How Effective is Pesticide Regulation? Evidence from the Groundwater Protection Program

Scott Somerville & Brittney Goodrich*

December 17, 2024

Abstract

When market-based instruments are impractical for addressing agricultural non-point source pollution, economists recommend regulations that incorporate farm management practices and environmental services to mitigate pollution. In this paper, we examine the adjustments farmers make to their pesticide programs in response to a policy delineating two types of regulated regions that differ in the required practices for pesticide usage based on local environmental conditions. Empirically, this study addresses the Groundwater Protection Program, which created a natural experiment through abrupt and uneven changes in the regulations governing the application of seven pesticides. Utilizing twenty-five years of field-level data, we estimate the program's impacts on the use of regulated active ingredients and the consequent environmental effects in the perennial crops almonds, citrus, and grapes using a difference-in-differences regression framework. Our analysis reveals that the program led to meaningful reductions in the use of regulated active ingredients in fields in regulated regions, but the effects varied substantially across crops. To test if growers replaced regulated ingredients with alternative pesticides, we examine the impact of the program on the environmental impact—an index that considers the potential harm of pesticides to water systems, human health, and wildlife—of alternative active ingredients per planted acre and find no significant effects. In a final set of regressions, we use the environmental impact of regulated and alternative active ingredients per planted acre as our dependent variable and find that the program led to significant reductions in citrus orchards and grape vineyards but no change in almond orchards.

*Scott Somerville is a Ph.D. candidate in the Department of Agricultural and Resource Economics at the University of California, Davis, and Brittney Goodrich is an Assistant Professor in the Department of Agricultural and Consumer Economics at the University of Illinois Urbana–Champaign. Scott Somerville is the corresponding author and can be reached at ssomerville@ucdavis.edu

1 Introduction

Pollution from pesticide residues has troubled citizens for decades (White, 1933) due to their link to adverse health outcomes (Qiao et al., 2012; Larsen, Gaines, and Deschênes, 2017) and environmental degradation (Grogan and Goodhue, 2012). Among the most pressing environmental issues posed by pesticide usage is the contamination of water supplies. Research has extensively documented the contamination of water resources, especially groundwater, by pesticides in the United States (U.S.) and elsewhere (Gilliom et al., 2006; Bexfield et al., 2020).

Identifying the source of pesticide contamination in groundwater is particularly difficult because of the long travel time between emission and detection and the indeterminate flow paths of water bodies and their contaminants. Environmental features like permeable soils, high rainfall, and shallow water tables increase groundwater susceptibility to contamination (Gilliom et al., 2006) and influence the external cost of pesticide sprays. Furthermore, the human and environmental costs of pesticides depend on the quantity of chemicals used, the application method and timing relative to other cultural practices like cultivation and irrigation, and the local population of people and wildlife. However, natural and management factors combine to make field-level measurements of pesticide emissions impractical and market-based instruments like taxes infeasible. Consequently, governments typically resort to uniform interventions, like chemical bans (Anderson, Opaluch, and Sullivan, 1985; Carter et al., 2005; Butler, 2018).

Ideally, policy instruments should vary according to the characteristics that influence pesticide emissions, like local environmental conditions and agricultural management practices (Zilberman and Millock, 1997). The challenge lies in achieving this variation without incurring prohibitive administrative costs. Zoning—whereby regulators target vulnerable regions with input controls—offers a potential compromise between uniform regulation and field-level controls (Falconer, 1998).

In 2004, the California Department of Pesticide Regulation (CDPR) implemented a zoning program called the Groundwater Protection Program to conserve groundwater resources from pesticide contamination. In total, the program designated 2.4 million acres of land as Groundwater Protection Areas (GWPAs), equivalent to 2.4% of California land area (USCB, 2024) and 10% of crop and ranch land (CDFA, 2023).[1] In designing the program, regulators and scientists used environmental characteristics to identify groundwater regions vulnerable to pesticide contamination via two pathways. The CDPR designated areas as either leaching GWPAs, where residues move downward in percolating water or runoff GWPAs, where residues move offsite to sensitive sites such as drainage wells. Inside GWPAs, growers choosing to apply any of the regulated active ingredients simazine, diuron, norflurazon, bromacil, atrazine, prometon, or bentazon, all of which are herbicides, must comply with certain conditions, including costly cultural practices, restrictions on application and irrigation timing, and obtaining a permit from their County Agricultural Commissioner. The rules for applying a regulated ingredient to fields differ between runoff and leaching GWPAs.

Chemical analyses of groundwater collected annually in 2000–2012 from 67 domestic wells in GWPAs reveal decreasing concentrations of simazine, diuron, and bromacil, which the researchers attribute to changes in pesticide use resulting from the Groundwater Protection Program (Troiano et al., 2013). However, the study falls short of comparing groundwater contaminant concentrations in GWPAs and non-regulated regions to provide the appropriate counterfactual trends required for causal inference.

Using reduced-form techniques, we exploit the natural experiment created by the Groundwater Protection Program to study the extent to which almond, citrus, and grape growers adjust their pesticide regime in response to the program, including differences in leaching and runoff areas and the associated environmental impacts. To this end, we leverage twenty-five years of Pesticide Use Reporting data, a database of California agricultural pesticide applications, and exploit changes in pesticide usage within GWPAs compared to changes outside GWPA regions in a difference-in-differences regression framework.

[1]Data limitations prevent us from calculating the share of cropland inside GWPAs.

We analyze the impacts of the Groundwater Protection Program on four outcomes. The first is a binary outcome indicating whether a field was treated with a regulated active ingredient.[2] The second analysis explores the program's consequences on human health and environmental quality dimensions using the environmental impact of regulated active ingredients, which we calculate using the Environmental Impact Quotient (EIQ)—an aggregate measure of the potential harm posed by an active ingredient to farm workers, consumers, fish, birds, beneficial insects, and groundwater (Kovach et al., 1992) providing a measure of the hazard inherent to an active ingredient. We calculate the environmental impact by multiplying the pounds of active ingredient per planted acre by the corresponding ingredient EIQ, then summing over the active ingredients used at the field level.

While the Groundwater Protection Program aims to safeguard groundwater, the fact that it targets a handful of active ingredients means that growers may switch to other chemicals with potentially worse outcomes for human and environmental health. Thus, our third analysis examines the impact of the program on the environmental impact of alternative active ingredients. Lastly, we examine the program's effect on the environmental impact of regulated and alternative active ingredients.

To address the external cost of diffuse pesticide pollution, governments have introduced non-market solutions to address some environmental problems of pesticides, such as regulatory reviews of new products (Zilberman and Millock, 1997), Integrated Pest Management (IPM) programs (Burrows, 1983), grower education (Goodhue, Klonsky, and Mohapatra, 2010; Jacquet, Butault, and Guichard, 2011; Zhou et al., 2020) and chemical bans (Anderson, Opaluch, and Sullivan, 1985; Carter et al., 2005; Butler, 2018) with varying degrees of effectiveness (Lee, den Uyl, and Runhaar, 2019). Indeed, economists have shown that spatially targeted policies provide economic advantages over uniform instrumentation in a number of agricultural settings, including externalities from groundwater pumping (Kuwayama and Brozović, 2013), nitrate leaching (Mapp et al., 1994; Martínez and Albiac, 2006), nutrient

[2]We use field as a general term for almond orchards, citrus groves, and grape vineyards.

runoff (Lankoski and Ollikainen, 2003), and soil carbon sequestration (Antle et al., 2003). However, evaluations of spatially targeted policies typically integrate field-level characteristics and management, details that are expensive to monitor, verify, and administer. Zoning offers a practical solution by delineating areas with relevant environmental characteristics.

Our study contributes to the small but growing literature on input zoning, whereby regulators restrict inputs on land with local features like permeable soils and groundwater wells (Thomsen and Thorling, 2003; Thomsen, Søndergaard, and Sørensen, 2004), rivers (Sieber et al., 2010), urban developments and highways (Goodhue, Schweisguth, and Klonsky, 2016), and schools (Goodhue et al., 2020). The Groundwater Protection Program differs from most other zoning policies, which tend to ban pesticide use in the defined areas and often fail to account for local environmental characteristics.

This paper also contributes to the growing literature on practice-based regulations (Ribaudo, 2008; Shortle and Horan, 2013; Zhang, 2018). Motivated by a ban on the pesticide Alicarb, Anderson, Opaluch, and Sullivan (1985) develop a model for determining field-level pesticide management practices for meeting drinking water standards and show that chemical bans, which are common in many agricultural regions (Donley, 2019), remove the opportunity for adjustments in pollution mitigation while keeping food affordable and might not be necessary to achieve drinking water standards. Furthermore, regulating a limited set of pesticides might lead to perverse outcomes. In one relevant example, Anderson et al. (2018) suggests that strict monitoring of organophosphate pesticides in California waterways led to toxic concentrations of the alternative active ingredient imidacloprid—a neonicotinoid.

Our study contributes to the zoning and practice-based regulation literature by providing insights into the extent to which growers in leaching and runoff GWPAs differ in their response to the program. Our findings indicate that the Groundwater Protection Program markedly reduced the use of regulated active ingredients, resulting in a reduction in the probability that growers treated leaching (resp. runoff) GWPA fields by 10 (resp. 11) percentage points in almond orchards, 5 (resp. 11) percentage points in citrus orchards, and 19 (resp. 13) percentage points in vineyards. The reductions in active ingredient use translate to a 73% reduction in the associated environmental impacts in almond orchards in leaching GWPAs and a 54% reduction in the associated environmental impacts in almond orchards in runoff areas. In grape vineyards in leaching and runoff areas, the program led to a 44% and 39% reduction in the environmental impact of regulated pesticides, respectively. In citrus groves, the program led to a 41% reduction in runoff GWPAs, but we found no significant effect in leaching areas. We also find evidence of within-farm spillover effects in citrus farms where growers with orchards in GWPAs reduced the environmental impact of regulated active ingredients by 14% in their fields outside GWPAs. But we find no evidence of within-farm spillovers in almonds and grapes.

Another key contribution is our assessment of the unintended outcomes of the program by switching to alternative chemicals. By analyzing the environmental impact of alternative active ingredients per planted acre, we find no significant change in almond orchards, citrus groves, and grape vineyards resulting from the program. Examining the program's impact on the environmental impact of herbicides (regulated and alternative active ingredients), we find that the effects varied by crop. In grape vineyards, we observed a 15% and 11% drop in the environmental impact of herbicides per planted acre in leaching and runoff GWPAs, respectively. In citrus, the program led to a 19% drop in the environmental impact of herbicides used in runoff GWPAs but had no effect among groves in leaching areas. We find no significant effect in almond orchards.

Policy reforms are vital to meeting environmental quality goals (Shortle and Horan, 2013). Consequently, the status quo of agricultural exemptions from environmental regulations is slowly changing (Zhang, 2018). Examining existing agricultural environmental regulations can provide vital insights for the future design of regulations. The Groundwater Protection Program offers a unique opportunity to study the grower response to a mandatory policy over sixteen years. This paper provides critical insights into growers' responses to a pesticide policy to prevent environmental degradation. These insights will help inform future regulatory efforts and enhance the performance of interventions designed to protect environmental quality in other regions.

The remainder of the paper is structured as follows. The next section discusses the regulatory background. Next, we describe the data sources, followed by the econometric methods. Subsequently, we present our main findings supported by several robustness checks. The last section concludes the paper.

2 Background

Since the passage of the Federal Water Pollution Control Act Amendments of 1972 (Clean Water Act), legislators have implemented a patchwork of regulations to address groundwater pollution from agricultural sources. However, federal water quality laws have largely passed responsibility for developing non-point source programs to state governments (Ribaudo, 2008), and clean water legislation typically target point sources, primarily factory and sewage treatment discharges and confined animal feeding operations such as large dairies. As a result, many water quality problems remain.

In the following subsections, we introduce the California legislation that led to the establishment of the Groundwater Protection Program, then discuss the program's features and relevance to almond, citrus, and grape industries.

2.1 The Pesticide Contamination Prevention Act

The Pesticide Contamination Prevention Act, passed by the California legislature in 1985, directed the California Department of Pesticide Regulation (CDPR) to identify pesticide active ingredients present in groundwater, pinpoint pesticide use cases that pose a risk to groundwater, and regulate those active ingredients to mitigate or prevent further pollution.[3] Following their mandate, the CDPR established the Groundwater Protection Lists (a) and

[3] The Pesticide Contamination Prevention Act extended the Farm and Agriculture Code to include sections 13141–13152. For further details, see https://www.cdpr.ca.gov/docs/emon/grndwtr/atrazine.htm

(b).[4]

List (a) comprises active ingredients detected in groundwater regulated by CDPR to mitigate groundwater contamination and prevent further pollution of critical water resources. Atrazine was the first active ingredient added to List (a) in 1987, leading to use restrictions in regions where it was detected (CDPR, 2024). The regions, called Pesticide Management Zones, follow the approximately one-square-mile section boundaries mapped in the Bureau of Land Management Public Land Survey System grid. In most cases, growers could continue to use List (a) chemicals if they agreed to follow specific management practices. By 1997, List (a) comprised seven herbicides: atrazine, bentazon, bromacil, diuron, norflurazon, prometon, and simazine.[5] Henceforth, we refer to the List (a) pesticides as regulated active ingredients. The seven regulated active ingredients include several products of national importance. In particular, atrazine and simazine were the most frequently detected pesticides in a national survey of surface and groundwater systems (Gilliom et al., 2006) and among the most widely used pesticides (in terms of pounds of active ingredient) in the U.S. (Weiben, 2021). By 2001, the CDPR extended the number of Pesticide Management Zones to 489 sections.

List (b) includes pesticides that CDPR deems to be a high risk for water contamination.[6] The CDPR monitors groundwater for List (b) active ingredients and, if detected, reviews the pesticide's use to determine whether it should be banned, added to List (a), or allowed to be used as currently permitted.

2.2 Groundwater Protection Program

In May 2004, the CDPR implemented the Groundwater Protection Program, converted the existing Pesticide Management Zones to Groundwater Protection Areas (GWPAs), and added 3,129 more sections to the inventory of regulated regions, taking the total number of

[4]The current Groundwater Protection Lists are printed in Title 3 of the California Code of Regulations Section 6800 (a) and (b).

[5]It exempts products with less than 7% diuron applied to foliage (mostly cotton defoliants).

[6]Section 6800(b) pesticides exceed certain thresholds for water solubility, soil adsorption, hydrolysis half-life, aerobic soil metabolism half-life, and anaerobic soil metabolism half-life.

GWPAs to 3,618.[7] The CDPR worked with environmental scientists to identify two pathways through which pesticides contaminate groundwater. They found that pesticides mainly enter groundwater in areas with coarse-textured soils by leaching residues from surface applications (Troiano et al., 2013). In areas with low-permeability soils, pesticides are carried by runoff water to sensitive sites such as abandoned groundwater wells, which provide a direct route to the groundwater. Using soil and groundwater data, CDPR mapped regions vulnerable to leaching and runoff and designated these as GWPAs. As shown in Figure 1, GWPAs are spread across the state, with most located in the San Joaquin Valley, the heartland of California agricultural production.

The Groundwater Protection Program prohibits the application of the seven regulated active ingredients in GWPAs unless the grower obtains a Restricted Materials Permit from their County Agricultural Commissioner's office specifying the management practice option that the grower agrees to adhere to.[8] Table 1 describes the GWPA categories with examples of management practices for regulated ingredients.

In leaching GWPAs, the percolation of pesticides through coarse-textured soils is the primary concern of regulators, and growers face constraints on the cultural practices related to irrigation management when applying a regulated active ingredient. Leaching GWPAs management option (1) in Table 1 is not relevant to citrus, almonds, or grapes because they are not planted in furrows, and growers typically apply regulated ingredients along tree and vine rows where irrigation water is applied. Leaching option (2) is extremely restrictive because almost all citrus, grapes, and almonds are irrigated (USDA, 2004), and San Joaquin Valley growers typically irrigate orchards, groves, and vineyards in seven to eight months of the year (Haviland et al., 2019; Murdock, Goodrich, and Sumner, 2022; Kallsen et al., 2021). The extent to which growers exceed crop irrigation requirements by a factor of 1.33, as in option (3), is unclear.

[7]The CDPR added a further 122 GWPAs in 2020.

[8]Additional statewide restrictions apply to pesticides applied in canals, ditches, and artificial recharge basins; these mostly apply to non-agricultural landscape management practices.

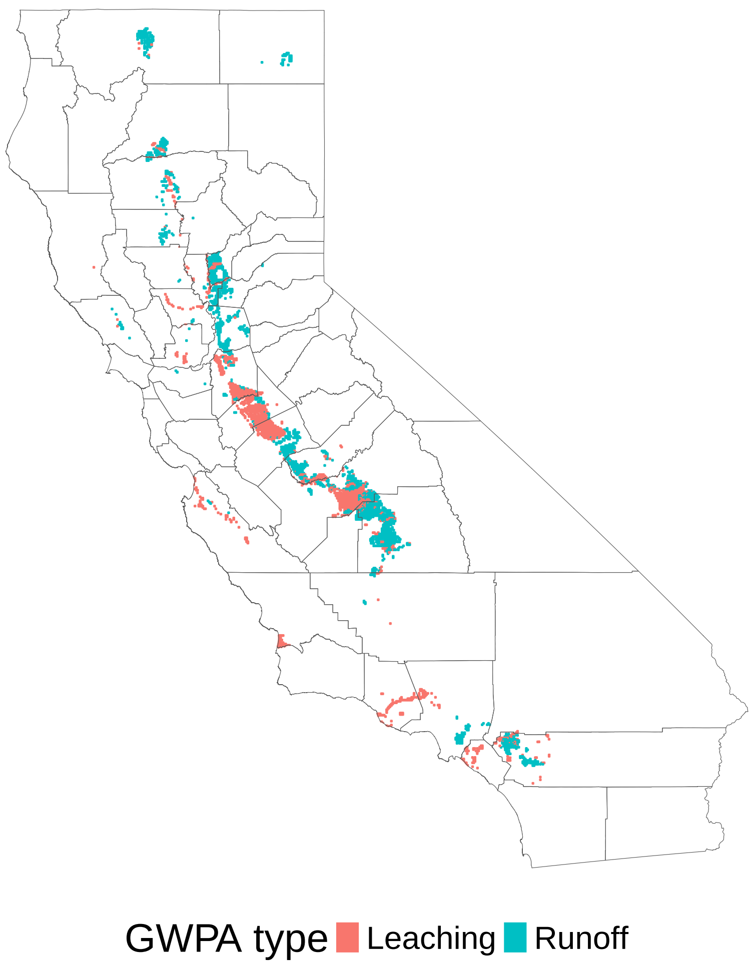

Figure 1: Groundwater Protection Areas in 2005

Note: each square represents the location of an approximately one square mile section designated as a GWPA.

