Coping Cyclones with Pesticides: Evidence from the Atlantic Basin of the US*

Shuddhasattwa Rafiq[1,*]

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Using U.S. county-level data, we uncover a relatively overlooked coping strategy employed by farmers in response to cyclones: increased pesticide application. By constructing and analyzing a novel dataset spanning 25 years of county-level tropical cyclone activity, pesticide use, and agricultural output, our difference-in-differences design reveals that farmers respond to cyclone shocks by applying more pesticides to protect their crops. On average, a typical U.S. farm applies an additional 2,153 kgs of pesticides in the year a cyclone occurs and 2,259 kgs in the following year—amounts that are approximately ten times higher than the farm's usual annual pesticide use. While this increased pesticide use raises concerns for human health, environmental sustainability, and economic outcomes, our heterogeneity analysis offers a more nuanced view. Farmers selectively boost pesticide applications to counter the rise in pests and pathogens that usually follow cyclones but notably refrain from increasing highly hazardous pesticides such as Chlorpyrifos, which is known for its severe health risks. These results hold robustly across eight measures of cyclone intensity—including rainfall, wind speed and duration, and a combined severity index. In terms of coping mechanisms, farmers not only intensify pesticide use on existing crops (intensive margin) but also expand their harvested acreage (extensive margin) to compensate for yield losses, with effects lasting up to four years after a cyclone event. Our simple COVID-19 exercise, at the end, reveals a strong positive link between past pesticide use and key COVID-19-related outcomes.

Keywords: Tropical Cyclone, Atlantic Basin, Pesticide Use, Difference-in-Differences.

JEL Classification: D74, I30, Q41

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Using U.S. county-level data, we uncover a relatively overlooked coping strategy employed by farmers in response to cyclones: increased pesticide application. By constructing and analyzing a novel dataset spanning 25 years of county-level tropical cyclone activity, pesticide use, and agricultural output, our difference-in-differences design reveals that farmers respond to cyclone shocks by applying more pesticides to protect their crops. On average, a typical U.S. farm applies an additional 2,153 kgs of pesticides in the year a cyclone occurs and 2,259 kgs in the following year—amounts that are approximately ten times higher than the farm's usual annual pesticide use. While this increased pesticide use raises concerns for human health, environmental sustainability, and economic outcomes, our heterogeneity analysis offers a more nuanced view. Farmers selectively boost pesticide applications to counter the rise in pests and pathogens that usually follow cyclones but notably refrain from increasing highly hazardous pesticides such as Chlorpyrifos, which is known for its severe health risks. These results hold robustly across eight measures of cyclone intensity—including rainfall, wind speed and duration, and a combined severity index. In terms of coping mechanisms, farmers not only intensify pesticide use on existing crops (intensive margin) but also expand their harvested acreage (extensive margin) to compensate for yield losses, with effects lasting up to four years after a cyclone event. Our simple COVID-19 exercise, at the end, reveals a strong positive link between past pesticide use and key COVID-19-related outcomes.

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1. Introduction

> "Finally, we must begin to bridge the cultural divide between the pesticide production and agriculture community on the one side and the public health community on the other."
>
> *Vice President Al Gore in Carson and Gore (1994)*

For evident interconnectedness between climate and plant growth, literature studying climate's impact on agriculture has mushroomed since Mendelsohn et al. (1994). While a substantial body of literature claim that climate change would generally have detrimental consequences on agriculture, they remain inconclusive depending on outcome they studied (yield versus value), proxies they used for climate (commonly used ones are temperature and precipitation), contexts studied (crop type, location, micro versus macro) and methods implemented (Olesen and Bindi, 2002; Lobell and Asner, 2003; Schlenker et al., 2005; Deschênes and Greenstone, 2007; McCarl et al., 2008; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Chen et al., 2016; Miao et al., 2016; Zhang et al., 2017, to name a few). On the contrary, literature identifying the impact of extreme weather events on agriculture is consensual not only in claiming that the increasing frequency of disasters is 'new normal,' but also in documenting their detrimental effects on agriculture (Emanuel, 2005; Pielke et al., 2008; Strobl, 2011, 2012a,b; Israel and Briones, 2013; Spencer and Polachek, 2015; Lesk et al., 2016; FAO, 2021a). To withstand the damaging effects of disasters like storms, droughts, floods, etc., agronomy literature documents that one of the commonly implemented adaptation strategies at the "intensive margin" is to increase the application of pesticides to protect crops from increased pests and pathogens (Oerke and Dehne, 2004; Sutherst et al., 2011; Perfecto et al., 2019).

In recent decades, pollutants such as CO_2 emissions due to climate and weather events have attracted enormous attention in academic literature and policy dialogues. Similar to other types of emissions, pesticide use can accelerate and safeguard economic output, yet it may also pose risks to environmental quality and public health (Anderson et al., 2004). While pesticide application in agriculture is vital to the global sustainability puzzle, contemporary agronomy literature has documented increased application and toxicity of pesticides to safeguard against climate-related increases in pests and pathogens. Despite this, little is known about the causal linkage between extreme weather events and pesticide use within the fields of environmental and agricultural economics. This study aims to fill that gap by investigating the impact of tropical cyclones (TCs) in the Atlantic Basin on pesticide usage patterns across counties in the United States.

The agricultural and biological sciences literature has extensively documented the rise in pests and pathogens linked to climate and weather events (Rosenzweig et al., 2001; Zalucki et al., 2002; Anderson et al., 2004; Sutherst et al., 2011). Amid the rise in weather-related extreme events in recent decades, there has been a surge in pest-induced losses of crops across all regions of the world since the 1940s (Oerke et al., 1995; Pimentel, 1997; Rosenzweig et al., 2001). In fact, Oerke et al. (1995) documents a more than 33-fold rise in both quantity and toxicity of pesticides used during the same period. Using Kenyan household-level data, Jagnani et al. (2020) argues that higher early-season temperatures lead to increased pesticide use and reduced fertilizer application in maize farming. This surge in pesticide application, aimed at protecting crops from pest-related losses, is often economically rational.

While the introduction of pesticides in the 1950s saved billions of dollars every year, it also triggered health problems (Murray, 1995; Whyatt et al., 2004; Burke et al., 2017; Lai, 2017) and environmental concerns (Heimlich and Ogg, 1982; Segerson, 1990). One of the earliest costs and benefits analyses of pesticide use in the US dates back to 1979 (Pimentel et al., 1978). Though pesticides offer many benefits by controlling pests harmful to crops and humans, more recent studies indicate that by the early 1990s, their costs may have begun to outweigh the benefits in the U.S. (Bourguet and Guillemaud, 2016). A 2017 United Nations report further suggests that it is possible to sustainably achieve higher food yields in the long run with minimal or no reliance on toxic chemicals (Thelin and Stone, 2013). Currently, the U.S. Environmental Protection Agency (EPA) has registered over 34,000 pesticide products derived from roughly 600 core chemicals, while 86,631 more chemicals (of which 42,039 are active) are regulated separately under the Toxic Substances Control Act (TSCA). [1] Although pesticides such as Chlorpyrifos (CPS) have been banned for domestic use in the U.S, their production for export and use in industrial agriculture continued for years (Carson and Gore, 1994). Only recently have scientists learned about the way exposure to certain types of pesticides affects the human immune system. Pesticides vary widely in their toxicity, and thus in their potential health risks. For example, while commonly used pesticides like 2,4-D and Glyphosate are considered less harmful to humans and approved by both the US and EU authorities, CPS is widely criticized and banned for its detrimental effects on human health. [2]

This paper contributes to two strands of literature associating agriculture with climate. First, this paper contributes to the rapidly growing literature on quantifying the potential economic impact of climate change-related extreme events on agriculture. Specifically, we provide the first estimates of the effects

[1] https://www.epa.gov/tsca-inventory/how-access-tsca-inventory

[2] https://www.epa.gov/pesticide-science-and-assessing-pesticide-risks/human-health-issues-related-pesticides for the US and https://www.pan-Europe.info/old/Archive/About%20pesticides/Banned%20and%20authorised.htm for EU regulations on pesticide.

of TCs on the US agricultural pesticide application. While much of the existing literature focuses on agricultural yields, it often lacks insight into the marginal impact of adaptive strategies employed by profit-oriented farmers in response to climate-driven exogenous shocks to production (Mendelsohn et al., 1994; Schlenker et al., 2005; Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Fisher et al., 2012; Burke and Emerick, 2016; Zhang et al., 2017). Our study addresses this gap by examining farmers' behavioral adjustments in input use—specifically, increased pesticide application—as a coping mechanism in response to extreme weather events such as TCs in the Atlantic Basin.

Second, this study builds on existing literature identifying climate change adaptation techniques in agriculture. Existing literature documents three major approaches to climate smart adaptation (CSA), crop rotations (Seo and Mendelsohn, 2008; Salazar-Espinoza et al., 2015; Arslan et al., 2017), changing agronomic practices like revised plantation timing, irrigation practices and improved soil and water conservation (Deressa et al., 2009; Arslan et al., 2015, 2017) and adjusting the inputs applied (Oerke and Dehne, 2004; Salazar-Espinoza et al., 2015; Aragón et al., 2018). While fertilizer application has been discussed and documented as a climate change adaptation input-related strategy (Mendelsohn et al., 1994; Rosenzweig and Parry, 1994; Paudel and Crago, 2019), none of the previous studies explored the possibility of pesticide use as an adaptation mechanism. We fill this gap by investigating farmers' pesticide application-related behavioral responses to disasters like TCs. In this regard, we not only contribute as one of the pioneers to study post-disaster pesticide use in the US agricultural sector but also analyze their usage pattern *i.e.*, post-TC application of less harmful *vis-à-vis* more hazardous pesticides. In this way, our natural experiment will enable us to gauge if there is any effect of banning policies and negative media coverage about harmful pesticides like CPS.

In this paper, we leverage spatially disaggregated data on the tracks of the universe of TCs in the US Atlantic coast, combined with the information on pesticide uses and agricultural output across 2354 counties from 1972 to 2017, to identify the overall impacts of TCs on pesticide use and investigate the heterogeneity across pesticides as a form of coping mechanism at the 'intensive margin.' To estimate the relationship between TCs and pesticide application practices, we rely on plausibly exogenous variations in TC shocks across the sample counties to measure their effect on pesticide use across types, regions, and coping mechanisms. Our cross-county database exhibits significant county-by-year variation in TC presence and intensity.[3] A key factor that makes storm events associated with TCs arguably exogenous

[3]For instance, some counties experience multiple TCs during the sample period: most notably, Baldwin County-12 TCs, DeSoto-11 TCs, Dare - 17 TCs, and Burlington - 11 TCs; while others (*e.g.*, Stewart, Van Buren, Andrews, Archer, and Graham) experienced no storms between 1992 and 2017. Figure 2 shows a map of TC counts across all counties in the sample.

is that even if farmers in a particular county expect storms in a given year based on a county's storm history, they cannot predict the exact path, frequency, or severity of storms within that year. Weather forecast models can predict the triggering factors for storms-*e.g.*, wind patterns and the ocean surface temperature within a short forecast window, but not in the medium and long term. A TC typically originates in the ocean surface due to temperature fluctuations and is guided by a complex mix of global and local meteorological forces, including air pressure, sea surface temperature, and wind patterns (Roy and Kovordányi, 2012). Despite recent improvements in storm prediction technology, accurately tracking TC paths continues to be a challenge (Regnier, 2008; Roy and Kovordányi, 2012; Landsea and Cangialosi, 2018). These atmospheric and oceanic variables, which determine whether a county lies in the path of a TC, are considered exogenous to economic and agricultural decisions. Since TCs occur unpredictably in both time and place, and their paths vary randomly across regions, their impact provides a quasi-random natural experiment (NHC2022, 2022; Dell et al., 2014; Rahman et al., 2022).

We employ an empirical strategy that exploits the random variation in the *timing* (*i.e.*, the year a TC occurs) and obtain qualitatively similar results using models that utilize variation in the *intensity* (*i.e.*, their frequency as well as physical severity) of TC exposure in affected counties compared with their storm-free counterparts. Our primary empirical model employs a difference-in-differences approach to compare the levels of agricultural activity in the US counties with and without TCs, with the additional inclusion of lagged TC variables (akin to a distributed lag model) to account for any persistent impact of storms on pesticide application. Our specifications for pesticide-related analysis include year-fixed effects to help absorb any aggregate shocks experienced by all counties, a county-fixed effect, that controls for time-invariant factors that are specific to each county like soil type or topology, and time trends to account for unobserved factors that affect pre-existing pesticide use and vary over time within each county (like cropping pattern, migration, agricultural technology, etc). For our mechanism analysis with agricultural activity, we use county fixed effects, year fixed effects, and state-by-year fixed effects to account for any state-specific trends in agricultural conditions (which might be driven, for example, by state-specific economic conditions, agricultural policies and extension activities, historical agricultural practices or other state-by-year specific factors). In all regressions, we include $\mathbf{X}_{it}$, a set of weather control variables, including quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C.

