# Invasive Fire Ants and the Long Term Impacts of Agroecosystem Adaptation

Michael Springborn[1]*, Joakim A. Weill[2] and Paul Mwebaze[3]

[1]Environmental Science and Policy, University of California, Davis, USA

[2]Federal Reserve Board of Governors

[3]University of Illinois, Urbana-Champaign

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> "It would appear that socialism really works in some circumstances. Karl Marx just had the wrong species."
>
> — Bert Hölldobler and Edward O. Wilson, Journey to the Ants: A Story of Scientific Exploration

**Abstract**

Imported fire ants (IFA) rank among the most ecologically disruptive non-native species, but their impacts on economic activities and well-being are not well understood. This paper leverages historical data spanning 75 years of IFA spread in the U.S., alongside health and agricultural records, to quantify the agricultural and human impacts of a major biological invasion. We find that IFA altered cropping outcomes, reduced pesticide use, and reduced infant mortality. Our findings highlight the complex and sometimes unexpected consequences of biological invasions on agricultural systems and human welfare.

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# 1 Introduction

International trade and travel have enabled the accidental introduction and spread of non-native species, causing major disruptions to ecological and human systems. Among introduced species, ants excel through their sophisticated social organization—a trait that influential entomologists Hölldobler and Wilson (1994) compared to the structure of human economic systems in the quote above. Imported fire ants (IFA) are a particularly successful invader: native to South America, they have spread to four other continents and are listed among the "World's Worst Invasive Alien Species" (Lowe et al., 2000; Wylie et al., 2020). Introduced accidentally in Mobile, Alabama, in 1918, IFA have since expanded throughout the U.S. southeast, covering more than 367 million acres across 14 states (USDA-APHIS, 2022).

While some non-native species impacts to economic activities and human welfare are immediate and obvious, others unfold gradually over time and are harder to identify. IFA, for example, are known to cause direct and widespread impacts: they damage crops and agricultural equipment, alter ecosystems by preying on native fauna and modifying soil structures, and send people to the hospital with painful stings. Many of these effects become evident quickly upon arrival of IFA and are well documented (Lard et al., 2006). Yet, given the scale of IFA's agroecosystem disruption, their impacts may intensify or ripple out over time—both as their invasion spreads and as agriculture adapts to this shock. Decades ago, Wilson (1958) observed that "[s]ome farmers who have heavily infested land are unable to hire sufficient help, and are forced to abandon land to the [imported fire] ants." However, IFA's long-term and indirect effects on agriculture and pesticide use remain uncertain. While their role as a major pest likely drove increased pesticide application, IFA also prey on crop pests, potentially reducing the need for chemical control (Wright et al., 1999; Williams et al., 2001). These opposing forces suggest a complex and evolving agricultural response, with broader implications for economic and human systems.

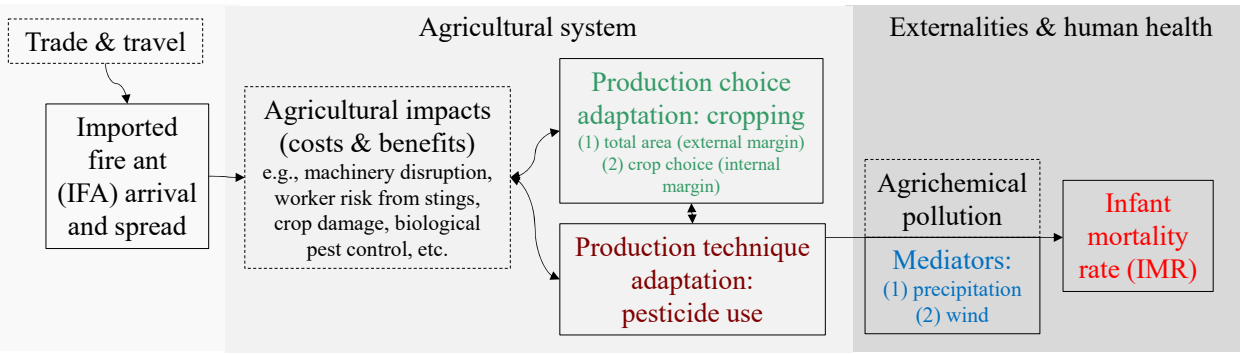
In this paper, we investigate the long-term effects of IFA on agriculture and infant mortality, as illustrated in Figure 1. We estimate how IFA affected human health and explore agricultural adaptation pathways by which these effects may have operated, i.e., through changes in area cropped, crop allocation, and pesticide application. We leverage data on the historical spread of IFA between 1918 and 2024 at the county-level, merged with historical USDA data on agricultural production (cotton and soybeans), recently developed historical series on overall crop area, USGS pesticide use estimates, and restricted health records on infant mortality. To identify the causal effects of

the biological invasion, we leverage the quasi-random variation generated by the introduction and spread of IFA, which are now present in over 900 counties and continue to spread.

We find that IFA lead to a strong and persistent *decline* in infant mortality: after the arrival of IFA in a county, the infant mortality rate (IMR, deaths relative to live births) gradually declines over the next three decades. The estimated effects are large—in our baseline specification, we find that IFA led to an average annual decline in the IMR of 1.47, equivalent to 3.6% of the overall decline in IMR during our study period (1942-2016). Heterogeneity analysis shows that estimated IMR effects are larger: (1) in less windy counties, (2) in counties with higher crop area and precipitation, and (3) for the nonwhite population. This is consistent with wind reducing exposure to pesticide spray drift, precipitation-driven mobilization of pesticide residues into water supplies, and nonwhite populations having more exposure to environmental contaminants. Agriculture sector results show that IFA have an negative estimated effect on pesticide use and overall crop area. Soybeans are a crop for which IFA would be expected to have substantial negative effects, which is confirmed by our finding of reduced area harvested. However, for cotton, for which IFA serve as an important biological control for pre-existing pests, we find a more gradual but consistent *increase* in area harvested. While IMR and crop area have declined substantially over time within our study area, we provide evidence in robustness tests that IMR and crop area results are not driven by these secular trends. Our results suggest that—in addition to the well-known negative impacts of IFA previously recorded—the arrival of these ants had long term benefits to human health likely stemming, at least in part, from adaptations in agricultural crop production choices and pesticide input use.

Our paper first contributes to the economics of biodiversity and ecosystem valuation literatures (Weitzman, 1992, 1998; Dasgupta, 2021). In particular, an emerging empirical literature exploits natural experiments to study the causal effects of individual species emergence or decline, as well as

Figure 1: Schematic of potential agricultural and human health impacts of IFA invasion.



the unintended consequences stemming from human responses (Larsen et al., 2024). Frank (2024) shows that the loss of bat populations in the U.S. due to the white-nose syndrome led farmers to increase pesticide use to substitute for the loss of natural pest controls, which increased human infant mortality. Taylor (2022) and Fletcher and Noghanibehambari (2024) find that spikes in agricultural pest pressure from the periodic emergence of cicada populations led to concurrent waves of increased pesticide use, which increased infant mortality and later-life male mortality. Frank and Sudarshan (2024) show that the expanded veterinary use of the painkiller diclofenac in India caused a dramatic loss of vultures and the livestock carcass removal service they provided, leading to a "large negative sanitation shock". Springborn et al. (2022) estimate that sudden loss of amphibian populations in Central America—decimated by a fungal pathogen—led to a spike in human incidence of malaria (likely due to an increase in mosquito populations). Our paper extends this literature by investigating the very long term impacts of an invasive species and highlighting its counter-intuitive benefits for infant health.

This paper also adds to the extensive body of research on drivers and impacts of agricultural adaptation (Hornbeck, 2010; Moscona and Sastry, 2023; Missirian, 2024), particularly in response to environmental change (Deschênes and Greenstone, 2007; Howden et al., 2007; Burke and Emerick, 2016; Carter et al., 2018; Sanders and Barreca, 2022). While most of this work focuses on agricultural adaptation to weather shocks and climate change, the impacts of biological invasions has remained understudied. Our work is closely related to a set of studies examining the spread of the boll weevil in the southern U.S. between 1892–1922 (Lange et al., 2009; Ager et al., 2017; Baker et al., 2020; Ager et al., 2020). We extend this literature by examining a particularly large scale and ongoing biological invasion, providing new insight into IFA's long run effects on agricultural activities.

Finally, we contribute to the environmental and health literature studying negative externalities posed by agricultural production and pesticide use (Larsen et al., 2017; Taylor, 2022; Dias et al., 2023; Skidmore et al., 2023; Frank, 2024; Reynier and Rubin, 2025). Kolok et al. (2023) note that "incidental (nonoccupational) pesticide exposure and adverse human health impacts has not been thoroughly studied and remains poorly understood". We also contribute to the study of the distribution of effects from this negative externality. Mirroring patterns for pollution more broadly, previous work has shown evidence of disparities in pesticide impacts. For example, (Donley et al., 2022) show that African American and Hispanic populations in the U.S. exhibit high urinary pesticide concentrations relative to white populations. Our results are consistent with this literature, though in our setting this emerges via (partial) amelioration of disparities.

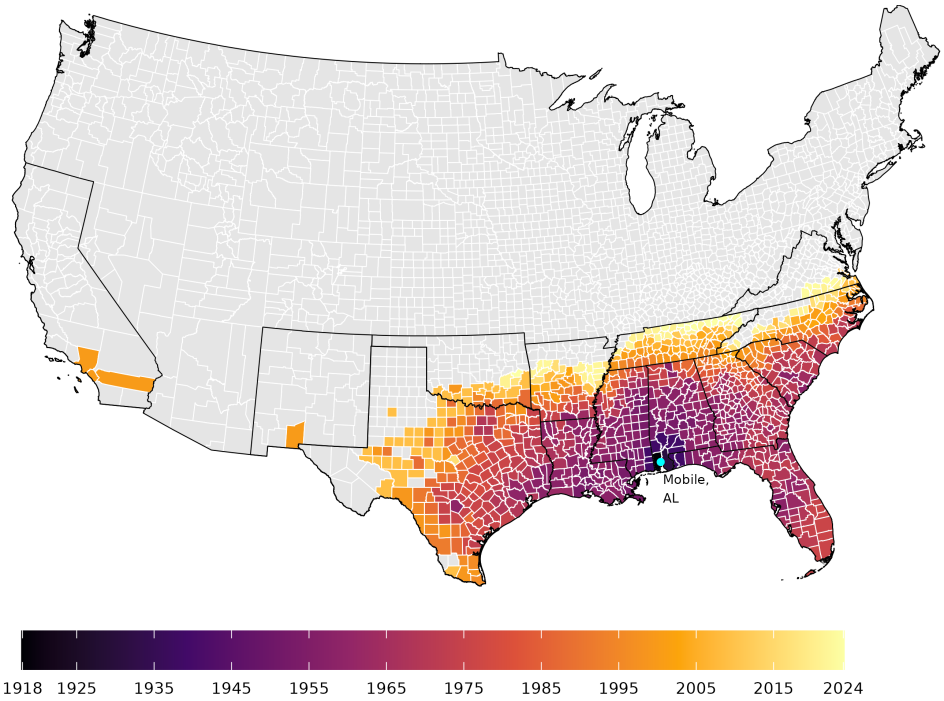
We begin in the next section by detailing key features of the IFA invasion, including current understanding of their impacts as well as public and private sector management responses. In Section 3 we present details and descriptive statistics for our data on IFA spread, population, health, agriculture, and weather outcomes. In Section 4 we specify our event study methodology and model variations considered for robustness before turning to results and discussion.

## 2 IFA background: ecology, impacts and response

Invasive IFA in the U.S. include red IFA and black IFA, or *Solenopsis invicta* and *Solenopsis richteri*, respectively. While red IFA is much more widespread, these two closely related species from South America often hybridize where they overlap. Once IFA colonies are known to exist in an area, the federal government establishes a quarantine for the invaded county. Our IFA arrival data is thus given by the year of federal quarantine for each county (discussed further below) as collated by the USDA Animal and Plant Health Inspection Service (APHIS) in their publicly available Imported Fire Ant Federal Quarantine map (USDA-APHIS, 2024). The dataset, extracted by USDA personnel and provided via email, covers the period between January of 1918 through mid-February of 2024. The timing of this 107-year invasion is mapped in Figure 2, which shows arrival in the Mobile, Alabama region and subsequent spread in all land directions. The cumulative number of counties invaded over time is shown in Appendix Figure A2. Based on this data, USDA-APHIS (2018) estimated the average spread rate at 11km per year for the period 1917-2017, though the rate slowed to 7km per year in the last several decades (1972-2017).

The distinctive biology of invading IFA species underscores why they might be expected to be unusually impactful. Ant species typically follow a *multicolonial* structure, which involves one queen in a nest, broad dispersal of new queens forming new colonies and aggression between neighboring colonies (Helanterä et al., 2009). In contrast, invasive IFA in the U.S. often show *unicolonial* social organization featuring supercolonies comprised of a network reaching "hundreds or thousands of nests, each with multiple queens" with increased genetic homogeneity. Ant nests within a supercolony eschew "behavioral boundaries (aggression)" (Pedersen et al., 2006) in favor of forming "the most extensive cooperative units known in nature" sometimes spanning hundreds of kilometers, "turn(ing) their extreme cooperation into extreme ecological dominance" (Helanterä et al., 2009).

