Crops, Insects, and Diseases: Ecological Consequences of Straw-Burning Ban*

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Abstract

This study demonstrates that environmental regulation can unintentionally alter ecological systems, generating offsetting health costs. Using China's staggered implementation of straw-burning bans as a quasi-experiment, we find that the ban led to a substantial increase in hospitalizations from insect-borne diseases, partially offsetting the gains from reduced air pollution. We show that the ban reduced cropland fires, increased insect populations, and spurred public defensive behaviors, suggesting that the policy facilitated disease transmission through ecological channels. These effects largely vanish where straw recycling is effectively implemented, highlighting the role of complementary policies in mitigating unintended consequences and enhancing environmental regulation benefits.

Keywords: Ecosystem disruptions, Straw-burning ban, Insect ecology, Vector-borne diseases, Agricultural fires

JEL Classification: Q57, Q51, Q50, Q10

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1 Introduction

Environmental policies aim to reduce pollution and improve human well-being. However, when such policies also alter ecological systems, they may generate unintended health risks that partially offset their intended benefits. Such ecological feedbacks generated by environmental regulation remain largely underexplored. As environmental change increasingly affects biodiversity, species interactions, and ecosystem services, understanding how environmental interventions reshape ecological systems and their consequences for human health has become increasingly important (Brock and Xepapadeas, 2003; Cardinale et al., 2012; Pecl et al., 2017; Blowes et al., 2019; Frank and Sudarshan, 2024; Frank et al., 2024; Liang et al., 2025).

This paper explores ecological–health transmission channels in the context of China's straw-burning ban. As one of the country's most stringent air pollution control policies, the ban aims to reduce seasonal agricultural fires and improve air quality. However, by altering local ecological conditions, the policy may also affect insect populations and the risks of vector-borne diseases, such as Lyme disease and tick-borne encephalitis.[1] Our findings suggest that these ecological responses generate unintended health costs that partially offset the policy's health benefits from cleaner air. At the same time, complementary straw-recycling policies appear to mitigate these unintended consequences by limiting ecological conditions favorable to disease vectors. These implications can extend beyond China, as many countries have adopted or are considering restrictions on open-field burning to control agricultural air pollution.[2]

Figure 1 illustrates the ecological transmission mechanism underlying our hypothesis. By suppressing agricultural fires, the straw-burning ban leads to the accumulation of unburned crop residues in fields. These residues provide food and shelter for arthropods as humid and warm ground cover, facilitating the overwintering and reproduction of arthropod species. With vector abundance, human exposure to both insect activity and vector-borne pathogens may rise.[3] Vector-borne diseases, which are closely linked to vector ecology, account for 17% of global infectious disease cases and cause over 700,000 deaths annually (WHO, 2024). These diseases impose substantial economic burdens, including both health-related losses and broader costs such as reduced productivity and increased public and private expenditures.[4] As crop residue accumulation underlies this ecological pathway, managing residues becomes a natural policy lever to mitigate

[1] In this study, vector-borne diseases adopt a broad definition encompassing health conditions arising from exposure to arthropods. This includes: (i) infectious diseases transmitted biologically by arthropod vectors; (ii) diseases transmitted mechanically by arthropods; and (iii) direct health consequences of arthropod exposure, such as parasitic infestations, allergic reactions, and toxic effects. For simplicity and consistency in exposition, we use the term "insects" broadly to denote arthropods, primarily including insects (e.g., mosquitoes, flies, beetles) and arachnids (e.g., ticks, mites, spiders). See more details in Section 2.2 and Appendix B.

[2] Open-field burning of crop residues is widespread in countries such as Russia, India, Thailand, and the Philippines, as well as other regions of Asia (Korontzi et al., 2006; Gadde et al., 2009; Kumar et al., 2015). In response, bans or restrictions on open-field burning have been introduced in many regions, including the U.S., the European Union, India, Brazil, and parts of Southeast Asia (Paraiso and Gouveia, 2015; Vagg, 2015; Huang et al., 2021).

[3] A growing ecological literature documents how land-use practices and vegetation management influence vector abundance and arthropod ecology (Samish and Alekseev, 2001; Allan, 2009; Gleim et al., 2014; Gallagher et al., 2022).

[4] For example, the annual economic burden of Lyme disease in the U.S. was estimated at $345–$968 million in 2016, with an average treatment cost of around $3,000 per case (Hook et al., 2022).

these health risks while preserving the air-quality benefits of the burning ban. We investigate the effects of the ban and provide complementary evidence related to residue management that is consistent with this mechanism and highlights its potential as a mitigating margin.

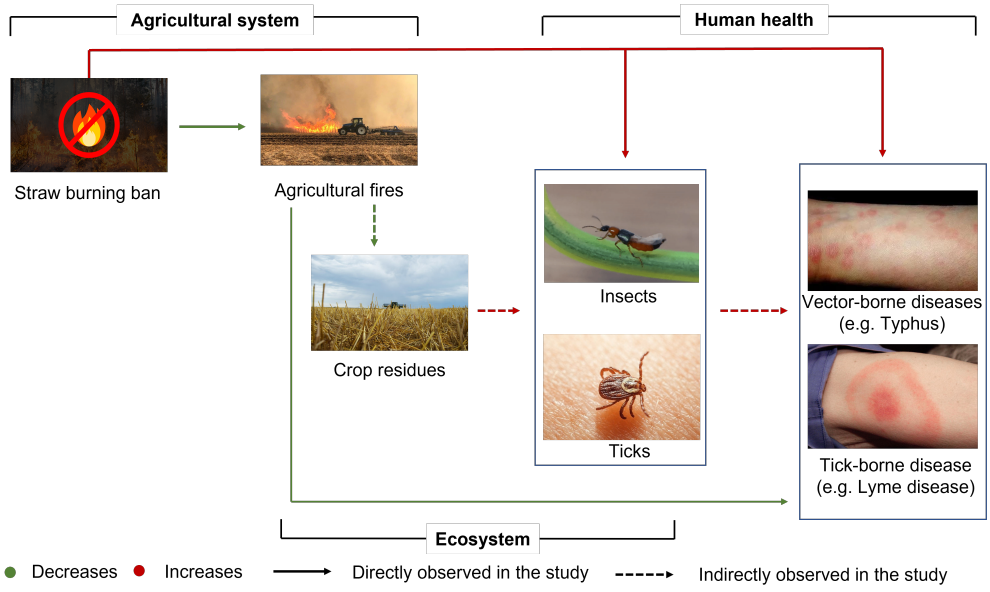


Figure 1: Ecological Framework Linking Straw-Burning Bans with Human Health

Notes: This figure illustrates the core ecological mechanism. By suppressing agricultural fires, the straw-burning ban leads to the accumulation of crop residues, which in turn enhances ecological suitability for arthropods and causes vector-borne diseases.

We construct a novel dataset that links straw-burning ban to health outcomes through ecological changes. We integrate comprehensive inpatient records from a representative subset of public hospitals nationwide with taxonomic observation data, satellite measures of fire activity and land cover, web search indices, and records of agricultural equipment adoption. We identify cases of vector-borne diseases using ICD-10 codes (listed in Table C1) widely used in epidemiology (WHO, 2024). We place emphasis on a severe subset—tick-borne diseases (listed in Table C2) including Lyme disease, tick-borne encephalitis, and Severe Fever with Thrombocytopenia Syndrome (SFTS), which are closely linked to agricultural environments and pose significant health risks, including fatality.

To estimate the health impacts of these policy-induced ecological changes, we exploit the staggered rollout of China's straw-burning ban across counties as a natural experiment. Implemented in a top-down manner, the timing and location of the policy were driven primarily by administrative and economic considerations rather than local health, ecological, or climatic conditions.[5] We implement a staggered Difference-in-Differences (DiD) design using county-by-year-quarter data, following the estimator proposed by Borusyak et al. (2024), which aligns with our identification structure and data granularity.[6] Our baseline specification includes county fixed effects,

[5]See Section 2 and 4.2 for a detailed discussion of policy rollout and identification.

[6]We also assess robustness using alternative staggered DiD estimators in Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin et al. (2022), which yield consistent results. See Section 4 for details.

year-quarter fixed effects, and province-by-quarter fixed effects to flexibly account for unobserved confounders. We further control for weather conditions, forest fire activity, hospital capacity, population, local economic conditions, medical infrastructure, and cropland coverage.

We provide a range of supporting evidence to assess the validity of our identification strategy. Pre-treatment trends indicate that treated and control counties followed similar trajectories prior to the policy. We also present evidence that the rollout of the ban was driven by national air pollution initiatives rather than local health conditions or vector-borne disease prevalence, consistent with the implementation patterns documented in the Air Pollution Monitoring and Disclosure (APMD) Program (Barwick et al., 2024). In addition, we show that our results are robust to controlling for concurrent policies and sample restrictions. Placebo tests on unrelated disease categories yield no significant effects, suggesting that the ban's effects on vector-borne diseases are unlikely to be driven by contemporaneous changes in general healthcare demand or supply.

Findings We document three main findings. First, China's straw-burning ban unintentionally increases hospitalizations and medical expenditures related to vector-borne diseases. On average, the policy raises hospitalizations by approximately 50% and inpatient medical costs by 70% relative to pre-treatment levels. These effects persist for several years following implementation, consistent with sustained ecological changes. A back-of-the-envelope calculation suggests that the associated increase in hospitalization costs exceeds $223 million annually, likely understating the full economic burden as it excludes outpatient care, productivity losses, and defensive investments.

These unintended health costs partially offset the benefits of improved air quality. Comparing across disease categories, we estimate that the increase in vector-borne disease burden offsets approximately 4.6% of the reduction in hospitalization expenditures for pollution-related conditions such as respiratory and cardiovascular diseases.[7] This result highlights a broader implication: environmental policies can generate non-trivial trade-offs when they alter ecological conditions.

Second, we provide evidence on the ecological mechanism linking the ban to health outcomes. The policy reduces cropland burning, which increases arthropod populations and ultimately leads to higher disease incidence. Drawing on multiple data sources, we document consistent patterns along this pathway: satellite data show substantial declines in fire activity; taxonomic observations indicate increases in relevant arthropod populations; and web search data capture heightened exposure and defensive responses to insect activity. An instrumental variable strategy further supports this interpretation, showing that reductions in agricultural burning increase vector-borne disease outcomes. Heterogeneity analyses reinforce this mechanism, with stronger effects observed in ecologically favorable settings, including wheat-producing regions, warmer climates, and peak agricultural seasons.

[7] This comparison is based on inpatient medical expenditures within the same dataset and empirical framework. It provides a partial accounting of health trade-offs, as it excludes mortality, outpatient care, and broader economic costs on both sides.

Third, we examine mitigation through residue management. We find that straw-recycling policies, by promoting the removal of crop residues, significantly attenuate the adverse health effects of the ban. In areas with recycling subsidies, adoption of straw-collecting equipment increases and the rise in vector-borne diseases is substantially reduced. These findings suggest that complementary policies targeting residue management can mitigate unintended health consequences while preserving the air-quality benefits of fire reduction. More broadly, they highlight the importance of incorporating ecological feedbacks into the design of environmental regulation, particularly in countries that restrict open-field burning.

Related Literature We contribute to a growing literature on the health consequences of biodiversity disruption. Recent studies show that ecological imbalances can have far-reaching effects on human well-being. Frank and Sudarshan (2024) link vulture extinction in India to higher mortality through impaired sanitation, while Frank et al. (2024) find that sparrow eradication during China's Four Pests Campaign reduced crop yields and raised death rates. In urban settings, Xing et al. (2023) find that large-scale afforestation in Beijing improved air quality but also increased pollen exposure and allergy-related emergency visits. Taylor (2021) and Frank (2024) show that ecological shocks, such as cicada emergence or bat declines can increase infant mortality by inducing more insecticide use, with lasting harm. Complementing this evidence, foundational work in *Science* and *Nature* emphasizes how biodiversity loss undermines ecosystem services and public health resilience (Cardinale et al., 2012; Pecl et al., 2017; Blowes et al., 2019). Building on this literature, we show that environmental policies, if overlooking ecological interactions, can unintentionally alter ecological dynamics in ways that offset their intended benefits.

Second, we contribute to the literature on the health and labor market effects of agricultural fires. Existing studies show that exposure to agricultural burning, primarily through elevated $PM_{2.5}$ (Guo, 2021), has substantial adverse effects on human health, including increased mortality (He et al., 2020; Garg et al., 2024), hypertension risks (Pullabhotla and Souza, 2022), adverse birth outcomes (Rangel and Vogl, 2019), and cognitive impairments (Zivin et al., 2020; Lai et al., 2022). Related work also highlights broader environmental consequences. Hong and Chen (2026) show that China's straw-burning ban increased pesticide use and worsened water pollution. We build on evidence that incentive-based policies can reduce burning and improve air quality. Jack et al. (2025) provide experimental evidence from northern India showing that payments for ecosystem services, particularly with partial up-front transfers, effectively discourage crop residue burning. Complementary studies on straw-recycling subsidies and biomass energy infrastructure point to similar policy potential (He et al., 2020; Cao and Ma, 2023; Nian, 2023). While the direct health and environmental benefits of fire-reduction policies are increasingly well understood, less attention has been paid to how reducing agricultural fires can alter ecological dynamics. We address this gap by documenting an ecological transmission channel linking fire reduction to vector-borne disease risks, and by quantifying how these feedback effects partially offset the intended health gains of environmental policies. Evidence further indicates that residue management such as

straw recycling can serve as a practical mitigating margin, incorporating ecological considerations into environmental policy design.

Third, our study adds to a broader literature linking ecosystem dynamics to socioeconomic changes. Prior work examines how infrastructure, trade, and place-based policies shape deforestation, biodiversity, and land use patterns (Asher et al., 2020; Garg and Shenoy, 2021; Taylor and Mayer, 2023; Abman and Lundberg, 2024; Carreira et al., 2024; Costa et al., 2025; Meng et al., 2025), often emphasizing the direct ecological impacts of economic development (Liang et al., 2025). A related strand of work shows that ecological disruptions such as deforestation or the spread of invasive species, can affect health outcomes including mortality, malaria incidence, birth outcomes, and obesity (Garg, 2019; Jones, 2019, 2023; Du et al., 2024). We show that policy-induced habitat change can reshape insect ecology and generate unintended health consequences by increasing the prevalence of native arthropod species that are otherwise balanced by ecological dynamics.

The rest of the paper is organized as follows. Section 2 describes the background of straw-burning ban policies in China and vector-borne diseases. Section 3 introduces the datasets. Section 4 illustrates the empirical strategy. Section 5 estimates the impact of the straw-burning ban policy on hospitalizations of vector-borne and tick-borne diseases and conducts various robustness checks. Section 6 displays evidence on the impact pathway of the policy. Section 7 examines how straw recycling policies mitigate the adverse impact and discusses the policy implications. Finally, Section 8 concludes.

2 Straw-Burning Ban and Vector-Borne Diseases

2.1 Straw-Burning Ban Policy

On-site straw burning, a traditional agricultural practice to clear crop residues after harvest, has been a significant source of air pollution in China, especially during the harvest season in rural areas (He et al., 2020). In response to its environmental and public health consequences, the Chinese government initiated a nationwide ban on straw burning, implemented progressively across regions in a staggered manner (Huang et al., 2021) (Figure 2).[8] This staggered rollout provides a quasi-experimental setting that enables causal identification of the policy's effects using a DiD framework.

Two features of the policy design are central to our empirical strategy. First, we examine the effects of straw-burning bans with credible enforcement. In our setting, enforcement at the county level was generally well institutionalized. To ensure accurate policy measurements, we restrict the analysis to mandates that include explicit performance-based enforcement mechanisms, such as formal assessment criteria and reward–punishment schemes tied to local compliance (see examples in Figure A2). These institutional features increase accountability and raise the expected cost of noncompliance for local officials. In parallel, the central government institutionalized satellite-

[8]Data source: Peking University Law Database, https://www.pkulaw.com. The construction of our policy rollout measure is detailed in Section 3.

based remote sensing to detect fire hotspots and integrated this information into official performance evaluations.[9] These measures enhanced the credibility, traceability, and uniformity of policy enforcement, supporting reliable policy measurement and robust identification.[10]

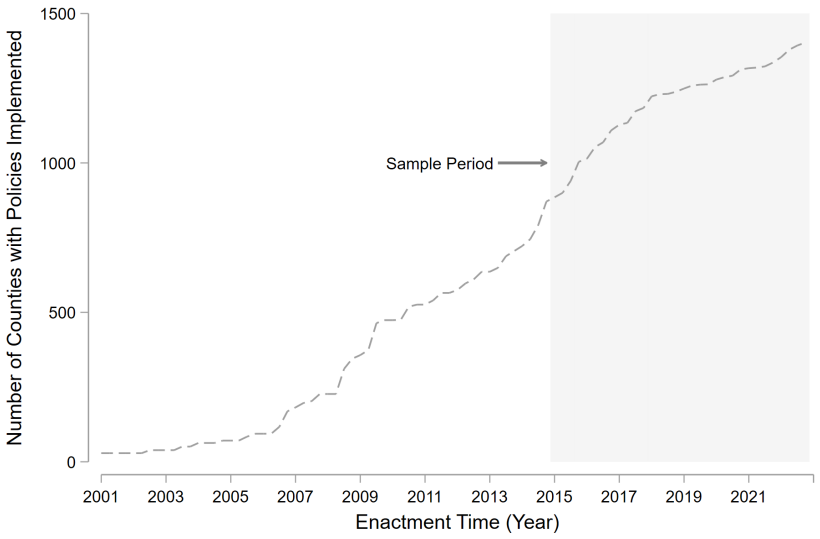


Figure 2: Rollout of China's Straw-Burning Ban Across Counties

Notes: This figure shows the number of counties that implemented the straw-burning ban policy with explicit evaluation criteria over time. The data are drawn from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2. Our main sample period is 2015–2022, based on hospitalization data availability. We show robustness checks for other outcomes using longer time spans wherever data are available.

The second feature of the policy design is that the timing of policy adoption was largely shaped by top-down administrative hierarchy. As detailed in Appendix D and illustrated in Figure D1, the ban was initially concentrated in the North China Plain and subsequently extended to northeastern, other northern, and southwestern provinces. Early implementation was prioritized in counties surrounding Beijing and other provincial capitals due to their political salience and alignment with national performance targets.[11] In Section 4.2, we further document that, conditional on administrative hierarchy, the timing of adoption is uncorrelated with pre-policy health infrastructure

[9] According to the *Notice on Implementing the National Environmental Protection Standards Formulation and Revision Projects*, the Satellite Environmental Application Center of the Ministry of Environmental Protection began revising the *Technical Specifications for the Application of Satellite Remote Sensing Monitoring of Straw Burning* in 2011, marking the institutionalization of remote sensing as a policy enforcement tool (see https://www.mee.gov.cn/gkml/hbb/bgth/201405/W020140512536749455371.pdf, in Chinese).

[10] Our analysis complements existing studies that rely on province-level straw-burning bans (e.g., Cao and Ma, 2023; Hong and Chen, 2026) through exploiting county–year variation. This finer-grained approach captures substantial within-province heterogeneity in enforcement and agricultural practices, and leverages staggered county-level policy adoption for improved causal inference.

[11] In 2008, the Ministry of Environmental Protection issued the *Notice on Further Strengthening Straw Burning Prohibition Work*, which banned open-air straw burning across all centrally administered municipalities, provincial capitals, and fifteen sub-provincial cities to improve air quality ahead of the Beijing Olympics (see https://www.mee.gov.cn/gkml/hbb/bwj/200910/t20091022_174595.htm, in Chinese).

and that treated and untreated counties followed parallel pre-trends, supporting the plausibility and exogeneity of the policy variation.

Crop Residue Management Following the ban, most regions lacked effective incentives or infrastructure for straw recycling. Because the cost of collection and transport exceeded the market value of the residues, farmers typically resorted to shredding and plowing the straw into the soil, leaving it to decompose in the fields. This practice, while compliant with the ban, contributed to residue accumulation and inadvertently created favorable conditions for insect breeding. Starting in 2016, several provinces launched straw-recycling subsidy programs to promote more systematic removal of residues (He et al., 2020). In Section 7, we provide further details on these practices and examine their role as a complementary policy tool in mitigating the unintended health effects of the ban.

2.2 Arthropods and Vector-Borne Diseases

Arthropods, such as mosquitoes, flies, and ticks, are key vectors that transmit infectious diseases to humans. These species can carry viruses, bacteria, and parasites that cause illnesses such as dengue, malaria, tick-borne encephalitis, and rickettsiosis.[12] Many of these disease-carrying species thrive in warm, humid environments with vegetation, organic matter, and crop residues. When straw is not cleared or burned after harvest, it creates suitable microhabitats that allow insects to survive the winter and reproduce in greater numbers. As a result, environmental policies that alter these habitats—intentionally or not—may influence vector populations and generate unintended consequences for public health.

