panel of Figure 3.3) becomes much smaller than the difference between θ^*_{i3t} and θ^*_{i4t} (right panel of Figure 3.3). More knowledge is lost when farmers apply knowledge across crops 3 and 4, which makes the difference between θ^*_{i3t} and θ^*_{i4t} larger. Because knowledge of crop 2 evolves faster than knowledge of crop 1, farmers rarely use θ_{i1t} to produce crop 2. So the distribution of θ_{i2t} in Figure 3.2 and θ^*_{i2t} in Figure 3.3 are similar.

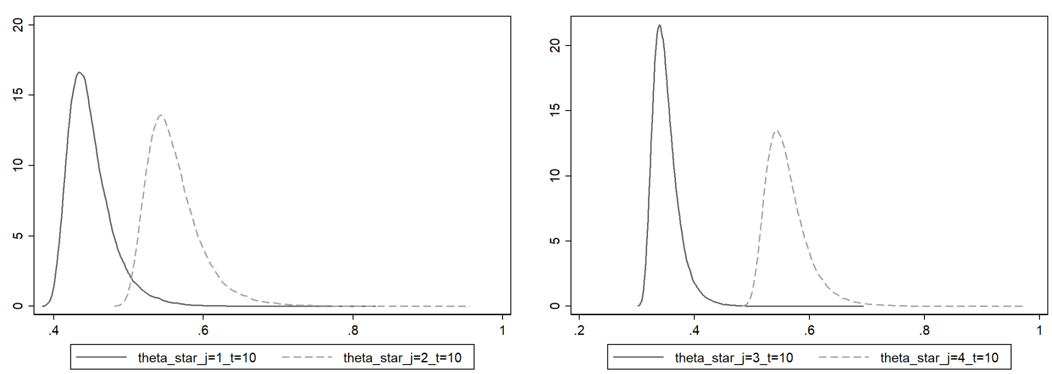


Figure 3.3: Distribution of Maximum Knowledge Available across Farmers at $t = 10$ for Each Crop

Figure 3.4 plots the distribution of crop acreage per farm of the four crops across farms at $t = 10$. More knowledge means less acreage is needed to produce the same quantity of product. Land demand for crops 2 and 4 is smaller than crop 1 and 3 respectively.

The gap in acreage distribution between crop 3 and 4 is larger than the gap between crop 1 and 2, consistent with the model implication that the acreage distribution reflects the knowledge distribution. If we plot the distribution of different farm size measures, such as crop revenue per farm or crop profit per farm, a similar pattern remains: the gap between crop 3 and 4 is larger than the gap between crop 1 and 2.

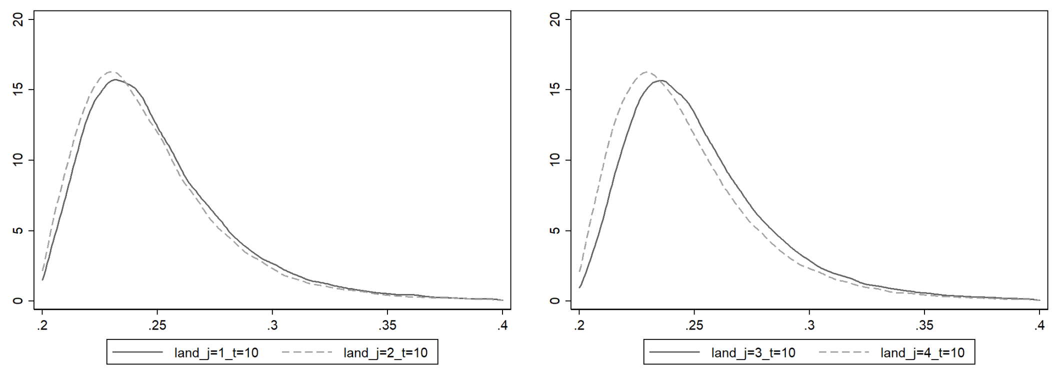


Figure 3.4: Distribution of Crop Acreage across Farmers at $t = 10$

Farmers compete for land in this model which makes the relative knowledge level matter when comparing the farm size distribution over time. At any time period, if a farmer has the same level of knowledge for crop 1 and 2, less profit is made from crop 2 because the knowledge of crop 2 evolves faster than that of crop 1, which means there are more farmers with a higher knowledge level of crop 2. Therefore, the acreage distribution shifts to the left for crop 2 more than crop 1 in the simulation (Figure 3.5). If we trace the evolution of crop acreage over time, crops 2 and 4 will have larger changes than crops 1 and 3, which is clear in Figure 3.5. So, more knowledge of a crop means less land is utilized for it.

The upper panel of Figure 3.5 shows the acreage distribution for crop 1 and 2 over

