Cicadian Rhythm: Insecticides, Infant Health, and Long-term Outcomes*

Charles A. Taylor†

January 2022

latest link

Abstract

Pesticides are linked to negative health outcomes, but a causal relationship is difficult to establish due to nonrandom pesticide exposure. I use a peculiar ecological phenomenon, the mass emergence of cicadas in 13 and 17-year cycles across the eastern half of the US, to estimate the short and long-term impacts of pesticides. With a triple-difference setup that leverages the fact that cicadas only damage tree crops and not agricultural row crops, I show that insecticide use increases with cicada emergence in places with high apple production. Exposed cohorts experience higher infant mortality and adverse health impacts, followed by lower test scores and higher dropout rates. I exploit geo-spatial sources of variation and find evidence for pesticide exposure through a water channel. Moderate levels of environmental pollution, not just extreme exposure, can affect human health and development. The study design, which encompasses the entire chemical era of US agriculture since 1950, provides insights into the regulation of pesticides in the US and globally. *JEL Codes: I10, Q10, Q53, Q57.*

*I am grateful for feedback received at the Heartland Environmental and Resource Economics Workshop (University of Illinois), Occasional Workshop on Environmental and Resource Economics (UCSB), Center for Environmental Economics and Policy (Columbia), BIOECON XXII Conference, OSWEET Workshop, USF Economics Seminar, Sustainable Development Seminar (Columbia), the Schlenker Lab, and the Seminar on Planetary Management.

†School of International and Public Affairs, Columbia University, 420 W 118th St, New York, NY 10027, email: cat2180@columbia.edu

1 Introduction

Farmers in the US spend $8 billion annually on pesticides (US EPA 2017). Modern pesticides, along with other technological advances in agriculture, have brought about significant increases in productivity in the post-war period (Jorgenson and Gollop 1992; Wang et al. 2015). But concerns have long been raised about the potential 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 Environmental Protection Agency (EPA) on account of their potential risk to humans (Buffington and Mcdonald 2006). Yet individual pesticide restrictions generally occur after decades of heavy use (see Figure 2), and many prominent pesticides currently in use—both in the US but also in agriculturally-intensifying developing countries—are under scrutiny. The efficient regulation of pesticides is hindered by a lack of causal evidence on their human impacts.

I use an ecological phenomenon, the emergence of periodical cicadas (*Magicicada septendecula*) in the eastern half of the US, as a source of quasi-exogenous temporal and spatial variation in the application of insecticides to identify their impacts on health. The 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 the summer of 2013.

I first show that farmers respond to a cicada emergence with a one-time increase in insecticide use of 13-22%. This response, however, is limited to places with a large proportion of woody crops like fruit trees—and not herbaceous row crops like corn and soy—reflecting the fact that cicadas only damage woody plants: adult cicadas lay their eggs in small branches and nymphs feed on tree roots. I further show that the response is limited to insecticides and not other agri-chemical channels like herbicide or fungicide use.

Having established the cicada-insecticide link, I use cicada emergence as my treatment to compare outcomes in high apple-producing counties during a cicada emergence (i.e., the *treated* group) to (i) those same counties in non-cicada years, (ii) non-apple producing counties in cicada years, and (iii) counties lacking endemic cicada broods (altogether, the *untreated* group). In treated counties, I find a corresponding increase in next-year infant mortality of 0.31 deaths per thousand births (5% of the current US average of 6) following a cicada emergence. The lagged effect reflects pesticide exposure during the year of conception, which manifests in next-year births. The main analysis is reduced form using a cicada-based treatment rather than an IV with pesticide data in part because granular pesticide data only recently became available (see Figure 1). While related studies have focused on the period since 2000 for this reason, the nature of cicadas with their 17-year revisit cycle enables me to analyze the entire chemical era of US agriculture since 1950.

Looking sub-annually, an analysis of the quarterly impacts shows that fetal exposure risk is greatest during the first trimester of pregnancy, which is in line with the fetal origins hypothesis. Treated counties also see an increase in the probability of premature births and other adverse infant health outcomes. I find evidence of long-term impacts in the form of lower elementary school test scores and increased high school dropout rates among exposed cohorts.

Exploiting spatially-explicit and high-resolution land use and hydrological data, I find that orchards in close proximity to population centers and surface waters are related to higher infant mortality—the latter implying a potential water exposure channel. Alternatively, I show that the negative effect occurs downstream but not upstream from a county, supporting a water exposure channel. This also suggests the presence of spatial spillovers in which the negative externality of pesticide runoff may extend beyond just the people living in an apple-intensive county.

The findings are generalizable outside of just agriculturally-intensive regions. Analyzing the major cicada broods individually, each covering a different geographic footprint of the eastern half of the US, I obtain similar estimates of the impact on infant mortality—implying the effect is not limited to one region or a set of treatment years. Further, 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 such as soy and corn which can account for the majority of total acreage in many counties. Baseline insecticide use is modest in apple-intensive counties: 14% lower than the average across all counties in my eastern US sample, and 19% lower than top-decile corn and soybean-producing counties. Apples as a crop account for only 1.4% of all US pesticide use.

Together these facts suggest that moderate levels of pesticides, not just extreme exposure, affect human health and development—in line with the emerging medical literature on subclinical toxicity, which posits that pesticides can have population-level effects via low-level toxin exposure over time through the ingestion in food, water, or air, in such ways that never amount to direct poisoning and thus are not observed by medical providers

(Landrigan 2018; Dias et al. 2019). And since this analysis looks only at average county-level impacts, it likely understates the health impacts among those living in close proximity to the application of insecticides.

Applying my results to a back-of-the-envelope calculation, 556 infant deaths can be attributed to insecticides in the limited context of apple production and cicadas, equating to a total welfare loss of $5.3 billion using the EPA's value of statistical life of $9.6 million (2020 dollars),[1] or $81 million annually from 1950 to 2016. The annual value of apple production in the sample counties ranged from $500 million to $1 billion in recent decades, so this cicada-driven response of infant mortality to insecticides could account for 8-16% of apple production value. For reference, organic apples cost 5-10% more to produce than conventional ones (Taylor and Granatstein 2013), suggesting that organic production may be cheaper after accounting for the social cost of insecticides. However, apple production in the eastern US accounts for only 0.5% of US pesticide use, so if these effects scale across other crops, the total welfare cost of insecticides could be 200x larger (see Conclusion section for further discussion).

In addition to contributing to the environmental and health economics literature on the health impacts of agricultural inputs, the long-term analysis enabled by the nature of cicadas provides insights into pesticide regulation. To this end, the paper finds that the effect of insecticides on infant mortality decreased following the ban of highly-scrutinized pesticides like organochlorides (e.g., DDT) before increasing again in recent decades. Given that the majority of insecticides used to date were eventually banned or cancelled after decades of heavy use, this paper raises important questions about whether toxic material regulation should be proactive versus reactive, and whether the burden of proof for demonstrating safety should fall on industry or regulators. The European Union, for example, is more stringent in regulating its €177 billion agricultural sector (Eurostat), and has banned most of the insecticides currently in use in the US (see Figure 2).

Pesticide regulation is a timely topic considering the many current lawsuits and regulatory debates.[2] Chlorpyrifos, the most widely-used insecticide in the US in recent years, was banned by the EPA as recently as August 2021. There are also increasing concerns about pesticide impacts on pollinators and ecosystems more generally (Potts et al. 2016), particularly in relation to neonicotinoids, a new class of insecticides that became widely-adopted since the 2000s (Frank and Tooker 2020).[3] A bill banning all organophosphates

[1] See link for EPA discussion on mortality risk valuation.

[2] See link for the recent $10 billion glyphosate herbicide settlement; link for a 2021 ruling against the EPA's attempt to reinstate aldicarb for insecticide use in Florida.

[3] See link for efforts by conservation groups to make the EPA account for pesticide risk to plants and ani-

and neonicotinoids was recently introduced in the US Senate.[4]

Further, an improved understanding of pesticide impacts and the role of regulation is relevant to major agricultural producers like China and Brazil, where pesticide use intensity is 5x and 2.4x higher, respectively, than the US (FAO 2020). Pesticide use in sub-Saharan Africa, on the other hand, is very low relative to the global average but is growing rapidly with little regulatory oversight (Snyder et al. 2015). In India, several EPA-banned pesticides remain widely in use (e.g., acephate, carbofuran, monocrotophos, chlorpyrifos) and DDT is still employed for public health purposes.[5]

The paper is structured as follows: the remainder of this Introduction provides background on the health effects of pesticides, trends in pesticide use and regulation, and the nature of cicadas and their relationship to insecticide use. Section 2 describes the data. Section 3 introduces the empirical approach and identification strategy. Section 4 shows the main results relating to the impact of pesticides on health and other outcomes. Section 5 includes several extensions, including spatial analyses, an investigation of exposure channels, and robustness checks. Section 6 contains a conclusion and discussion of policy implications.

1.1 Pesticides and health

Pesticides have long played an important role in society. Their use for both agricultural and human hygiene purposes is well documented in ancient Egypt, Rome, Greece, India, and China where application methods often involved the burning or powder-spreading of sulfur and arsenic compounds (Costa 1987). Today US farmers spend $8 billion annually on pesticides (US EPA 2017), a category that includes herbicides, fungicides, and insecticides. In the absence of insecticides, crop yields would be 18% lower on average (Oerke 2006). As an agricultural input, pesticides provide crop protection services that smooth yields, which is a different function than fertilizer, which boosts yields. In the context of this study, the risk of pests is particularly high for perennial crops like apples, where insects can destroy an asset with high upfront investment costs that could otherwise produce for many years (unlike annual crops). Further, insects can reduce yields for perennials both in the year of an infestation and the year afterwards through diminished plant productivity (Cerda et al. 2017).

Insecticides are toxic by design. Many were initially developed for warfare purposes. One

mals protected under the Endangered Species Act.

[4] See link for S.4406 - Protect America's Children from Toxic Pesticides Act.

[5] See link for a list of banned pesticides in India as of January 2021.

prominent insecticide type, organochlorides (e.g., DDT), opens sodium channels in the nerve cells; the two main insecticide classes currently in use in the US, carbamates and organophosphates, target the nervous system, acting similarly to the nerve agents in chemical weapons. US agriculture quickly became reliant on synthetic pesticides in the post-war period, and by the early 1950s organochlorides were the dominant insecticide class in use. Public concern about the unintended health and environmental impacts of pesticides increased throughout the 1960s, punctuated by Agent Orange's link to cancer during the Vietnam War and the ban of DDT in 1972 (EPA 1975; Carson 2002; Fallon et al. 1994).

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—and in particular their effect on highly vulnerable populations like infants. Fetal shocks, especially ones occurring early in a pregnancy, can have long-lasting impacts (Barker 1995; Almond and Currie 2011), and environmental shocks in particular, including heavy metal exposure and air pollution, have been causally linked to adverse outcomes at birth and later in life.[6]

Most estimates of the impact of pesticides on infant health come from non-randomized studies with small sample sizes (Jurewicz et al. 2006; Andersson et al. 2014), whereas others focus on occupationally-exposed groups who are unlikely to be representative of the broader population. Among farm workers, there is evidence of higher levels of stillbirths (Regidor et al. 2004) and birth defects (Garry et al. 2002), especially for conceptions occurring during the spring pesticide application season. Others highlight the impact of pesticide exposure during the first trimester (Bell et al. 2001) and a link between fertilizer chemicals in water and birth defects (Winchester et al. 2009). Schreinemachers 2003 find that birth defects increase with a county's wheat acreage, which is used as a proxy for herbicide exposure. 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*.

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 fertilizer pollution to adverse birth outcomes in India, while Lai 2017 uses a policy change in China to link pesticides to increased rates of disability. Dias et al. 2019 link herbicide use driven by genetically-modified crop adop-

[6] There is a rich literature documenting the impact of pollution on birth outcomes (Chay and Greenstone 2003; Currie and Neidell 2005; Currie and Walker 2011; Clay et al. 2014) and childhood and adult outcomes (Sanders 2012; Ebenstein 2012; Currie et al. 2014; Zheng et al. 2016; Isen et al. 2017; Deryugina et al. 2019; Colmer and Voorheis 2020; Persico et al. 2020).

tion to negative birth outcomes in Brazil. Others have have leveraged one-time ecological shocks for identification: a bat-killing fungus to obtain variation in insecticide use to show impact on infant mortality (Frank 2018), and responses to an invasive fly insect that produced adverse infant health outcomes (Jones 2020).

To my knowledge, this paper is the first to directly assess the subclinical impact of pesticides on health over a large scale (eastern half of the US), across a broad range of pesticide chemical types, and over a long time period (1950 to present), as visualized in Figure 1—and to link pesticide exposure to health effects and longer-term outcomes.

1.2 Pesticide trends and regulation

The next section provides context on the overall trends in pesticide use in the US. Appendix Figure A1 shows that among the main pesticide types, herbicide use increased rapidly through 1980, and then stabilized before increasing again in the 2000s following the mass adoption of genetically engineered, herbicide-tolerant crops and no-till agriculture. Insecticide use, on the other hand, which exceeded herbicide use for much of the 1960s, has been in decline since the mid-1970s.

In terms of quality characteristics, average pesticide application rates (i.e., pounds per acre over a year) declined by one half since the late 1960s, as shown in Appendix Figure A2, implying that pesticide efficiency increased starting in the 1970s. Potential impacts on humans and the environment, however, are a function of pesticide toxicity and persistence in addition to quantity. To this end, average toxicity[7] declined rapidly in the 1970s driven by the ban of DDT and toxaphene (primarily used on cotton) and aldrin (primarily used on corn), as well as the use of relatively less toxic insecticides like carbaryl, chloropyrifos, and pyrethroids (Fernandez-Cornejo et al. 2014).

Average pesticide persistence fell from 54% in 1968 to 25% in 2008, defined as the share of pesticides with a half-life greater than 60 days (Fernandez-Cornejo and Jans 1995). The 1970s saw a notable decrease in persistence with DDT and aldrin off the market, followed by an increase in the early 1990s coinciding with longer-lasting metolachlor and pendimethalin. Average persistence then declined in the mid-1990s with the large-scale adoption of glyphosate herbicide (Fernandez-Cornejo et al. 2014). Appendix Figure A3 shows that despite the increase in pesticide efficiency and change in pesticide composition,

[7] Toxicity refers to the chemical's risk to humans and the environment, and is estimated based on the inverse of the safe drinking water threshold (Kellogg et al. 2002) in terms of constituent concentration in parts per billion.

pesticide prices stayed relatively in line with average crop prices over the decades, with some periods of lower relative prices in the 1970s and 1980s and higher prices in the late 1990s and early 2000s. But relative to fuel and labor costs, pesticides became far less expensive over time.

Historical crop-specific estimates of insecticide use are often imputed for a given geography based on overall pesticide consumption and the acreage in a given land use. Looking at five major US crops, Appendix Figure A4 plots insecticide use trends with total quantity on the left panel and intensity (kg per acre) on the right. Cotton accounts for much of historical insecticide use and its decline can be attributed to several factors: the successful USDA Boll Weevil Eradication Program that began in the early 1970s and reduced insecticide use in cotton by 40 to 80% (Smith 1998), and the introduction of Bt cotton in the mid 1990s, which was genetically-engineered for pest resistance.

Regulation occurred in tandem with these changes in pesticide use. Since the ban of DDT in 1972, dozens of widely-used pesticides have been cancelled by the EPA. Figure 2 in Panel A shows that seven of the top ten insecticides used in the US in 1968 (Fernandez-Cornejo et al. 2014) were banned or cancelled, with only carbaryl, cryolite, and dicrotophos currently remaining in use. Remarkably, the top two insecticides used in 2008, chlorpyrifos and aldicarb, are banned as of 2021. Several of the remaining widely-used insecticides are the US are banned in the European Union. Panel B shows the primary insecticides used over the last seventy years in the US in terms of when they were registered for use with the EPA and when they were phased out. Two things to note: first, many of the insecticides were developed in the immediate post-war 1950s, and second, there has been a fairly consistent pattern of insecticide cancellation following several decades of intensive use.

To visualize the effect of regulation and technological change over time, Appendix Figure A5 plots long-term trends in insecticide use by active ingredient type, merging historical data at the national level (Aspelin 2003) with the more recent United States Geological Survey (USGS) county-level data used in this paper (USGS 2019). Similar to Appendix Figure A1, aggregate insecticide use peaks in 1975 then declines, but in terms of chemical type there is significant variation. Insecticide use is dominated by inorganics like arsenicals until about 1950, at which point the synthetic chemical age begins with organochlorides (led by DDT) driving insecticide growth. In the late 1960s organophosphates begin to replace organochlorides (DDT was banned in 1972). Organophosphates, in turn, are replaced by other types of insecticides starting in early 1990s, coinciding with increases in pyrethroid and neoincotinoid insecticide use as carbamates are phased out. Such patterns reflect the increasing proportion of organochlorides, then organophosphates, and then carbamates that were subject to EPA restrictions over time.[8]

The US is unique in pesticide regulation in that many pesticides are "voluntarily" deregistered by their corporate owners, which is different than the regulator-driven approach in most countries. In some cases, cancellation occurs under pressure from the EPA in response to mounting evidence on health impacts or legal challenges, and in other cases it can be an economic decision in the face of a product's declining sales, improved replacement pesticide availability, and patent lapses (Carroll 2016; Donley 2019). Nevertheless, all the cancelled insecticides listed in Figure 2 have well-documented health and environmental risks in the scientific literature, and each has also been banned in the European Union.[9]

It is also worth noting that pesticide producers in the US have faced increased regulatory scrutiny in recent decades associated with (i) the 1988 amendment to the Federal Insecticide, Fungicide, Rodenticide Act (FIFRA), which required the re-registration of all pesticides approved before 1984 under current scientific and regulatory standards, (ii) the Food Quality Protection Act (FQPA) in 1996 that reduced the allowable amount of pesticide residues on food crops, with an emphasis on risks to infants, and (iii) enhancements to FIFRA through the 2004 Pesticide Registration Improvement Act (2019).

1.3 Cicadas and Insecticides

Periodical cicadas (*Magicicada septendecula*) occur throughout the eastern half of the US.[10] Bob Dylan described the distinctive mating song of the cicada (colloquially called a locust) while receiving an honorary degree from Princeton in the summer of 1970:

[8] USGS data allows for some disaggregation by chemical type and land use at the state level. The bottom panel of Appendix Figure A5 sums insecticide use 'Orchards and grapes', a category that includes apple production, across eastern states in this study. Patterns are broadly consistent with the national trends since 1992 shown in Appendix Figure A1 in which insecticide use declines overall. However, organophosphates still account for the majority of insecticide use among orchards.

[9] In the US, the pesticide industry has to demonstrate to the EPA that a product "will not generally cause unreasonable adverse effects on the environment" defined as "any unreasonable risk to man or the environment, taking into account the economic, social, and environmental costs and benefits of the use of any pesticide" under the Federal Insecticide, Fungicide, and Rodenticide Act, U.S.C. §136 et seq. (1996) and "reasonable certainty of no harm" for pesticide residues on food under the Food Quality Protection Act Public Law 104-170 (1996). For comparison, the European Union places the burden of proof on companies to show that pesticides are safe (regulations 1107/2009 and 396/2005), requiring that "that industry demonstrates that substances or products produced or placed on the market do not have any harmful effect on human or animal health or any unacceptable effects on the environment." (2019).

[10] Several annual cicada species (i.e., non-periodical) exist globally, but the populations of such species do not tend to vary greatly year to year.

And the locusts sang, yeah, it give me a chill
Oh, the locusts sang such a sweet melody
Oh, the locusts sang their high whining trill
Yeah, the locusts sang and they were singing for me

These cicadas belonged to Brood X, the same cohort that visited the mid-Atlantic three 17-year cycles later in 2021. Altogether, there are fifteen extant broods, three of which are on 13-year cycles and twelve of which are on 17-year cycles. Rarely flying more than 50 meters from where they emerge from the ground, each brood returns to the same place at the cycle's end. Figure 3 maps each brood's range, cycle, and next year of emergence. Note that some counties receive multiple broods.

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 of tree roots before synchronously emerging in the late 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 values 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 the egg-laying and nymph-feeding 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, and utilizing insecticides to mitigate cicada damage is well established. Studies have documented the process and efficacy of spraying trees with insecticides to kill adult cicadas as well as soaking the soil with insecticides to control nymphs (Hamilton 1961; Cahoon and Danoho 1982),[11] while others recommended killing off understory grasses to starve young nymphs (Lloyd and White 1987). There are many publicly-available resources on cicada management for fruit growers, including information on pesticide use and application methods (Krawczyk 2017; Johnson and Townsend 2004). Insecticide ap-

[11] One study tested cicada nymph control using soil injections of carbaryl at a rate of 2 lb per tree (1982).

plication is intensive and repetitive during cicada emergence: a 2021 Purdue University guide (link) suggests that large commercial orchards re-apply insecticides every 3 to 4 days over the course of a month to prevent injury to young trees.

2 Data

Cicada data

The US Forest Service provides shapefiles with county-level presence-absence data on periodical cicadas by brood with emergences projected through 2031 (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. Distribution maps are derived from pioneering work done over a century ago (Marlatt 1898; 1907). These maps may overestimate current brood boundaries due to habitat loss and the misassignment of straggler cicadas (Marshall 2001), and have been updated to periodically (Simon 2014; J. Cooley et al. 2009; J. R. Cooley et al. 2016; J. R. Cooley et al. 2021). While there are examples of accelerations in cycles and changes in the range of broods (Lloyd and Dybas 1966; Williams and Simon 1995), cicada behavior and brood distribution has been remarkably consistent for the most part (Marshall 2001). For robustness, a recent map is utilized of eight cicada broods in five Mid-Atlantic states derived from field research and actual cicada presence/absence sightings.[12]

Agricultural, land use, and water 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 (ICPSR) compiled (Haines et al. 2014). Various measures of apple intensity are collected at the county-year level (i.e., number of acres and production in bushels).[13] I choose apples as the preferred measure of tree crops 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

[12] "Current Brood Distribution for Periodical Cicadas in the Mid-Atlantic Area." Source: https://cicada.info (persistent link)

[13] County-year data values of '(D)', which NASS uses to denote confidentiality, were coded as not available, and values of '(Z)', which denote 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. All measures of agricultural intensity are standardized by county land area.

the cicada-endemic eastern US states, with top producers in the Northeast (NY, MA, CT), Central-Midwest (PA, MI, OH), and the South (VA, NC). Figure 3 shows the states included in my analysis along with cicada presence and quantile of apple production intensity.

The USDA's Cropland Data Layer (CDL), a remotely-sensed, high-resolution (30m) measure of land use (NASS 2008), is used as an alternative to administratively-derived USDA census data. CDL data was spatially processed using Google Earth Engine. I use data from 2008, the earliest available CDL product that spans the entire US.

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 measured 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 for robustness checks. But since tree crops are long-term investments with an asset value over multiple decades, there is very little annual change in planted area, unlike row crops.

The upstream-downstream analysis utilizes USGS watershed boundaries of hydrologic unit code HUC-4 and HUC-12 to assign water flows between counties using flow relationships from the National Hydrography Dataset (NHD). Proximity of water bodies to a given land use is calculated using the water drainage network from NHD (Buto and Anderson 2020).

Groundwater potential is derived from a gridded global dataset of soil, intact regolith, and sedimentary deposit thicknesses (Pelletier et al. 2016). This measures the depth to reach unweathered bedrock, where groundwater is generally located. Places with shallow bedrock are less likely to have aquifers with extractable groundwater. The measure ranges from 0 to 50 meters, which is the maximum value for depths greater than 50 meters. Appendix Figure A15 shows a map of geological thickness averaged over US counties. A binary indicator is used for whether thickness is greater than 30m, which corresponds to 25% of all observations. Areas with greater thickness (i.e., over 30m) are more likely to have extractable groundwater. As confirmation, the bottom panel plots a LOESS (i.e., local regression) line over a scatter plot of all grid cells by FAO's estimate of area equipped for groundwater irrigation and soil/sedimentary thickness. There is an increasing relationship, with a kink around 30m, implying that the potential for groundwater irrigation increases around this point.

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. The preferred measure is the sum of all insecticide-categorized constituents using the 'EPest-high' measure in kilograms per county.[14] Petroleum-based oil products, which can be used as standalone insecticides but are mainly mixed with synthetic insecticides to aid in application practices, are omitted given their general lack of toxicity. Insecticide intensity is also standardized by county land area.

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 the Inter-university Consortium for Political and Social Research (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 rural with 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 to fill missing ICPSR observations. I address concerns about sample composition by running alternate analyses on a subset of observations ending in 1988, as well as a sample using IPUMS data which is available from 1990 to 2007 (Manson et al. 2020).[15]

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.

[14] The USGS pesticide dataset was classified by function (i.e., insecticide, herbicide, fungicide) like in Frank 2018. 160 of the constituents had insecticidal properties.

[15] Results hold whether using the infant mortality dataset constructed by combining the Linked Infant Birth/Death Files with historical ICPSR calculations, incorporating IPUMS data, or just using the ICPSR dataset which underwent additional data cleaning as described in Bailey et al. 2016.

Appendix Figure A8 shows the decline from 1950 to 2016 in infant mortality over time for both cicada and non-cicada endemic counties in the eastern states of the US, and Figure A10 is a map of average infant mortality and its change over time at the county level.

