Are Farmers Good Neighbors? Self-Regulation of Pesticide Applications near Schools and Daycares in California

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Abstract

We test whether California agricultural producers self-regulate their pesticide applications near public schools and licensed daycares using administrative data on all field-level applications with grower identifiers from 2009 to 2014. Agricultural producers can self-regulate their pesticide applications near schools and daycares by voluntarily conducting their applications on evenings and weekends, thereby minimizing the potential harm of drift. As a policy option, self-regulation is almost always within the regulator's choice set; however, it is typically difficult to measure the extent of self-regulation because data may not be available at the relevant observational level and strategic considerations may confound inference about decision-making. Our setting and administrative data allows us to overcome these challenges. The data suggest fields with more schools and daycares in their proximity are less likely to be sprayed between 6am and 6pm on weekdays; however, the magnitude of the effect is very small. Imposing the admittedly strong assumption of all else equal, our results suggest farmers would reduce their applications on school days from 56.0% to 53.2%. Whether or not the extent of this self-regulation is sufficient, or publicly optimal, remains an open question.

1 Introduction

The extent and efficacy of self-regulation is fundamental to the economic design and evaluation of regulation: the net benefit of government intervention is a function of the alternative opportunities in the regulator's choice set and self-regulation is almost always available in that choice set. With self-regulation in the context of a negative externality, an individual (or industry) voluntarily imposes constraints on itself to mitigate the undesirable consequences of its actions on others. Proponents argue self-regulation gives individuals greater discretion in how to meet public objectives and thus leads to faster, more flexible, and less expensive (to both firms and regulatory agencies) regulation. Firms can be motivated to take self-regulatory actions for any number of reasons, including the threat of regulation and pressure from consumers (Maxwell, Lyon, and Hackett, 2000; Anton, Deltas, and Khanna, 2004). Skeptics question the efficacy and stability of self-regulation. Without explicit sanctions, the threat of regulation may not be credible and firms could act opportunistically. The role of self-regulation is ultimately an empirical question: do individuals use their discretion to act in ways consistent with public goals or with their own private interests? However, measuring the extent and efficacy of self-regulation is difficult for two major reasons. First, it is not always possible to observe the pertinent decision at an individual level with sufficiently many observations. Second, the pertinent decision may be confounded by strategic considerations (e.g. market power).

In this paper we investigate self-regulation of pesticide applications by farmers near schools and licensed child day care centers in California. Our rich data set allows us to overcome these challenges. We observe the location, date, and time of each pesticide application at the field-level, made up of thousands of decisions made by thousands of independent decision makers. This includes unique individuals making multiple decisions on a given field and across multiple fields. Further, the competitive nature of agricultural production addresses the possibility of strategic considerations confounding an individual's decision: it is implausible that one farmer's decision on one pesticide application on one field would influence the price of their product. The negative externality in this setting is the potential adverse health consequences of pesticide exposure for children. Producers can minimize the probability of exposure by voluntarily conducting applications near schools or daycares in the evenings or on weekends. Anecdotal evidence suggests, by and large, farmers avoid problematic applications. The objective of this paper is to address the question: to what extent do farmers self-regulate their pesticide applications near schools and daycares?

We investigate this empirical question using rich, field-level data on pesticide applications in 13 major agricultural counties in California. These counties account for two-thirds of the state's total crop production value. The data is based on the California Department of Pesticide Regulation's Pesticide Use Report, which (through mandatory reporting requirements) records applications by pesticide product, application type, date and time of application, and grower-site identifiers. These detailed records cover over 1.8 million unique applications from Jan. 1, 2009 to Dec. 31, 2014 for over 200 crops, nearly 10,000 growers, over 25,500 fields, and nearly 4,000 unique product numbers. We supplement the Pesticide Use Report with spatial data on the number of public school and licensed child daycare addresses within concentric circles up to one mile from each field to conduct a robust empirical analysis.