Our empirical analysis yields at least five significant findings. First, farmers respond to TC events by increasing pesticide use to protect their agricultural yield. This increased use of pesticides may persist

beyond the year of the cyclone event, depending on the cyclone intensity and pesticide types. To put this in perspective, on an average U.S. farm of 463 acres, farmers apply an additional 2,153 kg of pesticides in the year of the cyclone and 2,259 kg in the subsequent year, which are ten times more than usual yearly pesticide use rates. Second, our heterogeneity analysis by pesticide type documents that these application increases are not uniform across all pesticide types. Notably, the rise in usage does not extend to CPS—a pesticide widely recognized for its high toxicity—indicating selective application behavior among farmers. Third, our location-based heterogeneity analysis reveals that the increases in pesticide use are mainly coming from Midwest, non-coastal, and non-coastal and non-Midwest counties. Fourth, our mechanism analysis related to agricultural productivity finds that crop yield losses can last up to four years after a cyclone. In response, farmers adapt not only by increasing pesticide use (an intensive margin strategy) but also by expanding the amount of land harvested (an extensive margin adaptation). Finally, our simple COVID-19-related exercise documents a significant positive association between historical pesticide use and COVID-19-related health outcomes.

The remainder of the paper is organized as follows. Section 2 provides the background on TCs in the Atlantic basin of the US and their expected effects on pesticide use. Section 3 describes the data used in this paper, followed by identification and estimation strategies in Section 4. Section 5 reports our findings, while Section 6 undertakes a very basic empirical exercise to assess the link between historical pesticide use and the COVID-19 outbreak. Section 7 concludes the paper.

2. Background

2.1. Tropical Cyclones in the Atlantic Basin and Agriculture

Tropical cyclones—the generic name for intense, rotating air systems that form over warm tropical waters and draw energy from the condensation of moisture in clouds—are referred to by various names around the world, such as hurricanes, typhoons, and cyclones (Bushra and Rohli, 2021). These storm systems with sufficient strength are usually meteorologically referred to as TCs if they are situated either in the North Atlantic or in the Northeast Pacific Regions (Strobl, 2012b). TCs can harm agricultural output in multiple ways. The first hazard that comes to mind for these TCs is intense winds (Anderson, 2022). When tracking TCs, scientists usually measure their intensity based on wind, using maximum sustained (typically, a 1-minute surface wind average) windspeed at 10m above ground. The severity of wind-related damage depends not only on the speed but also on the duration of the wind event (Sparks, 2003). Strong and persistent wind associated with TCs may directly cause structural damage to crops and farms

(Strobl, 2012b). A second intensity measure for a TC is rainfall. During TCs, extreme rainfall can lead to widespread inland flooding (Villarini et al., 2014). Consequently, heavy rainfall associated with TCs can be detrimental to agricultural yield (McCarl et al., 2008; Shi et al., 2021). The extent of such rainfall is strongly related to the maximum wind speed (Jiang et al., 2008; Jordan II and Clayson, 2008). To capture the multifaceted nature of cyclone intensity, this study employs eight distinct TC metrics: a binary storm indicator, number of storm in a county in a given year, storm-related rainfall, gust wind speed, sustained wind speed, duration of damaging gust wind speed, duration of damaging sustained wind speed, and a combined severity index. Section 3 of this paper offers a detailed description of each of these intensity measures.

2.2. *Tropical Cyclones, Rainfall, Wind and Agricultural Pesticide Use*

Despite tremendous advancements in agricultural technology and crop yield potential, food production remains highly vulnerable to climate variability and extreme weather events such as droughts, floods, and TCs (Rosenzweig et al., 2001; Spencer and Polachek, 2015). Excessive rainfall can wash away essential nutrients, and tornadoes with strong gusts can damage trees or increase their susceptibility to insects, pests and diseases. Temporal and spatial variations in meteorological conditions and storms can affect soil conditions, water availability, agriculture yields, and the prevalence of pests and pathogens. These factors, in turn, often drive increased pesticide use (Rosenzweig et al., 2001; Oerke and Dehne, 2004; Sutherst et al., 2011; Perfecto et al., 2019).

While vines constitute a significant category of pests within agricultural systems, several studies have also documented the presence and intensification of more traditional pests during storms and other weather-related disasters (Billings et al., 2004; Kohno et al., 2004; Gregory et al., 2009; Sutherst et al., 2011; Lamichhane et al., 2015). In the context of Puerto Rico, Torres (1992) records a notable outbreak of lepidopteran pests in Luquillo National Forest following TC Hugo. Whereas Hu et al. (2013) studies Typhoon Khanun in China and reports a large-scale infestation of the brown planthopper—a major pest in rice cultivation—after the 2005 storm. Within broader discussions on agricultural resilience, *resistance* refers to the farmer's capacity to endure cyclone-related damages such as crop loss from high winds and heavy rainfall. Drawing from interviews among coffee farmers of Puerto Rico, Perfecto et al. (2019) documents that, in response to the destruction caused by Hurricane Maria (a Category 4 cyclone in September 2017), farmers significantly increased their spending on (1) insecticides, (2) herbicides, and (3) fertilizers as part of their coping strategies.

Intensification of crop production is essential to meet the growing global demand for food (Sutherst et al., 2011). Achieving this boost in productivity requires a corresponding intensification of pest management, which often involves widespread pesticide application on farmland. For an individual farmer, pesticides are a key agricultural input that can help protect seeds and safeguard crops from unwanted plants, insects, bacteria, fungi, and rodents. Given the rise in weather-related shocks, it is reasonable to expect a global increase in pesticide use. Indeed, FAO (2021a) reports that, although pesticide use has stabilized recently, total application in the 2010s rose by over 50% compared to the 1990s, with pesticide use per hectare increasing from 1.80 kg to 2.66 kg. The same report has also documented that Oceania and the Americas had the highest growth rates in total pesticide use from the 1990s to the 2010s, with approximately 1.9- and 1.8-fold increases, respectively. In 2018, China was the largest pesticide user, applying 1,774 kilotonnes in agriculture, followed by the United States with 408 kilotonnes.

Pesticides are chemical or biological agents that are used to protect crops from insects, weeds, and infections. Pesticides are used in fruits, vegetables, wheat, rice, olives and canola pressed into oil, and on non-food crops such as cotton, grass, and flowers. While they can bring economic sustainability to the farmers through safeguarding and enhancing outputs, many are known to pose significant risks to human health and ecosystems. Pesticides can have negative environmental impacts through contamination of soil, water, and non-target plants and animals that can decrease biodiversity, and most importantly, they can also be detrimental to human health (FAO, 2021b). Extensive research has linked pesticide exposure to carcinogenic risks in humans (Pimentel and Hart, 2001; Pimentel, 2005). Chronic health issues documented in the literature include neurological, respiratory, and reproductive disorders, as well as various cancers (Pimentel, 2005). In another biological science study, Hart and Pimentel (2002) found that pesticides can cause sensory and cognitive impairments such as memory loss, language difficulties, and learning disabilities. Children appear particularly vulnerable to these effects due to their higher metabolic rates and differing capacities for pesticide detoxification compared to adults (Pimentel, 2005). In addition to human health concerns, pesticides negatively affect beneficial animals—including natural predators and parasites—as well as contribute to pest resistance, contaminate water sources, harm pollinators like honeybees and wild bees, and impact fisheries, wild birds, mammals, microbes, and invertebrates (Pimentel, 2005).

Not all pesticides are equally harmful or attract a similar amount of policy or media attention. For instance, CPS, the top-selling organophosphorus (OP) insecticide in the United States and throughout the world, has drawn significant attention due to extensive policy debates and media coverage in multiple

regions. CPS is commonly used on all fruits, vegetables, and wheat (CEEH, 2013). Like many xenobiotic chemicals, CPS is toxic to humans, and its widespread use has become a major public health issue worldwide (Burke et al., 2017). The primary route of pesticide exposure for most people—including infants, children, and adults—is through the consumption of contaminated food. Agricultural and occupational workers face additional risks by directly handling or inhaling pesticides, increasing their chances of both acute and chronic poisoning. Using individual birth and demographic characteristics for over 500,000 birth observations between 1997–2011 in the agriculturally dominated San Joaquin Valley, California, Larsen et al. (2017) has documented that agricultural pesticide exposure increased adverse birth outcomes by 5–9%, but only among the population exposed to very high quantities of pesticides (e.g., top 5th percentile, i.e., 4,200 kg applied over gestation).

While CPS has been completely banned across all European Union countries, in the United States, it has faced a long history of policy debates and regulatory actions, frequently covered by both national and local media. Due to concerns about the risks of subacute exposure to CPS among developing children, the Environmental Protection Agency (EPA) restricted its household use in 2000 (Lemus and Abdelghani, 2000). Several states — including California, Hawaii, New York and Maryland — have either banned or limited CPS use, with their attorneys general, along with those from Washington, Vermont, and Massachusetts, joining a national petition to prohibit CPS applications. This push to ban CPS began in 2007, when the Natural Resources Defense Council and the Pesticide Action Network formally petitioned the EPA to ban CPS, citing epidemiological studies linking CPS to brain development harm. Most recently, on August 18, 2021, the EPA announced a nationwide ban on CPS use for all food products. This two-decade campaign against CPS received widespread media attention.

3. Data and Measurement

We assemble a county-level panel spanning twenty five years of information on TC exposure, pesticide application, and agricultural production. A brief overview of these data sources is warranted.

3.1. Tropical Cyclone Exposure Data

Our tropical cyclone database is sourced from Anderson et al. (2020a,b), who has recently constructed a dataset, namely *tropicalcycloneexposuredata*—a county-level record of exposures of tropical storms to the Atlantic basin of the U.S. from 1988 to 2018. This dataset captures various storm-related hazards, including wind, rainfall, flooding events, and proximity to storm tracks, for counties in the eastern

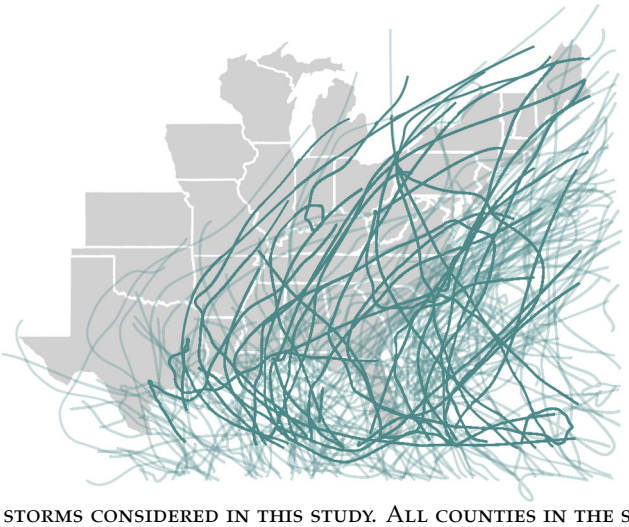


Figure 1: Study area and storms considered in this study. All counties in the states shown in this map were investigated. The lines show the paths of the study storms, which included all tracked storms in 1988–2018 that are recorded in HURDAT2 and that came within 250 kilometers of at least one U.S. county. Thicker lines show the tracks of storms whose names have been retired, indicating that the storm was particularly severe or had notable impacts.
Source: Anderson et al. (2020a,b)

United States. The data is publicly accessible on GitHub via `https://cran.r-project.org/package=tropicalcycloneexposure`. It includes all TCs between 1988 and 2018 that were tracked in HURDAT2 (Landsea and Franklin, 2013) and came within 250 km of at least one eastern U.S. County (Figure 1). This database, therefore, included all land-falling or near-land Atlantic basin TCs and excluded storms that never neared the United States.

Building on this database, we created a spatially disaggregated county-level dataset of disaster exposure by linking individual cyclone and storm IDs. Our database comprises 1,768 storm events, with the highest number of storms affecting a single county in one year being 13 (Figure 2). In terms of county-year distribution, 7,194 county years were affected by storms, while 53,838 county years were out of the storm path. Out of total of 2352 counties, 957 counties experienced at least one storm event (treated), while 1397 counties remained as controls, as there were no storm events. Figure 3 presents the year-to-year county-level total number of storm exposures between 1992 to 2017. Through this tropical cycloneexposure database, users can map exposures by county for a selected storm and can also identify all storms to which selected counties were exposed, based on user-specified thresholds (for example, the package allows the user to identify all storms that brought wind of 34 knots or higher to Miami-Dade County in Florida). Accordingly, we developed our county-level spatially disaggregated data on disasters based on individual-level cyclone and storm ID.