In runoff GWPAs, growers face four management options when using a regulated ingredient. Runoff option (1) in Table 1 requires growers to apply regulated ingredients in low rainfall months. However, the regulated active ingredients are all pre-emergent herbicides and only kill germinating plants. By April, enough weeds will have typically germinated to create a canopy that prevents chemicals from reaching the soil, lowering the efficacy of the spray. Option (2) requires costly infrastructure in most cases. In management options (3) and (4), growers can comply with the program by incorporating the spray into the land surface, where chemicals bind with soil particles to prevent runoff. However, land tilling around established trees and vines is a costly practice. Option (4) also allows growers to incorporate the ingredients into the soil surface by applying irrigation water by drip or micro-sprinkler. This might suit growers who can coordinate a regulated ingredient application with October irrigation. October is typically the last month almond, citrus, and grape growers irrigate fields before the dormant fall and winter months (Haviland et al., 2019; Murdock, Goodrich, and Sumner, 2022; Kallsen et al., 2021).

Table 1: Groundwater Protection Area Overview

GWPA category	Category description	Management practice options
Leaching	Pesticide residues and their breakdown products move from the land surface downward through the soil with percolating water to reach groundwater. Soils in these areas are coarse with relatively rapid infiltration rates.	(1) Growers can apply pesticides to the planting bed above the level of irrigation water in the furrow so it has no contact with leaching irrigation water. (2) No irrigation water is applied for six months. (3) The volume of irrigation water divided by the crop irrigation requirement is less than 1.33 for six months.
Runoff	Pesticide residues and their breakdown products are carried in runoff water through direct routes to groundwater, such as dry wells or drainage wells, poorly sealed production wells, soil cracks, or areas where leaching can occur. Soils in these areas may have a hardpan layer and/or low infiltration rates.	(1) The pesticide is applied between April 1 and July 31. (2) All irrigation runoff and all precipitation on and drainage through the field are retained onsite for six months after application (the retention area on the field should not have a percolation rate of more than 0.2 inches per hour). (3) The soil is disturbed within seven days before pesticide application by using a disc, harrow, rotary tiller, or other mechanical method. (4) The pesticide is incorporated on at least 90% of the area treated within seven days after pesticide application by a mechanical method or by low-flow irrigation (1/4 to 1 inch of water).

Source: Adapted from Cal. Code Regs. Tit. 3, §6487.4 and §6487.5

2.3 Weed Management in Almond, Citrus, and Grape Production

We apply our econometric framework to data from almonds, citrus, and grapes for four key reasons. First, they represent the leading crops by the value of production throughout the past two decades and occupy a large share of the cultivated cropland (CDFA, 2003; CDFA, 2022).[9] Second, regulated active ingredients are important herbicides in the growers' weed management toolbox, as measured by the acres treated with regulated and alternative active ingredients in 1996–2004 (see Appendix Table A1). In particular, citrus growers treated more acres with simazine and diuron than most other active ingredients, except for glyphosate, oxyfluorfen, and paraquat—three alternative herbicides. Third, almond, citrus, and grape crops represent key markets for the regulated active ingredients bromacil, diuron, norflurazon, and simazine, as shown in Appendix Table A2. Specifically, citrus growers use nearly all of the bromacil applied in pre- and post-program years. Additionally, citrus orchards are the dominant market for diuron products, almonds are the top market for norflurazone, while grape, citrus, and almond growers apply 39%, 35%, and 10% of the simazine, respectively. Lastly, concentrating on perennial crops allows us to track fields over time.

To further contextualize the Groundwater Protection Program and the relevance of herbicide restrictions to growers, it is worth highlighting some key facts about weed management common to almond, grape, and citrus cultivation. Weeds compete with crops for nutrients and water. They also block irrigation systems, provide habitat for insect pests and diseases, and impede other agricultural practices and harvest. The presence of weed seeds in the soil and seeds deposited in fields by the wind or animals makes weed management a perpetual challenge. To prevent infestations and eliminate established weeds, growers may use a combination of cultural and chemical practices, many of which are consistent with Integrated Pest Management programming. Examples include monitoring fields to identify weed species

[9] Grapes and almonds ranked as the second and third largest crops, respectively, in terms of farm receipts in 2003 and 2022 (CDFA, 2003; CDFA, 2022). Oranges—the top citrus crop—were the fourth largest commodity in 2022. Other major citrus crops include lemons and grapefruit.

and locations and target plants with the appropriate herbicide at the correct time. Mowing weeds before seed set prevents their spread and kills some species. Irrigation management can also play a role. Allowing the top two inches of soil to dry out between irrigation applications limits weed establishment (Grafton-Cardwell et al., 2003) and preventing water pooling in fields eliminates an ideal environment for weed growth.

3 Data

The CDPR began mandatory reporting of agricultural pesticide applications in 1990. These data are published in the Pesticide Use Report (PUR), which we use as our primary data source. This detailed database includes over thirty variables at the field level, including the active ingredients, treated acres, planted acres, crop, and the date of each application.[10] Combining a unique grower number, field name, and crop provides a unique field identifier, allowing us to track pesticide use on each field over time.

We limit our analysis to the years 1996 through 2020 due to inaccurate reporting of key variables in the early years of PUR. Similarly, we exclude Monterey County fields from our analysis due to persistent data issues.[11] Moreover, the variable for planted acres contains numerous inconsistent observations. To address this issue, we utilize the maximum treated acres within a field each year to obtain a more accurate estimate of field size and refer to this measurement as planted acres.

In the raw data, we observe several entries with extreme pounds per acre when dividing the quantity of active ingredients by the treated acre. We anticipate a low variance in the application rate per treated acre, as growers typically adhere to the product label's recommended application rate. To address this issue, we winsorize the data, which involves replacing application rates below the first percentile with values equal to the first percentile

[10]Growers may treat a portion of the field during a pesticide application. Therefore, the treated acres can be less than or equal to the field size—called planted acres in the PUR data.

[11]In 2003, Monterey County contained about 4% of California harvested grape acres, 0.4% of citrus acres, and no almond orchards (California Department of Food and Agriculture, 2004)

and setting application rates above the 99th percentile equal to the 99th percentile for each product. Visually appraising the data and using our best judgment, we believe that the extreme pounds per acre are due to misreported quantities of product. Therefore, we recovered a reliable quantity of active ingredients by multiplying the winsorized pounds per acre by the reported treated acres.

We include orange, lemon, tangerine, grapefruit, lime, tangelo, and pomelo crops in the citrus category. We focus on the aggregate citrus category because the plant varieties require similar herbicide management strategies (Grafton-Cardwell et al., 2003, 2019). Similarly, grapes include table, raisin, and wine grapes, which require similar weed management practices (Bentley et al., 2003; Haviland et al., 2015).

Pesticide Management Zones (PMZs)—the precursor to the Groundwater Protection Program—predate our available data and introduce a potential source of bias to our econometrics. We exclude growers with fields inside PMZs from the econometric analysis to overcome the potential bias that the PMZ program introduces.

We use two additional datasets from government sources. First is a spatial database of the geographic coordinates of section boundaries mapped by the Bureau of Land Management, called the California Public Land Survey System, which we match to pesticide use data using the section code. Second is a database of sections in GWPAs from the CDPR.

A small proportion of fields lie inside the CDPR-defined GWPA category called leaching/runoff.[12] In the combined leaching/runoff GWPA, growers that wish to use a regulated active ingredient must adopt management practices from the leaching and runoff options listed in Table 1. To include these observations in the analysis, we recode them as leaching GWPAs because leaching areas have a more stringent set of restrictions, and most leaching/runoff GWPAs are located close to leaching GWPAs.

[12] About 1% of almond orchards, 0.3% of citrus groves, and 0.4% of grape vineyards lie inside leaching/runoff GWPAs in our effective sample of fields with observations in the pre-program and post-program periods.

3.1 Definition of Herbicide Application Year

The CDPR began enforcing GWPA rules in May 2004 (Troiano et al., 2013), which coincides with the middle of the almond and grape growing season and the start of the summer months when growers do not typically apply regulated active ingredients. We find that growers typically apply pre-emergent herbicides—herbicides applied to soil and kill germinating plants—including all regulated ingredients during the fall and winter months, as shown in Appendix Figure A2. This finding is corroborated by the University of California's Cost Studies, which detail typical weed management practices (Haviland et al., 2019; Kallsen et al., 2021; Murdock, Goodrich, and Sumner, 2022). Therefore, we define annual periods from October 1st through September 30th to capture a typical regulated herbicide application season for almonds, citrus, and grapes. This definition means that almost all regulated active ingredient applications in the 2004 season occurred before the program enforcement in May. Thus, we use October 2003 through September 2004—the year before the regulation—as the reference year in the regressions and name the period 2004.

Post-emergent herbicides—sprayed on the leaves of growing weed plants—like glyphosate applied in the summer months before almond and grape harvest challenge our econometric estimation of the program impact on the environmental impact of alternative herbicides. For regressions involving alternative herbicides as the outcome variable, we estimate regressions with annual periods defined as June through May as a robustness check.

3.2 Identifying Alternative Active Ingredients

Understanding growers' use of alternative herbicides involves identifying active ingredients that target similar weeds as regulated chemicals. We use the manufacturers-specified target weed descriptions published by the CDPR to address this analytical challenge. Our list of 95 alternative herbicide active ingredients share at least one target weed species with a regulated chemical. Many alternative ingredients are minor, and we present the top 27 chemicals in Appendix Table A1. The main alternative herbicides are glyphosate, oxyfluorfen, paraquat, oryzalin, and 2,4-d. These top alternatives appear in the University of California Integrated Pest Management Guidelines for almonds, citrus, and grapes, further supporting our list of alternative active ingredients (Haviland et al., 2015, 2017; Grafton-Cardwell et al., 2019).

During the pre-program period of 1996–2004, citrus, grape, and almond growers had access to several alternative chemicals, including some recommended in the University of California Integrated Pest Management (UC IPM) guidelines—a public resource used by pest control advisers, growers, and farm advisers. The UC IPM guidelines from around 2003 recommend 12 active ingredients for weed control in almond orchards (Zalom et al., 2002), 18 active ingredients for weed control in citrus groves (Grafton-Cardwell et al., 2003), and 15 active ingredients for weed control in grape vineyards (Bentley et al., 2003). Additionally, as shown in Appendix Table A1, growers use a long list of alternative herbicide chemicals, with most ingredients used on a small proportion of treated acres. Of course, the number of alternative herbicide products is more nuanced than the UC IPM guidelines and data indicate because regulators approve pesticide formulations for specific crops rather than approving active ingredients.

3.3 Aggregation of Pesticides: Environmental Impact Quotient

Pesticides are difficult to aggregate. The heterogeneity of pesticide qualities, such as formulation with other chemicals and efficacy, means that the manufacturer's recommended quantity of active ingredient applied per acre can vary by an order of magnitude or more between two chemicals targeting similar pests. In addition, the quantity of product is inadequate for evaluating the environmental consequences of pesticide practices (Barnard et al., 1997). For these reasons, summing over the pounds of chemicals used provides an inappropriate single measure of pesticide quantities (Mullenn et al., 2005; Grogan and Goodhue, 2012).

To overcome these issues, we use the Environmental Impact Quotient (EIQ) to aggregate active ingredients and capture the potential environmental harm from a chemical. The EIQ is an average of three components: farm worker EIQ, consumer EIQ, and ecological

EIQ (Sambucci et al., 2019). The formula defining farm worker EIQ comprises indices (one through five) rating the ingredient's dermal toxicity multiplied by an index rating the chemical half-life on the plant surface. The consumer EIQ is defined similarly but combines an index rating the chemical's potential to leach into drinking water while the ecological EIQ incorporates indices of bee, bird, and fish toxicity. Each active ingredient in our study has an associated EIQ, and larger EIQs are associated with more environmental harm.

We multiply the EIQ by the pounds of the regulated active ingredient, then sum over the active ingredients, and divide by the planted acres to produce a measure of environmental impact per planted acre at the field level according to the following formula:

$$Environmental\ \ impact_{it} = \frac{1}{planted\ \ acres_{it}} \sum_{i} EIQ_i lb_{ait}$$

where a, i, and t denote the active ingredient, field, and year, respectively, and lb represents the annual pounds of active ingredient applied to the field. We follow a similar calculation for alternative (non-regulated) herbicides. The EIQ for relevant herbicides can be found in Appendix A Table A1.

4 Econometric Methods

We estimate several regression models based on the difference-in-difference framework to analyze the impacts of GWPAs on four outcomes: (1) the probability that a grower sprays a field with a regulated active ingredient within a year, (2) the environmental impact of regulated active ingredients per planted acre, (3) the environmental impact of alternative active ingredients per planted acre, and (4) the environmental impact of regulated and alternative herbicide active ingredients per planted acre. We consider fields as sprayed with a regulated active ingredient if they receive any amount of regulated active ingredient within the year. This definition means that if one acre of a ten-acre field is treated with a regulated active ingredient, we count the field as treated. Similarly, if a grower sprays the whole field multiple times with different regulated active ingredients, we count it as treated.

We use a fixed effects linear probability model using field, year, and county-by-year controls to evaluate the impact of GWPAs on the likelihood of growers using a regulated active ingredient. For the environmental outcomes, we employ a fixed effects Poisson pseudo maximum likelihood estimator. Additionally, we expanded the two-period difference-in-difference regressions to event study models with one treatment cohort to measure how treatment effects varied by year, thereby revealing how growers responded to the policy over time.

Given our lengthy twenty-five-year panel, growers plant new almond orchards and remove old ones, and some orchards change hands. Removing old orchards and changes in ownership lead to attrition in our sample and an unbalanced panel. It is a similar story for citrus groves and vineyards.[13] We assume that attrition is unrelated to GWPA treatment because weed management is a small share of the production costs, and growers face other opportunities to adapt to the program at a lower cost compared to removing the established perennial crop or selling the field.[14]

The Groundwater Protection Program is exogenous to trends in pesticide use in individual fields. Additionally, we assume that unobservable field-level time-varying factors do not affect GWPA assignment. Therefore, in the absence of the program, the treatment and control groups adjust their pesticide use in similar ways, and fields outside GWPAs within the same county serve as an appropriate counterfactual. We test for parallel pre-trends and present these results in section 5.3. In addition, we employ the Stable Unit Treatment Value Assumption (SUTVA), which ensures that the analysis adequately distinguishes between treatment and control groups. Growers with some fields inside and others outside GWPAs may violate SUTVA if the grower alters their pesticide practices across the whole farm in

[13] The life of almond orchards and vineyards is around 25 years while a typical orange and lemon grove will last for 40 years (Haviland et al., 2019; Kallsen et al., 2021; Murdock, Goodrich, and Sumner, 2022).

[14] Weed management is about 1% of almond production costs (operating and overhead), 1.5% of orange costs, and 2% of of the cost to produce wine grapes (Haviland et al., 2019; Kallsen et al., 2021; Murdock, Goodrich, and Sumner, 2022).

response to the program. To address concerns about potential violations of this assumption, we add controls for within-farm spillover effects in some of our regressions.

To further strengthen our identification strategy, we include county-by-year fixed effects. These controls address concerns regarding time-varying county-specific bias from weather and local administration of the Groundwater Protection Program. Weather is difficult to control econometrically in the current setting because growers face a broad window of opportunity—six months or more—to apply herbicides. Therefore, average or cumulative weather does not adequately reflect weed growth or practical issues like field access. Pre-emergent and post-emergent herbicides further complicate the identification of a relevant spraying window and associated weather variables. Furthermore, county agricultural commissioners administer the program by issuing permits with designated alternative management practices within GWPAs. During our long study period, the relative stringency and convenience of permitting across counties might change over time. Indeed, during the study period, some counties introduced permitting requirements and other restrictions on alternative herbicides, such as paraquat and 2-4D, due to local environmental and health concerns (Zalom et al., 2002; Grafton-Cardwell et al., 2003; Bentley et al., 2003). In our econometric models, the county-by-year fixed effects absorb the variation from regulatory shocks common to all growers in a county.

4.1 Difference-in-Differences

To construct the base regression equations, let Y_{it} denote the outcome variable for field i in year t and G_{it} denote the program treatment variable that equals one when field i is inside a GWPA in 2005 onwards and zero otherwise. Additionally, the symbol γ_i captures field fixed effects, τ_t denotes the year effect common across fields, δ_c denotes county fixed effects, and ε_{it} represents the idiosyncratic error. This notation is common to the econometric models specified below.