To identify the extent to which farmers self-regulate pesticide applications, we exploit spatial variation in the proximity of fields to schools (and daycares). Abstracting from particulars, pest incidence is likely to be highly spatially correlated; however, only some fields are close to schools. "Good neighbors" constrain their actions by not spraying on schooldays from 6am to 6pm, "bad neighbors" do not. In particular, our dependent variable is a discrete choice on whether or not the given pesticide application occurred between 6am and 6pm on a school day. Fields that are sufficiently close to schools form a quasi-treatment group. Fields that are not sufficiently close form a quasi-control group because they cannot incur external harm on the community, need not constrain their applications, and thus act fully within their own private interests.

The remainder of this manuscript proceeds as follows. In the next section we briefly discuss the health externalities from pesticide exposure and the institutional arrangements governing pesticide applications in California. The third section sets out our estimation strategy and analyzes its results. The fourth and final section concludes.

2 Background

Pesticides are a broad class of inherently toxic chemicals applied on numerous crops in a variety of circumstances to control insects, weeds, fungi, or rodents. Human exposure to pesticides can occur through ingestion, inhalation, or skin contact. Possible exposure-related illnesses have been reported more than 1.5 miles from application sites. The acute effects of exposure ranges from mild (headache, nausea, irritation of the skin, nose, eyes, or throat, and vomiting) to severe (convulsion, pulmonary edema, orthostatic hypotension, and poisoning death). Some common chemicals used in pesticides are known to be teratogenic, carcinogenic, or toxinogenic, leading to chronic effects such as birth defects (paternal or maternal prenatal exposure) and cancer. Children are particularly vulnerable to exposure because of frequent hand-to-mouth activity and to toxicity because of their smaller body size relative to volume of food, fluid or air intake. Thus, pesticide applications in the vicinity of schools and daycares require increased diligence, where the level of increased diligence required varies by application because the toxicity and risk of exposure vary by both pesticide and application method. Figure 1 summarizes reported pesticide illness incidents in California on a yearly basis

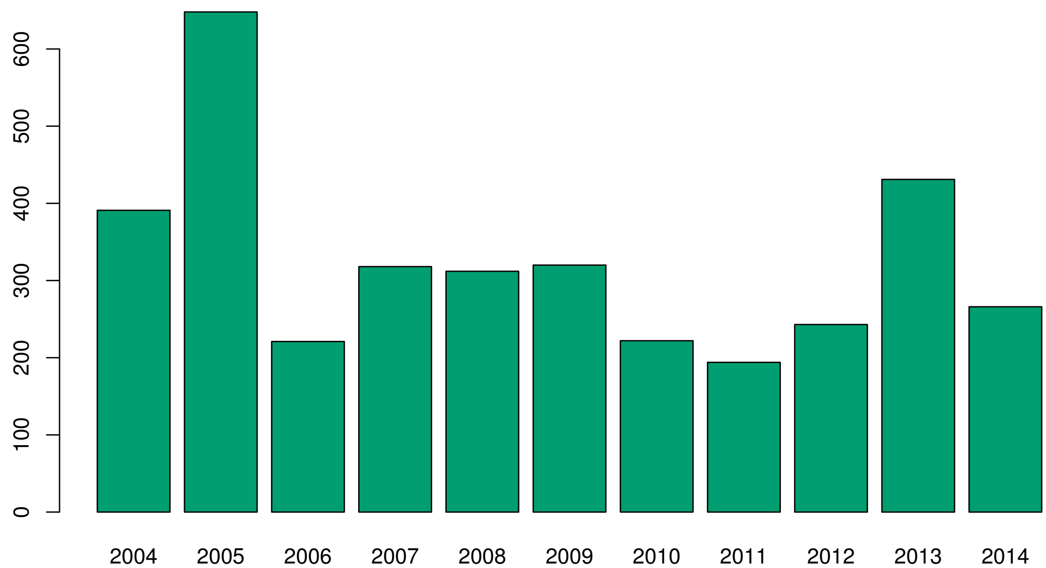

Figure 1: Pesticide illness incidents in California, 2004–2014

from 2004–2014.[1] Each year there are a few hundred cases, roughly 14% of which lead to a disability with an average of 2.9 days lost per case. Two or three cases per year result in a hospitalization with an average stay of 2.5 days.