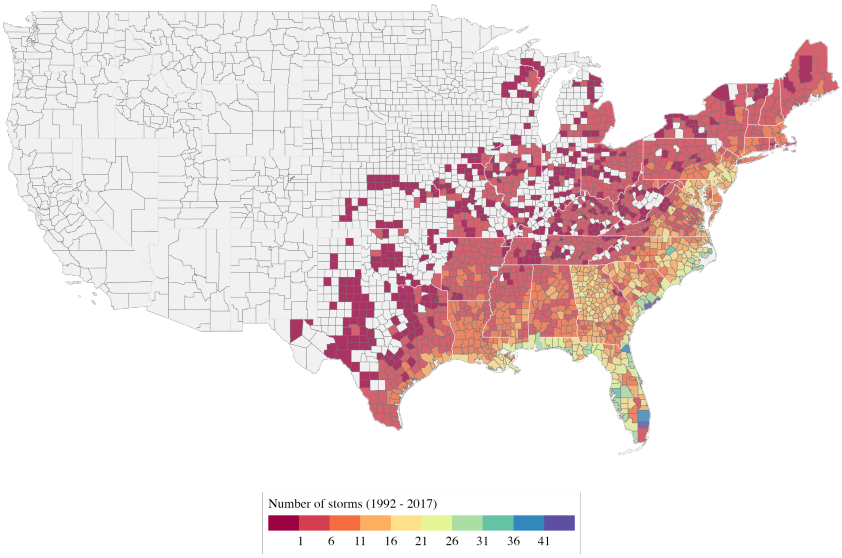


FIGURE 2: STORM COUNTS IN EACH COUNTY.

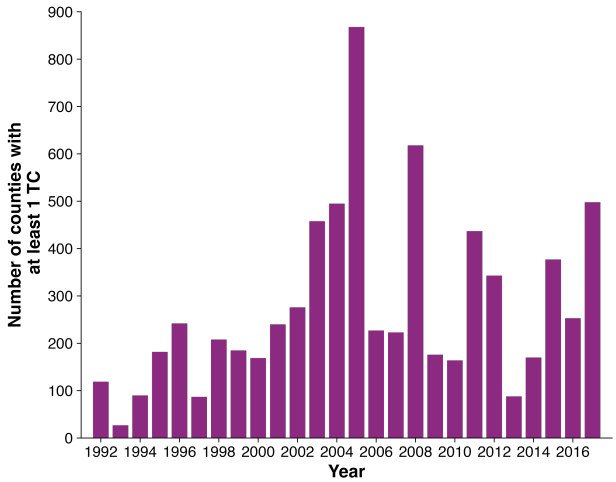


FIGURE 3: YEAR WISE COUNTY EXPOSURE TO STORMS
Source: Authors' own calculation based on (Anderson et al., 2020a,b).

As can be seen from Figure 3, 2004, 2005 and 2006 have been the years when highest number of counties suffered from severe storms. These events include major TCs (not exhaustive) like: 2004: TC Ivan (death toll 124 covering Texas, Florida, East Coast with an economic estimated damage of $19 billion), TC Charley, Frances and Jeanne in Florida (death tolls 10, 49 and 5 with economic damage of $15, $9 and $7.5 billion, respectively), 2005: TC Katrina (death toll 1836 covering Florida, Louisiana, Mississippi, Alabama with an economic damage of $125 billion), Evansville Tornado (death toll 25 covering Missouri, Indiana, Kentucky, Ohio with estimated damage of $92 million), TC Wilma (death toll 30 covering Florida, East Coast of the United States with a damage cost of $21 billion), TC Rita (death toll 120 covering Louisiana, Texas with economic damage of $10 billion), TC Dennis (death toll 15 covering Florida, Southeastern U.S with economic damage of $205 billion), and 2006: Tropical Storm Alberto (death toll 3 covering Florida, Georgia, North Carolina, and Virginia with $0.42 million), TC Ernesto (death toll 10 covering East Coast of US with $500 million economic damage).[4] This rich cyclone database enabled us to develop different measures of natural disaster as follows:

i. A binary variable equal to 1 if a disaster happens in a specific year. A county is considered to experience a natural hazard if it experiences at least one of the following disasters: storm tide, TC, winter storm, tornado, waterspout, tropical depression, tropical storm, and thunderstorm wind.
ii. The number disasters a county experienced in a specific year.
iii. Storm-related rainfall (in millilitre) which is measured as average of total daily rainfall from one day before to four day after (5-day window) the storm's closest approach to the county's population weighted centre.
iv. Gust wind speed (in meter per second (m/s)) which is measured as average of maximum gust wind speeds experienced in the county during storms.
v. Sustained wind speed (in m/s) which is measured as average of maximum sustained wind speeds experienced in the county during storms.
vi. Duration of damaging gust wind (in minutes) which is measured as average of durations for which gust winds were over 20 m/s in the county.
vii. Duration of damaging sustained wind (in minutes) which is measured as average of durations for which sustained winds were over 20 m/s in the county.
viii. An overall severity index constructed using principal component approach. This index captures average of rainfall volumes one day before a storm is closest, average of rainfall volumes on the day a

[4]Damages are estimated at 2005 USDs.

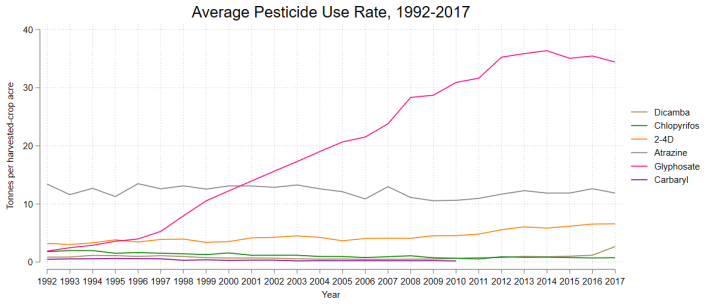


FIGURE 4: AVERAGE PESTICIDE USE RATE 1992-2017
Source: USGIS

storm is closest, average rainfall volume one day after a storm is closest, gust wind speed, sustained wind speed, duration of damaging gust wind, and duration of damaging sustained wind.

3.2. *Agricultural Pesticide Use Dataset*

County-level pesticide use data for the United States are drawn from the *Estimated Annual Agricultural Pesticide Use* for Counties of the Conterminous United States dataset from US Geological Survey (USGS). Specifically, USGS has compiled this large dataset from Wieben (2020) for the period 2013–2017, Baker and Stone (2015) for 2008–2012, and Stone (2013) for 1992–2009.

Estimates of annual agricultural pesticide use are provided as downloadable, tab-delimited files, organized by compound, year, state Federal Information Processing Standard (FIPS) code, county Federal Information Processing Standard code, and amount in kilograms (kg). Accordingly, we source annual pesticide use data from the Pesticide National Synthesis Project of United States Geological Survey. This county-level agricultural pesticide uses data spans from 1992 to 2017 with both aggregate and individual pesticide usage. As can be seen from Figure 4, the application of these individual pesticides has not been uniform over the years. While pesticides like Dicamba and 2,4-D which are rather less harmful, have experienced increasing applications over the years, the use of comparatively more hazardous ones like Chlopyrifos has been declining slowly.

Figure 5 presents an application map of two major pesticide types, 2,4-D and CPS, over four decades across the US. Linking maps of TCs in Figure 1 and pesticide use in Figure 5 reveals that most of the US agricultural pesticide use over the decades is concentrated in the eastern part of the country, for which, fortunately enough, we have historical disaster data from our tropical cycloneexposure datasets.

Appendix Table 2 presents descriptive statistics of major variables of our study. As can be seen from this table that, while our total observation for disaster is 610,323, our pesticide data observations range from 18,669 to 610,323 depending on the type of pesticide. To our identification's advantage, not all

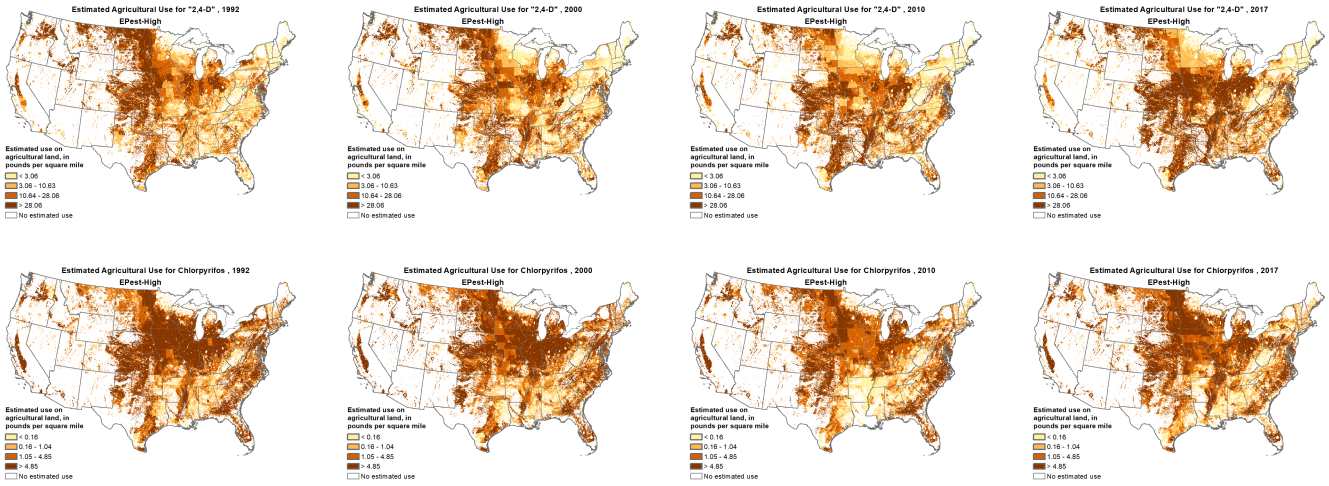


FIGURE 5: PESTICIDE USE MAP ACROSS TIME AND SPACE FOR TWO MAJOR PESTICIDES: 2,4-D (PANEL A) AND CPS (PANEL B)
Source: USGS

the year county combination has either a TC event or pesticide use, allowing us huge variation across counties and time. By combining these two databases, we have ended up with a master database covering 2352 counties over the period of 1992-2017 for each year, as tropical cycloneexposure data does not offer information for 654 counties for all years.

3.3. Crop Production Dataset

County-level crop data from 1992 to 2017 were obtained from the United States Department of Agriculture (USDA)'s National Agricultural Statistics Survey (NASS) Quick Stats Database (https://quickstats.nass.usda.gov/). We utilize county-level annual data on aggregate agricultural production and harvested area across all crops and crop-level data for 32 individual crops and categories, including field crops, fruit and tree nuts, and vegetables. We calculate yield based on production (output) and harvested area. Our main outcome variable is the overall yield at the county level. In additional analysis, we use crop-specific information to examine the susceptibility of major crops in each region to TC damage. Typical county maps for agricultural firm locations, planted acres, harvested acres, yield per harvested acre, and production are presented in USDA (2025), available at https://www.nass.usda.gov/Charts_and_Maps/Crops_County/index.php#cr. These maps also confirm that most of the agricultural activities in the US are based in the Eastern regions, which nicely aligns with our pesticide and weather data coverage.

4. Identification and Estimation Strategy

The estimation strategy builds on the premise that, conditional on various observed and unobserved factors, cyclones in the Atlantic basin are random in their timing and intensity. Therefore, this study assumes that the random assignment of cyclone timing and intensity across the US counties yields exogenous variation in farmers' adaptation strategy through the application of pesticide application efforts in time and intensity. Following previous literature on cyclones, we argue that cyclones are exogeneous for at least three reasons. First, Craghan (2003) documents that storms generally originate in the ocean, and their routes depend on the wind speed and direction. Since winds are atmospherically exogenous, the resulting variability in storm timing and intensity is also exogenous. Second, recent developments in meteorological techniques can provide relatively accurate early warnings regarding the destinations of storms shortly after they emerge. However, such a prediction is not possible until the source of the storm within the vast ocean has been geospatially identified. Since the source and timing of storms cannot be predicted before they originate, cyclones may form at any time in any place on the Earth. Third, a cyclone's direction cannot be redirected or controlled, even once the origination is pointed out. It is likely to batter down the coastal surface at some point without anyone knowing the exact time and intensity (Rahman et al., 2022). In a nutshell, taking all the earlier points together, cyclones are likely to be exogenous in terms of the timing of their occurrence, their frequency in a given year, their direction, which determines which particular county they are supposed to go through, and their physical severity of a given strike. One might argue that, given the cyclone season and past experience, the agriculture sector should be able to predict when to plant and harvest crops to avoid damage by TCs. While this month or season of the year does not apply to our context as we are using annual data, each TC itself is exogenous since its path, severity, and potential damage are unpredictable and hence cannot be in any way accounted for (Spencer and Polachek, 2015).

