The Cicada Song: the Impact of Insecticides on Infant Health and Long-term Outcomes*

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Abstract

This paper utilizes a peculiar ecological phenomenon, the mass emergence of cicadas in 13 and 17-year cycles, to identify the impact of pesticides on human health and long term development. I rely on the fact that cicadas only damage woody plants (e.g., apple trees), through egg laying in branches and subsequent nymph-feeding on roots—and not agricultural row crops. Using the natural temporal and geographic variation of cicada emergence, I show that a sharp increase in insecticide use coincides with cicada emergence in places with high levels of tree crop production. This is followed by a jump in next-year infant mortality as well as other negative infant health impacts. Looking at long-term effects, I find evidence of lower elementary school test scores and then higher dropout rates nearly two decades later among exposed cohorts. Finally, I exploit variation in groundwater well usage to find evidence that pesticide exposure occurs through the contamination of water supplies. *JEL Codes: I10, Q10, Q53, Q57.*

1 Introduction

Farmers in the US spend $7.9 billion annually on pesticides (US EPA 2017). Modern pesticides, along with other technological advances in agriculture, have brought about significant increases in productivity. But concerns have long been raised about the poten-

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tial negative environmental and health impacts of pesticides given their toxicity by design. Since the high-profile federal ban of DDT in 1972, dozens of pesticides have been banned by the EPA on account of their potential risk to humans and the environment (Buffington and Mcdonald 2006).

This paper focuses on insecticides, the second-most used type of pesticide after herbicides. I utilize an ecological phenomenon, the emergence of periodical cicadas (*Magicicada septendecula*), as a source of quasi-exogenous temporal and spatial variation in the application of insecticides to identify a potential causal channel for the impact of insecticides on health. My identification strategy hinges on the fact that cicadas emerge as mass broods in the same locations every 13 or 17 years such that each brood is linked to a specific year and unique geographic footprint. For example, Thomas Jefferson described the 'great locust years' of Brood II cicadas that arrived every 17 years at his home in Monticello, Virginia (Jefferson 1944). This same brood still emerges on schedule at Monticello 250 years later, most recently in summer 2013.

I find a significant increase in insecticide use in years and in counties experiencing a cicada emergence. This impact, however, is limited to places with a large proportion of woody crops like fruit trees—and not herbaceous row crops like corn and soy. This is because cicadas only damage woody plants. Nymphs feed on tree roots and adult cicadas lay their eggs in small branches.

Using apple production as a proxy for woody crop intensity, I exploit this variation and compare treated counties (i.e., counties with high apple production in years of a cicada emergence) to untreated counties. In the treated counties, I find a corresponding increase in county-wide insecticide use and subsequent increase in next-year infant mortality of 0.3 deaths per thousand births (the current mean in the US is six deaths) following a cicada emergence. The birth impact may extend into the second year as farmers continue applying higher levels of insecticide to control cicada nymph establishment. An investigation of the quarterly impacts aligns with the timing and patterns of insecticide usage by farmers. Treated counties also see an increased probability of premature births and other negative infant health outcomes. There is evidence of long-term impacts in the form of lower elementary school test scores and higher high school dropout rates among exposed cohorts.

The results are in line with the more general correlation I find between insecticide use and infant mortality at a national level—notwithstanding the influence of cicadas and land use. Furthermore, I find some evidence that the impact of insecticides on health manifests through a water channel. Counties with higher reliance on well water, whose groundwater source can be easily contaminated by agricultural runoff, experience greater negative impacts.

The findings are likely generalizable outside of just agriculturally-intensive regions. Tree crops cover a relatively small portion of US counties (always less than 5% of county land area, generally far less than 1%), especially compared to row crops like soy and corn which account for a majority of total acreage in many counties. Baseline pesticide use is moderate to low in most tree-intensive counties. These facts support the conclusion that moderate levels of pesticides, not just extreme exposures, can have impacts on human health and development. And since this analysis looks only at average effects at the county level, it likely understates the health impacts among those living in close proximity to insecticide application.

Overall this paper contributes to the environmental and health economics literature on the health impacts of agricultural inputs. This is a timely topic considering the many current pesticide lawsuits and regulation.[1] While acknowledging the importance of pesticides to agricultural productivity, the findings warrant caution in the over-application of insecticides. This paper also provides an example of how ecological phenomena like cicadas may be used to generate quasi-random variation that can be employed to answer important

[1] See link for debate on regulating the insecticide chlorpyrifos and link for glyphosate herbicide lawsuits.

economic and public health questions.

2 Background

2.1 Pesticides and health

Pesticides, and insecticides in particular, are toxic by design. Many were initially developed for warfare purposes. One prominent insecticide type, organochlorides (e.g., DDT), opens sodium channels in the nerve cells; another, organophosphates, targets the nervous system like the nerve agents in chemical weapons.

While laboratory and controlled studies have documented the negative impacts of pesticides on organisms and ecosystem services such as water quality, few have demonstrated a direct causal link between pesticides and human health. Almond and Currie 2011 show that fetal shocks, particularly ones occurring early in a pregnancy, can have long-lasting impacts. Environmental shocks including heavy metal exposure, high temperatures, and air pollution have been causally linked to adverse birth outcomes (Chay and Greenstone 2003, Zheng et al. 2016).

But there is little evidence causally linking pesticides to health outcomes like infant mortality, low birth weight, and premature birth. And no study, to my knowledge, has directly linked pesticide exposure to long-term outcomes like educational achievement and attainment.

Most estimates of the health impacts of pesticides come from non-randomized studies with small sample sizes (Jurewicz et al. 2006, Andersson et al. 2014). Many focus on occupationally-exposed groups like pesticide applicators who are unlikely to be representative of the broader population. Regidor et al. 2004 find higher levels of still births and infant deaths within 24 hours of birth, while Garry et al. 2002 document an increase in birth defects among farm families, especially for conceptions occurring during the spring pesticide application season. Bell et al. 2001 similarly highlight the impact of pesticide exposure during the first trimester. Winchester et al. 2009 find elevated levels of agricultural chemicals in water to be correlated with birth defects. Schreinemachers 2003 finds that birth defects increase with a county's wheat acreage, which is used as a proxy for herbicide exposure.

Larsen et al. 2017 use detailed spatial and micro-level panel data in California to show that pesticide exposure increases adverse birth outcomes among populations exposed to high quantities of pesticides (i.e., 95$^{\text{th}}$ percentile exposure). Brainerd and Menon 2014 exploit variation in planting times to link agrichemical exposure to adverse birth outcomes in India. Rauh et al. 2012 find evidence of long-term impacts in the form of lower IQ scores among a small sample of children exposed to insecticides in utero. Frank 2018 exploits a fungus that increases bat mortality, finding that farmers respond to the loss of insect-eating bats by using more insecticides which results in an increase in (primarily female) infant mortality.

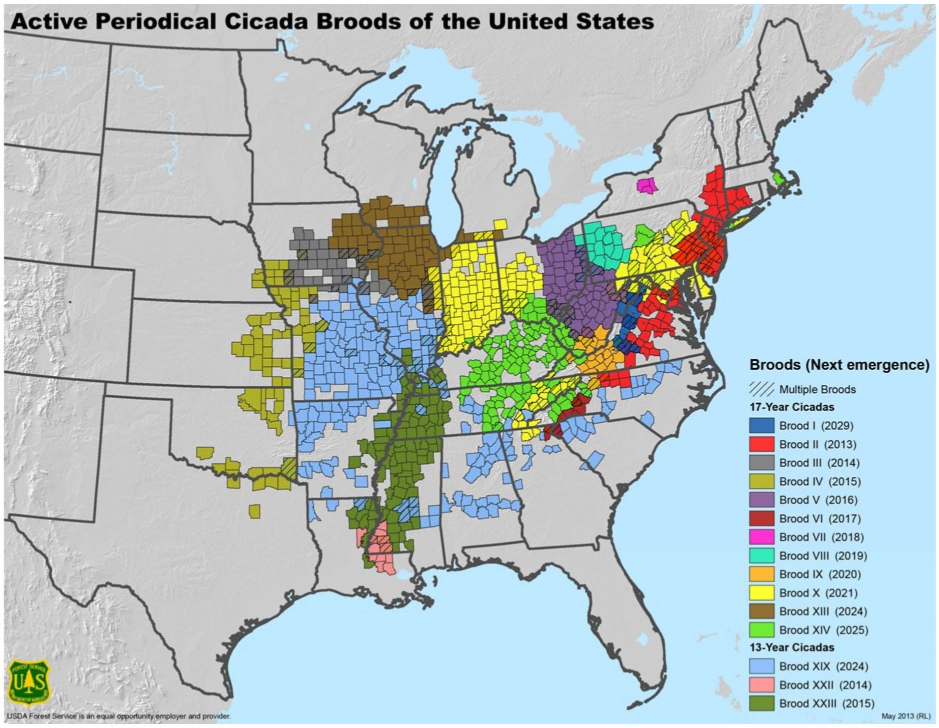
2.2 Cicadas and Insecticides

Periodical cicadas (*Magicicada septendecula*) occur throughout the eastern half of the US.[2] There are fifteen extant broods, three of which are on 13-year cycles and twelve of which are on 17-year cycles. Some counties receive two or more broods. Figure 1 is a map showing each brood's range, cycle, and next year of emergence.

There is ample agronomic and ecological research on cicadas and tree health, with a considerable focus on fruit trees in particular. Cicadas spend most of their lives underground feeding on the xylem fluids from the roots of deciduous trees before synchronously emerging in the spring at any given location. Emergence densities of 1.5 million cicadas per acre have been reported (Dybas and Davis 1962), representing some of the highest biomass val-

[2] There are several species of annual (i.e., non-periodical) cicadas that exist globally, including in ranges that overlap with periodical cicadas in the US. But the populations of such species do not tend to vary greatly year to year.

Figure 1



Source: Liebhold, A. M., Bohne, M. J., and R. L. Lilja. 2013. USDA Forest Service Northern Research Station.

ues of any naturally occurring terrestrial creature. Cicadas remain active for four to six weeks to mate and lay their eggs in small tree branches (i.e., oviposition), causing harm especially to young trees. When the eggs hatch, the nymphs fall to the ground to begin their development. Tree growth is further damaged by cicada nymphs feeding on tree roots, which can reduce growth by up to 30% (Karban 1980).

Both processes have a negative impact on orchard trees. In an early study, Hamilton 1961 reported a complete loss among unprotected young apple and pear trees in the Hudson Valley following a cicada event in 1945. Karban 1982 conducted an experiment on apple trees and found that removing cicada nymphs significantly increased wood accumulation relative to when nymphs were present.