A number of scientific studies have examined the health consequences of pesticide exposure for children in agricultural areas. Bradman et al. (1996) conducted a small study of 11 households in California's Central Valley, five of which had at least one farmworker in the house, including dust samples and hand residues on one child per house between the ages of 1 and 3. Residues were detected in all homes and the hand residue samples on three children suggested exposure could exceed federal EPA reference doses. Loewenherz et al. (1997) monitored children up to six years of age near orchards in central Washington state and found that children of pesticide applicators had significantly higher levels of pesticide exposure indicated by urine samples, with

[1] Source: California Pesticide Illness Query (`http://apps.cdpr.ca.gov/calpiq/index.cfm`).

proximity to the orchard being a strong indicator of exposure though not at an acutely hazardous level. Also in central Washington, Lu et al. (2000) found those living close (within 200ft or 60m) to treated orchards had significantly higher median levels of pesticide residue in housedust and metabolite concentrations in their urine with the magnitude on the order of five to nine times higher. Eskenazi et al. (2007) examined fetal exposure to pesticide residues in Mexican-American farm workers and found that prenatal concentrations were negatively associated with mental development, though postnatal concentrations up to 24 months did not have a statistically distinguishable effect. Other interesting studies in this vein have examined the impact of pesticides transmitted on vehicles and farmworkers on children's exposure (Curl et al., 2002); analyzed the level and type of birth defects, autism, and other reproductive outcomes in regions with higher agricultural activity (Garry et al., 1996, 2002; Roberts et al., 2007); and considered the differential impacts of a conventional versus organic diet on concentration of pesticide metabolites in children (Curl, Fenske, and Elgethun, 2003; Lu et al., 2008). Studies suggest that exposure can and does occur to children at school (Alarcon et al., 2005). Taken together, the scientific literature provides a clear justification for the potential harm that can be caused by improper pesticide applications.

Pesticide applications have also received attention in the agricultural economics literature. Early work considered productivity (e.g. Headley, 1968; Hall and Norgaard, 1973), welfare (e.g. Taylor and Frohberg, 1977), risk (e.g. Day, 1965; Feder, 1979), and the political considerations of pesticide use and regulation (e.g. van Ravenswaay and Skelding, 1985) . Davis, Caswell, and Harper (1992) examined the structure of legal liabilities faced by firms and their consequent incentives for protecting farmworkers from harmful exposures. Lichtenberg, Spear, and Zilberman (1993) argued reentry regulation provided a rational incentive for preventative applications of pesticides. An integrated impact of pesticide use on health impacts—the net impact of gains in productivity due to pesticides net the loss in productivity due to associated illnesses—were evaluated by Antle and Pingali (1994) and Pingali, Marquez, and Palis (1994) in a developing world context. A number studies consider more direct estimation of the social costs related to pesticide use versus crop damages (Pimentel et al., 1992; Wilson and Tisdell, 2001; Soares and de Souza Porto, 2009; Chambers, Karagiannis, and Tzouvelekas, 2010). In a context closely related to self-regulation and our empirical question, Goodhue, Klonsky, and Mohapatra (2010) found that an education program led California almond farmers to voluntarily substitute environmentally-friendly alternatives for their organophosphate pesticides.

In the United States minimum standards on pesticide use are set by the federal Environmental Protection Agency. Enforcement of these minimum standards is delegated to the states. The California Department of Pesticide Regulation operates within the state-level Environmental Protection Agency and was founded in 1991. Currently, the department has a staff of about 400 with an annual operating budget of $100 million. The department has the authority to register products—including the evaluation and licensing of new and current products—as well as human health assessment, worker safety, enforcement, and environmental monitoring. A topical issue at hand is the, "Proposed Rules on Agricultural Pesticide Use Near Schools and Child Day-care Centers" currently under consideration by the California Department of Pesticide Regulation.[2]

[2]See for example the public consultations of March 16, 2017; October 19, 2016; September 29, 2016; and April 29, 2015.