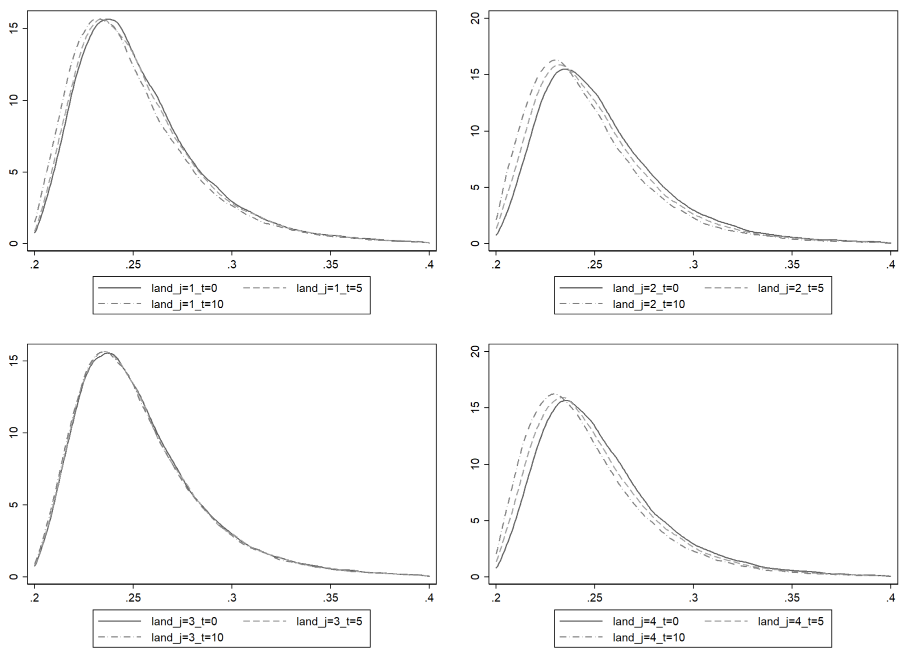


Figure 3.5: Distribution of Crop Acreage across Farmers at $t = 0$, $t = 5$, and $t = 10$

time. The lower panel plots the same distribution for crops 3 and 4. If we compare crops 1 and 3 to crops 2 and 4, the evolution pattern is similar to the evolution of knowledge showed in Figure 3.3. Crops 3 and 4 have a larger difference in the knowledge distribution than crops 1 and 2. Only 60% of knowledge remains when farmers apply knowledge across crops 3 and 4, which makes the gap between crops 3 and 4 larger.

By aggregating acreage from all crops, we obtain the distribution of farm size (left panel of Figure 3.6). The peak of the farm acreage distribution moves slight to the left and lower. The increase at the left tail of the acreage distribution is around the value 0.8, which is the acreage if a farmer grows all four crops at the minimum acreage. So the simulation models shows that there are more small farms operating at the minimal scale.

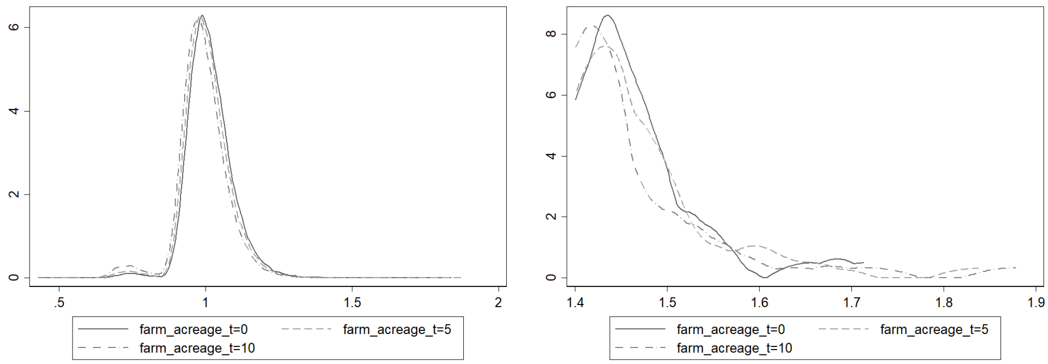


Figure 3.6: Distribution of Farm Acreage across Farmers for All Farmers and for Farmers with Acreage More than 1.4 at $t = 0$, $t = 5$, and $t = 10$

The right panel of Figure 3.6 enlarges the righthand side of acreage distribution to large farms with acreage more than 1.4, which shows that more large farms appear as the right tail of acreage distribution becomes longer over time.

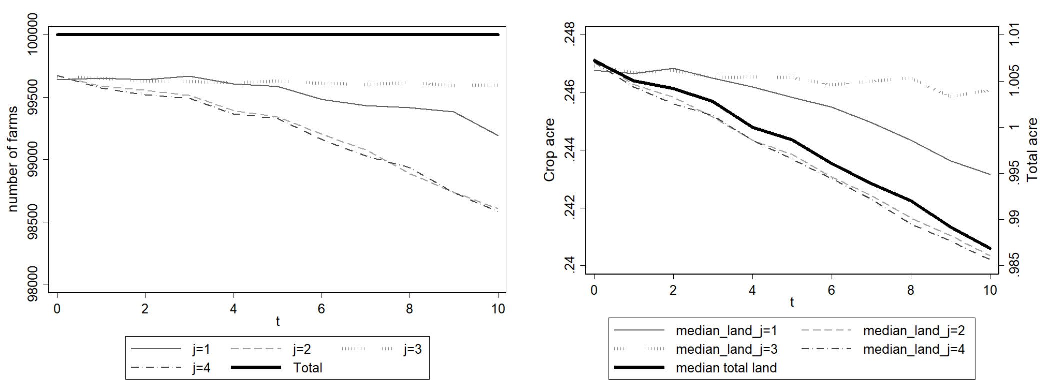


Figure 3.7: Number of Farmers and Median of Acreage for Each Crop and Total

Because the total land supply is fixed, more large farms means either other farms are getting smaller or the number of farms decreases or both. In Figure 3.7, the number of farms for each crop (on the left panel) has similar trends as the median land for each crop (on the right panel). The number of farms, plotted in the thick solid line in the left panel of Figure 3.7 remains constant because no farm has exited all crop production in the simulation. The median total acreage decreases as shown by the thick solid line in the right panel.