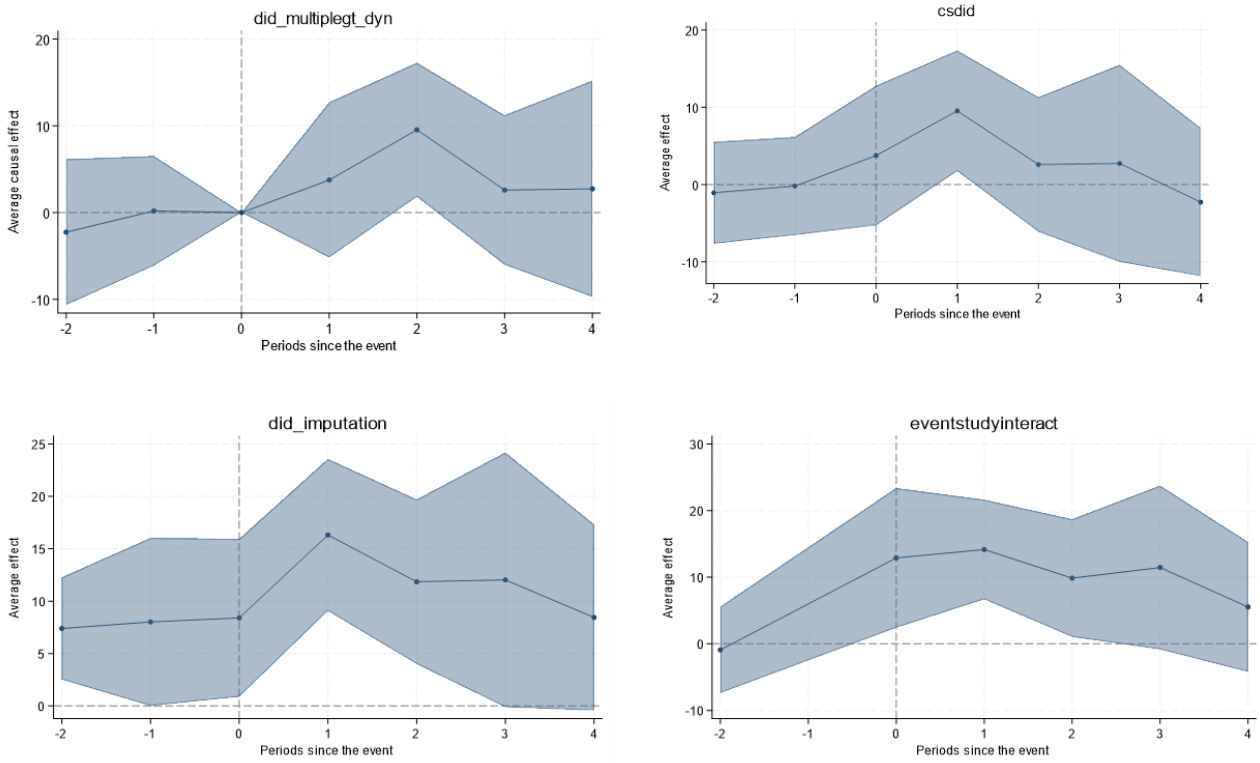
Since we use the spatio-temporal randomness in TC incidence to identify post-cyclone pesticide use patterns of the US farmers, our identification strategy does not require the levels of pesticide use between counties with and without storms to be equal in the absence of such weather shock. Rather, it assumes that the changes in the level of pesticide use between storm-affected and storm-free counties could have trended similarly in the absence of storms. In this regard, we leverage a Difference-in-Difference Event Study approach, utilizing the exogenous variation caused by TCs that occurred in the Atlantic Basin of the United States from 1992 to 2017. Since TCs strike in different years in different counties, in our context, we face the challenge of staggered treatment adoption. In our setting of heterogeneous treatment

effects, the traditional two-way fixed effect model, including leads and lags of treatment, can yield biased estimates. Fortunately, recent contributions from de Chaisemartin and D'Haultfœuille (2024), Callaway and Sant'Anna (2021), Borusyak et al. (2024), and Sun and Abraham (2021) correct the biases from this issue of contaminated lead and lag coefficients (Liu et al., 2025). Accordingly, in this paper, we adopt all four of them to develop a robust judgment about the parallel trend assumption under the special situation of staggered treatment adoption. Our Difference-in-Differences Event Study approach takes the following form:

$$p_{ct} = \sum_i \beta_i (H_c \times tropicalcyclone_{c,i}) + \pi' X_{ct} + \mu_{ct} + \vartheta_c + \delta_t + \varepsilon_{ct}, \tag{1}$$

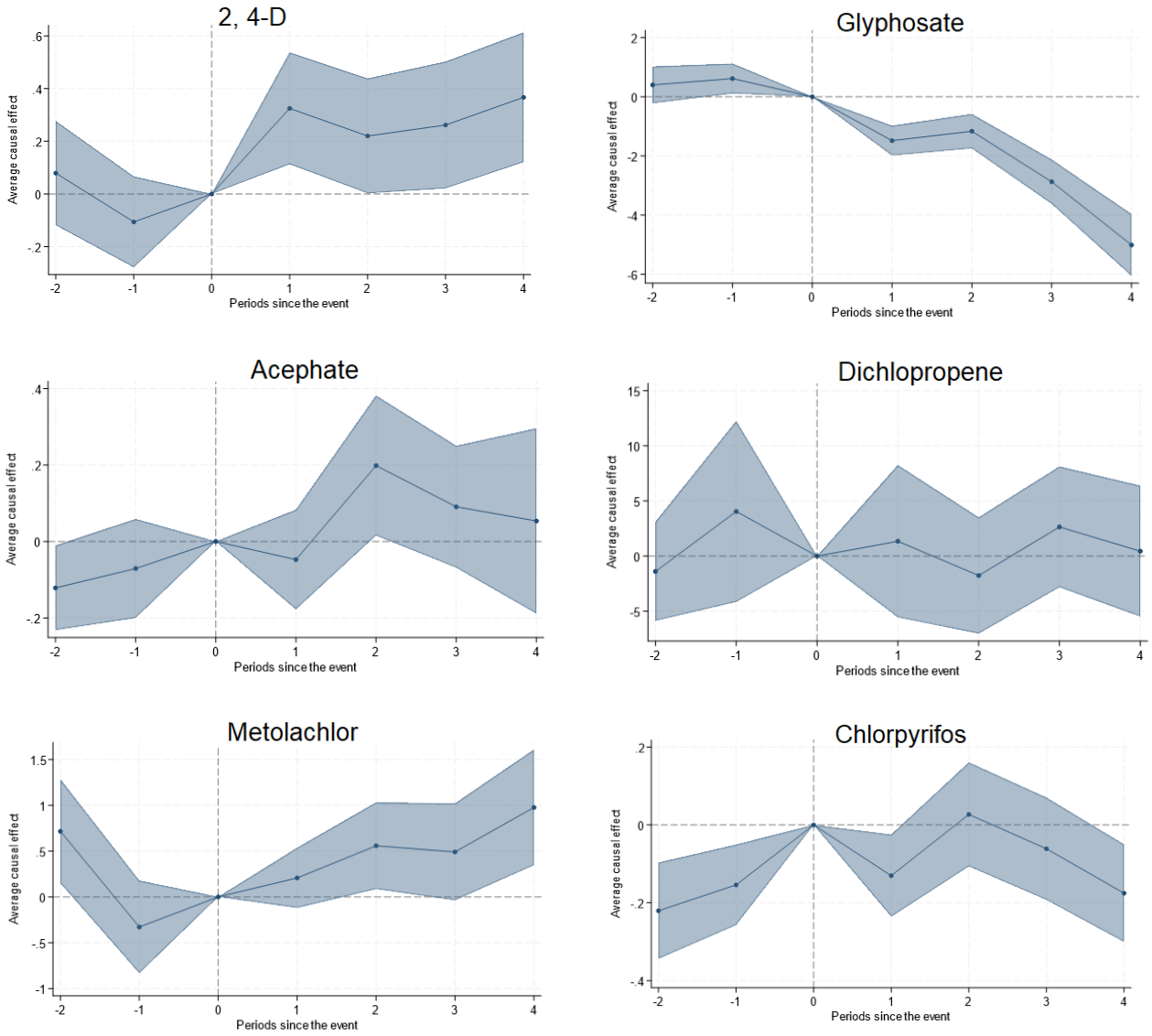
where p_{ct} is pesticide use rate of county c in year t, indicating the quantity of pesticides (thousand kgs) per harvested-crop acreage. H_c is a binary variable for TC exposure, which takes the value of 1 if a county is hit by the TC during the study period, and is equal to zero otherwise. $tropicalcyclone_{c,i}$ is a series of binary variables of i-period lead or lag relative to TC shocks in a county c. where p_{ct} is pesticide use rate of county c in year t, indicating the quantity of pesticides (thousand kgs) per harvested-crop acreage. H_c is a binary variable for TC exposure, which takes the value of 1 if a county is hit by the TC during the study period, and is equal to zero otherwise. $tropicalcyclone_{c,i}$ is a series of binary variables of i-period lead or lag relative to TC shocks in a county c. The coefficient β_i estimates the change in outcomes in TC counties relative to matched non-TC counties during time i. X_{ct} represents a set of weather-related factors like the quadratic of average maximum temperature, the quadratic of total precipitation, and degree days above 30°C. ϑ_t is the county fixed effects, controlling for any unobserved, time-invariant differences across counties. δ_t are the year fixed effects, which account for national trends across all the counties for each year. μ_{ct} controls for county-by-year fixed effects, which account for time-varying shocks that are specific to each county.

Figure 6 traces out the trend in pesticide use patterns year by year for the period leading up to the first storm in a county. Since we are using the annual pesticide usage rate, we estimate the effects of the TC from two years leading up to the event to four years after the event. All four estimation methods clearly indicate an increase in pesticide usage rate at least following the year of a TC event, while Borusyak et al. (2024) and Sun and Abraham (2021) indicate the increases to persist until the second and third year after the event, respectively. With regards to pre-TC trends, there is no trace of any significant trend even two years before the TC event strikes. Once the parallel trend hypothesis is cemented for the average pesticide use rate in thousand kg per acre, we investigate the same for six major individual pesticide types.



Notes. This figure presents the point estimates and 95% confidence intervals of the dynamic effects of TCs on average county-level pesticide use rate in thousand kg per acre. Fig. 5(a) reports estimates from de Chaisemartin and D'Haultfœuille (2024), Fig. 5(b) displays estimates from Callaway and Sant'Anna (2021), Fig. 5(c) presents results from Borusyak et al. (2024), and Fig. 5(d) presents estimates from Sun and Abraham (2021).

FIGURE 6: EVENT-STUDY: EFFECTS OF TCS ON AGRICULTURAL PESTICIDE USAGE RATE



Notes. This figure presents the point estimates and 95% confidence intervals of the dynamic effects of TCs on six different types of average county-level pesticide use rates in thousand kg per acre. While this figure reports estimations from de Chaisemartin and D'Haultfœuille (2024), corresponding findings from Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Borusyak et al. (2024) are presented in Figure 9.

FIGURE 7: EVENT-STUDY: EFFECTS OF TCS ON DIFFERENT TYPES OF AGRICULTURAL PESTICIDE USAGE RATE

Figure 7 plots the event study for six major types of pesticide usage rates under de Chaisemartin and D'Haultfœuille (2024). In these event study plots, we can trace a similar upward trend in pesticide application for three out of six major pesticide types. Among these three, the increases in use of 2,4-D and Metolachlor persist even after four years of the TC event, and for Acephate application upward trend seems to decline from the second year. There is no significant trend in Dichloropene applications. However, the small sample size for this pesticide type can restrict us from making any inference from the event study plot. Glyphosate use has been experiencing a downward trend even before the TC event. For Chlorpyrifos, there is a significant decline after the year of the TC event. Nonetheless , given the pre-trends, we can safely infer that farmers do not increase CPS application as they do for other pesticides like 2, 4-D, Metolachlor or Acephate. Corresponding results from three other methods Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Borusyak et al. (2024) are presented in Figure 9 in the Appendix. To sum up, our event study designs offer three significant insights. One, on average, farmers increase the application of pesticides following a TC event in the Atlantic basin. Two, these upward trends, nevertheless, are not homogeneous across all different pesticide types. Three, while farmers increase application of most of the major pesticide types, farmers tend to refrain from increasing Chlorpyrifos use in the aftermath of the event.

We now extend our empirical analysis with a two-way fixed-effect setup. Our primary estimation model with a distributed lag variable for storm exposure, with additional controls, is described below. The main specification is of the following form:

$$p_{ct} = \alpha_0 + \beta_1 tropicalcyclone_{ct} + \beta_2 tropicalcyclone_{ct-1} + \beta_3 tropicalcyclone_{ct-2} + \pi^{/} X_{ct} + \mu_{ct} + \vartheta_c + \delta_t + \varepsilon_{ct}, \quad (2)$$

where p_{ct} is pesticide use rate of county c in year t, indicating the quantity of pesticides (thousand kgs) per harvested-crop acreage[5]. $tropicalcyclone_{ct}$ represents TC shocks in the Atlantic basin (*i.e.*, a dummy taking a value of one if there was a TC-associated storm event within a county c in year t based on the TC exposure database) to measure a county's storm exposure. We also use seven other TC-related measures around a cyclone event to account for TC intensity. X_{ct} controls for relevant weather-related factors like the quadratic of average maximum temperature, the quadratic of total precipitation, and degree days above 30°C. μ_{ct} represents county-by-year fixed effects to account for any county-specific conditions, and ϵ_t is the error term. ϑ is county fixed effects, which control for permanent differences across counties.

[5]Note that there are two bound estimates for pesticide use rate: a low estimate and a high estimate. We calculate an average estimate from these two bounds and use this average estimate in our analyses

δ_t are year fixed effects to absorb any aggregate shocks experienced by all counties. We cluster standard errors at the county level throughout the analysis.