Education data

For educational achievement, I use standardized annual county-level test scores from the Stanford Education Data Archive 2.1 (Reardon et al. 2018). SEDA harmonized state and federal NAEP test results to create a spatially and temporally consistent dataset available for the seven years from 2009 to 2015. Despite the challenges in comparing state level test results, Kuhfeld et al. 2019 find high correlations between the SEDA data and NWEA's MAP Growth which is another nationally administered test given to a subset of the population. I average SEDA county data across the third, fourth, and fifth grades to produce an elementary school average score for each cicada exposure cohort (e.g., 3$^{\text{rd}}$ graders nine years after a cicada event, fourth graders ten years afterwards, and fifth graders eleven years afterwards).

For educational attainment, I construct a dataset on high school dropout rates using the National Center for Education Statistics (NCES) Local Education Agency 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.

Economic and demographic data

County-level economic data come from US Department of Commerce, Bureau of Economic Analysis. Decadal county-level migration rates are from Winkler et al. 2013. Summary statistics of the primary variables are included in Appendix Table A1.

3 Empirical Approach

Cicada emergence is anticipated by both tree growers and, to a certain extent, the general population. There is ample news coverage leading up to what some call 'cicada mania'. Appendix Figure A7 shows the Google Trends 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 spikes in 2004, 2013, and 2021 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. I have found no research or media reports documenting any aggregate increase in pesticide usage in cicada years, and nothing about the health risks related to cicadas and pesticide use. In fact, most media coverage highlights the fact that cicadas are harmless to humans.

Further, the greater Charlottesville region accounts for much of Virginia's fruit production, whereas Richmond and DC have few orchards. Yet public interest in cicadas follows similarly predictable patterns across regions—regardless of land use. 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.

Insecticide exposure and its potential impact on health should be related to the life cycle of the cicada, the risk to tree crops, and the timing of human exposure. Figure 4 provides a conceptual framework. If accurate, one would expect: first, an increase in insecticide use in the year of cicada emergence; second, birth impacts in the year following emergence, starting in the spring; and third, 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 is tested and confirmed in the analyses that follow.

3.1 Model

My approach involves first testing 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. 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. Cicada emergence for each brood is based on its endemic location and cycle time, as visualized in Figure 3. The cicada dummy is interacted with a fixed measure of tree crop intensity (e.g., apple production), $apple_i$, in county i. The sample is restricted to all the counties in the 34 states in the eastern half of the US that span the range of periodical cicadas, including non-cicada endemic counties in these states as well.

Functionally, the empirical approach consists of a triple-difference with temporal variation (i.e., is it a cicada emergence year?), spatial variation in cicada broods (i.e., is the cicada brood endemic to a given county?), and spatial variation in land use (i.e., is the county an intensive apple producer?). But since the cicada-presence absence variable collapses the first two forms of variation into one, the model specification looks more like a double-difference in practice.

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 in county i in state s in year t.

$$insecticide_{it} = \beta_1 cicada_{it} + \beta_2 cicada_{it} * apple_i + \alpha_i + \gamma_t + state_{s(i)} + \epsilon_{it} \tag{1}$$

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 and recessions. State time trends $state_{s(i)}$ account for trends that could be driven by state-level policy.[16] Note that this model does not separately estimate the effect of apple intensity, in itself, on outcomes because this measure is unvarying over time and thus subsumed by county fixed effects. 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, $t+1$:

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

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.

These reduced-form analyses are run separately using cicada emergence as the treatment rather than using cicadas as an instrument for insecticide use for several reasons: first,

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

county-level pesticide data only became available in recent decades, while the nature of cicadas allows for the analysis of health impacts from the beginning of the intensive chemical era of US agriculture in 1950—thereby enabling insights into the effects of pesticide types that since received scrutiny (i.e., organochlorides), ones currently in use, and ones banned in the US but still utilized in developing countries. The span of the datasets can be visualized in Figure 1, which shows that major changes in national-level insecticide use and infant mortality occurred in the 40-year period from 1950 and 1990.

Further, a dose response per kilogram of a 'general' insecticide does not have much meaning given that I use an aggregate measure of insecticide use: the composition of insecticides by chemical type changed so drastically over time in response to regulation and technological development as shown in Figure A5—often over the course of a 17-year cicada treatment life cycle. Such challenges in linking specific insecticide compounds to health outcomes are further exacerbated by the significant heterogeneity in pest management practices among apple producers across US geographies. Nevertheless, I revisit these questions about the implications for pesticide regulation and policy in the Conclusion section.

4 Results

4.1 Insecticides and cicadas

The first analysis examines the relationship between insecticide use and cicada emergence using Equation 1. The sample is limited to the 25 years from 1992 to 2016 in which county-level USGS pesticide data exist. Table 3 regresses insecticide use on a cicada dummy and the cicada dummy interacted with fixed top-decile indicators (top 10$^{\text{th}}$ percentile) of apple intensity.

Models (1) and (4) show the impact of cicada emergence on insecticide use alone. Models (2)-(3) and (5)-(6) additionally interact cicada emergence with the indicator for apple acreage and apple production in bushels. Models (4)-(6) replicate the analysis using log insecticide values, dropping the few counties with no documented insecticide use. Cicada emergence, in itself, is not associated with increased insecticide use except in apple-intensive counties. These places see an increase in pesticide use in the range of 6 to 7 kg km^{-2}, a moderately large effect given that mean county pesticide use is 9 kg km^{-2}, as seen in the summary statistics in Appendix Table A1. The log-transformed results imply that insecticide use increased 13-22% in apple-intensive counties during a cicada event.

Figure 5 plots the coefficients from Model (3) as an event study with the inclusion of leads and lags of cicada emergence.[17] The sample is limited to cicada-endemic counties (42% of full sample) in order to assign treatment event time, and the omitted period is the year before cicada emergence, d = -1. Models with alternate time trends are included for robustness (state, county, and no trend). The main model is approximated by the following equation:

$$insecticide_{it} = \sum_{d=-4}^{4} (\beta_{d1} cicada_{i,t+d} + \beta_{d2} cicada_{i,t+d} * apple_i) + \alpha_i + \gamma_t + state_{s(i)} + \epsilon_{it} \quad (3)$$

Insecticide use increases in the year of cicada emergence. This outcome aligns with the first prediction of the framework in Figure 4 in which farmers apply insecticides primarily to control the adult egg-laying population in the year of emergence. And given that cicada emergence is anticipated, any small uptick in insecticide use in the year prior could reflect pre-spaying to kill nymphs before the emergence (Cahoon and Danoho 1982).

As falsification tests, Appendix Table A2 shows that *only* insecticide use responds to cicada emergence in apple-intensive counties, while herbicide and fungicide use do not appear to change. This provides assurance that any resulting health impacts are attributable to insecticides and not a more general change in agricultural practices. Appendix Table A3 provides evidence that cicada emergence is *not* associated with increased insecticide use in agriculturally-intensive places containing a high proportion of soy and corn, which aligns with the fact that farmers understand that cicadas damage woody plants and not herbaceous row crops.

A similar insecticide response occurs using an aggregate measure of fruit tree production. However, fruit trees, which encompass a wide array of woody plants (including berries) with varying management practices, are less consistently measured across states and over time in the USDA census. As discussed in the Data section, apples are the historically-dominant tree crop in the US and production is well-distributed across the country: among the 247 counties in the top decile of apple producers in the eastern half of the US, 27 states have at least one major producer, as visualized in Figure 3. In addition, much of the agronomic and ecological literature focuses on the effect of cicadas on apple trees. It is also worth noting that the insecticide response is not clear when using a continuous measure of apple production instead of an indicator for top producers. As additional robustness, anal-

[17] 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 3 and in Virginia specifically in Appendix Figure A7.

yses are conducted using utilizing satellite-derived tree crop measures from the recently-developed Cropland Data Layer in Table A8 in the the Spatial Extensions section.

4.2 Cicadas and infant mortality

The primary analysis of this paper uses the model specified in Equation 2. Given the link established between cicada emergence and insecticide use, one would expect a relationship between cicada emergence and infant mortality in apple-intensive areas if insecticides indeed have an impact on health. Compared to the regressions using insecticide data, 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 are only available from 1992 to 2016, as visualized in Figure 1. The sample is restricted to after 1950 to encompass the post-war period when farmers used synthetic pesticides *en masse*.

The main results are included in Table 1, which regresses next-year infant mortality on cicada emergence.[18] Model (1) shows no significant impact of cicada emergence, in itself, on birth outcomes. Model (2) interacts cicada emergence with county apple acreage. Model (3) interacts cicada emergence with a dummy for high apple production (i.e., top decile counties). Models (4) and (5) use county area normalized apple production in bushels in 1964 and 1997, respectively, the years in which apple data in the agricultural census is the most extensive. All 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 geographic levels.

For interpretation, top decile apple counties see an increase in next-year infant mortality of 0.31 deaths per thousand. In terms of apple production levels, a one standard deviation in production on a cross-county basis is equal to 167 bushels km^{-2} in 1964 and 225 bushels km^{-2} in 1997 (the analyses use 1,000s of bushels as units). Therefore, a one standard deviation increase in county apple production, when accompanied by cicada emergence, is associated with an increase in infant mortality of about 0.1 deaths per thousand, or 1.7% over current levels.

Appendix Table A4 restricts the sample to the period from 1950 to 1988, allowing for a

[18] 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 6). Results are robust to varying the birth cutoff threshold, and Table A5 shows similar results weighting the regression by county births to allow for observations with less than five births. However, this model is not preferred given that lack of intensive apple production in populous, urban counties.

more balanced panel. As discussed in the Data section, the ICPSR infant mortality data are limited after 1988 to counties with populations over 100,000, while the infant mortality rates derived from restricted NCHS Infant Linked Birth/Death files are not available until 1995. Using this earlier time periods, the coefficients are about 20-25% larger. Appendix Table A7 shows results after log-transforming the dependent variable, and Table A6 employs other compilations of county-level infant mortality rates derived from restricted NCHS data, ICPSR, and IPUMS. The resulting coefficients are of very similar magnitude.

Figure 6 plots the cicada-apple interaction coefficients from Model (5) of Table 1 with the inclusion of cicada emergence leads and lags in the same way as Equation 3:

$$imr_{i,t+1} = \sum_{d=-4}^{4} (\beta_{d1} cicada_{i,t+d} + \beta_{d2} cicada_{i,t+d} * apple_i) + \alpha_i + \gamma_t + state_{s(i)} + \epsilon_{it} \tag{4}$$

Infant mortality increases in the year following cicada emergence. Similar patterns are produced in Appendix Figure A11 which plots the event study coefficients using county-level apple acreage as an alternate measure of apple intensity. These results align with the second prediction of the framework in Figure 4 and the coefficient plot in Figure 5, which shows an increase in pesticide use by tree growers in the year of cicada emergence. The increase in next-year infant mortality would follow from insecticide exposure among first trimester pregnancies during cicada emergence. Effect timing is discussed in the next section.

For the sake of brevity, the analyses that follow will use the continuous measure of apples intensity in terms of bushels of production in 1997 as the primary interaction term, as in Model (5) of Table 1. Orchards are a long-term investment with an asset value over multiple decades, so it is not surprising that 70% of counties in the top apple production decile in 1964 remained there in 1997. Further, the correlation in county-level production in bushels between 1964 and 1997 is 0.83, which is quite high during a time of significant agricultural change in the US.

4.3 Timing and sub-annual impacts

I next assess 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. In the annual analysis in Table A6, Model (4) shows an overall positive but less precise effect during this subset of years, and one in line with the estimates from the longer-duration analyses in Models (1)-(3). Looking sub-annually, Figure 7 shows that the effect is concentrated in period 6, which is the second quarter (April to June) of the year following cicada emergence.

Cicadas arrive in the late spring and insecticide spraying starts in June to control the adult population from laying their eggs in tree branches as well as throughout the summer to prevent cicada nymphs from establishing in the soil in order to mitigate detrimental growth effects (Hamilton 1961; Lloyd and White 1987). The first trimester of pregnancy is a high risk period for pollution exposure (Almond and Currie 2011). Summer conceptions occurring in June, July, or August, for example, would entail a first trimester coinciding with a period of high potential for insecticide exposure. Assuming full-term gestation, such births would occur the following March, April, or May, respectively. The elevated infant mortality in the second quarter (April to June) lines up with this first trimester-exposed cohort considering that two-thirds of infant deaths occur within the neonatal phase (i.e., first 28 days after birth), and much of the remaining deaths occur within the first three months of life (Ely and Hoyert 2018).

These sub-annual results further support the predictions of the framework in Figure 4 and align with known cicada behavior and orchard management practices. Going forward, I focus on annual impacts given the longer time series and the lack of sub-annual data for most other historical variables.

4.4 Brood analysis

The next section assesses impacts by individual cicada brood. This specification involves a difference-in-difference where the same counties are treated every 17 years. Neighboring counties that do not receive that cicada brood are used as a control. Table 2 shows the results for the largest of the five 17-year broods. Excluded are the two primary 13-year southern broods which are located in hotter areas with very little apple production, as visualized in Figure 3 and Figure A13.[19]

For comparison, Model (1) pools all the broods as done in the primary specification in Model (5) of Table 1. The remaining columns show a consistently positive effect for each brood in which apple-intensive counties experience higher infant mortality in the year following a cicada emergence. Figure 8 plots the leading and lagging coefficients as done in Figure 6 but includes neighboring counties as a control group. Each brood involves a dif-

[19] 13-year broods may also have different physiological mechanisms governing their development (White and Lloyd 1975).

ferent treatment year and different geographic footprint as seen in the maps: for example, Brood X, the Great Eastern Brood, emerges in three distinct pockets of the US in the summer of 2021.

For most of the broods, there is a clear increase in infant mortality in the year following a cicada event, which sometimes seems to extend into subsequent years.[20] The noisier coefficients may be attributable to the smaller sample size, different regional pest management practices, and the fact that some counties are treated twice by different broods. Overall, however, brood-level results provide increased confidence that the paper's main finding is not driven by a particular brood, location, or set of treatment years.

4.5 Change in effect over time

Next I test whether the observed relationship between cicada treatment and infant mortality has changed over time. As visualized in Appendix Figure A8, infant mortality decreased by 80% over the course of this study in both cicada and non-cicada endemic counties, 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 time period. Appendix Figure A10 shows a map of average infant mortality rates and their change over time. The average infant mortality rate is 16 deaths per thousand during the longer timeframe from 1950 to 2016, and 21 deaths during the balanced panel from 1950 to 1988. For the period when pesticide data are available from 1992 to 2016 the average is 7 deaths.

Figure 9 plots the main results from Table 1 but varies the sub-sample of years included. Using an overlapping rolling window of 25 years, infant mortality is elevated for most of the period from 1941 to 2016. Overall the coefficients are less precise, partly reflecting a reduction in statistical power as a result of the fewer observations in each temporal subsample. The coefficients are weakest and least precise in the period centered around the early 1980s, which could reflect a temporary response to the bans of the most toxic organochlorides like DDT, chlordecone, and aldrin in the 1970s. The effect appears to have picked back up starting in the 1990s, especially when looking at the bottom panel which uses the log infant mortality as the outcome variable—a specification included to assess infant mortality impacts in relative terms in light of the steep decline in historical infant mortality that occurred up through the 1990s, after which changes were small on an ab-

[20] An extended effect could reflect the possibility that insecticide treatments continue into the following year to control nymph establishment, or a delayed pesticide exposure from differential leaching rates into water, or the fact that infant mortality includes deaths that occur up to 12 months following birth.

solute level.[21] For an alternate approach, Figure 10 employs a single model that interacts the apple-cicada term with a natural cubic spline, allow the effect to vary over time. This produces a similar overall pattern, albeit noisier in light of the irregular treatment every 17 years.

4.6 Interpretation of effect

Such secular changes in baseline infant mortality make it difficult to interpret and compare coefficient magnitudes. A back-of-the-envelope calculation involves the following: Table 3 shows that among top decile apple counties, insecticide use increases during a cicada emergence by 6-7 kg km^{-2}. These same treated counties see an increase in next-year infant mortality rate by 0.31 (Table 1) and 0.47 based on the balanced panel from 1950-1988 (Table A4). Both equate to an approximate 2% increase over the average infant mortality rates during those periods of 16 and 21 respectively. Therefore, one additional kilogram of insecticide per km^2 could be equated to a 0.33% increase in the infant mortality rate. For context, one additional kilogram represents an approximate 10% increase over the sample mean insecticide use of 9 kg km^{-2}.

However, caution should be taken when estimating an average effect of a 'unit' of insecticide. For reasons discussed in the Empirical Approach section, an IV is not employed with cicadas as an instrument for insecticide use—primarily because of the relatively short overlap in county-level pesticide data and infant mortality data. Additionally, since the paper utilizes an aggregate measure of insecticides that sums up 160 insecticide constituents by weight, any dose response estimate requires unrealistic assumptions about the similarity of effects across a broad range of chemical constituents and over time.

By extension, it is challenging to link these results to a specific type of insecticide. There is little evidence that orchard growers and farm managers consistently choose one type of insecticide for cicada control, especially given that pest management practices vary greatly across the US. Additionally, different combinations of insecticide types are used depending on the cicada's stage of development (e.g., pyrethroid 'knock down' insecticides for live adults, carbamates for soaking soil to control nymphs). Finally, the composition of insecticides in terms of active ingredient has changed significantly over the course of this study such that an orchard manager would likely use a different set of insecticides over the course of a 17-year cycle. As shown in Figure 2, seven of the top ten insecticides used in 1968 (Fernandez-Cornejo et al. 2014) have been banned in the US or regulated out of use,

[21] Appendix Figure A9 replicates the analysis using 1964 apple intensity measure with similar results

and only carbaryl, cryolite, and dicrotophos currently remain in use, and as of 2021, the top two insecticides used in 2008, chlorpyrifos and aldicarb, are banned.

Notwithstanding the heterogeneity in insecticide use by compound, time, and location, the next analysis assesses whether background levels of pesticide influence infant health outcomes. The motivation is that medical responses often follow a sigmoid or logistic pattern, where the marginal effect of substances is highest at moderate dosage levels—while in other cases there may be a non-linear effect that occurs only after a certain threshold is exceeded. To this end, an additional interaction is added to the main model in Table 1 that accounts for the baseline level of insecticide use in a county. In other words, does infant mortality respond differently in tree crop-intensive places following a cicada emergence depending on the average level of insecticide use in that place? The coefficients are plotted in Figure A12 allowing for flexibility in the binning approach with three and five quantiles used to categorize baseline insecticide use. While the overall relationship is too noisy to be conclusive, the infant mortality effect appears to be strongest at lower and mid quantiles, i.e., *not* in places with the highest average insecticide use. This may imply that the one-time 'shock' from cicada-driven insecticide exposure has a greater toxicity effect at lower background insecticide levels—with potential diminishing effects at higher baselines.

While the nature of the empirical approach limits what can be said about any specific insecticide, the independence of the cicada treatment combined with the strong and consistent results (both overall in Table 1 and at the brood-level in Table 2), imply that insecticides as a general class have had a negative causal impact on infant mortality over more than half a century. Further, Figure 9 suggests that the effect persists in recent decades despite the increased regulation of pesticides and the change in the chemical types used.

4.7 Other infant health outcomes

Next I assess infant health impacts beyond mortality. Infant health measures like low birthweight have been linked to long-term cognitive development and labor market outcomes (Black et al. 2007; Figlio et al. 2014). Using NCHS Natality Data files from 1968 to 2016, I compute three binary measures of infant health. The first is Apgar score (indicator for a score below 7 out of 10), a quick assessment of infant newborn health based on appearance, pulse, grimace, activity, and respiration (hence acronym, Apgar). The second is premature birth (indicator if gestation period is under 37 weeks, the clinical threshold for premature birth). The last is birthweight (indicator if under 2,500 grams, the clinical threshold for low birthweight).

Table 4 shows regression results using the model specified in Equation 2. The cicada-apple interactions have a small but positive impact on the probability of adverse birth outcomes. The relationship is the clearest for premature birth, followed by low Apgar score. The birthweight coefficient is positive but not significant. These results are consistent with the public health literature on fetal exposure and pesticide impacts (Ling et al. 2018), as well as the main infant mortality findings given that low birthweight and premature birth is highly correlated with neonatal infant mortality (Ely and Hoyert 2018).

4.8 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 A9 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). County scores are pooled 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.

Figure 11 plots the impact with the inclusion of year leads and lags for top decile apple producing counties. There is a decline in average test scores of 1.1 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 crudely interpreted as a reduction of 11-13% of one grade-level's worth of learning. The same event study using level of apple production, rather than top decile, shows no precise effect.

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. Average dropout rate area calculated using NCES data across school districts at the county-year level from 1991 to 2009. Table A10 shows the results of regressing the twelfth-grade dropout rate on an indicator of whether there was a cicada event 19 years prior, which is interacted with the various apple intensity measures. Figure 12 plots the interaction coefficients using long-term cicada lags ranging from 16 years after emergence to 22 years. The dropout rate increases most at the 19-year point among exposed cohorts conceived during a cicada exposure, which is the time when these students would most likely be in the twelfth grade. The coefficients for the 16 to 18 year lags are also positive but of a smaller magnitude, implying that there may be impacts on exposed infants and toddlers.

The median twelfth-grade dropout rate during this period is 4 per hundred students, and the standard deviation in apple bushel production in 1997 is 0.225 thousand bushels km^{-2} (225 bushels). 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 0.18 per hundred students (0.225 x 0.80) using the coefficient from Model (3) of Table A10, or about a 5% increase. No effect is found, however, when using a dummy for top apple production decile instead of level of production.

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. However, I later test the relationship between cicadas and migration in Table A14 and find no evidence that people are migrating as an avoidance response.

While caution is warranted in interpreting these results given the lessened precision and consistency, the findings generally align with empirical literature on the cognitive impact of pre-natal and childhood exposure to environmental hazards like radiation (Almond et al. 2009), toxic waste (Persico et al. 2020), and lead (Aizer et al. 2018), as well as the medical literature linking insecticide use to adverse long-term cognitive outcomes (Rauh et al. 2012).

5 Extensions

5.1 Spatial extensions

I next employ a set of spatial extensions that provide both robustness checks on the main results and help elucidate potential pesticide exposure pathways. To this end, I create some new datasets that leverage the spatially-explicit nature of cicada emergence, land use, geological features, and water bodies.

5.1.1 Alternate apple intensity measures

The USDA's Cropland Data Layer (CDL) is a land use product at very fine 30m resolution derived from remotely-sensed data and surveys. As such, CDL can provide a spatially-explicit tree crop intensity alternative to the county-level administrative data on apple production from USDA NASS, which is used in the main analysis. Land uses are aggregated across different types of woody plants—all of which can be damaged by cicadas in theory: apples, all tree crops, all tree crops plus berries (also a woody plant), and forested land in general. Pixels in each given class are counted and summed within each county's borders to obtain area estimates, which are then converted to acres and normalized by county land area. Figure A13 includes maps of the various tree crop measures.

The main analysis in Table 1 is re-run with these CDL-derived measures of tree crop intensity in Appendix Table A8. Models (1)-(2) replicate past results with USDA estimates of apple production and acreage. Models (3)-(6) include the various CDL measures. All coefficients except the last are positive and significant. The CDL-derived magnitudes should be interpreted with caution given that area calculations involve pixel summation, which can produce aggregation bias that mis-estimates county cropland area (Lark et al. 2017). Accordingly, USDA census values of apple acreage in 1997 are on average five-times lower than the CDL in 2008. However, the county-level measures have a relatively strong correlation (r = 0.7). Appendix Figure A14 shows a scatter plot of the various census and CDL-derived land use measures.

Model (6) provides a falsification test in where there is no effect when cicada emergence is interacted with the general measure of forested land. While cicadas can damage all tree types, this finding makes sense given the lack of evidence of insecticide use in natural forests or plantation forestry operations, which unlike cultivated tree crops, do not provide an economic return to justify pesticide control for land managers.

5.1.2 Alternate cicada maps

Another concern could involve the precision of my cicada treatment data. As discussed in the Data section, most cicada maps are based on an original mapping exercise that occurred over a century ago (Marlatt 1907) that underwent some relatively minor revisions (Simon 2014). Utilizing this map is reasonable given the predictable and stationary nature of cicadas; however, current boundaries may shift in light of habitat loss and the misassignment of straggler cicadas (Marshall 2001). A more recent map of eight cicada broods in five Mid-Atlantic states was developed through field research and crowd-sourced cicada presence/absence sightings.[22] This map provides an alternative source of cicada treatment data. There are some material differences: among the five Mid-Atlantic states (DE, MD, PA, VA, WV), the new map disagrees with the absence of cicadas 1.7% of the time and

[22] "Current Brood Distribution for Periodical Cicadas in the Mid-Atlantic Area." Source: https://cicada.info (persistent link)

the presence of cicadas 29%. Therefore, the new map can be viewed as having a more conservative, limited range.

Table 5 shows regression results along with the baseline estimates from the main model. Despite the 90% smaller sample size of Mid-Atlantic states, the coefficients are very similar—with magnitudes that are generally larger and more precisely-estimated.

5.2 Water and other exposure pathways

What accounts for these impacts at the county level given that relatively few people live next to apple orchards? Given that only a small fraction of applied pesticides reach their targets (Pimentel and Levitan 1986), one potential explanation is that exposure occurs through contamination of water resources via pesticide runoff and leaching, also known as pesticide 'drift.' USGS has 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).