Vector-Borne Diseases Our primary health outcomes are hospitalizations and inpatient medical expenditures associated with diseases related to arthropod exposure. This category encompasses both infectious conditions transmitted by arthropod vectors (e.g., dengue, Lyme disease, and tick-borne encephalitis) and clinically significant non-infectious outcomes arising from arthropod exposure, including severe allergic, toxic, or immune-mediated reactions to bites or venom. The classification follows standard medical definitions and clinical coding conventions used in the epidemiological literature, and the complete list of included diagnoses is reported in Table C1. For expositional simplicity, we refer to this outcome category as vector-borne diseases.

Within this broader set, we analyze tick-borne diseases as a distinct category due to their severe health impacts and their role as representative vector-borne diseases in agricultural environments.[13] Tick populations are highly sensitive to ecological conditions, particularly vegetation

[12] Arthropods belong to the phylum *Arthropoda*, which mainly includes insects (e.g., mosquitoes, flies, beetles) and arachnids (e.g., ticks, mites, spiders). Diseases carried by arthropods can be transmitted from animals to humans (zoonotic transmission) and, in some cases, directly between humans. Appendix B provides additional biological and disease-related background.

[13] Ticks feed on the blood of animal hosts and often remain attached for several days. Because their bites are typically painless and difficult to detect, treatment is frequently delayed. Many tick-borne illnesses lack vaccines, and hospital-

density and soil moisture, both of which are influenced by the presence of unburned post-harvest straw. Many tick species overwinter as adults, making the post-harvest period critical for their survival and a driver of lasting disease risks. Table A1 shows that hospitalizations for vector-borne and tick-borne illnesses span all age groups, highlighting population-wide vulnerability.

The Lethal Risk of Vector-Borne Diseases Although insect bites are often seen as minor, vector exposure can lead to hospitalization or death when pathogens are involved or when individuals experience severe immune reactions (e.g., anaphylaxis or toxin-induced organ failure). To illustrate the severe—and in some cases, fatal—consequences of vector-borne diseases, we highlight SFTS, a highly virulent tick-borne illness that has gained growing attention over the past decade. Caused by the SFTS virus and transmitted primarily through infected tick bites, the disease is characterized by fever, vomiting, and platelet decline, and currently lacks effective vaccine or targeted antiviral therapy. In older adults, the case fatality rate can reach as high as 50% (Chen et al., 2025), and human-to-human transmission has been documented through contact with infected blood. For example, in May 2022, a cluster of four deaths in Xinyang, Henan Province, followed a single suspected tick exposure.[14] These facts underscore that vector-borne diseases are not minor or isolated threats but pose serious public health risks.

3 Data

3.1 Data Sources and Variable Construction

We construct our dataset by integrating multiple sources: hospitalization records, policy documents, satellite detections of agricultural burning, insect taxonomic observations, internet search indices, agricultural land-use measures, procurement of straw recycling equipment, and socioeconomic and environmental characteristics. These data allow us to capture the ecological and health pathways underlying the straw-burning ban. Details on data sources and main variable construction are provided below, with additional information in Appendix A.

Hospitalization Data Our primary health outcomes, hospitalizations and medical expenditures, are sourced from inpatient medical records.[15] Covering 2015–2022, the dataset includes approximately 21% of secondary and tertiary public hospitals across 30 provinces, forming the most comprehensive national sample currently available for public inpatient care in China.[16] The dataset

ization is often required for treatment or tick removal. See Table C2 for the full list of diseases, including Lyme disease, rickettsiosis, tick-borne encephalitis, SFTS, and tick paralysis.

[14] https://news.sina.cn/sh/2022-05-30/detail-imizirau5593009.d.html, in Chinese.

[15] We obtained legal access to the data from the Data Center for High-Quality Hospital Management at Peking University's Institute for Global Health and Development. The data were collected by an independent third-party provider for the purpose of monitoring electronic medical records. These data have been used in studies such as Lin et al. (2022), Wu et al. (2025), and Xiao et al. (2025).

[16] China's public hospital system is organized into a three-tier classification reflecting differences in infrastructure, service capacity, and quality of care. Public hospitals dominate inpatient service provision, with secondary and tertiary

includes records from all departments within each hospital. Data quality is consistently high, as records are tied to insurance reimbursement and subject to mandatory digital reporting protocols enforced by the National Health Commission.[17]

Each hospitalization record includes admission and discharge dates, ICD-10 codes for primary and secondary diagnoses, patient demographics (age, gender, and insurance type), and hospital characteristics (tier, class, and type). We construct total hospitalizations, corresponding expenditures, and hospital stays for several disease categories based on ICD-10 codes. These include vector-borne diseases (with tick-borne diseases as a subset), potential air-pollution-related conditions (e.g., respiratory and cardiovascular diseases), and several categories of vector-unrelated illnesses for placebo tests. For each county–quarter, we also calculate the number of hospitals (by tier/class/type) and total hospitalizations as control variables for hospital characteristics. The data also capture variation in patient demographics, including age and insurance type; the latter serves as a proxy for rural versus urban residency and supports our heterogeneity analyses.

While the panel is unbalanced due to hospitals entering and exiting the dataset at different times, we find no evidence of systematic selection correlated with the policy. The dataset was not compiled for administrative or policy-related purposes. Table A2 confirms that county inclusion, hospital-day coverage, and the presence of infectious disease departments are uncorrelated with policy rollout timing or administrative hierarchy. Further details are provided in Appendix A.1.

Policy Data We construct the policy treatment measure using official regulatory documents sourced from the Peking University Law Database—the most comprehensive and authoritative legal archive for Chinese regulations.[18] We collect all county- and prefecture-level city (hereafter "city") policy documents containing the keyword "straw-burning ban." To process the large volume of policy texts efficiently while maintaining coding accuracy, we employ a large language model (LLM) to assist with document classification and information extraction, followed by systematic validation using independent manual coding.[19] Each document is coded for two key features: (1) performance assessment mechanisms that explicitly link enforcement (e.g., fire hotspot counts) to cadre evaluations or personnel outcomes; and (2) the jurisdiction and implementation

institutions accounting for the vast majority of admissions, while primary hospitals contribute only 5.7%. Private hospitals account for less than 24% of admissions (National Health Commission of the People's Republic of China, 2022, 2023). Further details on the functions of hospitals at different tiers are provided in Appendix A.1.

[17] Inaccurate diagnoses can result in insurance denial and financial penalties due to insurance verification requirements. See Appendix A.1 for a detailed discussion of data quality.

[18] Peking University Law Database, https://www.pkulaw.com.

[19] We use GPT-4 to classify documents based on clearly specified coding rules and structured outputs. The model processes the full text of each regulation and returns binary indicators for ban status and the presence of performance assessment mechanisms, together with extracted policy dates. To validate the automated coding, trained research assistants independently coded all 2,075 documents using the same criteria without access to the LLM outputs. The two approaches show high agreement across the key variables: percent agreement reaches 91% for ban classification and 83% for performance assessment identification, with a Cohen's kappa of 0.80 for ban classification, indicating substantial agreement. For the cases with disagreement (roughly 10–20% of observations), we conduct manual review and correction based on the manual validation. The baseline policy measure therefore relies on both LLM and manually validated coding.

date. Based on these features, we define treatment as straw-burning bans with performance assessments. Figure A1 and A2 provide representative excerpts from these original regulations.

To ensure credible policy enforcement and to capture seasonal patterns, treatment status is assigned at the county–year–quarter level based on the earliest effective regulation at the county or city level.[20] A county is coded as treated beginning in the first year–quarter during which the ban was enforced for all three months. As a robustness check, we count the cumulative number of ban-related directives issued by each county, including repeated emergency notices and implementation plans. This variable captures the intensity of local enforcement effort. Appendix A.2 provides further details on treatment assignment.

Straw Burning and Air Pollution To capture straw-burning activity with high spatiotemporal precision, we combine two satellite products: the MODIS Burned Area Product (MCD64A1) and the MODIS Land Cover Type Product (MCD12Q1).[21] We identify straw-burning events by overlaying fire detections with cropland classifications following Assunçãoa et al. (2019). This procedure minimizes misclassification from forest fires. To minimize measurement error from other factors, we focus on harvest-season fires and aggregate the count and area of cropland fires to the county–year level. Our baseline analysis covers 2015 to 2022, consistent with the availability of hospitalization data. Results remain consistent when we extend the sample to a longer period (2001–2022). To isolate agricultural burning, we also construct analogous forest fire measures, which serve to mitigate potential confounding effects and control for broader fire dynamics. We further incorporate county-level measures of $PM_{2.5}$ and PM_{10} as key indicators examining policy's effects on ambient air quality.[22]

Insect Observations While direct data on arthropod activity on cropland are unavailable, we provide suggestive evidence by quantifying ecological responses using arthropod occurrence records from the Global Biodiversity Information Facility (GBIF), an international network that aggregates species occurrence data worldwide.[23] Each record includes geolocation, observation date, taxonomic classification (at the kingdom, phylum, and class levels), and observer ID. For the period 2015–2022, we compile 99,814 arthropod observations in China, including taxa such as *Insecta* and *Arachnida* (see Appendix B for taxonomic definitions and their relevance to transmission of vector-borne diseases). Our primary measure is the annual count of observations per county involving

[20] If a county-level regulation is available, we use its implementation date and policy features; otherwise, we adopt those of the corresponding city-level regulation.

[21] Both datasets are provided by NASA's Land Processes Distributed Active Archive Center. They are widely used in remote sensing research, independent of Chinese administrative reporting, and provide high-resolution measures of fire activity.

[22] $PM_{2.5}$ and PM_{10} are derived from China's national air quality monitoring platform, based on inverse distance-weighted averages of hourly station-level data.

[23] GBIF compiles data from diverse sources—including DNA barcodes and smartphone photographs—using standardized protocols such as Darwin Core. The resulting database contains hundreds of millions of species occurrence records, making it one of the most comprehensive biodiversity datasets available. It is widely used in ecological and conservation research (GBIF, 2025) and enables analysis of ecological change in settings where systematic ecological monitoring is otherwise limited.

these relevant taxa. To account for spatial and temporal variation in sampling effort, we control for the number of unique observers per county-year, following Liang et al. (2025).

Web Searches To capture public awareness, non-hospitalized medical burden, and behavioral response, we use the Baidu Search Index, which provides daily keyword search frequencies at the city level from 2009 onward.[24] We track search categories related to insect bites, bite symptoms and treatments, and defensive behaviors such as pest control (see Appendix A.3 for detailed keyword lists). Search data are geocoded at the city level. To align with the index structure, we assign treatment status accordingly, using the same empirical specification.[25]

Procurement of Straw Recycling Equipment To assess straw management, we construct a novel dataset from China's nationwide registry of agricultural machinery subsidy reimbursements.[26] The subsidy program mandates public disclosure of all subsidized transactions, providing granular data on each machinery purchase since 2018. For each transaction, the records include product name, equipment category, quantity, price, subsidy amount, transaction date, and county. We focus on the subset of straw-collecting machines and aggregate the data to the county–year–quarter level. Our constructed panel includes three key measures: the number of machines procured, total transaction value, and total subsidies received. This dataset enables us to document policy-induced responses in recycling adoption and link them to observed health outcomes.

Other Control Variables To account for potential confounders, we control for a comprehensive set of environmental and socioeconomic factors. Weather conditions, particularly temperature and precipitation, can influence both fire incidence and disease transmission. We use daily weather data from the NOAA Global Summary of the Day (GSOD) and aggregate it to the county-year-quarter level by computing inverse-distance weighted averages from nearby monitoring stations. To capture concurrent ecological shifts, we incorporate county-year measures of vegetation density from the GIMMS NDVI dataset.[27] Additional controls include GDP, population, hospital bed availability, and cropland area, sourced from the China County Statistical Yearbooks.

[24] Baidu is China's dominant search engine and a widely used platform for online information retrieval. The Baidu Search Index is a well-established tool for assessing public attention and sentiment among Chinese internet users. See Barwick et al. (2024) for examples of recent applications.

[25] Quarterly indices are constructed by summing daily search counts across keywords in each category, then averaging over all days in the quarter.

[26] Since 2004, the central government has implemented large-scale subsidy programs to promote agricultural mechanization, and under the *Implementation Guidelines for Agricultural Machinery Purchase Subsidies* (2015–2017, 2018–2020, 2021–2023), straw-recycling equipment has consistently qualified for support. See Figure E3 for examples of straw management equipment.

[27] NDVI (Normalized Difference Vegetation Index) is a widely used satellite-derived indicator of greenness. Values were obtained from Li et al. (2023).

3.2 Summary Statistics and Data Visualization

Table 1 presents summary statistics for the key variables. To maintain policy relevance, we exclude remote counties with negligible population or agricultural activity, primarily those that never recorded any fire incidents.

Table 1: Summary Statistics

	Mean	SD	Min	Max
Panel A: Agricultural Burning (County–Year, 2015–2022)				
Cropland fire detections (*count*)	0.396	1.281	0	6
Cropland burned area (*hectares*)	48.764	183.797	0	933.020
Panel B: Health Outcomes (County–Quarter, 2015–2022)				
Hospitalizations (count)				
Vector-borne diseases	24.779	49.362	0	752
Tick-borne diseases	1.548	6.691	0	180
Inpatient expenditure (1,000 CNY)				
Vector-borne diseases	122.973	334.453	0	5,548.714
Tick-borne diseases	7.600	42.453	0	1,271.026
Panel C: Arthropod Observations (County–Year, 2015–2022)				
Arthropod occurrence records (*count*)	1.276	3.203	0	12
Insect occurrence records (*count*)	1.181	3.097	0	12
Arachnid occurrence records (*count*)	0.157	1.050	0	12
Panel D: Web Search Behavior (City–Quarter, 2015–2022)				
Baidu Search Index: insect bites	3.171	4.943	0	26.992
Baidu Search Index: bite-related inquiries	3.427	5.240	0	24.667
Baidu Search Index: defensive behavior	3.998	6.728	0	38.575
Panel E: Straw-Recycling Equipment (County–Quarter, 2018–2022)				
Machines purchased (*count*)	0.367	3.426	0	102
Transaction value (*1,000 CNY*)	4.966	49.119	0	1,407.600
Total subsidy amount (*1,000 CNY*)	1.253	15.183	0	471.600

Notes: This table reports summary statistics for the main analysis variables. Cropland fire measures are derived from satellite-based products over cropland pixels while burned area is reported in units of hectares. Health outcomes and expenditures are totals per county-year-quarter aggregated from inpatient administrative records (expenditures in thousand CNY where indicated). Arthropod measures are counts of species occurrence records from the Global Biodiversity Information Facility (GBIF, `https://www.gbif.org`). These records are based on presence observations and our empirical specifications additionally account for reporting effort. Baidu variables are search-intensity indices available at the prefectural city level. Straw-recycling measures are derived from national agricultural machinery subsidy records and are reported in levels. Sample definitions and construction details are provided in Section 3 and Appendix A.

Figure 3 visualizes the spatiotemporal patterns of our sample. Panel (a) displays the distribution of vector-borne disease hospitalizations across counties. Cases are geographically widespread, and the age profile in Table A1 shows that all age groups are affected. Panel (b) presents the spatial relationship between agricultural fire incidence and vector-borne disease hospitalizations.

(a) Spatial Distribution of Hospitalizations for Vector-Borne Diseases

(b) Correlation between Agricultural Fires and Vector-Borne Disease Hospitalizations

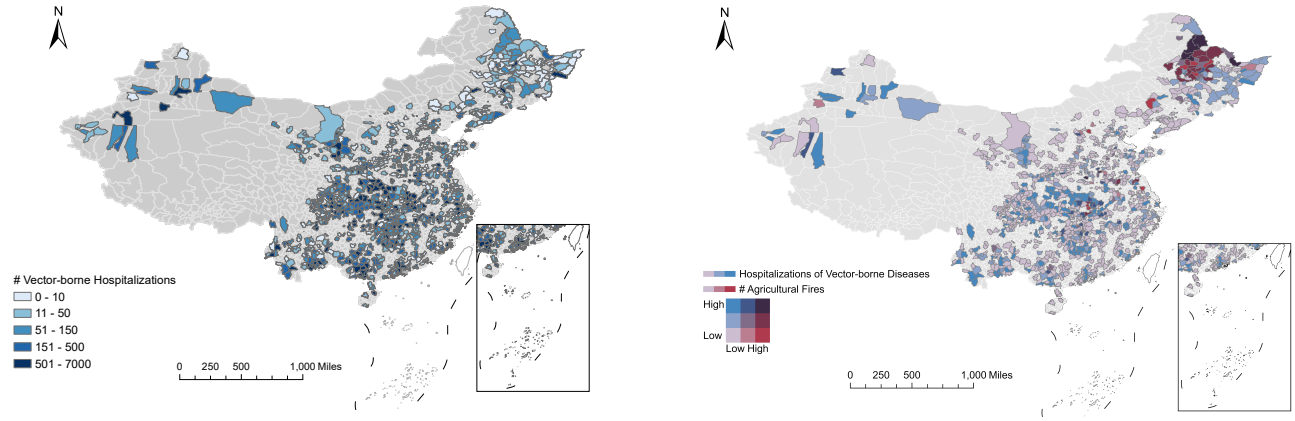


Figure 3: Spatial Distributions in Vector-Borne Hospitalizations and Agricultural Fires

Notes: Panel (a) maps average annual vector-borne disease hospitalizations across counties during 2015–2022. Counties without hospital reporting are shown in gray. Panel (b) maps the spatial relationship between agricultural fire incidence and vector-borne disease hospitalizations.

4 Empirical Strategy

4.1 Staggered DiD Estimator

To estimate the effect of China's straw-burning ban, we employ a DiD strategy that exploits the staggered policy rollout across counties. Implemented over multiple years, the ban led to accumulation of straw residue, triggering persistent ecological shifts. Tracing this ecological chain, we identify how the altered ecology facilitates the spread of vector-borne diseases.

The following equation summarizes our econometric strategy with a traditional two-way fixed effects (TWFE) representation:

$$Y_{c,yq} = \beta \cdot BAN_{c,yq} + \alpha \mathbf{X}_{c,yq} + \eta_c + \delta_{yq} + \gamma_{p,q} + \varepsilon_{c,yq}, \tag{1}$$

where c and p index the counties and provinces, respectively, and yq denotes the year-quarters. $Y_{c,yq}$ represents the ecological and health outcomes of interest, including hospitalizations and inpatient expenditures of vector-borne diseases, fire incidence, vector species populations, public awareness, and straw management equipment procurement. $BAN_{c,yq}$ signifies the treatment status for county c in year-quarter yq, taking on a value of 1 for periods subsequent to the implementation of the straw-burning ban in county c. β quantifies the causal effects post-implementation. We control for county (η_c), year-quarter (δ_{yq}), and province-by-quarter fixed effects ($\gamma_{p,q}$), and include weather conditions, forest fire activity, local health infrastructure, and socioeconomic characteristics in $\mathbf{X}_{c,yq}$. Standard errors are clustered at the county level.

Given recent studies of TWFE in staggered DiD settings, we implement the imputation-based estimator from Borusyak et al. (2024).[28] This method avoids negative weighting and allows for flexible fixed effects and unbalanced panels. Let D^{gt} denote treatment status and Y^{gt} the outcome for group g in period t, where g indexes counties grouped by policy adoption period. N_1 is the number of treated observations in treatment set $\Omega_1 = \{(g,t) : D^{gt} = 1\}$, with cardinality $N_1 = |\Omega_1|$. In Borusyak et al. (2024), untreated units are used to estimate fixed effects and covariate coefficients. We then impute counterfactual untreated outcomes for treated units and compute average treatment effects on the treated (ATT) as:

$$\hat{\tau}_{\text{ATT}} = \frac{1}{N_1} \sum_{(g,t,c)\in\Omega_1} \left(Y_c^{gt} - \hat{Y}_c^{gt}(0) \right), \tag{2}$$

where $\hat{Y}_{c,t}^{gt}(0)$ is the counterfactual untreated outcome imputed using untreated observations:

$$\hat{Y}_c^{gt}(0) = \hat{\alpha}\mathbf{X}_{c,t} + \hat{\eta}_c^g + \hat{\delta}_t^g + \hat{\gamma}_{p,t}^g \tag{3}$$

Our primary treatment variable is an indicator for whether a county has implemented a straw-burning ban. As shown in Figure 2 and Figure D1, the program was rolled out in a staggered fashion across counties over time. To establish the robustness of our findings, we conduct four additional checks. First, we replace the hospitalization count (with population as a control) with the hospitalization rate (hospitalizations per capita) as the dependent variable. Second, we employ alternative staggered DiD estimators from Sun and Abraham (2021) and Callaway and Sant'Anna (2021), accounting for treatment timing heterogeneity. Third, for count outcomes such as hospitalizations, we estimate a Poisson pseudo-maximum likelihood (PPML) model (Correia et al., 2020). Lastly, to explore treatment intensity, we apply the continuous-treatment DiD estimator from de Chaisemartin et al. (2022). All approaches yield consistent results.