Figure 2: Year of IFA federal quarantine by U.S. county.




Notes: Data are from the Imported Fire Ant Federal Quarantine map (USDA-APHIS, 2024), re-plotted here along with state boundaries for invaded states.

## 2.1 IFA impacts

Invading IFA have wide-ranging impacts on welfare including stinging people as well as damaging and disrupting infrastructure, ecosystems and agriculture. IFA stings are very painful, can cause severe allergic reactions and, in rare instances, anaphylactic shock and death (Solley et al., 2002; Lard et al., 2006). Annually, up to 50% of people living in fire ant areas are stung (deShazo et al., 1990) with an estimated 14 million people stung in the U.S. southeast (Drees, 2002). Anaphylaxis occurs in up to 6% of the individuals who are stung; the most recent survey results available attribute more than 80 deaths to anaphylactic reactions to fire ant stings (deShazo et al., 1990). Even simply the risk of exposure to IFA stings affects lifestyle choices, particularly recreational activities (Jetter et al., 2002). IFA damage infrastructure by chewing through material and depositing nesting material, showing a particular inclination for electrical equipment (APCP, 2025). IFA are efficient at displacing competing ant species and other invertebrates in ecosystems and often inflict damage to ground-nesting birds and mammals (Wright et al., 1999; Allen et al., 1995; Wojcik et al., 2001). In agricultural settings, Lard et al. (2006) note that IFA feed on crops, infest equipment (machinery, irrigation and electrical systems), and are a nuisance or worse for livestock and workers. A historical

photograph from Wilson (1958), shown in Appendix Figure A1, illustrates IFA mounds that "interfere with plowing and harvesting". Lard et al.'s (2006) rough estimate of the negative "economic impact" on agricultural was $428 million (in 1999 dollars). Including all sectors considered—control costs, medical and veterinary expenditures, electrical and agricultural equipment costs and losses, and crop and livestock losses—they estimate that the annual negative economic impact was $5.6 billion.[1]

## 2.2 Public and private responses to IFA and their health implications

The Federal regulatory program for IFA was enacted in 1958 with the initial goal of eradication (USDA, 2018). In 1972, the program's goal changed to pest containment by preventing the human-assisted spread of these species through a Federal quarantine that regulates the movement of commodities at high risk for transporting IFA. The quarantine program required certain regulated articles (such as nursery stock, sod and soil) not to be moved out of infested areas without proper treatment.

The widespread use of pesticides in IFA management has raised significant health concerns, particularly regarding infant health (Sittiwang et al., 2022). Organochlorides, once heavily used, persist in the environment, accumulating in soil and water. These chemicals have been linked to neurological disorders, developmental delays, and endocrine disruption, increasing risks of low birth weight and congenital abnormalities (von Ehrenstein et al., 2019). While largely phased out, their legacy contamination still poses long-term health risks in regions where they were extensively applied. Organophosphates, such as acephate and chlorpyrifos, were introduced as alternatives but come with acute neurotoxic risks. These chemicals interfere with nervous system development, leading to reduced IQ, attention deficits, and increased rates of preterm birth and respiratory distress—all factors linked to higher IMR. In recent decades, insect growth regulators (e.g., methoprene) along with bait formulations have been widely adopted, providing more selective and less environmentally damaging options (Oi et al., 2008). However, questions remain about their long-term endocrine effects and water contamination risks.

Non-pesticide methods for managing IFA, including physical and biological control, have been explored since the failure of early eradication efforts with chemical treatments in the 1950s and 1960s (Williams and deShazo, 2004). While these methods have been helpful for control in some

[1] Adjusting for inflation, in 2025 dollars these figures rise to $685 million and $10.1 billion, respectively. Additionally, the IFA invasion front has progressed since these estimates were generated.

areas, their overall impact on IFA populations has been slow and inconsistent, leading to their use mainly as a supplement rather than a replacement for pesticides (Drees and Gold, 2003). Biological control methods involve the introduction of natural predators and pathogens like decapitating phorid flies from the *Pseudacteon* genus and the parasitic protozoan *Thelohania solenopsae* (Williams and deShazo, 2004; Oi et al., 2008). Physical control methods—vegetation management, flooding of mounds, and mechanical barriers—have been employed with varying success. For example, frequent disturbance of mounds can discourage colony establishment, but re-invasion from untreated areas remains a challenge (Drees et al., 2013). While these non-chemical methods contribute to reducing fire ant densities, their effectiveness is highly site-dependent, making them less reliable as standalone control measures. Consequently, farmers and land managers have continued to rely primarily on pesticides, with non-chemical methods serving as complementary tools in integrated pest management programs (Drees and Gold, 2003). Overall, despite pesticide and non-pesticide control measures, IFA have continued to slowly but steadily expand in all land directions, as shown in Figure 2.

### 2.3 Crop-specific impacts and responses

In our analysis of crop-specific responses to IFA, we focus on soybeans and cotton because they have been widely grown over a long time frame in the U.S., produced with substantial pesticide use, and are expected to be impacted strongly—but differentially—by IFA. From the late 1940s through the 1980s, cotton was among the most pesticide-intensive crops, with an estimated one-third to one-half of all pesticides applied in the U.S. being used for cotton farming (Haney, 2001). Key pests such as the boll weevil (Anthonomus grandis), bollworm (Helicoverpa zea), and tobacco budworm (Chloridea virescens) drove extensive use of synthetic insecticides, including organophosphates, carbamates, and pyrethroids (Williams et al., 2001). Soybeans historically required fewer insecticides but have faced growing threats from soybean aphids (Aphis glycines), caterpillars, and stink bugs, prompting increased pesticide reliance in recent decades.

In soybean crops, IFA are generally detrimental both directly and indirectly (Jetter et al., 2002; Willis et al., 2001). They directly feed on seeds, young seedlings, and pods. This reduces germination, plant stand, and overall yield. IFA also protect aphids in order to feed on their honeydew. Such aphids extract sap from soybean plants and serve as a vector for various plant viruses. However, for cotton a more mixed set of impacts emerge where these ants act as both a pest and a beneficial insect. In cotton fields, IFA have been observed preying on key cotton pests

such as the boll weevil (*Anthonomus grandis*) and the cotton bollworm (*Helicoverpa zea*), specifically by feeding on the eggs and larvae of these pests (Jetter et al., 2002). This predatory behavior has led some researchers to consider IFA a natural biological control agent in cotton fields (Wright et al., 1999). Field experiments in Texas showed that IFA can significantly decrease bollworms and increase yields (Jetter et al., 2002).[2] Such beneficial impacts are not limited to cotton crops. IFA have also been observed to suppress pests in the production of sugarcane and pecans (Wright et al., 1999), prey on mites, horn flies and ticks plaguing livestock (Vinson, 2013), reduce rodents (Lard et al., 2006) and improve soil fertility by promoting aeration and redistribution of minerals (Jemal and Hugh-Jones, 1993).

# 3 Data

## 3.1 Health and population

Annual data on births, infant mortality and population are assembled from two sources. For 1942-1988 we use Inter-university Consortium for Political and Social Research (ICPSR) publicly available data on county-Level natality and mortality (Bailey et al., 2018). We use ICPSR's favored "fixed" variables wherever these are present. Since ICPSR masks counties with population below 100,000 after 1988, for 1989-2016 we obtained, by confidential agreement, the National Center for Health Statistics (NCHS) Compressed Mortality File 1989-1998 and 1999-2016 (NCHS, 2007; 2017). We focus on births and infant mortality by county of residence (and not occurrence). Infant deaths include those with the first 365 days of life. Our key metric is the annual infant mortality rate (IMR), which is the ratio of infant deaths to births. We are not able to differentiate between internal and external causes of mortality, e.g., as done by Frank (2024), since this distinction in the data is only available after 1988.[3] To address changes over time in county boundaries and county codes—Federal Information Processing Standards (FIPS) identifiers—we used the county crosswalk by Eckert et al. (2020).[4] For additional details on IMR data, see Appendix B.1.

[2] In two study areas in Texas, Sterling (1978) found that IFA consumed a weekly average of 22-66% of weevils and up to 85% of weevils at the consumption peak.

[3] Frank (2024) finds practically identical results for IMR whether using counts based on all causes of death or excluding external causes (accidents and homicides). His focus on health outcomes post-1988 also allows him to use infant mortality from external causes as a placebo test and finds (as expected) that this outcome does not show a statistically significant relationship with treatment.

[4] Most of these were instances in which a previously distinct county was consolidated into another county or simply renamed.

### 3.2 Agriculture

We leverage multiple agricultural metrics including the county fraction crop area in general, crop-specific outcomes and pesticide use. For annual fraction of each county devoted to cropland from 1915-2020, we use the annual 1km x 1km raster generated by Li et al. (2023) from their U.S. land use and land cover (LULC) datasets available at Li et al. (2022). To reconstruct these data, the Li et al. used multiple input datasets including "satellite-based LULC data (National Land Cover Database, NLCD), model-based land use datasets (i.e., HYDE3.2 baseline), census and inventory data, and other auxiliary data". Using county boundary shape files, we aggregated across pixels to generate the county-level cropland fraction.[5]

For levels of specific crops—cotton (acres harvested, 1947-2023) and soybean (acres harvested and production bushels, 1949-2023) we use data from the USDA's National Agricultural Statistics Service (NASS) Quick Stats database (USDA-NASS, 2024). Finally, for levels of pesticide application in agriculture from 1992-2019 in mass, we use output from the U.S. Geological Survey's National Water-Quality Assessment Project, specifically the Pesticide National Synthesis Project county-level pesticide use estimates (2023)–see Appendix B.2 for more details. Because IFA can plausibly impact insects, arachnids (ticks and mites), and weeds (as discussed above) we do not differentiate between insecticides and non-insecticides, in contrast to related prior studies (e.g., Taylor 2022; Frank 2024) for which an insecticide-specific effect was expected.

### 3.3 Weather

For annual precipitation we use NOAA's Climate Division Data (2024) which include county-level measures based on area-weighted averages of gridded estimates interpolated from weather station observations. We aggregate from the monthly to annual time step for 1915-2023. Global Wind Atlas (GWA) data on mean wind speed at a height of 10m on a 250m x 250m raster developed by Davis et al. (2023) was downloaded from Technical University of Denmark (2024). This GWA metric is a contemporary estimate based on downscaling coarser resolution (25-100km) data using fine scale topographic information and linearized flow modeling. We aggregate across pixels in the raster data to generate county-level averages.

[5]For their metric Li et al. (2023) focus on "cropland harvested area", which is intended to capture "row crops and closely sown crops, hay and silage crops, tree fruits, small fruits, berries, tree nuts, vegetables and melons, and miscellaneous other minor crops".

Table 1: Summary statistics

| Variable | N | Mean | Std. Dev. | Years | Source |
|---|---|---|---|---|---|
| Infant mortality rate per 1,000 births: | | | | | |
| All | 70,125 | 20.4 | 16.4 | 1942-2016 | |
| Whites | 52,012 | 11.4 | 11.7 | 1959-2016 | Bailey et al. (2018), NCHS (2007; 2017) |
| Nonwhites | 52,012 | 20.5 | 32.5 | 1959-2016 | |
| Births | 70,125 | 1,231 | 5,364 | 1942-2016 | |
| Population | 70,070 | 70,539 | 305,043 | 1942-2016 | |
| Overall crop fraction | 99,428 | 0.149 | 0.166 | 1915-2020 | Li et al. (2022; 2023) |
| Overall crop area ($km^2$) | 99,428 | 242 | 288 | 1915-2020 | |
| Cotton area harv. (acres, K) | 33,693 | 7.95 | 16.3 | 1947-2023 | USDA-NASS (2024) |
| Soybean area harv. (acres, K) | 15,900 | 16.4 | 37 | 1949-2023 | |
| Soybean prod. (bushels, M) | 15,900 | 0.482 | 1.21 | 1949-2023 | |
| Pesticide use (t) | 26,002 | 125 | 330 | 1992-2019 | USGS-NAWQA (2023) |
| Pesticide use ($kg/km^2$) | 26,002 | 73.1 | 153 | 1992-2019 | |
| Precipitation (in.) | 99,428 | 48.7 | 10.4 | 1915-2020 | NOAA-CDD (2024) |
| Wind (average, m/sec.) | 938 | 3.12 | 0.657 | N.A. | Davis et al. (2023) |

Notes: All variables are at the county-year level except for wind, which is county-only. m/sec. = meters per second; K = thousands; M = millions; t = metric ton.