The linear probability model, given in Equation (1), contains the dependent variable Y_{it}, which equals one if the grower applies one or more regulated active ingredients to field i in year t.

$$P(Y_{it} = 1|G_{it}, \gamma_i, \tau_t, \delta_c) = \gamma_i + \tau_t + \delta_c \tau_t + \alpha G_{it} + \varepsilon_{it} \quad (1)$$

The treatment coefficient α captures the average GWPA program effect from 2005 through 2020. The average treatment effect α is identified from within-field changes in regulated active ingredient use in GWPA fields relative to fields in the same county that are outside a GWPA.

Our focus on the binary outcome is motivated by two program features. First, regulated active ingredients are formulated as pre-emergent herbicides and only require one application for up to one year of weed control. The data broadly support this claim, as we find that only 3.7% and 2.4% of almond and grape fields, respectively, received two or more applications in the same year compared to 22% and 35% of almond and grape fields, respectively, that received one regulated application. In citrus, the share of groves receiving two or more regulated applications per year is slightly larger (10.7%) relative to the share that receives one application (34%) (see appendix Table A3). Second, the burden of obtaining a Restricted Materials Permit to apply regulated ingredients in GWPA is independent of the number of regulated ingredient applications.[15] Therefore, we expect that the program primarily affects whether the grower uses a regulated ingredient at all, rather than affecting the number of applications throughout the year.

To examine the effect of the GWPA program on the environmental impact of regulated and alternative active ingredients, we use a fixed effects Poisson regression of the following form:

$$Y_{it} = exp\{\gamma_i + \tau_t + \delta_c \tau_t + \beta G_{it}\}\varepsilon_{it} \quad (2)$$

where the treatment coefficient β captures the change in the log of environmental impacts per planted acre due to the GWPA policy. In the results tables, we transform the coefficient

[15]County Agricultural Commissioners issue Restricted Materials Permit for one year and include the names of the restricted pesticides and maps of fields where the grower plans to apply them (CDPR, n.d.)

β into a percentage impact, which we calculate as $e^{\beta} - 1$.

The specification in equation 2 requires the assumption of a multiplicative common trend and multiplicative treatment effect. The multiplicative model is preferable to linear estimation in the present case, where we expect that without the program, the environmental impact would change by the same proportion among GWPA and non-GWPA fields and where the effect of GWPA regulations is best described as a proportional change in environmental impacts relative to the counterfactual trend.

While the Poisson model is commonly used for count data, it is gaining popularity among researchers for estimating models with a nonnegative continuous dependent variable (Silva and Tenreyro, 2006; Blackburn, 2007; Silva and Tenreyro, 2010; Jean and Bureau, 2016; Kastoryano and Vollaard, 2023; Larch, Luckstead, and Yotov, 2024) including in policy evaluations estimated using the difference-indifference (Ciani and De Blasio, 2015; Staudt, 2020; Ciani, De Blasio, and Poy, 2022; Leider and Powell, 2022; Earnhart and Hendricks, 2023), triple differences (Bryan and Ozcan, 2021; Gonnot and Lanati, 2024), and event study frameworks (Park and Powell, 2021). Our preference for the Poisson model over other oft-used multiplicative models, such as log and inverse hyperbolic sine transformed models, is motivated by the following two reasons.

First, log-linear models estimated by ordinary least squares lead to biased estimates in the presence of heteroskedasticity, while the Poisson model estimated via pseudo maximum likelihood (PML) is consistent (Silva and Tenreyro, 2006; Ciani and Fisher, 2019). Inconsistent estimates from the OLS model arise if the treatment causes a shift in the mean and changes in the variance of the dependent variable for the treated group. This is because heteroskedastic log-transformed errors will be generally correlated with the covariates, while the Poisson PML estimator does not require statistical independence of the error term and is robust to different patterns of heteroskedasticity (Silva and Tenreyro, 2006).

Second, the Poisson model effectively handles dependent variables with a large share of zeros, which would otherwise lead to bias estimates in log or inverse hyperbolic sine transformed models (Silva and Tenreyro, 2011). The share of observations equaling zero in the pre-program years is 75%, 55%, and 62% in the almond, citrus, and grape data, respectively (see appendix table A3). These shares of zeros are large enough to cause concern in OLS estimations (Bellemare and Wichman, 2020), and can not be addressed by modeling the data generating process—for example, by a two-stage Tobit model—due to data limitations.

Additionally, it is helpful to note that the Poisson PML model provides a consistent estimate, even if the data are not generated as Poisson, so long as the expected mean is correctly specified, that is $E[Y_{it}|x] = exp(\beta x_{it})$ (Wooldridge, 1999; Silva and Tenreyro, 2006).

As described in Table 1, the rules for using regulated active ingredients differ according to the GWPA type. To distinguish the effects of leaching and runoff GWPAs, we extend our base regressions defined in Equations 1 and 2 with models that replace αG_{it} with the terms $\alpha_r G_{it}^{runoff} + \alpha_l G_{it}^{leaching}$. Here, α_r and α_l capture the treatment effect of runoff and leaching GWPAs, respectively.

In a second extension to our base equations, we control for potential within-farm spillover effects of the policy. To do this, we add a variable that equals one if the field is outside a GWPA managed by a grower with a field inside a GWPA in 2005 onwards and zero otherwise. In all regressions, we cluster standard errors by the field to allow for heteroskedasticity across fields and autocorrelation of the error terms over time for a field.

4.2 Event Study

We use event study regressions to explore how growers respond to leaching and runoff GWPAs over time, controlling for within-farm spillover effects. The event study has one treatment cohort regulated in the first year of the Groundwater Protection Program and affecting pesticide use from 2005—defined as October 2004 through September 2005—onwards. Although the event study framework is routinely applied to investigate events staggered over time, it has been utilized in prior literature to analyze interventions involving one treatment cohort

(Earnhart and Hendricks, 2023).

The event study model introduces additional notation, namely, G_i^{runoff} representing the time-invariant runoff treatment variable that equals one when field i is inside a runoff GWPA and zero otherwise, $G_i^{leaching}$ that equals one when field i is inside a leaching GWPA and zero otherwise, W_i denoting the time-invariant within-farm spillover control variable that equals one if the field is outside a GWPA managed by a grower with a field inside a GWPA, and T_t denoting a year dummy equal to one when $T = t$ and zero otherwise.

For regressions involving the binary outcome variable of field treated with a regulated active ingredient, we estimate a fixed effects linear probability model of the following form:

$$\begin{aligned} P(Y_{it} = 1 | G_i^{leaching}, G_i^{runoff}, W_i, \gamma_i, \tau_t, \delta_c) = \gamma_i + \tau_t + \delta_c \tau_t \\ + \sum_{\substack{T=1996 \\ T \neq 2004}}^{2020} (\alpha_l^T G_i^{leaching} T_t + \alpha_r^T G_i^{runoff} T_t + \omega^T W_i T_t) + \varepsilon_{it} \end{aligned} \tag{3}$$

where the treatment coefficient α_l^T identifies the change in the probability that growers spray leaching GWPA fields with regulated active ingredients in year T compared to the change in regulated active ingredient use in control fields in year T relative to the baseline year 2004. The treatment coefficients for runoff areas, α_r^T, and within farm spillover control fields, ω^T, have similar interpretations.

To examine the effect of the GWPA policy on the environmental impact of herbicides over time, we estimate the following fixed effects Poisson model:

$$Y_{it} = exp(\gamma_i + \tau_t + \delta_c \tau_t + \sum_{\substack{T=1996 \\ T \neq 2004}}^{2020} (\beta_l^T G_i^{leaching} T_t + \beta_r^T G_i^{runoff} T_t + \omega^T W_i T_t)) \varepsilon_{it}. \tag{4}$$

Here, the leaching treatment coefficient, β_l^T, has the interpretation of a $(e^{\beta_l^T} - 1) * 100$ percent change in the environmental impact per planted acre in year T relative to 2004.

5 Results and Discussion

We observe 9,482 almond orchards, 4,550 citrus groves, and 18,797 grape vineyards with observations in the pre-program (1996–2004) and post-program (2005–2020) periods. Table 2 provides the count and proportion of fields in leaching, runoff, and non GWPAs. Table 2 shows that a meaningful share of fields in our sample lie inside a GWPA and reveals that approximately ten times more almond orchards lie in leaching areas than runoff areas. Among grape vineyards, about twice as many vineyards belong to leaching areas compared to runoff, whereas for citrus, runoff areas contain four times as many groves as leaching GWPAs. The relative share of fields in leaching and runoff GWPAs has implications for how almond, citrus, and grape growers might respond to the program and supports our preferred regression specification that includes leaching and runoff treatment variables.

Table 2: Summary of Effective Sample of Fields by Groundwater Protection Area Regulation

	Count of fields			Share of fields (%)		
GWPA category	Almond	Citrus	Grape	Almond	Citrus	Grape
Leaching	2801	218	2144	29.54	4.79	11.4
Runoff	294	812	1005	3.10	17.85	5.35
Non-GWPA	6387	3520	15648	67.36	77.36	83.25

Table 3 presents summary statistics of the dependent variables for the pre-program (1996–2004) years. It shows that growers sprayed a higher proportion of GWPA fields with regulated active ingredients than control fields—counterfactual fields in non-GWPAs—, resulting in a higher environmental impact of regulated active ingredients per planted acre. The mean environmental impact of alternative active ingredients equals 39 in almond control and GWPA orchards, about ten times larger than the environmental impact from regulated ingredients. In vineyards, alternative ingredients have a larger environmental impact per planted acre among the control group than in the GWPA-treated group, 27 and 20, respectively, both of which are larger than the impact from regulated ingredients. In citrus groves, the environmental impacts of alternative active ingredients are similar across control and GWPA groves, equaling 29 and 26, respectively, but smaller than the impact of regulated ingredients, equal to 41 and 45, respectively.

Table 3: Summary Statistics: 1996–2004

		Control Fields		GWPA Fields	
Crop	Dependent variable	Mean	Std. Dev.	Mean	Std. Dev.
Almond	Share of fields sprayed with regulated active ingredients	0.22	0.42	0.32	0.47
Almond	Environmental impact of regulated active ingredients per planted acre	3.5	9.3	4.3	9.4
Almond	Environmental impact of alternative active ingredients per planted acre	39	47	39	59
Almond	Environmental impact of herbicide active ingredients per planted acre	43	49	44	61
Citrus	Share of fields sprayed with regulated active ingredients	0.44	0.5	0.46	0.5
Citrus	Environmental impact of regulated active ingredients per planted acre	41	72	45	81
Citrus	Environmental impact of alternative active ingredients per planted acre	29	54	26	72
Citrus	Environmental impact of herbicide active ingredients per planted acre	70	94	72	110
Grape	Share of fields sprayed with regulated active ingredients	0.33	0.47	0.52	0.5
Grape	Environmental impact of regulated active ingredients per planted acre	8.3	20	12	19
Grape	Environmental impact of alternative active ingredients per planted acre	27	56	20	53
Grape	Environmental impact of herbicide active ingredients per planted acre	35	62	32	58

Note: Statistics calculated using annual periods that coincide with pre-emergent herbicide application season beginning in October each year. For example, 1996 includes observations from October 1995 through September 1996.

While the mix and quantity of active ingredients feature in the calculation of environmental impacts, it is clear that regulated ingredients play a dominant role in the chemical weed management of citrus groves in pre-program years compared to almonds and grapes. The extensive use of regulated active ingredients in citrus groves compared to almond orchards and vineyards is further supported by data in Appendix Table A1. Dividing the acres treated with regulated active ingredients by the acres treated with regulated and alternative ingredients in Appendix Table A1 reveals that regulated active ingredients account for 34% of citrus acres treated with herbicides, compared to 21% in vineyards, and 8% in almond orchards.

As the next step in our analysis, we plot the four dependent variables for almond, citrus, and grape fields inside and outside GWPAs over time in Figures 2, 3, 4, and 5.

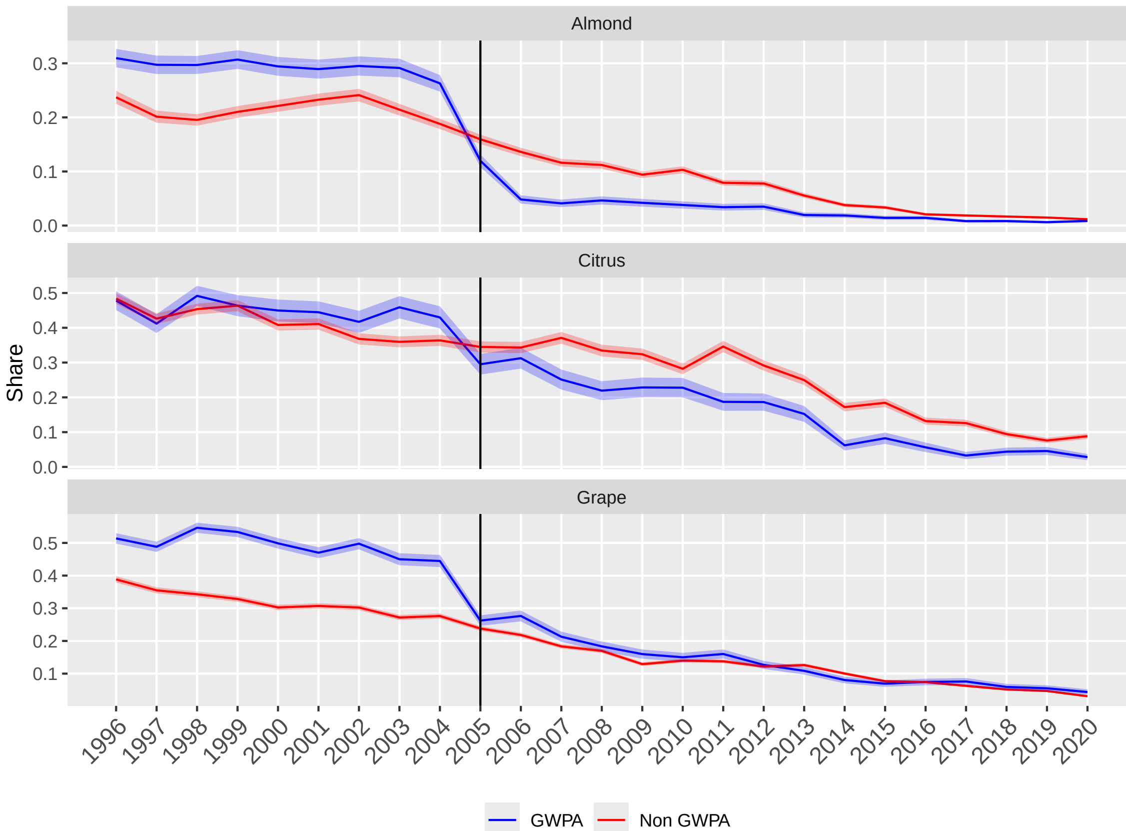

Figure 2: Share of fields treated with regulated active ingredient.

Figures 2 reveals kinks in the GWPA trends in 2005, the first year of the program. The almond GWPA trend exhibits the most dramatic effect, with the share of fields sprayed decreasing from about 30% to about 5% in 2007 before gradually declining through 2020. In contrast, the drop in the share of fields treated is less pronounced in citrus and grape GWPA fields, with both groups showing a slight increase in 2006 before dropping again in 2007. The control field trends do not reveal any response to the program in 2005 but trend

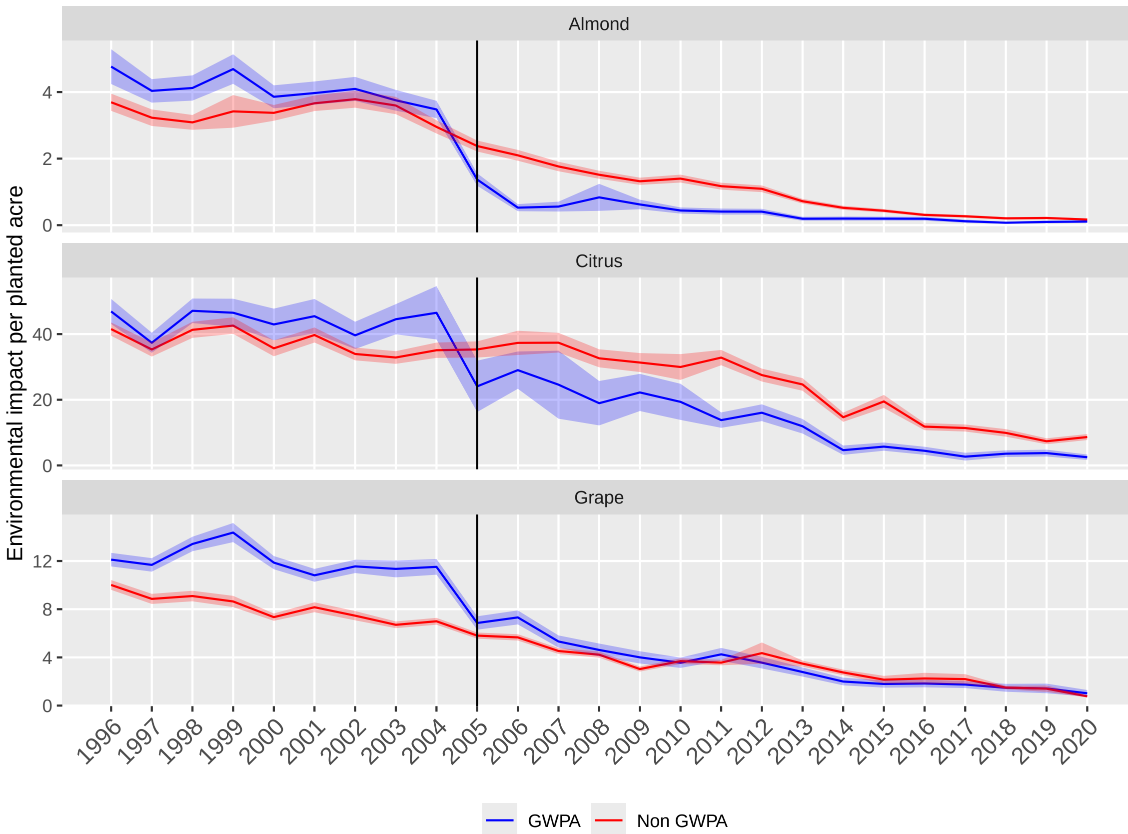

Figure 3: Environmental impact of regulated active ingredients per planted acre.

toward zero throughout the length of the panel.