4.2 Identification

Our empirical strategy relies on a difference-in-differences design that exploits the staggered rollout of the straw-burning ban across counties. Identification requires that, absent the policy, treated and untreated counties would have followed similar trends in the outcomes of interest. While this assumption is inherently untestable, we provide a range of empirical evidence and institutional context, suggesting that confounders are unlikely to drive our results.

Pre-treatment Trends We begin by assessing pre-treatment dynamics using event-study specifications (Figure 4). Results indicate no significant pre-treatment differences between treated and untreated counties, providing support for the parallel trends assumption. Similar patterns

[28] Traditional TWFE estimators can be susceptible to bias in settings with treatment effect heterogeneity across cohorts or over time due to negative weighting and "forbidden comparisons" problems (Goodman-Bacon, 2021; Sun and Abraham, 2021). The efficacy of staggered DiD approaches exists in comparing counties based on their individual policy inception timelines, offering a more refined and robust estimation.

are observed for related outcomes including agricultural fires, insect populations, and equipment adoption, further reinforcing the absence of differential pre-trends.

Assignment to Straw-Burning Ban Policy A key concern is that policy adoption may be endogenous: counties implemented the ban in response to ecological or health conditions. Institutional evidence suggests the program's rollout occurs independently of ecological and health changes, but closely mirrored to national air pollution control efforts and followed administrative sequencing similar to the Air Pollution Monitoring and Disclosure Program (Figure D2; Barwick et al., 2024). Consistent with this interpretation, Table D1 shows no systematic differences in healthcare capacity across adoption cohorts. Regression evidence further indicates that while adoption correlates with economic characteristics such as GDP and administrative rank, it is not associated with baseline health conditions or healthcare infrastructure (Table D2). These patterns reduce concerns that policy timing is driven by underlying trends in disease outcomes.

Fixed Effects and Time-Varying Controls Our baseline specification includes county, year-quarter, and province-by-quarter fixed effects, which absorb time-invariant county characteristics, macroeconomic shocks, and province-specific seasonal patterns. To address remaining concerns about time-varying confounders, we control for a comprehensive set of observable factors, including healthcare capacity (hospital types, beds, and utilization), weather conditions (temperature and precipitation), socioeconomic characteristics (GDP, population, cropland area), and ecological shocks (forest fire frequency and burned area). These controls help isolate variation in disease outcomes attributable to the policy rather than concurrent changes in local conditions.

Concurrent Policies The study period overlaps with several other policy initiatives, including greening programs, the Sponge City initiative, and healthcare and agricultural reforms.[29] Concerns about concurrent policies are mitigated by the fact that these policies were either implemented nationwide, following different rollout patterns, or are unlikely to affect vector ecology. Our fixed effects structure absorbs much of their potential influence. We further assess robustness by explicitly controlling for vegetation dynamics using NDVI and by excluding Sponge City pilot cities (Table E3). In addition, we restrict the sample to the pre-pandemic period to address potential disruptions associated with COVID-19 (Table E9). Across these specifications, the estimated effects remain stable, suggesting that our findings are not driven by concurrent policy changes.

Placebo Tests To assess whether our estimates reflect broader post-policy changes in healthcare utilization or economic conditions rather than ecological mechanisms, we conduct placebo tests using disease categories unlikely to be affected by arthropod exposure. Specifically, we examine *non–arthropod-related dermatoses*, *neoplasms*, and *bone fractures*. *Non–arthropod-related dermatoses* address the concern that the ban may have induced increased pesticide use, which could affect

[29] See Appendix D for details.

dermatological conditions. *Neoplasms* capture disease outcomes that may respond to changes in healthcare access, income, or environmental quality, but are unlikely to be linked to arthropod exposure. *Bone fractures* represent accidental injuries and serve as a benchmark outcome unrelated to ecological channels. As reported in Table E2, we find no statistically significant effects for these placebo outcomes. These results also rule out the alternative channel that improvements in air quality following the ban may have affected health outcomes.[30] They thus provide support for the interpretation that the estimated effects are consistent with an ecological transmission mechanism.

Spillover Effects Finally, we consider the possibility of spatial spillovers. While within-county adjustments are captured by our aggregated outcome measures, cross-county spillovers may arise if ecological changes extend beyond administrative boundaries. To address this concern, we re-estimate our baseline specification after excluding geographically adjacent treated–control county pairs. This restricted sample removes observations most likely to be affected by policy diffusion or ecological spillovers across borders. The estimated effects remain similar in both magnitude and statistical significance (Section 5.2), suggesting that cross-county spillovers are unlikely to bias our main findings.

4.3 Pathway Analyses and Policy Implications

We validate the ecological-health transmission channel via four complementary approaches. First, we estimate the effects of the straw-burning ban on intermediate ecological outcomes, including agricultural fires, insect populations, public awareness of insect exposure, and defensive behaviors. These analyses trace the ecological adjustments induced by the policy. Second, by instrumenting fire activity with policy rollout, we exploit the effect of agricultural fires on vector-borne disease outcomes. Third, we examine heterogeneity along dimensions predicted by the proposed mechanism. Specifically, we study variation across rural and urban areas, crop types with different pre-ban burning intensities, climatic conditions conducive to vector growth, and seasonal exposure patterns. These results provide further evidence consistent with an ecological transmission channel. Finally, we investigate the role of complementary policies, particularly those promoting post-ban straw residue management. Using regional variation in recycling subsidies and infrastructure, we examine whether improved residue management mitigates the adverse health effects associated with the ban.

[30] We also explicitly examine the relationship between $PM_{2.5}$ and vector-borne disease outcomes. As shown in Table D4, $PM_{2.5}$ is not systematically associated with vector-borne disease outcomes when we control for cropland and forest fires.

5 Straw-Burning Ban and Vector-Borne Diseases

5.1 Baseline Results

We begin by estimating the effect of straw-burning bans on the health burden of vector-borne diseases, measured by inpatient hospitalizations and associated medical expenditures. Baseline results, estimated using the Borusyak et al. (2024) estimator, are reported in Table 2. Panel A presents estimates for all vector-borne diseases (listed in Table C1); Panel B focuses on tick-borne diseases, a severe subset that includes conditions such as Lyme disease and SFTS (see Table C2). All specifications include county, year-quarter, and province-by-quarter fixed effects, along with controls for hospital characteristics, weather conditions, forest fires, and local socioeconomic conditions. In Columns (1) and (3), we apply the inverse hyperbolic sine (IHS) transformation to the outcome variables to accommodate zeros and skewness, and include population as a control. Columns (2) and (4) use per-capita measures (hospitalizations per 1,000 population and expenditures per capita).[31]

Panel A examines the impact of the straw-burning ban on vector-borne diseases. Column (1) shows that the ban increases hospitalizations by 50.2% relative to the pre-treatment mean, equivalent to approximately 14 additional cases per county per quarter (0.502×27.272).[32] Column (2) reports results using the per-capita hospitalization rate, indicating a 29.1% increase relative to the pre-treatment mean. Columns (3) and (4) present effects on medical expenditures. Column (3) implies a 75.2% increase in total expenditures, or approximately 107,113 CNY (142,438 $\times$ 0.752, about 15,594 U.S. dollars) per county per quarter. Column (4) shows that per-capita expenditures increase by 4,622 CNY per 100,000 people.[33] Panel B focuses on tick-borne diseases, a severe subset of vector-borne illnesses, and shows similarly significant impacts: hospitalizations rise by 21.2%, and medical expenditures increase by 30.6% relative to their pre-treatment means.

To assess the national economic burden of vector-borne diseases attributable to the straw-burning ban, we conduct a back-of-the-envelope calculation. Accounting for hospital coverage and policy exposure, we estimate that the annual increase in vector-borne hospitalization costs amounts to 1.48 billion CNY (approximately 222.6 million USD).[34] Of this total, 30.5 million CNY (approximately 4.59 million USD) is attributable to tick-borne diseases.[35] These estimates likely understate the full burden, as they exclude outpatient costs, productivity losses, and other indirect

[31] Results are robust to alternative transformations (e.g., $\log(1+x)$) and to PPML estimation; see Section 5.2.

[32] 27.272 is the mean quarterly hospitalizations before treatment for treated counties in our sample.

[33] It is important to note that our hospitalization data do not cover the full universe of medical facilities nationwide. The per-capita measures should be interpreted as lower-bound estimates of the true incidence and expenditure levels. This limitation does not affect the identification, and implies a potentially higher overall health burden associated with the policy.

[34] We first scale our estimates to the national level using a hospital coverage multiplier (2.32), based on the ratio of secondary and tertiary hospitals in our sample (2,788 across 1,252 counties) to the national system (14,668 across 2,843 counties), following National Health Commission of the People's Republic of China (2023). For 1,403 counties where the ban was implemented, the implied cost increase is $142,438 \times 0.752 \times 4 \times 1,403 \times 2.32 = 1.39$ billion CNY. Including primary hospitals—estimated to account for 6.2% of secondary and tertiary hospitalizations (National Health Commission of the People's Republic of China, 2022)—yields a total of 1.48 billion CNY (1.39×1.062).

[35] Computed as $7,217 \times 0.306 \times 4 \times 1,403 \times 2.32 \times 1.062 = 30.5$ million CNY.

effects. Nonetheless, they underscore a sizable and previously overlooked health cost associated with the straw-burning ban, operating through ecological feedbacks.

Event Study We implement an event study to assess the parallel trends assumption and to investigate the dynamic response of health outcomes to the straw-burning ban. The top and bottom panels of Figure 4 display the estimated effects on vector-borne disease hospitalizations and associated medical expenditures, respectively. The x-axis denotes quarters relative to policy implementation, with the vertical dashed line indicating the quarter of full policy rollout ($t = 0$). The shaded interval between $t = -1$ and $t = 0$ captures a transition period during which some counties began partial implementation.

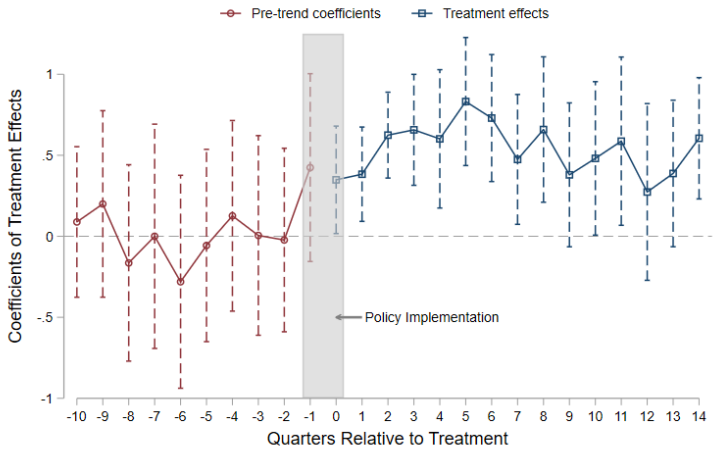
Pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. Following implementation, both outcomes increase significantly and remain persistently elevated. The effects continue to grow over approximately six quarters before plateauing, consistent with an adjustment toward a new ecological equilibrium. We also find parallel pre-trends for tick-borne diseases (Figure E1). The post-treatment dynamics exhibit a pronounced seasonal pattern, in line with established evidence on tick phenology (Gleim et al., 2014).

Table 2: Effects of Straw-Burning Bans on Disease Outcomes

	Hospitalizations		Medical Expenditure	
	IHS	Level/popu.	IHS	Level/popu.
	(1)	(2)	(3)	(4)
Panel A: Vector-Borne Diseases				
Straw-burning Ban (Post × Treated)	0.502***	1.118*	0.752***	4.622*
	(0.155)	(0.655)	(0.129)	(2.770)
Pre-treatment mean	27.272	3.847	142.438	17.646
Panel B: Tick-Borne Diseases				
Straw-burning Ban (Post × Treated)	0.212**	0.072**	0.306**	0.302**
	(0.089)	(0.032)	(0.063)	(1.395)
Pre-treatment mean	1.691	0.169	7.217	0.633
County FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,395	5,395	5,395	5,395

Notes: This table reports baseline estimates of the effect of county-level straw-burning bans on disease outcomes using the Borusyak et al. (2024) staggered DiD approach. The ban indicator equals one for treated counties after policy implementation. The sample spans 2015–2022 at the county–quarter level. The availability of hospitalization records are not systematically related to treatment status and do not affect the results (see Appendix Table A2). Columns (1) and (3) use inverse hyperbolic sine (IHS) transformations of the dependent variables. The IHS transformation accommodates skewed distributions and zero-valued outcomes while allowing interpretation comparable to log specifications. In the text, we report implied percentage effects evaluated at the pre-treatment mean of the treated counties. Columns (2) and (4) use the number of hospitalizations or medical expenditure (in 1,000 CNY) per 100,000 population as the dependent variables. Control variables include hospital capacity measures (hospital categories, numbers of hospitals and beds), weather conditions (average temperature and precipitation), forest fire exposure, and socioeconomic characteristics (cropland area and GDP). Columns (1) and (3) additionally control for population. All regressions include county, year-quarter, and province-quarter fixed effects. Standard errors clustered at the county level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(a) Effects on Hospitalizations for Vector-Borne Diseases



(b) Effects on Medical Expenditure for Vector-Borne Diseases

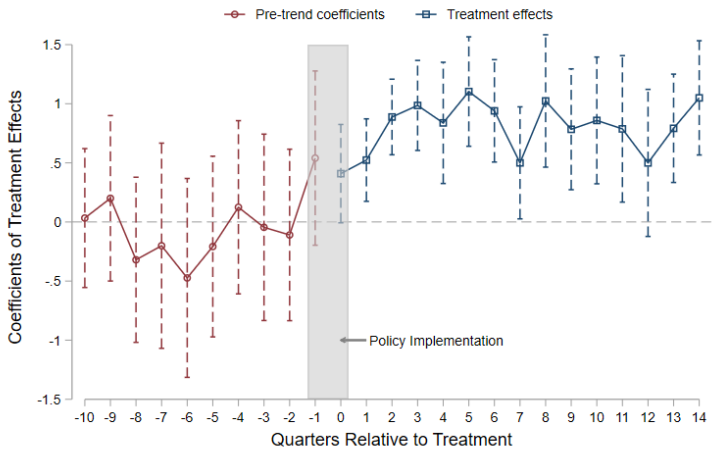


Figure 4: Effects of Straw-burning Bans on Vector-Borne Diseases: Event Study Plots

Notes: This figure reports dynamic treatment effects estimated using the Borusyak et al. (2024) DiD estimator. The coefficients show the impact of straw-burning bans on (a) hospitalizations and (b) medical expenditures for vector-borne diseases. The sample covers 2015–2022 at the county–quarter level. All specifications include county, year-quarter, and province-quarter fixed effects, along with controls for hospital capacity, weather, forest fire exposure, and socioeconomic characteristics. Vertical bars denote 95% confidence intervals with standard errors clustered at the county level. We fail to reject the joint null hypothesis that all pre-treatment coefficients equal zero (p = 0.05), alleviating concerns that policy adoption is driven by pre-existing changes in disease outcomes.

Impacts on Disease Severity To examine whether the straw-burning ban also affects disease severity, we analyze the total length of hospital stays for vector-borne and tick-borne diseases. Controlling for the number of hospitalizations, the estimates capture changes along the intensive margin — whether patients require longer treatment due to more severe illness. Table E1 reports the results. Column (1) indicates that the ban increases the total length of stay for vector-borne diseases by 6.0% (= 7.180/119.387), while column (2) shows a larger increase of 8.5% (= 0.399/4.682) for tick-borne diseases. This larger magnitude is consistent with the higher clinical severity typically associated with tick-borne diseases.

Placebo Tests A potential concern is that our estimated effects may reflect contemporaneous changes in income, underlying health conditions, healthcare utilization, or agricultural practices, rather than the ecological consequences of the straw-burning ban. To address this concern, we conduct placebo tests using disease categories plausibly related to these broader factors but unlikely to be affected by changes in arthropod exposure. Specifically, we examine hospitalizations for *non–arthropod-related* dermatoses, neoplasms (driven primarily by long-term biological processes), and bone fractures (typically resulting from accidents). As shown in Table E2, we find no statistically significant effects on either hospitalizations or medical expenditures for these outcomes, and the estimated coefficients are small in magnitude. These findings are inconsistent with the hypothesis that our findings are driven by broad changes in healthcare demand or supply, and instead provide further support for an ecological health transmission mechanism.

5.2 Additional Concerns and Robustness Checks

To further assess the validity of our baseline findings, we conduct a series of robustness checks, addressing potential confounding factors and alternative explanations, and comparing with other estimation strategies. Summary estimates are presented in Figure 5, while detailed results are reported in Appendix Table E3 through Table E11.

Concurrent Environmental Policies A potential concern is that other environmental policies implemented during the study period—particularly those affecting vegetation or water infrastructure—may confound our estimates through ecological channels. To address this, we conduct two sets of robustness checks: First, we control for county-level vegetation dynamics using NDVI, which captures changes associated with reforestation and green initiatives. Second, we exclude the 16 pilot cities of China's Sponge City Program, which may have affected local hydrological and ecological conditions. As shown in Table E3, our main findings remain intact across these specifications, suggesting that concurrent environmental policies are unlikely to drive our results.

Alternative Estimators We apply alternative estimation models and functional forms to validate our estimator. In addition to the baseline Borusyak et al. (2024) approach, we implement the staggered DiD estimators proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021). The results, reported in Table E4 and Table E5, are consistent with our baseline estimates. We also consider alternative outcome transformations and estimation frameworks. Specifically, we estimate models using $\log(1+x)$ transformations and a Poisson pseudo-maximum likelihood (PPML) specification appropriate for count data (Correia et al., 2020). As shown in Table E6 and Table E7, the estimated effects remain positive and statistically significant, indicating that our findings are not driven by functional form assumptions.

Treatment Intensity and Pre-Pandemic Subsample To account for variation in policy enforcement and coverage, we construct a continuous measure of treatment intensity based on the cumu-

lative number of straw-burning ban documents issued at the county level. We estimate dynamic effects using the estimator from de Chaisemartin et al. (2022) which can incorporate continuous treatment under staggered adoption. The results, reported in Table E8, are consistent with the baseline specification, indicating that the estimated effects are robust to alternative measurements of treatment. We further assess robustness by restricting the analysis to the pre-pandemic period (2015–2019). As shown in Table E9, the estimated effects remain similar in magnitude and statistically significant, alleviating concerns that COVID-19-related disruptions to healthcare utilization or reporting drive our results.

Cross-County Spillovers Our estimates may be biased if untreated counties are indirectly affected by nearby treated counties through ecological spillovers, such as the migration of disease vectors. To address this concern, we re-estimate the baseline models after excluding geographically adjacent treated–control county pairs. As reported in Table E10, the results remain stable in both magnitude and statistical significance. This suggests that cross-county spillovers are unlikely to explain our main findings.[36]

Within-County Spillover to Urban Areas Although our outcomes are aggregated at the county level—implicitly allowing for within-county spillovers—we further explore potential heterogeneity between rural and urban populations. While the ban primarily affects rural agricultural practices, increased vector populations may spill over into urban areas through migration or animal hosts, raising health risks for urban residents.

To investigate this, we classify patients by insurance type, using administrative categories described in Appendix A.1. Table A3 reports the distribution of these diseases across insurance types, while Table E11 presents the corresponding estimation results. We find significant increases in vector-borne disease hospitalizations for both rural and urban patients, with comparable magnitudes. For tick-borne diseases, the effects are larger among rural patients, consistent with the localized mobility of ticks. These patterns suggest that, although rural residents are more directly exposed, ecological spillovers can also elevate health risks in urban populations.

[36] A parametric approach to modeling spillovers is not well suited to staggered adoption settings due to the cumulative and spatially diffuse nature of ecological transmission.