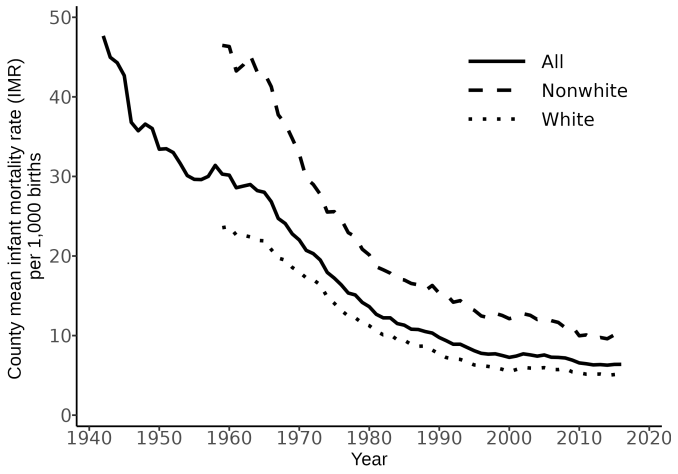
### 3.4 Descriptive statistics

In Table 1 we present summary statistics for variables used in our analysis. Figure 3 shows the annual mean of our main outcome variable, IMR, for the units included in our sample. We show the mean IMR for all infants—the focus of our main event study results in Section 5.1—and disaggregated into white and nonwhite subgroups. The IMR has declined substantially over our period of study; in Section 5.2 we assess the implications of this dynamic for our results. Mean annual IMR is 70-122% higher for nonwhites relative to whites across the 1959-2016 sample shown in Figure 3. We explore race subgroup estimates further in Section 5.3. Appendix Figure A12 shows annual mean levels for county crop area and pesticide use.

## 4 Event study methods and model variations

Our setting involves a large number of units (counties) treated at different times (with the arrival of IFA). Several recent papers highlight that when treatment effects are heterogeneous across cohorts, the two-way fixed effects (TWFE) estimator fails to recover a coherent average treatment effect, and

Figure 3: Mean annual infant mortality rate (IMR) for sample counties.




Notes: Means are county population-weighted. Year ranges are 1942-2016 for All and 1959-2016 for subgroups.

a heterogeneity-robust estimator should be used instead (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2021b; Sun and Abraham, 2021; Borusyak et al., 2024). In our case, "treatment" is staggered over several decades, and there is a priori no reason to expect that agricultural and/or human health outcomes would be uniformly affected across time and counties.

We use the estimator developed by Callaway and Sant'Anna (2021b) to recover the effect of IFA.[6] This choice is guided by the assumptions required for causal identification in the Callaway and Sant'Anna (2021b) setting, are plausible in our setting: (i) no (or limited) anticipation of treatment, (ii) (conditional) parallel trends in potential outcomes, (iii) absence of spatial spillovers (SUTVA).

Assumption (i) and (iii) are likely to hold because the full effects of IFA take time to materialize: the population of ants progressively build up for a few years after invasion, which makes it unlikely that farmers in un-invaded counties would adjust their agricultural activities before even seeing the first ant.

Assumption (ii) requires that our outcomes of interest (infant mortality, agricultural production, and pesticide use) would have evolved in parallel between treated and control units in the absence of treatment. This assumption is unlikely to hold across the entire United States, as the counties invaded by IFA in 2024 are predominantly in the South, and Southern and Northern counties

[6]The Callaway and Sant'Anna (CS) estimator generates difference-in-difference estimates for each cohort which are then re-aggregated to produce event-study estimates that are free of the known bias in TWFE estimates. We implement the estimator using the R package *did*, version 2.1.2 (Callaway and Sant'Anna, 2021a).

diverged along several dimensions over the 20th century. Accordingly, we restrict all our analyses to counties that are *eventually* invaded by IFA, and compare counties that are treated to counties that are treated later. All these counties are located in states below the parallel 36° north (see Figure 2).

There are two main potential threats to identification in our setting. First, despite our focus on invaded counties below the parallel 36° north, over the 20th century there might have been potential bio-climatic dynamics that unfolded in a systematic south-to-north direction. We note that from their initial establishment point in Alabama, IFA have spread further to the east and west than to the north and, furthermore, have spread roughly as far south into Texas and Florida as they have to Virginia in the north. Bio-climatic dynamics are therefore unlikely to have unfolded similarly in all directions from Mobile, Alabama. Second, infant mortality and crop area both declined substantially over our study period (Figure 3), and one might be concerned that our estimates could randomly pick up these dynamics. In placebo robustness checks below we provide evidence that IMR and crop area results are not driven by these overall trends.

In addition to estimating the effects of IFA across our entire sample, our research design also involves assessing heterogeneous sub-sample effects, i.e., whether and how estimates might vary based on the level of ecologically relevant variables.[7] These variables include county crop coverage, population density and weather (precipitation and wind). As discussed further below, these variables are intended to provide additional insights into possible mechanisms of the main effect, as they serve as windows into role of drivers of pre-existing pesticide exposure, fate and transport of pesticide contaminants and or quality of infrastructure to mitigate pesticide impacts.

When such a heterogeneity variable not only changes over time but is conceivably affected by treatment (arrival of IFA), this presents a design challenge. In particular crop coverage itself may shift subsequent to arrival of IFA (as we explore further below). In this case, for each county we use the crop coverage over the five years preceding treatment of the first unit, i.e., 1937-1941 in the case of our IMR sample.[8] Population density and precipitation are also dynamic but arguably not affected by treatment. Thus we use the mean over the IMR sample period (1942-2016). Finally, since wind speed is arguably exogenous and only available as a contemporary measure, we use estimates produced in 2023.

[7]This is distinct from the notion central to several recent advances in Difference-in-Differences addressing robust estimation in the presence of treatment effect heterogeneity, where the effect of participating in the treatment varies across units.

[8]Selecting, alternatively, crop coverage the year before treatment for each county would have the benefit of anchoring to a level present at the most relevant time (treatment) but when levels are changing systematically over time, this complicates the interpretation of the subsample. For example, if a given variable is falling over time, units in a lower quantile are more likely to be later treated units.

# 5 Results

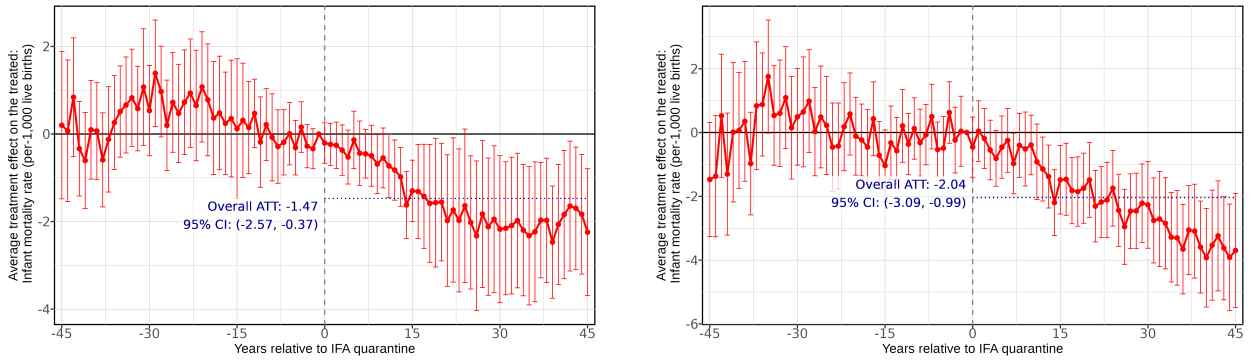
Unless otherwise noted, when reporting statistical significance of individual coefficients or the overall average treatment effect on the treated (ATT), we use the 5% level. The overall ATT represents the average of the event study coefficients estimated across a given treatment time horizon (e.g. as depicted in a given figure).

## 5.1 Infant mortality rate

Figure 4 presents event study estimates of the effect of IFA arrival on IMR, both with county population weights (4a) and without (4b). The regression weighted by population count reflects the area population average effect, while the unweighted estimates reflect the county average. For all of our IMR estimates, we present estimates over a 90-year event time horizon that spans from -45 to 45, with year 0 indicating the year of treatment. We find that subsequent to treatment, estimated coefficients begin to decline and become statistically significant after a decade. The county population-weighted overall ATT estimate is -1.47, representing a 7.2% decline in the annual IMR on average across the 45-years following IFA arrival, relative to the IMR average in our sample. This constitutes 3.6% of the overall decline in IMR observed between 1942 and 2016 (see Figure 3). While the estimated pre-treatment coefficients are noisy and not statistically different from zero, point estimates are declining from pretreatment year -20 to -10. This raises some concern about pre-trends and thus the key assumption of parallel trends. The estimates without population weights (4b) show negligible evidence of pre-trends, as well as treatment effects of stronger magnitude: the overall ATT estimate is approximately one-third greater and the maximum magnitude of individual coefficients is almost double.

In Appendix Figure A3 we explore the robustness of the event study estimates to the inclusion of covariates. Including wind in the model has no discernible effect on pre-trends and post-treatment coefficients, while including precipitation and crop land use fraction shows negligible evidence of pre-trends as well as treatment effects of stronger magnitude, where the overall ATT estimate is approximately one-third greater. Based on this evidence—and further evidence from county population quartile sub-samples presented below—we conclude that pre-trend concerns are minimal. Going forward we elect to focus on the base model without covariates as shown in Figure 4 for simplicity and because it represents a conservative estimate of the effect size relative to the extended models just discussed.

Figure 4: Estimated event study coefficients for infant mortality rate




(a) With county population weights

(b) Without county population weights

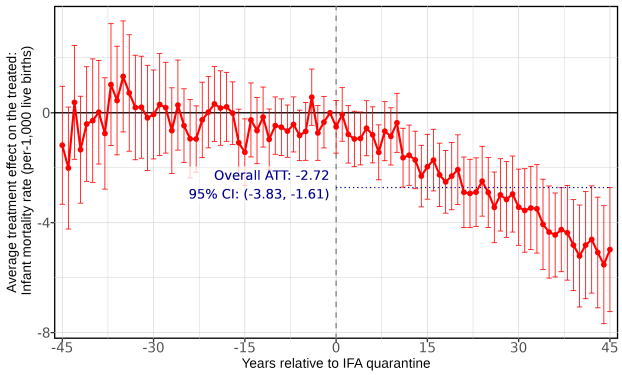
Notes: Figure 4 reports the event study estimates for the infant mortality rate outcome. County population weights are annual and whiskers represent the 95% confidence intervals.

### 5.1.1 Heterogeneity analysis

In our exploration of how IMR effects might differ by sub-samples based on quantiles of key variables, we first consider samples based on a single variable before extending the analysis to the intersection of quantiles for two variables. In Appendix Figure A4 we present estimates based on county population quartile sub-samples. While estimates are noisier due to smaller sub-sample sizes, the same pattern of increasingly negative effects on IMR is evident for each quartile. Effect sizes are most pronounced for the bottom three population quartiles and less pronounced for the most populous counties. When the sample is restricted to the lowest three population quartiles as shown in Figure 5 pre-trend concerns are minimal and effect sizes roughly double relative to the full sample.

We next turn to sub-samples based on variables that might be associated with the magnitude of the behavioral response and/or the fate and transport of pesticide contaminants: county crop coverage and population density and weather (precipitation and wind). For this univariate analysis, where each variable is considered separately in turn, in Appendix Figure A5 we present event study estimates for county sub-samples divided simply into below the median (left column) and above (right column). For two variables—precipitation and crop coverage—there is no substantial difference between sub-sample estimates, which essentially reflect those of the full sample. We return to these two variables below where a potential role does emerge once considered with other factors. For the other two variables we find substantial differences between sub-samples. First, we find that estimates for counties with population density below the median are over twice as strong as counties above. This could arise due to differences either in either levels of contaminants in the

Figure 5: Estimated event study coefficients for infant mortality rate for the first three population quartiles combined.




Notes: Figure 5 reports the event study estimates for the infant mortality rate outcome with county population weights based on a subsample that include the first three county population quartiles (i.e., excluding counties in the fourth quartile). Whiskers represent the 95% confidence intervals.

environment and/or differences in infrastructure. For example, more rural communities on average lag in water quality treatment capacity (Gasteyer and Vaswani, 2004). We also find that estimates are roughly double for counties with below median wind and not distinguishable from zero for those above. This would be consistent with wind dispersing airborne pollutants. For spread of potential pesticide toxins through the air, there are two main types of transport: primary drift at the moment of original application and later secondary drift through mobilization of residue on plants, dust and soil (Deziel et al., 2015). In the case of primary drift, it is intuitive that wind would generally serve to clear these particles from the airshed in which they were released. For secondary drift the net result is less straightforward: wind could conceivably serve both to mobilize this contaminant but also to clear it from its origin.

Given that human health impacts are arguably a combination of contaminant production and exposure as governed by subsequent fate and transport, we next consider sub-samples based on intersections of two variables. We present estimates based on the intersection of crop coverage with wind in Appendix Figure A6 and with precipitation in A7.[9] In the case of wind, we find negative and significant effects for all sub-samples except for below-median crop coverage and above-median wind. For these counties we might expect lower agricultural pesticide use and higher flushing of primary drift from wind. Effect magnitudes are strongest for below-median wind, mirroring univariate results.

[9]While the sample sizes for each subsample are not equal given the intersection of medians for two variables, for sub-samples considered here in Figures A6 and A7 the minimum of units (184) is not far from one quarter of the total number of units (230).