3 Estimation and results

3.1 Data

Administrative data on pesticide applications recorded at the field-level were provided by the California Department of Pesticide Regulation via the Pesticide Use Report. Pesticide applications have mandatory reporting requirements: all "agricultural applications" must be reported to county agricultural commissioners who report to the state-level agency. Failure to comply with these reporting requirements are punishable under the law with punishments including fines up to $5,000 and revocation of statewide licenses. "Agricultural applications" are broadly defined in the law to include parks, golf courses, rangeland, pasture, cemeteries and more (e.g. postharvest applications); so we restrict our analyses to what would more typically be referred to as agricultural use: applications for production of an agricultural commodity.[3] Mandatory reporting requirements have been in place since 1990, with updates made for quality control purposes in 2001 and new guidelines for reporting outliers in 2016.

The raw data set has 4,520,701 entries. We remove 21,561 entries corresponding to fumigations, all of which must be conducted outside of school hours when a school or daycare is within one-eigth of a mile from the nearest point of the application site. Table 1 provides an example entry in the PUR database. Any one application can include a number of different active ingredients so the Pesticide Use Report database is encoded such that there is one entry and corresponding use number per chemical applied. We remove all entries which are reported less than 1×10^{-4} pounds of the main chemical applied (i.e. the first and second entry in table 1) leaving us with 3,380,227 entries. Note that this still leaves us with multiple records per application,

[3] Defined by title 3 of the California code of regulations section 6000 as an unprocessed product of farms, ranches, nurseries and forests excepting livestock, poultry, and fish. More information on this data set and the publicly available version are available at: `http://www.cdpr.ca.gov/docs/pur/purmain.htm`.

which could bias or estimates. Since we do not condition on the main chemical by type or pounds applied, we use the first entry for the purpose of our analysis. Removing the repeated entries results in 1,855,153 unique observations for our analysis.

Our data set covers the 13 principle agricultural counties within the state from 2009 to 2014, which accounted for roughly two-thirds of the agricultural production by value.[4] Table 2 shows the number of entries by county-year. There are 204 unique crops recorded in the data set—from alfalfa, almond, and apple to peanut, root vegetable, and timothy grass—9,747 unique grower identifiers, 25,540 unique fields, and 3,887 unique product numbers. Note that the product number is assigned by the Department of Pesticide Regulation for each new product registration and thus corresponds to a unique California Registration Number. Eight crops recorded more than 50,000 applications during the sample period: almond (299,792), grape (239,275), wine grape (179,295), alfalfa (106,190), processing tomatoes (69,621), walnut (63,322), cotton (67,155), and orange (53,335). Unconditional on proximity to schools or daycares 55.6% of applications occur on weekdays between 6am and 6pm, 20.2% occur on weekends, and the remainder on weeknights.

Finally, we require information on the proximity of each field to schools and daycares. Using geographic information systems software, we counted the number of public schools and licensed daycare centres within concentric circles of a field in fixed increments. All data were loaded into a PostgreSQL database with all spatial data projected into a common coordinate system. Individual county crop maps were normalized to a common naming scheme and joined into a single layer. Addresses for schools and licensed child daycare facilities were obtained from the California Department of Education and California Department of Social Services, respectfully. We include separate categories for schools, daycares, urban buildings, residential buildings, and agricultural

[4] Data limitations prevent us from including two other major agricultural counties, Tulare and Monterey.)

Table 1: Abridged entry for one application (single grower on one field at one date and time) in the Pesticide Use Report.

Use	Acre	Prod.	Used	Chem.		Main Chem.	
No.	Treated	no.	(lbs)	Code	Type	Name	lbs.
1	4.00	38004	1.0163	NA	NA	NA	0
2	4.00	25801	0.7497	NA	NA	NA	0
3	4.00	54733	6.4944	1855	herbicide	glyphosate, isopropylamine salt	2.662
4	4.00	52973	0.0914	5130	herbicide	carfentrazone-ethyl	0.019
5	4.00	50623	10.2975	1868	herbicide	oryzalin	4.160

Notes: We have abridged the entries for the purpose of presenting in one short table. Each use number corresponds to one entry in the database. Information that has been suppressed includes: application date and time, grower id, site id, spatial site-identifiers, crop, county id, product names, and aerial/ground indicator. As explained in the main text, we exclude entries with less than 1×10^{-4} of main chemical applied. Values for pounds of main chemical applied have been rounded (in the actual data they are reported to seven digits).