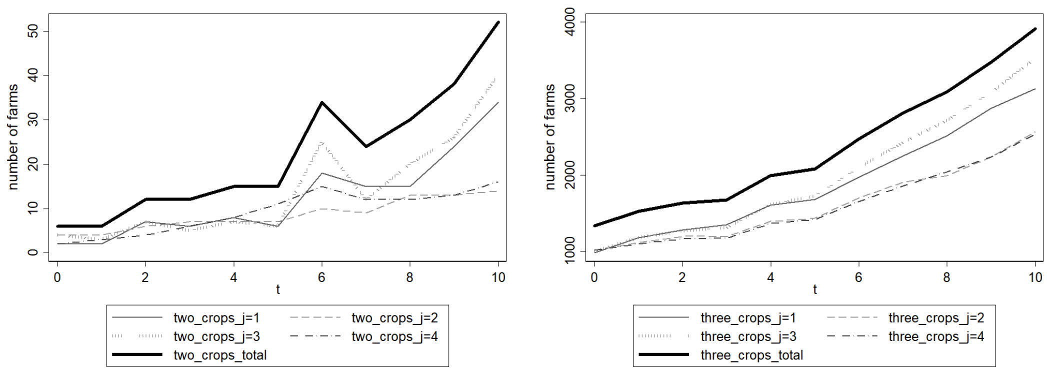


Figure 3.8: Number of Farmers Producing Two and Three Crops for Each Crop and Total

Regarding specialization, Figure 3.8 shows the number of farmers who grow two or three crops for each crop and total. On the left part, the thin solid line shows the number of farmers who grow only two crops and also grow crop 1. There is no farmer who specialized in only one crop after ten periods in this example. So an increase in the number of farmers who grow two or three crops means a decrease in the number of farmers who grow all four crops, which is evidence of specialization. As shown in the model section, the number of farmers who grow two crops are much smaller than the number of farmers who grow three crops because the knowledge evolves independently across crops. The total number of farms that grow two or three crops is plotted in thick solid line in Figure 3.8.

Notice that growers who produce only two or three crops are more likely to produce crops 1 and 3. The intuition behind this finding is that the knowledge distribution of crops 2 and 4 evolves faster, which results in an increase in the minimum level of knowledge required. So, farmers are less likely to meet the minimum threshold to produce crops 2 and 4.

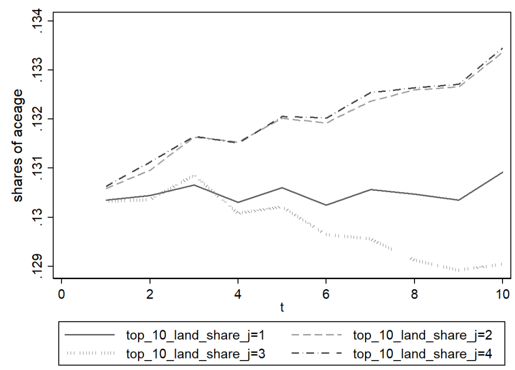


Figure 3.9: Acreage Share of the Top 10% Farmers by Acreage and Crop Over Time

Regarding consolidation, the model predicts that crops with higher learning rates have more consolidated production, which can be measured by the acreage share of the top producers. In Figure 3.9, the acreage share of the top 10% of farms are plotted for each crop. The top producers of crops 2 and 4 are expanding their acreage while the land operated by top producers of crop 3 is shrinking. This is caused by a flatter knowledge distribution for crops 2 and 4, as was shown in Figure 3.3. The knowledge distribution for crop 3 is highly concentrated, which means the difference in knowledge level across farmers is small.

To conclude the supply-side example, different learning rates create differences in farm size. Applying knowledge across crops can alter such differences. When budget share is the same for all crops, a higher learning rate leads to less acreage and more output. The evolution of knowledge also causes exit, which is measured by the decrease in the number of farms for each crop. Specialization is inevitable, and negatively correlated with learning rates.

3.3.2 A Demand-Side Example

To evaluate how the budget share and elasticity of substitution affect the farm size distribution and specialization, I eliminate the heterogeneity between crop pairs on the supply side. To do this, I simulate 2 crops in the demand-side example and let the learning rate $\alpha_1 = \alpha_2$. Knowledge cannot be applied across crops in this example, which makes the knowledge distribution identical for the two crops in each time period t.

The equilibrium prices defined in equation 3.7 can be simplified into equation 3.11. The parameter values are listed in Table 3.2.

$$p_{jt}^* = \frac{1}{\lambda}\bar{L}^{1-\lambda}h_t(\cdot)^{\lambda-1}a_j^{\frac{1-\lambda}{\lambda+\rho-\lambda\rho}}\left(\sum_{k=1}^{J}a_k(\cdot)^{\frac{1}{\lambda+\rho-\lambda\rho}}\right)^{\lambda-1} \tag{3.11}$$

Table 3.2: Parameters for the Demand-Side Example

Parameter	Definition	Value
$\boldsymbol{a}$	Budget share	(0.7,0.3)
$\boldsymbol{\alpha}$	Learning rate	(1,1)
$\boldsymbol{S}$	Knowledge substitution matrix	$\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$

By assuming crop 1 has a larger budget share than crop 2, more quantity is demanded of crop 1 than crop 2. This attracts farmers who have lower knowledge levels of crop 1 to enter the market. The model predicts that the acreage distribution of crop 1 will be to the left of the acreage distribution of crop 2. The simulation result comparing industry size distribution for difference share parameters is in Figure 3.10. Each panel shows acreage distributions under different value of ρ. The value of ρ represents whether crops are substitutes or complements. When crops are most substitutable, the acreage distribution becomes highly concentrated, which is shown in the right part of Figure 3.10. The acreage distribution of crop 2 is on the right side of crop 1 because it has a smaller budget share. Only knowledgeable farmers could survive in an industry with lower demand and price.