Most commercial tree growers and serious gardeners are well aware of the damage that cicadas can cause. Using insecticides to mitigate cicada damage is well documented. Hamilton 1961 describes the process and efficacy of spraying trees with insecticides to kill adult cicadas as well as soaking the soil with insecticides to control nymphs. Lloyd and White 1987 recommended killing off understory grasses to starve young nymphs. Penn State provides publicly-available online recommendations to tree fruit growers on cicada management, including on pesticide use and application methods (Krawczyk 2017).

3 Empirical Strategy

Cicada emergence is anticipated by both tree growers and, to a certain extent, the general population. There is often ample news coverage leading up to what some call 'cicada mania. Figure A1 in the Online Appendix shows a Google Trends chart of average monthly search volume for the word 'cicada' in metropolitan regions of Virginia, including Charlottesville, the area where Thomas Jefferson noted the creatures in his writings over two centuries ago. This event study demonstrates the distinct temporal pattern of periodical cicadas. The two distinct spikes in 2004 and 2013 coincide with the emergence years of the two endemic broods to the region.

Despite the public awareness, I argue that cicada emergence is effectively exogenous in relation to anything that could affect public health outcomes at a county level. Note that the Charlottesville region accounts for much of Virginia's fruit production, whereas Richmond and DC have few orchards. Yet Figure A1 shows that public interest in cicadas follows similar patterns across regions. Cicada emergence therefore would act as a quasi-experiment where tree-intensive counties receive more insecticides during emergence years relative to the same counties during non-emergence years, and where tree-intensive counties receive more insecticides relative to non tree-intensive counties in emergence years. I include several robustness checks and alternative specifications to ensure the exclusion restriction holds.

Further, insecticide exposure and its potential impact on health should be related on the life cycle of the cicada, the risk to tree crops, and the timing of human exposure. A conceptual model is provided below.

Figure 2

Timing Framework

Cicada behavior	Nymphs increasing feeding, size, moving toward surface	Cicada emergence and mating	Eggs hatch and tiny nymphs fall to ground	Nymphs bury themselves into ground, feeding on tree roots	Nymph establishment and passive feeding for next 13/17 years
Insecticide use	No documented pre-spraying of insecticides	Insecticide spraying to prevent cicadas from mating and laying eggs on tree branches	Insecticide spraying to kill the eggs and nymphs	Insecticide spraying to kill the nymphs before establishment	Insecticide spraying follow on ground treatment to kill nymphs
Timing	Spring (and year prior)	Summer	Fall (and late summer)	Winter	Spring (and throughout the following year)
Health impacts		*Potential maternal exposure to insecticides*			*First birth impacts from 1st trimester exposure previous summer, continuing through year*

If Figure 2 is accurate, one would expect: 1) an increase in insecticide use in the year of cicada emergence and the year after; 2) birth impacts in the year following emergence, starting in the spring and potentially continuing into the next year; and 3) yield impacts on tree crops beginning in the year before emergence as nymphs increase their root feeding and continuing for several years. Each of these propositions are tested and confirmed in the analyses that follow.

4 Data

4.1 Cicada data

The US Forest Service provides shapefiles with county-level presence-absence data on periodical cicadas by brood with emergences projected through 2031. The dataset was originally compiled from Koenig et al. 2011. Given the temporal and spatial consistency of cicada emergence, I extend the time series further into the past using each brood's 13 or 17-year cycle assuming that cicada emergence occurred in the same counties. While there are some examples of accelerations in cycles and changes in the range of broods (Williams and Simon 1995), cicada behavior has been remarkably consistent for the most part.

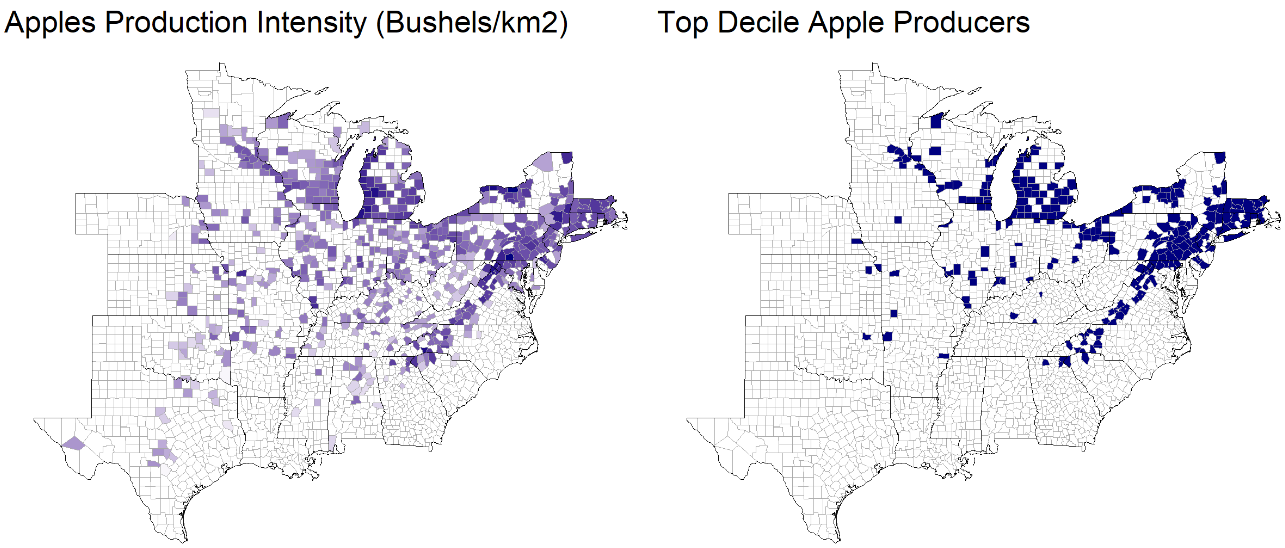
4.2 Agricultural data

The land use dataset comes from the USDA's National Agricultural Statistics Service (NASS) online tool and from the historical U.S. Census of Agriculture, available online through the Inter-university Consortium for Political and Social Research (Haines et al. 2014). I collected various measures of apple and woody crop intensity at the county-year level (i.e., number of trees, acres, production in bushels).[3] I choose apples as my preferred explanatory variable because apples are the historically dominant tree crop in the US. There is also ample agronomic and ecological literature on the effect of cicadas on apple trees, as described earlier. Apple production is well-distributed geographically among US states, with top producers in the Northeast (NY, MA, CT), Central-Midwest (PA, MI, OH), and the South (VA, NC) as shown in Figure 3.

Unfortunately, an annual time series cannot be constructed for tree crop variables for several reasons: the agricultural census takes place every five years, variables were not mea-

[3] County-year data values of '(D)', which NASS uses to denote confidentiality, were coded as not available, and values of '(Z)', which denotes being too small to estimate, were coded as zero. Given that only positive values are included in NASS output, excluded county-years are assumed to have a value of zero.

Figure 3



Source: USDA. For reference, among apple producing counties, the mean value is 99 bushels per km^2 and the highest value is 5,600 bushels per km^2 (or 56 bushels per hectare).

sured consistently over time, and surveys in the 1970s and 1980s only included 50% of counties. Therefore, I used a time invariant measure of county-level tree crop intensity, varying the base year as needed for analyses and robustness checks. All measures of agricultural intensity are standardized by county area.

4.3 Pesticide data

The United States Geological Survey (USGS)'s National Water-Quality Assessment Project provides county-level pesticide use data from 1992 to 2016 (USGS 2019). Information was compiled from surveys of farm operations in USDA Crop Reporting Districts and annual crop acreage reports. Information is available by chemical constituent. My preferred measure is the sum of all insecticide-categorized constituents using the EPest-high measure in kilograms per county. [4] Insecticide intensity is also standardized by county area.

[4] The USGS pesticide dataset was classified by reported function (i.e., insecticide, herbicide, fungicide) by Eyal Frank. 160 of the constituents had insecticidal properties.

4.4 Infant health data

Infant mortality and birth outcome data come from the National Center for Health Statistics (NCHS 2019). NCHS Natality Data Files contain full records for data publicly available from 1968 to 1988, while records from 1989 to 2016 were obtained under confidentiality agreement. NCHS Linked Birth-Infant Death Data Files contain confidential microdata from 1995 to 2016. For longer-term analysis of infant mortality, I use ICPSR's County-Level Natality and Mortality Data, 1915-2007 (Bailey et al. 2016). The ICPSR data are averaged annually and do not allow for within-year or demographic disaggregation aside from race. I use ICPSR's preferred 'fixed' variables whenever available.

ICPSR's resident infant death data become available starting in 1941 and are based on the residence county of the mother (rather than the county of birth occurrence). After 1988, ICPSR masks counties with populations less than 100,000, which presents challenges given that many of the counties of interest are agricultural and have populations lower than 100,000. Since the NCHS Linked Birth-Infant Death data begin in 1995, there is a data gap from 1989 to 1994 for low population counties. Starting in 1995 I use infant mortality rates derived from these linked files. I address concerns about sample composition by running alternate analyses on a subset of observations ending in 1988.[5]

I use the NCHS Linked Birth-Infant Death data from 1995 to 2016 to compute infant mortality rates at the sub-year level (i.e., quarter averages that can be linked to timing of insecticide application). I use NCHS Natality data from 1968 to 2016 to construct detailed birth outcome measures like Apgar scores, gestation time, and birth weight, as well as for constructing controls for maternal characteristics.

[5] Results hold whether using the infant mortality dataset constructed by combining the Linked Infant Birth/Death Files with historical ICPSR calculations, or using the ICPSR dataset which underwent some additional data cleaning as described in 2016.

4.5 Education data

For educational achievement, I use standardized annual county-level test scores from the Stanford Education Data Archive (Reardon et al. 2018), available for the seven years from 2009 to 2015. I average across the third, fourth, and fifth grades to produce an elementary school average score for each cicada exposure cohort (e.g., 3rd graders nine years after a cicada event, fourth graders ten years afterwards, and fifth graders eleven years afterwards).

For a measure of attainment, I construct a dataset on high school dropout rates using the National Center for Education Statistics Local Education Agency (School District) Universe Survey Dropout and Completion Data. I average across school districts to get county-level values from 1991 to 2008. My preferred measure is twelfth grade dropout rate, which is the total number of twelfth graders dropping out of high school in a given year divided by the total number enrolled.

4.6 Water use data

County-level data on private well and groundwater use come from USGS's Estimated Use of Water in the United States. Estimates are available every five years from 1985 to 2015. I construct an average intensity measure over the years by dividing the number of people in a county that are reliant on private wells by the total number in the county.

5 Model

My empirical approach consists of two main parts: I use a triple difference estimator to first test whether there is an increase in insecticide use in treated counties in cicada emergence years, and second, whether there is a follow-on impact on infant health and longer-term outcomes. I restrict the sample to all the counties in the 32 states in the eastern half of the US that span the range of periodical cicadas.[6]

[6] Note that there are some counties in some states in which cicadas never emerge.