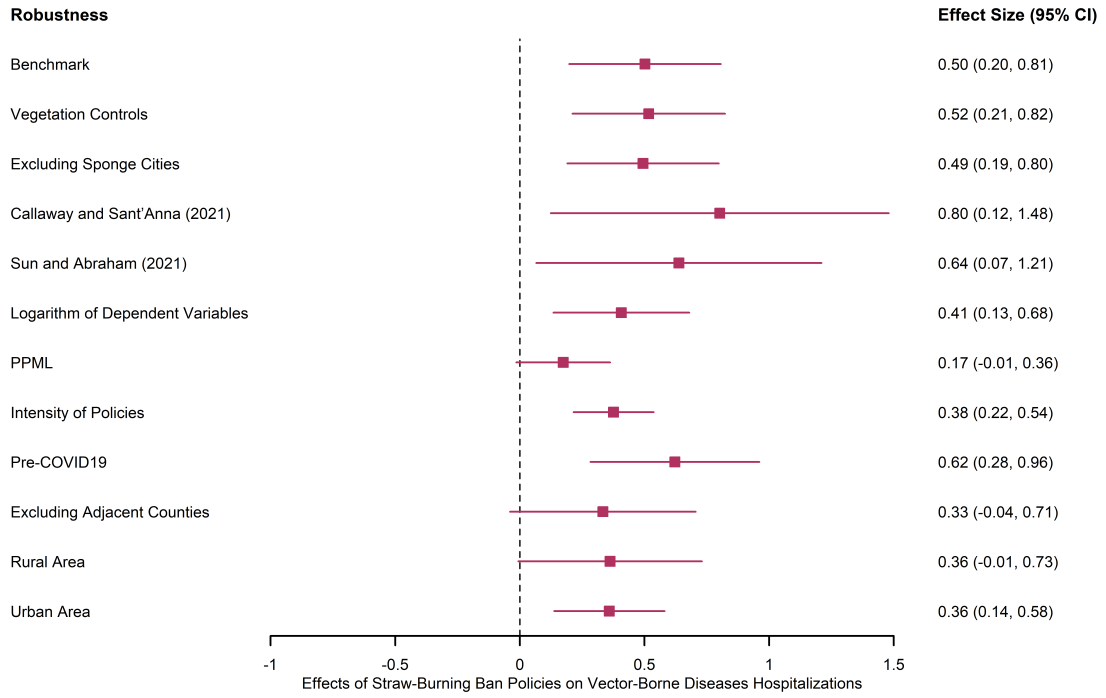


Figure 5: Robustness Checks of the Policy's Effects on Vector-borne Disease Hospitalizations

Notes: This figure presents results from various robustness checks on the effect of straw-burning bans on vector-borne disease hospitalizations. Points denote coefficient estimates while horizontal lines indicate 95% confidence intervals with standard errors clustered at the county level. Specifications vary by environmental controls, sample restrictions, estimators that account for staggered treatment timing, and functional forms. Across specifications, the estimated effect remains positive and economically meaningful. The regression results are detailed in Table E3 through Table E11.

5.3 Offsetting Benefits from Cleaner Air

To contextualize the magnitude of the ecological health costs, we compare them against the hospitalization benefits from reduced air pollution. Specifically, we estimate the effect of the straw-burning ban on hospitalizations and medical expenditures of two major categories of air pollution-sensitive conditions: respiratory and cardiovascular diseases.[37] Table E12 presents the results. Hospitalizations and medical expenditures for both respiratory and cardiovascular diseases declined significantly following the policy. Based on our estimates, the ban reduced quarterly medical expenditures by approximately 0.97 million CNY per county per year-quarter for respiratory diseases and 1.34 million CNY for cardiovascular diseases.

We benchmark these reductions against the increased hospitalization costs from vector-borne diseases. The additional expenditures associated with ecological changes offset roughly 4.6% ($= 0.107/(0.97 + 1.34)$) of the total hospitalization savings from improved air quality: 11.0% ($= 0.107/0.97$) of the benefits attributable to respiratory conditions and 8.0% ($= 0.107/1.34$) of those from cardiovascular conditions. These offsetting effects highlight a broader insight for envi-

[37] We use ICD-10 codes J00–J99 for respiratory diseases and ICD-10 codes I00–I99 for cardiovascular diseases following common classifications in the literature (Pestel and Wozny, 2021; Du et al., 2024).

ronmental policy: even when regulations successfully improve environmental quality, neglecting ecological feedbacks may generate unintended health risks that partially reverse intended gains.

An important caveat is that this offset ratio is based solely on inpatient medical expenditures. Due to data limitations, it excludes mortality, outpatient care, and productivity impacts from both the benefit side (improved air quality) and the cost side (increased vector-borne diseases). The ratio should therefore be interpreted as a partial accounting. While a more comprehensive assessment could alter its magnitude, it does not undermine the qualitative insight that ecological responses to environmental policies can generate nontrivial health costs.

6 Pathway of Impact

In this section, we investigate the ecological and behavioral mechanisms underlying the observed increase in vector-borne diseases following the straw-burning ban. Specifically, we examine whether the ban reduces agricultural fires, triggers ecological changes that boost insect populations, and consequently increases human exposure to disease vectors. Our analysis proceeds in four steps. First, we examine the policy's effect on straw burning. Second, we analyze changes in insect populations. Third, we explore behavioral responses using online search activity. Fourth, we further validate the mechanism using an instrumental variable approach and heterogeneity analyses.

6.1 Suppression of Agricultural Fires

We begin by evaluating the policy's impact on straw burning. Using county-year level data, we estimate the effects of the straw-burning ban on both the frequency of agricultural fires and the total area burned. To mitigate measurement error, we focus on the harvest season (May–July and September–November, consistent with He et al. (2020)). Our specification includes county and year fixed effects, alongside controls for weather conditions, forest wildfire incidence, grain planting area, GDP, and population.

Table 3 presents the results. Column (1) shows that the frequency of agricultural fires declines by 65.9% (0.453/0.687) relative to the pre-treatment mean. Column (2) shows that the total burned area decreases by 69.4% (59.818/86.233) relative to the pre-treatment mean, or 59.8 fewer hectares per county per year. Figure 6 displays the dynamic effects. An immediate and significant drop follows the ban, with impacts persisting for several years. The absence of pre-trends supports the parallel trends assumption. These results are robust to alternative fire activity measures and alternative samples (Table E13).[38] We also find corresponding declines in key pollutants associated with the straw-burning ban, including $PM_{2.5}$ and PM_{10} (Table E14).[39]

[38] In robustness checks, we employ a longer sample period where data are available (2001-2022). To address the possibility that a single plot may be burned multiple times within a season, we aggregate multiple detections within the same 1 km² grid and calendar month as a single fire event, mitigating measurement error from both spatial fragmentation and temporal clustering.

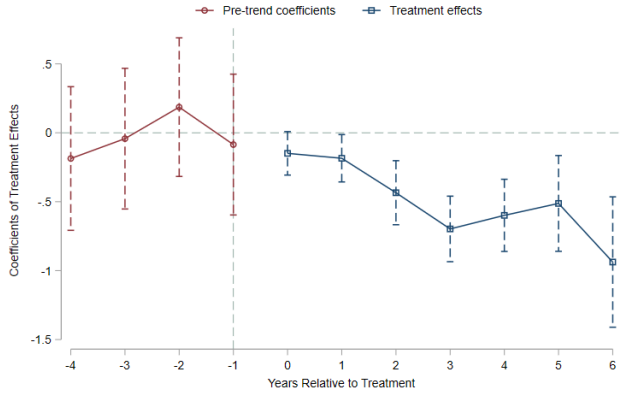
[39] These pollutants, released directly during combustion, are primary emissions associated with straw burning.

Table 3: Effects of Straw-Burning Ban Policies on Straw Burning Activity

	# Agricultural Fires (1)	Burned Area (hectares) (2)
Straw-burning ban (Post × Treated)	-0.453***	-59.818***
	(0.093)	(14.365)
Pre-treatment mean	0.687	86.233
County FE	✓	✓
Year FE	✓	✓
Controls	✓	✓
Observations	10,520	10,520

Notes: This table reports the effects of county-level straw-burning bans on agricultural burning activities. The sample spans 2015–2022. The ban indicator equals one for treated counties in periods after policy implementation. The dependent variables are (i) the number of agricultural fire detections and (ii) total burned area (in hectares), measured at the county-year level. Estimates are obtained using the Borusyak et al. (2024) staggered DiD approach. All specifications include county and year fixed effects. Controls include weather conditions (average temperature and precipitation), wildfire activity, lagged crop planting area, GDP, and population. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(a) Effects on Cropland Fire Frequency



(b) Effects on Cropland Fire Burned Area

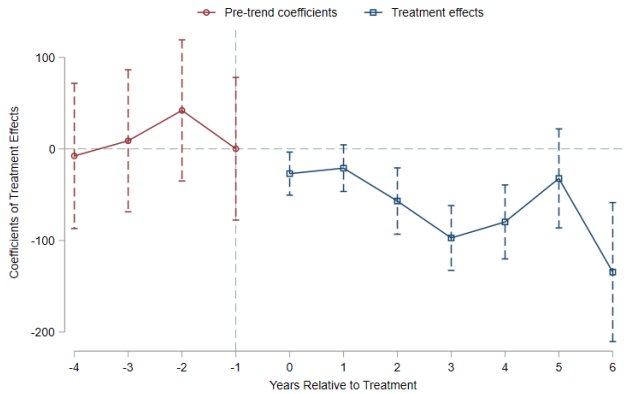


Figure 6: Effects on Cropland Fires: Event Study Plots

Notes: This figure reports dynamic effects of county-level straw-burning bans on (a) cropland fire frequency and (b) cropland burned area. Coefficients are estimated using the Borusyak et al. (2024) staggered DiD estimator to account for staggered treatment timing. All regressions include county and year fixed effects, along with weather variables, wildfire controls, crop planting area, GDP, and population. Standard errors are clustered at the county level.

6.2 Suggestive Evidence on Disease Vectors

Our empirical results document substantial increases in hospitalizations and medical expenditures following the straw-burning ban. A large body of agronomic and ecological research has established that straw return enhances soil fertility and increases the abundance and diversity of soil fauna, including microarthropods (e.g., Xie et al., 2022; Kautz et al., 2006; Yang et al., 2023). These findings suggest that the policy alter local ecological conditions in ways that facilitate the transmission of vector-borne diseases.

We provide suggestive evidence consistent with this mechanism. While direct measures of insect populations in human-adjacent environments (e.g., cropland edges or residential areas) are not feasible with available data, we apply our identification strategy to county-level species occurrence records. These records serve as an indirect proxy for broader ecological changes relevant to human exposure.

Using these data, we examine policy effects on insects and other arthropods that are commonly associated with vector-borne diseases or acute health risks.[40] Regression and event-study results are reported in Panel A of Table E15 and Figure E2. They show statistically significant post-policy increases in observed insect and arthropod counts, with no evidence of differential pre-trends.

As a robustness check, we additionally control for a proxy for outdoor activity to address the concern that greater post-policy outdoor exposure could mechanically increase reported insect observations. Specifically, we construct a measure based on the Baidu Search Index for terms related to outdoor recreation (see Table A4 for detailed keyword lists). The results, reported in Panel B of Table E15, remain highly consistent with the baseline estimates, suggesting that the observed increase in insect and arthropod counts is unlikely to be driven by greater outdoor activity following the ban.

The observed differences in the timing and magnitude of ecological versus health responses should not be interpreted as contradictory. Species observation data, while valuable, are sparse and noisy, capturing aggregate ecological abundance. In contrast, health data reflect acute outcomes that can respond immediately to changes in human–vector contact. More fundamentally, disease transmission is highly nonlinear. Small shifts in vector survival, activity, or spatial distribution can substantially elevate infection risk, potentially before a population-level increase becomes statistically detectable in generalized species occurrence data (Anderson and May, 1991; Kilpatrick and Randolph, 2012; Smith et al., 2012).

In addition, because the straw-burning ban primarily targeted air pollution reduction rather than vector control, individuals may not have immediately recognized or responded to heightened health risks, potentially delaying protective behavior. The ban may also have increased human exposure to vectors more directly, as handling crop residues—such as during collection, shredding, or plowing—can bring individuals into closer contact with insects associated with the

[40] We focus on three arthropod taxonomic categories: (i) total arthropods (*Arthropoda*), (ii) insects (*Insecta*), and (iii) *Arachnida*, a kind of non-insect arthropods with potential health risks. See Appendix B for details.

straw. Consistent with this interpretation, we observe larger health effects during harvest months, when human exposure to insects is highest (Table 5).

Overall, while these ecological data may not establish a direct causal link between the straw-burning ban and vector proliferation in human-exposed environments, they provide suggestive evidence consistent with a disease-transmission channel and complement the health results.

6.3 Insect Awareness and Defensive Behaviors

We use Baidu Search Index to assess public awareness and behavioral responses. At the city-by-year-quarter level, we estimate the policy's effects on search activity related to insect awareness and defensive behaviors, covering three keyword categories: general insect bites, inquiries about bite symptoms and treatment, and pest control (see Table A5 for detailed keyword lists).[41] Our specification includes city and province-by-year-quarter fixed effects to account for spatiotemporal variations in media attention, internet access, and socioeconomic conditions, and we control for weather and forest wildfires. The Baidu Search Index is available from 2009 onward. For our main analysis, we focus on the period 2015–2022 to maintain consistency with the hospitalization and wildfire data. We present results using the full 2009–2022 sample as a robustness check in the Appendix.

Table 4: Effects of Straw-Burning Bans on Insect Awareness and Defensive Behavior

	Insect Bite (1)	Bite Inquiries (2)	Defensive Behavior (3)
Straw-Burning Ban (Post × Treated)	0.270*	0.510*	0.362*
	(0.144)	(0.288)	(0.190)
Pre-treatment mean	2.771	1.633	3.499
City FE	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	6,190	6,190	6,190

Notes: This table reports the effect of city-level straw-burning bans on public attention and defensive responses proxied by the Baidu Search Index.[a] The dependent variables are city-by-quarter search indices for the listed insect-related topics. Estimates are obtained using the staggered DID estimator of Borusyak et al. (2024). All specifications include city and province-by-year-by-quarter fixed effects, and control for weather (temperature, precipitation), wildfire exposure, cropland area, GDP, population, and hospital capacity. The sample spans 2015–2022. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[a] Baidu Search Index data are available at the prefectural-level city level; county-level policy exposure is aggregated to the city level. More details about search indices for the listed insect-related topics are introduced in Table A5.

Table 4 shows significant increases in searches related to public awareness and defensive behaviors after the ban. Specifically, we observe higher search volumes for general insect bites (Column 1), queries about bite treatment (Column 2), and pest control (Column 3). Robustness checks using the longer panel from 2009 to 2022, as shown in Table E16, yield consistent and more signif-

[41] Baidu data represent the best available measurements for non-hospitalized health outcomes and individual risk perception of vector-borne diseases. We adopt a specification at the city–quarter level because the available search indices are at the city level.

icant results. Since not all insect-related illnesses lead to hospitalizations, our baseline estimates in Table 2 likely understate the full economic burden. The analysis of Baidu search activity thus complements the hospitalization data by capturing broader public responses—including potential non-severe cases—and revealing additional health-related costs and behavioral adjustments beyond those observed in inpatient records.

6.4 Evidence from an Instrumental Variable Approach

To further validate the mechanism, we directly estimate the effect of cropland fire incidence on vector-borne diseases. A potential concern is that fire incidence may be correlated with unobserved local factors, such as weather conditions, that also affect disease transmission. To address this, we instrument for cropland fire activity using the policy rollout. Table E17 presents the two-stage least squares results. The first stage confirms that the ban significantly reduced fires. In the second stage, this instrumented reduction translates into a significant increase in hospitalizations for vector-borne diseases. Specifically, the IHS-transformed hospitalization measure increases by 0.477 (computed as 0.165×2.891), an effect size comparable to the baseline estimate of 0.502 in Table 2. Together, these results reinforce our conclusion that fire suppression directly contributes to adverse health outcomes.

6.5 Mechanism Validation through Heterogeneity

We complement the above analyses by examining heterogeneity along three dimensions that capture variation in ecological risks and human exposure: (i) dominant grain type, which influences straw quantity and burning practices; (ii) regional climate, which affects vector survival and habitat suitability; and (iii) seasonal patterns of human exposure, particularly during harvest months or by residency. These results are presented in Table 5.

Heterogeneity by Major Grain The effects of the straw-burning ban are expected to be strongest in regions where open-field burning of residues was prevalent prior to the policy. Such variation is largely driven by post-harvest straw management practices, which differ across crops. Wheat provides a clear illustration: it was usually burned on-site due to its low-value straw and high collection cost (Wu et al., 2021). In contrast, higher-value straw from crops such as corn, sorghum, and sesame was more likely to be collected for fodder or fuel, resulting in lower pre-ban burning intensity.

Panel A of Table 5 reports the effects of the ban across counties by dominant grain type. Relative to the baseline in Table 2, Column (1) shows significantly larger effects in wheat-producing regions, while Column (2) shows smaller impacts elsewhere.

Heterogeneity by Climate We next assess heterogeneity across climatic conditions, a dimension ecologically relevant to vector-borne disease dynamics. Panel B splits counties by whether the av-

erage temperature in the coldest month exceeds $0^{\circ}C$—a critical threshold for arthropod overwintering and survival. The results show significant policy effects in regions with winter temperatures above $0^{\circ}C$, whereas in colder regions ($\leq 0^{\circ}C$) the effects are substantially smaller and statistically insignificant. These findings align with the hypothesized mechanism: warmer climates enhance the suitability of local environments for vector survival and reproduction.[42]

Table 5: Pathway-Based Heterogeneity on Vector-borne Hospitalizations: Crop Composition, Winter Temperature, and Agricultural Season

	(1)	(2)
Panel A. Crop Composition (County–Quarter)		
	Major wheat provinces	Other provinces
Straw-burning ban (Post × Treated)	1.189***	0.389**
	(0.405)	(0.162)
Observations	1,222	4,173
FE & controls: County, year-quarter, and province-quarter FE; baseline controls.		
Panel B. Winter Temperature (County–Quarter)		
	Cold-month temp $> 0^{\circ}$C	Cold-month temp $\leq 0^{\circ}$C
Straw-burning ban (Post × Treated)	0.813***	0.087
	(0.191)	(0.306)
Observations	3,876	1,519
FE & controls: County, year-quarter, and province-quarter FE; baseline controls.		
Panel C. Agricultural Season (County–Month)		
	Harvest months	Non-harvest months
Straw-burning ban (Post × Treated)	0.452***	0.312**
	(0.122)	(0.144)
Observations	7,508	7,445
FE & controls: County, year-month, and province-month FE; baseline controls.		

Notes: This table reports the heterogeneous effects of county-level straw-burning bans on hospitalizations for vector-borne diseases using the Borusyak et al. (2024) staggered DID estimator. The dependent variable is the inverse hyperbolic sine (IHS) transformation of county-level hospitalization counts. The ban indicator equals one for treated counties after policy implementation. Standard errors clustered at the county level are reported in parentheses. Panel A compares counties in major wheat-producing provinces (Henan, Shandong, Anhui, Hebei, Jiangsu, Hubei, Sichuan, Shaanxi, Shanxi, and Chongqing) to counties in other provinces (China Statistical Yearbook, 2006-2016). Panel B splits counties by whether the average temperature in the coldest month during 2015–2022 exceeds 0°C. Panel C compares harvest months (May–July and September–November) to non-harvest months, consistent with He et al. (2020). Baseline controls include hospital capacity measures, weather conditions (temperature and precipitation), forest fire exposure, and socioeconomic characteristics (cropland area, GDP, and population). Differences in N reflect split-sample definitions and the use of quarterly (Panels A–B) versus monthly (Panel C) aggregation, as well as outcome availability in the hospitalization data. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[42] A substantial body of research documents that warm environments support vector survival and activity, while colder regions naturally constrain vector dynamics. See Bale and Hayward (2010), Miao et al. (2019), França et al. (2020), and Ma et al. (2025).

Heterogeneity by Exposure If vector proliferation is a key intermediary, then human exposure should shape the health effects of the ban. Such exposure varies both temporally and spatially: it intensifies during harvest months and is greater in rural areas, where residents live in closer proximity to farmland and insect habitats. Consistent with this, Table E11 shows that health effects are more pronounced in rural areas, while also exhibiting spillovers into urban populations.

We further test this mechanism using county–year–month data, comparing health outcomes between harvest and non-harvest periods. Panel C of Table 5 shows significantly larger hospitalization impacts during harvest months, when human exposure to fields and insects is high. Together, these findings confirm a pathway in which the ban, by altering local ecology, increases human exposure to disease vectors.

7 Straw Residue Management and Policy Implications

Our preceding analysis shows that China's straw-burning ban, while effective in reducing cropland fires and improving air quality, is associated with an increase in vector-borne diseases. This finding highlights a central policy trade-off: how to mitigate unintended health consequences without undermining environmental objectives.

We provide evidence that complementary policies, promoting post-ban residue management, can help reconcile this trade-off. Specifically, regions with greater support for straw recycling exhibit negligible increase in disease incidence, whereas regions without such support experience substantial increases. These patterns are consistent with an ecological mechanism in which accumulated straw residues facilitate vector proliferation, and suggest that effective residue removal through recycling can jointly support pollution control and protect public health.