If cyclones are systematic rather than random events and are correlated with time-invariant county-specific characteristics like location, then ϑ_c will capture the complete list of permanent factors that may affect pesticide use patterns and TC events. Since our time-variant cyclone measure is exogenous and properly captures the dynamic nature of treatment, the estimated β_t should not be sensitive to controlling for country-specific time trends, as there will be little variation left to capture. In addition, any remaining variation will be uncorrelated with our measure of the TC. The error term ε in Equation (1) might be correlated across counties and time, and serial correlation could also appear in the cross-sectional dimension of the panel data, as a particular TC may simultaneously affect a series of neighboring counties. To allow for such biases in the standard error, we use heteroskedasticity and autocorrelation (HAC) consistent standard errors. For the identification assumption of our fixed effect model, we assume the condition of contemporaneous exogeneity, $Cov(tropicalcyclone_{ct}, \varepsilon_{ct})$=0. We do not expect this condition to be violated, given that TCs are random events in terms of their timing and severity and cannot be influenced by past agricultural activities. The storm indicator in Equation (1) assists us in estimating the average effect of all TC events on pesticide use.

5. Results

At this stage, we present our benchmark results in Table 1, representing the impacts of different TC-related variables on total pesticide use rate in kgs per harvested-crop acre. To identify the magnitude of a TC event, we have developed eight different measures, namely, the storm dummy, number of storms, storm-related rainfall, gust wind speed, sustained wind speed, duration of damaging gust wind, duration of damaging sustained wind, and an overall severity index using the principal component approach. To be precise about the effects of these various measures, we not only estimate contemporaneous event year (t) effects but also estimate the impacts of the TC event for the subsequent two years, the next year (t-1), and the year after (t-2). Results for all eight disaster measures indicate that farmers increase their application of pesticide in the year of the TC event. For seven out of eight, this increase persisted even in the following year, which is very much consistent with our event study results. To make a policy judgment from the results, according to column 2, in response to one extra cyclone event, farmers apply 4.65 and 4.88 thousand kgs more pesticides per acre of land in the event year and the following year, respectively. As per USDA's 2022 Census report, the average farm size in the

US is 463 acres (https://www.nass.usda.gov/Newsroom/2024/02-13-2024.php). Hence, for an average US agricultural farm, average pesticide application increases by 2,153 and 2,259 kgs in response to a TC event in the same year and the next. To put these numbers in perspective, according to USDA census data of 2022(https://www.nass.usda.gov/Publications/AgCensus/2022/Full_Report/Volume_1,_Chapter_1_US/st99_1_071_071.pdf), there are approximately 2 million agricultural farms in the US. Food and Agricultural Organination's FAOSTAT (https://www.fao.org/faostat/en/#data/RP indicates that, in the same year, US farmers applied around 427,232 tonnes of pesticides on their land. Dividing these two numbers gives us an estimate of average annual pesticide use in an average US farm as 0.214 tonnes or 215 kgs a year (multiply the mass value by 2000). Hence, in response to a cyclone event, the average U.S. farm in a cyclone-affected county applies more than ten times its usual amount of pesticides in both the year of the event and the following year. This is not surprising as farmers are expected to increase pesticide use following TCs to protect crops from pests, diseases, and weeds, thereby safeguarding the subsequent harvest. Rainfalls are often associated with cyclones, which may wash away and dilute pesticides from agricultural farms. Hence, as expected, farmers use a minimal 0.085 kg more pesticides per acre for one extra millimeter of precipitation in the year of the TC event (column 3).

[Table 1]

Winds drift pesticides, decreasing their effectiveness to safeguard crop production. Hence, to protect sustained harvest, farmers apply more pesticides during windy days around TC events (Kasner et al., 2021). This increase in use is found to be much higher and persistent than rainfalls. As our results indicate, in response to an extra meter of wind gust speed per second (m/s), on average farmers increase pesticide use rate by 1.923 and 1.820 kgs per acre in the year and the year after the event, respectively. A sustained wind speed of an extra meter per second (m/s) leads to an increase of 2.866 and 2.711 kgs on average in the year and the next of the TC. We also use two other measures for wind duration. Our first duration measure is the duration of damaging gust wind, representing the time (in minutes) gust wind was above 20 m/s in the county during the storm. Similar to wind speed measures, an additional minute of damaging gust wind leads to an increase in pesticide application by approximately 0.07 kgs more per acre for both years during and after the TC event. Our second wind duration indicator is defined as the duration of damaging sustained wind, documenting the time sustained wind was above 20 m/s in the county during the storm. In response to an extra minute of damaging sustained wind, farmers increase their agricultural pesticide use by 0.226 kgs per acre and 0.252 kgs per acre in the year of the cyclone and the next year of the cyclone, respectively. Our DID estimates for severity indexes are even higher, *i.e.* an

increase of 3.282 in the year and 3.696 in the year after the TC event on average. As mentioned earlier, all these results were estimated with year and county fixed effects as well as county-year-fixed effects and relevant weather-related controls. Once we establish the positive causal linkage between measures of storms and with increase in overall pesticide use, we now turn our attention to individual pesticide usage patterns.

5.1. Heterogeneity by Pesticide Type

Our first individual pesticide-based results are reported in Table 2, where we regress each of the major pesticide use rates on an overall index of TCs. In this table, we present the results for three consecutive years from the year of the TC event. In response to our principal component approach-based severity index, farmers invariably increase all five out of six pesticide types in the year of the event and the year after. In fact, for 2, 4-D, Glyphosate and Metolachlor, the application increases persist even for the third consecutive year after a TC event. Our result for Glyphosate contradicts the event study result in Figure 7. However, one can blame that on the pre-trend that existed in the event study figure for this pesticide. Nevertheless, the most interesting findings from this table are the absence of any significant coefficient for CPS. From a policy perspective, Chlorpyrifos, which is commonly known as Roundup in the US, is an intriguing pesticide. This particular pesticide is banned in many of the EU countries due to its harmful effects on health, particularly on infants. In the US, this is widely known for its harmful effects and the EPA is considering banning it altogether. Hence, while our result indicating farmers are using more pesticides as a coping mechanism against TCs is not very welcoming for health and environmental consequences, our findings for this notorious one are rather comforting. To verify the robustness of these findings, we run detailed estimations for individual pesticides.

[Table 2]

We present detailed results for individual pesticides through Appendix Tables 3 to 8. While farmers document an increase in pesticide application for all five pesticide types for most of the severity indexes, they refrain from using more CPS in the TC event and the year after. For example, in response to one extra TC in the event year (represented by column 2 row 3 for all the tables), coefficients for 2, 4-D, Glyphosate, Acephate, Dichlopropene, Metolachlor, and CPS are 0.104, 0.204, 0.033, 1.235, 0.440, and -0.022 kg per acre, respectively. Worth noting, all these coefficients are significant. The results for our overall indexes are also consistent with these findings. While we observe no significant results for CPS for any of the three years for the index, in the TC year and the year after 2,4-D, Glyphosate, Acephate, Dichlopropene, Metolachlor

applications increase by 0.106, 0.097, 0.028, 1.041, 0.228 (for t), and 0.033, 0.129, 0.038, 0.872, 0.215 (for t-1), respectively. As we found out that the copying pattern of farmers varies for different pesticides as well as for various intensity measures, now we explore the impacts across different regions of the US.

5.2. Heterogeneity by Regions

Table 3 presents results for different regions of the US. This table documents the effects of the binary TC indicator and the overall index on the average county-level pesticide use rate in kg per acre of land for the three consecutive years from the year of a TC event. We investigate these responses in counties near coastal, non-coastal, midwest, non-midwest, and non-midwest non-coastal counties. While we do not see much response from the coastline, we observe significant coping mechanisms implemented through increased pesticide use in Midwest, non-coastline, and non-coastline non-Midwest counties. Absence of any response from coastline counties can be due to the fact that farmers in these regions are either engaged in damage control measures or are in no condition to hope for the reversal of harvest, while farmers from all other regions seem to be proactive in regaining the harvest. As we have significantly unveiled the post-TC pesticide-related coping behavior of the farmers, we now bring the elephant in the room into view by asking one pertinent question. Do these TCs truly negatively impact agricultural activities for farmers to respond to and cope with? We do this by investigating these mechanisms in the next subsection.

[Table 3]

5.3. Agricultural Mechanisms

This study builds on the premise that farmers apply more pesticides to their land following a TC event as a possible coping strategy to safeguard against productivity loss. To test this, we resort to staggered DID. Figure 8 presents event studies for yield, area harvested, and production through implementing de Chaisemartin and D'Haultfœuille (2024). As we expect extended effects on agricultural activities, we follow through with TC impacts on agricultural activities from 4 years back (leads) to 6 years ahead (lags). While we do not observe any significant impact on overall production, there is clear evidence of a decline in agricultural yield between one and four years after a TC, accompanied by an increase in the area harvested from one to three years post-event. While the decrease in yield lends substantial justification for increased pesticide use by farmers, an increase in harvesting area documents farmers' adaptation behavior in the extensive margin. We augment our analysis with a detailed regression for both the binary and index treatments. Corresponding results from Table 4 document the loss of yield and an increase

in area harvested. Column 8 also reveals a significant production loss due to the overall index. Worth mentioning, the loss of yield is persistent even after three years of TC, which justifies farmers' response to implement adaptation strategies in both intensive and extensive margins.

[Figure 8]

So far, we have relied on existing literature to hypothesize the detrimental effects of pesticide use on human health. At this stage of the paper, we briefly investigate this with the recent COVID pandemic as an empirical case study. In the following section, we extend our analysis to investigate the association between historical pesticide use and human health by undertaking a simple correlation analysis in the context of the recent COVID-19 pandemic.

6. Historical Pesticide Use and COVID-19: A Simple Empirical Exercise

Drawing on the widely accepted view that pesticide exposure poses risks to human health, this section conducts a basic OLS-based correlational analysis to address a central question: do pesticides make us more vulnerable to infections and mortality? We then ask an additional question: how does a more accessible healthcare system interact with low pesticide use at the county level?

Experimental studies have reported that exposure to pesticides can exert damaging effects on the immune system (Costa et al., 2013; Fenga et al., 2014; Chen et al., 2014; Díaz-Resendiz et al., 2015; Ma and Li, 2015; Mokarizadeh et al., 2015). Recent epidemiological research also documents the impact of pesticide exposure and the risk of SARS-CoV-2 infection (Lopez et al., 2024). Recognizing obvious identification challenges to infer any type of causality, in this section, we implement a very basic OLS-type correlation analysis to see the link between historical pesticide use in a few county-level COVID-19 outcomes within just one and a half years of the COVID-19 breakout in the US between 21 Jan 2020 and 28 June 2021.

Our COVID-19 data is sourced from New York Times Github project (https://github.com/nytimes/covid-19-data). Before merging it with our original pesticide database, we have cross-checked this data with the Covid Act Now API data (https://apidocs.covidactnow.org/) and found them relatively consistent. In this simple exercise, we use two COVID-related outcome variables at the county level spanning between January 2020 and June 2021: COVID-19 cases, and COVID Deaths. Both of the indicators are normalized by population (million) in 2018. Our county-level controls come from two separate sources: Marks et al. (2021) and U.S. Census Bureau (https://www.ers.usda.gov/data-products/

county-level-data-sets/documentation/). Our control variables include education (percentage of adults with a bachelor's degree or higher during 2015-2019), poverty rate in 2019, death rate in 2018, social capital in 2018, net migration rate in 2019, unemployment rate in 2018, median household income in 2019, household median income as a percent of the State total median household income in 2019, urbanicity in 2018, road access in 2018, population density in 2018, jail rate in 2018, urgent care presence in 2018, proportion of male in 2018, proportion of black in 2018, police violence in 2018, and opioid prescriptions per 100 individuals in 2018. Descriptive statistics of all our pesticide usage and COVID-19-related variables are provided in Appendix Table 9. Before we merge our COVID outcomes and control with pesticide use data, we stack up our county-level pesticide use data to transform them into a state-level 24-year aggregate pesticide use database.

In this section, we try to capture the impacts of 25 years of pesticide use (1992 to 2017) on COVID-19 outcomes. To investigate the county-level impacts of pesticide use on COVID-19, we start with a basic bi-variate model of the following form:

$$Y_{sc} = \mu + \beta PesticideUse_{sc} + \pi^{/} X_{sc} + \vartheta_s + \varepsilon_{cs}, \tag{3}$$

where Y_{sc} is a COVID19-related outcome of interest in a county c within a state s between 21 June 2020 and 28 June 2021. $PesticideUse_{sc}$ represents the level of pesticide use in a county c over 1992-2016 within a state s. X_{sc} is a vector of controls, and ϑ_s is the state fixed effect.