For the first step, I specify a model with insecticide use intensity, $insecticide_{it}$, as the dependent variable, measured in kilograms of insecticide per km^2 land area in county i in year t. The independent variable is a cicada presence-absence dummy, $cicada_{it}$, taking the value of 1 if there is a cicada emergence in county i in year t, and 0 otherwise. I interact this cicada dummy with a measure of tree crop intensity (e.g., apple production), $apple_i$, in county i which is unvarying over time:

$$insecticide_{it} = \beta_1 cicada_{it} + \beta_2 cicada_{it} * apple_i + \alpha_i + \gamma_t + \epsilon_{it} \tag{1}$$

where α_i includes county fixed effects and γ_t includes year fixed effects. The former accounts for any time-invariant properties of the county that could affect outcomes. Year fixed effects account for national level time trends and annual anomalies like changes in commodity prices. Several other combinations of fixed effects are tested in both models, and state-level time trends are allowed in multi-decadal analyses to account for state-level patterns.[7] The coefficient of interest, therefore, is β_2, which estimates the change in insecticide use in tree crop-intensive counties driven by cicada emergence.

For health outcomes, I specify a model similar to Equation 1 but replace insecticide intensity with infant mortality rate (infant deaths per thousand live births), $imr_{i,t+1}$, in county i in the following year, $t+1$:

$$imr_{i,t+1} = \beta_1 cicada_{it} + \beta_2 cicada_{it} * apple_i + \alpha_i + \gamma_t + \epsilon_{it} \tag{2}$$

The coefficient of interest is again β_2, which estimates the change in infant mortality rate stemming from a cicada emergence in tree crop-intensive counties. In addition to imr, I test for other impacts of infant health and educational outcomes.

[7] State-year fixed effects should not be used because some cicada brood-years encompass much of certain states (i.e., Brood X and Indiana).

6 Results

6.1 Insecticides and Cicadas

The first analysis examines the relationship between insecticide use and cicada emergence using the model specified in Equation 1. The sample is limited to the 25 years from 1992 to 2016 in which county-level USGS pesticide data exist. Table 1 regresses insecticide use on a cicada dummy and the cicada dummy interacted with fixed top-decile indicators (top 10^{th} percentile) of tree crop intensity.

Table 1: Cicadas and Insecticides

	Insecticide use (kg/km2)					
	———Levels———			———Logs———		
	(1)	(2)	(3)	(4)	(5)	(6)
cicada	1.08	0.13	0.30	−0.05	−0.08	−0.07
	(1.38)	(0.95)	(0.99)	(0.04)	(0.04)	(0.05)
cicada:acres_HIGH		6.61			0.18	
		(3.46)			(0.07)	
cicada:bushels_HIGH			5.58			0.12
			(3.14)			(0.06)
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Observations	60,533	60,533	60,469	60,184	60,184	60,131
R^2	0.41	0.41	0.41	0.86	0.86	0.86

Notes: Linear regression. Dependent variable is county-level insecticide use, which is the combined sum of the USGS EPest-high values with insecticidal properties divided by county land area. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Models (2)-(3) and (5)-(6) include dummies for the top decile counties in apple intensity based on acreage and production per land area in 1997. Time series limited to USGS pesticide data, 1992 to 2016. County and year fixed effect dummies included. Standard errors clustered at the state level.

Apple production in bushels is my preferred measure of tree crop intensity. It is well distributed across the country. Among the 242 counties in the top decile of apple producers in the eastern half of the US, 25 states have at least one county in this group, as shown in the map in Figure 3.

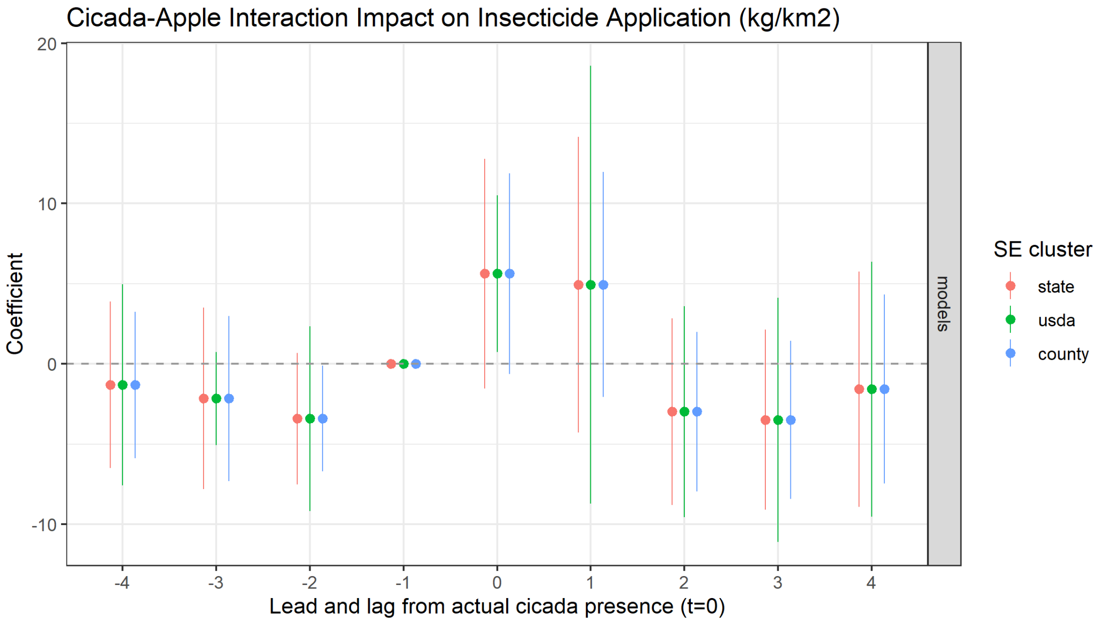
Model (1) shows the impact of cicada emergence on insecticide use alone. Models (2)-(3) interact cicada emergence with the top decile of apple acreage and apple production in bushels, respectively. Models (4)-(6) replicate the analysis using log insecticide values instead of levels.

Cicada emergence, in itself, is not associated with increased insecticide usage except in tree crop-intensive counties which see an increase in pesticide use in the range of 5-7 kg/km^2. This is a moderately large effect given that mean county pesticide use is 10 kg/km^2. Results are robust to using a measure of fruit acreage more broadly, a category including non-citrus (apples, peaches, tree nuts, etc.), citrus, and berry acres. Figure 4 plots the coefficients from Model (3) along with the inclusion of several leads and lags of cicada emergence.[8] Insecticide use increases only in the year of cicada emergence and the year following. This outcome aligns with the first prediction of the timing framework in Figure 2 in which farmers apply insecticides to control the adult egg-laying population in the year of emergence and the cicada nymphs in the year that follows.

Falsification tests are included in the Online Appendix. Table A1 shows that *only* insecticide use increases during cicada emergence, while herbicide and fungicide use do not appear to change. This provides confidence that any resulting health impacts are attributable to insecticides and not a more general change in agricultural practices. Table A2 shows that cicada emergence is *not* associated with increased insecticide use in agriculturally-intensive counties containing a high proportion of soy and corn, which aligns with the fact that cicadas harm woody plants and not herbaceous row crops (if anything, there may

[8] Leads and lags are limited to four years to reduce distortion of the event study from the fact that many counties receive more than one cicada brood, as seen in the national distribution map in Figure 1 and in Virginia specifically in Figure A1.

Figure 4



Notes: Event study based on Model (3) from Table 1 with the inclusion of cicada leads and lags. Observations with no leading or lagging cicada events during the sample time period are excluded to balance the panel. Solid lines show 95% confidence intervals. Standard errors are variously clustered at the state, USDA production region, and county level. Normalized to the year before cicada emergence.

even be a slight decline in insecticide use in highly row crop-intensive areas during cicada emergence).

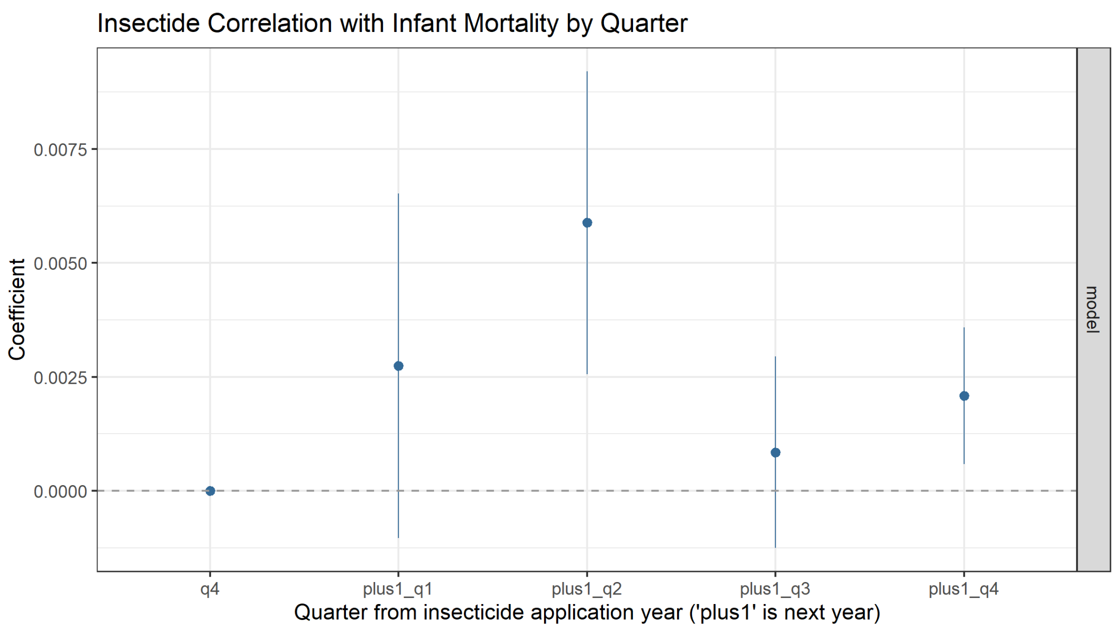
6.2 Insecticide and Infant Mortality Correlation

After establishing a relationship between cicadas and insecticide use, I examine potential impacts on infant mortality. Table A3 in the Online Appendix simply regresses infant mortality rate on insecticide use, ignoring any influence of cicadas or land use. The sample is restricted to the years 1992 to 2016 when both pesticide data and linked infant mortality data are available for all counties. There is a small but imprecise positive correlation between pesticide use and next-year infant mortality.[9]

[9] Figure A2 in the Online Appendix shows the correlation results of Table A3 after adding two annual leads and two lags of insecticide use to the regression. The birth impact is most clear in the year following insecticide application.