Table 2: Pesticide applications by county and year.

County	2009	2010	2011	2012	2013	2014	Total
Fresno	53971	66546	81957	85185	95073	106215	488947
Imperial	10938	14632	18446	22023	23502	32029	121570
Kern	21637	27495	31422	33198	39313	48354	201419
Kings	7738	9804	9810	12090	13108	20494	73044
Madera	16240	19046	24033	23792	26175	29082	138368
Merced	8138	11845	13700	14082	15284	19068	82117
Sacramento	5348	6164	6238	5919	6136	8391	38196
San Joaquin	26487	28758	33424	34710	38896	48247	210522
San Luis Obispo	2075	2070	2204	3142	3743	5034	18268
Santa Barbara	441	547	6431	5280	8508	12262	33469
Stanislaus	32807	34653	37668	39836	41315	46189	232468
Ventura	18346	23953	25825	26009	29671	33158	156962
Yolo	7177	8990	9472	9301	10614	14249	59803
Total	211343	254503	300630	314567	351338	422772	1855153

Note: This table shows the number of reported applications by year and county in the Pesticide Use Report data.

Table 3: Summary statistics for the number of daycares, schools, and both within respective distances.

	Number of Units			
Distance (ft.)	Mean	Median	SD	$\mathbb{1}_{(\#\text{ units} \geq 1)}$
		Daycare Buildings		
adjacent	0.003	0.0	0.102	0.002
330	0.015	0.0	0.213	0.009
660	0.037	0.0	0.310	0.021
1320	0.103	0.0	0.616	0.043
1980	0.265	0.0	1.553	0.070
2640	0.504	0.0	2.879	0.097
3960	1.279	0.0	9.128	0.160
5280	2.323	0.0	18.604	0.231
		School Buildings		
adjacent	0.007	0.0	0.116	0.005
330	0.029	0.0	0.301	0.016
660	0.037	0.0	0.349	0.020
1320	0.073	0.0	0.530	0.035
1980	0.149	0.0	0.845	0.065
2640	0.240	0.0	1.179	0.094
3960	0.578	0.0	2.066	0.172
5280	1.044	0.0	3.297	0.251
		Daycare + School Buildings		
adjacent	0.011	0.0	0.159	0.007
330	0.044	0.0	0.393	0.023
660	0.075	0.0	0.508	0.038
1320	0.175	0.0	0.895	0.067
1980	0.414	0.0	1.929	0.103
2640	0.743	0.0	3.393	0.139
3960	1.857	0.0	10.182	0.232
5280	3.367	0.0	20.352	0.319

Note: Columns (2) through (4) report the mean, median and standard deviation of the cumulative number of units of each type of building within the respective distances. Column (5) reports the share of records with one or more of the building type in the distance category.

Table 4: Summary statistics for the number of urban, residential, and agricultural buildings within respective distances.

Distance (ft.)	Number of Units			
	Mean	Median	SD	$\mathbb{1}_{(\# \text{ units} \geq 1)}$
Agricultural Buildings				
adjacent	3.854	3.0	5.503	0.897
330	7.844	6.0	9.089	0.964
660	9.274	7.0	11.233	0.974
1320	13.351	10.0	16.963	0.985
1980	20.411	15.0	25.595	0.991
2640	26.631	20.0	35.672	0.993
3960	46.248	34.0	60.662	0.996
5280	67.471	50.0	87.798	0.998
Residential Buildings				
adjacent	0.528	0.0	4.550	0.166
330	4.423	0.0	21.682	0.345
660	10.894	0.0	60.780	0.392
1320	31.442	0.0	182.833	0.496
1980	64.130	1.0	367.022	0.580
2640	108.170	2.0	610.600	0.636
3960	244.014	6.0	1374.781	0.731
5280	458.819	12.0	2627.857	0.790
Urban Buildings				
adjacent	0.571	0.0	4.644	0.183
330	4.633	0.0	21.906	0.376
660	11.331	0.0	61.311	0.425
1320	32.868	1.0	185.707	0.529
1980	67.121	2.0	373.198	0.619
2640	113.281	3.0	621.679	0.674
3960	256.305	6.0	1403.007	0.771
5280	483.631	14.0	2688.801	0.827