Such a channel relates to the literature on the effect of contaminated drinking water on health outcomes (Currie et al. 2013; Ebenstein 2012; Brainerd and Menon 2014), as well as Lai 2017 who finds negative health effects from pesticide exposure in locations reliant on surface water for drinking in China. Dias et al. 2019 link glyphosate exposure to adverse health outcomes via a water channel in Brazil. In the US, exposure to pesticides in drinking water is a real possibility among those reliant on private wells, as well as municipal water systems given that conventional water treatment generally does not remove and transform pesticides in finished drinking water (USEPA 2001). Aside from farm workers directly exposed to insecticides, the primary channel in which a population is exposed to insecticides is likely water

5.2.1 By spatial proximity to land features

Exposure pathways are tested using USDA's Cropland Data Layer, which allows land use to be sub-categorized within counties based on proximity to land features of interest. This enables for hypothesis testing of potential pesticide exposure pathways, or a sort of heterogeneity analysis to address the question: does the cicada-pesticide linkage to infant mortality vary based on the location of tree crops? Three such hypotheses are tested: that effects are greater if tree crops are in close proximity to (i) surface water, (ii) groundwater, and (iii) human population centers.

To accomplish this, I start with the CDL mapping for orchards utilized in Model (5) of Table A8. I use the broader orchard categorization rather than just apples pixels to account for difficulties in differentiating tree crop types from satellite imagery and other documented CDL biases (Lark et al. 2017). Further the broader orchard measure has the highest correlation with the USDA census estimate of apple acreage (Appendix Figure A14). This measure has the highest correlation. For surface water proximity, I take the sum of all such pixels in a county that are within 100 meters of a NHD surface water body like a stream or lake (Buto and Anderson 2020). For the second measure, I take the overlap between orchards and areas with groundwater potential based on a soil and sedimentary thickness measure (Pelletier et al. 2016) greater than 30 meters, as described in the Data section. For the third measure of population proximity, I only include orchards within 200 meters of land classified as 'developed' at a medium or high intensity where impervious surfaces account for at least 50% of total cover.[23]

A visualization of the geo-spatial data source can be seen in Appendix Figure A16. At a national level, the percentage tree crop and berry lands that are proximate to developed lands, groundwater, and surface water is 8%, 34%, 7%, respectively, using the buffers and thresholds described above. I further illustrate the tree crop categorization process in the top panel of Figure 13 for Ulster County, a location near New Paltz and Poughkeepsie just west of the Hudson river where Brood II cicadas are endemic.

The main analysis of the impact of cicadas on infant mortality is rerun using these constructed measures. The bottom panel of Figure 13 plots the resulting coefficients, where the red line plots results from Models (3)-(5) in Appendix Table A8 to show the overall effect of each CDL land use classification for comparison. The results suggest that proximity to both surface water and populated areas have a sizable effect on infant mortality. The coefficients are larger and statistically different than the baseline 'All' coefficient representing the average effect of the orchard land use. The story on groundwater is less clear given that coefficient is of similar magnitude and precision to the overall orchard measure. Taken together, these results suggest that both physical proximity to pesticide application matters and that pesticide exposure also occurs through a water channel via runoff from orchards.

[23] In such non-cropland cases, the Cropland Data Layer utilizes land cover data from USGS's National Land Cover Database (NLCD). Medium intensity includes single-family houses, and high intensity includes apartment complexes, row houses, and commercial/industrial spaces.

5.2.2 Upstream and downstream analysis

Next a spatial lag model is employed to test whether pesticide exposure occurs through a water channel. If such a channel exists, there should be negative effects downstream from a tree crop-intensive county after a cicada emergence. To do this, I classify counties as upstream or downstream of each other using the flow direction in the NHD Watershed Boundary Dataset at the granular HUC-12 watershed level. Then within each larger HUC-4 the distance between county centroids is calculated. The upstream-downstream distance relationship for an example subset of counties can be visualized in the top panel of Figure 14.

A regression is run using pooled data in which each county-year observation is linked to the associated infant morality levels of its neighboring counties within a watershed categorized by 50km distance bin. The analysis looks only at the subset of counties in the top decile of apple production and their watershed neighbors. Upstream counties that are 'treated' in a given year (meaning having high apple production and a cicada emergence) are dropped to isolate in-county treatment effects. The coefficient plot in the bottom panel of Figure 14 shows that the infant mortality effect remains elevated downstream from treated counties up to 200km away. And there is no clear effect on upstream counties. These results provide further evidence that pesticide exposure occurs at least partially through a water channel.

The upstream-downstream analysis also helps mitigate identification concerns of some spurious factor related to both cicadas and tree crop production driving the results. In such a case, the inclusion of upstream county outcomes in the regression serves as an control group to help isolate treatment effects in a way similar to others (Duflo and Pande 2007; Dias et al. 2019; Taylor and Druckenmiller 2021). Additionally, this analysis provides suggestive evidence of spatial spillovers: the negative effect of pesticides may extend beyond the county line into neighboring downstream counties up to several hundred kilometers away—which is in addition to the negative externalities borne by people living in the county with intensive tree crops.

5.3 Robustness Checks

There are certain factors that could undermine the cicada-infant mortality story by questioning the independence of the cicada treatment. Plausible confounders must affect apple-intensive counties differently than non-apple intensive counties *only* in the year of a cicada emergence (but not other times).

5.3.1 Yields and income

One candidate is agricultural yields. If cicadas decimate apple production, for example, there could be a health impact via an economic channel. The 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 15 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 Figure 4 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 undermine the infant mortality relationship. First, yield declines occur in the year prior and the year of a cicada emergence, but the infant mortality impact occurs in the year afterward. If the negative yield shock was driving the health effect, then I would expect an increase in infant mortality in the year of cicada emergence—which is not observed. Second, tree crops comprise a very small portion of the economic value of most counties. Among cicada-endemic counties, Adams County, PA, is the largest apple producer with 13,160 acres of apples. Its 2017 GDP was $3.9 billion while the combined value of *all* fruit production was $62 million, or just 1.6% of GDP.[24] 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.

To more formally test the income channel in agricultural settings, I regress in Table A11

[24] Among apples producers on the East Coast, Adams County is second to Wayne County, NY (23,685 acres), which does not have endemic cicadas. Its fruit production also comprises a small share of the economy: $110 million on a GDP of $4 billion, or 2.8%. Source: Bureau of Economic Analysis and USDA NASS.

measures of county-level farm income from the US Bureau of Economic Analysis spanning 1969 to 2016 on cicada emergence and the apple intensity interaction term. While there appears to be a weak negative relationship between farm income and cicadas in general, it does not appear that cicada emergence negatively affects economic outcomes in apple intensive counties.

5.3.2 Composition and Births

There may be concerns that the composition of mothers somehow changes. 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 variation in health outcomes. Table A13 is a balance table of maternal characteristics using NCHS natality data comparing those giving birth in the year following a cicada emergence versus other years. There is no meaningful difference in the mothers' average education level, racial makeup, weight gain, age, or cigarette consumption. Further, no evidence of migration was found, which could also change maternal composition.

Another factor that could complicate the cicada-infant mortality story is if cicadas alter behavior in ways that affect birth outcomes outside of the insecticide channel (e.g., if people engage in more or less risky behavior). A cicada's life is short, generally lasting only four to six weeks, so it seems unlikely that their emergence 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 places with fewer tree crops.

Table A12 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.[25] 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 in cicada-endemic counties averaged 87

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

million between 1950 to 2016. 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, on average, could be born each year in the US because of cicadas.

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

5.3.3 Migration

One may be concerned that people migrate over the long term to avoid the negative health impacts in apple intensive areas. This is unlikely given that there has been no past research documenting the cicada-pesticide-health link. Nevertheless, I test this in Table A14 by running a cross-sectional regression of county-level migration rates from 1960 to 1990 on a dummy of whether cicadas are endemic to a county, interacted with a dummy for top decile apple producing county at the beginning of the the period in 1964. Note that positive values represent net migration into a county. The average decadal rate from 1960 to 1990 was 2.3% and there is no evidence of out-migration or lower in-migration from apple intensive cicada counties. This holds both across states and within states, and using either net migration rates or absolute net migration.

6 Conclusion

Insecticides are important to agricultural productivity, but they 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 a 13-22% increase in insecticide use in places experiencing a cicada emergence—an effect limited to counties 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, there is a jump in next-year infant mortality by 0.31 deaths per thousand births, or a 5% increase over the current infant mortality rate. This estimate is very close to Frank 2021, who finds infant deaths increased by 0.33 per thousand in response to elevated insecticide use following a bat disease.

Looking at sub-annual impacts, the infant mortality effect is most pronounced when the heavy summertime application of insecticides in response to cicada emergence overlaps with the first trimester of pregnancy. This elevated risk of fetal exposure early in pregnancy aligns with the fetal origins hypothesis. Further, the results hold when analyzing the major broods individually, suggesting the effects are not specific to a particular brood, location, or set of treatment years. Treated counties also see adverse infant health outcomes including an increase in premature births and low Apgar score. There is also evidence of long-term cohort effects in the form of lower elementary school test scores and increased high school dropout rates.

I also find evidence that pesticide exposure occurs through the water channel. Tree crops in close proximity to surface water have a larger negative effect on infant mortality, and impacts manifest themselves downstream but not upstream from a county. This also suggests spatial spillovers in which the negative externality of pesticide use goes beyond those people living near an orchard.

Even accounting for water exposure, it may be surprising that apple orchards, with their small footprint of 0.1% of US cropland, can produce effects that are measurable at the county level and beyond. Adams County, PA, the largest apple producer in the cicada-endemic eastern US, has 13,160 acres of apple trees according to USDA, which is less than 4% of its land area. Among the top decile (10%) apple producers in the sample, the average county has apple production on 740 acres. This is a small fraction compared to places with intensive production of crops like soy and corn. For example, the average county in Illinois and Iowa has 210,000 and 230,000 acres of cropland, respectively, covering 59 to 63% of land area (USDA NASS). Further, apples account for 1.4% of pesticide use in the US, while crops like corn, soy, cotton, potatoes, sorghum, and wheat account for 86% (Appendix Figure A6). Together this supports the idea that externalities from agriculture occur beyond just intensively-farmed areas, and that moderate levels of pesticides, not just extreme exposure, can have negative human impacts.

We can calculate the total treated population by summing up the number of live births in top decile apple-producing counties in the year following a cicada emergence, which equals about 1.8 million births from 1950 to 2016. Using the estimate of 0.31 additional deaths per 1,000 births in top decile counties (Table 1), a back-of-the-envelope calculation implies an additional 556 infant deaths occur in total. Applying the EPA's value of statistical life of \$9.6 million (2020 dollars),[26] equates to a total welfare loss of \$5.3 billion or \$81 million per year. The aggregate annual value of apple production in the sample counties ranged from \$500 million to \$1 billion in recent decades (USDA NASS), so this cicada-driven response of infant mortality to insecticides could account for 8-16% of apple production value. For reference, organic apples cost 5-10% more to produce than conventional ones (Taylor and Granatstein 2013), suggesting that after taking into account the social cost of insecticides, organic production is cheaper.

However, the 'treatment' group used in the above calculation represents a very small portion of the population actually exposed to pesticides: the treatment only takes into account people in major apple-producing counties and an event that occurs once every 17 years. To consider aggregate national effects, we can scale this estimate up by overall insecticide use. The eastern counties in the sample represent about one third of US apple production, which equates to about 0.5% of total US pesticide use. So the aggregate effect could be 200x (assuming a similar pesticide-response among other crops, which is unlikely), equating to over \$1 trillion in damages across 1950 to 2016, or \$16 billion per year—which is double the \$8 billion spent annually on all types of pesticides in the US (US EPA 2017).

This back-of-the-envelope calculation should be not be taken as a realistic estimate. Rather, it provides an idea of what the total social cost of pesticides could be in the absence of other credible estimates: an advantage of this paper and the cicada-based identification strategy is that it applies across a wide geography (i.e., the eastern half of the US), long time period (i.e., 1950 to present), and broad array of pesticides types.

A high cost of pesticides should not come as a surprise given that the majority of insecticides used to date were eventually banned or cancelled after decades of heavy use (see Figure 2). Chlorpyrifos, the most widely-used insecticide in the US, was banned by the EPA as recently as August 2021. Many of the major insecticides currently in use in the US are banned in the European Union. Lawsuits related to pesticide damages amount to tens of billions of dollars.[27] There are increasing concerns about pesticide impacts on pollinators and ecosystems. Thus this paper raises important questions about whether toxic material regulation should be proactive versus reactive, and whether the burden of proof for demonstrating safety should fall on industry or regulators—an interesting comparison may be the differing approval processes for vaccines versus pesticides.

[26] See link for EPA discussion on mortality risk valuation

[27] See link for the recent \$10 billion glyphosate herbicide settlement.

Further, an improved understanding of pesticide impacts and the role of regulation is relevant in China and Brazil, where pesticide use intensity is 5x and 2.4x higher, respectively, than the US (FAO 2020), and in India where several EPA-banned pesticides remain widely used. Pesticide consumption in sub-Saharan Africa, on the other hand, is very low relative to the global average but is growing rapidly with little regulatory oversight (Snyder et al. 2015).

While acknowledging the benefits of pesticides to agricultural productivity, the findings warrant caution in the use of insecticides. This paper also provides a model of how ecological phenomena like periodical cicadas may be used to generate quasi-random variation to help answer important economic and public health questions—showing that humans remain beholden to the ancient cicadian rhythm.

References

Aizer, Anna, Janet Currie, Peter Simon, and Patrick Vivier. 2018. "Do low levels of blood lead reduce children's future test scores?" *American Economic Journal: Applied Economics* 10 (1): 307–41.

Almond, Douglas, and Janet Currie. 2011. "Killing Me Softly: The Fetal Origins Hypothesis." *Journal of Economic Perspectives* 25 (3): 153–172.

Almond, Douglas, Lena Edlund, and Mårten Palme. 2009. "Chernobyl's subclinical legacy: prenatal exposure to radioactive fallout and school outcomes in Sweden." *The Quarterly Journal of Economics* 124 (4): 1729–1772.

Andersson, Henrik, Damian Tago, and Nicolas Treich. 2014. *Pesticides and health: A review of evidence on health effects, valuation of risks, and benefit cost analysis.* TSE Working Paper 14-477. Toulouse School of Economics (TSE).

Aspelin, Arnold L. 2003. "Pesticide usage in the United States: Trends during the 20th century." *CIPM Technical Bulletin* 105:1–213.

Bailey, Martha, Karen Clay, Price Fishback, Michael R. Haines, Shawn Kantor, Edson Severnini, and Anna Wentz. 2016. *U.S. County-Level Natality and Mortality Data, January 1915-December 2007: Version 2.* https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/36603/versions/V2.

Barker, David JP. 1995. "Fetal origins of coronary heart disease." *Bmj* 311 (6998): 171–174.

Bell, Erin M., Irva Hertz-Picciotto, and James J. Beaumont. 2001. "A Case-Control Study of Pesticides and Fetal Death Due to Congenital Anomalies." *Epidemiology* 12 (2): 148. ISSN: 1044-3983.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes. 2007. "From the cradle to the labor market? The effect of birth weight on adult outcomes." *The Quarterly Journal of Economics* 122 (1): 409–439.

Brainerd, Elizabeth, and Nidhiya Menon. 2014. "Seasonal effects of water quality: The hidden costs of the Green Revolution to infant and child health in India." *Journal of Development Economics* 107 (C): 49–64.

Buffington, E.J., and S.K. Mcdonald. 2006. *Banned and Severely Restricted Pesticides, CEPEP, Colorado State University.* https://webdoc.agsci.colostate.edu/cepep/FactSheets/141BannedPesticides.pdf.

Burlando, Alfredo. 2014. "Power Outages, Power Externalities, and Baby Booms." *Demography* 51 (4): 1477–1500.

Buto, Susan G, and Rebecca D Anderson. 2020. *NHDPlus High Resolution (NHDPlus HR)—A hydrography framework for the Nation.* Technical report. US Geological Survey.

Cahoon, GA, and CW Danoho. 1982. "The influence of urea sprays, mulch and pruning on apple tree decline." *Res. Circ. Ohio Agr. Res. and Devel. Center* 272:16–19.

Carroll, Michael J. 2016. "The importance of regulatory data protection or exclusive use and other forms of intellectual property rights in the crop protection industry." *Pest management science* 72 (9): 1631–1637.

Carson, Rachel. 2002. *Silent spring.* Houghton Mifflin Harcourt.

Cerda, Rolando, Jacques Avelino, Christian Gary, Philippe Tixier, Esther Lechevallier, and Clémentine Allinne. 2017. "Primary and secondary yield losses caused by pests and diseases: Assessment and modeling in coffee." *PloS one* 12 (1): e0169133.

Chay, Kenneth Y., and Michael Greenstone. 2003. "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession." *The Quarterly Journal of Economics* 118 (3): 1121–1167.

Clay, Karen, Werner Troesken, and Michael Haines. 2014. "Lead and mortality." *Review of Economics and Statistics* 96 (3): 458–470.

Colmer, Jonathan, and John Voorheis. 2020. "The grandkids aren't alright: the intergenerational effects of prenatal pollution exposure."

Cooley, J, Gene Kritsky, M Edwards, J Zyla, D Marshall, K Hill, and Chris Simon. 2009. "The distribution of periodical cicada." *American Entomologist* 55 (2): 107.

Cooley, John R, Gene Kritsky, David C Marshall, Kathy BR Hill, Gerry Bunker, ML Neckermann, JIN Yoshimura, James E Cooley, and Chris Simon. 2016. "A GIS-based map of periodical cicada Brood XIII in 2007, with notes on adjacent populations of Broods III and X (Hemiptera: Magicicada spp.)" *Bulletin of the Entomological Society of America* 62 (4): 241–246.

Cooley, John R, David C Marshall, and Chris Simon. 2021. "Documenting Single-Generation Range Shifts of Periodical Cicada Brood VI (Hemiptera: Cicadidae: Magicicada spp.)" *Annals of the Entomological Society of America.*

Costa, Lucio G. 1987. "Toxicology of pesticides: a brief history." In *Toxicology of Pesticides,* 1–10. Springer.

Currie, Janet, Joshua Graff Zivin, Katherine Meckel, Matthew Neidell, and Wolfram Schlenker. 2013. "Something in the water: Contaminated drinking water and infant health." *Canadian Journal of Economics/Revue canadienne d'économique* 46 (3): 791–810.

Currie, Janet, and Matthew Neidell. 2005. "Air pollution and infant health: what can we learn from California's recent experience?" *The Quarterly Journal of Economics* 120 (3): 1003–1030.

Currie, Janet, and Reed Walker. 2011. "Traffic congestion and infant health: Evidence from E-ZPass." *American Economic Journal: Applied Economics* 3 (1): 65–90.

Currie, Janet, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell. 2014. "What do we know about short-and long-term effects of early-life exposure to pollution?" *Annu. Rev. Resour. Econ.* 6 (1): 217–247.

Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif. 2019. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review* 109 (12): 4178–4219.

Dias, Mateus, Rudi Rocha, and Rodrigo R Soares. 2019. "Glyphosate use in agriculture and birth outcomes of surrounding populations."

Donley, Nathan. 2019. "The USA lags behind other agricultural nations in banning harmful pesticides." *Environmental Health* 18 (1): 1–12.

Duflo, Esther, and Rohini Pande. 2007. "Dams." *The Quarterly Journal of Economics* 122 (2): 601–646.

Dybas, Henry S., and D. Dwight Davis. 1962. "A Population Census of Seventeen Year Periodical Cicadas." *Ecology* 43 (3): 432–444.

Ebenstein, Avraham. 2012. "The consequences of industrialization: evidence from water pollution and digestive cancers in China." *Review of Economics and Statistics* 94 (1): 186–201.

Ely, D, and D Hoyert. 2018. *Differences between rural and urban areas in mortality rates for the leading causes of infant death: United States, 2013–2015.*

EPA, US. 1975. *DDT Regulatory History: A Brief Survey (to 1975).*

Evans, Richard W., Yingyao Hu, and Zhong Zhao. 2010. "The fertility effect of catastrophe: U.S. hurricane births." *Journal of Population Economics* 23 (1): 1–36.

Fallon, Harold, D Tollerud, N Breslow, et al. 1994. "Veterans and agent orange: health effects of herbicides used in Vietnam." *Committee to review the health effects in Vietnam veterans of exposure to herbicides, Division of Health Promotion and Disease Prevention, Institute of Medicine* 26.

FAO, FAOSTAT. 2020. "World Food and Agriculture Statistical Yearbook." *FAO-Food & Agriculture Organization of the United Nation, Rome, Italy.*

Fernandez-Cornejo, Jorge, and Sharon Jans. 1995. "Quality-adjusted price and quantity indices for pesticides." *American Journal of Agricultural Economics* 77 (3): 645–659.

Fernandez-Cornejo, Jorge, Richard F. Nehring, Craig Osteen, Seth Wechsler, Andrew Martin, and Alex Vialou. 2014. "Pesticide Use in U.S. Agriculture: 21 Selected Crops, 1960-2008." *SSRN Electronic Journal.*

Figlio, David, Jonathan Guryan, Krzysztof Karbownik, and Jeffrey Roth. 2014. "The effects of poor neonatal health on children's cognitive development." *American Economic Review* 104 (12): 3921–55.

Frank, Eyal. 2018. "The Effects of Bat Population Losses on Infant Mortality through Pesticide Use in the U.S." *Unpublished Working Paper.*

———. 2021. "The Economic Impacts of Ecosystem Disruptions: Private and Social Costs From Substituting Biological Pest Control."

Frank, SD, and JF Tooker. 2020. "Opinion: Neonicotinoids pose undocumented threats to food webs." *Proceedings of the National Academy of Sciences* 117 (37): 22609–22613.

Garry, Vincent F, Mary E Harkins, Leanna L Erickson, Leslie K Long-Simpson, Seth E Holland, and Barbara L Burroughs. 2002. "Birth defects, season of conception, and sex of children born to pesticide applicators living in the Red River Valley of Minnesota, USA." *Environmental Health Perspectives* 110 (Suppl 3): 441–449.

Haines, Michael, Price Fishback, and Paul Rhode. 2014. *United States Agriculture Data, 1840 - 2012: Version 4.* https://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/35206/versions/V4.

Hamilton, D. W. 1961. "Periodical Cicadas, Magicicada Spp., as Pests in Apple Orchards." *Proceedings of the Indiana Academy of Science* 71:116–121.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker. 2017. "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970." *Journal of Political Economy* 125 (3): 848–902.

Jefferson, Thomas. 1944. *Thomas Jefferson's Garden Book, 1766-1824: With Relevant Extracts from His Other Writings.* American Philosophical Society.

Johnson, DW, and LH Townsend. 2004. *Periodical cicadas in Kentucky.*

Jones, Benjamin A. 2020. "Invasive Species Control, Agricultural Pesticide Use, and Infant Health Outcomes." *Land Economics* 96 (2): 149–170.

Jorgenson, Dale W., and Frank M. Gollop. 1992. "Productivity Growth in U.S. Agriculture: A Postwar Perspective." *American Journal of Agricultural Economics* 74 (3): 745–750.

Jurewicz, Joanna, Wojciech Hanke, Carolina Johansson, Christofer Lundqvist, Sandra Ceccatelli, Peter Van Den Hazel, Margaret Saunders, and Rolf Zetterstrom. 2006. "Adverse health effects of children's exposure to pesticides: What do we really know and what can be done about it." *Acta Paediatrica* 95 (s453): 71–80.

Karban, Richard. 1980. "Periodical cicada nymphs impose periodical oak tree wood accumulation." *Nature* 287 (5780): 326–327.

———. 1982. "Experimental removal of 17-year cicada nymphs and growth of host apple trees." *Journal of the New York Entomological Society:* 74–81.

Kellogg, Robert L, Richard F Nehring, Arthur Grube, Donald W Goss, and Steven Plotkin. 2002. "Environmental indicators of pesticide leaching and runoff from farm fields." In *Agricultural productivity,* 213–256. Springer.

Koenig, Walter D., Leslie Ries, V. Beth K. Olsen, and Andrew M. Liebhold. 2011. "Avian predators are less abundant during periodical cicada emergences, but why?" *Ecology* 92 (3): 784–790.

Krawczyk, Grzegorz. 2017. "Tree Fruit Insect Pest - Periodical Cicada." *Penn State Extension.* https://extension.psu.edu/tree-fruit-insect-pest-periodical-cicada.

Kuhfeld, Megan, Thurston Domina, and Paul Hanselman. 2019. "Validating the SEDA Measures of District Educational Opportunities via a Common Assessment." *AERA Open* 5 (2): 2332858419858324.

Lai, Wangyang. 2017. "Pesticide use and health outcomes: evidence from agricultural water pollution in China." *Journal of environmental economics and management* 86:93–120.

Landrigan, Philip J. 2018. "Pesticides and human reproduction." *JAMA internal medicine* 178 (1): 26–27.

Lark, Tyler J, Richard M Mueller, David M Johnson, and Holly K Gibbs. 2017. "Measuring land-use and land-cover change using the US department of agriculture's cropland data layer: Cautions and recommendations." *International journal of applied earth observation and geoinformation* 62:224–235.

Larsen, Ashley E., Steven D. Gaines, and Olivier Deschenes. 2017. "Agricultural pesticide use and adverse birth outcomes in the San Joaquin Valley of California." *Nature Communications* 8 (1): 302.

Ling, Chenxiao, Zeyan Liew, Ondine S Von Ehrenstein, Julia E Heck, Andrew S Park, Xin Cui, Myles Cockburn, Jun Wu, and Beate Ritz. 2018. "Prenatal exposure to ambient pesticides and preterm birth and term low birthweight in agricultural regions of California." *Toxics* 6 (3): 41.

Lloyd, Monte, and Henry S Dybas. 1966. "The periodical cicada problem. II. Evolution." *Evolution:* 466–505.