Figure 5 plots the coefficients by quarter. The time series is further limited to 1995-2016 when sub-annual Infant Birth/Death data is available. Note that 'q4' is the last quarter of the insecticide application year (i.e., October to December), and 'plus2_q4' is the last quarter of the second year following insecticide application. There is a peak in the positive association between insecticide use and infant mortality in the second quarter of the following year. This makes sense given that insecticide use tends to occur in late spring and summer for row crops and the fact that fetuses are highly susceptible to environmental shocks early in a pregnancy (Almond and Currie 2011).

Figure 5



Notes: Event study based on Table A3 but run at the quarterly level. Time series limited to 1995 to 2016. Excludes observations with less than five births and with zero infant deaths in a year. Includes county and year fixed effects plus quarterly fixed effects to address naturally-occurring fixed differences by season. Solid lines show 95% confidence intervals. Normalized to the 4th quarter of insecticide application year.

These correlations should be interpreted with caution given that the results are significant only after dropping county-year observations with zero infant deaths. All US counties and crop types are included in this analysis, and each can have different pesticide treatment practices, as well as potential pesticide exposure pathways. Further, these estimates could be biased given potential omitted variables and endogeneity concerns, as well as the limited time series beginning only in the 1990s.

6.3 Cicadas and Infant Mortality

To more directly address causality, I run the model specified in Equation 2. Given the link established between cicada emergence and insecticide usage, as well as the correlation between insecticides and infant mortality, one would expect a relationship between cicada emergence and infant mortality in tree crop-intensive areas if insecticides indeed have an impact on health. In contrast to the regressions in Table A3 and Figure 5, this analysis allows for the use of a much longer time series. ICPSR starts tracking resident infant mortality at the county level in 1941, while USGS pesticide data is only available from 1992 to 2016. I restrict the sample to after 1950, which encompasses the post-WWII era when farmers started using synthetic pesticides at a large scale.

Table 2 regresses next-year infant mortality on cicada emergence.[10] Model (1) of shows no significant impact of cicada emergence, in itself, on birth outcomes. Model (2) interacts cicada emergence with a dummy for high apple production (i.e., top decile counties). These counties experience an increase in infant mortality of 0.3 deaths per thousand. Models (3) and (4) use actual county-level apple production in bushels in 1964 and 1997, respectively. The 1964 measure of apple intensity helps address endogeneity concerns related to apple production changing over time. All health outcome standard errors are clustered at the state-level, which is the administrative level at which birth records are collected and aggregated. General results hold if standard errors are clustered at other levels.

For interpretation, a one standard deviation in apple production is equal to 170 bushels/km^2 in 1964 and 230 bushels/km^2 in 1997 on a cross-county basis. Therefore, a one standard

[10] In the main specification, counties with less than five births in a given year are dropped to minimize the inclusion of unreasonably high infant mortality rates due to small sample size (i.e., if there are two births in a county, and one death, IMR is 500 compared to the current US average of six). Results are robust to varying the birth cutoff threshold. Table A4 in the Online Appendix replicates this regression but weights by average number of births in order to include observations with less than five births.

Table 2: Cicada Impact on Infant Mortality, 1950-2016

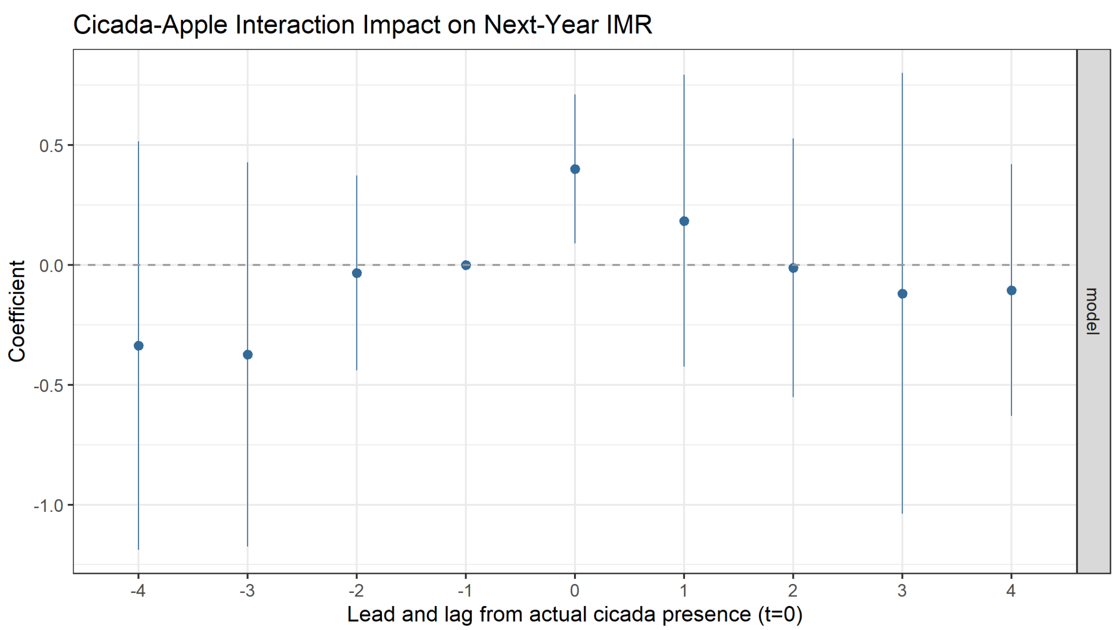
	Dependent variable:			
	Next-Year Infant Mortality Rate (IMR)			
	(1)	(2)	(3)	(4)
cicada	0.07	0.03	0.05	0.06
	(0.12)	(0.14)	(0.13)	(0.13)
cicada:bushels_HIGH		0.28		
		(0.16)		
cicada:bushels_1964			0.54	
			(0.15)	
cicada:bushels_1997				0.42
				(0.17)
County FE	X	X	X	X
State FE	X	X	X	X
Observations	142,608	141,814	141,694	141,814
R^2	0.52	0.52	0.52	0.52

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Excludes county-year observations with less than 5 births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997, while bushels 1997 and bushels 1964 is the actual level of apple production in those years. Time series from 1950 to 2016. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

deviation increase in county apple production, when accompanied by cicada emergence, is associated with an increase in infant mortality of 0.1 deaths per thousand.

Table A5 in the Online Appendix limits the sample to 1950-1988, which allows for a more balanced panel. As discussed in the Data section, the ICPSR infant mortality dataset is limited after 1988 to counties with populations over 100,000, while the infant mortality rates derived from confidential NCHS Infant Linked Birth/Death files are not available until 1995. The coefficients in Table A5 are larger in magnitude and more significant, better reflecting what is likely a primarily rural phenomenon. The general results also hold when using log-values for infant mortality.

Figure 6



Notes: Event study with level of apple production based on Model (4) of Table 2, but including cicada leads and lags. Observations with no leading or lagging cicada events during the sample time period are excluded to balance the panel. Solid lines show 95% confidence intervals. Normalized to the year before cicada emergence.

Figure 6 plots the cicada-apple interaction coefficients from Model (4) of Table 2 with the additional inclusion of cicada emergence leads and lags.[11] Infant mortality increases only

[11] Figure A3 in the Online Appendix shows the event study using Model (2) with the top decile apple intensity indicator. The general pattern holds when using an apple production baseline of 1964 instead of 1997.

in the year following cicada emergence and there is a noisier indication that this impact may extend through the second year. This aligns with the second prediction of the timing framework in Figure 2 and reflects the coefficient plot in Figure 4, which shows a two-year increase in pesticide use explainable because farmers control for both the cicada adult population and their feeding nymphs in the following year.

6.4 Interpretation of Infant Mortality Impact

Infant mortality has decreased by 80% over the course of this study, from a national average of 30 deaths per thousand in 1950 to the current average of 6, so the interpretation of coefficient magnitudes depends on the span of the sample. For the longer timeframe from 1950 to 2016 the average infant mortality rate is 16, for the balanced panel from 1950 to 1988 the average is 21, and for the period when pesticide data is available from 1992 to 2016, the average is 7. This warrants some caution when interpreting and comparing coefficient magnitudes.

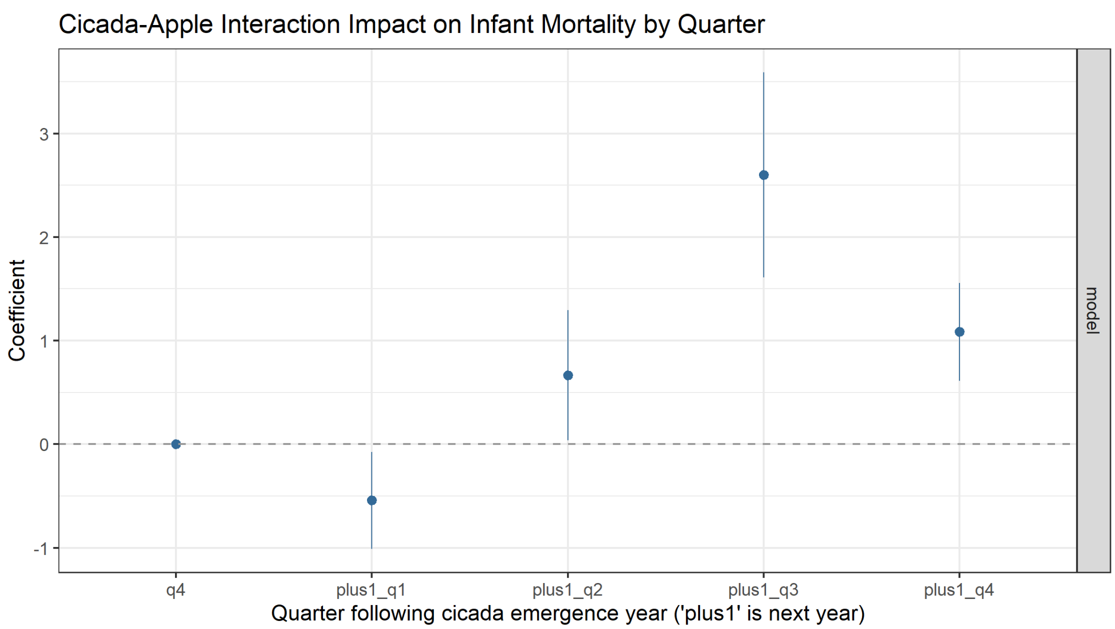
Table 1 shows that among top decile apple counties, insecticide use increases during a cicada emergence by 5-7kg/km^2. These same treated counties see an increase in next-year infant mortality by 0.28 to 0.45 deaths per thousand, based on Table 2 and the balanced panel in Table A4, respectively. This equates to about a 2% increase over the sample average infant mortality rates. In terms of insecticide use, each additional kilogram of insecticide per km^2 can be equated, therefore, to an increase in the infant mortality rate by one-third of a percent. For context, mean insecticide use across counties and over time is 10 kg/km^2, so one more kilogram represents an approximate 10% increase over the sample mean.