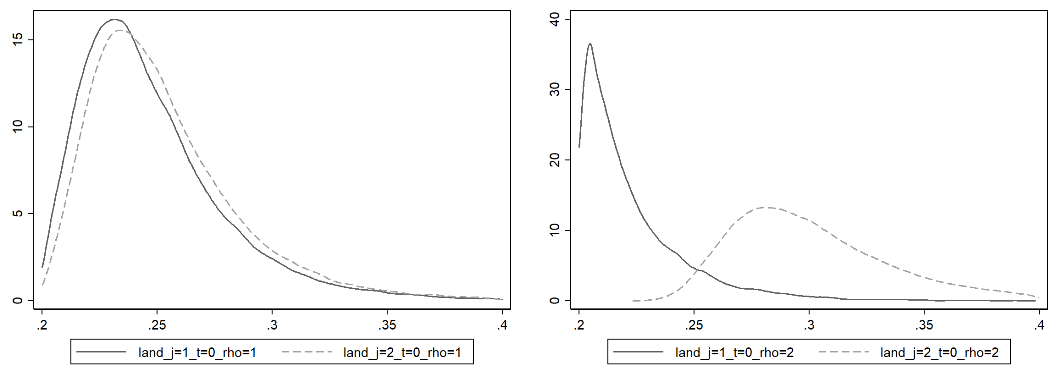


Figure 3.10: Distribution of Acreage across Farmers for $\rho = 1$ and $\rho = 2$ at $t = 0$

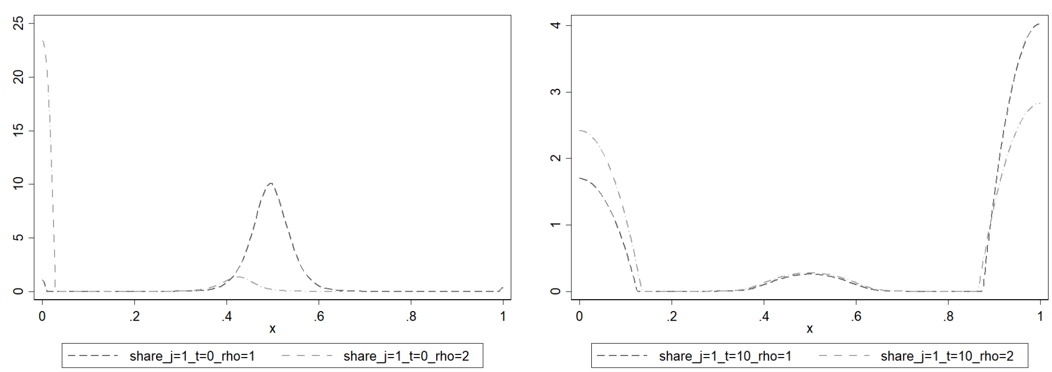


Figure 3.11: Distribution of Acreage Share across Farmers for $\rho = 1$ and $\rho = 2$ at $t = 0$ and $t = 10$ for Crop 1

When looking at the land allocation between crop 1 and 2, a large ρ is associated with more specialization, which is mainly caused by farmers shifting acreage from the crop with a larger budget share to the crop with a smaller budget share. When crops are not substitutable, farmers' land demands depend on their knowledge of both crops as well as equilibrium prices. For farmers who have the same stock of knowledge regarding two crops, the acreage of crop 1 is larger than that of crop 2 because the price of crop 1 is higher. When goods become more substitutable, those farmers could devote more land to crop 2 because the price of crop 1 drops. Figure 3.11 illustrates this implication for crop 1 in the simulation results. In the left panel of Figure 3.11, most growers allocate about half of their acreage to crop 1 when ρ is 1. As ρ increases to 2, a large share of growers no longer produce crop 1 at the initial time period. On the right panel of Figure 3.11, the probability mass in the middle decreases, which means more farmers are specialized in producing only one crop at $t = 10$. Even when $\rho = 2$, the number farms produced only crop 1 is still larger than the number of farms specialized in crop 2 at $t = 10$. This is consistent with the model prediction that farmers specialized in crops with large budget shares.

To conclude the demand-side example, the budget share is negatively related to the crop acreage per farm and farmers will specialize in producing crops with larger budget shares. Specialization is positively related to the elasticity of substitution. When crops are perfect substitutes, we essentially revert to the one-commodity model and farmers will only produce one crop in each time period.

3.4 Conclusion

The total number of farms in the U.S. has remained steady at around two million over the last thirty years. However, the number of very small and very large farms has increased. Another trend in farming is specialization. As mentioned in MacDonald et al. (2018), the average number of commodities produced on individual farms has decreased over time.

In this essay, I introduced a partial equilibrium model with heterogeneous farmers to explain changes in farm size and specialization. This model focuses on the distribution of crop-based knowledge, and attributes farmers' decisions to the evolution of knowledge. Knowledge can be applied across crops to varying degrees, which plays an important role in this model. Farmers learn from others through imitation, which changes the distribution of knowledge and, ultimately, the farm size distribution.

Two simulation examples are provided to understand the impact of model parameters individually and collectively. The results show that parameters including the learning rate, budget share, and the elasticity of substitution determine the land demand for each crop. A higher learning rate leads to less acreage and more output. Knowledge substitution across crops mitigates difference created by the difference in learning rate. A lager budge share is associated with more farmers, smaller farm size, and a larger share of acreage within a farm. Specialization is positively correlated to the elasticity of substitution. Future work could extend the current theoretical model to an open economy or incorporate knowledge evolution in the non-ag sector.

Conclusion

In this dissertation, I explored topics regarding the farm size distribution and specialization in the context of conventional and organic agriculture in California. I compared the environmental impacts of pesticide use in the two production systems and quantified the connection between farm size and pesticide use in organic production.