Lloyd, Monte, and JoAnn White. 1987. "Xylem Feeding by Periodical Cicada Nymphs on Pine and Grass Roots, With Novel Suggestions for Pest Control in Conifer Plantations and Orchards." 87:5.

Manson, Steven, Jonathan Schroeder, David Van Riper, T Kugler, and S Ruggles. 2020. "IPUMS national historical geographic information system: Version 15.0 [dataset]. doi: 10.18128/D050." *V15. 0. Deposited* 17.

Marlatt, Charles Lester. 1898. *The periodical cicada.* US Department of Agriculture, Division of Entomology.

———. 1907. *The periodical cicada.* 71. US Department of Agriculture, Bureau of Entomology.

Marshall, David C. 2001. "Periodical cicada (Homoptera: Cicadidae) life-cycle variations, the historical emergence record, and the geographic stability of brood distributions." *Annals of the Entomological Society of America* 94 (3): 386–399.

NASS, USDA. 2008. "USDA National Agricultural Statistics Service Cropland Data Layer." *Publ. Crop. data layer. URL https://nassgeodata. gmu.edu/CropScape/(accessed September 2021).*

NCHS. 2019. *National Vital Statistics System.* https://www.cdc.gov/nchs/data_access/vitalstatsonline.htm.

Oerke, E-C. 2006. "Crop losses to pests." *The Journal of Agricultural Science* 144 (1): 31–43.

Pelletier, Jon D, Patrick D Broxton, Pieter Hazenberg, Xubin Zeng, Peter A Troch, Guo-Yue Niu, Zachary Williams, Michael A Brunke, and David Gochis. 2016. "A gridded global data set of soil, intact regolith, and sedimentary deposit thicknesses for regional and global land surface modeling." *Journal of Advances in Modeling Earth Systems* 8 (1): 41–65.

Persico, Claudia, David Figlio, and Jeffrey Roth. 2020. "The developmental consequences of Superfund sites." *Journal of Labor Economics* 38 (4): 1055–1097.

Pimentel, David, and Lois Levitan. 1986. "Pesticides: amounts applied and amounts reaching pests." *Bioscience* 36 (2): 86–91.

Potts, Simon G, Vera Imperatriz-Fonseca, Hien T Ngo, Marcelo A Aizen, Jacobus C Biesmeijer, Thomas D Breeze, Lynn V Dicks, Lucas A Garibaldi, Rosemary Hill, Josef Settele, et al. 2016. "Safeguarding pollinators and their values to human well-being." *Nature* 540 (7632): 220–229.

Rauh, Virginia A., Frederica P. Perera, Megan K. Horton, Robin M. Whyatt, Ravi Bansal, Xuejun Hao, Jun Liu, Dana Boyd Barr, Theodore A. Slotkin, and Bradley S. Peterson. 2012. "Brain anomalies in children exposed prenatally to a common organophosphate pesticide." *Proceedings of the National Academy of Sciences* 109 (20): 7871–7876.

Reardon, Sean F., Andrew D. Ho, Erin M. Fahle, Demetra Kalogrides, and Richard DiSalvo. 2018. *Stanford Education Data Archive (SEDA).* Accessed June 28, 2019. https://purl.stanford.edu/db586ns4974.

Regidor, E., E. Ronda, A. M. García, and V. Domínguez. 2004. "Paternal exposure to agricultural pesticides and cause specific fetal death." *Occupational and Environmental Medicine* 61 (4): 334–339.

Sanders, Nicholas J. 2012. "What doesn't kill you makes you weaker prenatal pollution exposure and educational outcomes." *Journal of Human Resources* 47 (3): 826–850.

Schreinemachers, Dina M. 2003. "Birth malformations and other adverse perinatal outcomes in four U.S. Wheat-producing states." *Environmental Health Perspectives* 111 (9): 1259–1264.

Simon, Chris. 2014. "Evolution of 13-and 17-year periodical cicadas (Homoptera: Cicadidae: Magicicada)." *Bulletin of the ESA* 34 (4): 163–176.

Smith, James W. 1998. "Boll weevil eradication: area-wide pest management." *Annals of the Entomological Society of America* 91 (3): 239–247.

Snyder, Jason, Jennifer Smart, Joey Goeb, and David Tschirley. 2015. *Pesticide use in sub-Saharan Africa: estimates, projections, and implications in the context of food system transformation.* Technical report.

Taylor, Charles A, and Hannah Druckenmiller. 2021. "Wetlands, Flooding, and the Clean Water Act." *Working Paper.*

Taylor, Mykel, and David Granatstein. 2013. "A cost comparison of organic and conventional apple production in the state of Washington." *Crop Management* 12 (1): 1–7.

US EPA, OCSPP. 2017. *Pesticides Industry Sales and Usage 2008 - 2012 Market Estimates.* Reports and Assessments.

USEPA. 2001. *The incorporation of water treatment effects on pesticide removal and transformations in Food Quality Protection Act (FQPA) Drinking Water Assessments.*

USGS. 2019. *NAWQA The Pesticide National Synthesis Project.* https://water.usgs.gov/nawqa/pnsp/usage/maps/county-level/.

Wang, Sun Ling, Paul Heisey, David Schimmelpfennig, and V. Eldon Ball. 2015. "Agricultural Productivity Growth in the United States: Measurement, Trends, and Drivers." *Economic Research Service, Paper No. 189.*

White, Jo Ann, and Monte Lloyd. 1975. "Growth rates of 17 and 13-year periodical cicadas." *American Midland Naturalist:* 127–143.

Williams, Kathy S, and Chris Simon. 1995. "The ecology, behavior, and evolution of periodical cicadas." *Annual review of entomology* 40 (1): 269–295.

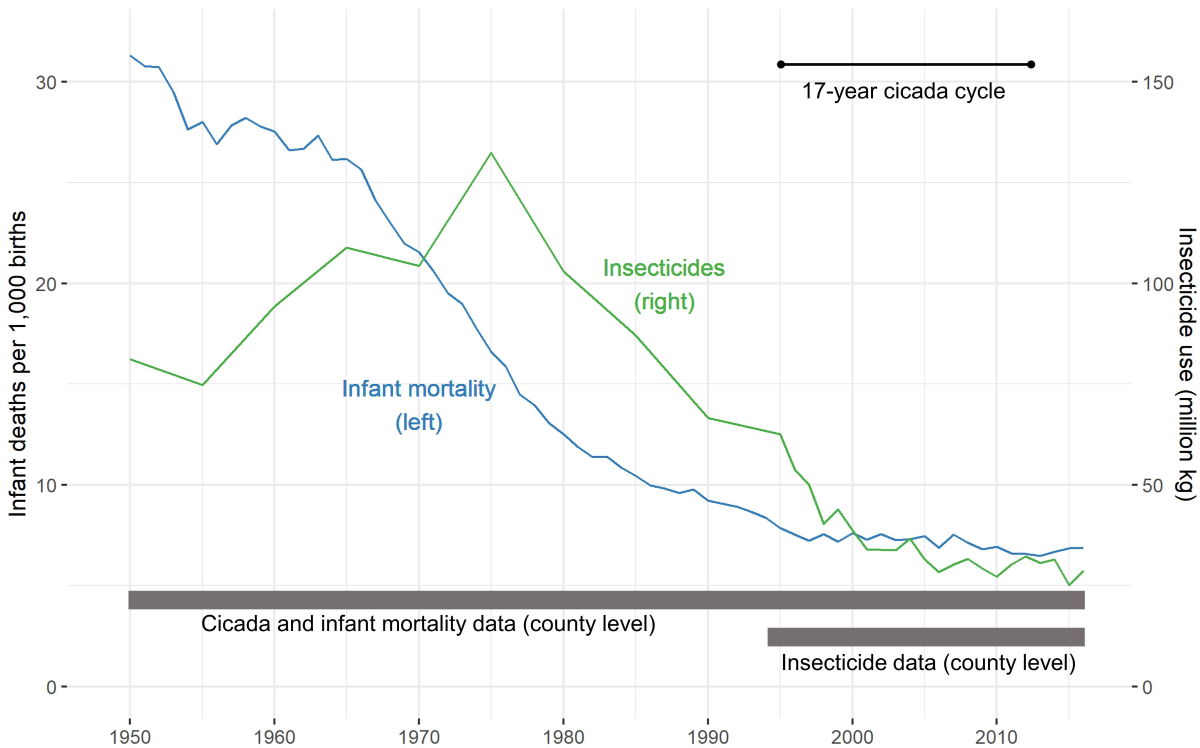
Winchester, Paul D, Jordan Huskins, and Jun Ying. 2009. "Agrichemicals in surface water and birth defects in the United States." *Acta Paediatrica (Oslo, Norway : 1992)* 98 (4): 664–669.

Winkler, Richelle, Kenneth M Johnson, Cheng Cheng, Paul R Voss, and Katherine J Curtis. 2013. "County-specific net migration by five-year age groups, Hispanic origin, race and sex 2000-2010."

Zheng, T, J Zhang, KE Sommer, BA Bassig, XC Zhang, J Braun, SQ Xu, et al. 2016. "Effects of environmental exposures on fetal and childhood growth trajectories." *Annals of global health* 82 (1): 41–99.

Figures

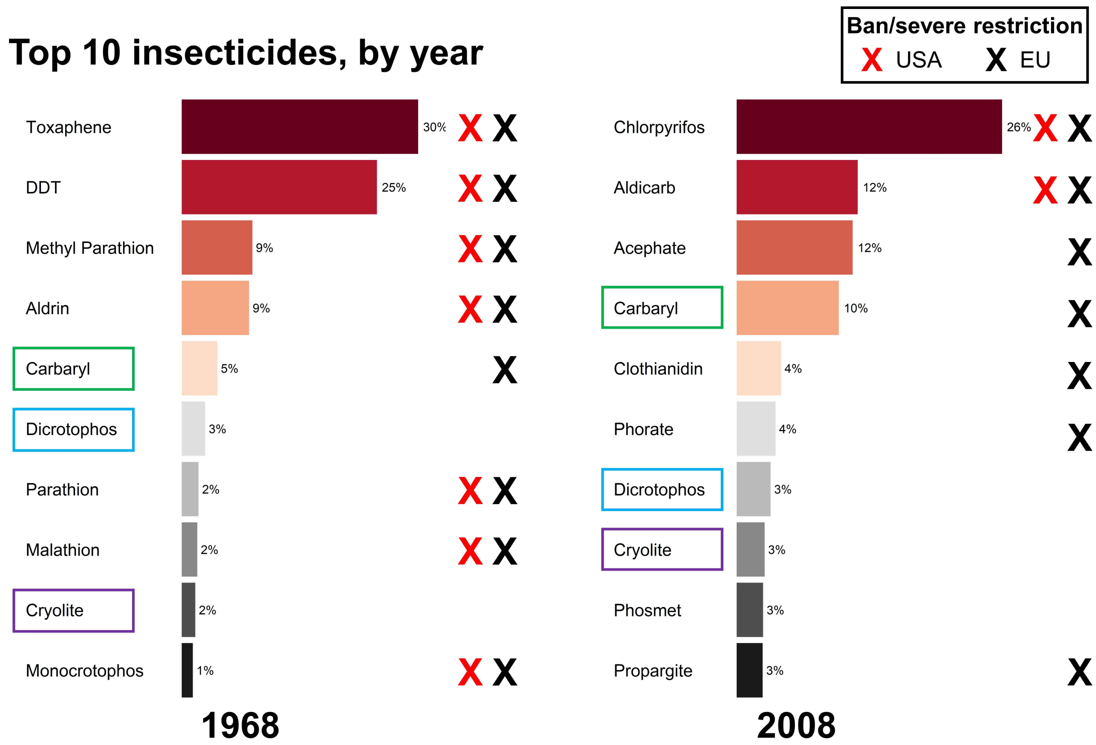
Figure 1



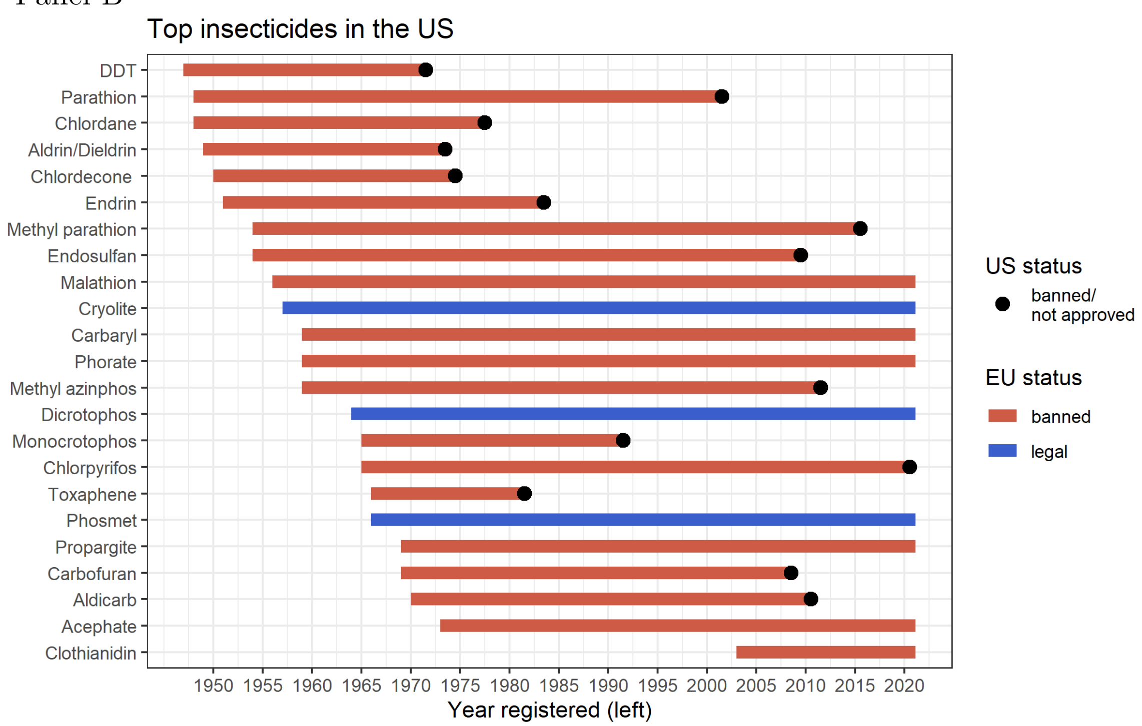
Notes: National level trends in infant mortality (NCHS 2019; Bailey et al. 2016. National-level insecticide data in five-year intervals from EPA (Aspelin 2003) prior to 1995, combined with recent aggregated county-level data from USGS (USGS 2019). Pesticide categorizations adjusted such that datasets are comparable.

Figure 2

Panel A



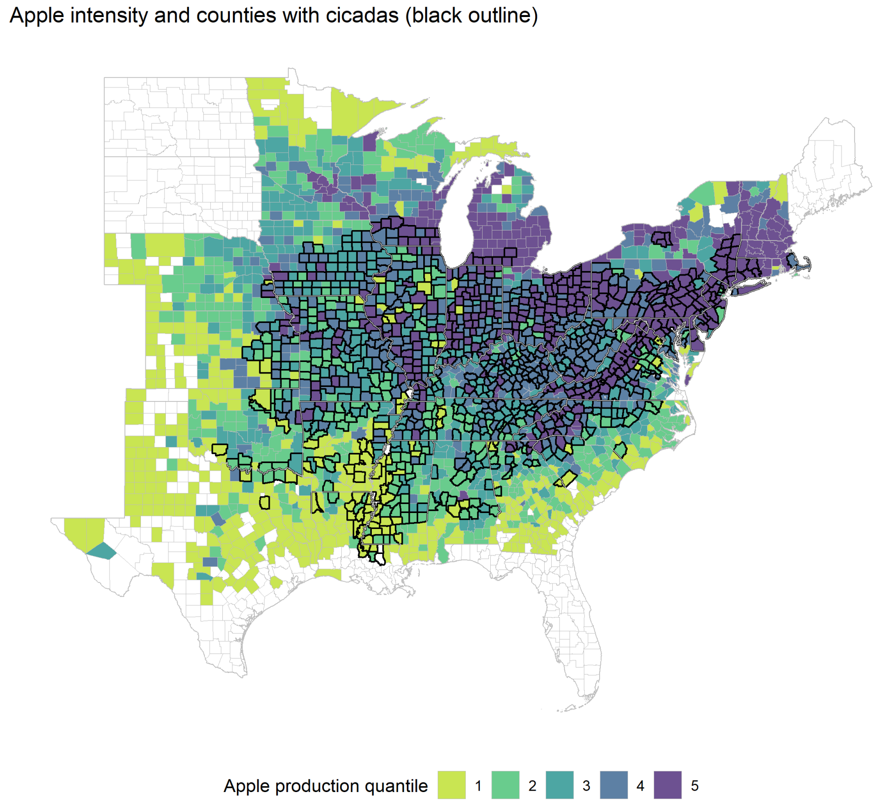
Panel B



Notes: Panel A shows insecticide use by active ingredient for 21 major crops in 1968 and 2008. Panel B shows insecticide registration and cancellation over time. Clothianidin is still used in the EU under emergency authorization. For the US, regulatory status includes both EPA bans and the loss of registration. Endrin, monocrotophos, parathion, methyl parathion, aldicarb, methyl azinphos, and endosulfan were not re-registered and thus no longer approved by EPA. Data from the EPA Office of Pesticide Programs, USDA (Fernandez-Cornejo et al. 2014), and Donley 2019.

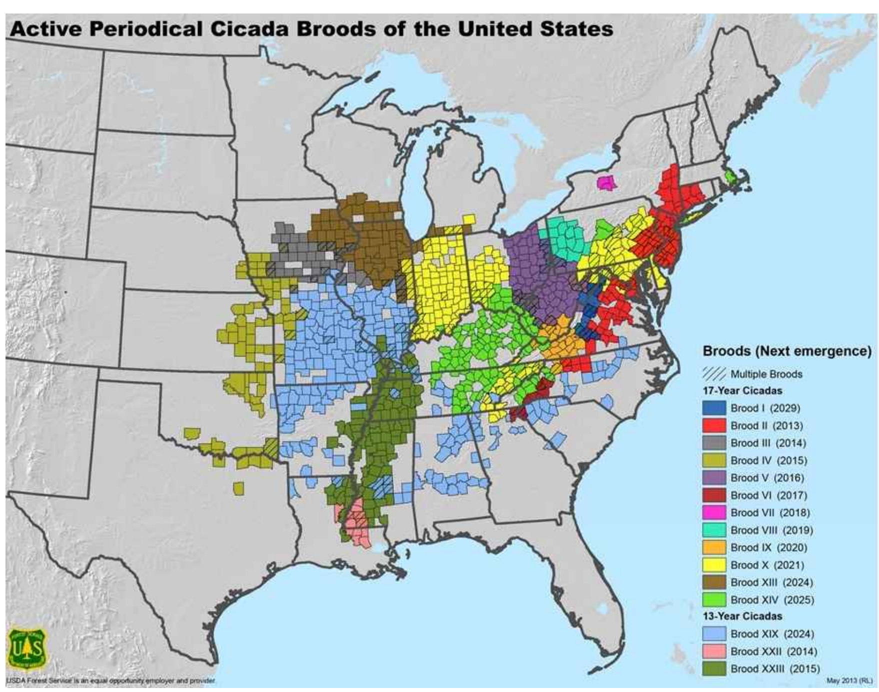
Figure 3

Panel A



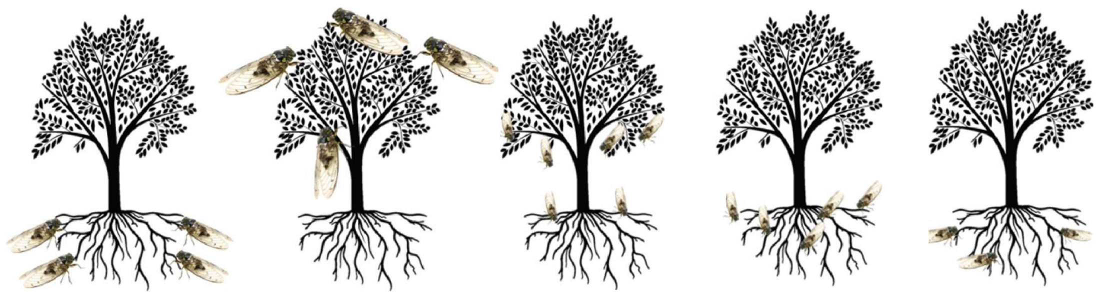
Notes: USDA census average values in 1964 and 1997.

Panel B



Source: Liebhold et al. 2013, USDA Forest Service Northern Research Station.

Figure 4: Timing Framework



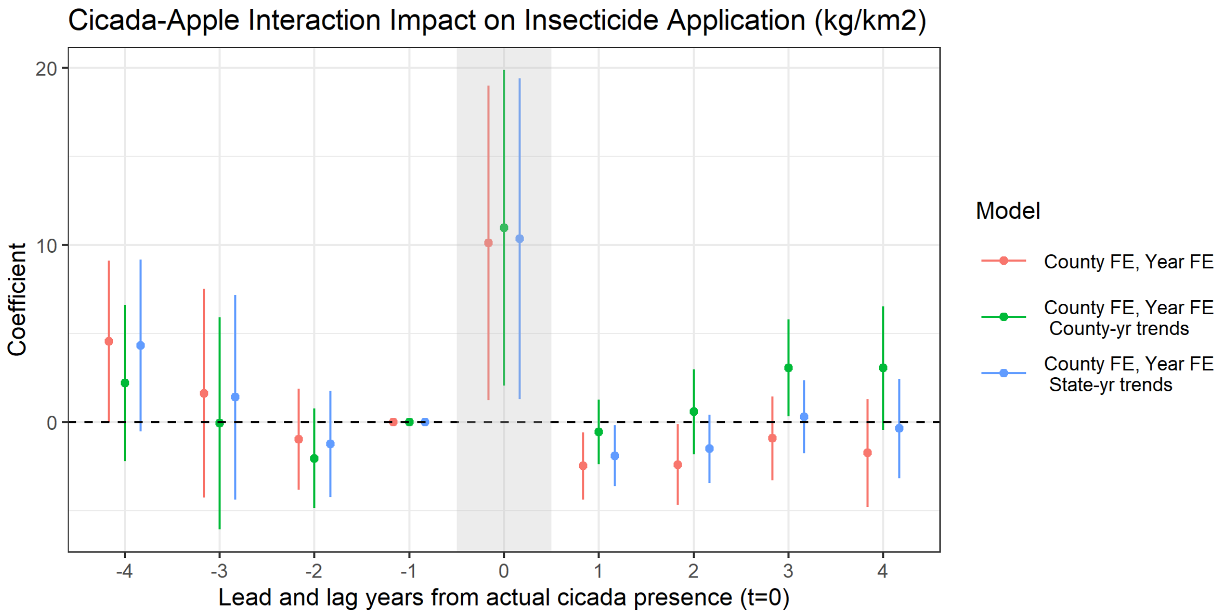
Timing	Spring and year(s) prior	Summer	Fall (and late summer)	Winter	Next spring (and throughout the following year)
Insecticide use	Some documented insecticide pre-spraying to kill nymphs before emergence	Primary spraying to prevent cicadas from mating and laying eggs in tree branches	Spraying to kill eggs and nymphs	Ground spraying/soil soaking to kill nymphs before establishment	Follow on treatments to kill nymphs
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

Health effects

Maternal exposure to insecticides
(primary timing = solid line;
other potential timing = dashed line)

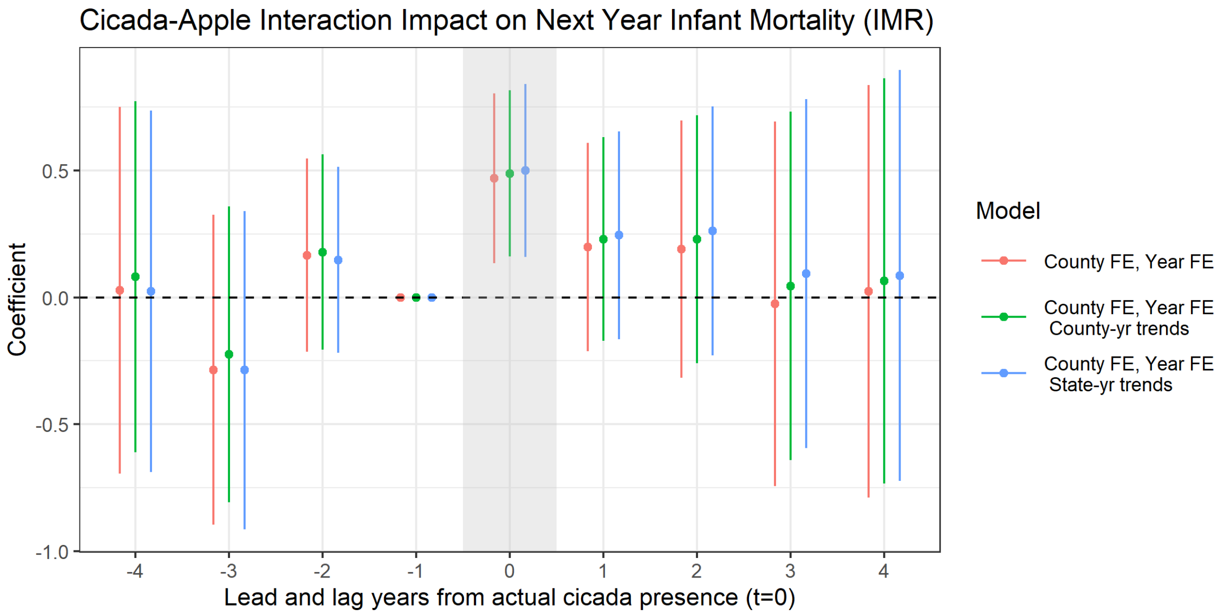
First birth impacts from 1st trimester exposure in previous summer

Figure 5



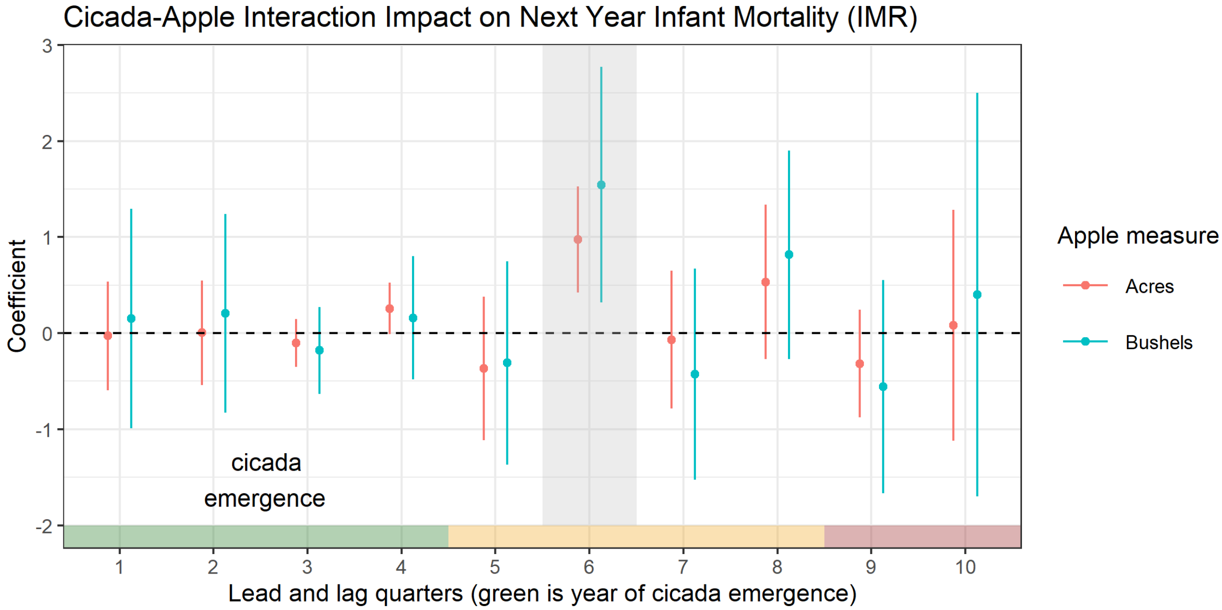
Notes: Event study based on Model (3) from Table 3 for top decile apple producing counties with the inclusion of cicada leads and lags. Sample limited to counties with cicada events and to observations with no leading or lagging cicada events during the period to balance the panel. Models allow for different fixed effects and geographic trends. Standard errors clustered at the state level. Solid lines show 95% confidence intervals. Normalized to the year before cicada emergence.