Linking these results to a specific type of insecticide is challenging because I use an aggregate measure of insecticide use that sums up 160 insecticide constituents by weight. Further, there is little evidence that orchard growers and farm managers consistently choose one type of insecticide over others for cicada control, especially given that pest management practices vary greatly across the US and over time.

6.5 Timing and Sub-annual Impacts

Figure 7 shows the impact on infant mortality by quarter. This analysis is limited to the period from 1995 to 2016 when Linked Infant Birth/Death Files are available that allow for sub-annual aggregation. There is an overall positive next-year impact aligning with the main results of the longer-duration analyses from 1950-2016 in Table 2 and Figure 6, implying that the cicada-insecticide relationship to infant mortality holds later in the sample time period. The effect is largest in the third quarter of the year that follows, occurring one quarter later than the results in Figure 5, which simply regresses quarterly infant mortality on previous year's insecticide use—notwithstanding cicadas and land use.

Figure 7



Notes: Event study is based on Model (4) of Table 2 but run at the quarterly level. Time series limited to 1995 to 2016. Apple intensity interaction measure is bushels in 1997. Excludes observations with less than five births and with zero infant deaths in a year. Includes county and year fixed effects to address naturally-occurring fixed differences by season. Solid lines show 95% confidence intervals. Normalized to the fourth quarter of the cicada emergence year.

An explanation for this difference in timing is that insecticide application practices differ between row crops and tree crops. The average national effect would be dominated by row crops since apples account for only 1.4% of pesticide use in the US, while crops like corn, soy, cotton, potatoes, sorghum, and wheat account for 86% (Fernandez-Cornejo et al. 2014). Insecticides are generally applied to row crops in the spring and summer and would affect early stage pregnancies and infants born earlier in the following year. For orchards experiencing a cicada emergence, cicadas arrive in the summer and much of the insecticide application also targets the nymphs which cause significant damage (Hamilton 1961, Lloyd and White 1987), as described in the timing framework in Figure 2. Pesticide application would continue into the fall and through the next spring and summer, thus affecting birth outcomes later in the next year as well as potentially the year afterwards.

6.6 Other Infant Health Outcomes

Next I assess infant health impacts other than infant mortality. Using NCHS Natality Data files from 1968 to 2016, I compute three binary measures of infant health. The first is Apgar score (dummy for a score below 7 out of 10), a measure of the health of newborns based on a quick assessment of infant appearance, pulse, grimace, activity, and respiration (hence acronym, Apgar). The second is premature birth (dummy if gestation period is under 37 weeks, the cutoff for premature birth). The last is birthweight (dummy if under 2500 grams, the threshold for low birthweight).

Table 3 shows regression results using the model specified in Equation 2. Cicada-apple interaction has a small but positive impact on the probability of adverse birth outcomes. The relationship is the clearest for premature birth, followed by low birthweight and Apgar score.[12] Overall, these results are consistent with the public health literature (Ling et al. 2018), as well as a story in which insecticide exposure harms infants and increases the

[12] All interaction coefficients are positive except Apgar scores in top apple decile counties, which is close to zero. The interaction with bushels of production, however, is positive and weakly significant.

Table 3: Cicada-Apple Interaction Impact on Other Birth Outcomes

	Next-year birth outcome					
	Prob. Low Apgar		Prob. Premature		Prob. Low Birthweight	
	(1)	(2)	(3)	(4)	(5)	(6)
cicada	−0.0003	−0.0004	−0.0008	−0.0007	−0.0010	−0.0007
	(0.0006)	(0.0005)	(0.0009)	(0.0008)	(0.0006)	(0.0006)
cicada:bushels_HIGH	−0.0004		0.0010		0.0019	
	(0.0008)		(0.0023)		(0.0009)	
cicada:bushels		0.0016		0.0018		0.0013
		(0.0009)		(0.0005)		(0.0015)
County FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Observations	82,009	82,009	107,611	107,611	110,378	110,378
R^2	0.1017	0.1017	0.2033	0.2033	0.2580	0.2580

Notes: Linear regression. Dependent variables are various next-year birth outcomes averages at the county level: Apgar low is a dummy for a score below 7 out of 10 (time series from 1978 to 2016); Premature is a dummy if gestation is under 37 weeks (time series from 1968 to 2016); Birthweight low is a dummy if under 2500 grams (time series from 1968 to 2016). Excludes county-year observations with less than 5 births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for counties in the top decile of apple production and Bushels is intensity of apple production in 1997. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

probability of infant death in the first year.

6.7 Education and Long-Term Impacts

I now look at the potential impact on educational achievement via elementary school cohorts exposed to a cicada emergence during conception or during the first year of life. Table A6 in the Online Appendix shows the impact on county-level scores in math and English language arts using Stanford Education Data Archives NAEP-equivalent test scores (Reardon et al. 2018). I pool county scores by cicada exposure cohorts, i.e., averaging the scores of third graders 9 years after a cicada event, fourth graders 10 years after, and fifth graders 11 years after. Models (2) and (4) include leads and lags of the cicada dummy to test the temporal relationship.

Figure 8

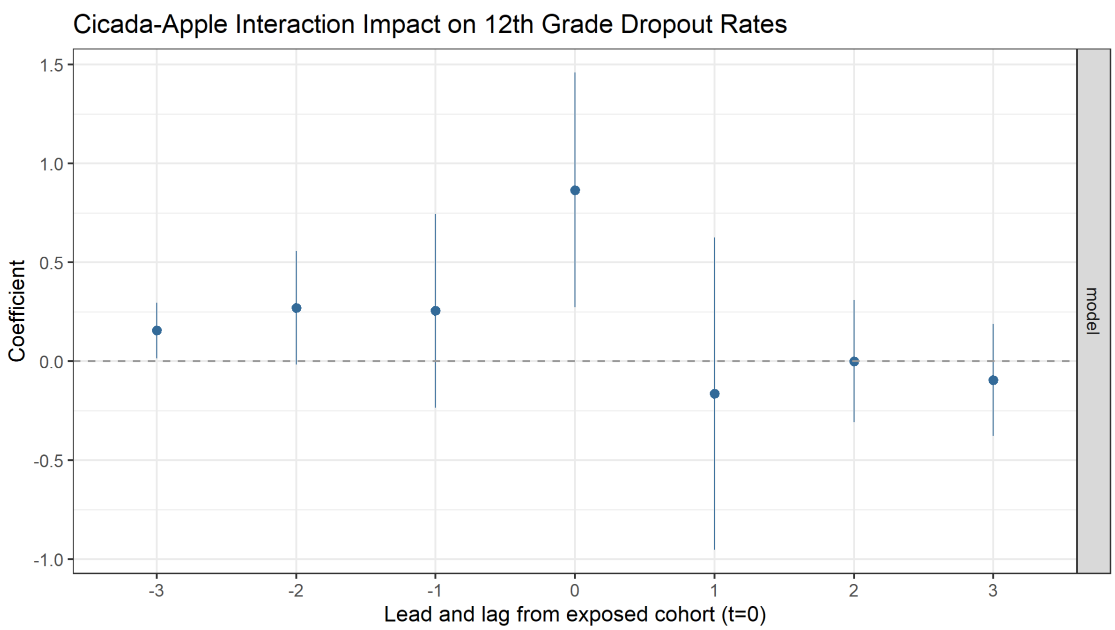
Notes: Event study is based on models in Table A6. Time series limited to 2006-2015 using Stanford Education Data Archive Based on average 'cicada exposure cohort': 3rd graders 9 years after cicada exposure, 4th graders 10 years after, and 5th graders 11 years after. Solid lines show 95% confidence intervals.

Figure 8 plots the impact with the leads and lags. There is a decline in average test scores of 1 to 1.3 NAEP-equivalent points among exposed cohorts. Each successive grade level

NAEP score is, on average, 10 points higher, so this coefficient can be interpreted as a reduction of 10-13% of one grade-level's worth of learning.

Next I analyze even longer-term impacts: whether cohorts conceived during a cicada emergence in tree crop-intensive counties experience a change in educational attainment. Using NCES data, I calculate the average dropout rate across school districts at a county-year level from 1991 to 2009. Table A7 in the Online Appendix shows the results of regressing the twelfth grade dropout rate on the cicada-apple interaction term. Model (2) includes long-term cicada lags ranging from 16 years after emergence to 22 years, plotted in Figure 9. We see an increase in the dropout rate 19 years later of exposed cohorts conceived during a cicada exposure, which is when these students would most likely be in the twelfth grade. The lag terms from 16 to 18 years are also positive but of a smaller magnitude, implying that there may be impacts on exposed infants and toddlers.

Figure 9



Notes: Event study is based on models in Table A7. 12th grade dropout rates averaged across school districts at a county-year level from 1991-2009. Bushels production by county. Solid lines show 95% confidence intervals.

The median twelfth grade dropout rate during this period is four per hundred students, and the standard deviation in apple bushel production in 1997 is 0.23 thousand bushels/km^2.

Therefore, in the event of a cicada emergence, counties with one standard deviation higher apple intensity see an increase in the future dropout rate by 0.19, or about 5%. The same results, however, are not found when using a dummy for top apple production decile instead of production intensity.

It is important to note that the composition of counties over time is unknown. Since many people move in and out of counties over the course of two decades, it is not possible to know if those conceived during a cicada emergence were the same individuals in the county taking the elementary school tests and attending high school. Nevertheless, these findings align with Rauh et al. 2012 and provide evidence that insecticides can have long-term cognitive impacts that affect life outcomes beyond just infant health.

7 Water Mechanism

It may be surprising that tree crop acreage, given its small footprint, can produce effects that are measurable at the county level. The largest apple producer in our sample, which spans the cicada endemic states of the Eastern US, is Wayne County, NY. It has about 20,000 acres of apples trees, which is less than 5% of its land area. This is a small fraction compared to counties that intensively grow soy and corn, where row crops comprise a majority of the land. As such, only a small proportion of any county's population would be in close physical proximity to orchards.

Aside from farm workers directly exposed to insecticides, the primary channel in which a population is exposed to insecticides is likely water.[13] Insecticides are known to run off from agricultural fields into streams and groundwater. The United States Geological Survey (USGS) found pesticides present in 54% of the 1,034 shallow groundwater sites sampled from 1993 to 1995 across 20 major hydrologic basins in the US (USGS 2019).