We further extend the above Equation (2) by introducing the Medicaid expansion status of a particular state and interacting it with the level of the low level of pesticide usage. We dichotomize the level of pesticide use (County) by creating a dummy variable for those counties with the bottom decile of the pesticide use; the interaction of the Medicaid variable with the low level of pesticide use offers a simple Difference-in-Difference type estimator $\sum$, as we show below:

$$Y_{sc} = \mu + \alpha County_{sc} + \beta State_{medexp} + \sum State_{medexp} * County_{sc} + \pi^{/} X_{sc} + \vartheta_s + \varepsilon_{cs}, \tag{4}$$

where $State_{medexp}$ is a dummy for the states which chose not to opt for the expansion of the Medicaid program and and $County_{sc}$ is a dummy for counties consuming either the lowest decile of the distribution of the pesticide usage for the whole period between 1992 and 2017.

The results from a simple ordinary least squares (OLS) analysis are provided in Table 5. Our bare-bone bi-variate analysis shows that total pesticide and CPS uses are positively correlated to COVID-

19 normalized cases and deaths. Worth mentioning, while our pesticide uses are in thousand kgs, COVID cases and deaths are normalized by the respective county's population of 2018. Models 3 and 4 offer results after we include several controls with state-fixed effects to tease out time-invariant state characteristics. We endeavored to include as many COVID-19 and Pesticide use relevant controls as we could to deal with omitted variable bias. Once we allow for all the county-level controls, coefficients for normalized cases concerning both the pesticide use-related variables are highly significant. Under this specification, both total pesticide and CPS use are again significantly linked with COVID-19 deaths.

We now continue with our different estimators for non-Medicaid states and counties consuming pesticides at the lowest 10% and 5% rates. As per the definition of these two dummies, we expect states that have not endorsed Medicaid would have a positive coefficient to normalized cases and deaths, while coefficients for counties with the lowest pesticide consumption levels would be negative concerning these two COVID-related outcomes. Our results for models 5 and 6 indicate very much the same as we have hypothesized. Coefficients for all pesticides and CPS are highly significant for both normalized COVID-19 cases and normalized COVID-19 deaths. non-Medicaid state dummies are positive for both COVID-19 cases and deaths. Interestingly enough, our interaction terms for non-Medicaid and the lowest level of pesticide use are all positive and significant. To check the robustness of our results, we develop a counterfactual of the top 10 highest pesticide-consuming counties. As expected, the impacts of higher levels of pesticide use lead to significant and positive coefficients for COVID cases and deaths [6]. As a note of caution about the results from this section, while our results appropriately point out the fact that pesticide use and non-participation in the Medicaid program both have significantly negative impacts on COVID-19 outcomes, we remain skeptical about claiming them as exact causation.

7. Conclusion

Epidemiological and agricultural studies independently highlight the severe economic, environmental, and human health impacts of both natural disasters and pesticide use. However, the crucial connection between disasters and pesticide application remains largely underexplored in existing research. To fill this gap, our study employs a quasi-natural experiment using a novel, large-scale weather-pesticide-agriculture dataset to investigate the causal impact of TCs on county-level agricultural pesticide use across the United States from 1992 to 2017.

[6] Results not reported, to be furnished upon request.

Our results indicate that, on average, farmers increase pesticide applications to protect crop yields following TC events. This elevated use often extends beyond the year of the cyclone, varying with cyclone intensity and pesticide type. To illustrate, for a typical U.S. farm of 463 acres, pesticide use rises by approximately 2,240 kg in the year of the cyclone event and 2,380 kg in the following year, which is ten times the usual yearly pesticide application rate.

Our heterogeneity analysis by pesticide type documents that, these application increases are not uniform across all pesticide types. Notably, CPs—a pesticide known for its high toxicity—are consistently excluded from increased use. Our results offer bittersweet news relating to health, environmental, and economic concerns. While coping with TCs, with higher use of pesticides is detrimental for these outcomes, it is somewhat reassuring that some farmers refrain from intensifying the use of particularly hazardous chemicals like CPS. Geographic analysis indicates that the bulk of the increased pesticide use comes from Midwest, non-coastal, and non-coastal & non-Midwest counties.

Our agricultural productivity-related mechanism analysis shows a loss of yield for an extended period of four years following a cyclone event. To mitigate these losses, farmers respond not only by increasing pesticide use (an intensive margin adjustment) but also by expanding harvested land area (an extensive margin strategy).

As an endnote, in 1992, eight pounds of pesticides were used in the U.S. for every man, woman, and child. Introducing Rachel Carson's Silent Spring, the US Vice President Al Gore made a call to push hard for the use of non-toxic substances, he wrote, "Finally, we must begin to bridge the cultural divide between the pesticide production and agriculture community on the one side and the public health community on the other (Carson and Gore, 1994)." Our simple correlation analysis reveals the detrimental impact of historical pesticide use on the health outcomes related to the COVID-19 pandemic. Given the deleterious effects of pesticides on human health and well-being, it is a moral imperative to reduce pesticide use. Our simple COVID-19 analysis also highlights that health-related institutional innovations can play a major role in alleviating some of these health effects.

Tables

TABLE 1: **Effect of natural disaster on agricultural pesticide usage rate**

	Average Pesticide Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	3.685**							
	(1.652)							
Storm Dummy (t-1)	5.379**							
	(2.276)							
Storm Dummy (t-2)	-0.517							
	(2.408)							
Number of storms (t)		4.650***						
		(1.261)						
Number of storms (t-1)		4.884***						
		(1.641)						
Number of storms (t-2)		-2.702						
		(1.671)						
Storm related rainfall (t)			0.085***					
			(0.026)					
Storm related rainfall (t-1)			0.007					
			(0.026)					
Storm related rainfall (t-2)			-0.055					
			(0.046)					
Mean gust wind speed (t)				1.923***				
				(0.475)				
Mean gust wind speed (t-1)				1.820***				
				(0.637)				
Mean gust wind speed (t-2)				-0.588				
				(0.560)				
Mean sust. wind speed (t)					2.866***			
					(0.708)			
Mean sust. wind speed (t-1)					2.711***			
					(0.949)			
Mean sust. wind speed (t-2)					-0.876			
					(0.835)			
Dur. of damg. gust wind (t)						0.074***		
						(-0.024)		
Dur. of damg. gust wind (t-1)						0.075***		
						(0.028)		
Dur. of damg. gust wind (t-2)						-0.027		
						(0.024)		
Dur. of damg. sust. wind (t)							0.226***	
							(0.072)	
Dur. of damg. sust. wind (t-1)							0.252***	
							(0.082)	
Dur. of damg. sust. wind (t-2)							0.012	
							(0.058)	
Overall index (t)								3.282***
								(0.877)
Overall index (t-1)								3.696***
								(1.296)
Overall index (t-2)								-0.477
								(1.169)
Observations	56,310	56,310	56,310	56,310	56,310	56,310	56,310	56,310
R-squared	0.863	0.863	0.866	0.863	0.863	0.864	0.864	0.863

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are the duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE 2: **Effect of tropical cyclone (index) on agricultural pesticide usage rate**

Dependent variable: Pesticide Use Rate (thousand kg per acre)						
Pesticide Type	2,4-D	Glyphosate	Acephate	Dichloropropene	Metolachlor	Chlorpyrifos
Model	(1)	(2)	(3)	(4)	(5)	(6)
Overall index (t)	0.106***	0.097*	0.0281***	1.041***	0.228***	-0.008
	(0.017)	(0.0056)	(0.010)	(0.244)	(0.040)	(0.008)
Overall index (t-1)	0.033**	0.129**	0.038**	0.872***	0.215***	0.004
	(0.018)	(0.053)	(0.015)	(0.291)	(0.035)	(0.012)
Overall index (t-2)	0.046***	0.126**	-0.022**	0.241	0.121***	0.007
	(0.015)	(0.061)	(0.009)	(0.199)	(0.022)	(0.010)
Observations	56,282	53,947	40,971	16,785	44,769	55,300
R-squared	0.721	0.931	0.684	0.745	0.699	0.640

Notes. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE 3: **Regional effect of tropical cyclone on agricultural pesticide usage rate**

	Dependent variable: Pesticide Use Rate (thousand kg per acre)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
StormD (t)	3.685**		2.087		3.883**		0.462		2.857	
	(1.652)		(6.000)		(1.670)		(1.864)		(1.839)	
StormD (t-1)	5.379**		-13.327		7.103***		7.771***		5.589**	
	(2.276)		(8.418)		(2.548)		(2.727)		(2.262)	
StormD (t-2)	-0.517		-20.307**		3.459*		5.222***		1.914	
	(2.408)		(10.076)		(1.790)		(2.003)		(1.995)	
Index (t)		3.282***		1.296		4.387***		2.543***		3.544***
		(0.877)		(1.698)		(1.051)		(0.869)		(1.050)
Index (t-1)		3.696***		-2.318		6.192***		3.207***		5.669***
		(1.296)		(1.817)		(1.988)		(1.274)		(1.984)
Index (t-2)		-0.477		-4.357**		2.252**		-0.804		1.889*
		(1.169)		(2.079)		(1.092)		(1.186)		(1.126)
Observations	56,310	56,310	4,085	4,085	52,225	52,225	18,107	18,107	34,118	34,118
R-squared	0.863	0.863	0.845	0.895	0.845	0.846	0.860	0.863	0.838	0.839
Region	All Count.	All Count.	Coast.	Coast.	Non-Coast.	Non-Coast.	Midwest	Midwest	Non-Mid., Non-Coast.	Non-Mid., Non-Coast.

Notes. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.. All Count., Coast., Non-Coast., Midwest, Non-Coast. & Non-Mid. represents all, all coastline, non-coastline, midwest, and non-midwest & non-coastline counties, respectively.

TABLE 4: **Effect of tropical cyclone on agricultural activities**

	Agricultural Activities in Log)							
Activity Type	Crop Yield	Crop Yield	Area Harvested	Area Harvested	Area Planted	Area Planted	Total Production	Total Production
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	-0.036**		0.005		0.001		-0.029	
	(0.018)		(0.008)		(0.008)		(0.020)	
Storm Dummy (t-1)	-0.033*		0.020**		0.003		-0.014	
	(0.019)		(0.009)		(0.009)		(0.020)	
Storm Dummy (t-2)	-0.027		0.010		-0.001		(0.008)	
	(0.018)		(0.008)					
Overall index (t)		-0.022***		0.001		0.004		-0.021***
		(0.007)		(0.003)		(0.002)		(0.008)
Overall index (t-1)		-0.016**		0.007***		0.001		-0.009
		(0.007)		(0.003)		(0.003)		(0.008)
Overall index (t-2)		-0.012**		0.000		-0.000		-0.011*
		(0.006)		(0.003)		(0.003)		(0.006)
Observations	46,749	46,749	46,837	46,837	42,147	42,147	46,812	46,812
R-squared	0.784	0.784	0.944	0.944	0.963	0.963	0.898	0.898

Notes. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and state-year fixed effects. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

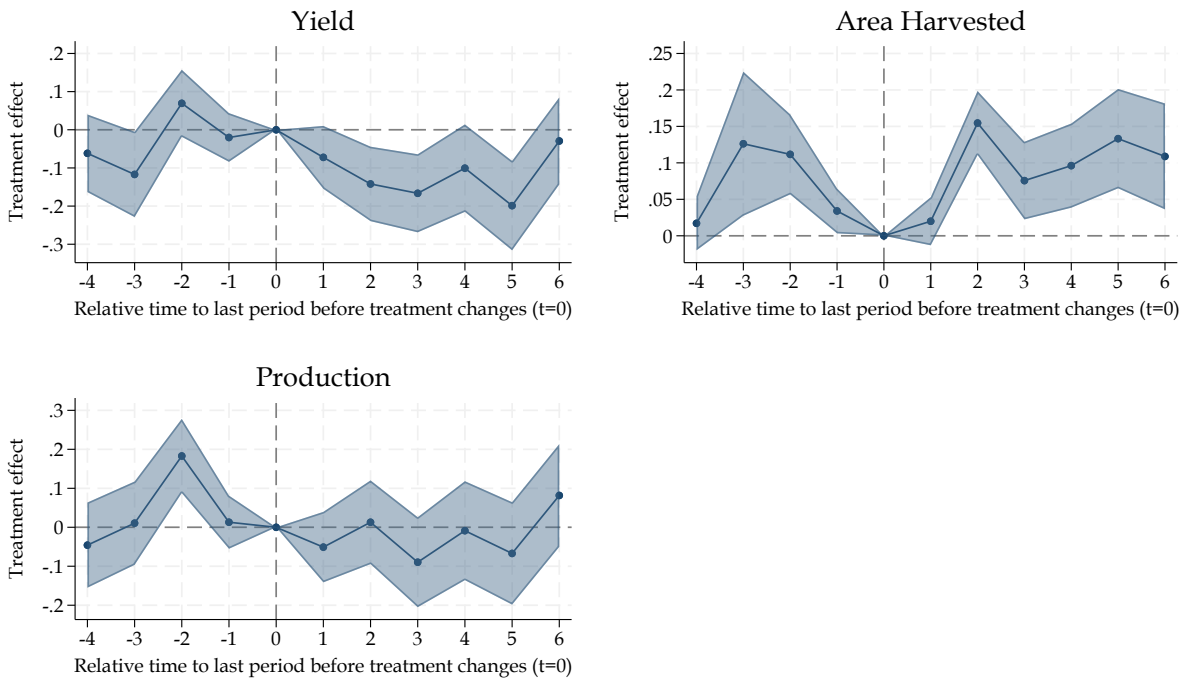


Figure 8: Event-study Effects of TCs on Agricultural Activities

TABLE 5: **Effect of historical pesticide use on Covid19-related health outcomes**