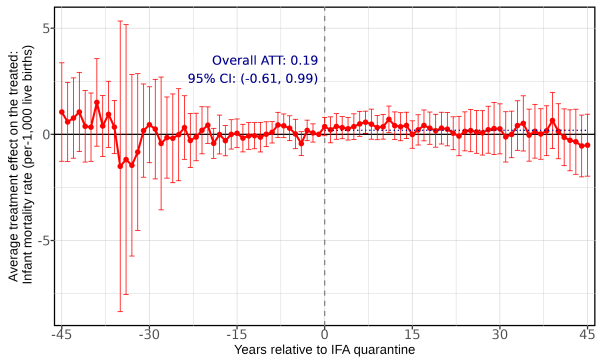
A priori, the effect of increasing precipitation on eventual human exposure to pesticides is not clear and not necessarily monotonic. Precipitation can mobilize pesticides from plants, dust and soil into water supplies. On the other hand, increasing precipitation could also dilute pollutants in water flows on the ground and/or serve to reduce air pollution by removal from the air (wet deposition) or reducing wind-borne transport of pesticide-laced dust and soil particles. In contrast with univariate results from above wherein no substantial difference was found for either variable, when crop coverage and precipitation sub-samples are intersected—as shown in Appendix Figure A7—we find interesting heterogeneity in effects. The starkest result is that when crop coverage and precipitation are both above their median, the magnitude of the effect is roughly double that of our full sample result. This would be consistent with precipitation-driven mobilization of pesticide residues into water supplies. We also note that even when crop coverage and precipitation are below their median, we find a negative and significant effect, below but of similar magnitude to our full sample results. This, taken together with wind results from above suggests that if indeed the mechanism operates through pesticide exposure, the evidence is consistent with both airshed and water-borne exposure.

In our final bivariate analysis, we consider sub-samples from intersecting medians of population density and weather variables. Intersecting population density and wind (not shown) simply reinforces univariate results: the strongest effects (triple the magnitude of the full sample result) emerges when both variables are below their median (and when both are above their median the estimate is indistinguishable from zero). Results for population density and precipitation are shown in Figure A8. The starkest outcome is that counties with below median population but above median precipitation show an effect magnitude more than double that of the full sample (while the other sub-sample estimates range from just below to around half the magnitude from the full sample). This result would be consistent with the possibility that lagging water treatment infrastructure in lower population density areas is a modulating factor in exposure to pesticides.

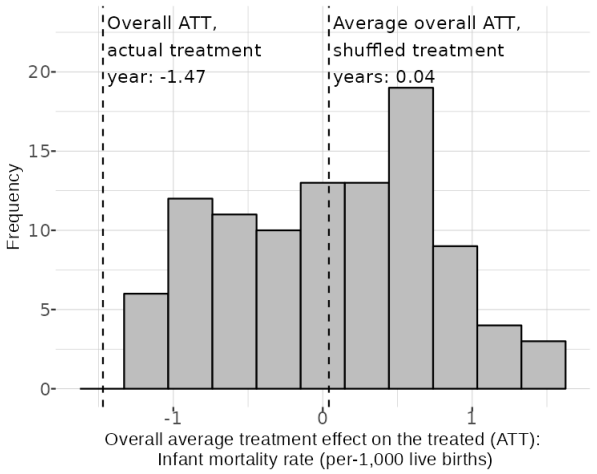
### 5.2 Placebo test

A potential concern with our result above—infant mortality declines subsequent to IFA arrival—is that our event-study estimates could be picking up the general dynamics of the long downward trend in IMR shown in Figure 3. If this were the case, we would expect to see similar event-study coefficients (declining IMR over time) regardless of where counties treated in a given year are located. To assess how "unlikely" our estimates are if they were purely due to chance, we implement

Figure 6: Event-study estimates for infant mortality rate from a placebo test based on randomly shuffled event years across units.




(a) Event-study estimates from one pseudo-record.




(b) A histogram of overall ATT estimates from 100 pseudo-records for event year with reference values for the average value across pseudo-records and the actual value.

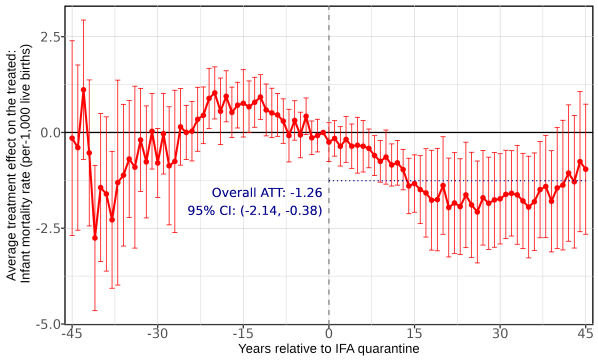
a version of Fisher's exact test by reassigning the actual vector of IFA arrival years across counties. We generate 100 such "pseudo-records" (randomly assigned vectors of arrival years) and estimate Callaway-Sant'Anna event-study coefficients for each. Figure 6a shows estimates from one run, and Figure 6b shows the histogram of the overall ATT estimates, based on all 100 runs. We find that the mean across this set of placebo ATT estimates (0.04) is near zero and the true overall ATT estimate (-1.47) lies outside the range of placebo estimates. While only suggestive, such an extreme effect is unlikely to be due to random chance and likely reflects an actual impact of fire ants on infant mortality.

### 5.3 Infant mortality outcomes for racial subpopulations

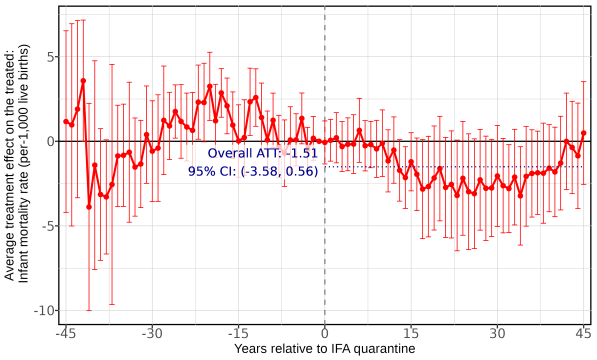
Racially disaggregated data on county-level births and infant mortality is first available in 1959 for the categories of white and nonwhite.[10] From 1959-1967, this subpopulation birth event data is not reported for almost one-third of counties (across various states and population levels). We consider two samples. The first sample is longer, spanning 1959-2016, but drops counties for all years when these data are not available between 1959-1967 (to maintain a balanced panel). The second sample (1967-2016) is shorter and, while no counties are dropped due to missing birth event data, some are

[10]Race is specified as the race of the infant through 1993 and thereafter the mother.

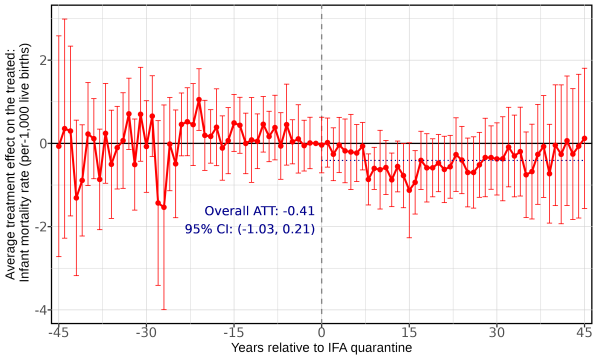
Figure 7: Estimated event study coefficients for infant mortality rate by race




(a) All.




(b) Nonwhite.




(c) White.

Notes: Figure 7 reports the event study estimates for the infant mortality rate outcome with county population weights for (a) all, (b) nonwhite and (c) white births and deaths. Data panel spans 1959-2016, county population is race-specific and whiskers represent the 95% confidence intervals.

no longer included because they are treated between 1959 and 1968.[11] We address observations with zero births (and thus an undefined IMR) in the same manner as for the main sample above—see Appendix B.1 for further details.

In Figure 7 we show event study results for the longer sample (1959-2016) with population weights. Compared to the main sample—starting in 1942, shown in Figure 4—event study results in Figure 7 for all and nonwhite show stronger pre-trend issues in the years surrounding -16 and -38. Unweighted results, shown in Appendix Figure A9), exhibit only minor pre-trend issues. Overall, the results for white IMR for both samples exhibit only minor pretend issues, emerging at the very beginning of the pre-treatment range.

Turning to overall ATT estimates with county population weights in Figure 7, the estimate

[11]The longer sample starting in 1959 includes 521 counties over 58 years. The shorter sample starting in 1968 includes 632 counties over 49 years.

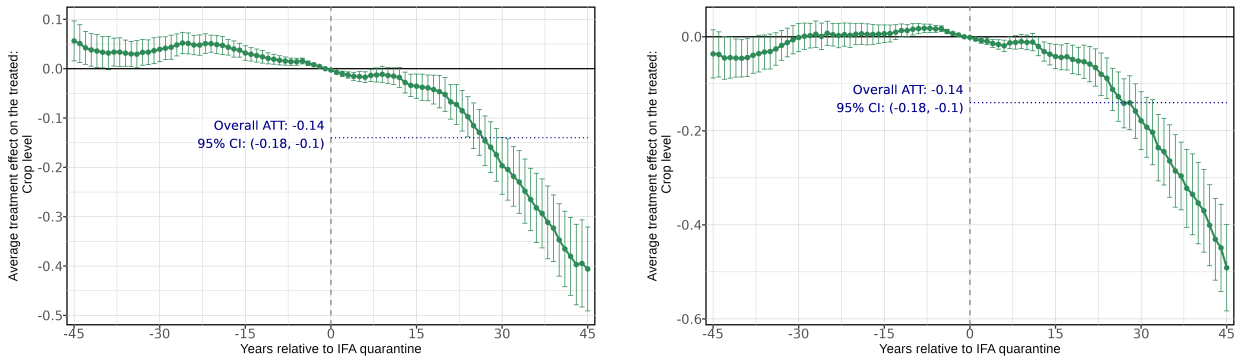
for all, i.e., the pooled sample, is -1.26. Relative to this baseline, the overall ATT magnitude for the subpopulation of whites (A9a) is smaller (-0.41) and for nonwhites is larger (-1.51). While the estimate for the pooled sample is statistically significant at the 5% level, the subpopulation estimates are noisier and not statistically significant. A handful of individual coefficients for the subpopulations are statistically significant. For the unweighted estimates in Appendix Figure A9, the results are qualitatively similar, except the overall ATT estimate for the subpopulation of whites actually becomes positive in sign but is not statistically significantly different from zero.

Results for the shorter sample starting in 1968—shown in Appendix Figures A11 and A10 (unweighted and weighted respectively)—are qualitatively similar to the longer sample results summarized above in most respects; pre-trend issues, weighted versus unweighted results, and relative subpopulation estimates. However, for the overall ATT, the divergence of the nonwhite subpopulation estimate from all is even stronger, increasing from 20% greater in magnitude in the longer sample to 74% greater in this shorter sample.

### 5.4 Agricultural outcomes

Next we estimate the effects of IFA arrival on agricultural outcomes directly, starting with overall crop area, then crop-specific effects and finally pesticide use. While the impacts on pesticide use are of most immediate relevance in our setting, pesticide use data are severely limited, only available from 1992 onward, while overall crop area data are available starting in 1915 and crop-specific data starting in late 1940's.

Figure 8: Estimated event study coefficients for log of crop area




(a) Covariates: none.

(b) Covariates: wind and precipitation.

Notes: Figure 8 reports the event study estimates for the natural log of crop area ($km^2$) outcome without and with covariates. Whiskers represent the 95% confidence intervals.

Figure 8a shows event study estimates using the natural log of county crop area as the outcome. Pre-trend coefficients are positive and significant, but they follow a relatively flat path and are small in magnitude. In contrast, post-treatment coefficients become sharply negative after ten years, with an overall ATT at -0.14. To further assess the parallel trend assumption, we estimate the same model while controlling for precipitation and wind, either together as shown in Figure 8b or separately (Appendix Figure A14). Within the Callaway-Sant'Anna framework, controlling for covariates implies that causal identification relies on a conditional parallel trend assumption. We find that controlling for covariates substantially shrinks pre-trend coefficients while post-treatment effects are either very similar (8b) or stronger (A14).

To assess whether our event-study estimates could be picking up the general dynamics of the downward trend over time in county average crop area (see Appendix Figure A12), we replicate the placebo test conducted above for the IMR outcome (using 100 "pseudo-records" that reflect randomly re-assigned event years across treated units). The results are shown in Appendix Figure A13. We find that the overall ATT estimates from these pseudo-records are centered approximately around zero—with a mean of -0.0012—and the treatment effect based on the true sample (-0.14) falls outside the distribution of these placebo estimates. Overall, these results provide further support for the causal interpretation of the effects of IFA on crop area.

We next consider the impacts of IFA on soybeans and cotton. These two crops are of particular interest because they are widely planted across our study area. The effects of IFA on these crops are expected to differ due to their distinct agroecological interactions. While IFA can have direct negative impacts on any type of agricultural production, as noted in the introduction, IFA is also a predator of common cotton pests. By altering pest pressures and production costs, IFA may influence the relative profitability of cultivating soybean versus cotton, potentially driving shifts in crop allocation toward cotton if it becomes comparatively more advantageous.