The trends in the environmental impact of regulated active ingredients in Figure 3 follow a broadly similar pattern in almonds, citrus, and grapes to those in Figure 2. Differences in the patterns of trend lines between the figures are driven by the pounds per acre applied, although the mix of active ingredients also plays a role.

Overall, Figures 2 and 3 provide evidence that changes in regulated active ingredient use around 2005 result from the Groundwater Protection Program. The similar trends in 1996–2004 add further validity to our assumption that GWPA-treated and control fields would have followed similar trends in the absence of the program. We formally test the parallel pre-trends assumption via our event study analysis and a series of robustness checks.

Figure 4 plots the trends in the environmental impact of alternative active ingredients per planted acre. It reveals a sharp increase among citrus groves in GWPAs in the first three

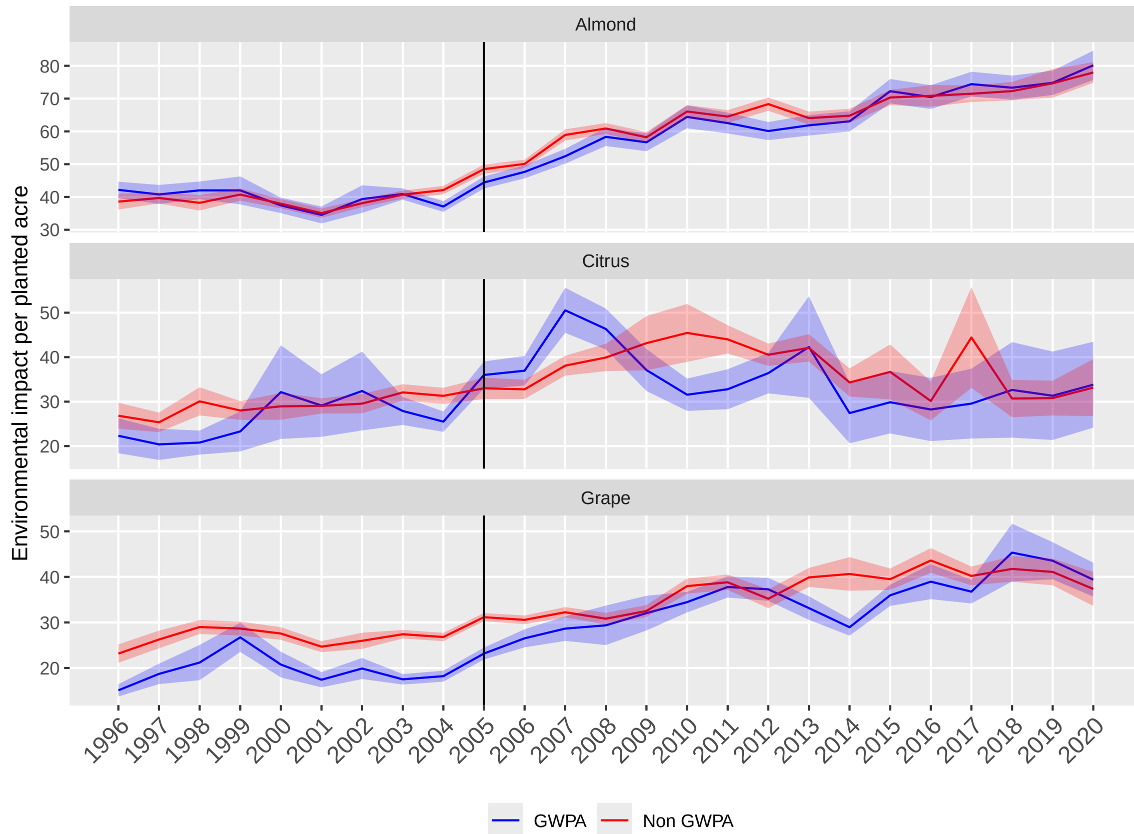

Figure 4: Environmental impact of alternative active ingredients per planted acre.

years of the program relative to non-GWPA groves, followed by a decrease in subsequent years. For grapes, Figure 4 shows an increasing trend in GWPA and non-GWPA vineyards, with the GWPA vineyards increasing at a faster rate in the first six years of the program. In almond orchards, the environmental impact of alternatives per planted acre in GWPA and non-GWPAs follow similar trends, increasing from around 40 in 1996–2004 to 80 in recent years. Zhan and Zhang (2014) also observed a significant rise in the kilograms of herbicides used per planted acre in almond orchards starting in 2001, which they attribute to a shift in weed management practices and increasing weed resistance to glyphosate. The authors mention that simazine and norflurazone, two regulated ingredients, were replaced with herbicides that were less likely to leach. Still, they do not provide any policy context for this change.

Figure 5 shows the trends in the environmental impact of herbicides (regulated and

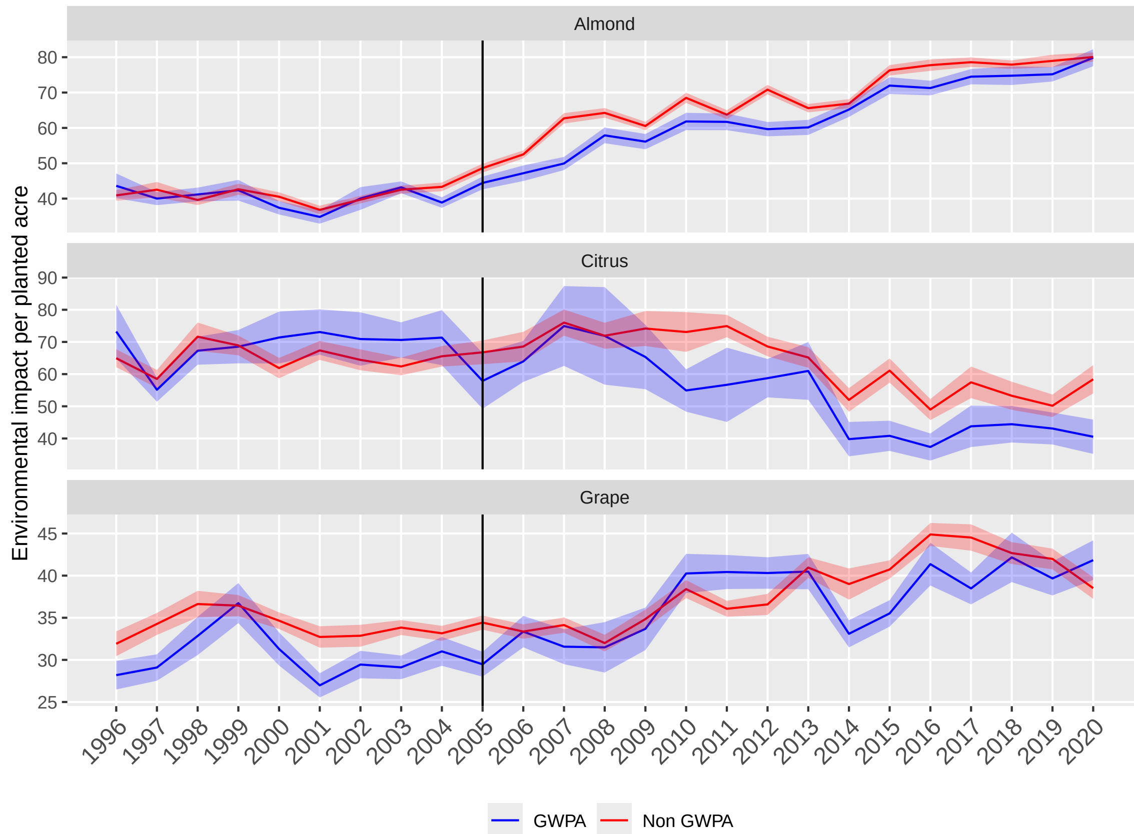

Figure 5: Environmental impact of regulated plus alternative active ingredients per planted acre.

alternative active ingredients) per planted acre but reveals no obvious discontinuity in the trends resulting from the program. In almond and grape fields, alternative ingredients have a larger environmental impact per planted acre than regulated ingredients. Therefore, their trend in Figure 5 increased during the program. In citrus, the opposite is true, with regulated ingredients exhibiting a larger environmental impact in pre-program years than alternative ingredients. Therefore, we find that the environmental impact of herbicides decreased in GWPA and non-GWPA citrus groves during the program, as shown in Figure 5.

Over the 1996–2021 study period, the quantity of regulated active ingredients used decreased significantly among our sample of almond orchards, grape vineyards, and citrus groves, as supported by Figures 2 and 3 and across all agricultural uses in California, as shown in Appendix Figure A1.[16] Explaining the drop in regulated active ingredient use among growers not directly affected by the Groundwater Protection Program is difficult because of the lack of appropriate data from other regions to serve as a control group. Therefore, ascribing the extent to which the program affected statewide regulated active ingredient use is beyond the scope of this study. Nonetheless, herbicide use in fields in non-program regions serves as an appropriate counterfactual.

5.1 Difference-in-Differences

Results tables 4, 5, 6 and 7 include estimates of three model specifications for each crop that provide the following estimates: (1) the average treatment effect of a field being assigned to a GWPA, (2) the average treatment effects of a field being assigned to a leaching or runoff GWPA, and (3) the average treatment effects of a field being assigned to a leaching or runoff GWPA and the within-farm spillover effect of a field outside a GWPA that is managed by a grower with a field inside a GWPA. Comparing estimates across these specifications reveals meaningful differences in the effects of leaching and runoff GWPA treatments and the impact of within-farm spillover controls on the GWPA treatment effects.

Estimation results of Equation 1, presented in Table 4, strongly indicate that the Groundwater Protection Program led to a decrease in applications containing regulated active ingredients relative to control fields. Panel A contains estimates of the average treatment effect of GWPAs and shows that the probability that grape growers applied a regulated active ingredient decreased by 16 percentage points. The program effect was slightly smaller in citrus and almond fields. However, the mean share of almond fields sprayed with a regulated active ingredient in the pre-program period was small (32%) compared to citrus (46%) and grapes (52%). Therefore, in percentage terms, GWPA treatment led to a 31% decrease in the share of almond fields treated with regulated active ingredients, a 31% decrease in the

[16] The ingredient bentazon is the exception, and the quantity used in California increased from about one thousand pounds in 1996 to eight thousand pounds in 2020. However, growers use bentazon on a small share of cropland, primarily legumes.

share of grape fields treated, and a 13% drop in the share of citrus fields treated.

Table 4: Impact of the Groundwater Protection Program on the Probability Growers Treated Field With Regulated Active Ingredients

	Almond (1)	Citrus (2)	Grape (3)
Panel A: Average GWPA treatment effect			
GWPA	-0.10***	-0.06***	-0.16***
	(0.01)	(0.02)	(0.01)
Observations	130,292	58,378	177,879
R^2	0.41	0.47	0.46
Panel B: Average effect of leaching and runoff GWPAs			
Leaching GWPA	-0.10***	-0.01	-0.18***
	(0.01)	(0.02)	(0.01)
Runoff GWPA	-0.11***	-0.08***	-0.11***
	(0.03)	(0.02)	(0.01)
Observations	130,292	58,378	177,879
R^2	0.41	0.47	0.46
Panel C: Average effect of GWPAs with spillover control			
Leaching GWPA	-0.10***	-0.05*	-0.19***
	(0.01)	(0.03)	(0.01)
Runoff GWPA	-0.11***	-0.11***	-0.13***
	(0.03)	(0.02)	(0.02)
Field outside GWPA,	-0.01	-0.09***	-0.03***
grower has field inside a GWPA	(0.01)	(0.02)	(0.01)
Observations	130,292	58,378	177,879
R^2	0.41	0.47	0.46

Note: Regressions include year, field, and county by year fixed effects. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Distinguishing between GWPA types, as in Panel B of Table 4, we find the largest effect on grape fields in leaching GWPAs. For instance, the probability that growers treated grape fields in leaching GWPAs with a regulated active ingredient decreased by 18 percentage points compared to an 11 percentage point drop among fields in runoff areas. In almonds, the coefficients on leaching and runoff are similar. We find no significant change in the probability that growers treated citrus fields in leaching GWPAs with regulated active ingredients and an 8 percentage point drop in runoff areas. These results provide evidence that growers respond differently to the leaching and runoff rules. In particular, grape growers are more likely to respond to the leaching area rules by eliminating regulated active ingredients from their pesticide program.

Panel C reveals that the program effect spills over into citrus and grape fields outside GWPAs that are managed by growers with fields inside GWPAs. These "weakly-treated" citrus and grape fields exhibit a 9 and 3 percentage point drop, respectively, in the probability of being sprayed with a regulated active ingredient. The coefficients on fields outside GWPAs have the same sign as the leaching and runoff point estimates, leading to an increase in the magnitude of the GWPA treatment effects and demonstrating the full extent of the Groundwater Protection Program compared to control fields. The sign of the within-farm spillover effect is not surprising for several reasons. First, many of the regulated active ingredients are used on other crops and in other regions. Therefore, we do not expect large or persistent price effects that may incentivize growers to use regulated active ingredients in non-GWPA fields. Second, it is inconvenient for a grower to purchase, store, and apply different herbicide products across their farm. Lastly, the program likely increased awareness of pesticide groundwater contamination among farmers in GWPAs. This potential explanation is supported by the findings of Beach and Carlson (1993), who show that herbicide leaching and water quality characteristics are important factors in explaining farmer pesticide purchases. In addition, many growers hire professional pest control advisers, who likely consider similar price, convenience, and environmental factors when providing pest management recommendations.

Next, we turn to the effect of the program on the environmental impact of regulated active ingredients per planted acre, which we estimate by fixed–effect Poisson regression as defined in Equation 2. Panel A of Table 5 reveals that GWPA treatment led to a 70%, 35%, and 44% decrease in the environmental impact of regulated active ingredients per planted acre in almond, citrus, and grape fields, respectively. Panel B shows that leaching GWPAs have a larger effect than runoff areas for almonds and grapes. Controlling for within-farm spillovers, as in Panel C, we find a 14% reduction in the environmental impact per acre among citrus fields outside GWPAs that are managed by a grower with a field inside a GWPA. However, the within-farm spillover effects among almond and grape fields are small and insignificant.

Table 5: Impact of the Groundwater Protection Program on the Environmental Impact of Regulated Active Ingredients Applied per Planted Acre

	Almond	Citrus	Grape
	(1)	(2)	(3)
Panel A: Average GWPA effect			
GWPA	-0.70***	-0.35***	-0.44***
	(0.02)	(0.05)	(0.02)
Observations	67,294	45,448	115,764
Pseudo R^2	0.39	0.47	0.37
Panel B: Average effect of leaching and runoff GWPAs			
Leaching GWPA	-0.73***	-0.09	-0.45***
	(0.02)	(0.18)	(0.03)
Runoff GWPA	-0.54***	-0.37***	-0.40***
	(0.07)	(0.05)	(0.04)
Observations	67,294	45,448	115,764
Pseudo R^2	0.40	0.47	0.37
Panel C: Average effect of GWPAs with spillover control			
Leaching GWPA	-0.73***	-0.16	-0.44***
	(0.03)	(0.16)	(0.03)
Runoff GWPA	-0.54***	-0.41***	-0.39***
	(0.07)	(0.05)	(0.04)
Field outside GWPA,	0.01	-0.14**	0.05
grower has field inside a GWPA	(0.06)	(0.06)	(0.04)
Observations	67,294	45,448	115,764
Pseudo R^2	0.40	0.47	0.37

Note: Regressions include year, field, and county by year fixed effects. Estimates presented here equal the relative impacts of a discrete change in GWPA treatment calculated using the formula $e^{\beta} - 1$. Multiplying the point estimate presented by 100 equals the effect in percentage terms. We calculated the standard errors of the relative impacts using the Delta method. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Furthermore, we find that 81% of almond orchards, 63% of citrus groves, and 74% of grape vineyards in our sample never receive a regulated active ingredient application. For these fields, the environmental impact outcome equals zero in all periods and is perfectly predicted by the field fixed effect. Such fields provide no information for estimating the treatment effects and are dropped before estimating the Poisson model (Silva and Tenreyro, 2010). Hence, the regressions presented in Table 5 include fewer observations than those estimated by the linear probability model.