	Models					
Variable	Bi Variate	Bi Variate	With Controls	With Controls	Medicaid*Lowest 10%	Medicaid*Lowest 5%
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: COVID19 Cases						
Total Pesticide Use	0.26***		0.32***			
	(0.082)		(0.081)			
Chlorpyrifos		21.28***		27.604***		
		(8.045)		(8.694)		
non-Medicaid					5,843.1088**	5314.41***
					(1,325.129)	(2534.117)
Lowest 10% use (L_{10})					-16,186.306***	
					(4,061.277)	
non-Medicaid*L_{10}					8822.541**	
					(3028.751)	
Lowest 5% use (L_5)						-19423.63***
						(4165.358)
non-Medicaid*L_5						10020.77*
						(6317.562)
Panel B: COVID19 Deaths						
Total Pesticide Use	0.00**		0.005***			
	(0.000)		(0.002)			
Chlorpyrifos		0.04		0.448**		
		(0.099)		(0.175)		
non-Medicaid					424.79***	404.59***
					(43.229)	(43.908)
Lowest 10% use (L_{10})					-439.593***	
					(127.204)	
non-Medicaid*L_{10}					377.826***	
					(128.190)	
Lowest 5% use (L_5)						-439.593***
						(127.204)
non-Medicaid*L_5						338.89*
						(187.24)
Observations	3,063	3,063	3,063	3,063	2,691	2,691
Controls	No	No	Yes	Yes	Yes	Yes
State Fixed effects	No	No	Yes	Yes	Yes	Yes

Notes. The number of Covid cases/deaths is normalized by population (cases per million of residents). county = 1 if a county's pesticide usage belongs to the bottom or top 10%/25% of the whole sample. stateD = 1 if a state is Alabama, Florida, Georgia, Kansas, Mississippi, North Carolina, South Carolina, South Dakota, Tennessee, Texas, Wisconsin, or Wyoming. List of control variables at county level: poverty rate 2019, deathrate2018, socialcapital2018, net migration rate2019, unemployment rate 2018, median household income 2019, urbanicity2018, road access2018, population density2018, jail rate2018, urgent care2018, proportion male2018, proportion black2018, police violence2018, opioid per1002018. While pesticides are in thousand kg, CPS is the most used pesticide in the US with detrimental health effects. All regressions except for the bi-variate controls for state-fixed effects and standard errors are clustered around counties.. ***, **, and * Significance at 1%, 5%, and 10%.

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Appendix

TABLE A1: **Storms covered in tropical cyclone exposure data**

Year	Storms	Distance	Wind	Rain	Flood	Tornado
1988	Alberto, Beryl, Chris, Florence, Gilbert, Keith, AL13, AL14, AL17	x	x	x		x
1989	Allison, Chantal, Hugo, Jerry	x	x	x		x
1990	AL01, Bertha, Marco	x	x	x		x
1991	Ana, Bob, Fabian, AL12	x	x	x		x
1992	AL02, Andrew, Danielle, Earl	x	x	x		x
1993	AL01, Arlene, Emily	x	x	x		x
1994	Alberto, AL02, Beryl, Gordon	x	x	x		x
1995	Allison, Dean, Erin, Gabrielle, Jerry, Opal	x	x	x		x
1996	Arthur, Bertha, Edouard, Fran, Josephine	x	x	x	x	x
1997	AL01, Ana, Danny	x	x	x	x	x
1998	Bonnie, Charley, Earl, Frances, Georges, Hermine, Mitch	x	x	x	x	x
1999	Bret, Dennis, AL07, Floyd, Harvey, Irene	x	x	x	x	x
2000	AL04, Beryl, AL09, Gordon, Helene, Leslie	x	x	x	x	x
2001	Allison, Barry, Gabrielle, Karen, Michelle	x	x	x	x	x
2002	Arthur, Bertha, Cristobal, Edouard, Fay, Gustav, Hanna, Isidore Kyle, Lili	x	x	x	x	x
2003	Bill, Claudette, AL07, Erika, Grace, Henri, Isabel	x	x	x	x	x
2004	Alex, Bonnie, Charley, Frances, Gaston, Hermine, Ivan, Jeanne, Matthew	x	x	x	x	x
2005	Arlene, Cindy, Dennis, Emily, Katrina, Ophelia, Rita, Tammy Twenty-Two, Wilma	x	x	x	x	x
2006	Alberto, Beryl, Chris, Ernesto	x	x	x	x	x
2007	Andrea, Barry, Erin, Gabrielle, Humberto, Ten, Noel	x	x	x	x	x
2008	Cristobal, Dolly, Edouard, Fay, Gustav, Hanna, Ike, Kyle, Paloma	x	x	x	x	x
2009	One, Claudette, Ida	x	x	x	x	x
2010	Alex, Two, Bonnie, Five, Earl, Hermine, Nicole, Paula	x	x	x	x	x
2011	Bret, Don, Emily, Irene, Lee	x	x	x	x	x
2012	Alberto, Beryl, Debby, Isaac, Sandy	x	x		x	x
2013	Andrea, Dorian, Karen	x	x		x	x
2014	Arthur	x	x		x	x
2015	Ana, Bill, Claudette	x	x		x	x
2016	Bonnie, Colin, Eight, Hermine, Julia, Matthew	x	x		x	x
2017	Cindy, Emily, Harvey, Irma, Jose, Nate, Philippe	x	x		x	x
2018	Alberto, Chris, Florence, Gordon, Michael	x	x		x	x

Source: tropical cycloneexposure package description at https://cran.r-project.org/web/packages/tropical cycloneexposure/vignettes/tropical cycloneexposure.html

TABLE A2: **Summary Statistics**

	count	mean	sd	min	max
Major Storm Related Indicators:					
Storm Dummy	61,0323	0.11	0.32	0	1
Number of storm event in a county	61,0323	0.17	0.56	0	6
County-year number of severe gust wind of all storm	61,0323	0.06	0.29	0	4
County-year number of severe sustained wind of all storm	61,0323	0.01	0.11	0	3
County-year mean rain level of all storms mm/day	61,0323	4.71	22.58	0	336.90
Mean of distances to all storms, despite being exposed or not	61,0323	0.01	0.01	0	1.91
Number of exposures to damaging gust wind of above 20m/s	61,0323	0.13	0.43	0	4
Number of exposures to damaging sustained wind of above 20m/s	61,0323	0.04	0.22	0	3
Number of exposures to sustained wind speed of above 99 percentile	61,0323	0.05	0.26	0	4
Major Pesticide Use Related Variables:					
County-year average-estimated quantity of pesticide (thousand kg per acre)	61,0323	105.905	221.10	0	8001.57
County-year average-estimated quantity of $2_{4D}(thousandkgperacre)$	61,0323	4.44	6.92	0	232.53
County-year average-estimated quantity of Glyphosate (thousand kg per acre)	58,660 3	20.04	35.68	0	390.93
County-year average-estimated quantity of Acephate (thousand kg per acre)	45,069	0.78	3.14	0	136.96
County-year average-estimated quantity of Dichloropropene (thousand kg per acre)	18,669	13.43	47.04	0	2652.15
County-year average-estimated quantity of Metolachlor (thousand kg per acre)	49,360	4.59	11.57	0	291.47
County-year average-estimated quantity of CPS (thousand kg per acre)	59,985	1.14	2.45	0	71.75
Agriculture, Weather and Other Related Variables:					
Average Yield	51,075	116.33	429.74	0	54065.32
Total Area Harvested (arce)	51,293	110516.00	133339.30	0	1596200.00
Total Area Planted (arce)	51,293	98577.29	141911.00	0	1760500.00
Average Max Temperature (°C)	42,563	19.54	4.06	7.90	31.66
Total Precipitation (mm)	61,041	1113.916	321.79	52.81	2797.97
No. degree days above 30°C	61,041	52.58	58.45	0.00	581.63
Amount of Nitrogen in Fertilizer (kg)	49,049	2989059	3571473	168.00	3.58e+07
Amount of Phosphorus in Fertilizer (kg)	49,049	464708.20	538169.80	33.00	6456197
Coastal Dummy	61,032	0.07	0.25	0.00	1.00
Midwest Dummy	61,041	0.32	0.46	0.00	1.00

Notes: Observations are at the county level. The sample period is 1992–2017 for all data, except fertilizer data (1992–2012).

TABLE A3: **Effect of natural disaster on 2,4-D usage rate**

	2,4-D Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	0.191***							
	(0.053)							
Storm Dummy (t-1)	0.114**							
	(0.051)							
Storm Dummy (t-2)	0.211***							
	(0.053)							
Number of storms (t)		0.104***						
		(0.030)						
Number of storms (t-1)		0.058***						
		(0.026)						
Number of storms (t-2)		0.143***						
		(0.029)						
Storm related rainfall (t)			0.001					
			(0.001)					
Storm related rainfall (t-1)			-0.002**					
			(0.001)					
Storm related rainfall (t-2)			0.002*					
			(0.001)					
Mean gust wind speed (t)				0.054**				
				(0.010)				
Mean gust wind speed (t-1)				0.004				
				(0.007)				
Mean gust wind speed (t-2)				0.032***				
				(0.009)				
Mean sust. wind speed (t)					0.081***			
					(0.015)			
Mean sust. wind speed (t-1)					0.006			
					(0.011)			
Mean sust. wind speed (t-2)					0.048***			
					(0.013)			
Dur. of damg. gust wind (t)						0.000***		
						(0.000)		
Dur. of damg. gust wind (t-1)						0.000		
						(0.000)		
Dur. of damg. gust wind (t-2)						0.000		
						(0.000)		
Dur. of damg. sust. wind (t)							0.001*	
							(0.000)	
Dur. of damg. sust. wind (t-1)							0.000	
							(0.000)	
Dur. of damg. sust. wind (t-2)							0.000	
							(0.000)	
Overall index (t)								0.106***
								(0.017)
Overall index (t-1)								0.033*
								(0.018)
Overall index (t-2)								0.046***
								(0.015)
Observations	56,282	56,282	56,282	56,282	56,282	56,282	56,282	56,282
R-squared	0.721	0.721	0.720	0.721	0.721	0.721	0.721	0.721

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE A4: **Effect of natural disaster on Glyphosate usage rate**

	Glyphosate Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	0.273**							
	(0.139)							
Storm Dummy (t-1)	0.336**							
	(0.164)							
Storm Dummy (t-2)	0.067							
	(0.173)							
Number of storms (t)		0.204***						
		(0.077)						
Number of storms (t-1)		0.389***						
		(0.085)						
Number of storms (t-2)		0.214**						
		(0.100)						
Storm related rainfall (t)			0.011***					
			(0.003)					
Storm related rainfall (t-1)			0.003					
			(0.002)					
Storm related rainfall (t-2)			0.005*					
			(0.003)					
Mean gust wind speed (t)				0.050*				
				(0.027)				
Mean gust wind speed (t-1)				0.125***				
				(0.031)				
Mean gust wind speed (t-2)				0.110***				
				(0.030)				
Mean sust. wind speed (t)					0.074*			
					(0.040)			
Mean sust. wind speed (t-1)					0.186***			
					(0.047)			
Mean sust. wind speed (t-2)					0.164***			
					(0.045)			
Dur. of damg. gust wind (t)						0.001**		
						(0.000)		
Dur. of damg. gust wind (t-1)						0.001**		
						(0.000)		
Dur. of damg. gust wind (t-2)						0.001***		
						(0.000)		
Dur. of damg. sust. wind (t)							0.002*	
							(0.001)	
Dur. of damg. sust. wind (t-1)							0.002**	
							(0.001)	
Dur. of damg. sust. wind (t-2)							0.003***	
							(0.001)	
Overall index (t)								0.097*
								(0.056)
Overall index (t-1)								0.129**
								(0.053)
Overall index (t-2)								0.126**
								(0.061)
Observations	53,947	53,947	39,848	53,947	53,947	53,947	56,282	53,947
R-squared	0.931	0.931	0.940	0.931	0.931	0.931	0.931	0.931

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE A5: **Effect of natural disaster on Acephate usage rate**