Note: Columns (2) through (4) report the mean, median and standard deviation of the cumulative number of units of each type of building within the respective distances. Column (5) reports the share of records with one or more of the building type in the distance category.

buildings—the latter three of which are used as controls. The fixed increments correspond to 1mi$\times(0, \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{3}{8}, \frac{1}{2}, \frac{3}{4}, 1)$ = (adjacent, 330ft, 660ft, 1320ft, 1980ft, 2640ft, 3960ft, 5280ft). We use a test a number of different specifications to ensure the robustness of the results to specification error. Summary statistics for the number of units in each concentric circle by unit are provide in tables 3–4. Note the number of daycare and school buildings within each concentric circle tends to be much lower than the number of agricultural, urban, and residential buildings. This is largely not surprising as one school/daycare serves many residents. However, it could pose estimation problems as only 0.7% of fields have an adjacent school or daycare building and only 13.9% (31.9%) of fields have an school or daycare building within one-half (one) mile. In comparison, 89.7% of fields have an adjacent agricultural building, 16.6% an adjacent residential building and 18.3% an adjacent urban building, which increases to 96.4%, 34.5%, and 37.6%, respectively, within 330ft.

3.2 Identification approach

The dependent variable for our empirical problem is defined as:

$$y_{tjk} = \begin{cases} 1 & \text{if application within 6am to 6pm on a weekday} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

for application at time t by grower j on field k, which implies we will want to use a discrete choice model. Note we include all weekdays, including the summer, because although school may be out of session schools are routinely used by children (e.g. daycamps, sporting events, etc.). As a starting point we use a linear probability model:

$$P(y_{tjk} = 1|x_k, z_{tjk}) = \alpha_0 + \alpha_j + x'_{tk}\beta + \boldsymbol{z}'_{tjk}\boldsymbol{\gamma} + u_{tjk} \tag{2}$$

where α_0 is a constant-term and α_j represents an individual grower's unobserved average propensity to spray on schooldays (analogous to a fixed-effect). The variable of interest β uses data x_{tk}, which in our base specification is a dummy variable for whether or not their is a school or daycare adjacent to the field begin sprayed. Note this variable varies across fields, indicated by subscript k, and is allowed to vary over time t. The vector of control variables $\boldsymbol{z}_{tjk}$ and corresponding coefficients $\boldsymbol{\gamma}$ include the number of agricultural, urban, and residential buildings in proximity to the field, county fixed-effects, year dummies, and a dummy variable for aerial or ground application of the pesticide (we would expect aerial applications to be potentially more harmful as its is easier for them to travel in the wind to potentially harmful locations). Finally, u_{tjk} is a well-behaved error-term. Recalling (**??**), our prior is that $\beta < 0$—farmers are less likely to apply their pesticides in the schoolday window when they are close to a school or daycare.

Intuitively, this model uses two sources of variation to identify the propensity of farmers to avoid applications during the schoolday window. The first source of variation is cross-sectional: by including grower fixed-effects, we estimate β off variation in changes in grower behavior for fields that are close to schools or daycares and those that are not. This is important because there could be a great deal of unobservable heterogeneity in an individual farmer's preferences for when to conduct their pesticide appications. In other words, we exploit spatial variation in the proximity of fields to schoolsites because pest incidence is likely to be highly spatially correlated but only some fields are close to schoolsites. We view "good neighbors" as constraining their actions by avoiding applications on schooldays from 6am to 6pm. In contrast, "bad neighbors" do not. Fields that are sufficiently close to schoolsites form a quasi-treatment group. Fields that are not sufficiently close form a quasi-control group because they cannot incur external harm on the community, need not constrain their applications, and thus act fully within their own private interests.

The second source of variation is temporal: the number of schools or daycares near a field can change over time due to, for example, urban development. That being said, the variation in the number of schools or daycares over time is very small. Thus, the vast majority of our identifying variation is cross-sectional.