Table 6: Impact of the Groundwater Protection Program on the Environmental Impact of Alternative Active Ingredients Applied per Planted Acre

	Almond	Citrus	Grape
	(1)	(2)	(3)
Panel A: Average GWPA effect			
GWPA	0.03	-0.02	-0.11***
	(0.03)	(0.09)	(0.03)
Observations	128,662	54,108	168,101
Pseudo R^2	0.38	0.48	0.45
Panel B: Average effect of leaching and runoff GWPAs			
Leaching GWPA	0.03	-0.12	-0.10***
	(0.03)	(0.16)	(0.04)
Runoff GWPA	0.06	0.04	-0.12***
	(0.05)	(0.08)	(0.04)
Observations	128,662	54,108	168,101
Pseudo R^2	0.38	0.48	0.45
Panel C: Average effect of GWPAs with spillover control			
Leaching GWPA	0.04	-0.03	-0.04
	(0.03)	(0.18)	(0.05)
Runoff GWPA	0.07	0.13	-0.06
	(0.05)	(0.09)	(0.05)
Field outside GWPA,	0.01	0.22**	0.14***
grower has field inside a GWPA	(0.02)	(0.10)	(0.04)
Observations	128,662	54,108	168,101
Pseudo R^2	0.38	0.48	0.45

Note: Regressions include year, field, and county by year fixed effects. Estimates presented here equal the relative impacts of a discrete change in GWPA treatment calculated using the formula $e^{\beta} - 1$. Multiplying the point estimate presented by 100 equals the effect in percentage terms. We calculated the standard errors of the relative impacts using the Delta method. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 shows the regression results with the environmental impact of alternative active ingredients as the dependent variable. Results from the almond and citrus regressions reveal no statistically significant impacts of GWPA treatment on the environmental impacts of alternative ingredients across all three specifications. In the grape regressions, we find statistically significant negative coefficients on GWPA (shown in panel A) and leaching and runoff GWPAs (shown in panel B). However, the leaching and runoff GWPA treatment coefficients lose statistical significance and diminish in magnitude when controlling for within-farm spillovers, as shown in panel C.

The fourth and final outcome we analyze is the environmental impact of regulated plus alternative active ingredients per planted acre. Focusing on Panel C of Table 7, we find that almond growers adjusted their pesticide use in such a way that the program led to no effect on the environmental impact of herbicides, with point estimates that are small and not statistically different from zero. On the other hand, grape growers changed the mix and quantity of herbicides used, resulting in a 15% drop in the associated environmental impacts in leaching areas and an 11% drop in runoff areas. We also find evidence of program spillover effects among grape growers, with a 12% increase in the environmental impact of herbicides per planted acre in fields outside GWPAs managed by growers with fields inside a GWPA. In citrus crops, the environmental impact of herbicides decreased by 19% in runoff GWPAs and did not significantly change in leaching areas.

5.2 Event Study

We extend our difference-in-differences regressions by conducting event study plots as defined in Equations 3 and 4. The plots show year-specific treatment effects for leaching and runoff GWPAs relative to the base year 2004, the year immediately before the program. The regressions that generate Figures 6, 7, 8 and 9 include controls for within-farm spillovers, which we exclude from the figures for clarity.

As shown in Figure 6, the leaching and runoff treatment effects on the share of fields sprayed with a regulated active ingredient are significantly negative in each year of the policy for almonds and grapes. In citrus, runoff GWPA treatment resulted in significantly negative effects in all but the last two years post-program implementation. In almonds, fields in GWPAs exhibit an 18–20 percentage point reduction in the probability growers sprayed a

Table 7: Impact of the Groundwater Protection Program on the Environmental Impact of Herbicide Active Ingredients Applied per Planted Acre

	Almond (1)	Citrus (2)	Grape (3)
Panel A: Average GWPA effect			
GWPA	0.01	-0.16***	-0.19***
	(0.03)	(0.04)	(0.02)
Observations	128,662	55,368	168,201
Pseudo R^2	0.37	0.48	0.41
Panel B: Average effect of leaching and runoff GWPAs			
Leaching GWPA	0.01	-0.07	-0.20***
	(0.03)	(0.13)	(0.03)
Runoff GWPA	0.02	-0.19***	-0.16***
	(0.04)	(0.04)	(0.03)
Observations	128,662	55,368	168,201
Pseudo R^2	0.37	0.48	0.41
Panel C: Average effect of GWPAs with spillover control			
Leaching GWPA	0.02	-0.08	-0.15***
	(0.03)	(0.12)	(0.03)
Runoff GWPA	0.03	-0.19***	-0.11***
	(0.05)	(0.05)	(0.04)
Field outside GWPA,	0.02	-0.02	0.12***
grower has field inside a GWPA	(0.02)	(0.05)	(0.03)
Observations	128,662	55,368	168,201
Pseudo R^2	0.37	0.48	0.41

Note: Regressions include year, field, and county by year fixed effects. Estimates presented here equal the relative impacts of a discrete change in GWPA treatment calculated using the formula $e^{\beta} - 1$. Multiplying the point estimate presented by 100 equals the effect in percentage terms. We calculated the standard errors of the relative impacts using the Delta method. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

regulated active ingredient in 2006, an effect that diminishes through 2020. In citrus fields, the treatment effect is larger in magnitude in runoff GWPAs in all program years relative to leaching areas.

Figure 7 displays the treatment effects on the environmental impacts of regulated active ingredients per planted acre and shows significant reductions in almond and citrus fields in most years of the policy. Multiplying the point estimate by 100 gives the treatment effect in percentage terms. For example, the environmental impact of regulated ingredients used in almond leaching GWPA fields declined by 50% in 2005 and 84% in 2006, relative to 2004, and remained around -75% through 2019. Grape leaching and runoff GWPA fields show a significant drop in the environmental impact in 2005 of 25%, an effect that increases in magnitude in most years through 2015.

Figure 8 shows the program impacts on the environmental impacts of alternative active ingredients. The almond estimates reveal significant treatment effects of leaching GWPAs in 2008, 2015, and 2017, but otherwise, point estimates of leaching and runoff GWPAs are close to zero. The citrus estimates show positive and significant effects in runoff GWPAs in 2005 through 2008. However, these effects might have resulted from factors other than the program as we find positive coefficients on runoff GWPAs in the three years prior to the program. Leaching GWPA treatment had no significant effect on the environmental impact of alternative ingredients used on citrus groves. In grape vineyards, the program had no significant impact on the environmental impact of alternative ingredients until 2015, when we found negative and significant effects from leaching and runoff areas.

Figure 9 depicts the results for the environmental impact of regulated plus alternative herbicides. The citrus estimates reveal significant negative runoff treatment effects in 2007–2011 and 2014. We can see that the citrus leaching GWPA point estimates tend to be negative in 2005 through 2011, with a significant estimate in 2010, then tend to be positive in later years, with a significant estimate in 2017. This apparent jump in environmental impacts is driven by the extensive use of glyphosate in lemon and orange orchards, which increased the mean environmental impact of herbicides in leaching GWPA citrus fields between 2004 and 2017. During the same period, the mean environmental impact of herbicides in control fields dropped, contributing to the large relative change in treated fields. The almond treatment effects are close to zero throughout the program. In grape fields, the runoff GWPA treatment effect ranges from -10% to -25% through 2014, with effects that are significantly different from zero in seven of the ten years, then increases in magnitude to about -30% from 2015 through 2020. During the 2015–2020 period the grape runoff GWPA point estimates are significantly different from zero. Grape leaching GWPAs follow a similar pattern.

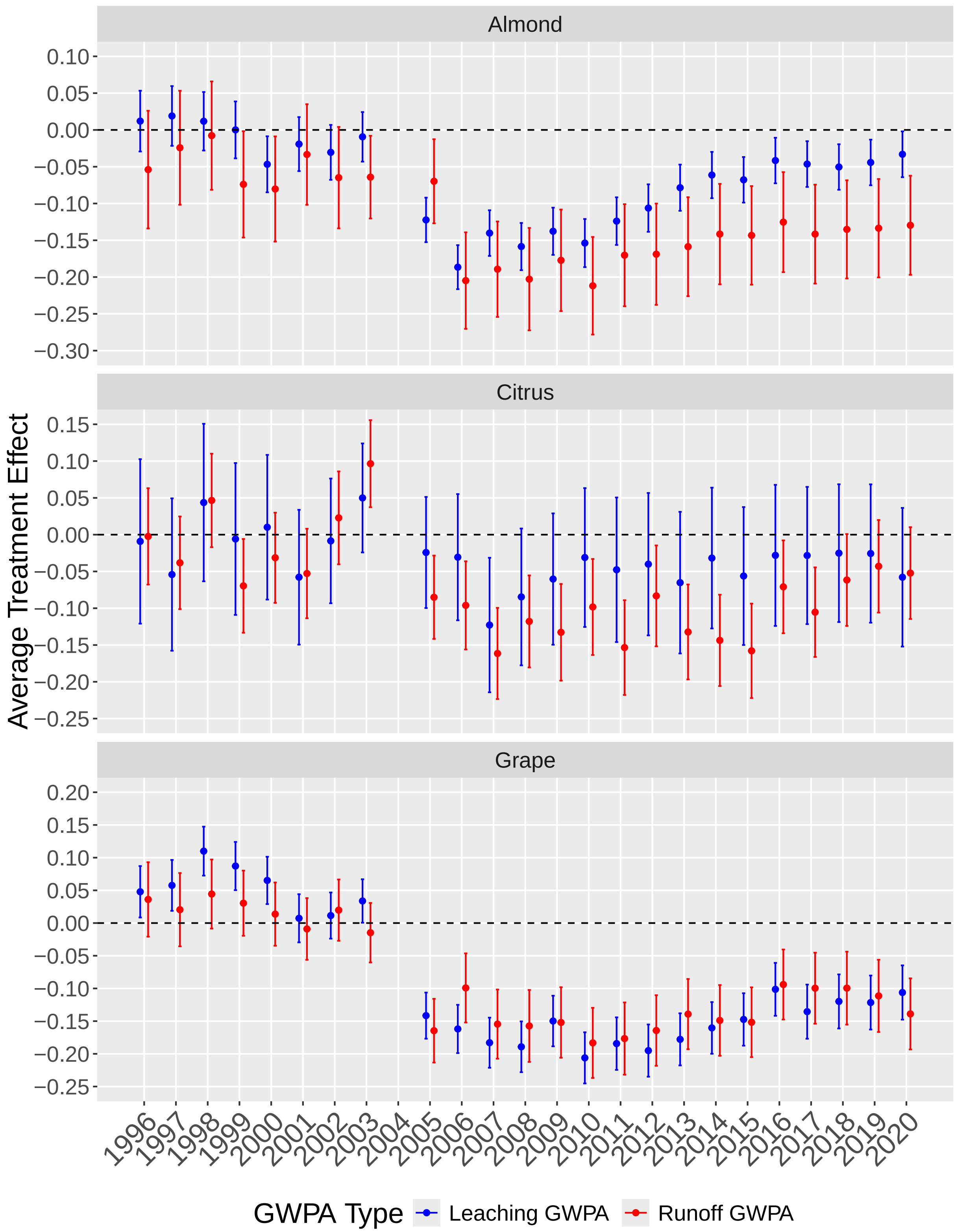

Figure 6: Effect of the Groundwater Protection Program on the probability growers sprayed fields with regulated active ingredients.

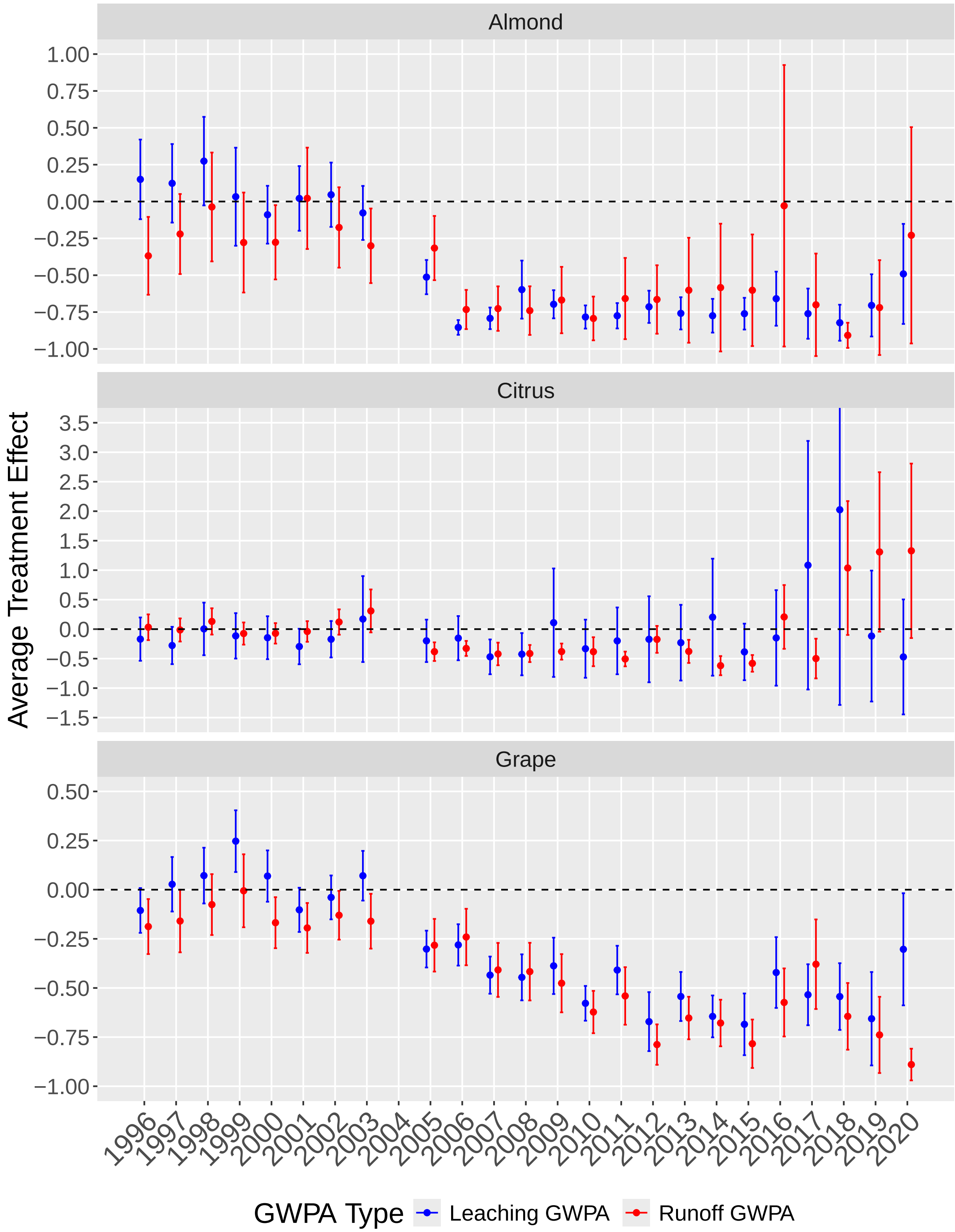

Figure 7: Effect of the Groundwater Protection Program on the environmental impact per planted acre of regulated active ingredients.

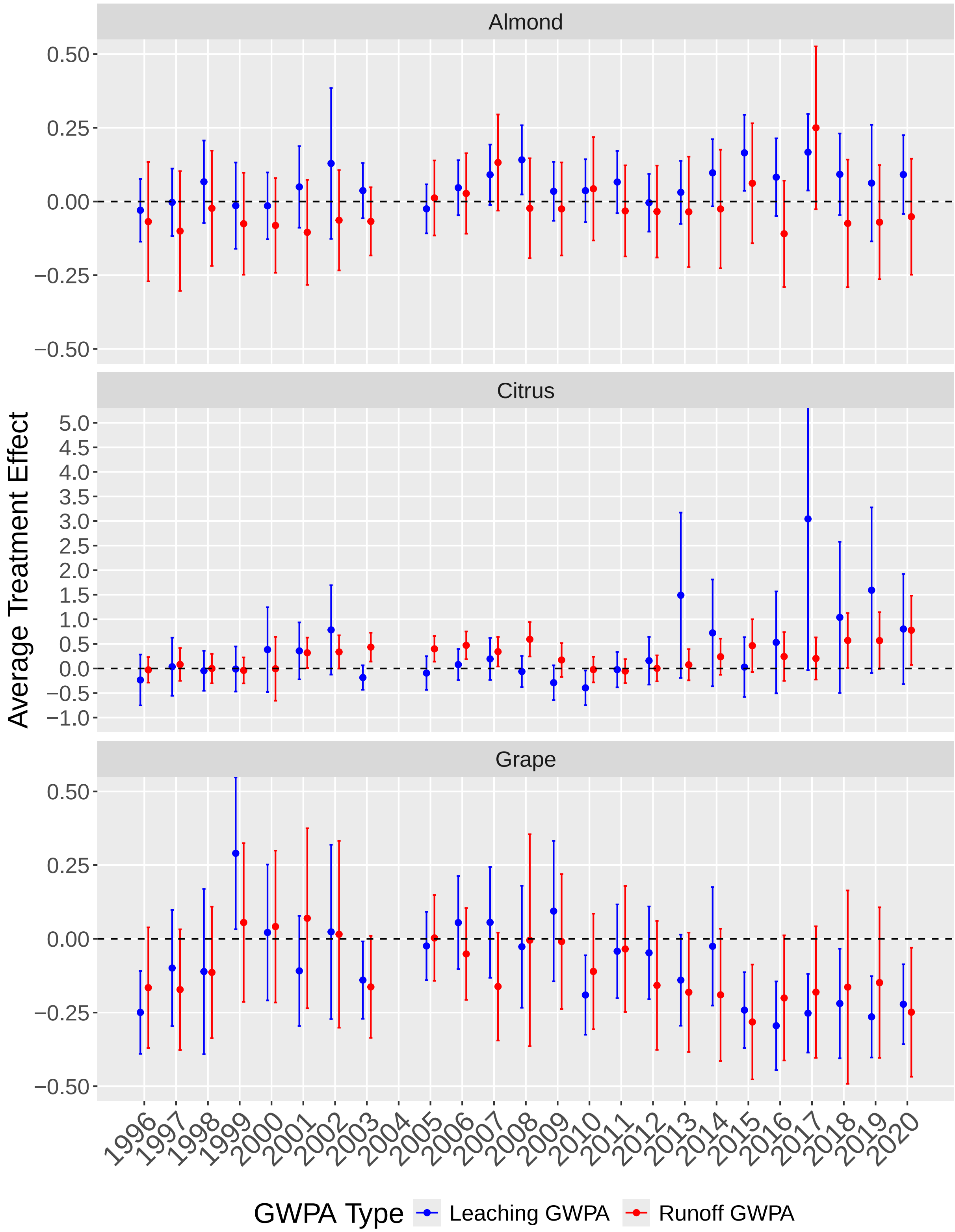

Figure 8: Effect of the Groundwater Protection Program on the environmental impact per planted acre of alternative active ingredients.