7.1 Why Recycle, and Why Subsidize It?

Straw management practices in China vary widely across regions. After harvest, farmers must clear residues to prepare for the next planting cycle. Straw burning, though banned, was historically attractive because it offered a fast and low-cost solution to residue clearance. Straw management, by contrast, involves substantial fixed and variable costs. While straw can be crushed and incorporated into soil ("straw returning"), this practice slows decomposition and fosters moist habitats conducive to insect breeding. Removing straw through recycling reduces such ecological risks, but is labor-intensive, requires specialized machinery, and yields low market returns for farmers under China's smallholder system.[43]

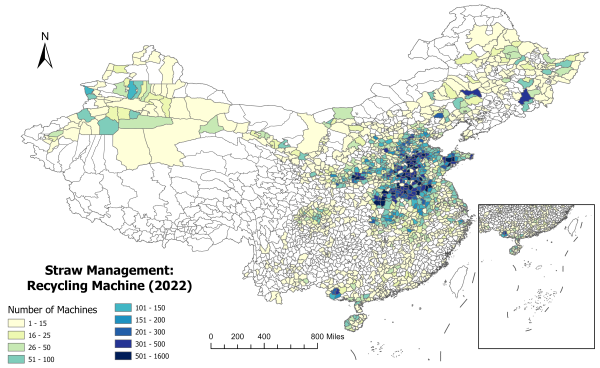
Recognizing these economic barriers, the central government launched a straw-recycling subsidy program in 2016 targeting ten provinces (He et al., 2020; Cao and Ma, 2023; Nian, 2023). The

[43] Figure E3 provides two examples of the post-harvest straw management machines. Straw balers used for recycling (e.g., models 4JS-150 and 4JS-200) cost about 13,000 CNY per unit, compared to 8,000 CNY for straw incorporators (e.g., 1JH-200, 1JHY-230). Beyond equipment costs, collection itself is labor-intensive: collection and transport costs can exceed the purchase price offered for straw, which is often below 150 CNY per ton. See https://www.nea.gov.cn/2012-06/18/c_131660381.htm (in Chinese). As a result, without subsidies, recycling is financially unattractive.

initiative allocated over 1 billion CNY (approximately 150 million USD) to support recycling machine procurement and incentivize collection, transportation, and storage.[44] The program significantly affects straw recycling through promoting procurements of recycling machines. Consistent with policy motivations, the program disproportionately targets regions characterized by more abundant cropland (and thus greater straw availability), steeper terrain conducive to mechanization, and higher baseline air pollution levels (reflecting stronger pollution control incentives). In contrast, we find nonsignificant correlations between program placement and pre-existing fire trends or health infrastructure (see Table D3).

Figure 7 illustrates the adoption of straw-recycling machine in China, providing visual evidence of expanding recycling capacity following the subsidy program. Panel (a) shows the spatial distribution of procurements in 2022, highlighting substantial clustering in central and eastern provinces where the ban was more widely enforced. Panel (b) presents the national trend, revealing a marked increase in procurement intensity starting in 2016, with clear seasonal patterns reflecting post-harvest demand.

(a) Spatial Distribution of Straw Recycling Machine Procurement



(b) Trend of Straw Recycling Machine Procurements

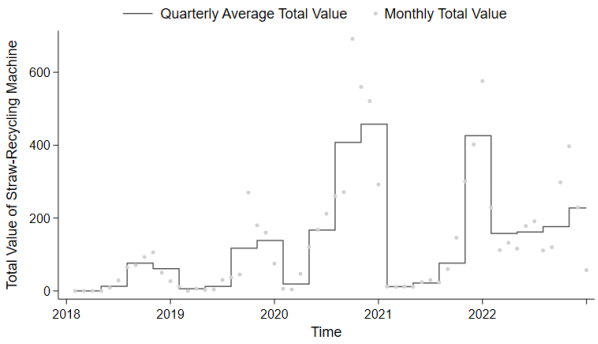


Figure 7: Straw Recycling Machine Procurement

Notes: Panel (a) displays the spatial distribution of county-level straw recycling machine procurement in 2022. Panel (b) shows the aggregate national procurement value over time. Data are aggregated at the county level.

To assess the extent of straw recycling following the ban and the role of subsidies, we examine the impact of the straw-burning ban on straw-recycling machine procurement, comparing responses across banned regions with and without recycling support.[45] Table 6 reports the results. Column (1) shows that the ban significantly increased the number of machines procured, total procurement value, and subsidy amount. To explore heterogeneity, we split the treatment group based on participation in the provincial recycling subsidy program in He et al. (2020), while maintaining a consistent control group. Column (2) shows that the effects are concentrated in subsidized regions, where machine procurement and subsidies rise sharply. In contrast, column

[44] See http://nys.mof.gov.cn/bgtGongZuoDongTai_1_1_1_1_3/201605/t20160526_2021673.htm and https://gs.mof.gov.cn/zhengcefagui/201609/t20160905_2412062.htm for detailed policies (in Chinese).

[45] Machine procurement data are from China's agricultural mechanization subsidy disclosure system. See Section 3.1 for details.

Table 6: Effects of Straw-Burning Ban Policies on Straw Recycling Machine Procurement

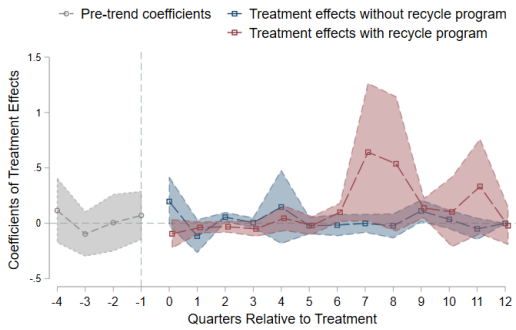
	Straw Recycling Machine Procurement		
	All counties (1)	With recycle program (2)	Without recycle program (3)
Panel A: Number of Machines			
Straw-burning Ban (Post × Treated)	0.095***	0.122***	0.047
	(0.034)	(0.047)	(0.032)
Panel B: Total Procurement Value			
Straw-burning Ban (Post × Treated)	0.652***	0.909***	0.202
	(0.212)	(0.281)	(0.277)
Panel C: Subsidy Amount			
Straw-burning Ban (Post × Treated)	0.551***	0.758***	0.190
	(0.175)	(0.229)	(0.234)
County FE	✓	✓	✓
Year-Quarter FE	✓	✓	✓
Province-Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	4,022	3,946	3,889

Notes: This table reports the heterogeneous effects of county-level straw-burning bans on straw-recycling machine procurement. The unit of observation is the county-by-year-quarter level. The dependent variables are the inverse hyperbolic sine (IHS) transformations of (i) the number of machines procured, (ii) total procurement value, and (iii) subsidy amount. The ban indicator equals one for treated counties after policy implementation. Columns (2) and (3) split treated counties by participation in the provincial recycling subsidy program (as described in He et al. (2020)). The control group is held fixed across columns and consists of never-treated and not-yet-treated counties in the DiD design. Therefore, observation counts in Columns (2) and (3) are not additive and need not sum to Column (1). All specifications include county, year-quarter, and province-quarter fixed effects and the baseline control set. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

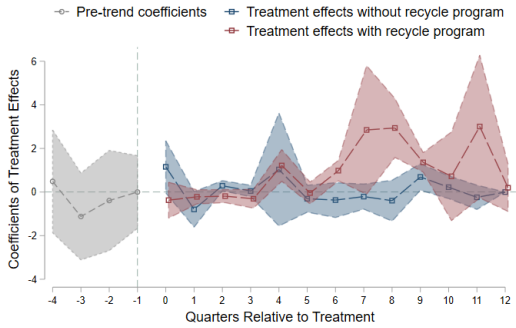
(3) reveals much smaller and statistically insignificant effects in areas without recycling support. These patterns are corroborated by the event-study plots in Figure 8, which show a clear post-ban divergence between subsidized and non-subsidized counties.[46]

[46]Event study plots of the impacts of the straw-burning ban on straw-recycling machinery procurement in the full sample are displayed in Figure E4.

(a) Heterogeneous Effects on the Number of Machine Procurements



(b) Heterogeneous Effects on Total Value of Machine Procurements



(c) Heterogeneous Effects on the Subsidy of Machine Procurements

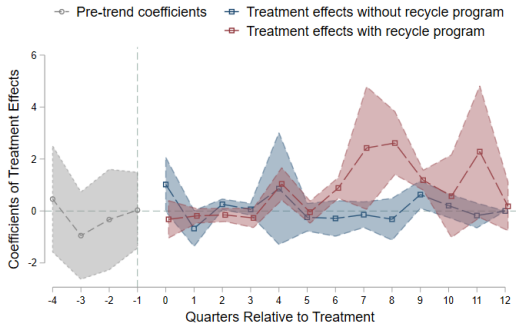


Figure 8: Heterogeneous Effects on Machine Procurements by Recycling Support: Event Study Plots

Notes: This figure illustrates the heterogeneous dynamic effects of the straw-burning ban by the presence of recycling support on straw-recycling machine procurements using the imputation DiD event-study approach (Borusyak et al., 2024). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of machine procurements (Panel [a]), the IHS transformation of total value of machine procurements (Panel [b]), the IHS transformation of subsidies of machine procurements (Panel [c]), measured at the county-by-year-quarter level. The treatment group is split based on participation in the provincial recycling subsidy program described in He et al. (2020), while the control group includes both never and not yet treated units. The regression includes county fixed effects, province-by-quarter fixed effects, and year-quarter fixed effects. Control variables include average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. The x-axis is quarters relative to treatment. The y-axis presents the estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

7.2 Health Effects by Straw-Recycling Subsidy Coverage

We verify above that the recycling subsidy program increases the procurement of straw-recycling machinery and may therefore mitigate the ban's unintended health effects by facilitating residue

removal. To test this, we estimate heterogeneous impacts of the straw-burning ban on vector-borne disease hospitalizations, conditional on recycling subsidy coverage. Specifically, we split the treated counties into two groups based on their participation in the provincial recycling subsidy program, while maintaining a common control group. This design allows us to cleanly isolate the additional mitigating effect attributable to the recycling subsidy program, alleviating concerns about differential control group composition.

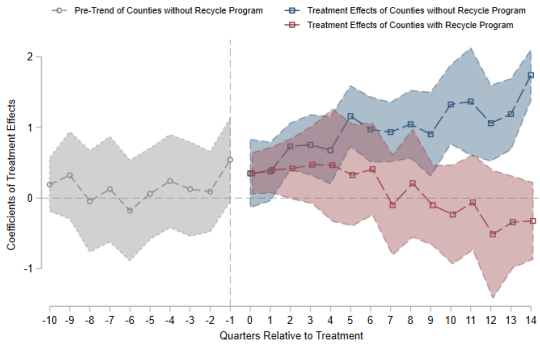
Table 7 presents the results. Columns (1) and (2) show that counties with recycling subsidies experience no significant increases in vector-borne disease incidence following the ban, whereas unsubsidized counties do. Columns (3) and (4) reveal a similar pattern for medical expenditures. All regressions control for weather, fire incidence, and health infrastructure, and include county, year-quarter, and province-by-quarter fixed effects. Event-study estimates in Figure 9 support these findings: health outcomes diverge after the straw-buring ban between subsidized and unsubsidized counties.

Table 7: Straw-burning Ban, Recycle Measures, and Vector-Borne Diseases

	Vector-Borne Diseases			
	Hospitalizations		Medical Expenditure	
	(1) without Recycle	(2) with Recycle	(3) without Recycle	(4) with Recycle
Straw-burning Ban (Post × Treated)	0.889***	0.001	1.097***	0.305
	(0.172)	(0.252)	(0.205)	(0.263)
County FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,192	5,132	5,192	5,132

Notes: This table reports the heterogeneous effects of county-level straw-burning bans on vector-borne disease outcomes. The dependent variables are inverse hyperbolic sine (IHS) transformations of hospitalization counts and medical expenditures. The treatment group is split based on participation in the provincial recycling subsidy program described in He et al. (2020), while the control group is held fixed across columns and consists of never-treated and not-yet-treated counties in the DiD framework. Consequently, observation counts in Columns (1) and (2) (and (3) and (4)) are not additive. All specifications include county, year-quarter, and province-quarter fixed effects, along with the baseline control set. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(a) Heterogeneous Effects on Vector-Borne Disease Hospitalizations



(b) Heterogeneous Effects on Vector-Borne Disease Medical Expenditure

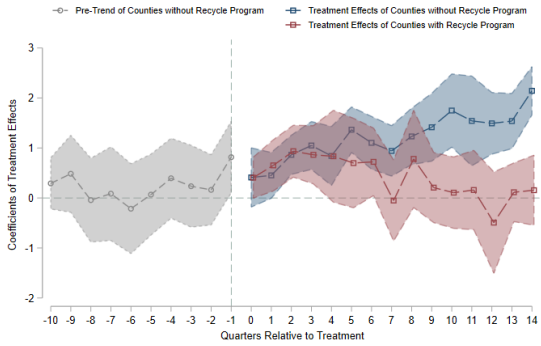


Figure 9: Heterogeneous Effects on Health Outcomes by Recycling Support: Event Study Plots

Notes: This figure shows the dynamic effects of the straw-burning ban on vector-borne diseases by the presence of recycling support. Panels (a) and (b) report event-study estimates for the IHS transformed number of inpatient admissions and medical expenditures for vector-borne diseases, at the county–year–quarter level, respectively. The treatment group is split based on participation in the provincial recycling subsidy program described in He et al. (2020), while the control group includes both never and not yet treated units. The fixed effects and control variables are the same as in Figure 4. The x-axis shows quarters or years relative to treatment, and the y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

As a robustness check, we construct an alternative measure of recycling capacity. Following Cao and Ma (2023) and Nian (2023), we use the number of biomass power plants as a proxy for local straw recycling infrastructure. Table E18 shows consistent patterns: areas with stronger recycling infrastructure experienced smaller and insignificant health effects from the ban. Figure E5 further confirms a similar divergence in the event-study plots across the two groups.

Together, the evidence reveals a clear inverse relationship between vector-borne disease outcomes and the intensity of straw recycling. These findings support the ecological mechanism and highlights the importance of pairing bans with effective residue management policies.

7.3 Policy Implications: Subsidized Straw Recycling

Our findings suggest that standalone straw-burning bans risk generating ecological feedbacks that impose unintended health costs. By altering field-level habitats, uncollected residues can intensify insect populations and disease transmission. Straw recycling, whether promoted through subsidies or infrastructure investment, can substantially reduce these risks. The limited machinery uptake in non-subsidized areas highlights the necessity of government intervention: subsidies are essential to enable effective straw recycling, given its high fixed costs and low returns.

Importantly, the fiscal costs of these subsidies are modest relative to their environmental and health benefits. He et al. (2020) estimate that the health gains from air quality improvements attributable to subsidy-induced compliance alone outweigh the program costs, even without accounting for the avoided vector-borne disease burden documented in this study. Our analysis thus underscore the importance of integrated policy design: combining bans with context-appropriate recycling support can mitigate ecological feedbacks while preserving air quality gains. This insight extends beyond China; as many developing countries confront similar environmental trade-

offs, China's experience offers a scalable template for residue management that advances both ecological and public health objectives.

8 Conclusion

This paper uncovers an unintended health consequence of China's straw-burning ban. While the policy improves air quality by reducing agricultural fires, it also disrupts local ecosystems, fostering insect proliferation and increasing the incidence of vector-borne diseases. The resulting rise in medical costs offsets a nontrivial share of the health benefits from cleaner air, highlighting the complex trade-offs involved in environmental governance. We trace these adverse health impacts to a clear ecological transmission mechanism: by reducing open-field burning, the policy creates favorable habitats for disease vectors, triggering increases in insect populations and subsequently elevating public concern and defensive behaviors. Crucially, we find that these negative effects are significantly mitigated in regions with effective straw residue management such as recycling subsidies or more extensive biomass infrastructure.

These findings carry important policy implications. They demonstrate that standalone bans, while well-intentioned, may backfire if ecological feedbacks are overlooked. Effective residue removal, especially when supported by targeted recycling subsidies, can neutralize these unintended harms. We document that such subsidies increase machinery adoption. In turn, these measures help reduce vector-borne disease incidence and preserve the environmental benefits of the original policy. Given the high costs of recycling and the low private returns, our results point to public subsidies as a cost-effective complement to bans.

More broadly, this study highlights the need to incorporate ecological dynamics into the design of environmental regulations. Anticipating ecosystem feedbacks can help prevent the risks arising from ecological shifts, ultimately enabling more balanced and effective governance.

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Appendices

This online appendix provides additional details on the data cleaning process, the construction of key variables, policy background, tests of the identification assumptions, and robustness checks for the empirical analysis.

A Data Cleaning

A.1 Health Data

Functions of Hospitals at Different Tiers China's public hospital system is structured into three tiers. Secondary hospitals are regional centers that offer comprehensive healthcare services to multiple communities. Tertiary hospitals represent the highest level, providing advanced and specialized care alongside more intensive research and training functions. While private hospitals account for a small share of inpatient services, public secondary and tertiary hospitals dominate the treatment of serious illnesses, including vector-borne and tick-borne infections, and therefore form the backbone of our sample.

Data Quality The quality of the hospitalization data is reliably high, owing to two institutional mechanisms. First, hospital records form the basis for both public and private insurance reimbursements. The National Healthcare Security Administration requires diagnostic and procedural accuracy for patient classification into standardized payment groups. Misclassification can result in reimbursement denial and financial penalties. Second, participation in the electronic reporting system is mandatory under National Health Commission regulations. Hospital performance evaluations conducted by local health authorities include assessments of digital medical record systems. In practice, attending physicians complete diagnostic fields, which are then verified and coded by trained clinical coders to ensure accuracy and adherence to standardized ICD-10 and procedure classifications (Huang et al., 2023).

Variable Construction and Cleaning Procedure We process the raw hospitalization records into county-by-year-quarter data using a three-step cleaning procedure, designed to capture seasonal patterns and ensure accurate measurement of disease trends. First, we identify all hospitalization records with a primary diagnosis corresponding to vector-borne diseases. We exclude entries with implausibly low medical expenditures (below 100 CNY) or extreme outliers arising from decimal errors (e.g., misplacement of decimal points). We then aggregate the cleaned records to the hospital-day level, summing the number of admissions and total expenditures. Second, to address missing data, we distinguish between true zeros and data absence. If a hospital recorded at least one inpatient admission for any infectious disease in a given year, then missing vector-borne admissions on a given day are imputed as zero. If a hospital did not record any infectious disease

admissions in that year, missing observations are treated as genuinely missing. Third, we aggregate the resulting hospital-day level data to the county-by-year-quarter level. This aggregation both smooths random fluctuations and aligns with the seasonal nature of disease transmission, enabling robust analyses of policy effects on disease outcomes. The same procedure is applied to construct measures for tick-borne diseases.

Demographic Structure of Hospitalizations Table A1 presents the age distribution of hospitalizations due to vector-borne and tick-borne illnesses. We observe cases across all age groups, suggesting broad vulnerability within the population and supporting the relevance of population-wide policy evaluation.

Appendix Table A1: Distribution of Hospitalizations: by Age Group

	Vector-Borne Diseases		Tick-Borne Diseases	
	Freq.	Percent	Freq.	Percent
0	15,111	4.87%	973	4.74%
1-4	34,759	11.19%	5,915	28.73%
5-19	51,892	16.71%	1,956	9.50%
20-39	53,889	12.58%	2,590	17.35%
40-59	87,818	28.27%	4,439	21.56%
60+	67,117	21.61%	4,714	22.89%

Addressing Selection of Data Although hospitals enter and exit the panel, we find no evidence that selection is correlated with policy rollout. We implement a series of selection tests to formally assess this concern. Appendix Table A2 reports results from three sets of regressions, each designed to test for potential selection along different dimensions.

In Columns (1) and (2), we use a balanced county-by-year-quarter panel and define the dependent variable as an indicator for whether an observation appears in our main estimation sample (as used in Table 2). Column (1) controls county, year-quarter, and province-by-quarter fixed effects. Column (2) replaces county fixed effects with city-level administrative indicators, which are constant within cities and enable variation in institutional status to be identified.

Columns (3) and (4) shift the outcome to the inverse hyperbolic sine (IHS) transformation of total hospital-day counts in each county–year–quarter. These regressions examine whether our coverage intensity is systematically related to either the policy rollout or city's administrative status. Column (3) uses the same DiD framework as Column (1), while Column (4) again includes administrative level indicators.

Finally, Columns (5) and (6) use a balanced hospital-by-year-quarter panel to examine whether the presence of an infectious disease department—where patients with vector-borne diseases typically seek treatment—is correlated with the straw-burning ban or city administrative level. Regressions are estimated via OLS with hospital and time fixed effects.

Appendix Table A2: Examining the effects of straw-burning ban policy or city administrative level

	(1)	(2)	(3)	(4)	(5)	(6)
	Sample inclusion (county-year-quarter)		Hospital-day coverage (IHS, county-year-quarter)		Infectious disease department (hospital-year-quarter)	
Treatment (=1)	0.021		0.071		-0.017	
	(0.021)		(0.105)		(0.019)	
Administrative Level 1		-0.007		0.021		0.002
		(0.026)		(0.139)		(0.014)
Administrative Level 2		0.007		0.033		0.006
		(0.022)		(0.133)		(0.015)
County FE	✓		✓			
Province-Quarter FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Hospital FE					✓	
Observations	46,302	73,396	46,302	73,396	42,332	73,348
R-squared		0.150		0.155		0.085

Notes: To assess potential sample selection issues, we construct a balanced county-year-quarter (Columns [1]-[4]) or hospital-year-quarter (Columns [5]-[6]) panel dataset. In Columns (1) and (2), the dependent variable is an indicator for whether a county-year-quarter observation appears in our main estimation sample. In Columns (3) and (4), the dependent variable is the inverse hyperbolic sine (IHS) transformation of the total hospital-day counts for each county-year-quarter observation. In Columns (5) and (6), the dependent variable is an indicator of whether a hospital contains an infectious disease department in each year-quarter. Columns (1), (3), and (5) estimate staggered DiD regressions (Borusyak et al., 2024). Columns (2), (4), and (6) estimate OLS regressions.