Figure 6



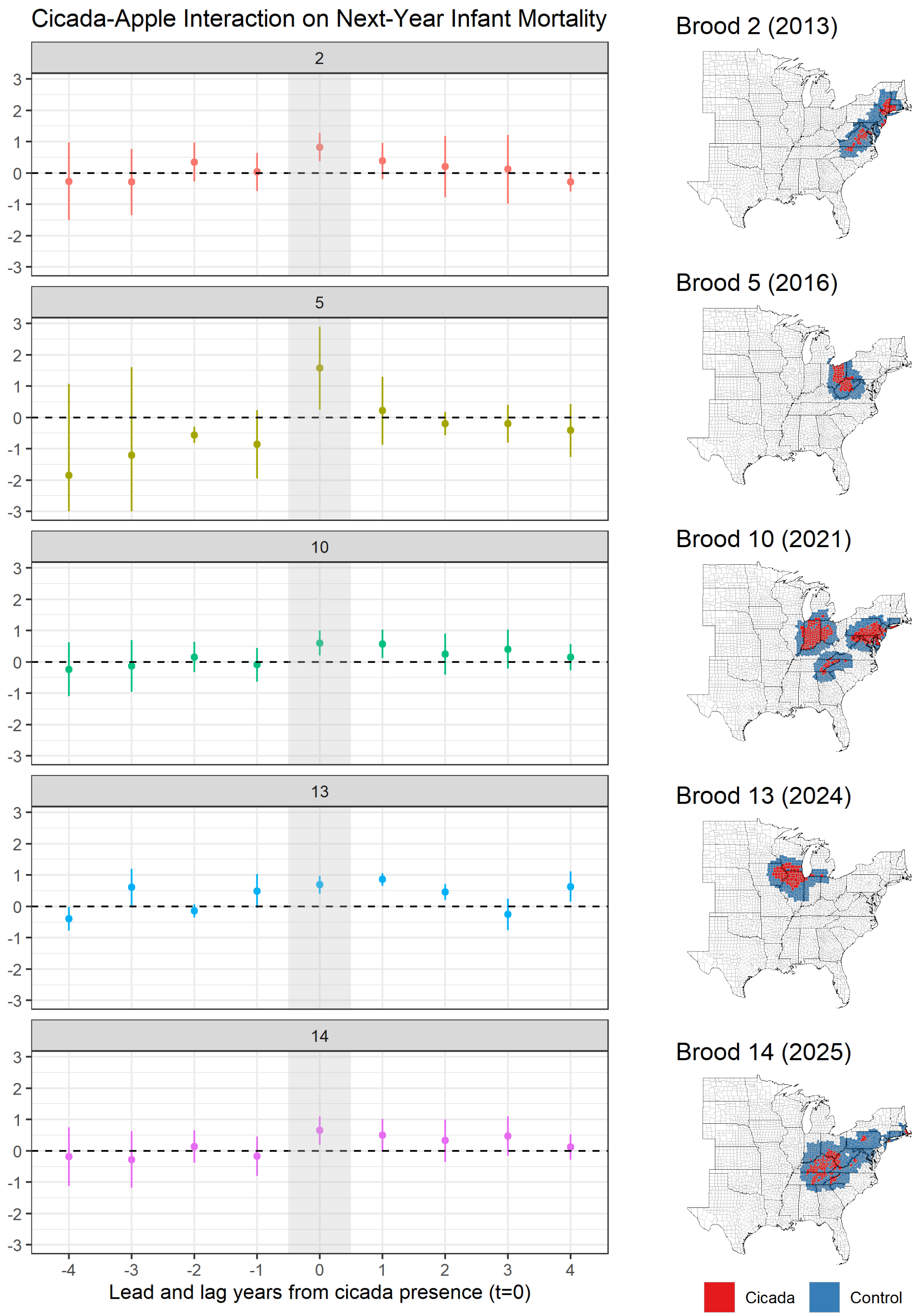
Notes: Event study based on Model (5) of Table 1 for level of apple production with the inclusion of cicada leads and lags. Sample limited to counties with cicada events and to observations with no leading or lagging cicada events during the period to balance the panel. Models allow for different fixed effects and geographic trends. Standard errors clustered at the state level. Solid lines show 95% confidence intervals. Normalized to the year before cicada emergence.

Figure 7



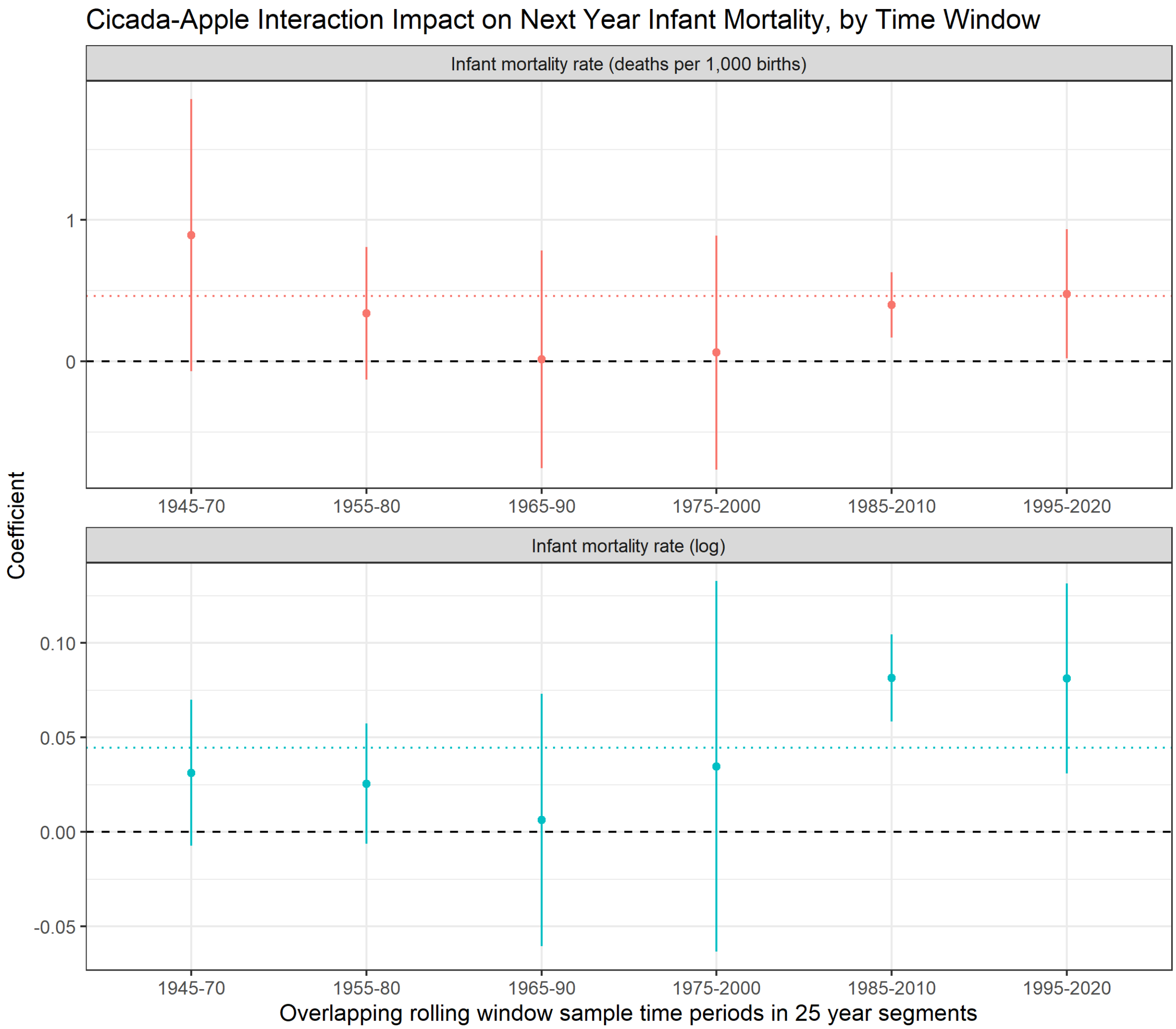
Notes: Output similar to Model (5) of Table 1 but with quarterly IMR as outcome variable estimated using separate regressions. Time series limited to 1995 to 2016. Apple intensity interaction measure is apple crop acreage or production in bushels in 1997. Green area is the year of cicada emergence, yellow is the next year, and red is the third year. Gray area is the second quarter in the year following cicada emergence. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure 8



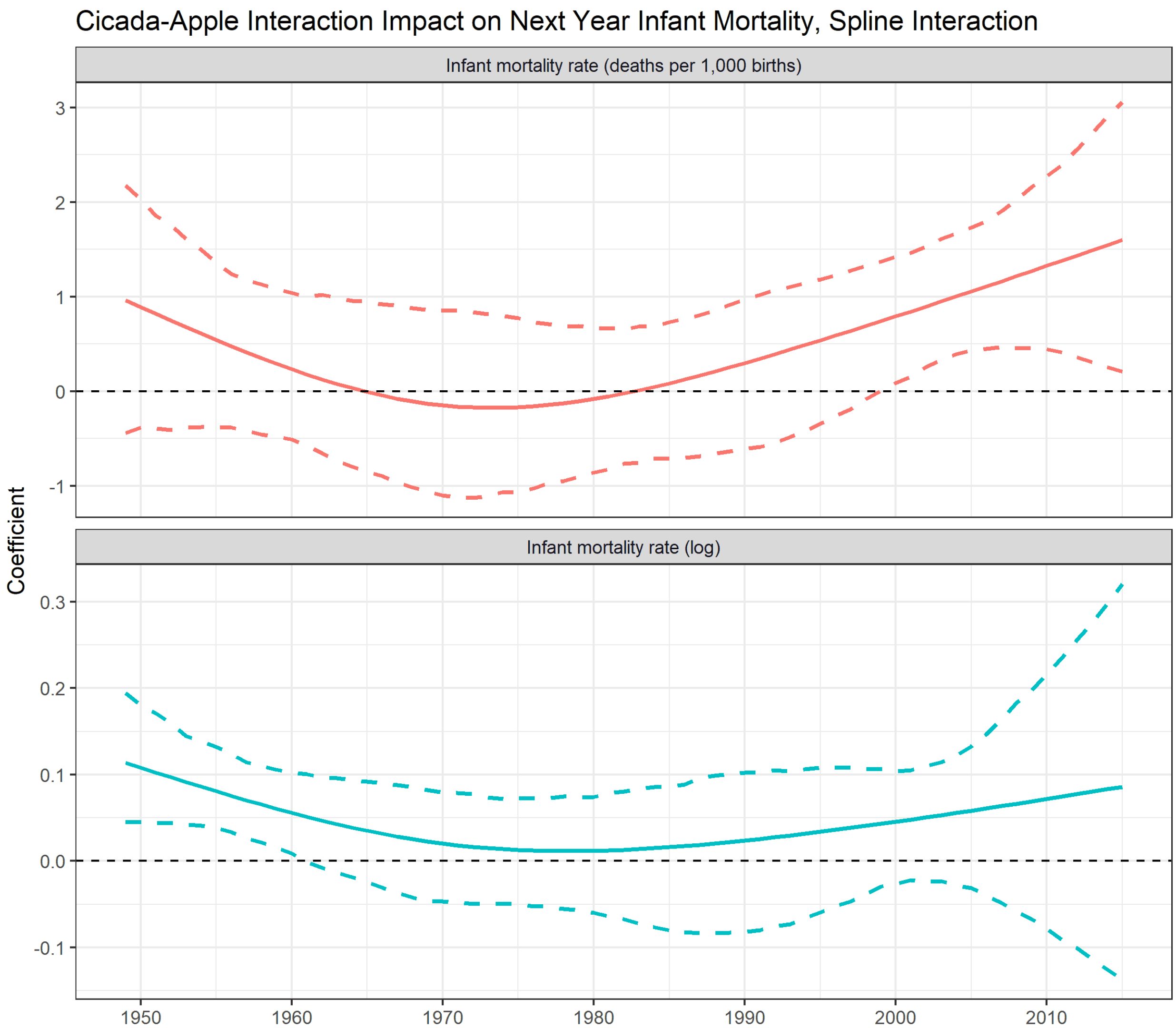
Notes: Event study by cicada brood based on Table 2, but including cicada leads and lags. Sample includes counties receiving the given brood (red), as well as those within 100km of treatment area (blue). State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals. Coefficients relative to omitted years outside of four years plus/minus a cicada event.

Figure 9



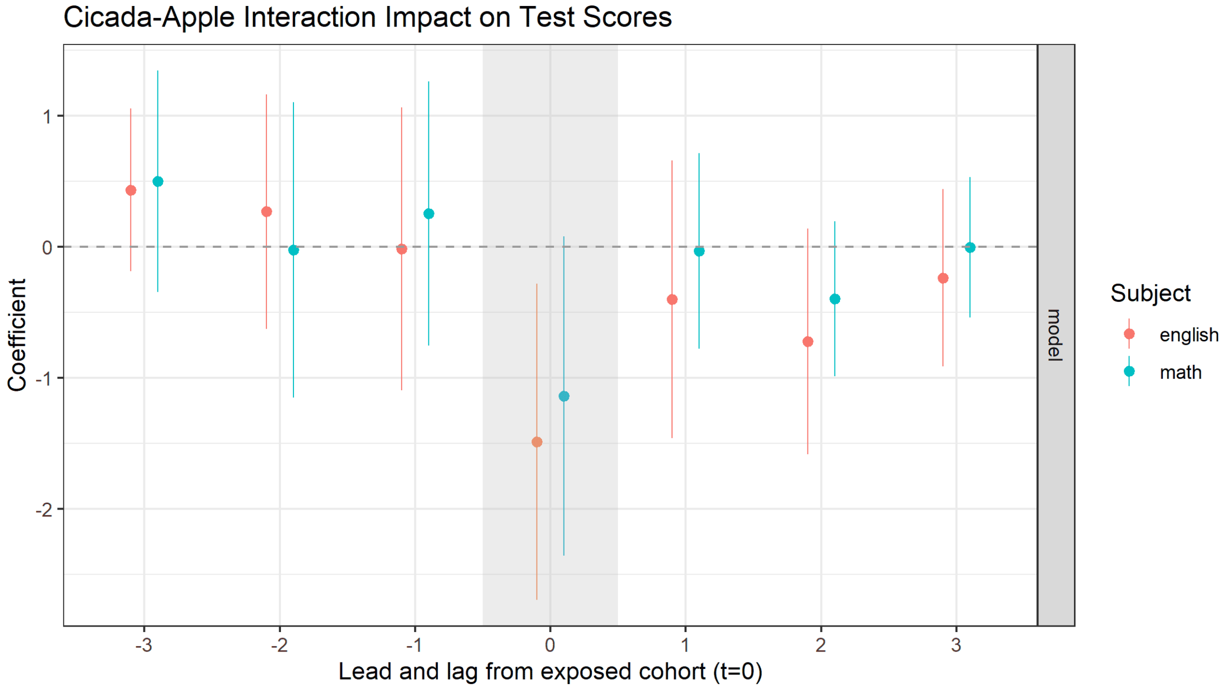
Notes: Coefficient plot based on Model (5) of Table 1 of separate regressions with differing overlapping sample windows of 25 years. Note that the time period for the last column ends in 2016. Top chart models infant mortality rate, while the bottom uses logged value as the outcome variable. Dotted colored lines show point estimates for main sample time period from 1950 to 2016. Both charts utilize apple production intensity in 1997 for the interaction term. Alternate approaches include using apple production data in 1964 in Appendix Figure A9 and a natural cubic spline in Figure 10. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure 10



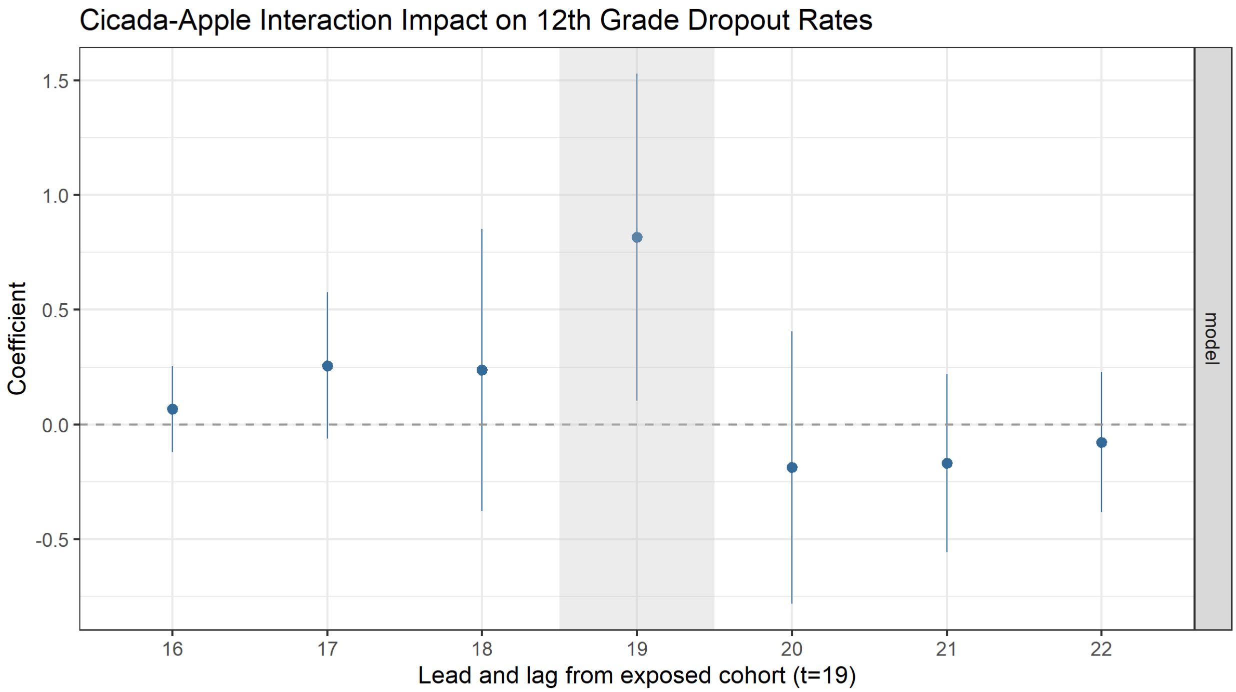
Notes: Coefficient plot of the interaction of the explanatory variable, i.e., interaction of apple production intensity in 1997 and cicada emergence as in Model (5) of Table 1, with a natural cubic spline by year with three degrees of freedom (two knots). State-level annual time trends and county and year fixed effect dummies included. Dotted lines show 90% confidence interval bootstrapped 500 times using stratified random sampling with replacement at the state level to reflect error term correlation.

Figure 11



Notes: Event study based on Models (2) and (5) in Table A9 using NAEP-equivalent Stanford Education Data Archive data. Scores area averaged by cicada exposure cohort: 3rd graders 9 years after cicada exposure, 4th graders 10 years after, and 5th graders 11 years after. Apple intensity measure is top decile of apple production. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

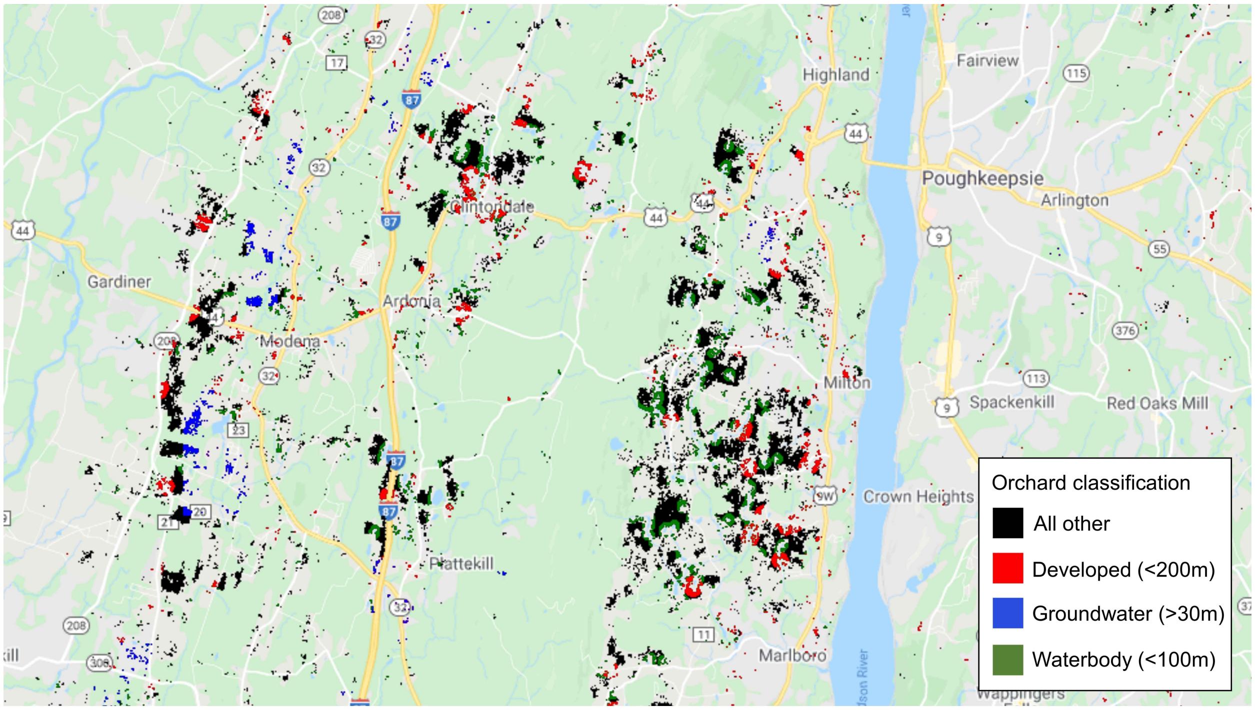
Figure 12



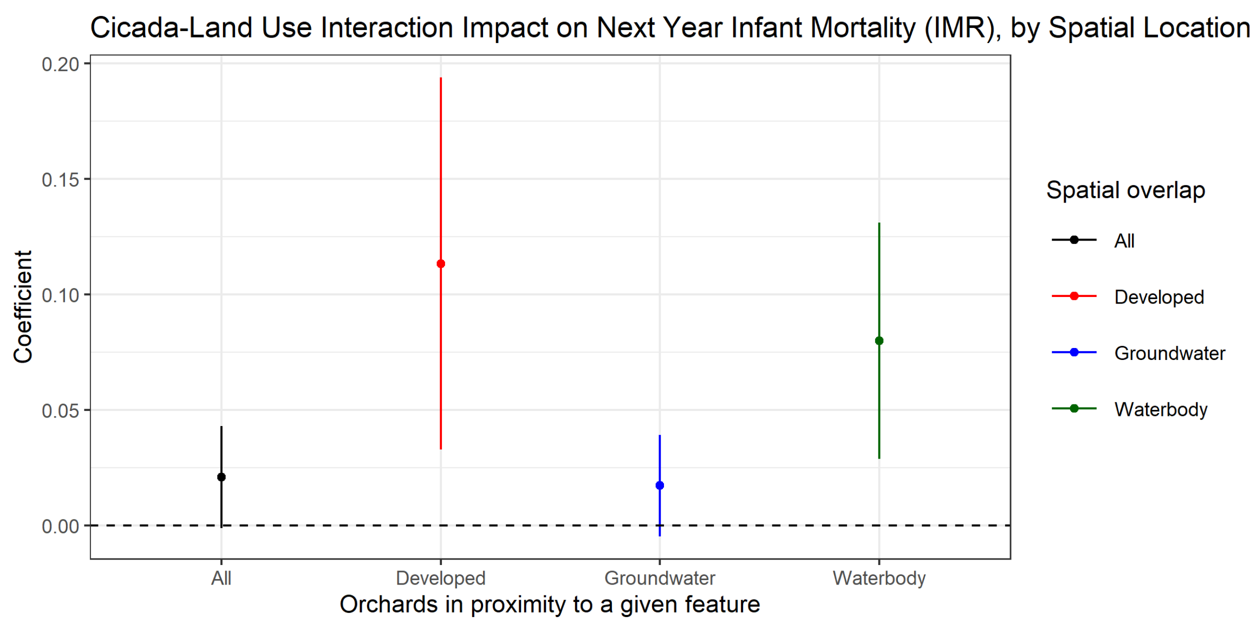
Notes: Event study based on Model (3) in Table A10 using level of apple production. 12^{th} grade dropout rates averaged across school districts at a county-year level from 1991-2009. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure 13