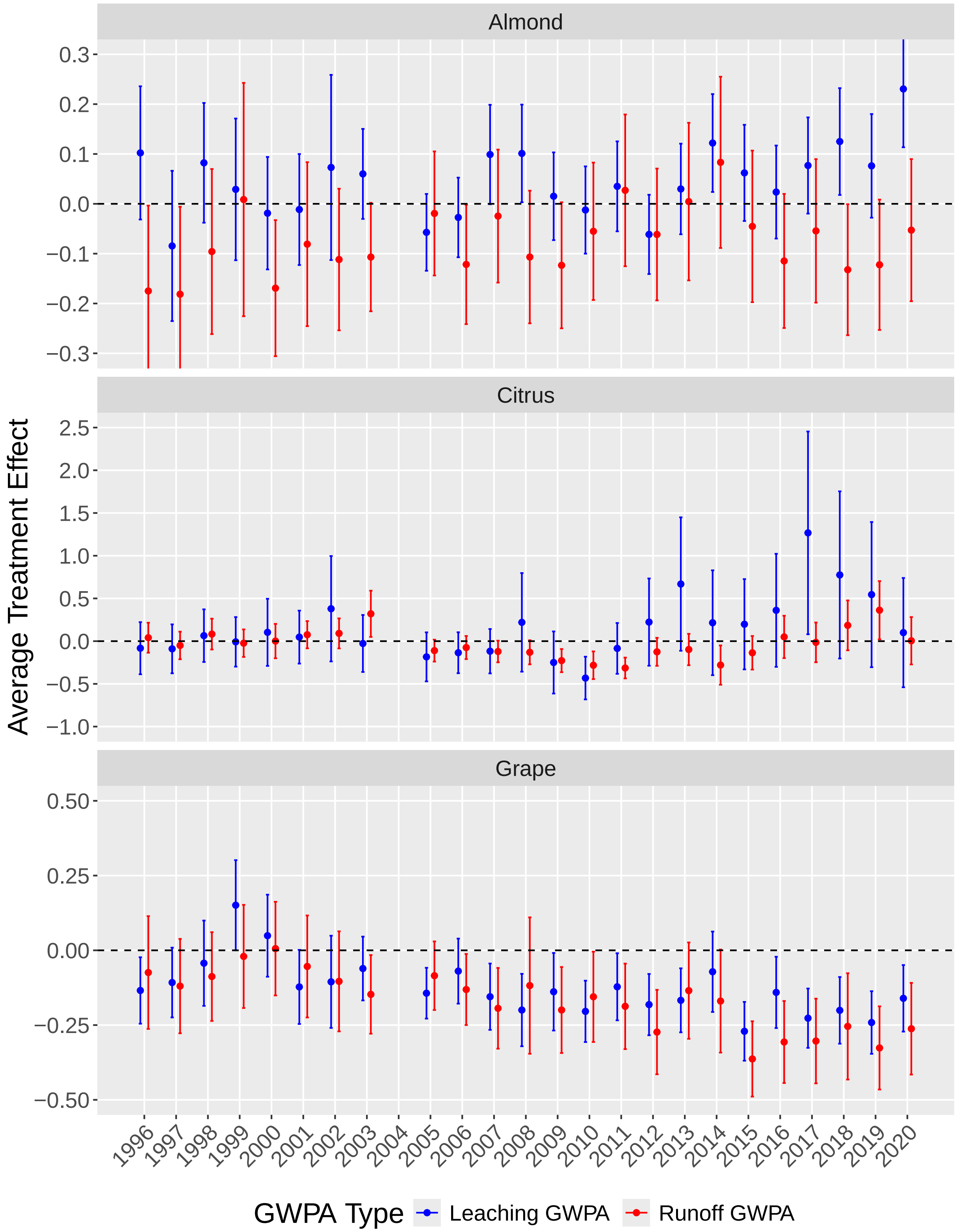

Figure 9: Effect of the Groundwater Protection Program on the environmental impact per planted acre of herbicides.

5.3 Robustness Checks

Identifying the program treatment effect hinges on the assumption that treated and control fields follow parallel trends in 1996–2004. To formally test this assumption, we conduct a series of regressions that augment the difference-in-differences models with terms that capture the differences in slopes between treated and control groups. The augmented version of equation (1) used to capture pre-trend slopes takes the following form:

$$P(Y_{it} = 1) = \gamma_i + \tau_t + \delta_c\tau_t + \alpha^{pre} Year D_t^{pre} G_i + \alpha^{post} Year D_t^{post} G_i + \varepsilon_{it} \tag{5}$$

where $Year$ denotes the year variable, D_t^{pre} and D_t^{post} denote indicator variables that equal one for observations in the pre-treatment and post-treatment periods, respectively, and G_i denotes an indicator variable equal to one for fields in a GWPA. Coefficient α^{pre} captures the difference in slopes between GWPA and control fields in 1996–2004.

To test the parallel pre-trends assumption for regressions of the effect GWPA program on the environmental impact of regulated and alternative active ingredients, we alter equation (2) as follows:

$$Y_{it} = exp\{\gamma_i + \tau_t + \delta_c\tau_t + \beta^{pre} Year D_t^{pre} G_i + \beta^{post} Year D_t^{post} G_i\}\varepsilon_{it} \tag{6}$$

where variables have the same definition as those in equation (5) and the coefficient of interest, β^{pre}, captures the difference in pre-program trends between GWPA and control fields.

We extend equations (5) and (6) with terms that capture differences in pre-trends between control fields and fields in leaching GWPAs, runoff GWPAs, and fields outside GWPAs that are managed by a grower with a field inside a GWPA. For clarity, we only present estimates of the coefficients that capture differences in pre-trends. These results are presented in Appendix Table A4, A5, and A6.

With respect to the share of fields treated with regulated active ingredients, we find parallel pre-trends in treated and control fields in almond orchards as shown in Appendix Table A4. The citrus regressions reveal that the probability a field was treated with a regulated ingredient increased in GWPA fields in the pre-program period. However, the runoff GWPA pre-trend coefficient in our preferred regression in panel C is only significant at the 10% level. In grapes, there is evidence of small negative pre-trends in leaching GWPA fields relative to control fields in regressions that control for within-farm spillovers (see panel C), which is significant at the 5% level and biases our estimates.

The pre-trend estimates for the regressions with the environmental impact of regulated active ingredients per planted acre as the dependent variable (shown in Appendix Table A5) reveal positive pre-trends in almond and grape runoff GWPAs (see panel B) which lose significance when controlling for within-farm spillover effects (panel C). In the pre-trends test of our preferred regressions, shown in panel C, we find pre-trends in almond leaching and weakly treated fields and citrus weakly treated fields, but these are only significant at the 10% level. However, as we show in Figure 7, the yearly point estimates for almond leaching GWPAs in 1996–2004 are not statistically different from zero, and the negative pre-trend is the result of large positive point estimates for 1996–1998. In the pre-trend test of the impact of the program on the environmental impact of herbicides per planted acre, we find the pre-trend for almond orchards outside GWPA managed by growers with fields inside a GWPA is negative and significant at the 5% level (as shown in Appendix Table A6, panel C).

Turning to the environmental impact of regulated and alternative active ingredients, we find parallel pre-trends between treated and control fields across all crops (see Appendix Table A6). However, the test of the almond orchards outside GWPAs managed by growers with a field inside a GWPA reveals a negative and significant pre-trend.

In a second set of robustness checks, we redefine the annual periods as June through May and estimate models involving the environmental impact of herbicides (regulated and alternative ingredients) per planted acre. As shown in Appendix Table A7, the summer months of June through September account for a meaningful share of the acres treated with alternative active ingredients. Our definition of annual periods of October through September used for our primary regressions means that we include herbicide applications in June through September 2004 as pre-program applications, despite the program beginning in May 2004. Estimating equation (2) using years defined as June through May, we find no notable differences in the point estimates or standard errors, as shown in Appendix Table A8, compared to the results estimated using the October through September period definition presented in Table 7. Estimating the event study model given in equation (4) using years defined as June through May produces a pattern of point estimates shown in Appendix Figure A3 similar to the estimates in Figure 9.

6 Concluding Remarks

Pesticides protect crops against disease, predation, and competitive species, prevent food-borne illness from vector-borne disease and microbial contamination (Cooper and Dobson, 2007), and support low-cost food production and farm profitability. When faced with environmental degradation from non-point source emissions of pesticides, regional and national governments often implement uniform regulations (Finger et al., 2017), including product bans (Donley, 2019). However, pesticide bans might not be necessary to achieve environmental quality goals (Anderson, Opaluch, and Sullivan, 1985). Targeting regulatory efforts towards the most vulnerable zones can achieve environmental quality goals at a lower cost than uniform restrictions. Incorporating a menu of cultural practices differentiated by targeted region further reduces compliance costs relative to product bans.

The Groundwater Protection Program set pesticide management standards for seven herbicide active ingredients detected in groundwater. The program standards vary depending on the local environmental conditions and the pathway—leaching or runoff— to groundwater contamination. Troiano et al. (2013) pointed to decreasing trends in groundwater concentrations of simazine, diuron, and bromacil as evidence of the success of the program. However, until now, little was known about the extent to which farmers responded to the program and whether the response differed in leaching or runoff areas.

Using 25 years of pesticide use data, we show that the program substantially reduced the share of fields treated with regulated active ingredients and their environmental impacts. The largest reductions were seen in leaching GWPAs, which required strict irrigation management standards to prevent pesticides from moving through coarse-textured soils into groundwater. Growers in runoff GWPAs also reduced the use of regulated active ingredients, which require specific land cultivation practices to prevent chemicals from moving across the land surface to sensitive sites like abandoned irrigation wells. We find some evidence that the program spilled over into citrus fields outside GWPAs managed by growers with fields in GWPAs.

A major concern regarding policies that focus on a handful of inputs is that producers increase the use of other environmentally harmful practices. Here, we find that the environmental impact of alternative active ingredients per planted acre in almond orchards, citrus groves, and grape vineyards. Additionally, we find that GWPA treatment had no significant impact on the environmental impact of herbicides (regulated and alternative ingredients) per planted in almond orchards but led to a significant decrease in citrus groves and grape vineyards.

Governments seek practical, politically feasible policy options to address worsening environmental quality from diffuse agricultural emissions. Targeting regions with measured pollution or environmental features characteristic of vulnerable zones offers a compromise between impractical field-level measurement of emissions and costly regional input bans. Offering a menu of management options differentiated by pollution pathway can further lower the cost of achieving environmental goals while providing more opportunities for growers to adapt to the regulation. This paper provides critical insights into a spatially targeted and differentiated pesticide program. Given the adjustment opportunities inherent in the program, our results highlight the extent to which crop industries respond differently, likely due to relative differences in pest pressure and market conditions.

References

Anderson, B.S., B.M. Phillips, J.P. Voorhees, X. Deng, J. Geraci, K. Worcester, and R.S. Tjeerdema. 2018. "Changing Patterns in Water Toxicity Associated with Current Use Pesticides in Three California Agriculture Regions." *Integrated Environmental Assessment and Management* 14:270–281, https://doi.org/10.1002/ieam.2005.

Anderson, G.D., J.J. Opaluch, and W.M. Sullivan. 1985. "Nonpoint Agricultural Pollution: Pesticide Contamination of Groundwater Supplies." *American Journal of Agricultural Economics* 67:1238–1243, https://doi.org/10.2307/1241408.

Antle, J., S. Capalbo, S. Mooney, E. Elliott, and K. Paustian. 2003. "Spatial heterogeneity, contract design, and the efficiency of carbon sequestration policies for agriculture." *Journal of Environmental Economics and Management* 46:231–250, https://doi.org/10.1016/S0095-0696(02)00038-4.

Barnard, C., S. Daberkow, M. Padgitt, M.E. Smith, and N. Uri. 1997. "Alternative measures of pesticide use." *Science of the Total Environment* 203:229–244, https://doi.org/10.1016/S0048-9697(97)00151-4.

Beach, E.D., and G.A. Carlson. 1993. "A Hedonic Analysis of Herbicides: Do User Safety and Water Quality Matter?" *American Journal of Agricultural Economics* 75:612–623, https://doi.org/10.2307/1243568.

Bellemare, M.F., and C.J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics* 82:50–61, https://doi.org/10.1111/obes.12325.

Bentley, W.J., F.G. Zalom, J. Granett, R.J. Smith, L.G. Varela, A.H. Purcell, W.D. Gubler, J. Stapleton, G.M. Leavitt, L.G. Varela, R.J. Smith, B.B. Westerdahl, C.L. Elmore, and D.R. Donaldson. 2003. "UC IPM Pest Management Guidelines: Grape." University of California Agriculture and Natural Resources, Publication Number 3448, Davis, CA, July.

Bexfield, L.M., K. Belitz, B.D. Lindsey, P.L. Toccalino, and L.H. Nowell. 2020. "Pesticides and Pesticide Degradates in Groundwater Used for Public Supply Across the United States: Occurrence and Human-Health Context." *Environmental Science & Technology* 55:362–372, https://doi.org/10.1021/acs.est.0c05793.

Blackburn, M.L. 2007. "Estimating wage differentials without logarithms." *Labour Economics* 14:73–98, https://doi.org/10.1016/j.labeco.2005.04.005.

Bryan, K.A., and Y. Ozcan. 2021. "The impact of open access mandates on invention." *Review of Economics and Statistics* 103:954–967, https://doi.org/10.1162/rest_a_00926.

Burrows, T.M. 1983. "Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis." *American Journal of Agricultural Economics* 65:806–810, https://doi.org/10.2307/1240471.

Butler, D. 2018. "EU expected to vote on pesticide ban after major scientific review." *Nature* 555:150–152, https://doi.org/10.1038/d41586-018-02639-1.

California Department of Food and Agriculture. 2004. "2003 County Agricultural Commissioners' Data." Sacramento, CA, September, https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/2003/200308cactb00.pdf.

—. 2024a. "2022–2023 California Agricultural Statistics Review." Sacramento, CA, https://www.cdfa.ca.gov/Statistics/PDFs/2022-2023_california_agricultural_statistics_review.pdf.

—. 2024b. "California County Agricultural Commissioners' Reports Crop Year 2021–2022." Sacramento, CA, March, https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/2022/2022_county_agricultural_commissioner_report_revised.pdf.

California Department of Pesticide Regulation. 2024. "Pesticide Contamination Prevention Act Review Process Triggered by Detections of Atrazine in Groundwater." https://www.cdpr.ca.gov/docs/emon/grndwtr/atrazine.htm (accessed June 28th 2024).

—. no date. "The permit process for restricted pesticides." https://www.cdpr.ca.gov/docs/dept/factshts/permitting.pdf.

Carter, C.A., J.A. Chalfant, R.E. Goodhue, F.M. Han, and M. DeSantis. 2005. "The Methyl Bromide Ban: Economic Impacts on the California Strawberry Industry." *Applied Economic Perspectives and Policy* 27:181–197, https://doi.org/10.1111/j.1467-9353.2005.00220.x.

Ciani, E., and G. De Blasio. 2015. "European structural funds during the crisis: evidence from Southern Italy." *IZA Journal of Labor Policy* 4, 20. https://doi.org/10.1186/s40173-015-0047-4.

Ciani, E., G. De Blasio, and S. Poy. 2022. “A freeway to prosperity? Evidence from Calabria, South of Italy.” *Economics of Transportation* 29, 100250. https://doi.org/10.1016/j.ecotra.2022.100250.

Ciani, E., and P. Fisher. 2019. “Dif-in-Dif Estimators of Multiplicative Treatment Effects.” *Journal of Econometric Methods* 8(1), 20160011. https://doi.org/10.1515/jem-2016-0011.

Cooper, J., and H. Dobson. 2007. “The benefits of pesticides to mankind and the environment.” *Crop Protection* 26:1337–1348, https://doi.org/10.1016/j.cropro.2007.03.022.

Donley, N. 2019. “The USA lags behind other agricultural nations in banning harmful pesticides.” *Environmental Health* 18, 4, https://doi.org/10.1186/s12940-019-0488-0.

Earnhart, D., and N.P. Hendricks. 2023. “Adapting to water restrictions: Intensive versus extensive adaptation over time differentiated by water right seniority.” *American Journal of Agricultural Economics* 105:1458–1490, https://doi.org/10.1111/ajae.12361.

Falconer, K. 1998. “Managing diffuse environmental contamination from agricultural pesticides: An economic perspective on issues and policy options, with particular reference to Europe.” *Agriculture, Ecosystems & Environment* 69:37–54, https://doi.org/10.1016/S0167-8809(98)00095-4.

Finger, R., N. Möhring, T. Dalhaus, and T. Böcker. 2017. “Revisiting Pesticide Taxation Schemes.” *Ecological Economics* 134:263–266, https://doi.org/10.1016/j.ecolecon.2016.12.001.

Gilliom, R.J., J.E. Barbash, C.G. Crawford, P.A. Hamilton, J.D. Martin, N. Nakagaki, L.H. Nowell, J.C. Scott, P.E. Stackelberg, G.P. Thelin, and D.M. Wolock. 2006. “The Quality of Our Nation’s Waters—Pesticides in the Nation’s Streams and Ground Water, 1992–2001.” U.S. Geological Survey Circular 1291, https://doi.org/10.3133/cir1291.

Gonnot, J., and M. Lanati. 2024. “Visa policy and international student migration: Evidence from Canada.” *Journal of Economic Geography* 1, lbae034. https://doi.org/10.1093/jeg/lbae034.