In essay 1, I found that pesticides used in organic agriculture had lower environmental impacts per acre on surface water, groundwater, soil, air, and pollinator comparing to conventional production, measured by the PURE index. The difference between the two pesticide programs was decreasing over time mainly due to the increasing in pesticide use in organic agriculture, consistent with findings in Läpple and Van Rensburg (2011). I found that farm size and farmer experience were correlated with the environmental impacts of pesticide use. Increases in farm size were associated with increases in the environmental impacts of pesticide use in all dimensions. Increases in farmer experience were associated with increases in the environmental impacts of pesticide use to surface water and groundwater, and decreases in the impacts on soil, air, and pollinators.

In essay 2, I investigated pesticide use in organic agriculture. The pesticide portfolio changed for organic growers over the past two decades. Sulfur use became less important and grower started to use new AIs such as spinosad and azadirachtin. The number of organic farm and organic acreage have both increased. However, the organic acreage of large farms increased disproportionately over time, signaling consolidation. The crop mix has also changed with vegetables increasing their share of organic acreage. The consolidation process has consequences for pesticide use as farms with more organic acreage used sulfur and fixed copper pesticides more frequently, holding other variables constant. Sulfur has zero impact on air, as measured by VOC emissions, and copper hydroxide is more toxic to aquatic organisms comparing to other AIs used in organic agriculture. Therefore, the change in the farm size distribution has implications for the environmental impacts of organic agriculture.

Essay 3 presents a theoretical model to explain the change in farm size distribution and specialization in the U.S. agriculture. The model features the evolution of the distribution of crop-specific knowledge through a learning by doing mechanism. The model implies that land will become more concentrated in a smaller number of farms as long as the knowledge evolves faster for operators of those farms. Farmers will choose to produce a subset of crops as they accumulated crop-specific knowledge.

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Appendices

Appendix A

Insecticides and Fungicides Used in Conventional and Organic Agriculture

One way to demonstrate the difference in insecticide and fungicide use between conventional and organic agriculture is to group AIs based on their Mode of Action (MoA). There are 31 MoA groups for insecticides classified by the Insecticide Resistance Action Committee (IRAC) (IRAC, 2020) and 78 MoA groups for fungicides classified by the Fungicide Resistance Action Committee (FRAC) (FRAC, 2020).

In Figure A.1, 18 MoA groups with fewer than 1 million acres treated in 2015 are combined into the category "other". The most used insecticide group in 2015 is IRAC_3, which includes pyrethroids and pyrethrins. The group IRAC_1, organophosphates and carbamates, was widely used in conventional fields but has been largely replaced by other

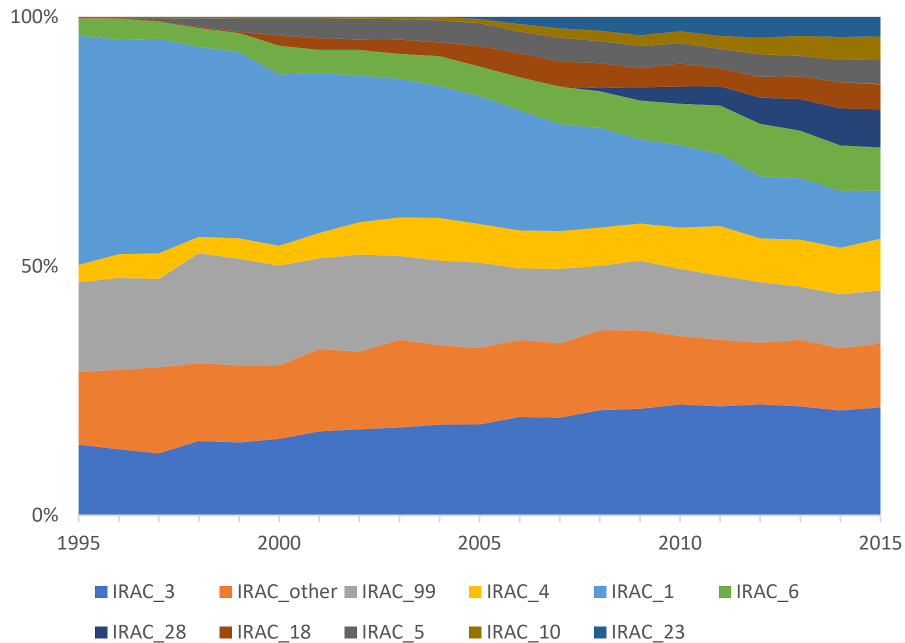

Figure A.1: Share of Insecticide Treated Acreage in Conventional Agriculture by MoAs: 1995 - 2015

AIs because organophosphates are associated with negative health outcomes and have been regulated (Eskenazi et al., 1999, Lerro et al., 2015). Conventional growers have adopted AIs from different IRAC groups. For example, the diamides, the broad-spectrum insecticides in IRAC_28, were quickly adopted after 2008 when chlorantraniliprole and flubendiamide, the two major AIs in the group, were registered with EPA .