Private water well users, as opposed to those on centralized public systems, would be more

[13] Insecticides can also spread through aerial drift with wind.

exposed to insecticides via this water channel. USGS reports that 15% percent of the US population gets its drinking water from private wells, where the quality and safety are not regulated, while 26% of people in the average US county get their water from private wells. This county-level figure is higher than the national average because people in densely populated areas tend to be supplied by public systems, while most private well users live in rural areas.

Using USGS data, I test whether there is heterogeneity in birth outcomes based on water source in Table 4. The measures of water exposure include the proportion of county population reliant on private wells ('well'), as well as the relative degree of groundwater reliance for domestic use ('gw'). I take the average from 1985 to 2015 and create an indicator based on whether the county is below the national median ('low') or above ('high'). Models (1) and (4) replicate the primary specification in Table 2 for comparison. We see that apple-intensive counties with more private wells and more domestic groundwater reliance tend to have larger and more precise infant mortality coefficients than those with lower private well use.

One may be concerned that reliance on private wells or groundwater may simply reflect the rural versus urban division described earlier, which may in turn explain these results. Table A8 in the Online Appendix addresses this by interacting the cicada-apple intensity measure with an indicator of how urban a county is, as derived from USDA's rural-urban continuum code. The water relationship holds.

As a caution, this evidence for a likely pesticide contamination pathway should not be interpreted as a specific mechanism given the heterogeneity across the US in terms of soil structure, precipitation patterns, and the timing and structure of horological flows—none of which are incorporated into the models.

Table 4: Cicada-Apple Interaction Impact on Infant Mortality via Water Channel

	Dependent variable:					
	Next Year Infant Mortality Rate (IMR)					
	—Bushels in 1964—			—Bushels in 1997—		
	(1)	(2)	(3)	(4)	(5)	(6)
cicada	0.05	0.06	0.06	0.06	0.06	0.06
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
cicada:bushels	0.54			0.42		
	(0.15)			(0.17)		
cicada:bushels:well_low		−0.66			0.90	
		(1.20)			(1.44)	
cicada:bushels:well_high		0.58			0.41	
		(0.13)			(0.17)	
cicada:bushels:gw_low			−2.92			−2.30
			(1.44)			(1.72)
cicada:bushels:gw_high			0.59			0.43
			(0.14)			(0.17)
County FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Observations	141,694	141,694	141,694	141,814	141,814	141,814
R^2	0.52	0.52	0.52	0.52	0.52	0.52

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Excludes county-year observations with less than 5 births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels is the actual level of apple production in 1964 and 1997. The low and high values for proportion of the population using private wells (well), and domestic groundwater reliance (gw), describe whether the county is above or below the national county median for that indicator. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

8 Robustness Checks

8.1 Yield Impacts

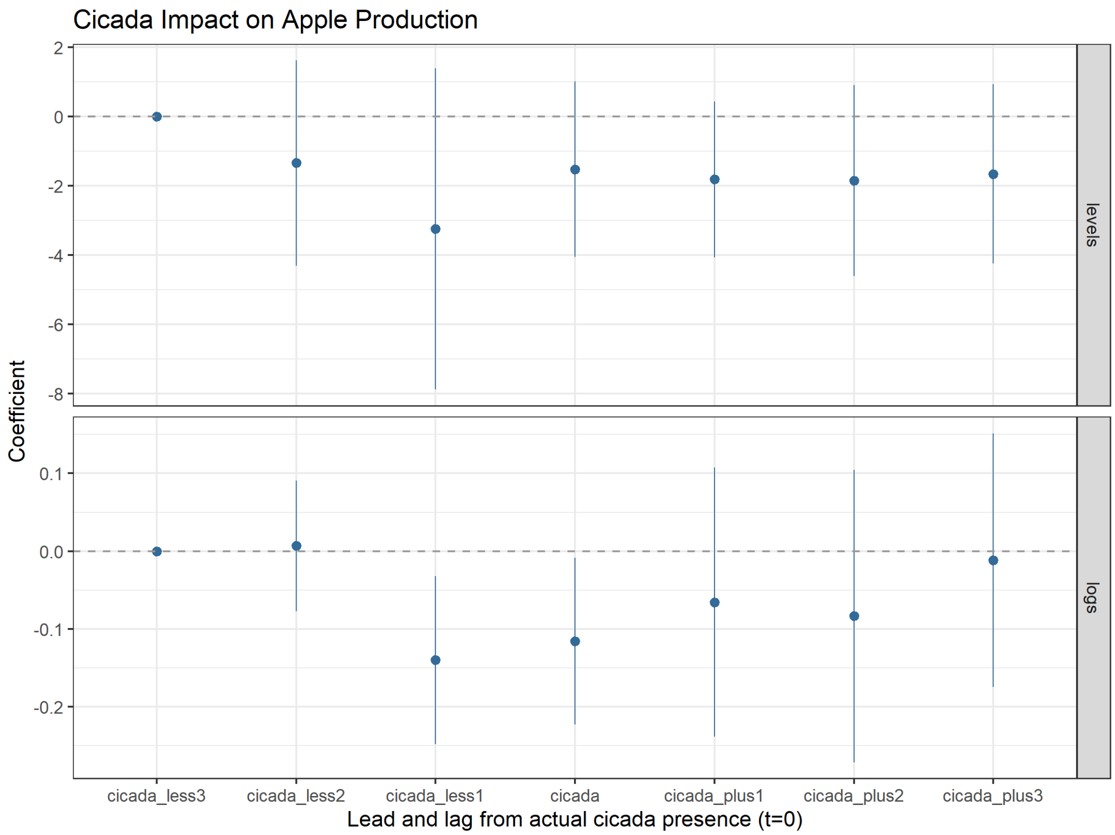
There are certain factors that could undermine the cicada-infant mortality story. Plausible candidates need to affect tree crop-intensive counties in the year following cicada emergence in ways that are different than those same counties in other years, as well as other tree crop-intensive counties in that same year that did not experience a cicada emergence.

One candidate is agricultural yields. If cicadas decimate apple production, for example, there could be a health impact via an economic channel. Our main dataset comes from the agricultural census which is collected approximately every five years and thus does not allow for testing annual shocks. USDA does, however, track annual apple production for a subset of 170 counties in the states of Virginia, South Carolina, Kansas, Pennsylvania, and New Jersey from 1972 to 2012. Using this limited data, I regress county-level apple production on leads and lags of cicada emergence. Figure 10 plots the coefficients, with level of production on the top panel and log production on the bottom panel.

While there is no significant relationship with level of production, the log values show a decrease in apple production in the year before and the year of cicada emergence. A weaker but non-significant effect seems to persist afterward. Nymphs feed strongly on roots leading up to emergence as well as in the years that follow during their establishment. The timing of this yield impact aligns with the third prediction of the timing framework in Figure 2 and partly justifies why orchard owners apply insecticides. It also aligns with the agronomic and ecological literature showing that cicadas reduce tree growth, with feeding nymphs being a major main culprit (Karban 1982). This negative yield impact, however, is less than the 30%-plus reduction in tree growth observed in natural settings in the absence of insecticides.

There are two main reasons that this economic channel is unlikely to explain the infant

Figure 10



Notes: Event study of cicada impact on apple production. Dependent variable is county-level apple production in millions of bushels. Upper panel is levels, lower panel is log values. Annual time series is from 1972 to 2011 for select states with annual production data. Observations with no leading or lagging cicada events during the sample time period are excluded to balance the panel. County and state-year level fixed effect dummies included. Solid lines show 95% confidence intervals. Normalized to three years before cicada emergence.

mortality relationship. First, yields decline in the year before and the year of a cicada emergence, but there is no evidence of an increase in infant mortality until the year afterwards. Second, tree crops comprise a very small portion of the economic value of most counties. For example, Wayne County, NY, the largest apple producer in the eastern half of the US, has a county GDP in 2012 of $3 billion according to the Bureau of Labor Statistics. The combined value of all fruit production is $79 million according to USDA NASS, or just 2.5% of GDP. Taken together, it seems unlikely that a yield-based economic channel is the main driver of observed health impacts, especially ones that are averaged over an entire county.

8.2 Births

The other factor that could complicate the cicada-infant mortality story is if cicada emergence alters behavior in ways that affect birth outcomes outside of the insecticide channel (e.g., if cicadas make people engage in more or less risky behavior). Since cicada emergences are short-lived, generally lasting only four to five weeks, it seems unlikely that cicadas would *in themselves* alter average outcomes at the county level over the course of the entire following year. Further, one would have to believe that people in counties with a high proportion of tree crops behave differently in response to cicadas than people in counties with fewer tree crops.

Table 5 shows the results of a regression of next-year birth rate on cicada emergence and apple intensity. Birth rate is computed with ICPSR natality data as total annual births per thousand people (crude) and thousand women of child-bearing age (ages 15-44). The apple-cicada interaction coefficients are close to zero and insignificant for the most part. Behavior, as it relates to number of births, is not different in apple-intensive 'treated' counties relative to untreated counties.

However, overall births seem to increase in the year following a cicada emergence. This interesting finding holds after controlling for various combinations of fixed effects and time trends.[14] I calculate a back-of-the-envelope estimate using the crude birth rate impact of 0.11 per thousand and the fact that the population averaged 87 million between 1950 to 2016 in the counties with a cicada presence . Since cicadas emerge every 16 years on average (3 broods have 13-year cycles, 12 broods have 17-year cycles), this means that an additional 600 people could be born in the US each year, on average, because of cicadas.

This modest but strange result could reflect a dynamic similar to that found in Evans et al. 2010 and Burlando 2014 where birth rates increase after hurricanes (when people are forced to stay inside) or power outages. Or perhaps there is a physiological effect that sci-

[14] In the main specification, I include state-year fixed effects to account for anomalous state-level sampling processes related to birth counts.

Table 5: Cicada-Apple Interaction Impact on Birth Rates

	Dependent variable:					
	All people (Crude)			Female Age-Specific		
	(1)	(2)	(3)	(4)	(5)	(6)
cicada	0.11	0.12	0.11	0.40	0.45	0.40
	(0.03)	(0.04)	(0.03)	(0.17)	(0.20)	(0.17)
cicada:bushels_HIGH		−0.08			−0.31	
		(0.06)			(0.53)	
cicada:bushels			−0.05			0.01
			(0.04)			(0.21)
County FE	X	X	X	X	X	X
State-Year FE	X	X	X	X	X	X
Observations	140,125	140,125	140,125	140,125	140,125	140,125
R^2	0.84	0.84	0.84	0.74	0.74	0.74

Notes: Linear regression. Dependent variable is next-year birth rate. Models (1)-(3) show the crude birth rate (births per 1000 people). Models (4)-(6) show births per thousand women of child bearing age (ages 15-44). Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production, and bushels is actual level of production in 1997. County and state-year level fixed effect dummies included. Standard errors clustered at the state level.

ence has yet to uncover, one that occurs when humans witness millions of frenzied creatures emerging from over a decade underground only to live for a few weeks, just long enough to sing a shrill song, mate, and die.