Across all specifications, the results consistently show no statistically significant relationship between sample inclusion, hospital-day coverage, or departmental availability and either the policy or city administrative level. This provides evidence that selection into our sample is unlikely to bias our main estimates.

Medical Insurance Distribution Our dataset records patients' enrollment in various basic medical insurance schemes, allowing us to distinguish between rural and urban populations. Rural residents are primarily covered by the New Rural Cooperative Medical Scheme (NCMS), while urban residents are typically enrolled in either the Urban Employee Basic Medical Insurance (UEBMI)—which covers formally employed individuals—or the Urban Resident Basic Medical Insurance (URBMI), which served unemployed and informally employed urban populations until 2017. Following reforms beginning in 2017, the URBMI gradually absorbed rural participants in some regions, but the NCMS was not merged into the urban schemes in reverse. To minimize misclassification, we categorize NCMS enrollees as rural, and UEBMI enrollees as a representative urban subgroup, while URBMI patients are excluded from rural–urban subgroup comparisons.

As shown in Appendix Table A3, 24.4% of vector-borne disease hospitalizations are among NCMS patients, 19.6% among UEBMI patients, and 32.0% among URBMI patients. An additional 16.3% of patients are uninsured, and 7.8% are covered by other schemes such as commercial or poverty-assistance programs. This distribution supports our ability to examine heterogeneity in health impacts across insurance types and rural–urban divides.

Appendix Table A3: Distribution of Hospitalizations: by Medical Insurance Type

	Vector-Borne Diseases		Tick-Borne Diseases	
	Cases	Percent	Cases	Percent
NCMS	73,324	24.39%	4,821	23.70%
UEBMI	58,891	19.59%	3,137	15.42%
URBMI	96,244	32.01%	7,637	37.54%
No insurance	48,927	16.27%	3,265	16.05%
Others	23,291	7.75%	1,485	7.30%

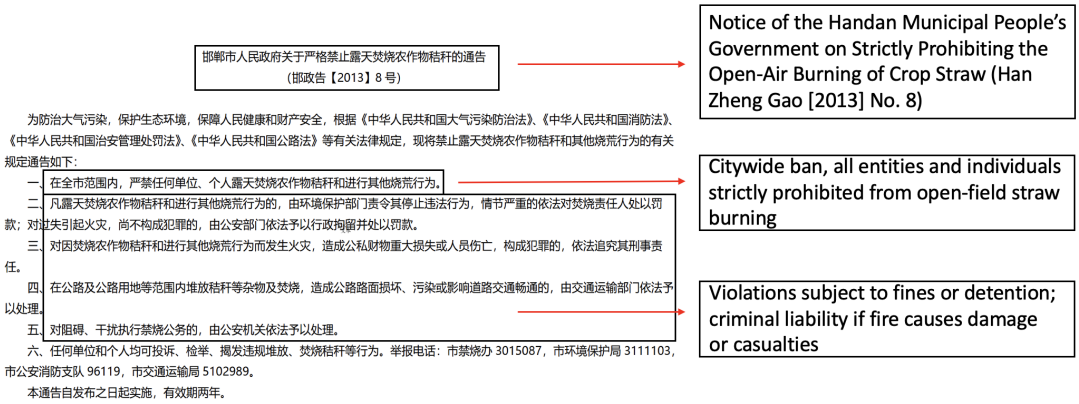
Notes: The category *Others* includes medical poverty assistance, commercial health insurance, etc.

A.2 Policy Data Cleaning Details

Data Retrieval and Coding We identified local regulatory documents referencing the term "straw-burning ban" from the Peking University Law Database, spanning March 1993 to September 2024. Each policy was coded by an LLM and also manually reviewed independently, and further classified based on whether it included assessment mechanisms (e.g., enforcement metrics or penalties for local officials). In total, 1,015 policies contained such assessment mechanisms.

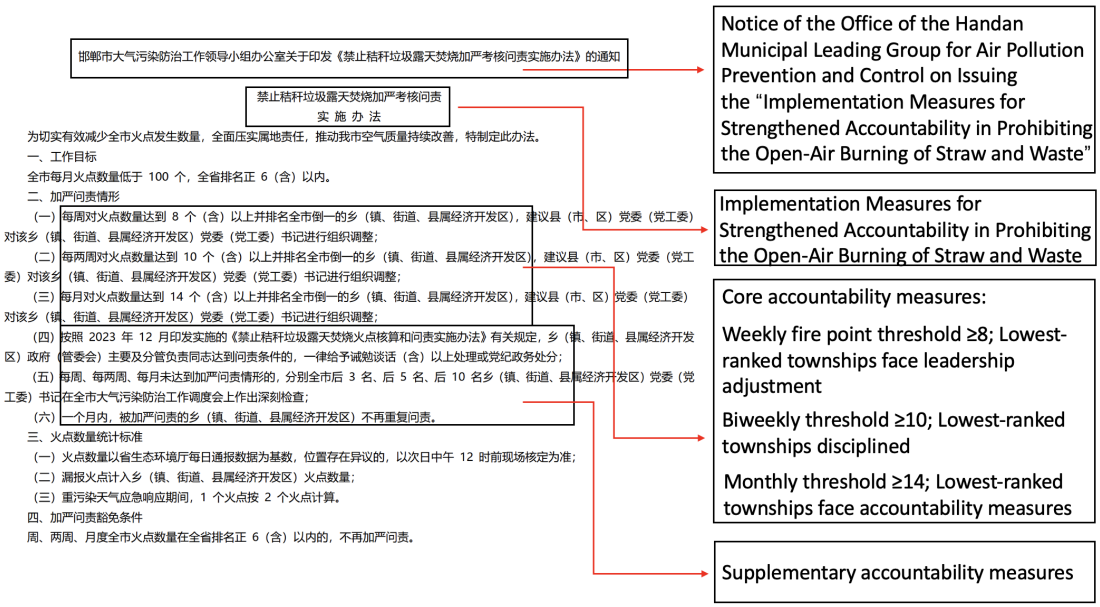
Illustrative Examples The following examples highlight how policy content varies in strictness across jurisdictions and over time. Figure A1 shows a basic straw-burning ban without assessment criteria, which states "*Across the entire city, all entities and individuals are strictly prohibited from burning crop straw or engaging in any other open-field burning activities*." This type of policy imposes blanket prohibitions on open-field burning and assigns enforcement responsibilities to environmental agencies. Figure A2 presents a more stringent ban that includes accountability mechanisms for local officials. For instance, one policy document states: "*If 14 or more fire points occur in a month and the township ranks last citywide, an organizational adjustment of the party secretary is again recommended*."

Policy-Issuing Authority Earlier in the policy timeline, 12 national-level regulations were issued between 1997 and 2012. They often focused on specific risk zones near transportation infrastructure (e.g., within 15 km of airports, 2 km of highways/railways, and 1 km of national/provincial roads).[1] Among the 1,015 policies with accountability features, 196 were issued at the provincial level, 705 at the prefecture-city level, and 114 at the county level.



Appendix Figure A1: A Typical Straw-Burning Ban Policy without Assessment Measures

[1] See Ministry of Ecology and Environment: https://www.mee.gov.cn/gkml/zj/wj/200910/t20091022_171920.htm (in Chinese).



Appendix Figure A2: A Typical Straw-Burning Ban Policy with Assessment Measures

A.3 Supplementary Datasets

Straw Burning and Forest Wildfire To identify fire activity across China, we rely on satellite-based remote sensing products widely used in environmental economics and earth science. Our primary source is the MODIS Burned Area Product (MCD64A1), which provides geolocated data on fire presence, timing, and burned area extent. This dataset has been extensively validated against Landsat 8 OLI imagery, with global accuracy metrics showing standard errors below 6%, a high coefficient of determination ($r^2 > 0.70$), and a regression slope above 0.79 relative to reference ground truth data (Smith et al., 2016; Roy et al., 2019).

A known limitation of burned area products is the under-detection of fire types. To improve detection accuracy, we overlay burned area pixels with land cover classification data from the MODIS Land Cover Type Product (MCD12Q1), following the methodology of Assunçãoa et al. (2019).[2] By distinguishing burning events that occur on croplands versus forests, we are able to classify each fire event as agricultural burning or forest wildfire. This integration—conducted using ArcGIS spatial analysis tools—enhances classification precision and reduces measurement error from fire heterogeneity.

Insect Observation Data Insect population is measured using open-access records from the Global Biodiversity Information Facility (GBIF). The raw dataset comprises point-level observa-

[2]Data sources: Up-to-date information on datasets, formats, and quality is available from the Land Processes DAAC at https://doi.org/10.5067/MODIS/MCD12Q1.006 for MCD12Q1 and https://modis-fire.umd.edu/ for the MODIS Fire and Burned Area products.

tion trips, which we aggregate to the county–year level to match our main panel structure. To limit the influence of extreme values, we winsorize the top 5% of arthropod observations but leave the lower tail unchanged because zero counts are common. We treat *Insecta* and *Arachnida* as subgroups under the phylum *Arthropoda*. We winsorize their observations to ensure they do not exceed the maximum of the overall arthropod distribution.

Web Search Intensity (Baidu) We construct a proxy for outdoor activity based on the Baidu Search Index for terms related to outdoor recreation such as "parks" and "camping." A full list of search terms and categories is provided in Table A4.

Appendix Table A4: Specific Search Terms on Baidu Related to Outdoor Activities

Category	Terms for Baidu Search Index (in Chinese Pinyin)
Outdoor activity	hu4wai4, hu4wai4xiu1xian2, hu4wai4jian4shen1, hu4wai4huo2dong4, hu4wai4sheng1huo2, hu4wai4bei4bao1, hu4wai4yun4dong4, gong1yuan2, sen1lin2gong1yuan2, jiao1ye3gong1yuan2, fang4feng1zheng1, ta4qing1, ding4xiang4yue4ye3, tu2bu4, tu2bu4lv3xing2, tan4xian3, su4xi1, pan1bing1, pan1deng1, deng1shan1, deng1shan1xie2, huang1dao3sheng1cun2, huang1ye3qiu2sheng1, yuan3zu2, ye3ying2, lu4ying2, lu4ying2deng1, lu4ying2zhuang1bei4, tian1mu4, zhang4peng2, camel, mu4gao1di2, di2ka3nong2, chong1feng1yi1, hu4wai4bei4bao1, deng1shan1xie2

Notes: The number following each Chinese character represents its tone.

In addition, to track public awareness and behavioral responses related to insect bites, we collect Baidu Search Index for keywords related to insect bites and symptoms, treatment of insect bites, and pest control measures. A full list of search terms and categories is provided in Table A5.

Appendix Table A5: Specific Search Terms on Baidu Related to Insect Bites, Treatment, and Defensive Behaviors

Category	Terms for Baidu Search Index (in Chinese Pinyin)
Insect bite	wen2chong2ding1yao3, chong2yao3pi2yan2, chong2yao3xing2pi2yan2, chong2yao3, du2chong2
Symptoms or treatment of insect bites	What medicine quickly reduces swelling and itching after insect bites; How to quickly reduce swelling and itching after a mosquito bite; What are the symptoms after a tick bite (in Chinese)
Defensive behaviors	qu1chong2, qu1chong2yao4, mie4chong2, sha1chong2, sha1chong2ji4, ni3chu2chong2ju2zhi3, chu2chong2ju2su4, xiang1mao2chun2, xiang1mao2you2

Notes: The number following each Chinese character represents its tone.

Crop Planting Maps We incorporate high-resolution crop planting data to support heterogeneity analyses related to straw availability. Specifically, we use gridded winter wheat planting maps from Dong et al. (2020), covering 11 provinces that together account for over 98% of China's winter wheat. We aggregate wheat planting areas to the county-year level for the period 2011–2022, capturing spatial variation in agricultural intensity and straw-burning pressure.

Biomass Power Plants To track straw utilization, we extract firm registration records from the Industrial and Commercial Firm Registry Database, focusing on firms whose business scope includes biomass power generation via direct combustion or gasification of agricultural and forestry residues. Following the classification strategy of Cao and Ma (2023), we construct a county-year panel indicating the presence of newly established biomass power plants. This variable captures variation in local straw demand for power generation and serves as a proxy for alternative straw disposal options.

B Additional Background of the Link between Arthropods and Vector-Borne Diseases

Arthropods, including both insect and non-insect taxa, constitute a diverse group of disease vectors and agents of direct health harm, with substantial implications for public health. This section provides an overview of medically relevant arthropod groups and illustrates how ecological changes—such as those induced by straw-burning bans—may unintentionally increase the incidence of arthropod-related diseases. These background insights inform the interpretation of our empirical findings and support the ecological plausibility of the disease pathways we examine.

Insects as Biological Vectors of Infectious Diseases Within the class *Insecta*, several orders contain species that are well-established biological vectors of infectious diseases. Specifically, the insect serves as a biological vector in which pathogens undergo essential development or replication before transmission to humans or animals (Laroche et al., 2018). Most prominently, *Diptera* includes mosquitoes (Culicidae), which transmit malaria, dengue fever, Zika virus, chikungunya, yellow fever, Japanese encephalitis, and lymphatic filariasis—conditions responsible for widespread global morbidity and mortality (WHO, 2024). Sandflies (Phlebotominae) transmit leishmaniasis and bartonellosis, while blackflies (Simuliidae) transmit onchocerciasis. These vectors breed and thrive in humid environments with standing water or decaying organic matter—conditions that may become more prevalent when fire suppression leads to increased surface biomass.

Other insect orders also play important roles in disease transmission. Tsetse flies (Glossinidae) in *Diptera* transmit African trypanosomiasis, while fleas (Siphonaptera) transmit plague and murine typhus. Lice (Phthiraptera) serve as vectors for epidemic typhus, relapsing fever, and trench fever.

Insects as Mechanical Vectors and Direct Agents of Health Harm Beyond biological transmission, insects also act as mechanical vectors, carrying pathogens on their external body surfaces or within their digestive tracts without requiring pathogen development. Houseflies (*Musca domestica*) and other synanthropic flies are among the most important mechanical vectors. They breed in decaying organic matter and can transport over 100 types of pathogens—including bacteria, viruses, and protozoa—to human food and surfaces. Documented diseases mechanically transmitted by houseflies include bacterial dysentery (Shigella spp.), typhoid fever (Salmonella Typhi), cholera (Vibrio cholerae), anthrax (Bacillus anthracis), hepatitis A, and trachoma, as well as parasitic infections such as ascariasis (Emerson et al., 2004; Khamesipour et al., 2018). Cockroaches, particularly *Blattella germanica* and *Periplaneta americana*, similarly serve as reservoirs and mechanical vectors for a broad range of pathogens, including those causing typhoid fever, dysentery, and cholera (Nasirian, 2019). Their close association with human living environments makes them critical contributors to foodborne disease transmission.

Other biting flies, particularly horse flies and deer flies (Tabanidae), also serve as important mechanical vectors. Tabanids are large, hematophagous insects that inflict painful bites and can

mechanically transmit pathogens between large mammals, including humans. Laboratory and field studies have documented tabanid transmission of Bacillus anthracis (anthrax), Brucella spp. (brucellosis), Francisella tularensis (tularemia), and Coxiella burnetii (Q fever) (Foil, 1989). Although their role in natural transmission cycles is less well quantified than that of houseflies or cockroaches, tabanids are recognized as important mechanical vectors in agricultural and peri-agricultural settings where livestock and humans may be exposed.

Insects also cause direct health harm through stinging, biting, or contact with toxic secretions. In *Hymenoptera* (bees, wasps, hornets, and ants), venomous stings range from mild local irritation to systemic toxic effects and life-threatening anaphylaxis (Golden, 2003). In *Lepidoptera*, stinging caterpillars (the larval stage of moths and butterflies) possess venomous bristles (setae) that can cause dermatitis and allergic reactions (Hossler, 2010). In *Coleoptera*, *Paederus* beetles release pederin, a potent vesicant that causes blistering dermatitis (paederus dermatitis) upon skin contact (Frank and Kanamitsu, 1987). Occupational exposure to beetles such as *Tenebrio molitor* has been linked to asthma and allergic dermatitis, particularly among agricultural workers (Jeebhay et al., 2005). Additionally, ingestion of blister beetles (Meloidae) can cause cantharidin poisoning in both humans and livestock (Tagwireyi et al., 2000). These direct effects, ranging from dermatitis and urticaria to systemic toxicity, constitute a substantial portion of arthropod-related health burdens, independent of infectious disease transmission.

Non-insect Arthropods and Vector-Borne Diseases Outside the insect class, arthropods in *Arachnida* contribute to disease risks through envenomation, allergic reactions, and pathogen transmission.

Ticks, especially *Ixodes scapularis* (the black-legged tick), are major vectors of bacterial and protozoal diseases, including Lyme disease, babesiosis, anaplasmosis, ehrlichiosis, and tick-borne encephalitis (Adrion et al., 2015; CDC, 2022; ECDC, 2025). They are considered the second-most important vector group after mosquitoes in terms of global health impacts (Sonenshine and Roe, 2014). Tick populations depend heavily on shaded, humid microenvironments with dense vegetation—conditions sensitive to ecological disturbances such as fire suppression. Ticks also serve as vectors for Coxiella burnetii, the causative agent of Q fever, which has been detected in multiple tick species worldwide, including Dermacentor, Hyalomma, and Rhipicephalus (Körner et al., 2021).

Mites also pose health risks. Chigger mites (*Trombiculidae*) transmit scrub typhus (*Orientia tsutsugamushi*) and can cause allergic dermatitis through direct skin contacts (Koh et al., 2010). Some mite species also act as mechanical carriers of fungal spores and bacteria, particularly in agricultural environments. Additionally, evidence suggests that mites may play a role in the transmission of hantaviruses, the causative agents of hemorrhagic fever with renal syndrome (HFRS). Experimental studies have demonstrated that the rat mite Ornithonyssus bacoti can acquire, maintain, and transmit Hantaan virus to susceptible hosts, and viral persistence in mites has been documented for up to 22 days post-infection (Yu and Tesh, 2014). While aerosolized rodent excreta

remains the primary route of human infection, mite involvement in animal-to-animal transmission suggests a potential amplifying mechanism that may contribute to human exposure risk in agricultural environments.

Ecological Mechanisms Linking Fire Suppression and Vector Proliferation Straw-burning bans, by reducing fire frequency, alter the ecological landscape in ways that favor vector proliferation. Increased surface vegetation and organic residue create microhabitats with greater humidity, thermal insulation, and protection from predators—conditions known to support larger populations of mosquitoes, ticks, and mites (Allan et al., 2003; Gleim et al., 2019). Controlled fire has historically served as a natural population control mechanism for many vector species; its removal may therefore shift local disease dynamics toward increased incidence of bites, infestations, and vector-borne infections. These ecological mechanisms support the plausibility of the vector-borne health impacts we observe following the ban.

C Disease Categories for Empirical Analyses

Appendix Table C1: ICD-10 codes for Vector-Borne Diseases

Disease name	**ICD-10 codes**
Cholera	A00
Typhoid and paratyphoid fevers	A01
Shigellosis	A03
Other bacterial intestinal infections	A04
Other bacterial foodborne intoxications, not elsewhere classified	A05
Acute amebic dysentery	A06.0
Plague	A20
Tularemia	A21
Anthrax	A22
Brucellosis	A23
Bartonellosis	A44
Louse-borne relapsing fever	A68.0
Tick-borne relapsing fever	A68.1
Relapsing fever, unspecified	A68.9
Lyme disease	A69.2
Trachoma	A71
Epidemic louse-borne typhus fever due to Rickettsia prowazekii	A75.0
Typhus fever, unspecified	A75.9
Q fever	A78
Trench fever	A79.0
Rickettsialpox due to Rickettsia akari	A79.1
Other specified rickettsioses	A79.8
Rickettsiosis, unspecified	A79.9
Mosquito-borne viral encephalitis	A83
Arthropod-borne viral encephalitis, unspecified	A85.2
Dengue	A90; A91
Chikungunya virus disease	A92.0
Other specified mosquito-borne viral fevers	A92.8
Sandfly fever	A93.1
Colorado tick fever	A93.2
Other specified arthropod-borne viral fevers	A93.8

ICD-10 codes for Vector-Borne Diseases, cont.