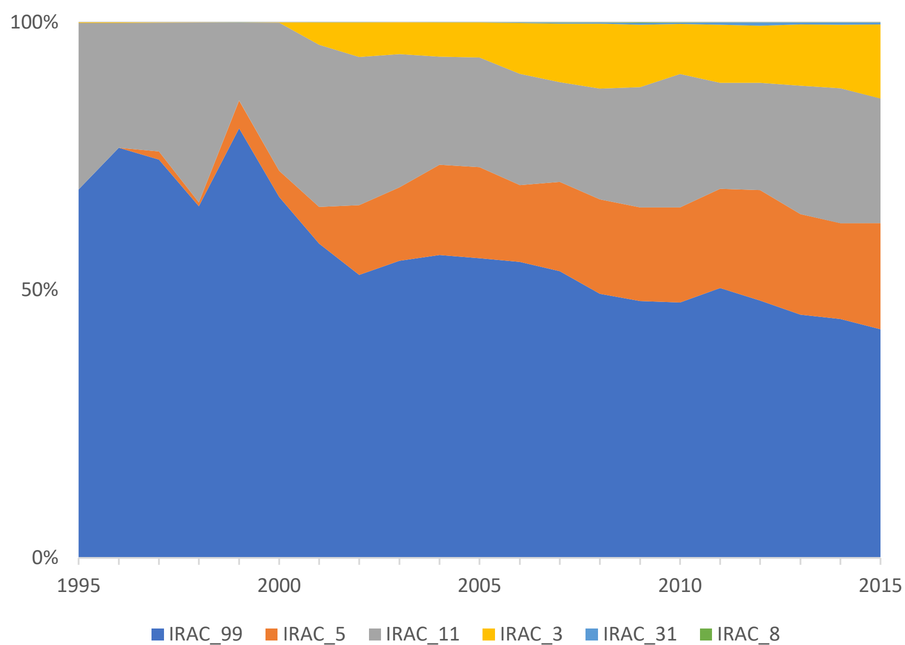

Figure A.2: Share of Insecticide Treated Acreage in Organic Agriculture by MoAs: 1995 - 2015

Organic growers have limited insecticide choices as shown in Figure A.4. AIs with unknown MoA, such as sulfur and azadirachtin, were widely used in organic fields. Other common AIs include spinosad in group FRAC_5, acillus thuringiensis (Bt.) in group

FRAC_11 and pyrethrins in group FRAC_3.

For fungicides, the situation is similar. A variety of MoAs are available for conventional growers as shown in Figure A.3. For organic growers, copper and sulfur, in group FRAC_M01 and FRAC_M21 respectively, accounted for more than half of the treated acreage for fungicides in 2015.

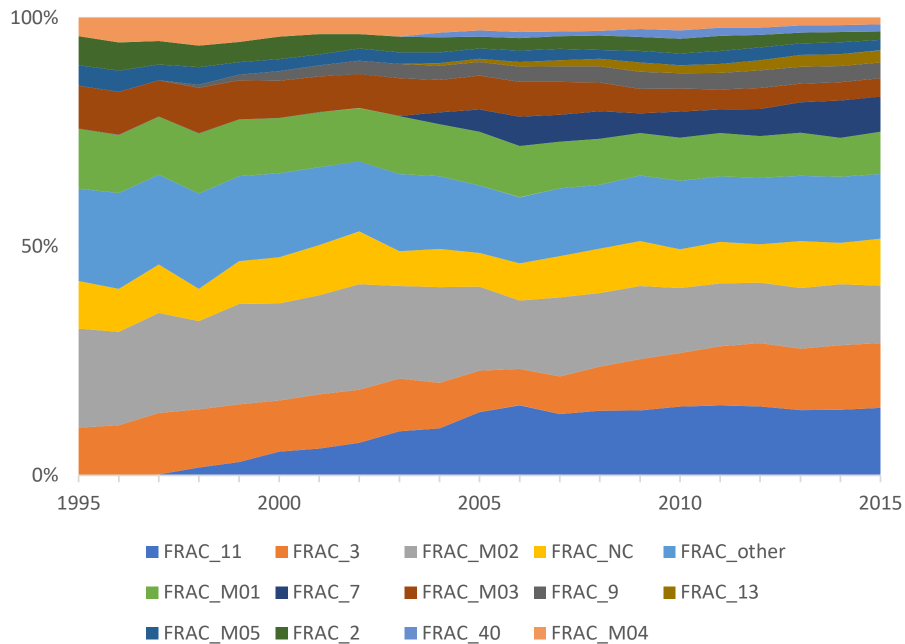

Figure A.3: Share of Fungicides Treated Acreage in Conventional Agriculture by MoAs: 1995 - 2015

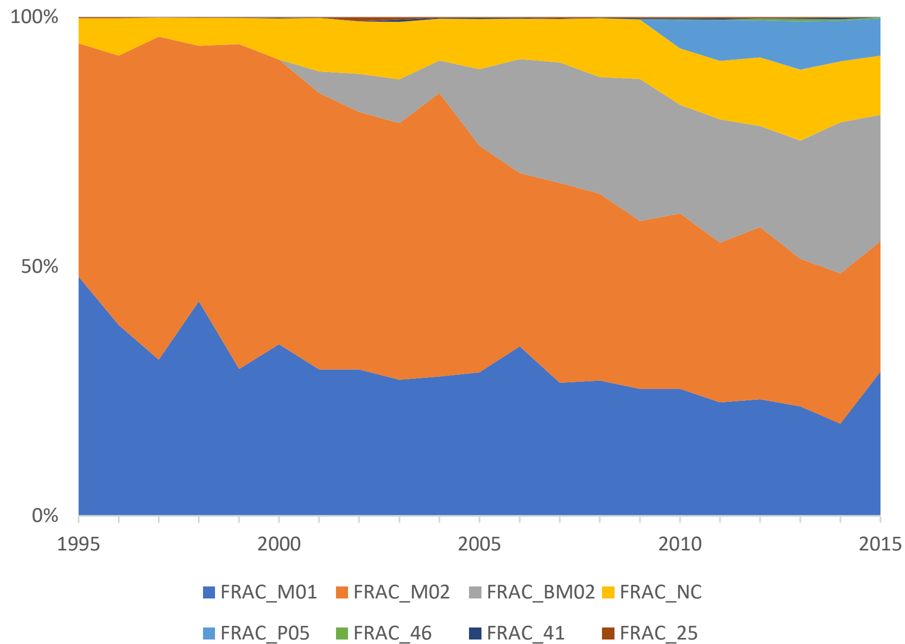

Figure A.4: Share of Fungicide Treated Acreage in Organic Agriculture by MoAs: 1995 - 2015