Panel A - Spatial location of orchards, illustration for Ulster County, NY



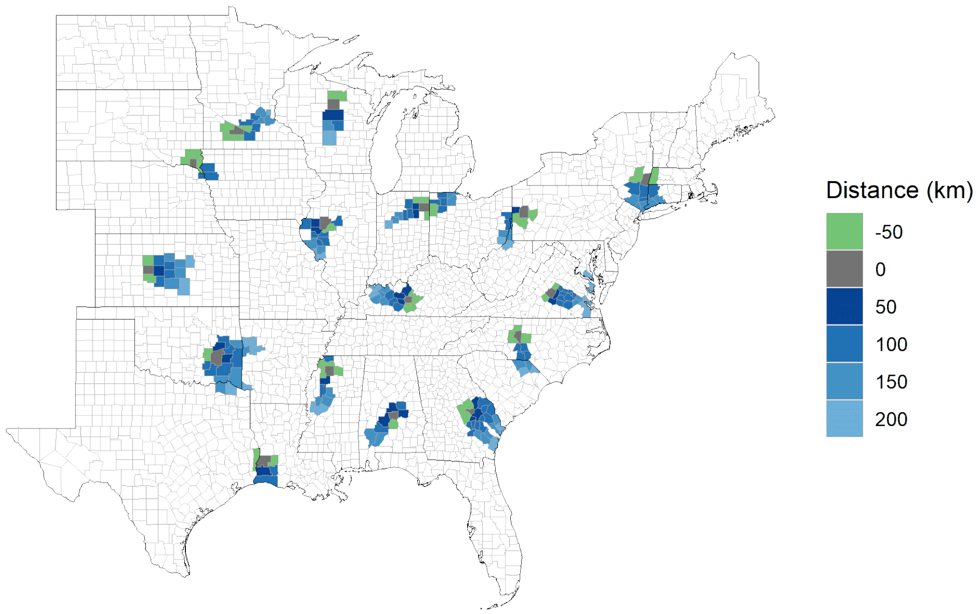
Panel B - Entire sample regression with spatial location of orchards



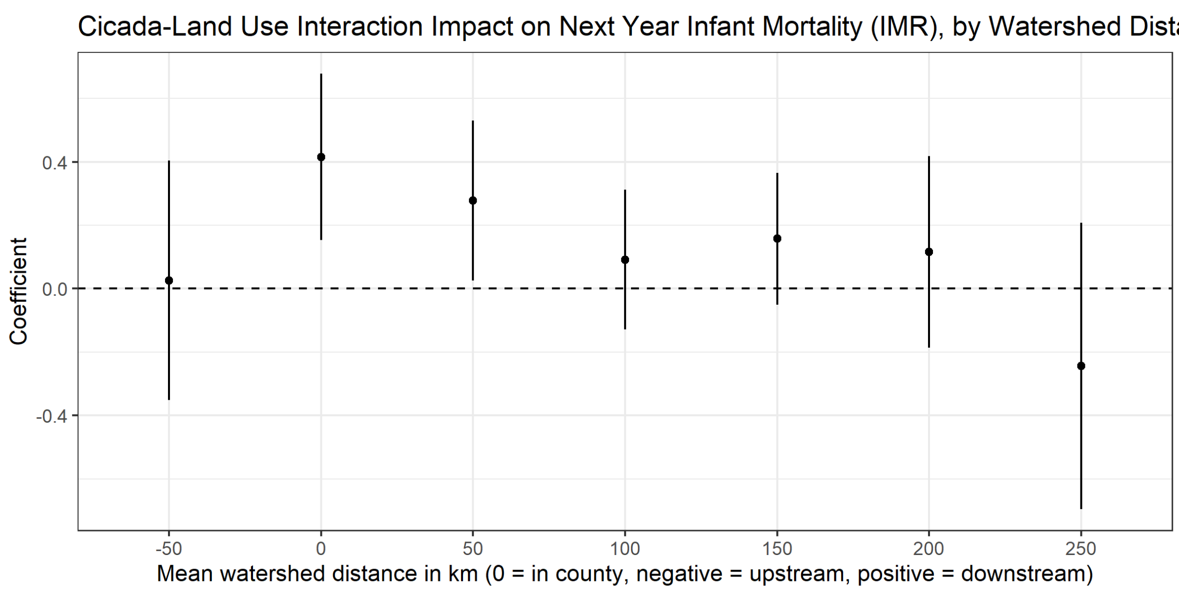
Notes: **Panel A** shows orchard locations in Ulster County, NY, about 80 miles north of New York City and just west of the Hudson River. Cropland Data Layer categorizations of land use in 2008. Background colors are classified as orchard (i.e., tree crops or berries) at 30m resolution. Green areas are subset of these within 100 meters of a NHD surface water body (7% of all orchards). Blue areas are subset overlapping soil and sedimentary thickness levels over 30 meters (34% of all). Red areas fall within 200m of medium or high intensity development (8% of all). Image created using Google Earth Engine. **Panel B** plots of interacted coefficients from Model (5) of Table A8 but with orchards categorized by proximity to land features, as described above. Colors match those in map. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure 14

Panel A - County flow direction by watershed distance (example counties)

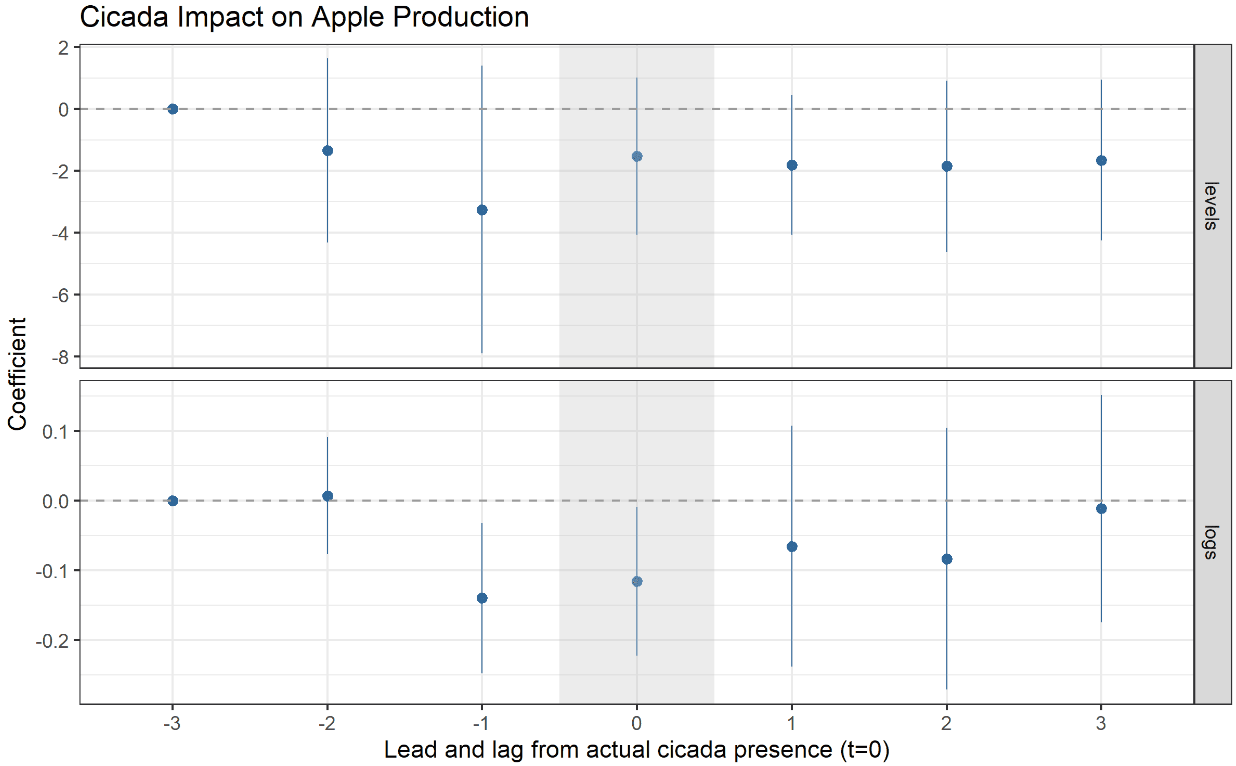


Panel B - Spatial lag model by watershed distance



Notes: **Panel A** shows watershed classification for a subset of example counties based on their relative location within the USGS HUC-4 watershed and the flow direction between counties based on finer-resolution HUC-12 watersheds. For a reference county in grey (distance 0), upstream counties are green (negative distance) and downstream are blue (positive distance). A value of '100', for example, includes all counties 50 to 100km downstream of a reference county. Based on the nature of hydrological flows, there are fewer counties upstream than downstream for any given county. For ease of visualization, only upstream and downstream counties within 50km upstream and 200km downstream of the reference county are colored. **Panel B** is a coefficient plot of the spatial lag model with pooled data in which each county-year observation is linked to the associated infant morality levels of its neighboring counties within a watershed by 50km distance bin. To showcase cicada treatment, only counties in the top decile of apple production and their watershed neighbors are included. Upstream counties that are 'treated' in a given year (meaning having high apple production and a cicada emergence) are dropped to isolate in-county treatment effects. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure 15



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 (Virginia, South Carolina, Kansas, Pennsylvania, and New Jersey). Observations with no leading or lagging cicada events during the period are excluded to balance the panel. State-level annual time trends and county and year fixed effect dummies included. Solid lines show 95% confidence intervals. Normalized to three years before cicada emergence.

Tables

Table 1: Cicada Impact on Infant Mortality, 1950-2016

	Dependent variable:				
	Next-Year Infant Mortality Rate (IMR)				
	(1)	(2)	(3)	(4)	(5)
Cicada	0.08	0.06	0.04	0.05	0.07
	(0.12)	(0.13)	(0.14)	(0.13)	(0.13)
Cicada x Apple acres		0.26^{***}			
		(0.08)			
Cicada x Bushels (decile)			0.31^{*}		
			(0.16)		
Cicada x Bushels 1964				0.60^{***}	
				(0.16)	
Cicada x Bushels 1997					0.46^{**}
					(0.18)
County FE	X	X	X	X	X
Year FE	X	X	X	X	X
State-Yr Trend	X	X	X	X	X
Observations	145,369	145,369	145,369	145,369	145,369
R^2	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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997 and 1964. 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. *p<0.1; **p<0.05; ***p<0.01

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

	Dependent variable:					
	Next-Year Infant Mortality Rate (IMR)					
	All	Brood 2	Brood 5	Brood 10	Brood 13	Brood 14
	(1)	(2)	(3)	(4)	(5)	(6)
Cicada	0.07	0.22	0.11	0.20	−0.10	0.13
	(0.13)	(0.25)	(0.19)	(0.16)	(0.17)	(0.15)
Cicada x Bushels	0.46**	0.61***	0.82***	0.46**	0.54**	0.49**
	(0.18)	(0.15)	(0.15)	(0.17)	(0.18)	(0.19)
County controls	All	<100km	<100km	<100km	<100km	<100km
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	145,369	16,910	11,331	38,353	13,455	37,083
R^2	0.52	0.66	0.60	0.61	0.58	0.60

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 apple production in 1997 per county land area. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table 3: Cicadas and Insecticides

	Insecticide use (kg km^{-2})					
	——Levels——			——Logs——		
	(1)	(2)	(3)	(4)	(5)	(6)
Cicada	1.36	0.28	0.56	−0.01	−0.04	−0.03
	(1.39)	(0.87)	(0.94)	(0.04)	(0.04)	(0.05)
Cicada x Apple Acres		7.32*			0.20***	
		(3.75)			(0.07)	
Cicada x Apple Bushels			5.81*			0.12*
			(3.36)			(0.06)
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	61,133	61,133	61,133	60,784	60,784	60,784
R^2	0.39	0.39	0.39	0.88	0.88	0.88

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. Interacted covariates include the top decile counties in apple acreage and apple production in bushels per land area in 1997. Time series limited to USGS pesticide data, 1992 to 2016. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table 4: 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	−0.045	−0.041	−0.068	−0.065	−0.080	−0.074
	(0.053)	(0.053)	(0.082)	(0.082)	(0.059)	(0.058)
Cicada x Acres	0.135**		0.143***		0.161	
	(0.056)		(0.036)		(0.109)	
Cicada x Bushels		0.157*		0.184***		0.133
		(0.087)		(0.054)		(0.150)
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	83,426	83,426	109,387	109,387	112,165	112,165
R^2	0.102	0.102	0.205	0.205	0.261	0.261

Notes: Linear regression. Dependent variables are various next-year birth outcomes averaged 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). Each dummy is multiplied by 100. 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. Covariates include apple acreage and apple production in bushels in 1997. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table 5: Cicada-Apple Interaction Impact on Infant Mortality, by Cicada Map Source

	Dependent variable:									
	Next Year Infant Mortality Rate (IMR)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cicada	0.08	0.03	0.06	−0.05	0.04	−0.10	0.05	−0.05	0.07	−0.02
	(0.12)	(0.26)	(0.13)	(0.26)	(0.14)	(0.25)	(0.13)	(0.25)	(0.13)	(0.26)
Cicada x Acres			0.26***	0.37**						
			(0.08)	(0.09)						
Cicada x Bushels (decile)					0.31*	0.46**				
					(0.16)	(0.13)				
Cicada x Bushels 1964							0.60***	0.70*		
							(0.16)	(0.27)		
Cicada x Bushels 1997									0.46**	0.62***
									(0.18)	(0.12)
Map	Original	New	Original	New	Original	New	Original	New	Original	New
County FE	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X	X	X	X	X
Observations	145,369	15,179	145,369	15,179	145,369	15,179	145,369	15,179	145,369	15,179
R^2	0.52	0.61	0.52	0.61	0.52	0.61	0.52	0.61	0.52	0.61

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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997 and 1964. Mapping describes the sample: 'Original' replicates the primary analysis and 'New' uses the recent presence-absence map for the Mid-Atlantic. 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. *p<0.1; **p<0.05; ***p<0.01

Appendix

Cicadian Rhythm: Insecticides, Infant Health and Long-term Outcomes

Charles A. Taylor[1]

[1] School of International and Public Affairs, Columbia University, 420 W 118th St, New York, NY 10027. Email: cat2180@columbia.edu

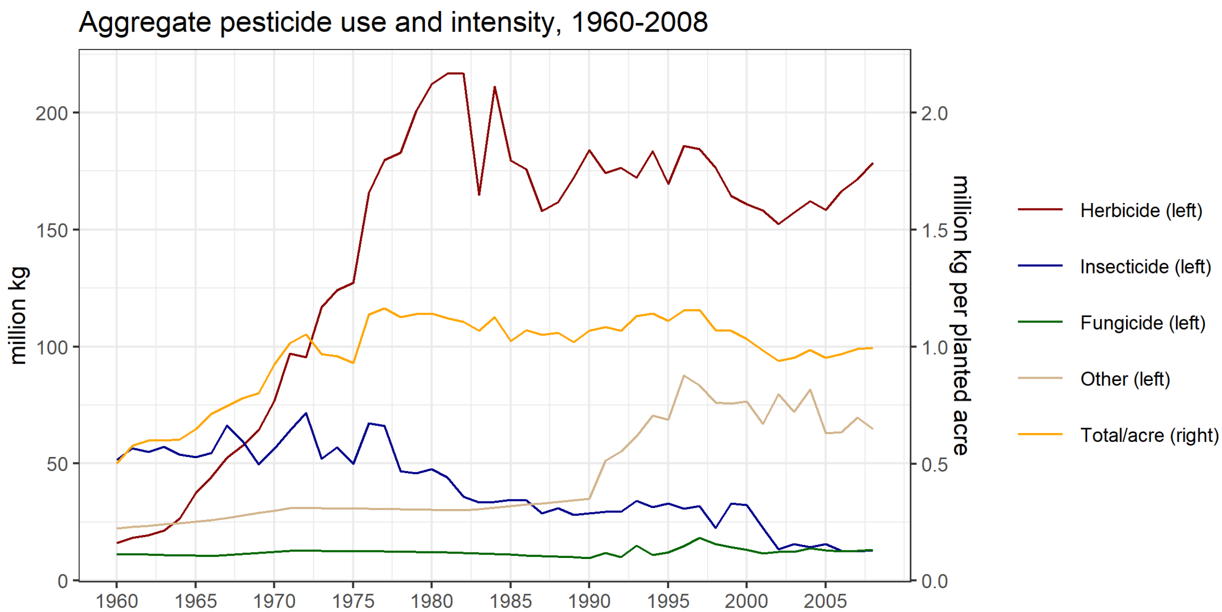
List of Figures

List of Tables

Figures

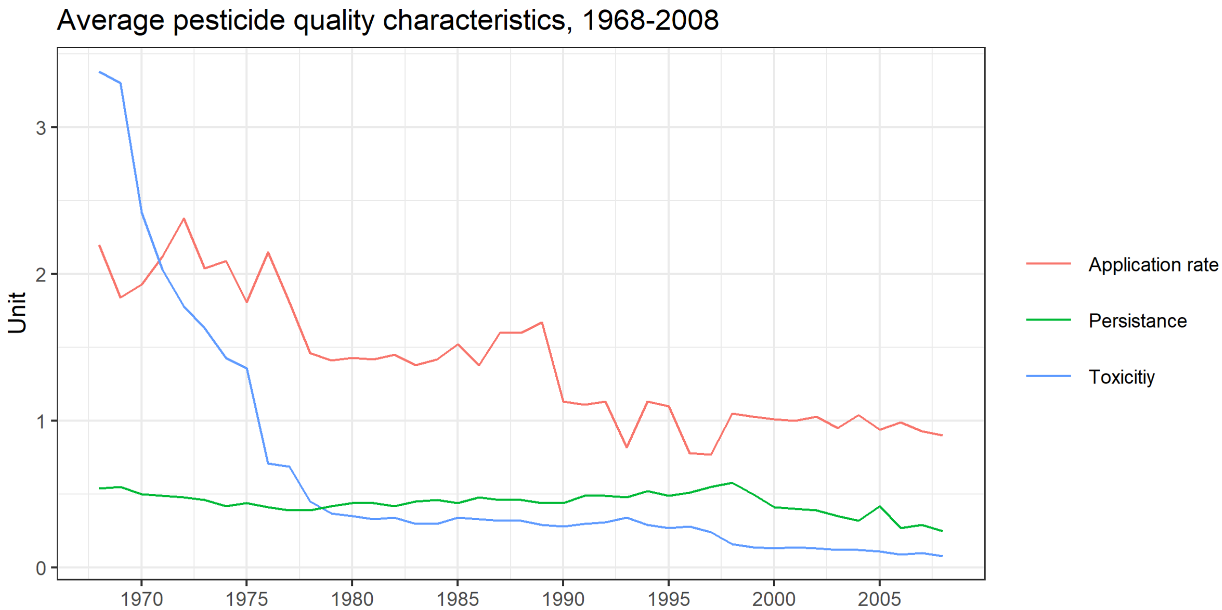
Pesticide trends

Figure A1: Pesticide use trends, 1960-2008



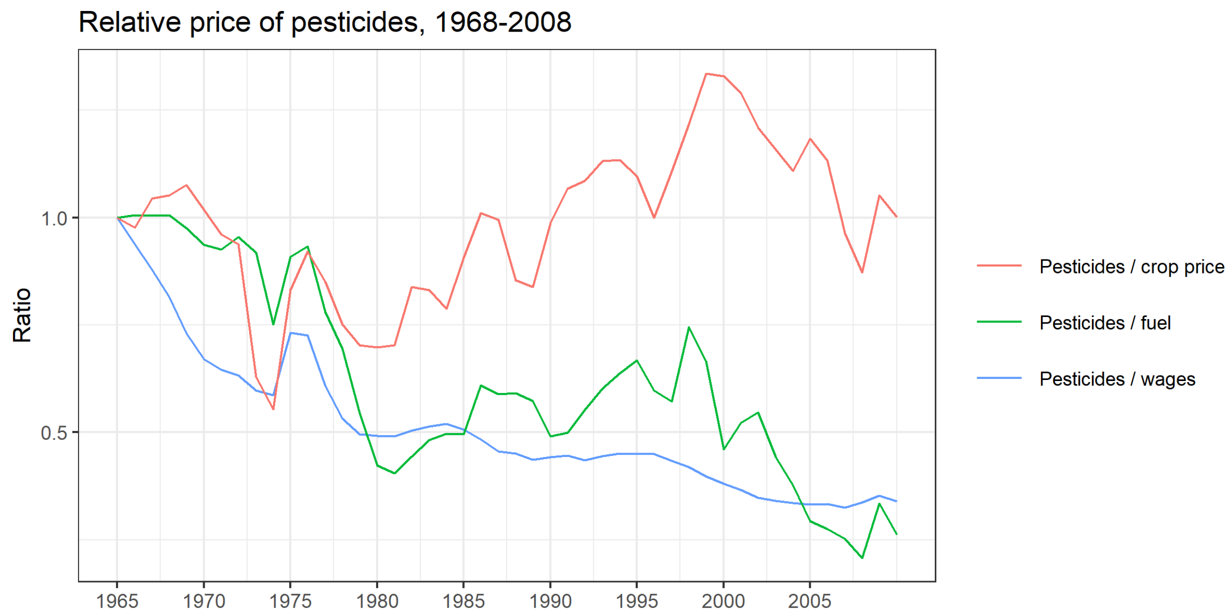
Notes: Data for top 21 crops from USDA (Fernandez-Cornejo et al. 2014). Other pesticides include soil fumigants, desiccants, harvest aids, and plant growth regulators.

Figure A2: Pesticide characteristic trends, 1968-2008



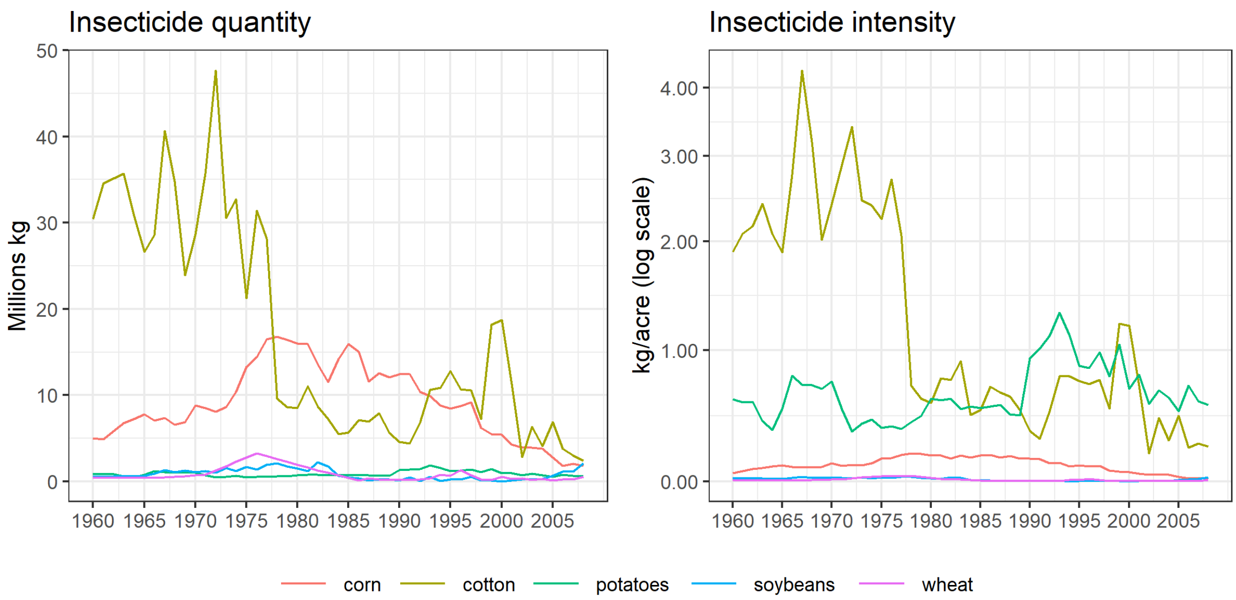
Notes: Average pesticide characteristics weighted by use in terms of pounds of active ingredients for four major US crops: corn, soybeans, cotton and sorghum. Application rate is in pounds of active ingredient applied per acre in one application times the number of applications per year. Toxicity is based on the inverse of the average safe drinking water threshold (Kellogg et al. 2002) in terms of constituent concentration in parts per billion. Persistence is an indicator for the share of pesticides with a half-life less than 60 days (Fernandez-Cornejo and Jans 1995). Data from USDA (Fernandez-Cornejo et al. 2014).