3.3 Estimation results

To use the identifying variation identified in the previous section, we restrict our sample to those applications where there is within grower variation in $\mathbb{1}_{(d \wedge s) \in \epsilon)}$. In the vast majority of cases in our sample, there is no cross-sectional or temporal within grower variation, and as a result we lose a large portion of our sample: we are left with 13,781 observations across 26 growers.

Panel A of table 5 presents estimation results with robust standard errors for the restricted sample. In this first specification, we consider whether there is a daycare *or* school next to the sample. The coefficient on adjacent school or daycare is only statistically non-positive at the 5% level in specification (4) with the full set of controls. Note that in this case it is also joint-significant, though only at the 10% level: an F-test indicates inclusion of the adjacent school or daycare variable increases the explanatory variable of the model over just using the control variables ($F = 3.6623$, $p = 0.05568$). While the direction of the coefficient agrees with our prior, the magnitude is fairly small. Unconditionally, the growers in our restricted sample conduct their applications on school days 56.0% of the time. In contrast, our estimates imply that if all these growers were adjacent to a school or daycare, they would conduct 53.2% of their applications on school day. One concern that could be raised about the specification of $P(\cdot)$ as $\mathbb{1}_{(d \wedge s) \in \delta}$ is that public schools may be more salient in the mind of farmers than daycares, which are typically less differentiated from other residential

Table 5: Estimated effect of adjacent daycare or school on propensity to spray on schoolday.

	(1)	(2)	(3)	(4)
A. Union of Adjacent School or Daycare				
Coefficient of interest				
Adjacent school or daycare	−0.001	−0.015	−0.017	−0.030
(Robust standard error)	(0.016)	(0.016)	(0.016)	(0.017)
One-sided t-test p-value	0.466	0.164	0.139	0.034
B. Separated Adjacent School and Daycare				
Coefficients of interest				
Adjacent school	0.014	−0.015	−0.012	−0.025
(Robust standard error)	(0.027)	(0.026)	(0.026)	(0.026)
One-sided t-test p-value	0.704	0.285	0.317	0.169
Adjacent daycare	−0.018	−0.001	−0.002	−0.007
(Robust standard error)	(0.024)	(0.023)	(0.023)	(0.023)
One-sided t-test p-value	0.229	0.481	0.466	0.377
C. Model Description				
Controls				
Year fixed effect	N	Y	Y	Y
Aerial fixed effect	N	Y	Y	Y
Adjacent residential/urban/agriculture building	N	N	N	Y
Observations	13,781	13,781	13,781	13,781
R^2	0.000	0.127	0.127	0.128

buildings. To address this concern we re-estimate the model separating out adjacent schools and adjacent daycares. Interestingly, including schools and daycares separately reduces the model fit (the sum of squares decreases by 0.2088 at the expense of an extra degree of freedom) and does not provide a statistically significant improvement in fit over a controls-only model ($F = 1.2713$, $p = 0.2805$). Panel B presents the results of Panel A in table 5 under this alternative specification. Both coefficients are closer to zero than when identified together, suggesting the concern over salience is not supported by the data. Re-conducting the counterfactual experiment above results in the same qualitative conclusion but with an even smaller effect.

4 Conclusion

In theory economic reasoning dictates self-regulation is the best approach if it has the highest (risk-adjusted) net present benefit to the community. Yet, there has been very little discussion on how to do this in practice. In this paper we examined if, and if so to what extent, California agricultural producers self-regulate their pesticide applications near schools and daycares by conducting their applications on evenings or weekends. Our paper also illuminates the need for a discussion amongst economists on how exactly self-regulation should be approached and evaluated. While strong and contextually-appropriate evidence of the form and extent of self-regulation plays an important role in this discussion, by no means does it paint a complete picture. Farmers may constrain their pesticide applications to avoid external harm, community members may still not agree to a regime of self-regulation. The magnitude of their collective self-regulation regulation may not be sufficient or optimal. Farmers are by no means heterogeneous and, given the number of independent decision makers, some may not comply. At the same time, the consequences and risks of non-compliance are unclear to farmers, regulators, or community members. Even if farmers act in the public interest in this case, they may not be willing to do so when it comes to environmental externalities (e.g. drift, water pollution, resistance, etc.).

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