	Acephate Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	0.041							
	(0.034)							
Storm Dummy (t-1)	0.096**							
	(0.044)							
Storm Dummy (t-2)	0.015							
	(0.032)							
Number of storms (t)		0.033**						
		(0.017)						
Number of storms (t-1)		0.063***						
		(0.024)						
Number of storms (t-2)		-0.008						
		(0.014)						
Storm related rainfall (t)			-0.001**					
			(0.001)					
Storm related rainfall (t-1)			-0.002***					
			(0.001)					
Storm related rainfall (t-2)			0.000					
			(0.001)					
Mean gust wind speed (t)				0.013***				
				(0.005)				
Mean gust wind speed (t-1)				0.009				
				(0.006)				
Mean gust wind speed (t-2)				-0.011***				
				(0.004)				
Mean sust. wind speed (t)					0.020***			
					(0.007)			
Mean sust. wind speed (t-1)					0.014			
					(0.009)			
Mean sust. wind speed (t-2)					-0.016***			
					(0.006)			
Dur. of damg. gust wind (t)						-0.000		
						(0.000)		
Dur. of damg. gust wind (t-1)						0.000		
						(0.000)		
Dur. of damg. gust wind (t-2)						-0.000***		
						(0.000)		
Dur. of damg. sust. wind (t)							0.000	
							(0.000)	
Dur. of damg. sust. wind (t-1)							0.000	
							(0.000)	
Dur. of damg. sust. wind (t-2)							-0.000***	
							(0.000)	
Overall index (t)								0.028***
								(0.010)
Overall index (t-1)								0.038**
								(0.015)
Overall index (t-2)								-0.022**
								(0.009)
Observations	40,971	40,971	40,971	40,971	40,971	40,971	40,971	40,971
R-squared	0.684	0.684	0.719	0.684	0.684	0.684	0.684	0.684

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE A6: **Effect of natural disaster on Dichloropene usage rate**

	Dichloropene Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	2.329***							
	(0.670)							
Storm Dummy (t-1)	-0.789							
	(0.611)							
Storm Dummy (t-2)	1.144							
	(0.699)							
Number of storms (t)		1.235***						
		(0.309)						
Number of storms (t-1)		0.589						
		(0.439)						
Number of storms (t-2)		0.436						
		(0.382)						
Storm related rainfall (t)			0.036					
			(0.029)					
Storm related rainfall (t-1)			0.058***					
			(0.017)					
Storm related rainfall (t-2)			0.003					
			(0.013)					
Mean gust wind speed (t)				0.456***				
				(0.114)				
Mean gust wind speed (t-1)				0.520***				
				(0.152)				
Mean gust wind speed (t-2)				0.147				
				(0.103)				
Mean sust. wind speed (t)					0.679***			
					(0.169)			
Mean sust. wind speed (t-1)					0.775***			
					(0.226)			
Mean sust. wind speed (t-2)					0.218			
					(0.153)			
Dur. of damg. gust wind (t)						0.003***		
						(0.001)		
Dur. of damg. gust wind (t-1)						0.004***		
						(0.001)		
Dur. of damg. gust wind (t-2)						0.001		
						(0.001)		
Dur. of damg. sust. wind (t)							0.004	
							(0.003)	
Dur. of damg. sust. wind (t-1)							0.015***	
							(0.004)	
Dur. of damg. sust. wind (t-2)							-0.000	
							(0.002)	
Overall index (t)								1.041***
								(0.244)
Overall index (t-1)								0.872***
								(0.291)
Overall index (t-2)								0.241
								(0.199)
Observations	16,785	16,785	16,785	16,785	16,785	16,785	16,785	16,785
R-squared	0.744	0.744	0.762	0.745	0.7455	0.745	0.745	0.745

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE A7: **Effect of natural disaster on Metolachlor usage rate**

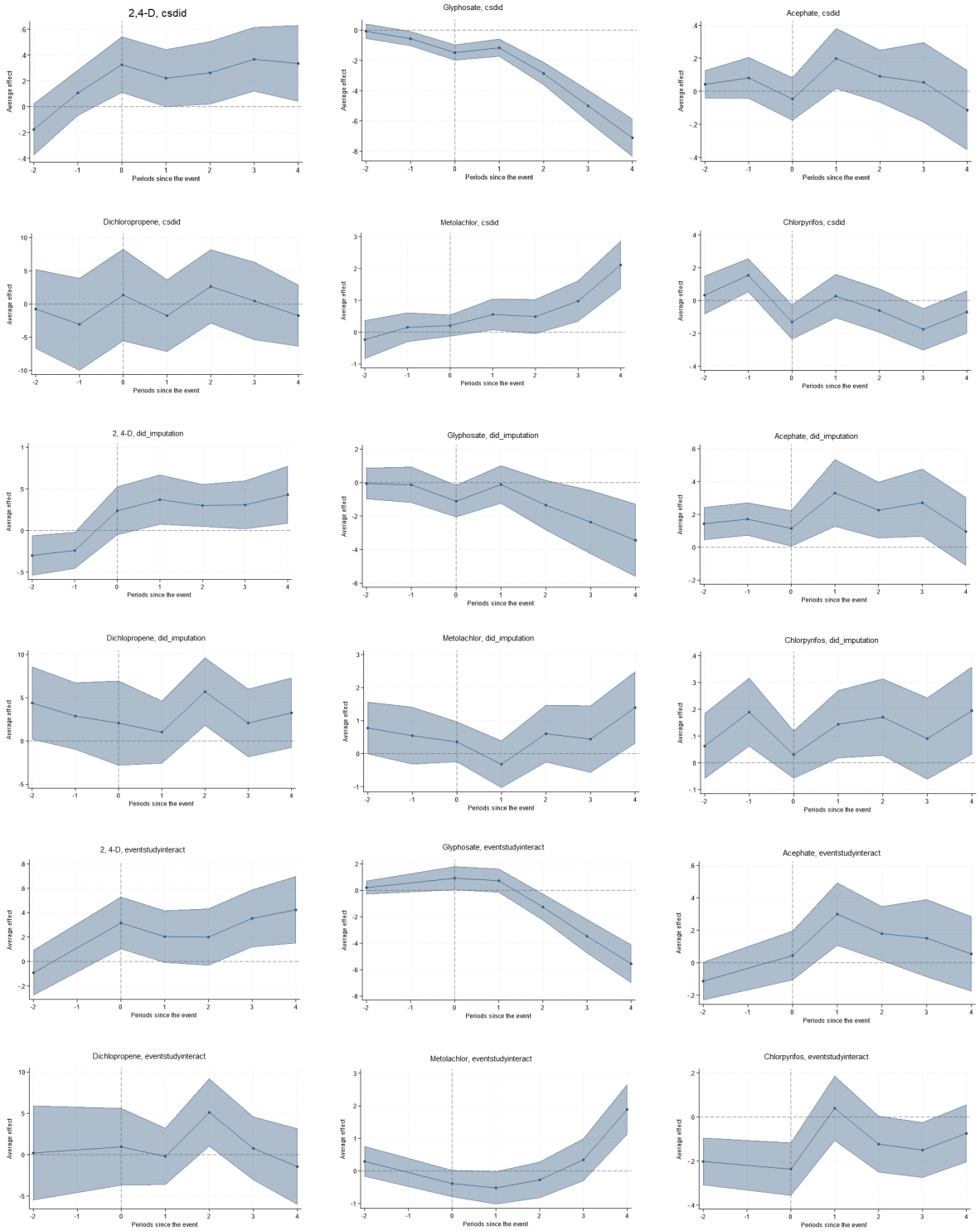
	Metolachlor Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	0.550***							
	(0.096)							
Storm Dummy (t-1)	0.503***							
	(0.088)							
Storm Dummy (t-2)	0.520***							
	(0.087)							
Number of storms (t)		0.440***						
		(0.065)						
Number of storms (t-1)		0.365***						
		(0.057)						
Number of storms (t-2)		0.352***						
		(0.041)						
Storm related rainfall (t)			0.001					
			(0.002)					
Storm related rainfall (t-1)			0.013***					
			(0.002)					
Storm related rainfall (t-2)			0.002					
			(0.002)					
Mean gust wind speed (t)				0.041**				
				(0.014)				
Mean gust wind speed (t-1)				0.048***				
				(0.017)				
Mean gust wind speed (t-2)				0.046***				
				(0.034)				
Mean sust. wind speed (t)					0.062***			
					(0.022)			
Mean sust. wind speed (t-1)					0.071***			
					(0.025)			
Mean sust. wind speed (t-2)					0.068***			
					(0.020)			
Dur. of damg. gust wind (t)						0.000***		
						(0.000)		
Dur. of damg. gust wind (t-1)						0.001***		
						(0.000)		
Dur. of damg. gust wind (t-2)						0.000***		
						(0.000)		
Dur. of damg. sust. wind (t)							0.001**	
							(0.000)	
Dur. of damg. sust. wind (t-1)							0.001***	
							(0.000)	
Dur. of damg. sust. wind (t-2)							0.001***	
							(0.000)	
Overall index (t)								0.228***
								(0.040)
Overall index (t-1)								0.215***
								(0.035)
Overall index (t-2)								0.121***
								(0.022)
Observations	44,769	44,769	31,463	44,769	44,769	44,769	44,769	44,769
R-squared	0.698	0.699	0.786	0.698	0.699	0.698	0.698	0.699

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.

TABLE A8: **Effect of natural disaster on Chlorpyrifos usage rate**

	Use Rate (thousand kg per acre)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Storm Dummy (t)	-0.021							
	(0.018)							
Storm Dummy (t-1)	0.050**							
	(0.024)							
Storm Dummy (t-2)	0.101***							
	(0.022)							
Number of storms (t)		-0.022*						
		(0.011)						
Number of storms (t-1)		0.024						
		(0.015)						
Number of storms (t-2)		0.041**						
		(0.016)						
Storm related rainfall (t)			-0.002***					
			(0.000)					
Storm related rainfall (t-1)			-0.000					
			(0.000)					
Storm related rainfall (t-2)			0.000					
			(0.001)					
Mean gust wind speed (t)				-0.008*				
				(0.004)				
Mean gust wind speed (t-1)				-0.0043				
				(0.005)				
Mean gust wind speed (t-2)				0.004				
				(0.005)				
Mean sust. wind speed (t)					-0.012*			
					(0.006)			
Mean sust. wind speed (t-1)					-0.006			
					(0.008)			
Mean sust. wind speed (t-2)					0.005			
					(0.007)			
Dur. of damg. gust wind (t)						-0.000**		
						(0.000)		
Dur. of damg. gust wind (t-1)						-0.000		
						(0.000)		
Dur. of damg. gust wind (t-2)						-0.000		
						(0.000)		
Dur. of damg. sust. wind (t)							-0.000**	
							(0.000)	
Dur. of damg. sust. wind (t-1)							-0.000	
							(0.000)	
Dur. of damg. sust. wind (t-2)							-0.000*	
							(0.000)	
Overall index (t)								-0.008
								(0.008)
Overall index (t-1)								0.004
								(0.012)
Overall index (t-2)								0.007
								(0.010)
Observations	55,300	55,300	55,300	55,300	55,300	55,304	55,304	55,300
R-squared	0.640	0.640	0.640	0.640	0.640	0.337	0.337	0.640

Notes. Storm-related rainfall is in 5-day window from the previous day. Damaging wind is represented by above 20m/s. Dur. of damg and sust. are duration of damaging and sustained, respectively. All dependent variables are in log form. All regressions include quadratic of average maximum temperature, quadratic of total precipitation, degree days above 30°C, county fixed effects, year fixed effects and county-specific time trend. Robust standard errors, clustered by county, in parentheses. ***, **, and * Significance at 1%, 5%, and 10%.



Notes. This figure presents the point estimates and 95% confidence intervals of the dynamic effects of TCs on six different types of average county-level pesticide use rates in thousand kg per acre under Callaway and Sant'Anna (2021), Sun and Abraham (2021), and Borusyak et al. (2024).

FIGURE 9: EVENT-STUDY: EFFECTS OF TCS ON DIFFERENT TYPES OF AGRICULTURAL PESTICIDE USAGE RATE

TABLE A9: **Summary Statistics-COVID19 Experiment**

Variables (county level)	count	mean	sd	max
COVID Related:				
Cases	3,136	10,614	40,316	1,249,971
Deaths	3,136	191	894	33,412
Pesticide Related:				
Total Pesticide: avg (kg)	3.063	3,553,549	9,545,225	2,783,478
Chlorpyrifos: avg (kg)	3.063	39,083	119,693	3,663,742
Controls:				
Poverty Rate 2019	3,133	14.45343	5.801304	47.70
Death Rate 2018	3,134	10.39319	2.723174	25.56
Social Capital 2018	3,134	0.314495	12.34623	126.183
Net Migration Rate 2019	3.063	39,083	119,693	3,663,742
Unemployment Rate 2018	3,133	4.102394	1.469324	18.80
Median Household Income 2019	3,133	55689.13	14479.31	151806
Urbanicity 2018	3,142	4.636219	1.510359	6.00
Road access 2018	3,142	0.4108848	0.4920727	1.00
Population density2018	3,142	3.783759	1.786235	11.17522
Jail rate 2018	2,991	0.0037877	0.0085222	0.164971
Urgent care 2018	3,142	0.6228517	0.4847497	1.00
Proportion male 2018	3,142	50.08585	2.379575	79.00
Proportion Black 2018	3,140	9.930127	14.70459	87.50
Police Violence 2018	3,142	0.2364736	0.4249839	1.00
Opioid per 100 2018	2,881	61.80562	32.73067	311.30

Notes: COVID cases, deaths, and fatality rates are between 21 Jan 2020 and 28 June 2021. Normalized variables are normalized by county population in 2019. Pesticides are in kgs aggregated from 1992 to 2017 at individual county levels.