Figure A3: Pesticide price trends, 1968-2008



Notes: NASS agricultural price indices from USDA (2014).

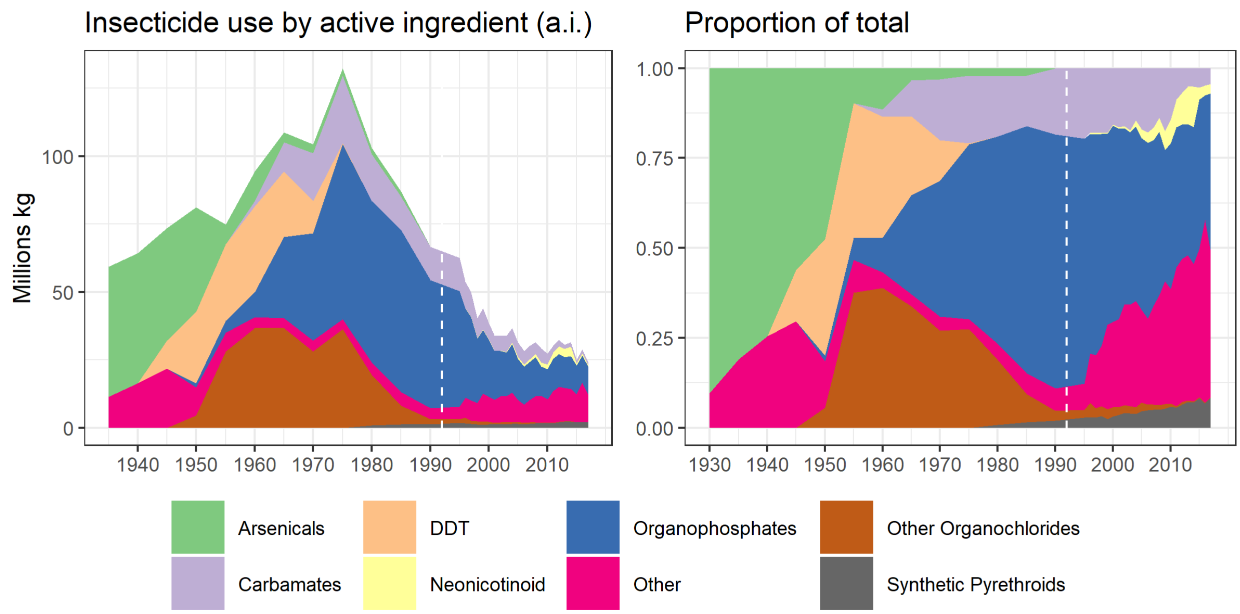
Figure A4: Insecticide use trends for five major crops, 1960-2008



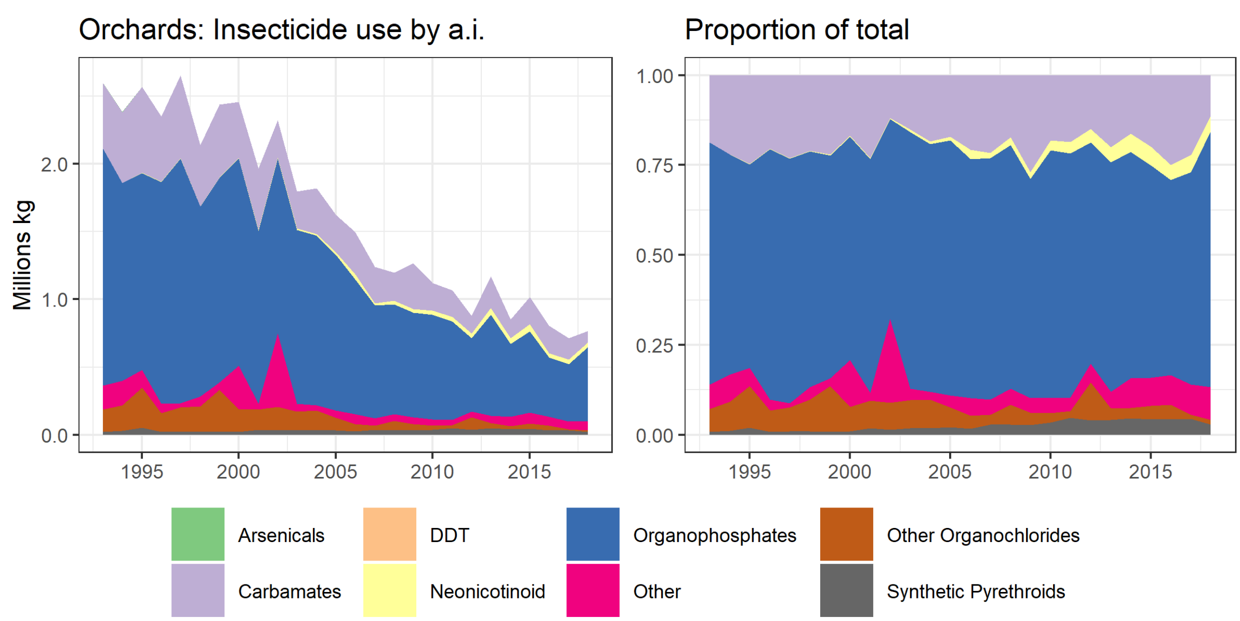
Notes: Data from USDA (2014)

Figure A5: Insecticide use trends at national level, 1935-2016

Panel A: National trends across all land uses, 1935-2016

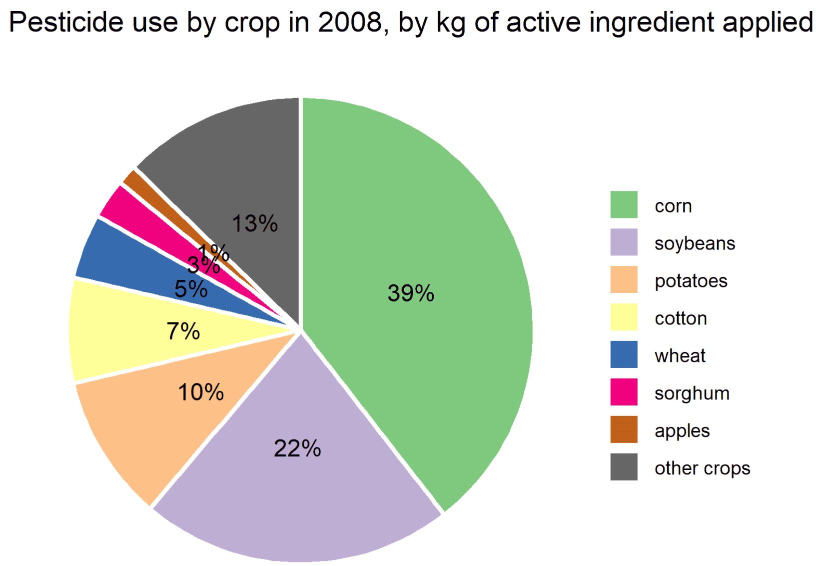


Panel B: Recent trends in for orchards and grapes, 1993-2016



Notes: Panel A: national-level insecticide data in five-year intervals from EPA (Aspelin 2003) prior to 1995, combined with recent aggregated USGS county-level data (USGS 2019). Pesticide categorizations adjusted such that datasets are comparable. Panel B: State-level insecticide data for 'orchards and grapes' summed across eastern states in sample (2019).

Figure A6: Pesticide use by crop, including apples



Notes: Data from USDA (Fernandez-Cornejo et al. 2014)

Other figures

Figure A7: Cicada interest by region

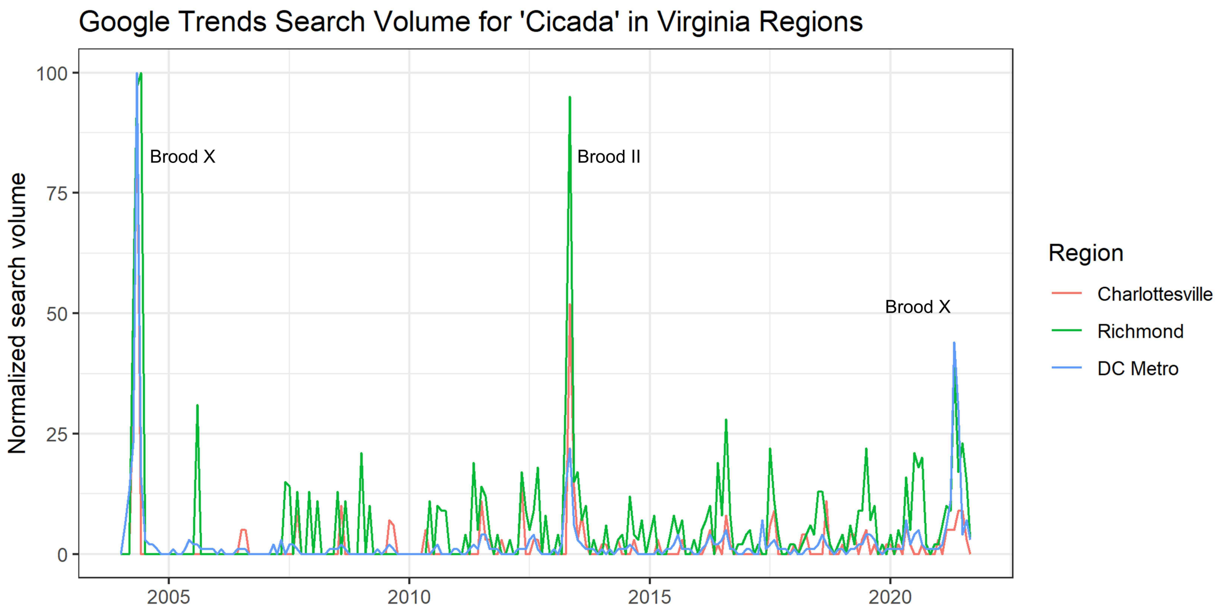


Figure A8: Infant mortality trends by cicada endemic status, 1950-2016

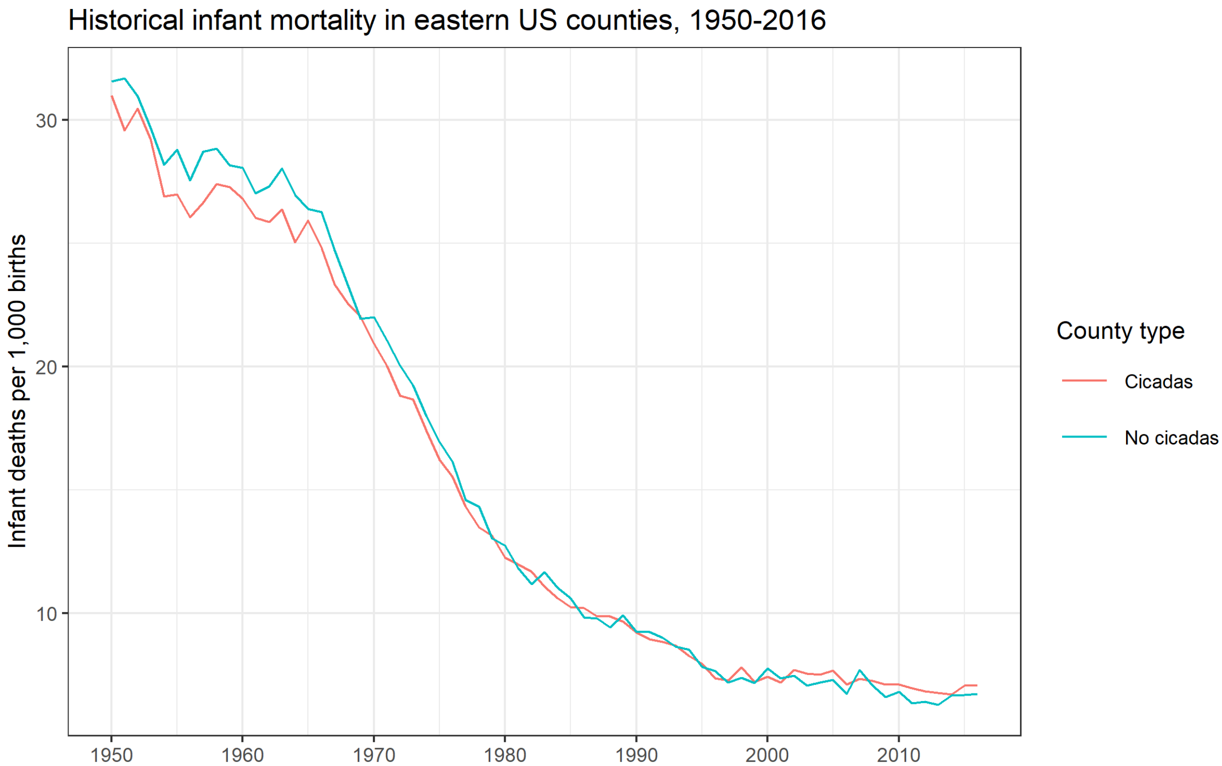
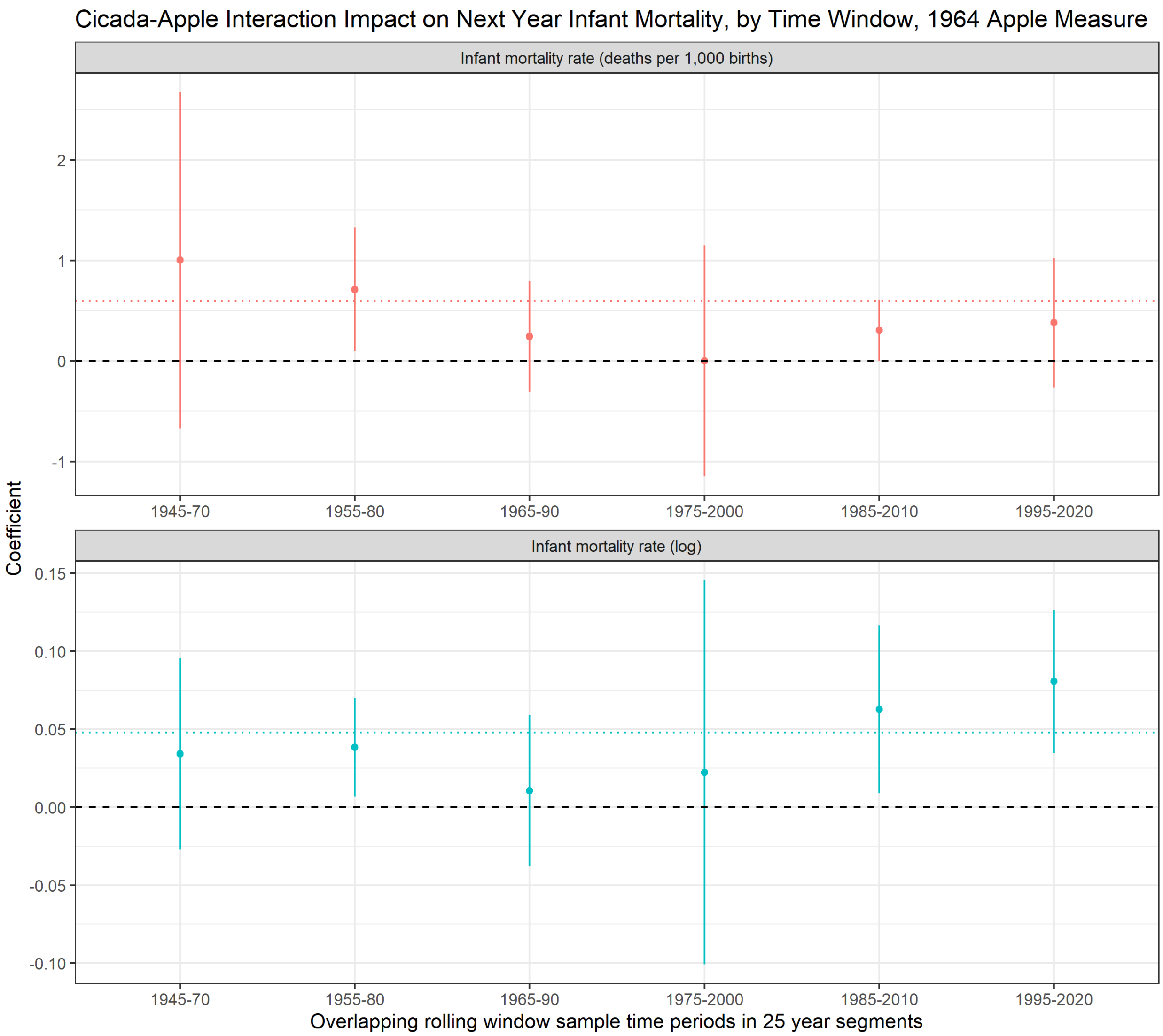
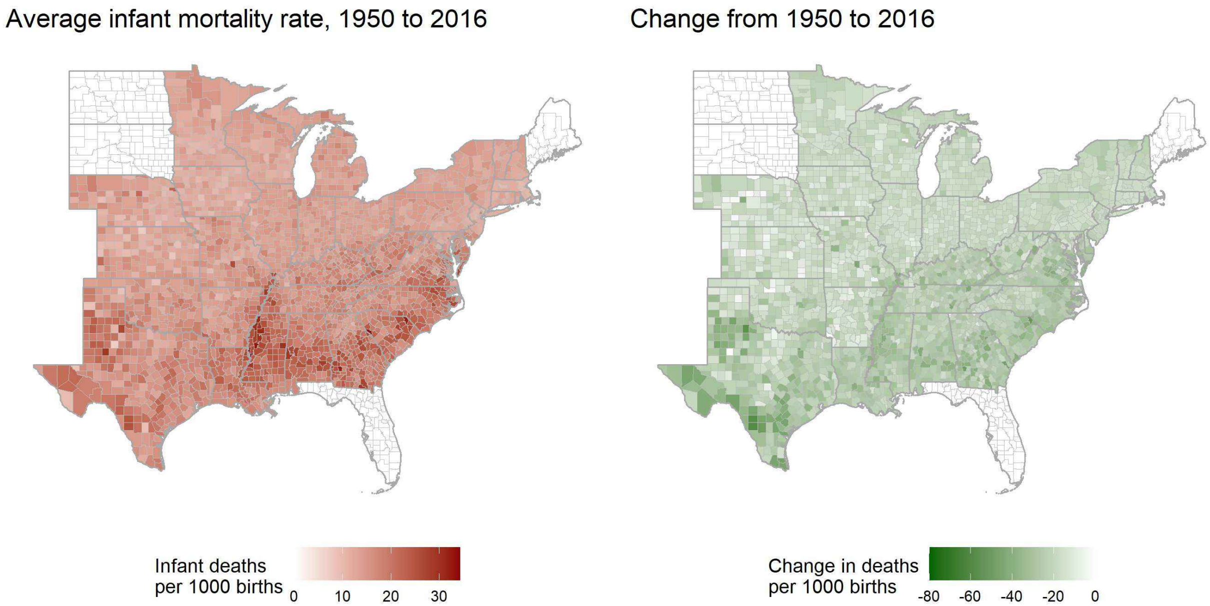


Figure A9: Infant mortality effect by time window, 1964 apple production



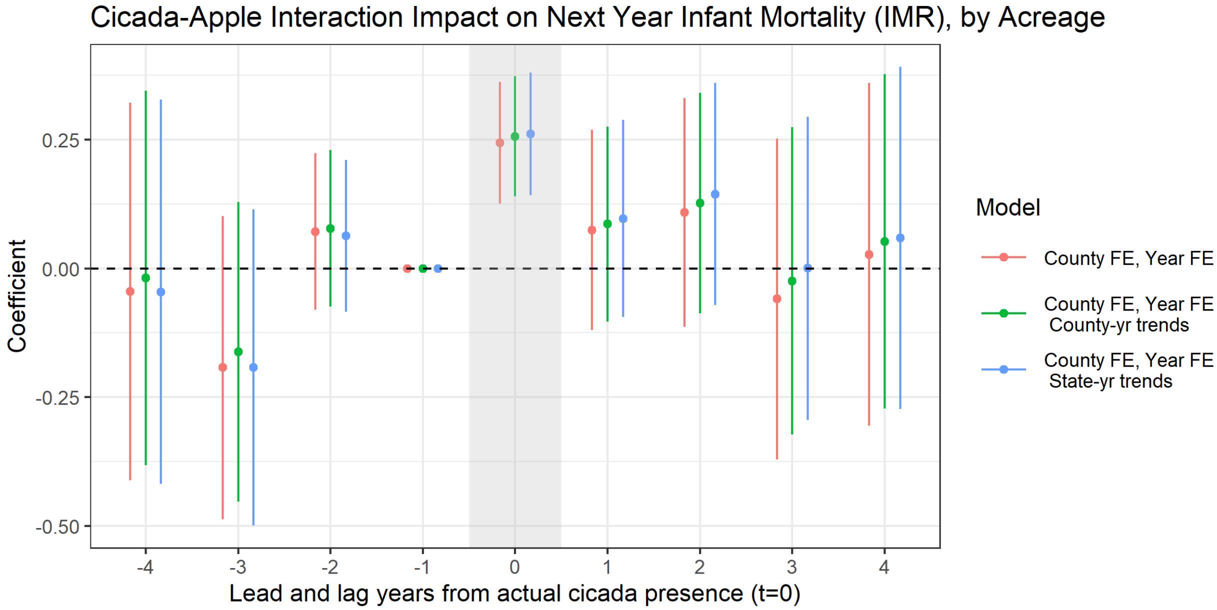
Notes: Coefficient plot based on Model (4) of Table 1 using apple production intensity in 1964 and separate regressions with differing overlapping sample windows of 25 years. Note that the time period for the last column ends in 2016. Top chart models infant mortality rate, while the bottom uses logged value as the outcome variable. Dotted colored lines show point estimates for main sample time period from 1950 to 2016. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. Solid lines show 95% confidence intervals.

Figure A10: Map of average infant mortality and its change over time



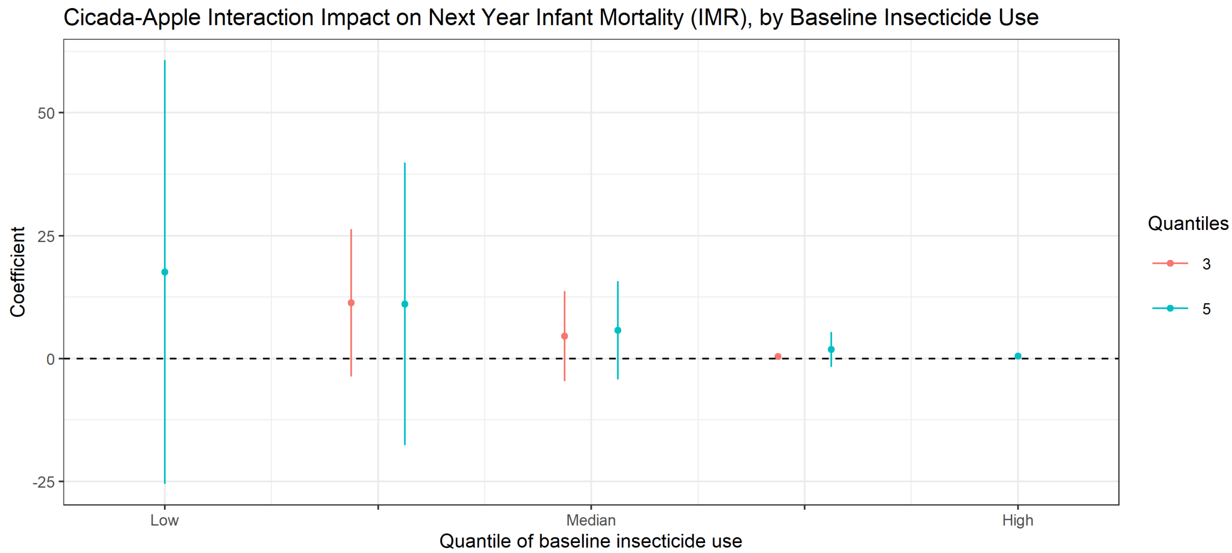
Notes: County-level sample mean infant mortality rate is 16 deaths per 1000 from 1950-2016. Change is calculated from the difference between average infant mortality rates in the first ten year period 1950-1960 (mean IMR 29) and the last period 2006-2016 (mean IMR 7), for an average decrease in 22 deaths per 1,000.