Goodhue, R.E., K. Klonsky, C. DeMars, S. Blecker, J. Steggall, M. Zhang, and R. Van Steenwyk. 2020. “Financial effect of limiting pesticide use near schools for almonds in nine counties depends on soils and weather.” *California Agriculture* 74:23–29, https://doi.org/10.3733/ca.2020a0001.

Goodhue, R.E., K. Klonsky, and S. Mohapatra. 2010. "Can an Education Program Be a Substitute for a Regulatory Program that Bans Pesticides? Evidence from a Panel Selection Model." *American Journal of Agricultural Economics* 92:956–971, https://doi.org/10.1093/ajae/aaq032.

Goodhue, R.E., M. Schweisguth, and K.M. Klonsky. 2016. "Revised chloropicrin use requirements impact strawberry growers unequally." *California Agriculture* 70:116–123, http://dx.doi.org/10.3733/ca.2016a0002.

Grafton-Cardwell, E.E., R.A. Baldwin, J.O. Becker, A. Eskalen, S.G. Gautam, C.J. Lovatt, S. Rios, J.E. Adaskaveg, B.A. Faber, D.R. Haviland, K.J. Hembree, J.G. Morse, and B.B. Westerdahl. 2019. "UC IPM Pest Management Guidelines: Citrus." University of California Agriculture and Natural Resources Publication Number 3441, Davis, CA, April.

Grafton-Cardwell, E.E., J.G. Morse, N.V. O'Connell, P.A. Phillips, C.E. Kallsen, D.R. Haviland, H.D. Ohr, J.A. Menge, J.O. Becker, B.B. Westerdahl, C.W. Coggins, C.J. Lovatt, A. Shrestha, and N.V. O'Connell. 2003. "UC IPM Pest Management Guidelines: Citrus." University of California Agriculture and Natural Resources Publication Number 3441, Davis, CA, July.

Grogan, K.A., and R.E. Goodhue. 2012. "Spatial Externalities of Pest Control Decisions in the California Citrus Industry." *Journal of Agricultural and Resource Economics* 37:156–179, https://www.jstor.org/stable/23243055.

Haviland, D.R., L.J. Bettiga, L.G. Varela, R.A. Baldwin, J.A. Roncoroni, R.J. Smith, B.B. Westerdahl, W.J. Bentley, K.M. Daane, A. Eskalen, H. Ferris, W.D. Gubler, K.J. Hembree, C.A. Ingels, L.R. Wunderlich, F.G. Zalom, and I. Zasada. 2015. "UC IPM Pest Management Guidelines: Grape." University of California Agriculture and Natural Resources Publication Number 3448, Davis, CA, July.

Haviland, D.R., E.J. Symmes, J.E. Adaskaveg, R.A. Duncan, J.A. Roncoroni, W.D. Gubler, B. Hanson, K.J. Hembree, B.A. Holtz, J.J. Stapleton, K.E. Tollerup, F.P. Trouillas, and F.G. Zalom. 2017. "UC IPM Pest Management Guidelines: Almond." University of California Agriculture and Natural Resources Publication Number 3431, Davis, CA, August.

Haviland, D.R., M. Yaghmour, E.J. Fichtner, B.L. Sanden, M. Culumber, M. Viveros, D. Stewart, and D.A. Sumner. 2019. "Sample Costs to Establish an Orchard and Produce Almonds: San Joaquin Valley South." University of California Agriculture and Natural Resources Cooperative Extension, Agricultural Issues Center, and University of California Davis Department of Agricultural and Resource Economics.

Jacquet, F., J.P. Butault, and L. Guichard. 2011. "An economic analysis of the possibility of reducing pesticides in French field crops." *Ecological Economics* 70:1638–1648, https://doi.org/10.1016/j.ecolecon.2011.04.003.

Jean, S., and J.C. Bureau. 2016. "Do regional trade agreements really boost trade? Evidence from agricultural products." *Review of World Economics* 152:477–499, http://dx.doi.org/10.1007/s10290-016-0253-1.

Kallsen, C.E., G.W. Douhan, K. Jetter, D. Stewart, and D.A. Sumner. 2021. "Sample Costs to Establish an Orchard and Produce Oranges: San Joaquin Valley South." University of California Agriculture and Natural Resources Cooperative Extension and University of California Davis Department of Agricultural and Resource Economics.

Kastoryano, S., and B. Vollaard. 2023. "Unseen annihilation: Illegal fishing practices and nautical patrol." *ournal of Environmental Economics and Management* 122:102881, https://doi.org/10.1016/j.jeem.2023.102881.

Kovach, J., C. Petzoldt, J. Degni, and J. Tette. 1992. "A Method to Measure the Environmental Impact of Pesticides." New York's Food and Life Sciences Bulletin 139, https://hdl.handle.net/1813/55750.

Kuwayama, Y., and N. Brozović. 2013. "The regulation of a spatially heterogeneous externality: Tradable groundwater permits to protect streams." *Journal of Environmental Economics and Management* 66(2):364–382, http://dx.doi.org/10.1016/j.jeem.2013.02.004.

Lankoski, J., and M. Ollikainen. 2003. "Agri-environmental externalities: a framework for designing targeted policies." *European review of agricultural economics* 30:51–75, https://doi.org/10.1093/erae/30.1.51.

Larch, M., J. Luckstead, and Y.V. Yotov. 2024. "Economic sanctions and agricultural trade." *American Journal of Agricultural Economics* 106:1477–1517, https://doi.org/10.1111/ajae.12473.

Larsen, A.E., S.D. Gaines, and O. Deschênes. 2017. "Agricultural pesticide use and adverse birth outcomes in the San Joaquin Valley of California." *Nature Communications* 8, 302, https://doi.org/10.1038/s41467-017-00349-2.

Lee, R., R. den Uyl, and H. Runhaar. 2019. "Assessment of policy instruments for pesticide use reduction in Europe; Learning from a systematic literature review." *Crop Protection* 126, 104929, https://doi.org/10.1016/j.cropro.2019.104929.

Leider, J., and L.M. Powell. 2022. "Longer-term impacts of the Oakland, California, sugar-sweetened beverage tax on prices and volume sold at two-years post-tax." *Social Science & Medicine* 292, 114537. https://doi.org/10.1016/j.socscimed.2021.114537.

Mapp, H.P., D.J. Bernardo, G.J. Sabbagh, S. Geleta, and K.B. Watkins. 1994. "Economic and Environmental Impacts of Limiting Nitrogen Use to Protect Water Quality: A Stochastic Regional Analysis." *American Journal of Agricultural Economics* 76:889–903, https://doi.org/10.2307/1243749.

Martínez, Y., and J. Albiac. 2006. "Nitrate pollution control under soil heterogeneity." *Land Use Policy* 23:521–532, https://doi.org/10.1016/j.landusepol.2005.05.002.

Mullenn, J.D., J.M. Alston, D.A. Sumner, M.T. Kreith, and N.V. Kuminoff. 2005. "The Payoff to Public Investments in Pest-Management R&D: General Issues and a Case Study Emphasizing Integrated Pest Management in California." *Applied Economic Perspectives and Policy* 27:558–573, https://doi.org/10.1111/j.1467-9353.2005.00264.x.

Murdock, J., B. Goodrich, and D.A. Sumner. 2022. "Sample Costs to Establish a Vineyard and Produce Wingrapes: San Joaquin Valley—North 2021." University of California Agriculture and Natural Resources Cooperative Extension and University of California Davis Department of Agricultural and Resource Economics.

Park, S., and D. Powell. 2021. "Is the rise in illicit opioids affecting labor supply and disability claiming rates?" *Journal of Health Economics* 76, 102430. https://doi.org/10.1016/j.jhealeco.2021.102430.

Qiao, F., J. Huang, L. Zhang, and S. Rozelle. 2012. "Pesticide use and farmers' health in China's rice production." *China Agricultural Economic Review* 4:468–484, https://doi.org/10.1108/17561371211284821.

Ribaudo, M.O. 2008. "Non-point Pollution Regulation Approaches in the US." In J. Albiac and A. Dinar, eds. *The Management of Water Quality and Irrigation Technologies*. London, Routledge, pp. 83–101, https://doi.org/10.4324/9781849773126.

Sambucci, O., J.M. Alston, K.B. Fuller, and J. Lusk. 2019. "The Pecuniary and Non-pecuniary Costs of Powdery Mildew and the Potential Value of Resistant Grape Varieties in California." *American Journal of Enology and Viticulture* 70:177–187, https://doi.org/10.5344%2Fajev.2018.18032.

Shortle, J., and R.D. Horan. 2013. "Policy Instruments for Water Quality Protection." *Annual Review of Resource Economics* 5:111–138, https://doi.org/10.1146/annurev-resource-091912-151903.

Sieber, S., D. Pannell, K. Müller, K. Holm-Müller, P. Kreins, and V. Gutsche. 2010. "Modelling pesticide risk: A marginal cost–benefit analysis of an environmental buffer-zone programme." *Land Use Policy* 27:653–661, https://doi.org/10.1016/j.landusepol.2009.08.021.

Silva, J.M.C.S., and S. Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics* 88:641–658, https://www.jstor.org/stable/40043025.

—. 2010. "On the existence of the maximum likelihood estimates in Poisson regression." *Economics Letters* 107:310–312, https://doi.org/10.1016/j.econlet.2010.02.020.

Silva, J.S., and S. Tenreyro. 2011. "Further simulation evidence on the performance of the Poisson pseudo-maximum likelihood estimator." *Economics Letters* 112(2):220–222, https://doi.org/10.1016/j.econlet.2011.05.008.

Staudt, J. 2020. "Mandating access: assessing the NIH's public access policy." *Economic Policy* 35(102):269–304, https://doi.org/10.1093/epolic/eiaa015.

Thomsen, R., V.H. Søndergaard, and K.I. Sørensen. 2004. "Hydrogeological mapping as a basis for establishing site-specific groundwater protection zones in Denmark." *Hydrogeology Journal* 12:550–562, https://doi.org/10.1007/s10040-004-0345-1.

Thomsen, R., and L. Thorling. 2003. "Use of Protection Zones and Land Management Restore Contaminated Groundwater in Denmark." *EOS, Transactions American Geophysical Union* 84(7):63–64, https://doi.org/10.1029/2003EO070005.

Troiano, J., C. Garretson, A. Dasilva, J. Marade, and T. Barry. 2013. "Pesticide and Nitrate Trends in Domestic Wells where Pesticide Use is Regulated in Fresno and Tulare Counties, California." *Journal of Environmental Quality* 42:1711–1723, https://doi.org/10.2134/jeq2013.06.0219.

U.S. Census Bureau. 2024. "California Profile." https://data.census.gov/profile?q=california&g=040XX00US06 (accessed on May 21st, 2024).

U.S. Department of Agriculture. 2004. "Farm and Ranch Irrigation Survey (2003)." Washington DC, November.

Weiben, C.M. 2021. "Preliminary estimated annual agricultural pesticide use for counties of the conterminous United States, 2019." U.S. Geological Survey Data Release, https://doi.org/10.5066/P9EDTHQL.

White, W.B. 1933. "Poisonous Spray Residues on Vegetables." *Industrial & Engineering Chemistry* 25:621–623, https://doi.org/10.1021/ie50282a010.

Wooldridge, J.M. 1999. "Distribution-free estimation of some nonlinear panel data models." *Journal of Econometrics* 90(1):77–97, https://doi.org/10.1016/S0304-4076(98)00033-5.

Zalom, F.G., R.A. Van Steenwyk, W.J. Bentley, R.L. Coviello, R.E. Rice, L.C. Hendricks, C. Pickel, M.W. Freeman, B.L. Teviotdale, G.W. D, J.J. Stapleton, M.V. McKenry, and T.S. Prather. 2002. "UC IPM Pest Management Guidelines: Almond." University of California Agriculture and Natural Resources Publication Number 3431, Davis, CA, May.

Zhan, Y., and M. Zhang. 2014. "Spatial and temporal patterns of pesticide use on California almonds and associated risks to the surrounding environment." *Science of the Total Environment* 472:517–529, https://doi.org/10.1016/j.scitotenv.2013.11.022.

Zhang, W. 2018. "Costs of a Practice-based Air Quality Regulation: Dairy Farms in the San Joaquin Valley." *American Journal of Agricultural Economics* 100:762–785, https://doi.org/10.1093/ajae/aax085.

Zhou, L., F. Zhang, S. Zhou, and C.G. Turvey. 2020. "The peer effect of training on farmers' pesticides application: a spatial econometric approach." *China Agricultural Economic Review* 12:481–505, https://doi.org/10.1108/CAER-01-2019-0003.

Zilberman, D., and K. Millock. 1997. "Financial incentives and pesticide use." *Food Policy* 22:133–144, https://doi.org/10.1016/S0306-9192(97)00004-3.

A Appendix Tables

Table A1: Herbicide EIQ and Total Acres Treated in 1996–2004

Active ingredient	EIQ	Almond	Citrus	Grape
		100,000 acres treated		
Panel A. Regulated active ingredients				
Simazine	21.52	9.491	11.416	23.935
Diuron	26.47	0.008	12.486	6.598
Norflurazon	17.50	4.598	1.639	4.203
Bromacil	12.63	0.001	3.777	0.001
Atrazine	22.85	0.008	0.000	0.001
Prometon	24.46	0.000	0.000	0.001
Bentazon, sodium salt	18.67	0.000	0.000	0.000
Panel B. Alternative herbicides				
Glyphosate, isopropylamine salt	15.33	69.494	47.613	56.038
Oxyfluorfen	33.82	38.367	2.470	27.745
Paraquat dichloride	24.73	18.725	2.831	25.832
Oryzalin	18.10	6.163	0.768	8.442
2,4-d, dimethylamine salt	20.67	6.869	0.563	1.528
Trifluralin	18.83	1.812	0.699	2.053
Glyphosate-trimesium	15.33	2.442	0.246	1.104
Pendimethalin	30.17	1.354	0.294	0.844
Glyphosate, diammonium salt	15.33	2.186	0.157	0.137
2,4-d, diethanolamine salt	16.67	1.964	0.034	0.002
Napropamide	12.57	0.567	0.136	0.940
Glyphosate, monoammonium salt	15.33	0.613	0.639	0.266
Glyphosate	15.33	0.583	0.188	0.422
Sethoxydim	20.89	0.095	0.002	1.088
2,4-d	17.33	0.895	0.050	0.185
2,4-d, triethylamine salt	27.23	0.895	0.050	0.185
Glufosinate-ammonium	20.20	0.162	0.000	0.574
Glyphosate, potassium salt	15.33	0.382	0.048	0.078
Eptc	9.43	0.349	0.000	0.000
Halosulfuron	20.20	0.308	0.002	0.001
Msma	18.00	0.084	0.182	0.004
Fluazifop-p-butyl	28.71	0.056	0.016	0.145
Thiazopyr	15.07	0.078	0.039	0.087
Isoxaben	23.67	0.045	0.008	0.032
Diquat dibromide	39.20	0.005	0.002	0.061
Clethodim	17.00	0.011	0.002	0.013
Mcpa, dimethylamine salt	22.67	0.016	0.000	0.004
Others	–	0.061	0.024	0.088

Note: We use the EIQ of a similar chemical when the EIQ data does not contain an exact match. For example, we use the glyphosate EIQ for all glyphosate salts. There are 68 other alternative herbicide active ingredients not listed here, each used to treat less than 2,000 acres in 1996–2004 with EIQ values ranging from 11 to 47. We include these other chemicals in our analysis.

Table A2: Pounds and Share of Regulated Active Ingredients Used on Almond Orchards, Citrus Groves, Grape Vineyards, and Other Crops in 1996–2004

Active Ingredient	Crop	Pounds	Share (%)
Atrazine	Almond	181	0.04
Atrazine	Citrus	32	0.01
Atrazine	Grape	67	0.01
Atrazine	Others	470,991	99.94
Bromacil	Almond	56	0.01
Bromacil	Citrus	432,451	99.02
Bromacil	Grape	59	0.01
Bromacil	Others	4,178	0.96
Diuron	Almond	669	0.01
Diuron	Citrus	2,127,211	39.95
Diuron	Grape	482,266	9.06
Diuron	Others	2,714,918	50.98
Norflurazon	Almond	408,676	24.64
Norflurazon	Citrus	211,361	12.74
Norflurazon	Grape	323,689	19.52
Norflurazon	Others	714,782	43.10
Prometon	Almond	0	0.00
Prometon	Citrus	0	0.00
Prometon	Grape	2	7.14
Prometon	Others	26	92.86
Simazine	Almond	495,011	8.25
Simazine	Citrus	2,108,251	35.12
Simazine	Grape	2,329,290	38.80
Simazine	Others	1,070,952	17.84

Table A3: Share of Annual Field Observations by Number of Regulated Active Ingredient Applications

Crop	Number of regulated AI applications	Pre-program period (1996–2004) %	Program period (2005–2020) %
Almond	0	74.56	91.27
Almond	1	21.76	7.42
Almond	>1	3.69	1.31
Citrus	0	55.36	70.97
Citrus	1	33.99	23.28
Citrus	>1	10.65	5.75
Grape	0	62.18	82.20
Grape	1	35.43	16.79
Grape	>1	2.39	1.01

Note: The shares for each crop in pre-program years (1996–2004) sum to 100%. The same is true for post-program (2005–2020) shares. We calculated the shares by estimating the count of regulated active ingredient applications to a field within a year, then summing over the years and dividing by the number of field-by-year observations. We consider regulated active ingredient applications within 2 weeks of each other as the same application to account for products applied as a tank mix and fields that take multiple days to spray. We include all observations (GWPA and non GWPA fields) in our calculation.