In Figure 9 we show event study estimates for the effect of IFA arrival on soybean harvested acres (9a) and production in bushels (9b) as well as harvested acres of cotton (9c).[12] Cotton estimates are based on annual data from 1947-2023 and soybean from 1949-2023. Since data for these crops is not available for some states until after a particular year, results presented here are based on a subset of states in our study region–see Appendix B.2 for further details. We discuss results for samples with fewer years but more states further below. While the models for results in Figure 9 do not include weights or covariates, in Appendix Figure A15 we show results using county crop area

[12]Production of cotton is not available as it is for soybean.

as weights and precipitation as a covariate.

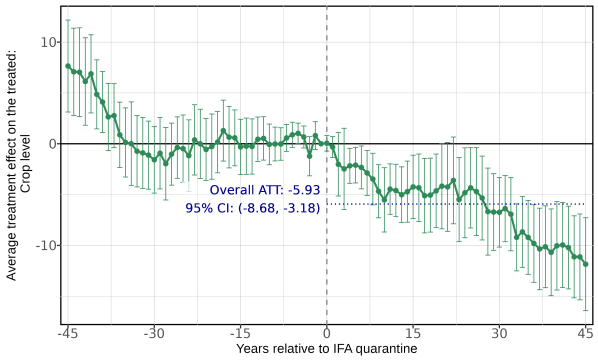
For the crop-specific models in Figures 9 and A15, pre-trend concerns are minimal going back for 30-35 years, while some coefficients depart from zero around 40 years prior to treatment. For both soybean outcomes, estimates become negative and statistically significant almost immediately upon the arrival of IFA. The overall ATT estimate for harvested acres of soybeans is -5.9, which is 36% of the mean level in our sample. These estimated negative effects are even starker when weights and a precipitation covariate are included (see Figure A15a and A15b). These results confirm intuition that follows from the generally negative impacts expected for IFA on soybean crops. Post-treatment, the coefficients for cotton in Figure 9c are slow to respond, but, consistent with the agronomic idea that IFA benefit cotton (see Section 2.1), the estimates become systematically positive after about 25 years. The overall ATT estimate for harvested acres of cotton is 1.57, which is 20% of the mean level in our sample. When including crop area weights and precipitation as a covariate, post-treatment effects become larger and more precisely estimated (Figure A15c). The directions for these estimated effects—negative for soybeans and positive for cotton—are opposite of the general trends over time in annual county mean levels (shown in Appendix Figure A12b).

As a robustness check, we generated estimates (not shown) from alternative samples in which earlier years are dropped but additional states are added, as discussed above and detailed in Appendix B.2. For both soybean outcomes, we estimate samples starting in 1955, 1961 and 1972. Results from all samples are consistent with those in Figure 9a and 9b, though the negative path of post-treatment coefficients is less steep and around half of the models result in statistically significant estimates, while the other half are borderline but not statistically significant. For cotton, we consider samples starting in 1951, 1954 and 1972. The results are consistent with those in Figure 9c, for the longest two samples, but for the shortest sample (starting 1972) estimates are near zero and not statistically significant.

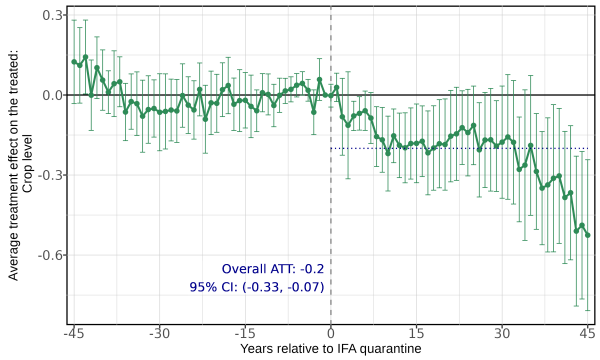
### 5.5 Pesticide outcomes

In Figure 10 we show event study estimates of the effect of IFA arrival on pesticide use, both in raw mass (metric tons) and mass per unit county area (kg/km$^2$). Compared to all other outcome variables considered above, our pesticide use estimates are based on the shortest time horizon (27 years, 1992-2019) due to the limited availability of county-level data. Thus the event-study window considered is shorter (+/- 20 years). For both outcomes, estimated pre-treatment coefficients are close to zero and do not follow any particular trend. Post-treatment, the estimated coefficients

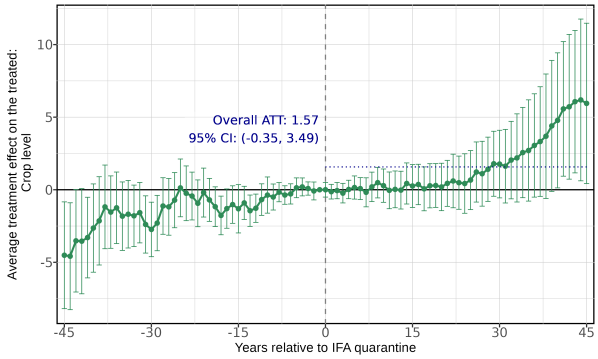
Figure 9: Event-study estimates for specific crops with no weights or covariates.




(a) Outcome: soybeans (harvested acres, K).




(b) Outcome: soybeans (bushels produced, M).




(c) Outcome: cotton (harvested acres, K).

Notes: Figure 9 reports the event study estimates for specific crop outcomes without weighting. Whiskers represent the 95% confidence intervals.

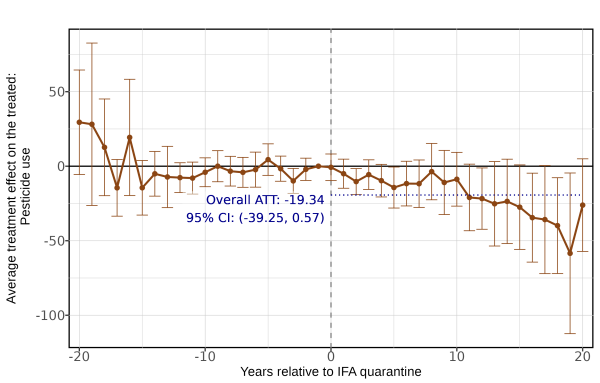
trend negative. This trend is sharper for the pesticide use expressed in raw mass, although point estimates are noisy due to the small sample size. The overall ATT estimate (-19.34) represents a decline of 15% relative to the sample mean for pesticide use. For the mass per county area outcome, the estimates are generally negative but are not statistically significant. Appendix Figure A16 shows that the estimated effects for raw mass pesticide use are similar when including precipitation as a covariate, although slightly noisier.[13]

# 6 Discussion

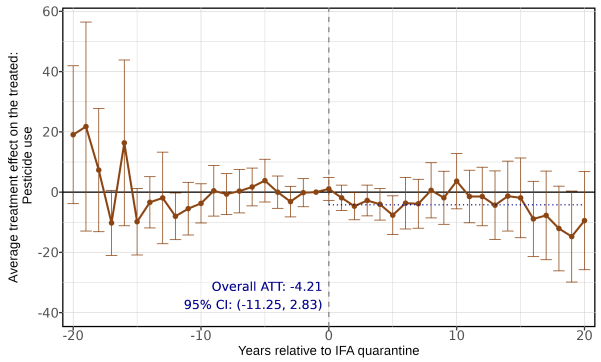
Shocks to ecosystems—whether due to loss of key species or introduction of consequential invaders—have implications for natural environments and working landscapes that are often difficult to discern.

[13]Event study estimates for pesticide use in mass per unit area (not shown) with precipitation as a covariate are not well-behaved—coefficients for the decade before treatment deviate extremely from zero.

Figure 10: Event-study estimates for pesticide use.




(a) Outcome: pesticide use (t).




(b) Outcome: pesticide use per county area ($kg/km^2$).

Notes: Figure 10 reports the event study estimates for pesticide use outcomes in (a) raw mass, and (b) mass per county area. Whiskers represent the 95% confidence intervals.

Key factors driving this identification challenge include human behavioral adaptations unfolding over the long-term, combined with complex ecological dynamics that are difficult to pick out against background variation.

The magnitude of our baseline model estimate of the impact of IFA arrival on IMR—on average a decrease of 1.47 deaths per 1,000 live births—is 2.7-4.7 times larger than estimates of IMR increases by Taylor (2022) from cicada emergence (0.31) and Frank (2024) from white nosed bat syndrome (0.54). Taylor (2022) notes that tree crop acreage and pesticide use (the focus of their paper) are much less extensive than for row crops. The estimate in Frank (2024) is based on dynamics that unfolded in 2006 and later, an era in which pesticide toxicity and infant mortality were both much lower than the mid-20th century period included in our analysis. Our findings complement these existing analyses, though from the opposite direction of an estimated *decrease* in pesticide use and infant mortality. Our results suggest that this effect is associated with longer-term agricultural adaptations, including overall cropping, crop choice and use of pesticides. Evidence on fate and transport factors like precipitation and wind further supports pesticide impacts as a key mechanism.

To estimate the average annual number of infant deaths avoided, we multiply our estimate of the overall average annual decrease in deaths per 1,000 live births (1.47) by the annual number of births (in thousands) for counties in years in which IFA have been present for up to 45 years (the extent to which our IMR effect is estimated). We estimate that the average number of annual infant deaths avoided is 807. Applying the EPA's recommended central estimate for the value of statistical life (EPA, 2025), adjusted to 2025 dollars, results in an annual average benefit of $9.6 billion.

Our estimate of the economic benefits from avoided infant mortality is similar to Lard et al.'s (2006) estimate of the net negative economic impact of $10.1 billion (in 2025 dollars). However, we note that these benefits and costs estimates are insufficient to provide a net welfare effect of IFA since Lard et al.'s estimate is not a welfare measure and many impacts, especially on ecosystems, have yet to be estimated. However, these figures show that the long run secondary effects of invasive species that arise from economic adaptation can be a first order concern when aiming to quantify the economic costs of invasive species.

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# 7 Acknowledgments

**Data availability.** Data and code will be made available for access, except for restricted data on infant mortality after 1988. Instructions for applying to access this restricted data from the U.S. National Center for Health Statistics are available online at `https://www.cdc.gov/nchs/nvss/nvss-restricted-data.htm`.

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# Appendix

## A IFA historical context

Figure A1: A historical photo reproduced from Wilson (1958) showing IFA mounds across a field in Lowndes County, Mississippi.



## B Additional details on data processing

### B.1 IMR

For the IMR outcome estimation, we drop three "independent cities" in Virginia (Emporia, Franklin and Poquoson) that are missing infant mortality and population data for multiple decades and are also small (current populations less than 13,000). There are three counties in our dataset (Jackson County GA, Chesapeake VA, and Miami-Dade FL) for which population data in particular is missing for a substantial portion of years. These counties are dropped when our estimates are population-weighted.

For instances in which county-year births are zero, we set the IMR equal to zero. Besides the handful of instances in which births overall are equal to zero for a given county-year, the count of births for nonwhites is zero for 121 counties (around 4% of the sample). Since these counties have low population levels for nonwhites (always less than 3,800), the potential impact of this approach will be stronger for non-weighted estimates than for those with subpopulation weights.

### B.2 Agriculture

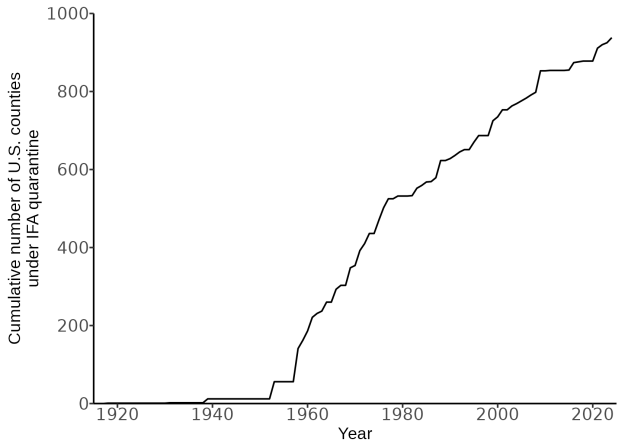
Our baseline cotton estimates are based on annual data from 1947-2023 for counties in seven states (AL, AR, GA, MS, NC, NM, and VA). Data for counties in other states does not begin until later. Setting the cutoff in later years drops earlier years from the sample (since we maintain a balanced panel) but adds counties from additional states: by 1951, OK and TN; by 1954 LA; and by 1972 FL, TX, and SC. California is excluded. Our baseline soybean estimates cover 1949-2023 for four states (AL, AR, TN, VA). Later cutoffs include: by 1955, LA and MS; by 1961 FL, GA, and OK; and by 1972, NC, SC and TX. There are no data for California and New Mexico.

The USDA-NASS (2024) pesticide use database includes two different measures—"EPEST-low" and "EPEST-high"—which differ only in treatment of missing data (specifically, instances in which a Crop Reporting District was surveyed but reporting for a given pesticide-crop pair is not reported). Following Taylor (2022) we use the "EPEST-high" measure, which relies on estimates based on information from bordering areas to address gaps in the reported values.