Appendix B

Active Ingredients in the Microbial Group

Table B.1: Name and Chemical Code for Active Ingredients in the Microbial Group

Active ingredient name	chemical code
bacillus thuringiensis (berliner)	86
encapsulated delta endotoxin of bacillus thuringiensis var. kurstaki i	2337
pseudomonas fluorescens, strain a506	2842
encapsulated delta endotoxin of bacillus thuringiensis var. san diego	3005
bacillus thuringiensis (berliner), subsp. aizawai, gc-91 protein	3843
gliocladium virens gl-21 (spores)	3854
bacillus thuringiensis (berliner), subsp. aizawai, serotype h-7	3856

bacillus thuringiensis (berliner), subsp. israelensis, serotype h-14	3857
bacillus thuringiensis (berliner), subsp. kurstaki, serotype 3a,3b	3858
bacillus thuringiensis (berliner), subsp. kurstaki, strain eg 2348	3859
bacillus thuringiensis (berliner), subsp. kurstaki, strain eg2371	3860
bacillus thuringiensis (berliner), subsp. kurstaki, strain sa-11	3862
streptomyces griseoviridis strain k61	3937
paecilomyces fumosoroseus apopka strain 97	3964
bacillus thuringiensis, var. kurstaki delta endotoxins cry 1a(c) and c	3965
myrothecium verrucaria, dried fermentation solids & solubles, strain a	3966
bacillus thuringiensis (berliner), subsp. kurstaki strain sa-12	3970
trichoderma harzianum rifai strain krl-ag2	3977
bacillus thuringiensis subspecies kurstaki, genetically engineered str	3988
beauveria bassiana strain gha	3993
bacillus thuringiensis, subsp. kurstaki, strain hd-1	4023
bacillus thuringiensis subspecies kurstaki strain bmp 123	4024
bacillus thuringiensis, subsp. aizawai, strain sd-1372, lepidopteran a	5226
bacillus thuringiensis var. kurstaki, genetically engineered strain eg	5325
qst 713 strain of dried bacillus subtilis	5447
coniothyrium minitans strain con/m/91-08	5753
bacillus pumilus, strain qst 2808	5770
bacillus thuringiensis, subsp. kurstaki, strain abts-351, fermentation	5829
bacillus thuringiensis, subsp. israelensis, strain am 65-52	5841
purpureocillium lilaciunum strain 251	5861

bacillus thuringiensis, subsp. aizawai, strain abts-1857	5879
aspergillus flavus strain af36	5887
streptomyces lydicus wyec 108	5891
bacillus subtilis var. amyloliquefaciens strain fzb24	5934
pantoea agglomerans strain e325, nrrl b-21856	5945
ulocladium oudemansii (u3 strain)	5980
chromobacterium subtsugae strain praa4-1	6024
aureobasidium pullulans strain dsm 14940	6026
aureobasidium pullulans strain dsm 14941	6027
burkholderia sp strain a396 cells and fermentation media	6064
bacillus amyloliquefaciens strain d747	6082
trichoderma virens strain g-41	6084

Appendix C

Allowed and Prohibited Ingredients

In general, synthetic substances are prohibited and nonsynthetic substances are allowed in organic agriculture with a few exceptions. The National List of Allowed and Prohibited Substances (National List) specifies 15 categories of synthetic substances that can be used in crop production because they do not contribute to the contamination of crop, soil, or water. Growers are allowed to use them when non-chemical approaches, such as crop rotation or introduction of predators, are not sufficient. Ten categories of natural substances are prohibited in organic crop production due to various reasons including adverse health effects. In addition, substances can be added or removed from the National List through individual petitions. We manually checked ingredients in the PUR database against the National List and petitions to categorized them into as either "allowed" or "prohibited" ingredients.

Two pesticide product lists developed by the Organic Materials Review Institute (OMRI) and the Washington State Department of Agriculture (WSDA) are also included in the list of allowed and prohibited ingredients. OMRI is a non-profit organization that reviews and certifies products for use in organic agriculture in the United States and Canada. Pesticide and fertilizer manufacturers submit applications and associated fees to OMRI for reviews of their products, which are added to the list if they comply with OMRI's organic regulations. Products certified by OMRI can use the OMRI seal on their packaging/labeling and are required to renew their information every year. Currently the OMRI list contains more than 7,500 products that are allowed for use in organic crop and livestock production, processing, and handling. The WSDA list is constructed in the same way with a slightly lower application fee. We cross-referenced product names in the OMRI and WSDA lists with the PUR database product lists to obtain the AI (AI) information in those products. Such ingredients were then categorized as allowed for use in organic production.

Products registered with OMRI or WSDA require an annual renewal and the historical versions of the lists were not available for all years. We are able to locate lists from OMRI for years 2000, 2002-2008, 2012-2016, 2019-2020 and WSDA for years 2017 and 2019-2020, and subjected each of them to this product-matching method. To fill in some of the remaining gaps in the incomplete historical record, pesticide product labels bearing the logos for either the "OMRI Listed For Organic Use," the USDA NOP "For Organic Production" or "WSDA certified" were also added to the list when found.