Table A4: Pre-Trends Test of the Impact of the Groundwater Protection Program on the Probability Growers Treated Field With Regulated Active Ingredients

	Almond (1)	Citrus (2)	Grape (3)
Panel A: GWPA			
Year × Pre-treatment × GWPA	0.002	0.007**	-0.003
	(0.002)	(0.004)	(0.002)
Panel B:Leaching and runoff GWPAs			
Year × Pre-treatment × Leaching GWPA	-0.008	0.008	-0.077
	(0.017)	(0.007)	(0.680)
Year × Pre-treatment × Runoff GWPA	0.0001	0.007*	-0.071
	(0.018)	(0.004)	(0.679)
Panel C: Leaching and runoff GWPAs with spillover control			
Year × Pre-treatment × Leaching GWPA	-0.992	0.008	-0.007**
	(3.975)	(0.008)	(0.003)
Year × Pre-treatment × Runoff GWPA	-0.984	0.007*	-0.001
	(3.975)	(0.004)	(0.004)
Year × Pre-treatment × Field outside GWPA	-0.995	-0.002	-0.004
	(3.975)	(0.004)	(0.002)

Note: Regressions that produce estimates in Panel A are defined in equation (5). Panels B and C show pre-trend estimates of regressions that extend equation (5) to include leaching, runoff, and field outside GWPA that is managed by a grower with a field inside GWPA variables and associated interaction variables. We only show estimates for pre-trends here for brevity and clarity. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Pre-Trends Test of the Impact of the Groundwater Protection Program on the Environmental Impact of Regulated Active Ingredients Applied per Planted Acre

	Almond (1)	Citrus (2)	Grape (3)
Panel A: GWPA			
Year × Pre-treatment × GWPA	-0.005	0.006	0.009
	(0.012)	(0.013)	(0.006)
Panel B:Leaching and runoff GWPAs			
Year × Pre-treatment × Leaching GWPA	-0.016	0.028	0.005
	(0.013)	(0.029)	(0.007)
Year × Pre-treatment × Runoff GWPA	0.047**	0.003	0.019*
	(0.024)	(0.014)	(0.011)
Panel C: Leaching and runoff GWPAs with spillover control			
Year × Pre-treatment × Leaching GWPA	-0.028*	0.042	0.003
	(0.015)	(0.030)	(0.008)
Year × Pre-treatment × Runoff GWPA	0.036	0.014	0.017
	(0.025)	(0.015)	(0.012)
Year × Pre-treatment × Field outside GWPA	-0.026*	0.025*	-0.004
	(0.014)	(0.014)	(0.009)

Note: Regressions that produce estimates in Panel A are defined in equation (6). Panels B and C show pre-trend estimates of regressions that extend equation (6) to include leaching, runoff, and field outside GWPA that is managed by a grower with a field inside GWPA variables and associated interaction variables. We only show estimates for pre-trends here for brevity and clarity. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Pre-Trends Test of the Impact of the Groundwater Protection Program on the Environmental Impact of Herbicide Active Ingredients Applied per Planted Acre

	Almond	Citrus	Grape
	(1)	(2)	(3)
Panel A: GWPA			
Year × Pre-treatment × GWPA	0.01	0.01	0.001
	(0.01)	(0.01)	(0.01)
Panel B:Leaching and runoff GWPAs			
Year × Pre-treatment × Leaching GWPA	0.008	0.011	0.004
	(0.006)	(0.023)	(0.007)
Year × Pre-treatment × Runoff GWPA	0.014	0.008	0.008
	(0.012)	(0.010)	(0.009)
Panel C: Leaching and runoff GWPAs with spillover control			
Year × Pre-treatment × Leaching GWPA	0.001	0.019	0.004
	(0.007)	(0.024)	(0.008)
Year × Pre-treatment × Runoff GWPA	0.008	0.015	0.008
	(0.012)	(0.011)	(0.010)
Year × Pre-treatment × Field outside GWPA	-0.014**	0.016	0.001
	(0.006)	(0.011)	(0.007)

Note: Regressions that produce estimates in Panel A are defined in equation (6). Panels B and C show pre-trend estimates of regressions that extend equation (6) to include leaching, runoff, and field outside GWPA that is managed by a grower with a field inside GWPA variables and associated interaction variables. We only show estimates for pre-trends here for brevity and clarity. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Monthly Share of 2004 Acres Sprayed With Herbicides

	Alternative AIs			Regulated AIs		
Month	Almond	Citrus	Grape	Almond	Citrus	Grape
			%			
Jan	9.9	3.7	14.5	19.5	14.7	19.9
Feb	7.4	5.4	18.1	10.6	17.4	29.1
Mar	6.8	7.8	14.7	6.7	14.4	25.9
Apr	10.9	8.4	9.4	6.5	3.0	2.5
May	11.1	9.9	10.2	5.3	1.2	0.4
Jun	12.6	14.3	7.6	2.3	0.8	0.7
Jul	13.3	13.2	5.3	4.4	0.7	0.1
Aug	5.1	12.4	1.5	0.6	0.3	0.1
Sep	1.6	8.7	1.2	0.2	0.3	0
Oct	3.6	4.4	1.6	3.9	3.7	0.4
Nov	9.5	6.2	7.0	20.4	26.4	7.3
Dec	8.1	5.7	9.0	19.6	17.1	13.6

Note: Monthly shares calculated as the sum of crop acres sprayed with alternative herbicide active ingredients divided by the crop acres sprayed with alternative ingredients in 2004. We use similar calculations for regulated active ingredients. Columns sum to 100.

Table A8: Robustness Check of the Impact of the Groundwater Protection Program on the Environmental Impact of Herbicide Active Ingredients Applied per Planted Acre Using Annual Period June through May

	Almond	Citrus	Grape
	(1)	(2)	(3)
Panel A: Average GWPA effect			
GWPA	0.003	-0.17***	-0.19***
	(0.03)	(0.04)	(0.02)
Observations	124,678	52,350	163,719
Pseudo R^2	0.37	0.48	0.41
Panel B: Average effect of leaching and runoff GWPAs			
Leaching GWPA	-0.01	-0.10	-0.20***
	(0.03)	(0.12)	(0.03)
Runoff GWPA	0.01	-0.18***	-0.16***
	(0.04)	(0.04)	(0.03)
Observations	124,678	52,350	163,719
Pseudo R^2	0.37	0.48	0.41
Panel C: Average effect of GWPAs with spillover control			
Leaching GWPA	0.01	-0.12	-0.15***
	(0.03)	(0.12)	(0.03)
Runoff GWPA	0.03	-0.20***	-0.11***
	(0.05)	(0.05)	(0.04)
Field outside GWPA,	0.04	-0.04	0.12***
grower has field inside a GWPA	(0.02)	(0.05)	(0.03)
Observations	124,678	52,350	163,719
Pseudo R^2	0.37	0.48	0.41

Note: Regressions include year, field, and county by year fixed effects. Estimates presented here equal the relative impacts of a discrete change in GWPA treatment calculated using the formula $e^{\beta} - 1$. Multiplying the point estimate presented by 100 equals the effect in percentage terms. We calculated the standard errors of the relative impacts using the Delta method. Standard errors in parentheses are clustered by field. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Appendix Figures

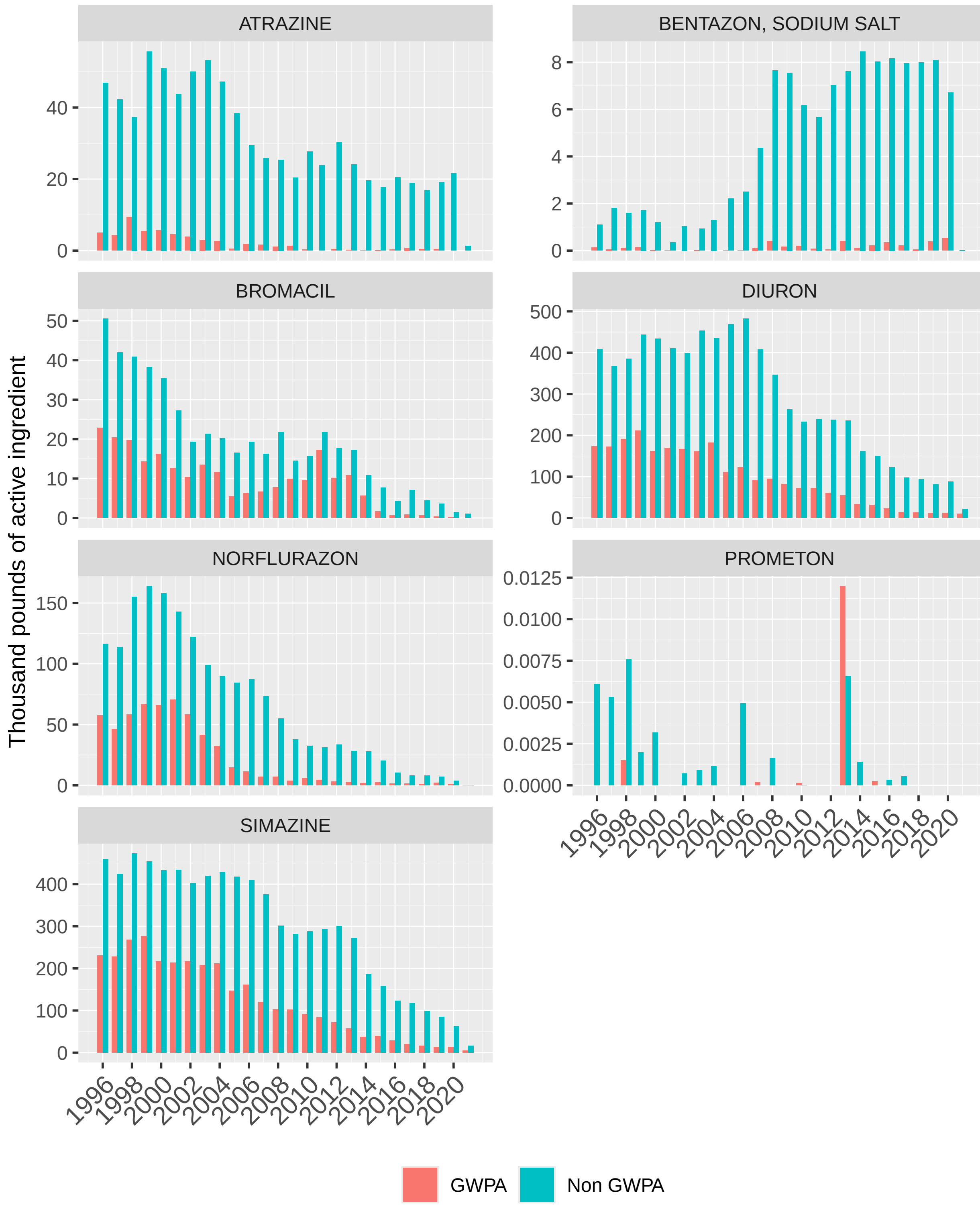

Figure A1: Annual quantity of regulated active ingredients used in California

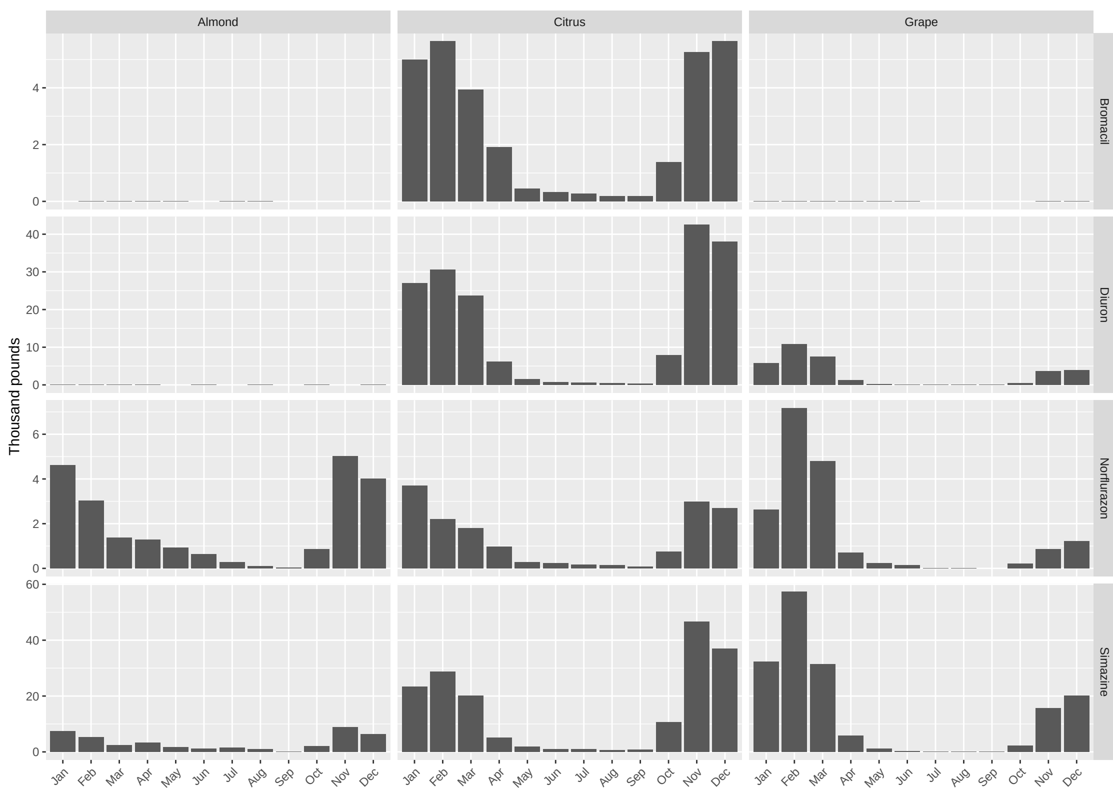

Figure A2: Mean pounds of regulated active ingredient used in 1996–2020 by month.

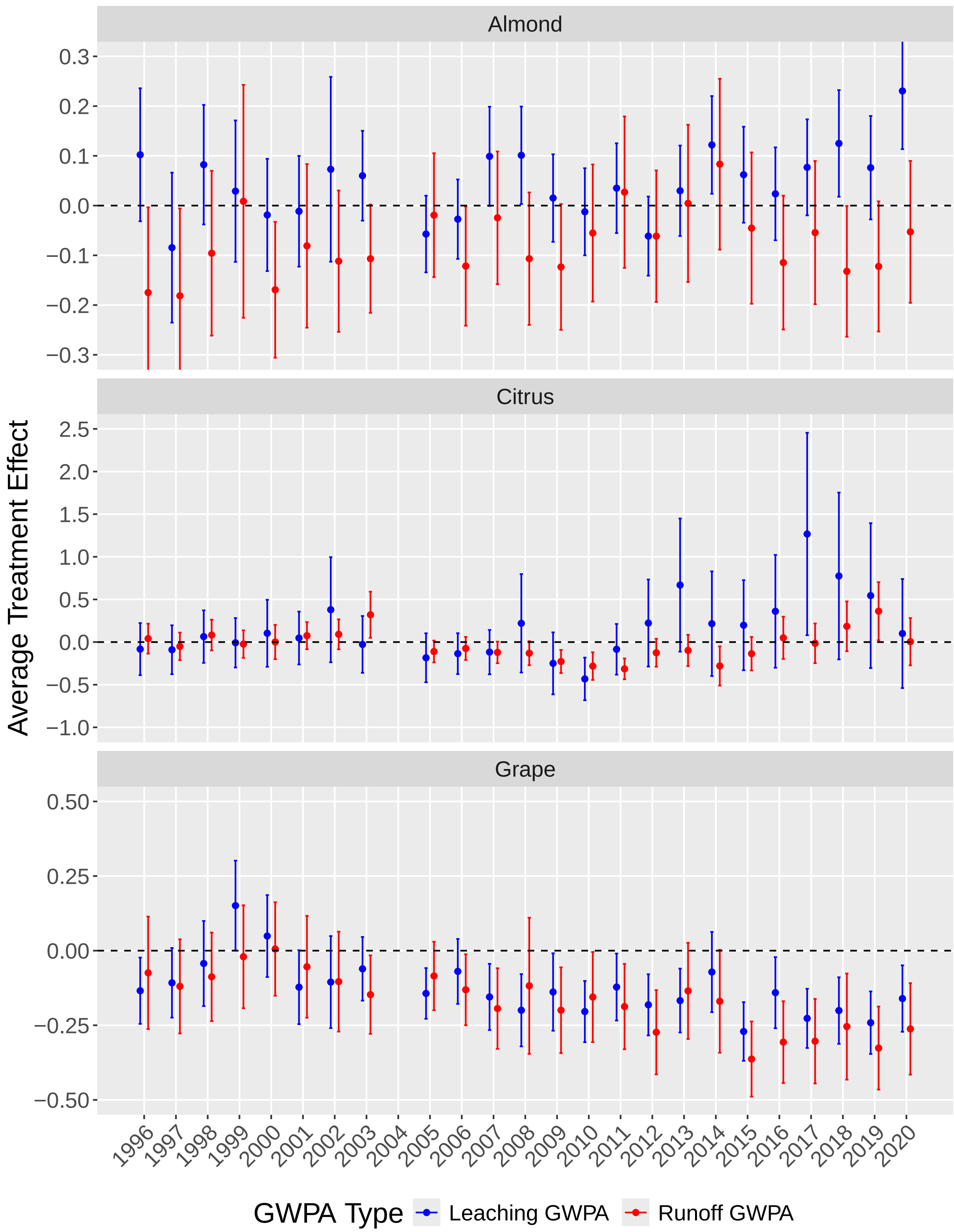

Figure A3: Robustness check of the effect of the Groundwater Protection Program on the environmental impact of herbicides per planted acre using annual periods of June through May