## C Additional results

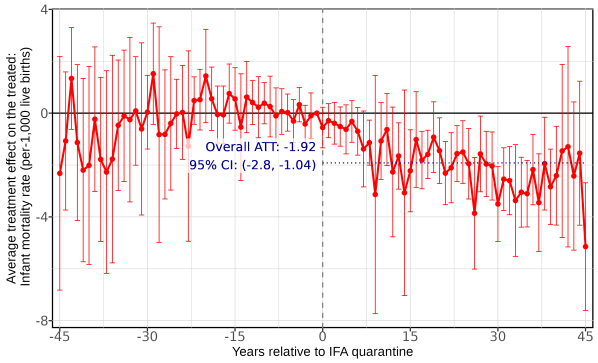
### C.1 Additional descriptive statistics

Figure A2: Cumulative number of counties under federal quarantine for IFA, 1918-2024

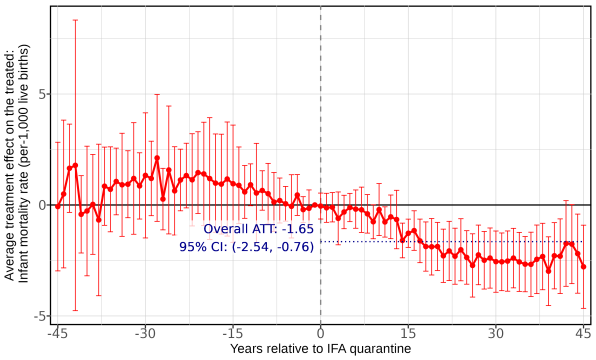



### C.2 Additional results for the infant mortality rate outcome

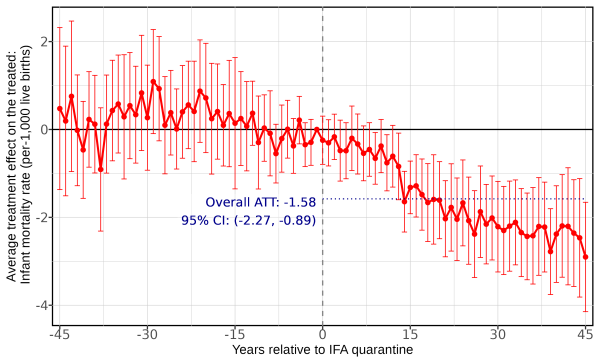
Figure A3: Estimated event study coefficients for infant mortality rate with covariates



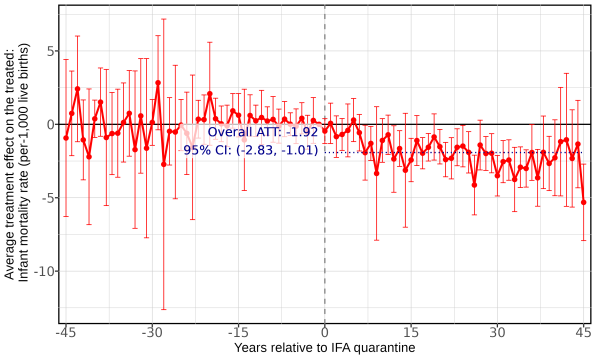

(a) Covariate: precipitation.




(b) Covariate: wind.



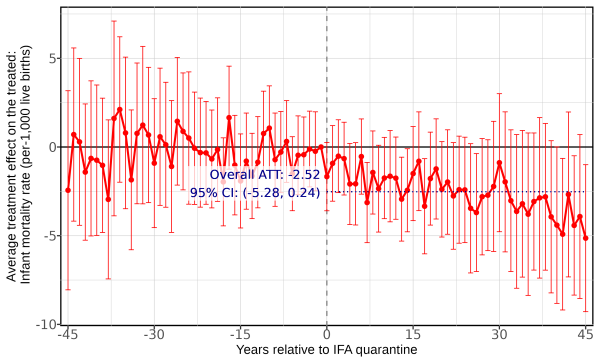

(c) Covariate: crop land use fraction.



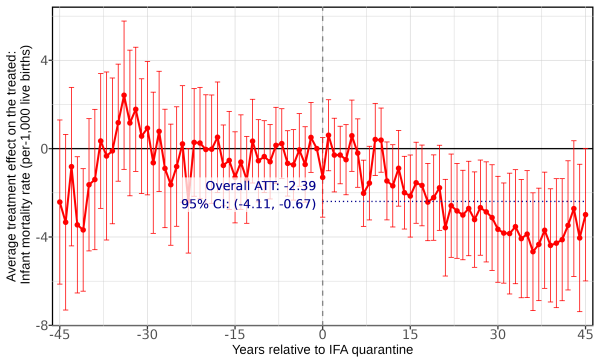

(d) Covariates: precipitation and crop land use fraction.

Notes: Figure A3 reports the event study estimates for the infant mortality rate outcome with county population weights and including covariates: precipitation (top left), wind (top right), crop land use fraction (bottom left) and precipitation and crop land use fraction together (bottom right). Whiskers represent the 95% confidence intervals.

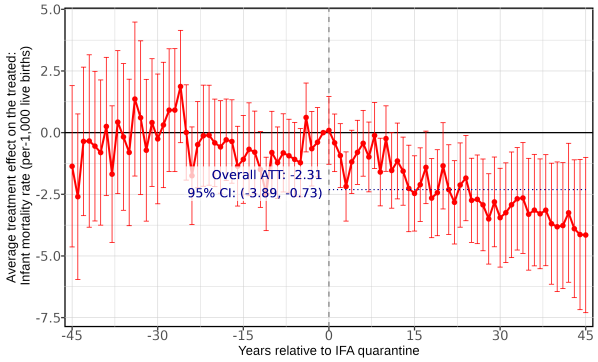
Figure A4: Estimated event study coefficients for infant mortality rate by population quartile



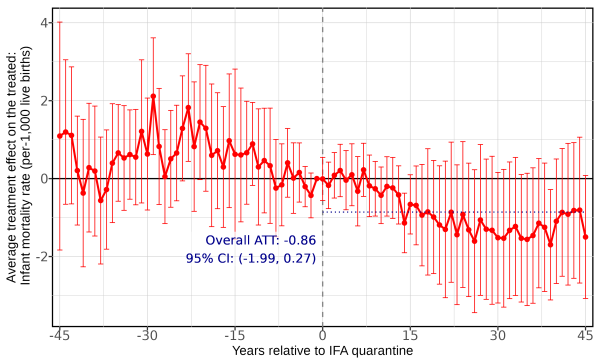

(a) Quartile 1.




(b) Quartile 2.



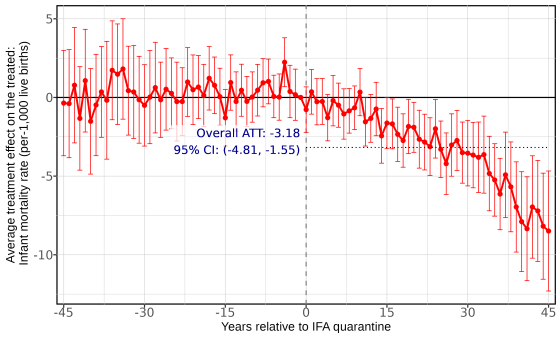

(c) Quartile 3.



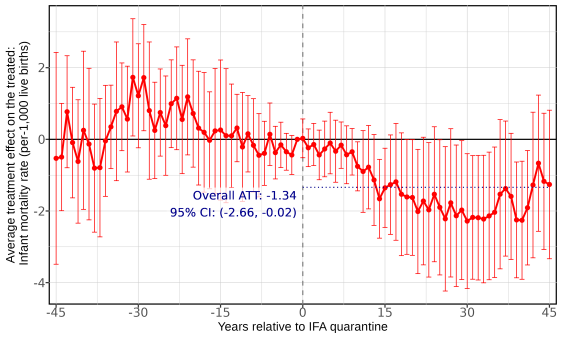

(d) Quartile 4.

Notes: Figure A4 reports the event study estimates for the infant mortality rate outcome with county population weights based on subsamples for each individual county population quartile. Whiskers represent the 95% confidence intervals.

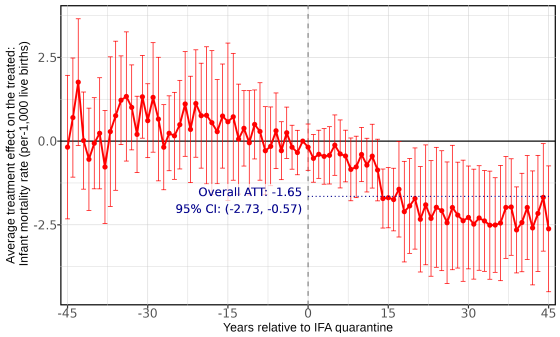
Figure A5: Estimated event study coefficients for IMR, county sub-samples based on median splits



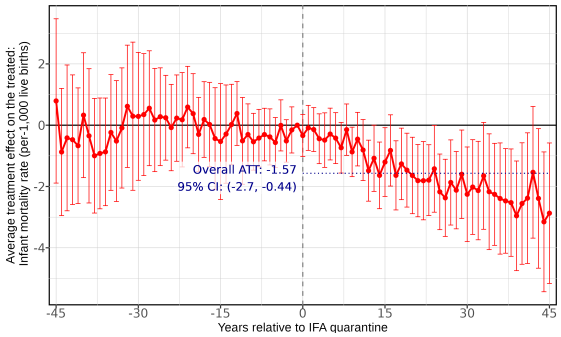

(a) Population density: low.



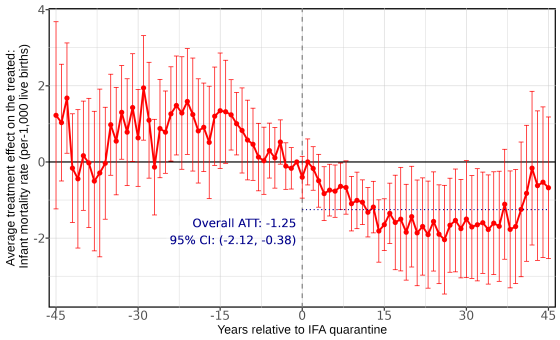

(b) Population density: high.



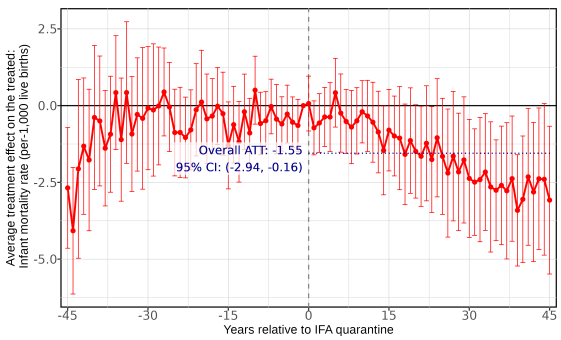

(c) Crop area fraction: low.



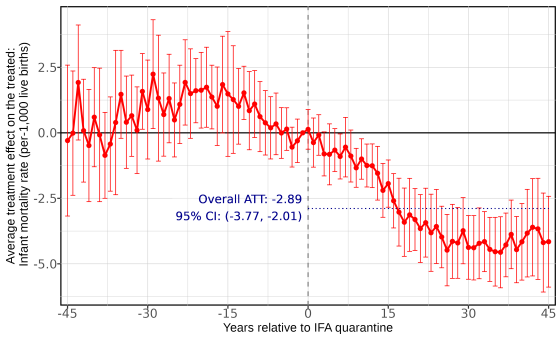

(d) Crop area fraction: high.



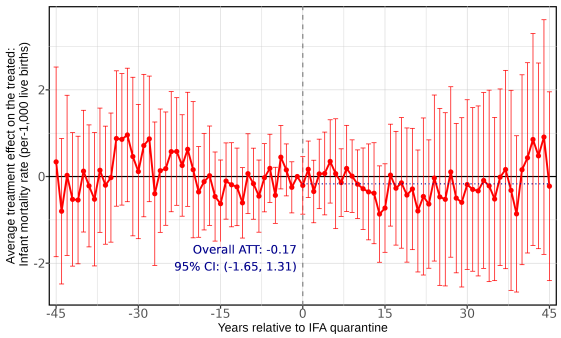

(e) Precipitation: low.




(f) Precipitation: high.



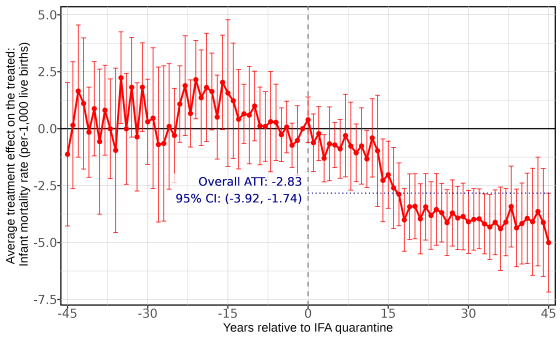

(g) Wind speed: low.