8.3 Maternal characteristics

Finally, there may be concerns that the composition of mothers may somehow change. In other words, maybe the mothers in tree crop-intensive counties who give birth in the year following cicada emergence are somehow different in ways that could explain some of the health outcomes. To control for this, I rerun the specification from Equation 2 in Table 6 but include several maternal controls, including age, education, race, weight gain during pregnancy, and cigarette consumption during pregnancy. This limits the sample from 1990 to 2009 when all these variables were tracked on birth certificates. For reference, Model (1) replicates the main specification from Model (4) in Table 2. Model (2) performs the same analysis over the restricted sample time period. Models (3)-(5) show that the cicada-apple interaction coefficient remains significant and little changed with maternal controls.

Table 6: Cicada-Apple Interaction Impact on Infant Mortality, Maternal Characteristics

	Dependent variable:				
	Next-Year Infant Mortality Rate (IMR)				
	(1)	(2)	(3)	(4)	(5)
cicada	0.06	−0.17	−0.16	−0.17	−0.16
	(0.13)	(0.17)	(0.17)	(0.17)	(0.18)
education			−0.02	−0.02	−0.03
			(0.06)	(0.06)	(0.08)
age			−0.03	−0.03	−0.02
			(0.06)	(0.06)	(0.07)
black				0.70	0.76
				(0.51)	(0.52)
cig					0.02
					(0.05)
wtgain					0.04
					(0.04)
cicada:bushels	0.42	0.43	0.43	0.44	0.43
	(0.17)	(0.22)	(0.22)	(0.22)	(0.22)
County FE	X	X	X	X	X
State FE	X	X	X	X	X
Observations	141,814	33,020	33,020	33,020	33,020
R^2	0.52	0.15	0.15	0.15	0.15

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Excludes county-year observations with less than 5 births. Maternal characteristics are annual county averages for education, age, a dummy for race (black versus non-black), number of cigarettes smoked during first trimester, and maternal weight gain. Outliers were dropped above the sample 99.9th percentile value to control for erroneous entries. Cicada dummy takes the value of 1 if there is a cicada emergence in the county in that year. Bushels is county apple production in 1997. Model (1) shows the main model results from 1950 to 2016. Model (2) replicates this with the restricted sample from 1990 to 2009 with data that includes all maternal characteristics. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

9 Conclusions

Insecticides are critical to agricultural productivity, but they also pose risks to the population that are difficult to measure. In this paper, I use the mass emergence of periodical cicadas in 13 and 17-year cycles to identify the impact of insecticides on human health.

I find an increase in insecticide use in counties experiencing a cicada emergence that is limited to areas with a large amount of woody crops (i.e., apple trees), as opposed to herbaceous row crops like corn and soy. This is because cicadas only damage woody plants: nymphs feed on tree roots and adult cicadas lay their eggs in small branches.

I exploit this variation to compare treated counties (i.e., counties with high levels of apple production that experience a cicada emergence) to untreated counties. In the treated counties, we see a jump in next-year infant mortality by 0.3 deaths per thousand births. The birth impact may extend into the second year as farmers continue applying higher levels of insecticide to control cicada nymph establishment. Sub-annual impacts align with the timing and patterns of insecticide usage by farmers.

Treated counties see an increase in premature births and other negative infant health outcomes. There is also evidence of long-term cohort effects in the form of lower elementary school test scores and higher high school dropout rates. I then demonstrate that aggregate insecticide exposure is likely through the water channel.

The findings may be generalizable beyond just very agriculturally-intensive areas. Tree crops cover a relatively small portion of US counties and total pesticide use is relatively low in most tree-intensive counties, especially compared to row crop agriculture. Together this supports the idea that moderate levels of pesticides, not just extreme exposures, can have negative health impacts.

Overall this paper contributes to the environmental and health economics literature on the health impacts of agricultural inputs. While acknowledging the large benefits of pesticides to agricultural productivity, the findings warrant caution in the over-application of insecticides. This paper also provides an example of how ecological phenomena like cicadas may be used to generate quasi-random variation that can be employed to answer important economic and public health questions.

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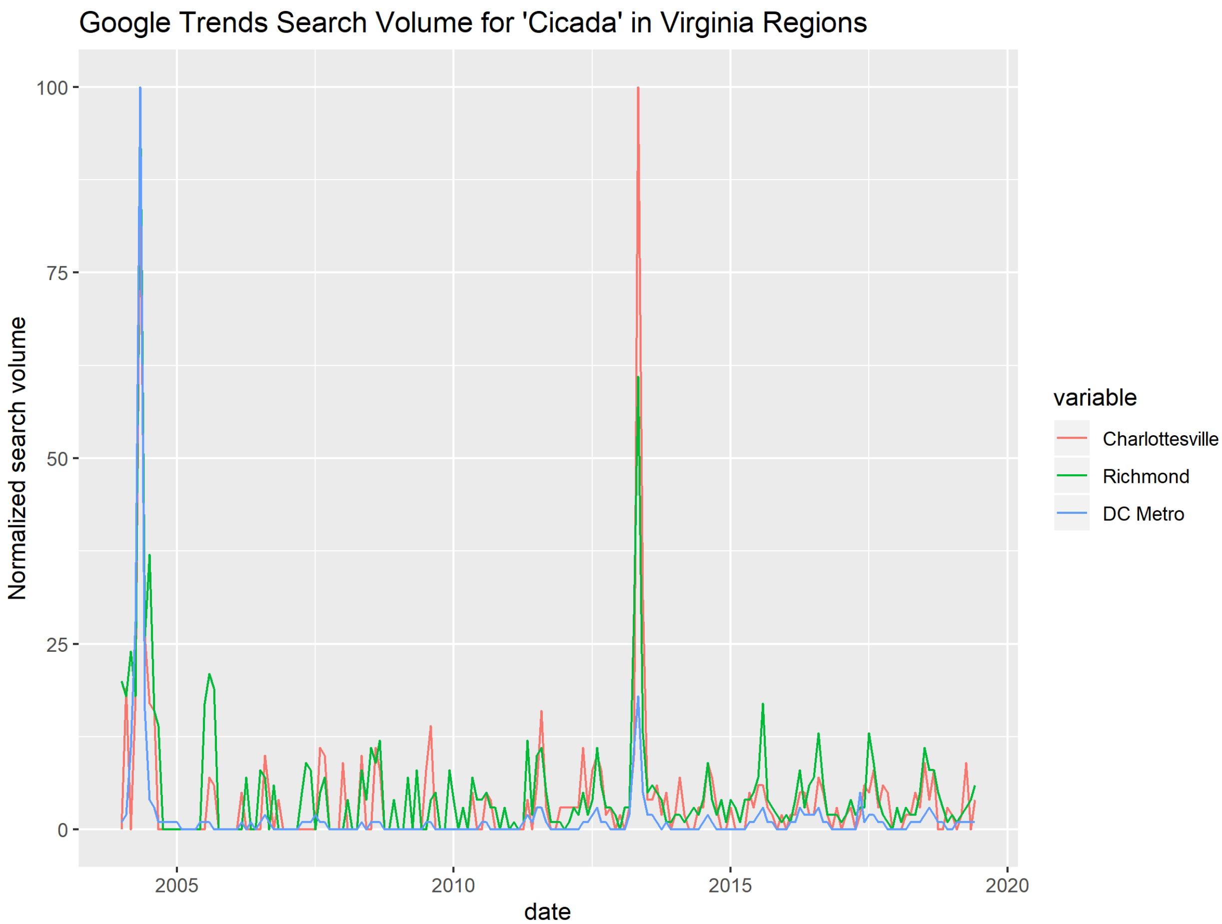
10 Online Appendix

10.1 Cicada awareness event study

Figure A1



Source: Google Trends

10.2 Pesticide response to cicadas

Table A1: Falsification by Pesticide Type (kg/km2)

	Dependent variable:		
	Insecticide	Herbicide	Fungicide
	(1)	(2)	(3)
cicada	0.30	1.01	−0.08
	(0.99)	(1.12)	(0.42)
cicada:bushels_HIGH	5.58	−2.48	0.94
	(3.14)	(1.84)	(1.54)
County FE	X	X	X
Year FE	X	X	X
Observations	60,469	60,469	60,469
R^2	0.41	0.84	0.54

Notes: Linear regression. Dependent variable is county-level pesticide use divided by county land area. Pesticide use is the combined sum of the USGS EPest-high values for constituents with insecticidal, herbicidal, and/or fungicidal properties. Many pesticides had multiple properties. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997. Time series limited to USGS pesticide data, 1992 to 2016. County and year fixed effect dummies included. Standard errors clustered at the state level.

Table A2: Falsification by Crop (kg/km2)

	Dependent variable:		
	Insecticide use (kg/km2)		
	(1)	(2)	(3)
cicada	0.30	1.33	0.51
	(0.99)	(1.53)	(1.13)
cicada:bushels_HIGH	5.58		5.46
	(3.14)		(3.10)
cicada:corn_soy_HIGH		−2.08	−1.61
		(1.47)	(1.23)
County FE	X	X	X
State FE	X	X	X
Observations	60,469	60,533	60,469
R^2	0.41	0.41	0.41

Notes: Linear regression. Dependent variable is county-level insecticide use, which is the combined sum of the USGS EPest-high values with insecticidal properties divided by county land area. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997. Corn_Soy HIGH is a dummy for the top decile counties in the combined corn and soy production by county area, averaged during the sample period. Time series limited to USGS pesticide data, 1992 to 2016. County and year fixed effect dummies included. Standard errors clustered at the state level.