Figure A11: Infant mortality event study by acreage



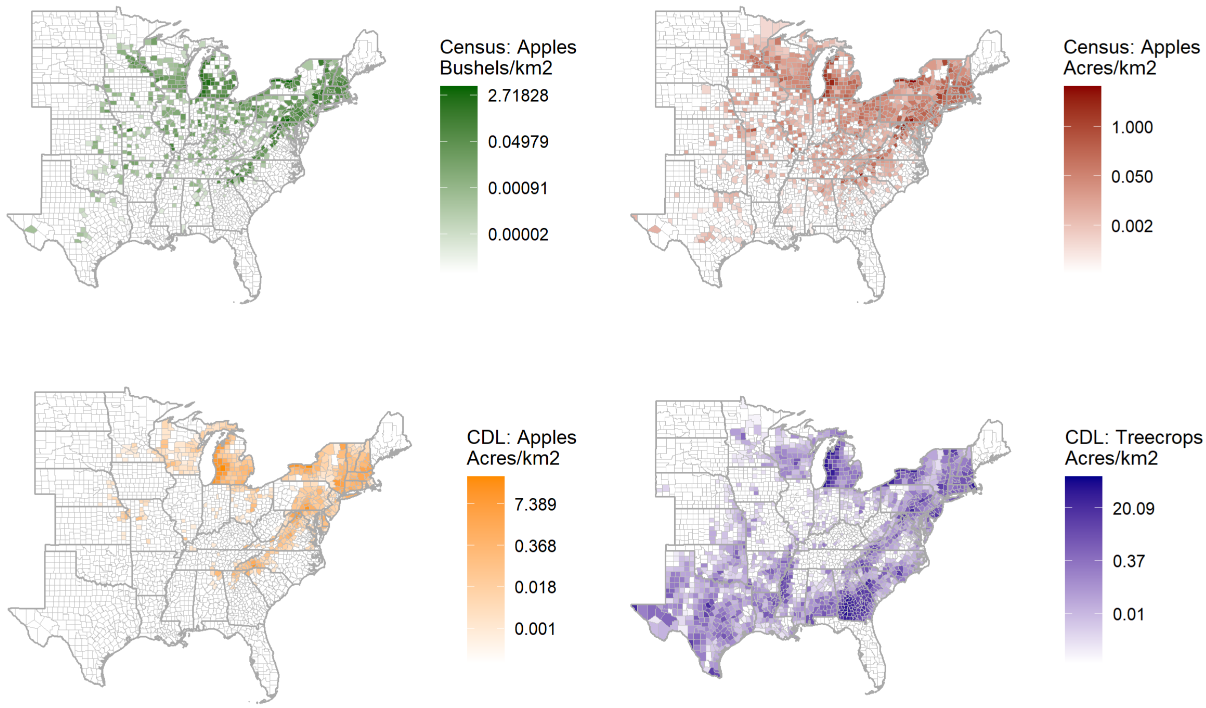
Notes: Event study based on Model (2) of Table 1 for apple acreage with the inclusion of cicada leads and lags. Sample only includes counties with cicada events and observations with no leading or lagging cicada events during the period are excluded to balance the panel. Models allow for different fixed effects and geographic trends. Standard errors clustered at the state level. Solid lines show 95% confidence intervals. Normalized to the year before cicada emergence.

Figure A12: Infant mortality response by baseline level of insecticide use



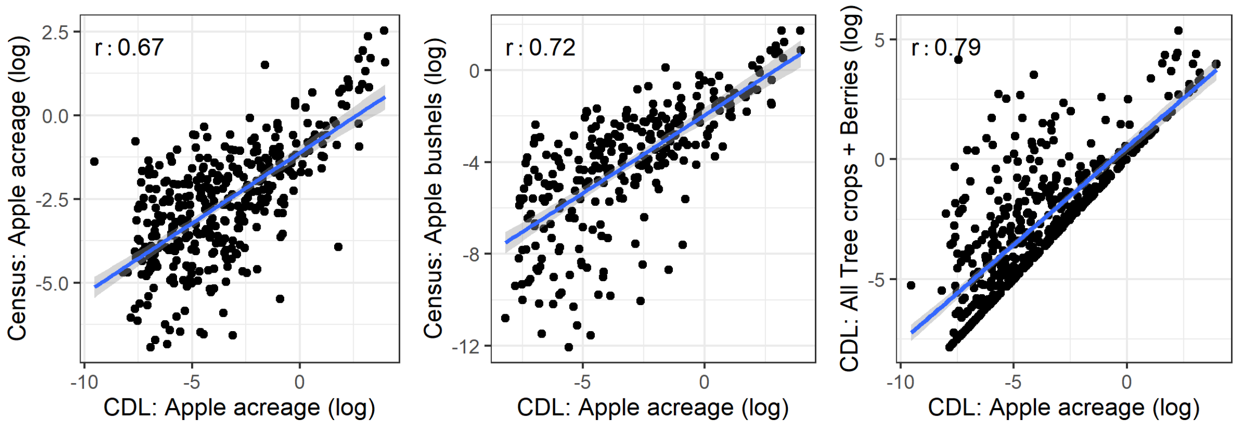
Notes: Coefficient plot of models from Table 1 with an additional interaction for baseline insecticide use. Quantiles are assigned based on county-level average insecticide use over time for counties with non-zero apple production. The red line assigns 3 quantiles and centers the coefficients on the median label to align with the 5-quantile green lines.

Figure A13: Maps of county-level apple intensity from Census and Cropland Data Layer



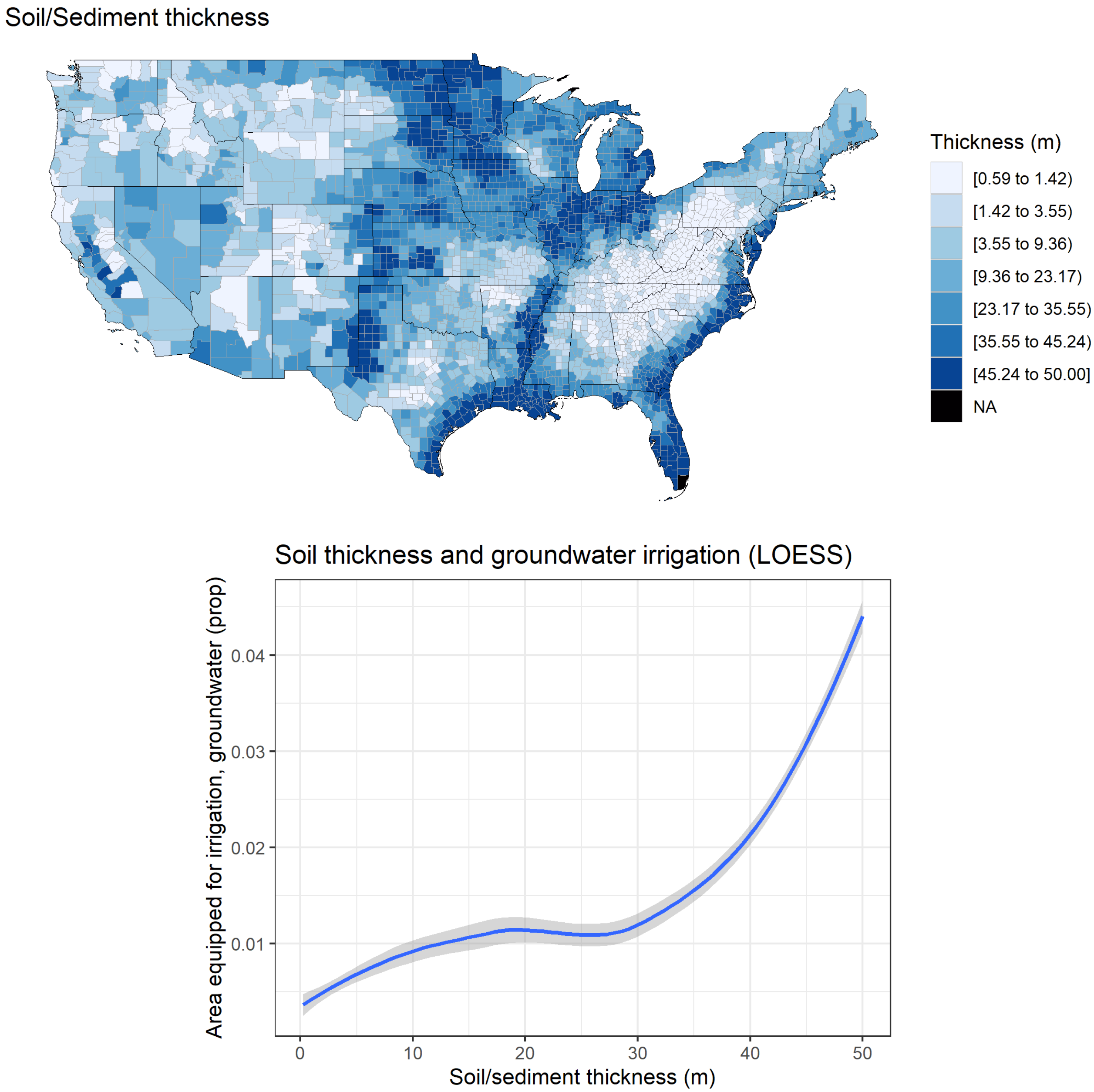
Notes: Top panel shows USDA census estimates of apple production (left) and acreage (right) in 1997. Bottom panel shows 2008 Cropland Data Layer-derived apple acreage (left) and combined tree crop and berry acreage (right), including apples. Florida, Maine, North Dakota, and South Dakota are outside the cicada endemic range and omitted from map.

Figure A14: Apple measures from Census and Cropland Data Layer



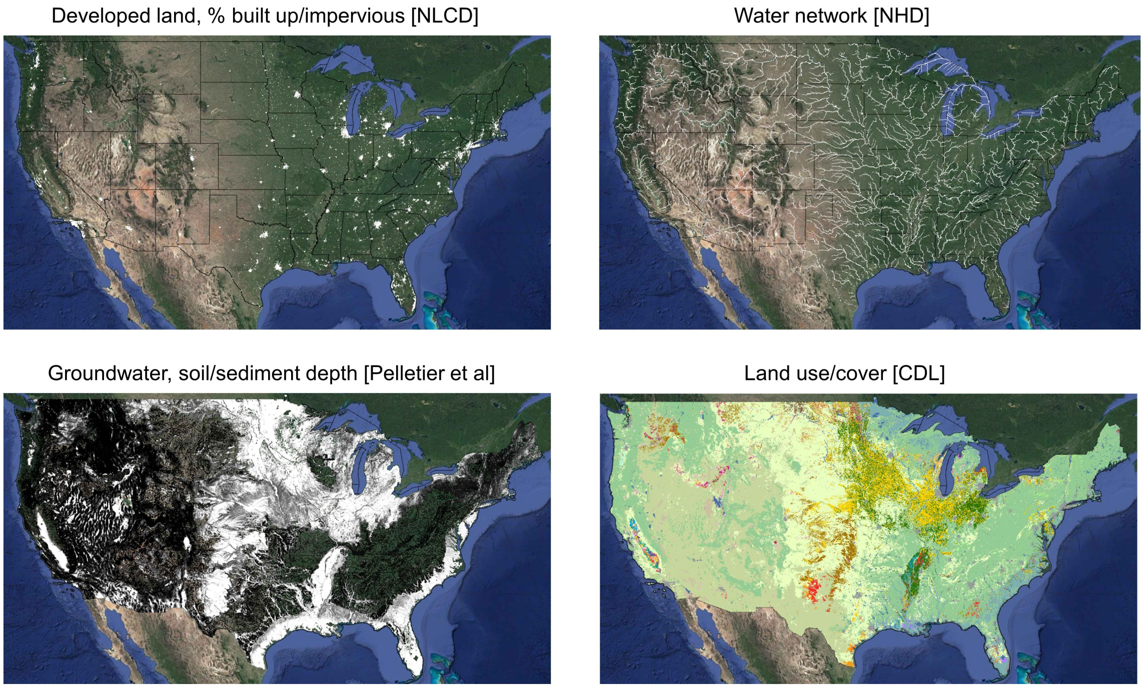
Notes: Scatter plot of average county-level tree crop intensity. Left panel plots Cropland Data Layer-derived apple acreage (x-axis) and USDA census estimate of apple acreage in 1997 (y-axis). Center panel plots USDA census estimate of apple production in bushels (y-axis) instead. Right panel plots CDL-derived apple acreage (x-axis) and the aggregate sum of all tree crop and berry acreage (y-axis), which includes apples. All values are normalized by county land area and log-transformed.

Figure A15: Groundwater and soil/sediment thickness



Notes: Top panel shows groundwater potential average over US counties, derived from gridded global data set of soil, intact regolith, and sedimentary deposit thicknesses (Pelletier et al. 2016). Darker colors denote greater suitability for groundwater extraction. Bottom panel shows the relationship between this soil/sediment thickness measure and irrigation at the grid cell level globally.

Figure A16: Visualization of geo-spatial data sources



Notes: Top left chart shows developed areas based on the proportion of impervious surfaces in a 30m grid cell. Top right chart is a visualization of NHD data on the water drainage network. Bottom left chart shows groundwater potential based on a soil and sedimentary thickness level (2016). Bottom right is a visualization of the Cropland Data Layer where each color is a different land use or cover in a 30m grid cell. Images created using Google Earth Engine.

Tables

Summary statistics

Table A1: County-level Summary Statistics, 1950-2016

Statistic	Mean	St. Dev.	Min	Max	N
Cicada proportion	0.03	0.2	0	1	167,551
Population	67,323.4	196,018.9	0.0	5,523,035.0	145,256
Births	1,168.5	3,620.2	0.0	127,338.0	162,705
Infant deaths	18.8	69.3	0.0	3,421.0	152,127
IMR (deaths/1,000)	15.8	13.8	0.0	1,000.0	152,107
Apple (1,000 bushels), 1964	31.3	203.9	0.0	5,336.7	167,551
Apple (1,000 bushels), 1997	33.9	320.0	0	8,808	167,551
Apple (acres)	86.0	654.5	0	19,590	167,551
Insecticide (kg)	12,994.8	38,509.4	0.0	3,042,894.0	61,133
Area (km2)	1,630.9	1,070.1	38.7	16,180.5	167,551
Apple (1,000 bushels/km2), 1964	0.02	0.2	0.0	3.4	167,551
Apple (1,000 bushels/km2), 1997	0.02	0.2	0	6	167,551
Apple (acres/km2)	0.1	0.5	0	13	167,551
Insecticide (kg/km2)	9.2	29.0	0.0	2,147.7	61,133

Pesticide response to cicadas

Table A2: Falsification by Pesticide Type

	Dependent variable:		
	Insecticide	Herbicide	Fungicide
	(1)	(2)	(3)
Cicada	0.56	0.65	−0.19
	(0.94)	(1.07)	(0.36)
Cicada x Bushels	5.81*	−2.03	0.97
	(3.36)	(1.93)	(1.61)
County FE	X	X	X
Year FE	X	X	X
State-Yr Trend	X	X	X
Observations	61,133	61,133	61,133
R^2	0.39	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 is a dummy for the top decile counties in apple production in 1997. Time series limited to USGS pesticide data, 1992 to 2016. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A3: Falsification by Crop

	Dependent variable:		
	Insecticide use (kg km^{-2})		
	(1)	(2)	(3)
Cicada	0.56	1.53	0.68
	(0.94)	(1.55)	(1.08)
Cicada x Bushels	5.81*		5.73*
	(3.36)		(3.30)
Cicada x Corn and Soy		−1.45	−0.97
		(1.47)	(1.18)
County FE	X	X	X
Year FE	X	X	X
State-Yr Trend	X	X	X
Observations	61,133	61,133	61,133
R^2	0.39	0.39	0.39

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 is a dummy for the top decile counties in apple production in 1997. 'Corn and Soy' 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. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Impacts on infant mortality

Table A4: Cicada Impact on Infant Mortality, 1950-1988 (Balanced)

	Dependent variable:				
	Next-Year Infant Mortality Rate (IMR)				
	(1)	(2)	(3)	(4)	(5)
Cicada	0.12	0.09	0.05	0.09	0.10
	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)
Cicada x Apple Acres		0.30**			
		(0.12)			
Cicada x Bushels (decile)			0.47**		
			(0.20)		
Cicada x Bushels 1964				0.69**	
				(0.32)	
Cicada x Bushels 1997					0.50**
					(0.23)
County FE	X	X	X	X	X
Year FE	X	X	X	X	X
State-Yr Trend	X	X	X	X	X
Observations	95,860	95,860	95,860	95,860	95,860
R^2	0.43	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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997 and 1964. 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. *p<0.1; **p<0.05; ***p<0.01

Table A5: Cicada Impact on Infant Mortality, 1950-2016, Weighted by Births

	Dependent variable:				
	Next-Year Infant Mortality Rate (IMR)				
	(1)	(2)	(3)	(4)	(5)
Cicada	0.12^{*}	0.10	0.12^{*}	0.10	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Cicada x Apple Acres		0.17^{**}			
		(0.07)			
Cicada x Bushels (decile)			0.001		
			(0.11)		
Cicada x Bushels 1964				0.34^{*}	
				(0.18)	
Cicada x Bushels 1997					0.35^{**}
					(0.14)
County FE	X	X	X	X	X
Year FE	X	X	X	X	X
State-Yr Trend	X	X	X	X	X
Observations	149,845	149,845	149,845	149,845	149,845
R^2	0.81	0.81	0.81	0.81	0.81

Notes: Linear regression. Dependent variable is next-year infant mortality rate (deaths per 1000 live births). Regression weighted by the number of county births. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997 and 1964. 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. *p<0.1; **p<0.05; ***p<0.01

Table A6: Cicada Impact on Infant Mortality, 1950-2016, by IMR source

	Dependent variable:			
	Next-Year Infant Mortality Rate (IMR)			
	(1)	(2)	(3)	(4)
Cicada	0.066	0.038	0.106	−0.132
	(0.127)	(0.128)	(0.151)	(0.166)
Cicada x Bushels	0.463**	0.457**	0.453**	0.460*
	(0.178)	(0.167)	(0.220)	(0.227)
IMR measure	Baseline	Baseline + IPUMS	ICPSR	NCHS Linked
County FE	X	X	X	X
Year FE	X	X	X	X
State-Yr Trend	X	X	X	X
Observations	145,369	156,012	105,719	47,497
R^2	0.521	0.515	0.479	0.132

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 apple production in 1997 per county land area. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A7: Cicada Impact on Infant Mortality, 1950-2016, Log Values

	Dependent variable:				
	Log of Next-Year Infant Mortality Rate (IMR)				
	(1)	(2)	(3)	(4)	(5)
Cicada	0.003	0.001	0.0002	0.001	0.002
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Cicada x Apple Acres		0.022^{***}			
		(0.007)			
Cicada x Bushels (decile)			0.020		
			(0.012)		
Cicada x Bushels 1964				0.049^{***}	
				(0.013)	
Cicada x Bushels 1997					0.046^{***}
					(0.013)
County FE	X	X	X	X	X
Year FE	X	X	X	X	X
State-Yr Trend	X	X	X	X	X
Observations	130,352	130,352	130,352	130,352	130,352
R^2	0.619	0.619	0.619	0.619	0.619

Notes: Linear regression. Dependent variable is the log of 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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997 and 1964. 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. *p<0.1; **p<0.05; ***p<0.01

Spatial extensions

Table A8: Cicada Impact on Infant Mortality, 1950-2016, by land use measure

	Dependent variable:					
	Next-Year Infant Mortality Rate (IMR)					
	(1)	(2)	(3)	(4)	(5)	(6)
Cicada	0.07	0.06	0.07	0.07	0.07	0.28
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.33)
Cicada x Apples bushels	0.46^{**}					
	(0.18)					
Cicada x Apples Acres		0.26^{***}				
		(0.08)				
Cicada x Apples (CDL)			0.07^{**}			
			(0.03)			
Cicada x Tree crops (CDL)				0.05^{**}		
				(0.02)		
Cicada x Tree crops + berries (CDL)					0.02^{*}	
					(0.01)	
Cicada x Forest land (CDL)						-0.0004
						(0.001)
Land data source	Census	Census	CDL	CDL	CDL	CDL
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	145,369	145,369	145,369	145,369	145,369	145,369
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. Covariates using USDA census data include bushels of apple production in 1997 (Model 1) and apple acreage (Model 2), covariates using USDA 2008 Cropland Data Layer 30m pixel data aggregated to the county level include apple area (Model 3), Tree crops area includes land in Apples, Cherries, Peaches, Citrus, Pecans, Almonds, Walnuts, Pears, Pistachios, Prunes, Olives, Oranges, Pomegranates, Nectarines, Plums, Apricots, Christmas Trees, and Other Tree Crops (Model 4) and this plus berries (Model 5) and all forested area (Model 6). All tree crop measures normalized by dividing by county land area. 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. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Educational impacts

Table A9: Cicada-Apple Interaction Impact on Elementary School Test Scores

	NAEP-equivalent average test scores					
	Math			English		
	(1)	(2)	(3)	(4)	(5)	(6)
Cicada	0.20	0.33	0.21	0.02	0.18	0.02
	(0.23)	(0.26)	(0.22)	(0.24)	(0.27)	(0.24)
Cicada x Apple acres	-0.51^{***}			-0.31		
	(0.10)			(0.20)		
Cicada x Bushels (decile)		-1.15^{**}			-1.27^{**}	
		(0.54)			(0.56)	
Cicada x Bushels			-1.15^{***}			-0.72^{*}
			(0.38)			(0.40)
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	10,866	10,866	10,866	11,557	11,557	11,557
R^2	0.91	0.91	0.91	0.90	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 include 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 2009 to 2015. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A10: Cicada-Apple Interaction Impact on Dropout Rates (19 years later)

	Dependent variable:		
	Dropout rate per 100 students		
	(1)	(2)	(3)
Cicada	−0.10	−0.09	−0.10
	(0.13)	(0.15)	(0.13)
Cicada x Apples acres	0.27*		
	(0.16)		
Cicada x Bushels (decile)		0.04	
		(0.25)	
Cicada x Bushels			0.80**
			(0.33)
County FE	X	X	X
Year FE	X	X	X
State-Yr Trend	X	X	X
Observations	23,051	23,051	23,051
R^2	0.22	0.22	0.22

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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997. State-level annual time trends and county and year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Robustness

Table A11: Cicada Impact on Farm Income per Capita

	Dependent variable:					
	Farm Income ($1,000s)			Farm Income (Log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Cicada	-1.032^{*}	-0.899	-0.909	-0.057^{*}	-0.055^{*}	-0.056^{*}
	(0.608)	(0.597)	(0.600)	(0.032)	(0.030)	(0.030)
Cicada x Apples Acres	1.058			0.028		
	(1.090)			(0.030)		
Cicada x Bushels (decile)		0.428			0.057	
		(1.029)			(0.051)	
Cicada x Bushels			0.268			0.025
			(0.407)			(0.020)
County FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State-Yr Trend	X	X	X	X	X	X
Observations	118,232	118,232	118,232	105,746	105,746	105,746
R^2	0.617	0.617	0.617	0.735	0.735	0.735

Notes: Linear regression. Dependent variables are BEA county-level farm income per capita from 1969 to 2016. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Cicada is a dummy variable taking the value of 1 if there is a cicada emergence in the county in that year. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997. State-level annual time trends and county and year level fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A12: Cicada-Apple Interaction Impact on Birth Rates

	Dependent variable:							
	All people (Crude)				Female Age-Specific			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cicada	0.11***	0.11***	0.12***	0.11***	0.29	0.29	0.32	0.29
	(0.03)	(0.03)	(0.04)	(0.03)	(0.21)	(0.22)	(0.28)	(0.22)
Cicada x Apple acres		−0.04				0.01		
		(0.03)				(0.10)		
Cicada x Bushels (decile)			−0.08				−0.17	
			(0.06)				(0.61)	
Cicada x Bushels				−0.05				0.06
				(0.04)				(0.24)
County FE	X	X	X	X	X	X	X	X
State-Year FE	X	X	X	X	X	X	X	X
Observations	142,193	142,193	142,193	142,193	142,193	142,193	142,193	142,193
R^2	0.84	0.84	0.84	0.84	0.73	0.73	0.73	0.73

Notes: Linear regression. Dependent variable is next-year birth rate. Models (1)-(4) show the crude birth rate (births per 1000 people). Models (5)-(8) 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. Covariates include apple acreage, a dummy for the top decile apple production, and apple production in bushels in 1997. County and state-by-year fixed effect dummies included. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01

Table A13: Maternal Characteristics in Cicada Years and Non-cicada Years

Variable	Cicada.year	Non.cicada.year	t.value
Education	12.664	12.616	-0.788
Black proportion	0.071	0.074	0.664
Weight gain	30.713	30.638	-0.426
Age	26.346	26.388	0.485
Cigarettes	1.795	1.924	1.267

Notes: Notes: Analysis includes counties in the top decile of apple production averaged over 1964 and 1997 with endemic cidadas. Maternal characteristics for those giving birth one year after a cicada event.

Table A14: Cicada Impact on Long-term Migration, 1960 to 1990 cross-section

	Dependent variable:			
	Net Migration Rate		Net Migration (1,000s)	
	(1)	(2)	(3)	(4)
Cicada Endemic	0.029	0.057*	−1.704	6.869
	(0.047)	(0.028)	(5.218)	(4.399)
Cicada x Apple Top Producer	0.046	0.012	2.178	6.124
	(0.042)	(0.031)	(7.758)	(9.463)
Constant	0.027		1.444	
	(0.044)		(4.021)	
State FE		X		X
Observations	2,423	2,423	2,423	2,423
R^2	0.002	0.153	0.0001	0.044

Notes: Linear regression. County-level cross section. Dependent variable in Models (1)-(2) is long-term migration rates calculated as the sum of net migration in the four decades between 1960 and 1990 divided by the average county population during that period. Models (3)-(4) is the sum of net migration over that time in thousands of people. Cicada Endemic is a dummy variable if cicadas are endemic to the county. Apple top prodcuer is a dummy for top decile counties in apple production at the beginging of the period in 1964. Standard errors clustered at the state level. *p<0.1; **p<0.05; ***p<0.01