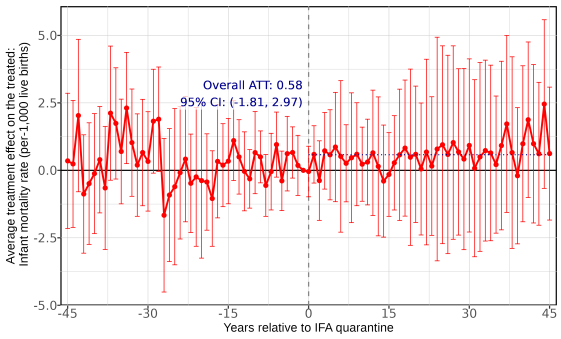

(h) Wind speed: high.

Notes: Figure A5 reports event study estimates for the infant mortality rate outcome for county sub-samples that are below the median or "low" (left column) and above median or "high" (right column) for the following variables: population density (top), crop fraction (2nd row), precipitation (3rd row), and wind (bottom). Estimates are weighted by county population and whiskers represent the 95% confidence intervals.

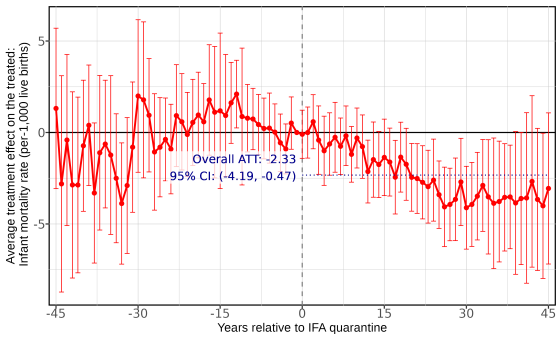
Figure A6: Estimated event study coefficients for county bivariate sub-samples for crop coverage and wind based on median splits



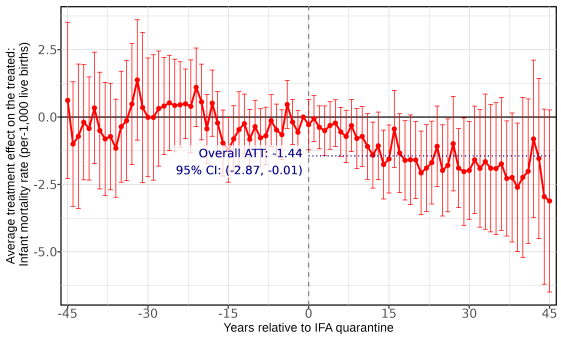

(a) Crop coverage: low, wind: low.




(b) Crop coverage: low, wind: high.



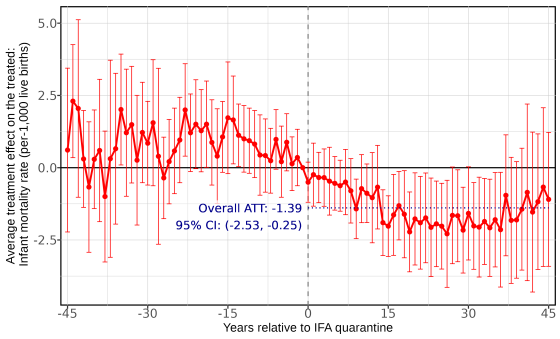

(c) Crop coverage: high, wind: low.



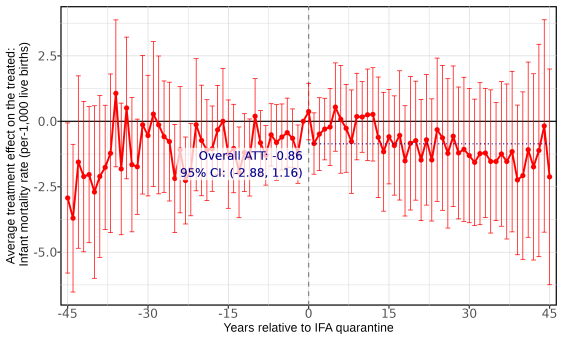

(d) Crop coverage: high, wind: high.

Notes: Figure A6 reports event study estimates for the infant mortality rate outcome for county sub-samples based on the intersection of crop coverage (1937-1941) with wind. Crop coverage is below the median or "low" in the first row and the wind variable is below the median or "low" in the first column. Estimates are weighted by county population and whiskers represent the 95% confidence intervals.

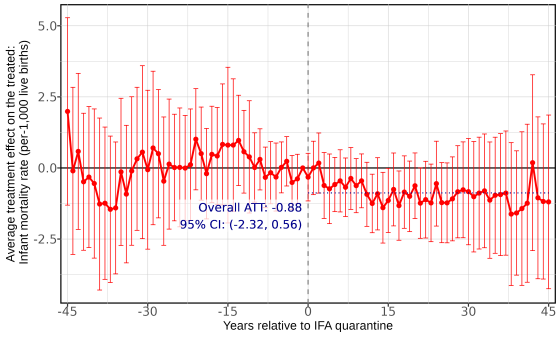
Figure A7: Estimated event study coefficients for county bivariate sub-samples for crop coverage and precipitation based on median splits



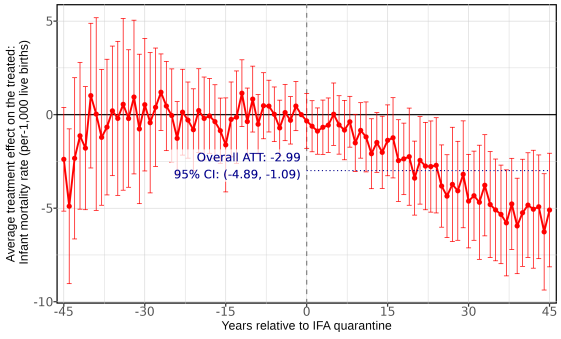

(a) Crop coverage: low, precipitation: low.




(b) Crop coverage: low, precipitation: high.



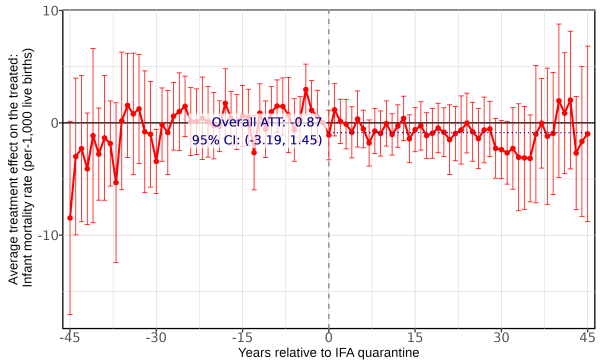

(c) Crop coverage: high, precipitation: low.



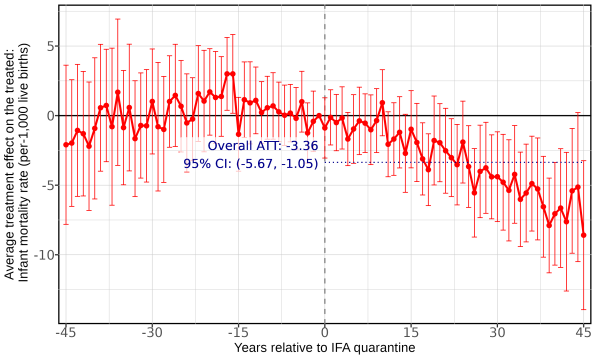

(d) Crop coverage: high, precipitation: high.

Notes: Figure A7 reports event study estimates for the infant mortality rate outcome for county sub-samples based on the intersection of crop coverage (1937-1941) with precipitation. Crop coverage is below the median or "low" in the first row and the precipitation variable is below the median or "low" in the first column. Estimates are weighted by county population and whiskers represent the 95% confidence intervals.

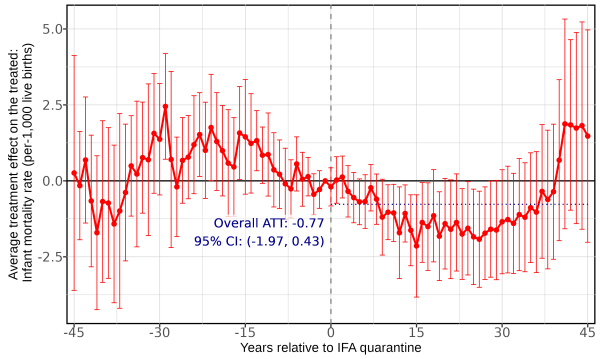
Figure A8: Estimated event study coefficients for county bivariate sub-samples for population density and precipitation based on median splits



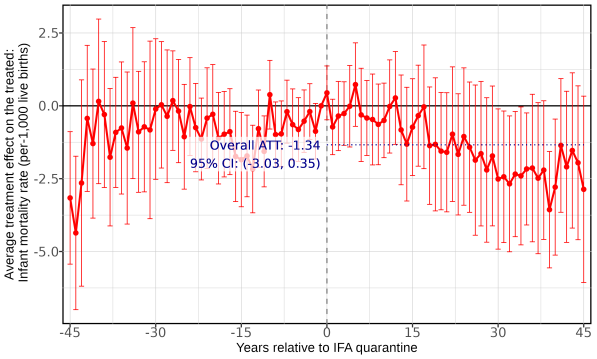

(a) Population density: low, precipitation: low.




(b) Population density: low, precipitation: high.



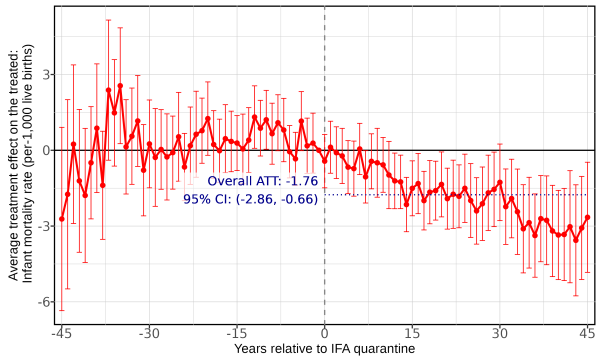

(c) Population density: high, precipitation: low.



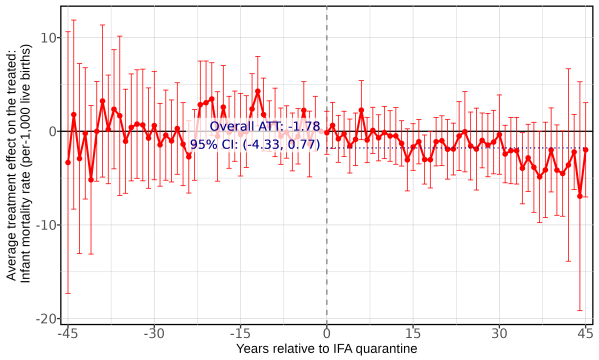

(d) Population density: high, precipitation: high.

Notes: Figure A8 reports event study estimates for the infant mortality rate outcome for county sub-samples based on the intersection of population density and with precipitation. Population density is below the median or "low" in the first row and precipitation is below the median or "low" in the first column. Estimates are weighted by county population and whiskers represent the 95% confidence intervals.

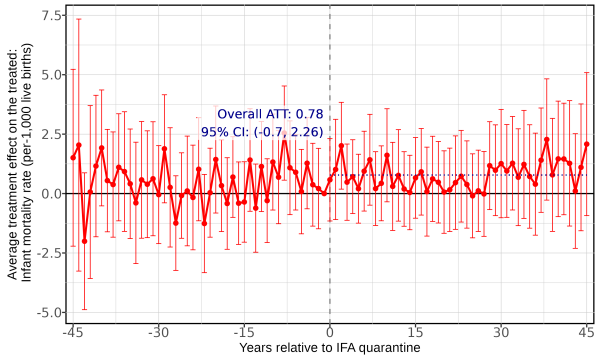
Figure A9: Estimated event study coefficients for infant mortality rate by race with no county population weights




(a) All.



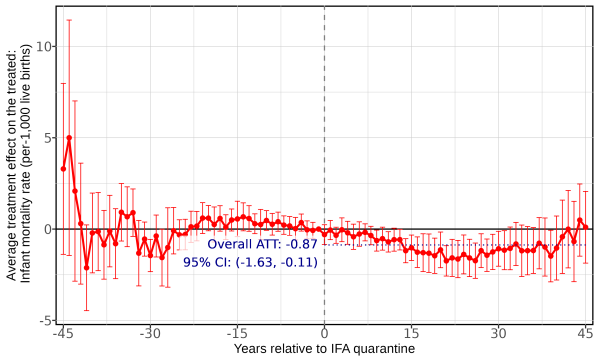

(b) Nonwhite.



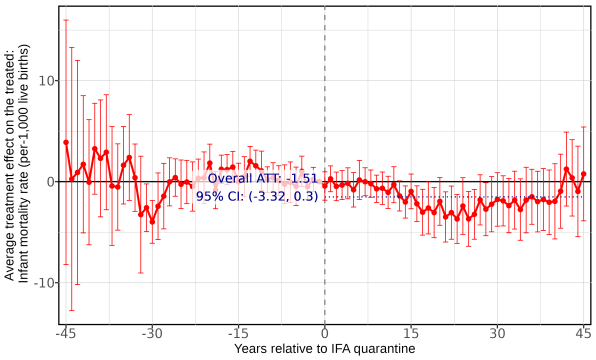

(c) White.