Disease name	ICD-10 codes
Yellow fever	A95
Crimean-Congo hemorrhagic fever	A98.0
Omsk hemorrhagic fever	A98.1
Kyasanur forest disease	A98.2
Hemorrhagic fever with renal syndrome (HFRS)	A98.5
Malaria	B50; B51; B52; B53; B54
Leishmaniasis	B55
African trypanosomiasis	B56
Onchocerciasis	B73
Loiasis	B74.3
Mansonelliasis	B74.4
Scabies	B86
Myiasis	B87
Acarine dermatitis	B88.000x004; B88.000x006
Acute atopic conjunctivitis	H10.1
Allergic contact dermatitis, unspecific cause	L23.9
Paederus dermatitis	L24.800x002
Unspecified contact dermatitis due to other agents	L25.800x001
Pruritus	L29
Urticaria	L50
Papule	R23.800x001
Toxic effect of venom of other arthropods	T63.4

Note: This table adopts a broad definition of arthropod-related health outcomes. It includes: (i) classic vector-borne diseases transmitted biologically by arthropods (e.g., mosquitoes, ticks, fleas, lice, sandflies, tsetse flies, blackflies); (ii) diseases transmitted mechanically by houseflies, cockroaches, and tabanid flies, as documented in the entomology and epidemiology literature (Foil, 1989; Emerson et al., 2004; Khamesipour et al., 2018; Nasirian, 2019); (iii) diseases for which mites may serve as vectors or amplifiers, such as scrub typhus and hemorrhagic fever with renal syndrome (Yu and Tesh, 2014); and (iv) direct health consequences of arthropod exposure, including parasitic infestations (e.g., scabies, myiasis), allergic reactions (e.g., dermatitis, urticaria), and venom toxicity (Frank and Kanamitsu, 1987; Tagwireyi et al., 2000; Jeebhay et al., 2005). For tick-borne diseases, see Appendix Table C2. Classification follows a cross-reference of ICD-10 codes with the above literature and standard epidemiological references (CDC, 2022; WHO, 2024; ECDC, 2025). See Appendix B for more details.

Appendix Table C2: ICD-10 codes for Tick-Borne Diseases

Disease name	**ICD-10 codes**
Tick-borne relapsing fever	A68.1
Lyme disease	A69.2
Q fever	A78
Other specified rickettsioses	A79.8
Rickettsiosis, unspecified	A79.9
Colorado tick fever	A93.2
Other specified arthropod-borne viral fevers	A93.8
Crimean-Congo hemorrhagic fever	A98.0
Omsk hemorrhagic fever	A98.1
Kyasanur forest disease	A98.2

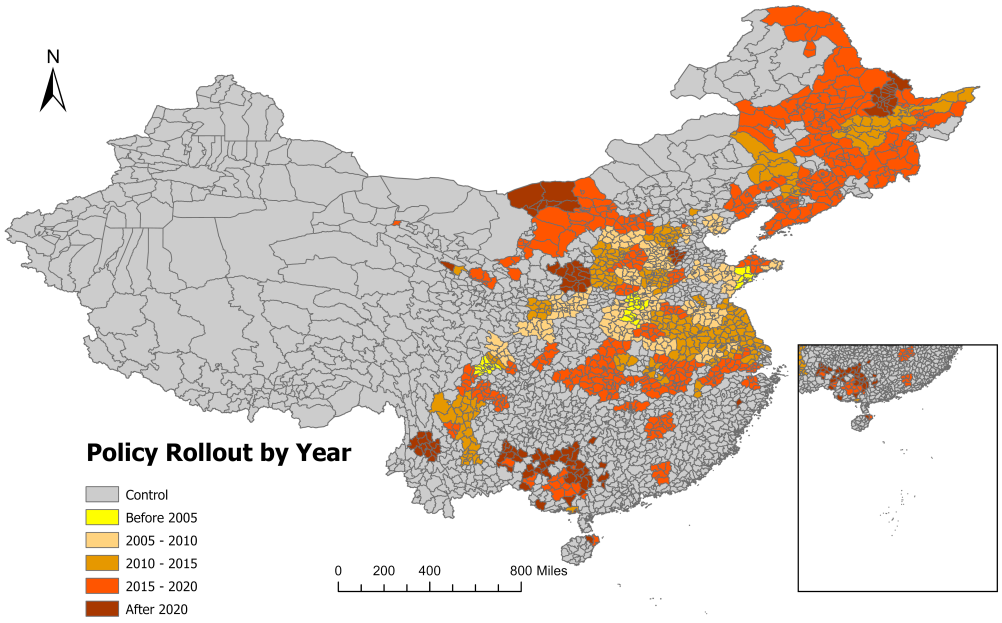
Note: This table lists tick-borne diseases included in our analysis, following the broad definition of arthropod-related health outcomes described in Appendix Table C1. Tick-borne diseases are primarily transmitted through the bite of infected ticks (Ixodidae and Argasidae), which serve as biological vectors. The list includes conditions caused by bacteria (e.g., Lyme disease, relapsing fever, rickettsioses), viruses (e.g., tick-borne encephalitis, Crimean-Congo hemorrhagic fever, Colorado tick fever), and the protozoan pathogen responsible for babesiosis. For diseases such as Q fever, ticks may play a role in the enzootic cycle alongside other transmission routes (Körner et al., 2021). Classification follows standard epidemiological references (CDC, 2022; WHO, 2024; ECDC, 2025). See Appendix B for more details.

D Supplementary Analyses Supporting Identification Strategy

The straw-burning ban represents one of China's most stringent efforts to reduce air pollution. Like other major environmental initiatives—such as the Air Pollution Monitoring and Disclosure (APMD) program—its implementation was largely top-down, shaped by pre-existing administrative hierarchies and political priorities, rather than by local health or ecological conditions (Barwick et al., 2024).

Figure D1 illustrates the geographic sequence of policy rollout, showing that early adoption concentrated in the North China Plain, followed by expansions into northeastern, northern, and southwestern regions. Figure D2 further compares the rollout timing of the straw-burning ban and the APMD program, revealing a strong positive correlation: counties that adopted the APMD program early also implemented the straw-burning ban early.[3]

These patterns suggest that rollout timing was not driven by local health needs or ecological conditions but followed a national sequence of administrative hierarchy and political prioritization. This provides support for the plausibility of our identification strategy.

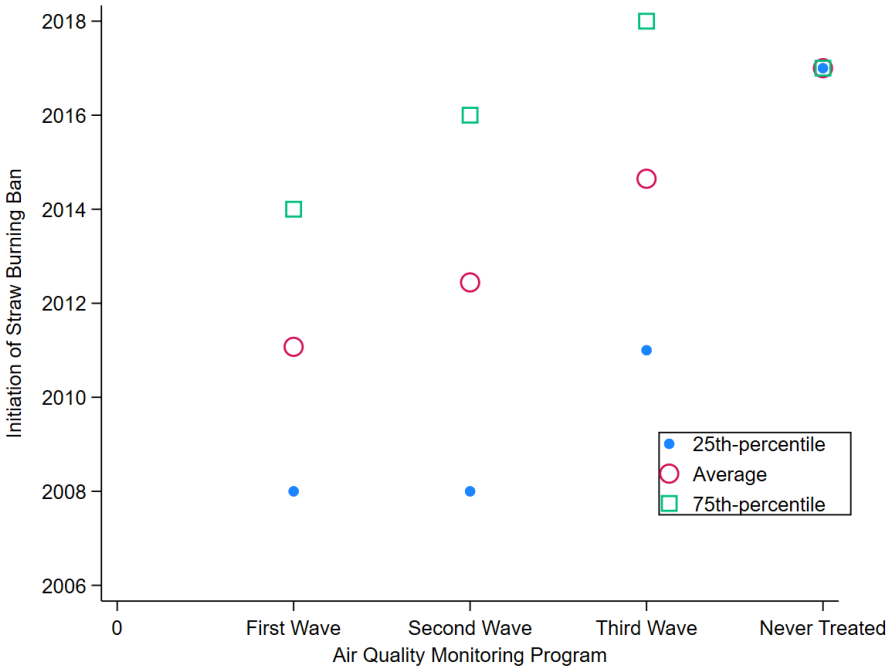


Appendix Figure D1: Roll-out of China's Straw Burning Ban Policies

Notes: This figure illustrates the rollout of straw-burning policies. The data are obtained from the Peking University Law Database (`https://www.pkulaw.com`) and are described in detail in Appendix A.2.

[3] Among counties that never adopted the straw-burning ban, more than 80% belong to the third (and final) wave of the APMD program.

Appendix Figure D2: Straw Burning Ban and Air Pollution Monitoring and Disclosure Program Rollouts



Notes: The data are obtained from Barwick et al. (2024) and the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.

Policy Rollout and Regional Covariates Table D1 summarizes baseline economic, agricultural, and health infrastructure characteristics by rollout wave. Three patterns emerge: first, since the rollout followed a top-down administrative hierarchy, earlier-adopting counties tend to have higher GDP and larger populations, consistent with rollout sequencing favoring more economically and politically prominent regions. Second, while treated counties generally have more cropland—reflecting the policy's targeting of agricultural burning—earlier adopters do not have systematically more cropland than later ones. This suggests that cropland area was not the primary driver of rollout timing. Third, we examine whether health infrastructure differs across counties with varying policy rollout timing. While treated counties exhibit more total hospital beds than untreated ones, there are no significant differences in per capita bed counts or in the number of hospitals, suggesting similar baseline health system capacity across treatment status.

Table D2 provides further evidence. Conditional on administrative tier, county-level hospital bed counts do not significantly predict the policy's adoption status. This supports the claim that health infrastructure did not determine rollout, indicating that policy adoption is plausibly exogenous to baseline health conditions.

Concurrent Agricutural and Health Policies Another concern is whether other policies implemented during the same period confound our results. Several major agricultural reforms—such as agricultural tax abolition, land transfer pilots, and insurance subsidies—overlapped temporally with the straw-burning ban. However, most of these were either national in scope or provincial pilot programs whose timing and geography were not aligned with the straw-burning rollout. More importantly, none of them directly affect insect ecology or vector-borne disease pathways.

Likewise, no concurrent health interventions plausibly influence our outcome of interest, i.e., ecological shifts and vector-borne diseases. The centralized drug procurement program (launched in 2020) targeted prices of drugs for cancer, cardiovascular, and psychiatric conditions—unrelated to vector-borne diseases. The Diagnosis-Related Group (DRG) reform altered hospital billing incentives but had no expected effect on disease incidence.

We conduct placebo tests on unrelated conditions, including *non-arthropod-related dermatoses*, bone fractures (typically due to accidents), and neoplasms (linked to long-term biological processes). As shown in Table E2, we detect no significant treatment effects for these outcomes, confirming that the observed effects are not driven by concurrent health policies, changes in the health system, or unrelated disease trends.

Straw Recycling Policy and Regional Covariates Straw management involves substantial fixed and variable costs. To alleviate the economic burden of recycling, the central government launched a straw-recycling subsidy program in 2016, targeting ten provinces. We conduct a county-level analysis to examine the factors associated with the implementation of this policy, as shown in Table D3. Column (1) shows that the straw recycling policy indicator is not significantly responsive to the five-year cropland fire change rates prior to 2015. Column (2) indicates that the policy is more likely to be adopted in counties with larger total cropland area (which affects the aggregate amount of straw), steeper terrain slopes (which influence the feasibility of using agricultural machinery), and higher PM2.5 concentrations (suggesting that the policy is also motivated by air quality concerns). Column (3) further includes the cropland fire rate, which remains insignificant, while the other three factors continue to show strong and significant associations. Finally, Column (4) adds controls for regional GDP and hospital beds per capita. The results show that GDP is positively and significantly associated with policy implementation, whereas hospital infrastructure is not. Taken together, these patterns indicate that, conditional on observable geographic and economic characteristics, recycling subsidy placement is uncorrelated with pre-existing fire trends or health infrastructure. This supports the validity of our subsidy-based heterogeneity analysis.

Appendix Table D1: Characteristics of Counties by Roll-out Waves of Straw-Burning Bans

	(1)	(2)	(3)	(4)	(5)	(6)
Policy Adoption Time	Before 2011	2011-2014	2015-2018	2019-2022	Ever Treated	Never-Treated
Number of Counties	526	345	367	165	1,403	1,348
GDP (10^9 *CNY*)	19.85	14.91	12.31	7.17	15.21	13.64
	(30.19)	(37.84)	(14.34)	(10.01)	(27.88)	(37.97)
Population (10^3)	568.86	475.64	465.84	347.12	492.54	436.10
	(323.07)	(298.63)	(274.03)	(249.32)	(304.27)	(394.11)
Cropland (*100* km^2)	6.58	9.06	9.46	7.04	8.00	5.82
	(5.54)	(11.00)	(10.43)	(7.84)	(8.86)	(6.22)
Hospital Beds	1,471.02	1,115.27	1,221.37	910.32	1,251.22	995.57
	(852.92)	(696.05)	(745.55)	(658.84)	(788.66)	(793.10)
Hospital Beds per 10^3 People	3.07	3.00	3.26	3.24	3.12	2.75
	(2.43)	(2.66)	(3.74)	(3.27)	(2.99)	(2.36)
Number of Hospitals Observed	2.65	2.67	2.66	2.61	2.66	2.63
	(0.37)	(0.37)	(0.37)	(0.39)	(0.37)	(0.39)

Notes: The table reports the characteristics of counties in different rollout waves of the straw-burning ban policy. Cropland size, GDP, population, number of hospital beds, and hospital beds per 1000 people are measured by the 2001-2015 average. The last row refers to the average number of observed hospitals in each county in our dataset. Standard deviations are in parentheses.

Appendix Table D2: Determinants of Straw Burning Ban Status

	2015-2022		2001-2022	
	(1)	(2)	(3)	(4)
	Ever-Treated	Ever-Treated	Ever-Treated	Ever-Treated
Hospital Beds (10^3)	0.004	0.001	0.004	-0.006
	(0.016)	(0.016)	(0.013)	(0.013)
Cropland (100 km^2)	0.010***	0.010***	0.009***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
GDP (10^9 CNY)	-0.001**	-0.001	-0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
$PM_{2.5}$ ($\mu g/m^3$)	0.004***	0.004***	0.011***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Administrative Level 1		-0.037		0.136***
		(0.030)		(0.024)
Administrative Level 2		0.131***		0.180***
		(0.029)		(0.024)
R^2	0.050	0.064	0.160	0.181
Observations	1,832	1,832	2,669	2,669

Notes: This table presents the determinants of the straw-burning ban status. In Columns (1)–(4), the dependent variable is a treatment-group indicator. Following Barwick et al. (2024), the dummy variable 'Administrative Level 1' denotes cities in the Jing-Jin-Ji Metropolitan Region, the Yangtze River Delta Economic Zone, the Pearl River Delta Metropolitan Region, directly administered municipalities, and provincial capitals; the dummy variable 'Administrative Level 2' denotes the 2007-designated Environmental Improvement Priority Cities and the 1997–2007 National Environmental Protection Exemplary Cities. Cropland size, GDP, number of hospital beds, and $PM_{2.5}$ are measured using the 2001–2015 averages. Standard errors are reported in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table D3: Straw Recycling Policy and Regional Covariates

	(1)	(2)	(3)	(4)
		Indicator for Straw Recycling Policy		
Cropland Fire Change Rate	-0.000		0.001	0.000
	(0.001)		(0.001)	(0.001)
Cropland ($100km^2$)		0.008***	0.006***	0.006***
		(0.001)	(0.001)	(0.001)
Slope		-0.029***	-0.045***	-0.046***
		(0.002)	(0.004)	(0.004)
PM2.5		0.005***	0.003***	0.004***
		(0.000)	(0.001)	(0.001)
Hospital Beds				-0.019
				(0.014)
GDP ($10^9 CNY$)				-0.002***
				(0.001)
R^2	0.000	0.300	0.274	0.289
Observations	920	2,714	913	905

Note: This table presents the association between the straw recycling policy and county-level covariates. The cropland fire change rate is calculated as the average annual change in cropland fires from 2011 to 2015, divided by the average number of cropland fires over the same period, and is computed only for counties that experienced at least one fire during 2011–2015. *** p <0.01, ** p <0.05, * p <0.1.

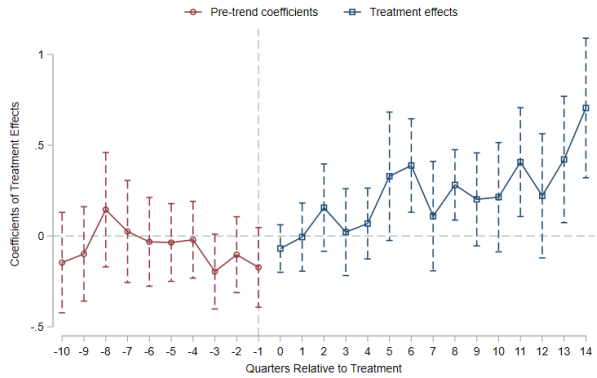
Appendix Table D4: $PM_{2.5}$ and Vector-Borne Diseases

	Vector-Borne Hospitalizations			
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.007	0.136	0.130	0.130
	(0.126)	(0.116)	(0.116)	(0.116)
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls		✓	✓	✓
Weather Controls			✓	✓
Cropland and Forest Fire Controls				✓
Observations	15,927	15,927	15,800	15,800

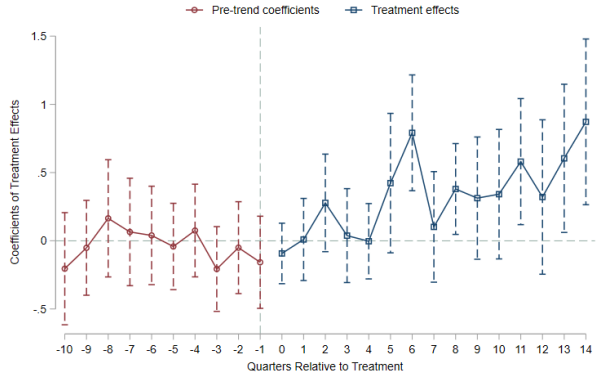
Note: This table presents the association between $PM_{2.5}$ and hospitalizations of vector-borne diseases. The model includes county and province-by-year-quarter fixed effects. Hospital controls include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, along with the average number of annual hospitalizations. Weather controls include the average temperature and precipitation. Cropland and forest fire is measured by the occurrence and burned area of croland and forest wildfires. Robust standard errors are in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

E Supplementary Figures and Tables

(a) Effects on Hospitalizations of Tick-Borne Diseases



(b) Effects on Medical Expenditure of Tick-Borne Diseases

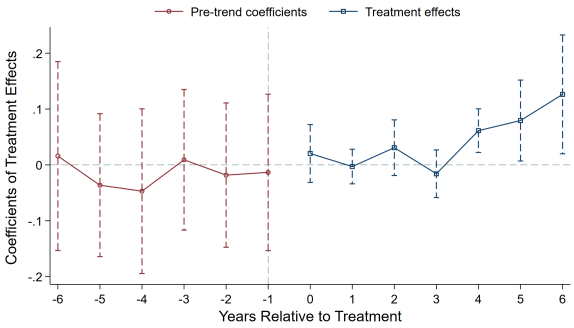


Appendix Figure E1: Effects on Tick-Borne Diseases: Event Study Plots

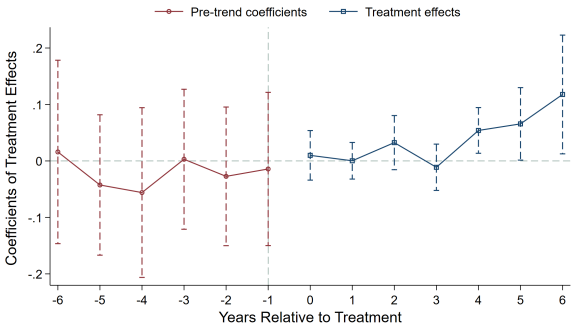
Notes: This figure illustrates the dynamic effects of the straw-burning ban on tick-borne disease hospitalizations using the imputation DiD event-study approach (Borusyak et al., 2024). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions (Panel [a]) and the IHS transformation of total medical expenditures (Panel [b]) for tick-borne diseases, measured at the county-by-year-quarter level. The regression includes county fixed effects, province-by-quarter fixed effects, and year-quarter fixed effects. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. The x-axis is quarters relative to treatment. The y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

The gradual increase in tick-borne diseases is consistent with the complex, multi-year life cycles of ticks, which are constrained by slower demographic turnover and a strong dependence on stable host-reservoir densities (Randolph, 2004). Unlike insects, ticks require significant time for pathogens to establish across different life stages, resulting in a lagged epidemiological response to environmental interventions.