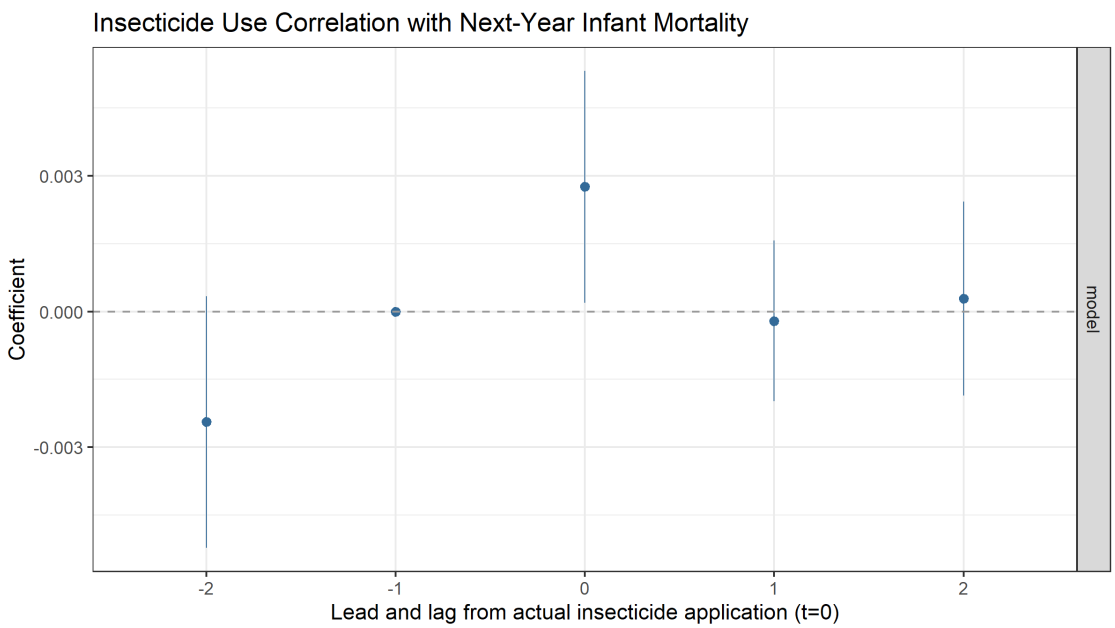
10.3 Insecticide and infant mortality correlation

Table A3: Insecticide Use Correlation with Infant Mortality

	Dependent variable:		
	Next-Year Infant Mortality Rate (IMR)		
	(1)	(2)	(3)
insecticide_use	0.0016	0.0013	0.0024
	(0.0015)	(0.0015)	(0.0014)
>5 births		X	X
>0 IMR			X
County FE	X	X	X
Year FE	X	X	X
Observations	53,880	45,956	37,648
R^2	0.0976	0.1333	0.5338

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Insecticide use is the combined sum of the USGS EPest-high values with insecticidal properties, divided by county area. Time series limited to USGS pesticide data, 1992 to 2016. Models (2)-(3) exclude county-year observations with less than five births. Model (3) is further limited to observations with at least one infant death. County and year fixed effect dummies included. Standard errors clustered at the state level.

Figure A2



Notes: Event study based on Model (3) from Table A3 with the inclusion of two leads and lags of insecticide use. Time series limited to availability of USGS pesticide data, 1992 to 2016. Excludes observations with zero infant deaths. Solid lines show 95% confidence intervals. Normalized to the year before current year insecticide use.

10.4 Cicada-apple impacts on infant mortality

Table A4: Cicada Impact on Infant Mortality, 1950-2016, Weighted by Births

	Dependent variable:			
	Next-Year Infant Mortality Rate (IMR)			
	(1)	(2)	(3)	(4)
cicada	0.16	0.13	0.14	0.15
	(0.08)	(0.09)	(0.09)	(0.09)
cicada:bushels_HIGH		0.14		
		(0.12)		
cicada:bushels_1964			0.44	
			(0.24)	
cicada:bushels_1997				0.31
				(0.15)
County FE	X	X	X	X
State FE	X	X	X	X
Observations	128,644	128,541	128,419	128,541
R^2	0.72	0.72	0.72	0.72

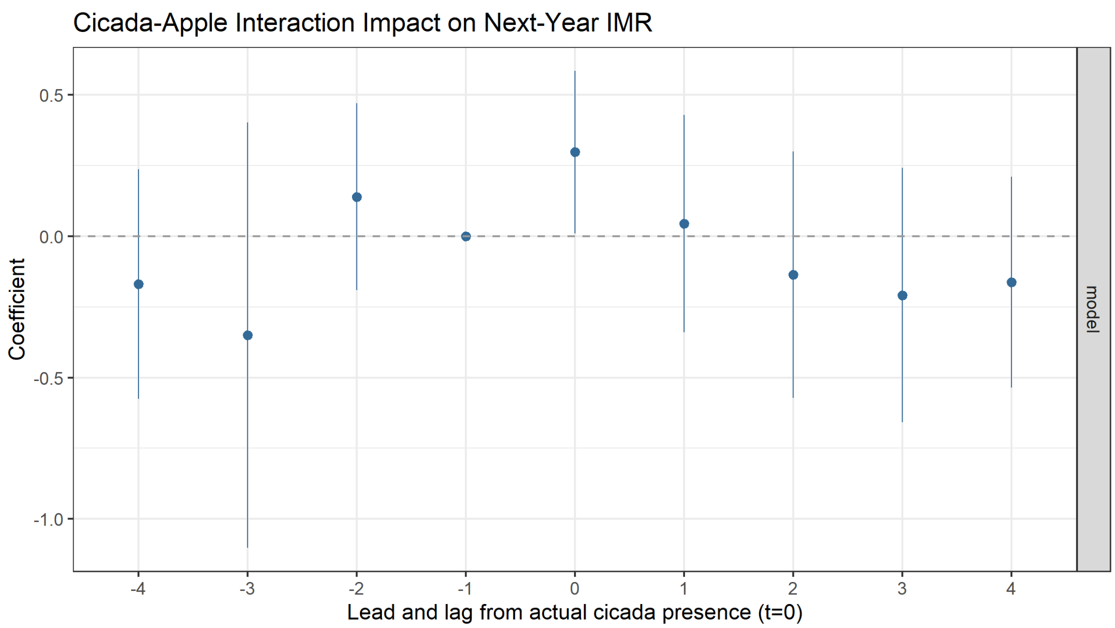
Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Regression weighted by the number of county births. Counties categorized as urban excluded to reflect what should be a primarily agricltural channel. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997, while bushels 1997 and bushels 1964 is the actual level of apple production in those years. Time series from 1950 to 2016. State-level annual time trends and county and state fixed effect dummies included. Standard errors clustered at the state level.

Table A5: Cicada Impact on Infant Mortality, 1950-1988

	Dependent variable:			
	Next-Year Infant Mortality Rate (IMR)			
	(1)	(2)	(3)	(4)
cicada	0.12	0.06	0.09	0.11
	(0.16)	(0.18)	(0.17)	(0.17)
cicada:bushels_HIGH		0.45		
		(0.20)		
cicada:bushels_1964			0.70	
			(0.32)	
cicada:bushels_1997				0.51
				(0.23)
County FE	X	X	X	X
State FE	X	X	X	X
Observations	94,896	94,445	94,359	94,445
R^2	0.43	0.43	0.43	0.43

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Excludes county-year observations with less than 5 births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997, while bushels 1997 and bushels 1964 is the actual level of apple production in those years. Time series limited to 1950-1988, when infant mortality data is available for all counties. State-level annual time trends and county and state fixed effect dummies included. Standard errors clustered at the state level.

Figure A3



Notes: Event study with top decile apple producing counties based on Model (2) of Table 2, but including cicada leads and lags. Observations with no leading or lagging cicada events during the sample time period are excluded to balance the panel. Solid lines show 95% confidence intervals. Normalized to the year before cicada emergence.

10.5 Educational impacts

Table A6: Cicada-Apple Interaction Impact on Elementary School Test Scores

	NAEP-equivalent average test scores			
	Math		English	
	(1)	(2)	(3)	(4)
cicada	0.33	0.22	0.16	0.02
	(0.26)	(0.23)	(0.27)	(0.24)
cicada:bushels_HIGH	−1.05		−1.14	
	(0.49)		(0.52)	
cicada:bushels		−1.16		−0.73
		(0.38)		(0.40)
County FE	X	X	X	X
State FE	X	X	X	X
Observations	10,733	10,733	11,379	11,379
R^2	0.91	0.91	0.90	0.90

Notes: Linear regression. Dependent variable is county-level averages of Stanford Education Data Archive's NAEP-equivalent test scores averaged for all elementary school students (grades 3-5) in the same 'cicada exposure cohort'. For example, scores are the average of 3rd graders 9 years after cicada exposure, 4th graders 10 years after cicada exposure, and 5th graders 11 years after cicada exposure. Annual scores available from Spring 2009 to Spring 2015. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels HIGH is a dummy for the top decile counties in apple production in 1997. Non-interacted cicada coefficients are excluded from output for brevity. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

Table A7: Cicada-Apple Interaction Impact on Dropout Rates

	Dependent variable:	
	Dropout rate per 100 students	
	(1)	(2)
cicada_plus16:bushels		0.16
		(0.07)
cicada_plus17:bushels		0.27
		(0.15)
cicada_plus18:bushels		0.26
		(0.25)
cicada_plus19:bushels	0.80	0.87
	(0.31)	(0.30)
cicada_plus20:bushels		−0.16
		(0.40)
cicada_plus21:bushels		0.001
		(0.16)
cicada_plus22:bushels		−0.09
		(0.14)
County FE	X	X
State FE	X	X
Observations	22,716	22,716
R^2	0.23	0.23

Notes: Linear regression. Dependent variable is 12th grade dropout rates. Dropout rates are averaged across school districts at a county-year level and available from NCES from 1991 to 2009. Cicada lags are a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year (i.e., cicada_plus19 denotes a cicada occurrence 19 years before the year of the dropout observation). Bushels is the level of apple production in 1997. Coefficients of the non-interacted cicada lags are omitted from output for brevity. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.

10.6 Water channel

Table A8: Cicada-Apple Interaction Impact on Infant Mortality via Water Channel

	Dependent variable:					
	Next Year Infant Mortality Rate (IMR)					
	—Bushels in 1964—			—Bushels in 1997—		
	(1)	(2)	(3)	(4)	(5)	(6)
cicada	0.05	0.06	0.06	0.06	0.06	0.06
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
cicada:bushels	0.54			0.42		
	(0.15)			(0.17)		
cicada:bushels:well_low		−0.59			0.91	
		(1.37)			(1.48)	
cicada:bushels:well_high		0.65			0.42	
		(0.36)			(0.14)	
cicada:bushels:gw_low			−2.84			−2.31
			(1.35)			(1.75)
cicada:bushels:gw_high			0.67			0.43
			(0.36)			(0.14)
cicada:bushels:urban		−0.08	−0.10		−0.02	0.01
		(0.43)	(0.44)		(0.37)	(0.36)
County FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Urban control		X	X		X	X
Observations	141,694	141,694	141,694	141,814	141,814	141,814
R^2	0.52	0.52	0.52	0.52	0.52	0.52

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Excludes county-year observations with less than 5 births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Bushels is the actual level of apple production in 1964 and 1997. The low and high values for proportion of the population using private wells (well), and domestic groundwater reliance (gw), describe whether the county is above or below the national county median for that indicator. Urban is a dummy indicator of whether the county is below the national median of USDA's rural-urban continuum code between 1990-2013. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level.