Notes: Figure A9 reports the event study estimates for the infant mortality rate outcome with no county weights for (a) all, (b) nonwhite, and (c) white births and deaths. Data panel spans 1959-2016 and whiskers represent the 95% confidence intervals.

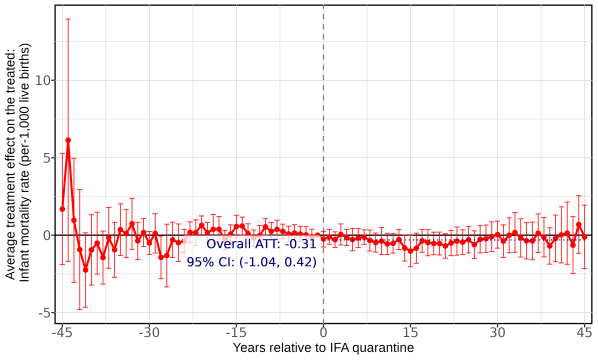
Figure A10: Estimated event study coefficients for infant mortality rate by race for a sample starting in 1968




(a) All.



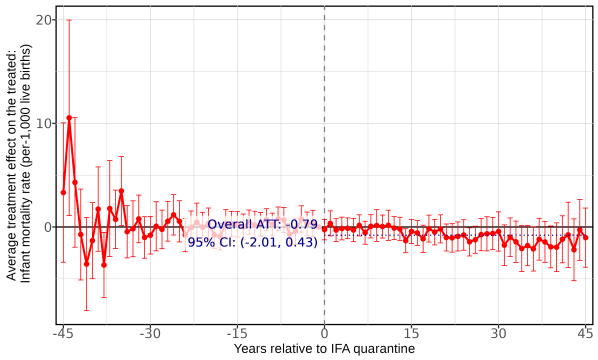

(b) Nonwhite.



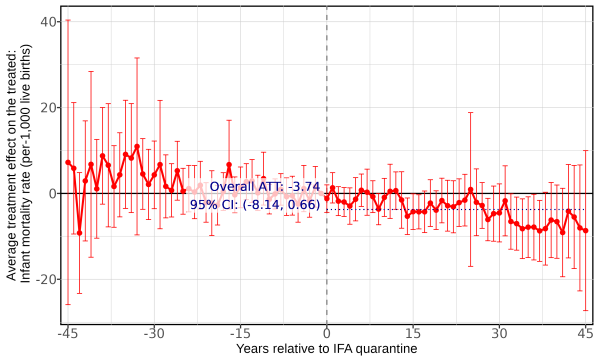

(c) White.

Notes: Figure A10 reports the event study estimates for the infant mortality rate outcome with county population weights for (c) all, (b) nonwhite, and (a) white births and deaths. Data panel spans 1968-2016, county population is race-specific and whiskers represent the 95% confidence intervals.

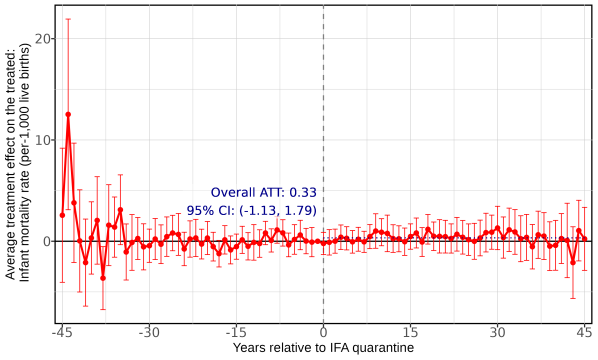
Figure A11: Estimated event study coefficients for infant mortality rate by race for a sample starting in 1968 with no county population weights




(a) All.




(b) Nonwhite.

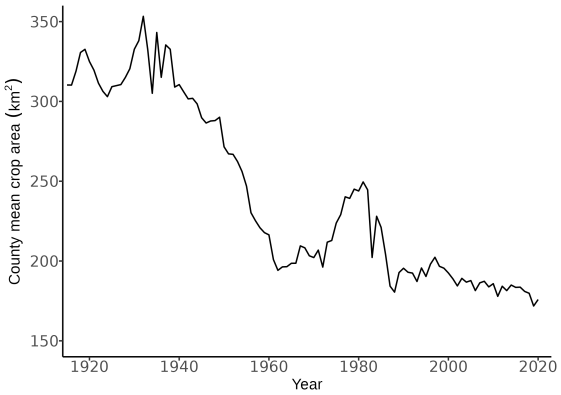



(c) White.

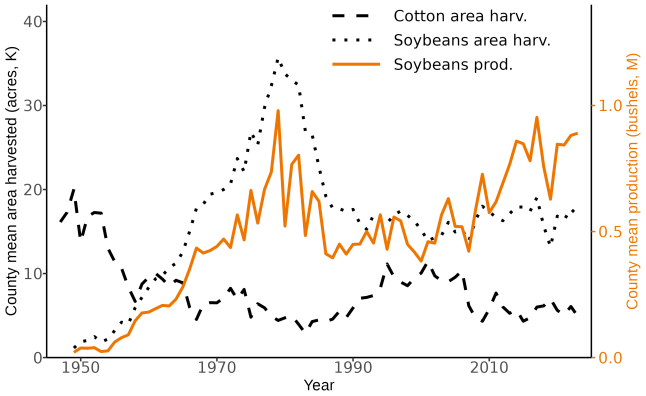
Notes: Figure A11 reports the event study estimates for the infant mortality rate outcome with no county weights for (a) all, (b) nonwhite, and (c) white births and deaths. Data panel spans 1968-2016 and whiskers represent the 95% confidence intervals.

## C.3 Additional results for agricultural outcomes

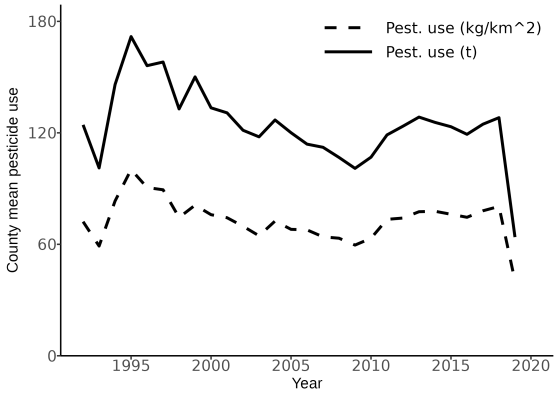
Figure A12: Mean annual levels of agricultural variables for sample counties.




(a) Crop area.




(b) Soybean and cotton levels.




(c) Pesticide use.

Sources: Crop area (Li et al., 2023), soybean and cotton levels (USDA-NASS, 2024), and pesticide use levels (USGS-NAWQA, 2023).

Figure A13: Event-study estimates for log crop level from a placebo test based on randomly shuffled event years across units.

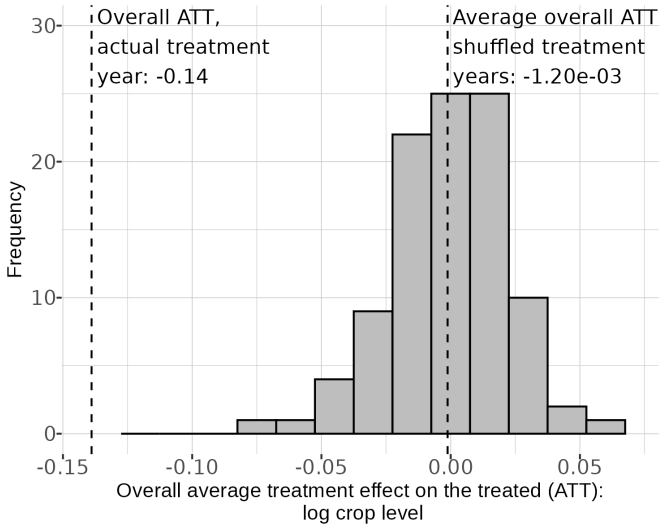
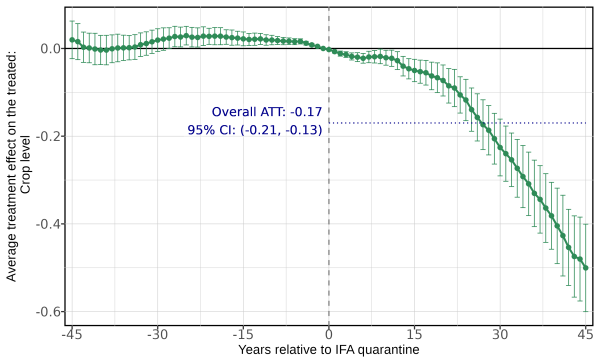
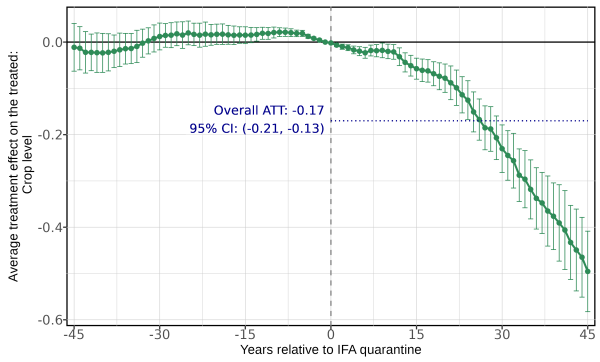



Figure A14: Estimated event study coefficients for log of crop area with individual covariates.



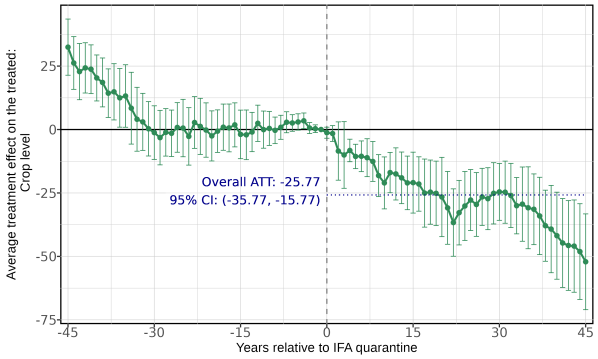

(a) Covariate: wind.



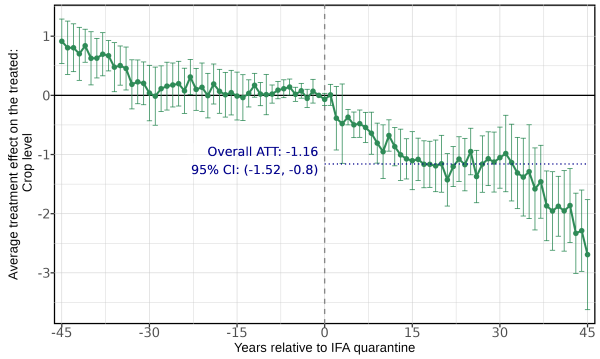

(b) Covariate: precipitation.

Notes: Figure A14 reports the event study estimates for the natural log of crop area ($km^2$) outcome with covariates: wind (left) and precipitation (right). Whiskers represent the 95% confidence intervals.

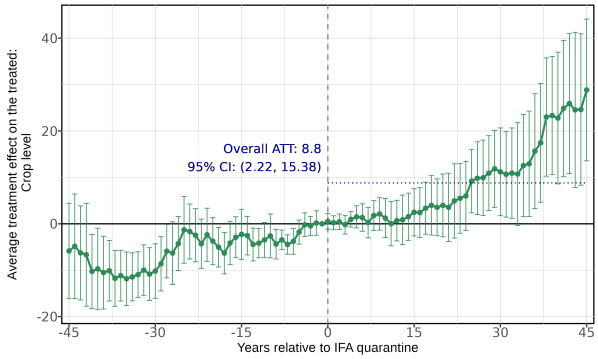
Figure A15: Event-study estimates for specific crops with weights and a covariate.




(a) Outcome: soybean (harvested acres, K).



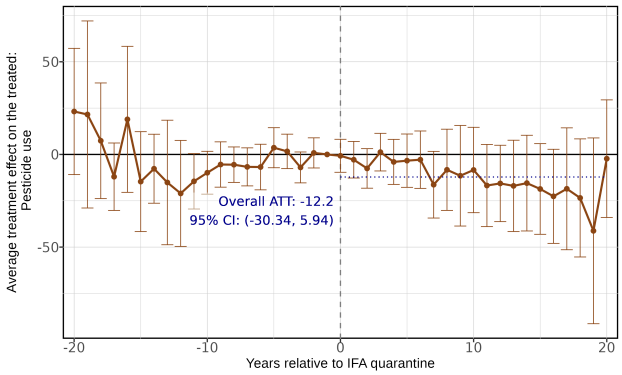

(b) Outcome: soybean (bushels produced, M).




(c) Outcome: cotton (harvested acres, K).

Notes: Figure A15 reports the event study estimates for specific crop outcomes with county crop area weights and precipitation as a covariate. Whiskers represent the 95% confidence intervals.

Figure A16: Estimated event study coefficients for pesticide use with precipitation as a covariate




Notes: Pesticide use is in metric tons (t). Whiskers represent the 95% confidence intervals.