Because the OMRI- and WSDA-certified products are listed based on voluntary applications, there could be products that are allowed for use in organic production but missing from one or both of the lists. For example, pesticide product Adox^{TM} BCD-25, which contains sodium chlorite, a synthetic substance allowed in organic handling, is registered in WSDA's list but not OMRI's list. This supports my method which considers ingredients, rather than strictly registered pesticide products, to identify organic fields.

Even with information from the National List and the OMRI and WSDA product lists, some ingredients recorded in the PUR database cannot be easily categorized as allowed or prohibited. For example, petroleum-based oils are allowed to use as insecticides in organic agriculture but are not allowed for weed control. Therefore, we cannot categorize its usage as the PUR database did not provide the information about the growers' purpose. However, those ingredients, represent less than 1% of the pesticide applications in organic fields, so they are considered as prohibited ingredients in my analysis as a conservative measure.

Appendix D

Inert Ingredients in Organic Fields

In addition to the pesticide active ingredients (AIs), NOP also includes regulations on inert ingredients. NOP Guidance No. 5008 states that:

> Parties reviewing pesticide product ingredients for compliance with the NOP are advised to use EPA's August 2004 list, minus the revoked inert ingredients, to verify that inert ingredients are listed as List No. 4A or 4B.

However, the PUR database does not report inert ingredients and they are not normally listed on the label. For adjuvant products, all ingredients are considered as inerts and have not been recorded in the PUR database since 2004. The allowed and prohibited AI lists are constructed using the "CHEM_CODE" variable in the PUR database, which makes the strictly AI-based variable incapable of incorporating inert ingredient information. Each "CHEM_CODE" is a unique number assigned to each AI chemical by

California Department of Pesticide Regulation. Products that contain prohibited inert ingredients will be considered as allowed in the AI-based calculation, which overstates organic acreage. However, this is only a minor issue because the product-level OMRI and WSDA certifications are based on the full list of ingredients, including inert ingredients, when products are registered. So my method indirectly addresses this caveat by using the OMRI and WSDA product lists in addition to the allowed/prohibited AI lists.

Appendix E

Organic Fields Identified from the PUR Database by Counties

Table E.1: Organic Acreage, Average Farm Size, and Number of Organic Farms by County: 1995, 2005, and 2015

County	Total organic acreage			Average farm size			Number of organic farms		
	1995	2005	2015	1995	2005	2015	1995	2005	2015
Alameda	67	53	39	22	18	16	3	5	19
Amador	948	516	51	49	62	11	34	13	7
Butte	1,891	2,740	4,849	300	235	334	39	75	110
Calaveras	9	57	36	9	17	7	1	4	9
Colusa	1,475	874	1,491	167	135	328	20	16	28
Contra Costa	282	273	416	31	52	98	38	30	42
El Dorado	19	93	121	4	3	4	5	33	62
Fresno	10,060	16,867	22,424	97	168	197	247	576	713
Glenn	1,108	1,425	1,089	100	46	105	22	110	50
Humboldt	27	62	15	3	8	2	9	12	15
Imperial	5,316	5,203	27,829	362	327	2,322	92	162	1,167
Kern	6,812	11,213	34,495	701	3,621	10,652	168	339	835
Kings	590	2,027	5,844	98	342	535	16	70	115
Lake	92	560	520	18	31	40	5	32	46

Lassen	0	0	77	0	0	77	0	0	1
Los Angeles	2	50	12	1	8	2	4	10	6
Madera	2,713	4,470	6,577	116	112	573	57	97	120
Marin	13	117	116	4	49	97	3	28	25
Mendocino	2,285	3,444	3,310	66	163	121	94	141	155
Merced	2,199	2,829	3,496	124	242	311	61	86	75
Modoc	0	70	246	0	70	61	0	1	4
Monterey	3,160	12,103	27,173	99	581	1,953	115	1,328	4,738
Napa	1,675	2,784	4,375	47	70	90	118	186	355
Nevada	46	67	71	4	9	9	17	13	40
Orange	196	109	109	25	15	19	35	27	59
Placer	41	1,408	2,192	6	450	353	8	32	82
Riverside	578	3,633	6,309	22	820	888	52	166	289
Sacramento	883	165	454	69	17	82	33	17	17
San Benito	645	2,579	4,645	30	752	516	48	513	722
San Bernardino	170	492	5	20	173	1	18	10	5
San Diego	125	686	1,731	3	21	96	51	79	172
San Joaquin	3,863	3,223	1,372	58	75	99	118	127	100
San Luis Obispo	3,736	2,511	6,084	66	92	825	123	149	225

San Mateo	5	23	48	2	8	9	3	8	20
Santa Barbara	1,039	2,859	4,941	56	73	168	181	311	408
Santa Clara	216	562	770	13	67	62	35	88	140
Santa Cruz	397	1,094	2,056	24	170	397	46	168	304
Shasta	332	297	16	47	45	2	10	21	12
Siskiyou	92	157	687	31	31	248	3	10	21
Solano	995	1,027	983	37	98	54	38	25	48
Sonoma	1,185	1,340	4,563	29	62	114	133	216	366
Stanislaus	1,530	2,998	958	64	82	88	47	112	70
Sutter	1,454	2,479	3,842	113	188	342	48	51	58
Tehama	358	1,444	342	31	35	16	22	83	33
Trinity	0	12	1	0	4	1	0	3	1
Tulare	3,752	9,004	7,229	71	105	407	154	380	396
Tuolumne	10	9	47	10	3	18	1	4	5
Ventura	1,765	941	4,880	213	241	228	104	67	411
Yolo	3,255	2,843	5,659	107	143	429	71	81	149
Yuba	250	519	489	40	72	131	10	42	50

Note: Counties without any organic acreage in 2015 are excluded.