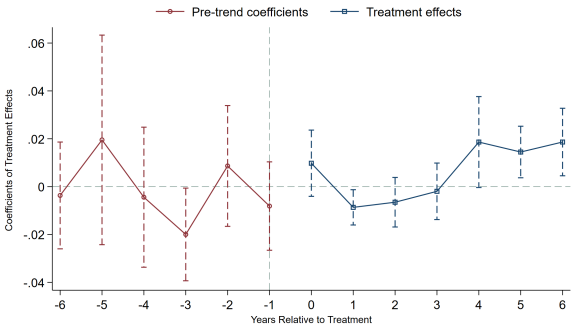
(a) Effects on Arthropoda Population



(b) Effects on Insecta Population



(c) Effects on Arachnida Population



Appendix Figure E2: Effects on Insect Population: Event Study Plots

Notes: This figure illustrates the dynamic effects of the straw-burning ban on insect population using the imputation DiD event-study approach (Borusyak et al., 2024). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of observations for arthropoda, insecta, and arachnida species, measured at the county-year level. The regression includes county and year fixed effects. Control variables include the IHS transformations of the number of unique observers and GDP, average temperature and precipitation, and frequency and burned area of forest wildfires. The x-axis is years relative to treatment. The y-axis presents the estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

(a) Example for Straw Returning Machine



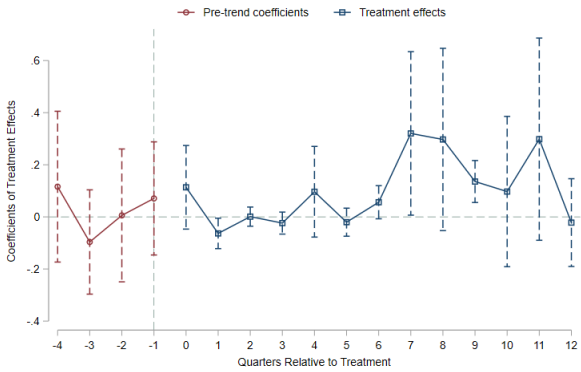
(b) Example for Straw Collecting Machine



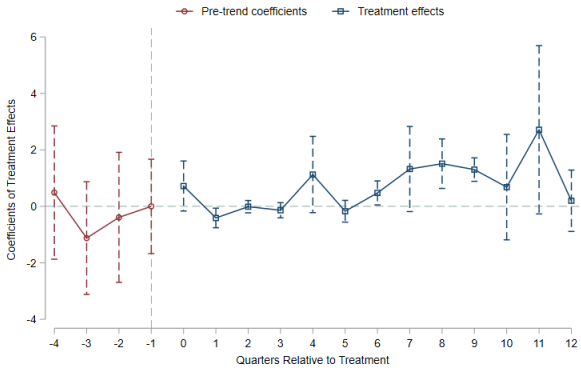
Appendix Figure E3: Straw Management Machines

Notes: Panel (a) shows an example of a straw incorporator used for returning residues to the soil. Panel (b) shows an example of a straw baler used for straw collection.

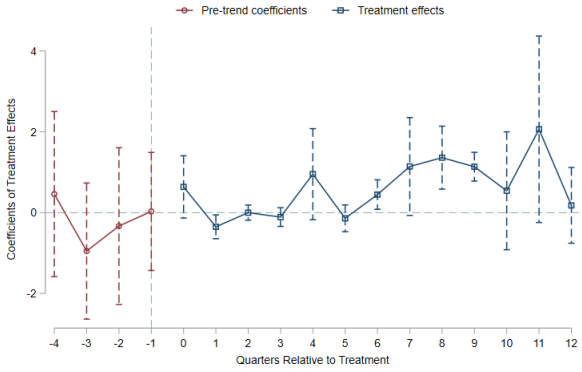
(a) Effects on Number of Machine Procurements



(b) Effects on Total Value of Machine Procurements



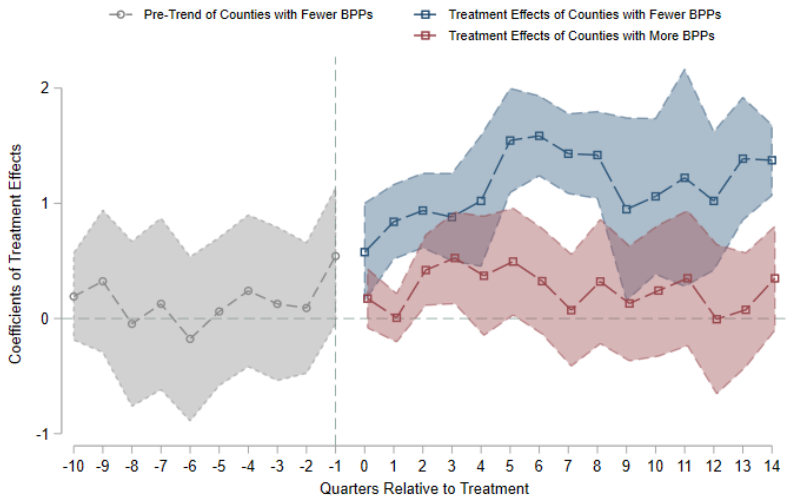
(c) Effects on Subsidies of Machine Procurements



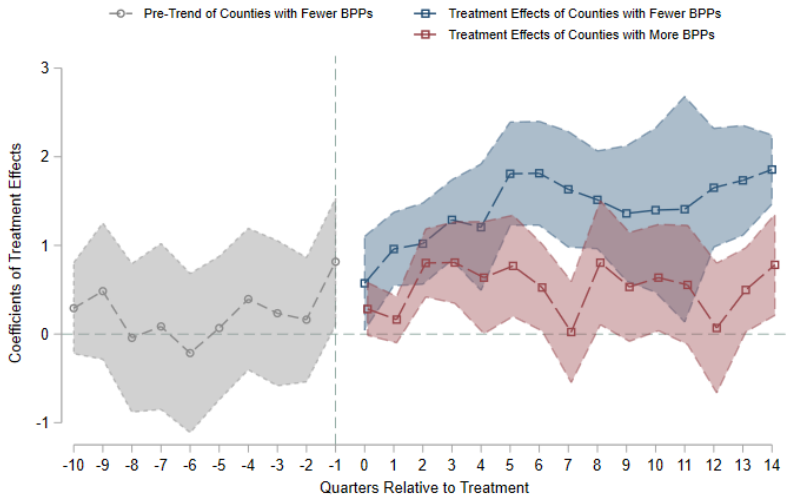
Appendix Figure E4: Effects of Straw-burning Ban on Machine Procurements: Event Study Plots

Notes: This figure illustrates the dynamic effects of the straw-burning ban on straw recycle machine procurements using the imputation DiD event-study approach (Borusyak et al., 2024). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of machine procurements (Panel [a]), the IHS transformation of total value of machine procurements (Panel [b]), the IHS transformation of subsidies of machine procurements (Panel [c]), measured at the county-by-year-quarter level. The regression includes county fixed effects, province-by-quarter fixed effects, and year-quarter fixed effects. Control variables include average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. The x-axis is quarters relative to treatment. The y-axis presents the estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

(a) Heterogeneous Effects on Hospitalizations by Number of Biomass Power Plants



(b) Heterogeneous Effects on Medical Expenditure by Number of Biomass Power Plants



Appendix Figure E5: Event Study of Straw-Burning Ban by Number of Biomass Power Plants

Notes: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne diseases by different recycling measures. The dependent variable is the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions (Panel [a]) and the IHS transformation of total medical expenditures (Panel [b]) for vector-borne diseases, measured at the county-by-year-quarter level. The treatment group is split based on the number of biomass power plants, while the control group includes both never and not yet treated units. The fixed effects and control variables are the same as in Figure 4. The x-axis shows quarters relative to treatment, and the y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

Appendix Table E1: Effects of Straw-Burning Ban Policies on Hospital Stays of Vector-Borne and Tick-Borne Diseases

	Vector-Borne Diseases	Tick-Borne Diseases
	(1)	(2)
Straw-Burning Ban	7.180*	0.399***
	(4.281)	(0.151)
Pre-treatment mean	119.387	4.682
No. Hospitalizations	✓	✓
County FE	✓	✓
Province-Quarter FE	✓	✓
Year-Quarter FE	✓	✓
Controls	✓	✓
Observations	5,391	5,391

Notes: This table reports the effects of the straw-burning ban on the length of hospital stays for vector-borne and tick-borne diseases. The dependent variables are the total number of hospitalization days for vector-borne and tick-borne diseases. The unit of observation is the county–year–quarter. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E2: Placebo Test on Unrelated Diseases

	Hospitalizations			Medical Expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-arthropod-related Dermatoses	Fracture	Neoplasm	Non-arthropod-related Dermatoses	Fracture	Neoplasm
Straw-Burning Ban	-0.001	-0.014	0.011	0.005	-0.011	0.005
	(0.009)	(0.021)	(0.026)	(0.006)	(0.038)	(0.036)
County FE	✓	✓	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	5,864	5,864	5,864	5,864	5,864	5,864

Notes: This table presents the impacts of straw-burning ban policies on hospitalizations for diseases unrelated to vectors. The dependent variables are the IHS transformations of hospitalizations and medical expenditures for **non-arthropod-related dermatoses**, **fractures**, and **neoplasms**. The unit of observation is the county–year–quarter level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E3: Robustness Checks: Controlling for Vegetation and Excluding "Sponge Cities"

	Vector-Borne Disease Hospitalizations		Vector-Borne Disease Medical Expenditure	
	(1)	(2)	(3)	(4)
	Vegetation Controls	Exclude Sponge Cities	Vegetation Controls	Exclude Sponge Cities
Straw-Burning Ban	0.517***	0.494***	0.763***	0.740***
	(0.156)	(0.155)	(0.176)	(0.174)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,328	5,296	5,328	5,296

Notes: This table presents robustness tests accounting for potential confounding effects from concurrent greening policies. The unit of observation is the county–year–quarter level. Columns (1) and (3) control for vegetation growth (e.g., increased greenness from reforestation or greenfield expansion). Columns (2) and (4) exclude the 16 pilot cities in China's Sponge City Program to rule out confounding effects from concurrent changes in urban water and green infrastructure. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E4: Effects of Straw-Burning Ban Policies Estimated Using Callaway and Sant'Anna (2021)

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.802**	0.941*	0.434**	0.576**
	(0.346)	(0.494)	(0.186)	(0.250)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	6,801	6,801	6,801	6,801

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases using the method of Callaway and Sant'Anna (2021). The unit of observation is at the county-by-year-quarter level. The dependent variables are the IHS transformation of the hospitalizations and medical expenditure for vector-borne and tick-borne diseases. Observations never treated and not yet treated are used as the control group. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, and burned area of forest wildfires. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E5: Effects of Straw-Burning Ban Policies Estimated Using Sun and Abraham (2021)

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.638**	0.683*	0.332**	0.300
	(0.292)	(0.372)	(0.168)	(0.278)
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	1,830	1,830	1,830	1,830

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases using the method of Sun and Abraham (2021). The unit of observation is at the county-by-year-quarter level. The dependent variables are the IHS transformation of the hospitalizations and medical expenditure for vector-borne and tick-borne diseases. Observations never treated and not yet treated are used as the control group. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, population, GDP, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E6: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Log of the Dependent Variables

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.407***	0.649***	0.176**	0.266**
	(0.139)	(0.159)	(0.071)	(0.117)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,395	5,395	5,395	5,395

Notes: This table presents the impacts of straw-burning ban policies on hospitalizations and medical expenditures for vector-borne and tick-borne diseases. The dependent variables are the logarithmic transformations ($\log(1+y)$) of the outcome variables. The unit of observation is the county–year–quarter level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E7: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Fixed-Effects PPML Estimation

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.160*	0.157	0.338**	0.440***
	(0.092)	(0.098)	(0.133)	(0.136)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	6,612	6,612	4,995	4,995

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases estimated using the PPML method (Correia et al., 2020). The unit of observation is at the county-by-year-quarter level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, frequency and burned area of forest wildfires, average temperature, precipitation, and relative humidity. Robust standard errors are in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E8: Effects of Intensity of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases using de Chaisemartin et al. (2022)

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
ATT	0.216***	0.196***	0.018	0.070**
	(0.047)	(0.053)	(0.028)	(0.035)
County FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,525	4,525	4,525	4,525

Notes: This table presents the impacts of the intensity of straw-burning ban policies on vector-borne and tick-borne diseases by estimating the Weighted Average Slope (WAS) parameters introduced in de Chaisemartin et al. (2022). The unit of observation is at the county-by-year-quarter level. The explanatory variable is the cumulative number of straw-burning bans with policy assessment that have been implemented, with the average number of policy documents in treated counties being 1.74. The dependent variables are the IHS transformation of the hospitalizations and medical expenditure for vector-borne and tick-borne diseases. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, forest area, wheat planting area, GDP, population, value added of the primary industry, and number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E9: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Alternative Sample Periods (2015-2019)

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.622***	0.948***	0.256**	0.402**
	(0.173)	(0.213)	(0.123)	(0.185)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	3,030	3,030	3,030	3,030

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases, using data from 2015-2019, excluding the COVID-19 pandemic period. The unit of observation is at the county-by-year-quarter level. The dependent variables are the IHS transformation of the hospitalizations and medical expenditure for vector-borne and tick-borne diseases. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E10: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Excluding Adjacent Counties with Staggered Policy Timing

	Vector-Borne Diseases	
	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.333*	0.494**
	(0.190)	(0.204)
County FE	✓	✓
Province-Quarter FE	✓	✓
Year-Quarter FE	✓	✓
Controls	✓	✓
Observations	5,267	5,267

Notes: This table presents the effects of the straw-burning ban excluding geographically adjacent counties with non-synchronous policy adoption. The dependent variables are the IHS transformations of hospitalizations and medical expenditures for vector-borne diseases. The unit of observation is the county–by-year–quarter level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E11: Effects on Vector-Borne Diseases for Rural and Urban Residents

	Hospitalizations			
	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Rural	Urban	Rural	Urban
Straw-Burning Ban	0.362*	0.359***	0.317***	0.051*
	(0.188)	(0.113)	(0.077)	(0.030)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,702	5,101	4,702	5,101

Notes: This table presents the heterogeneous effects of straw-burning ban policies on hospitalizations and medical expenditures for vector-borne diseases by rural–urban status, as indicated by individuals' medical insurance. The dependent variables are the IHS transformations of hospitalizations and medical expenditures for vector-borne and tick-borne diseases. The unit of observation is the county-by-year-quarter level. Columns (1) and (3) use the sample of patients covered by the New Rural Cooperative Medical Scheme (NCMS), whereas Columns (2) and (4) use the sample of patients covered by the Urban Employee Basic Medical Insurance (UEBMI). See Appendix A.1 for more details. The number of observations is smaller than in the benchmark results reported in Table 2 because some hospitals do not record patients' types of medical insurance. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E12: Effects of Straw-Burning Ban Policies on Respiratory and Cardiovascular Diseases

	Respiratory Diseases		Cardiovascular Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	-0.113**	-0.077**	-0.114***	-0.070*
	(0.046)	(0.033)	(0.044)	(0.070)
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,672	5,672	5,672	5,672

Notes: This table presents the impacts of straw-burning ban policies on hospitalizations for respiratory and cardiovascular diseases. The dependent variables are the IHS transformations of the number of inpatient admissions and medical expenditures for respiratory and cardiovascular diseases. The unit of observation is the county–year–quarter level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the province level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E13: Effects of Straw-Burning Ban Policies on Straw Burning: Alternative Fire Measures

	2001-2022		Fire Incidence within $1km^2$	
	(1)	(2)	(3)	(4)
	# Straw Burning	Burned Areas	# Straw Burning	Burned Areas
Straw-Burning Ban	-0.363***	-59.665***	-0.224***	-55.322***
	(0.048)	(7.303)	(0.050)	(14.729)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	34,150	34,150	10,249	10,249

Notes: This table presents the effects of straw-burning ban policies on the number and burned area of agricultural fires using different measures of fire. Columns (1)–(2) use data from 2001-2022. Columns (3)–(4) use data from 2015-2022. The dependent variables are the original value of the number of agricultural fires in harvest seasons and the burned area in harvest seasons (10,000 hectares) in Columns (1) and (2). In Columns (2) and (4), we use aggregated cropland fire points in harvest seasons within 1 km^2 as the measure. Each observation is at the county–year level. The model includes county and year fixed effects. Control variables include average temperature and precipitation, frequency and burned area of forest wildfires, lagged wheat and corn planting areas, GDP (logarithmic), and population (logarithmic). Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E14: Effects of Straw-Burning Ban Policies on Air Pollutants

	$PM_{2.5}$	PM_{10}
	(1)	(2)
Straw-Burning Ban	-1.247***	-2.266***
	(0.388)	(0.565)
County FE	✓	✓
Year FE	✓	✓
Controls	✓	✓
Observations	10,135	10,095

Notes: This table presents the impacts of straw-burning ban policies on $PM_{2.5}$ and PM_{10}. The unit of observation is at the county-year level. The model includes county and year fixed effects. Control variables include average temperature, precipitation, relative humidity, and cloud gray, as well as frequency and burned area of forest wildfires, cropland area, and population. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E15: Effects of Straw-Burning Ban Policies on Insect Population

	Arthropoda	Insecta	Arachnida
	(1)	(2)	(3)
Panel A: Main specification			
Straw-Burning Ban	0.030**	0.026**	0.004
	(0.014)	(0.013)	(0.003)
County FE	✓	✓	✓
Year FE	✓	✓	✓
Controls	✓	✓	✓
Observations	10,290	10,287	10,280
Panel B: Robustness check			
Straw-Burning Ban	0.032**	0.030**	0.004
	(0.015)	(0.014)	(0.003)
Proxy for outdoor activity	✓	✓	✓
County FE	✓	✓	✓
Year FE	✓	✓	✓
Controls	✓	✓	✓
Observations	9,805	9,804	9,796

Notes: This table presents the effects of straw-burning ban policies on insect observation using the imputation DiD estimator of Borusyak et al. (2024). The dependent variable is the inverse hyperbolic sine (IHS) transformation of the number of recorded observations of species within each taxonomic category per county-year. The regression sample spans from 2015 to 2022, and covers six years prior to and six years after policy implementation. The model includes county and year fixed effects. Control variables include the number of unique observers (IHS-transformed), weather characteristics (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), and GDP (IHS-transformed). In Panel B, we further control for a proxy for outdoor activities, which is constructed from the Baidu Search Index of terms related to outdoor activities such as outdoor recreation, parks, and camping. Standard errors (in parentheses) are clustered at the city level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E16: Effects of Straw-Burning Bans on Insect Awareness and Defensive Behavior (2009-2022)

	Insect Bite	Bite Inquiries	Defensive Behavior
	(1)	(2)	(3)
Straw-Burning Ban	0.545***	0.253*	0.592***
	(0.109)	(0.142)	(0.121)
Pre-treatment mean	2.264	0.698	3.340
City FE	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	11,346	11,346	11,346

Notes: This table reports the effect of city-level straw-burning bans on public attention and defensive responses proxied by the Baidu Search Index, using data from 2009-2022. The dependent variables are city-by-quarter search indices for the listed insect-related topics. Estimates are obtained using the staggered DID estimator of Borusyak et al. (2024). All specifications include city fixed effects and province-by-year-by-quarter fixed effects, and control for weather (temperature, precipitation), wildfire exposure, cropland area, GDP, population, and hospital capacity. Standard errors are clustered at the prefectural-level city level. The sample spans 2009–2022. [a] *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[a] Baidu Search Index data are available at the prefectural-level city level; county-level policy exposure is aggregated to the city level. More details about search indices for the listed insect-related topics are introduced in Table A5.

Appendix Table E17: Effects of Cropland Fires on Vector-Borne Diseases Using Instrument Variable Method

	Cropland Fires	Vector-Borne Diseases	
	First Stage	Hospitalizations	Medical Expenditure
Straw-Burning Ban	-0.165***		
	(0.051)		
Cropland Fires		-2.891**	-2.905*
		(1.444)	(1.565)
County FE	✓	✓	✓
Year FE	✓	✓	✓
Controls	✓	✓	✓
First stage *F*-stat	10.521		
Observations	2,875	2,875	2,875

Notes: This table presents the effects of cropland fires on vector-borne disease hospitalizations using the straw-burning ban policy as an instrumental variable (IV). The main explanatory variable in Columns (2) and (3) is the total burned area of cropland fires. The IV is the straw-burning ban with policy assessment. The unit of observation is the county–year level. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature, relative humidity, and precipitation, frequency and burned area of forest wildfires, forest area, cropland area, GDP, population, and the number of hospital beds. Robust standard errors are in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E18: Straw-burning Ban, Recycle Measures, and Vector-Borne Diseases: Alternative Recycle Measures

	by Biomass Power Plants			
	Hospitalizations		Medical Expenditure	
	(1)	(2)	(3)	(4)
	$<$ median	$>$ median	$<$ median	$>$ median
Straw-Burning Ban	1.070***	0.219	1.298***	0.480**
	(0.180)	(0.190)	(0.238)	(0.207)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,084	5,240	5,084	5,240

Notes: This table presents the heterogeneous effects of straw-burning ban policies on hospitalizations and medical expenditure for vector-borne diseases across counties with different straw recycling infrastructure. The dependent variable is the inverse hyperbolic sine (IHS) transformation of hospitalization counts (columns [1] and [2]) and medical expenditure (columns [3] and [4]) at the county-by-year-quarter level. The treatment group is split based on whether average biomass power plants is below and above the national median (8.5 plants per county). The control group is held fixed across columns and consists of never-treated and not-yet-treated counties in the DID framework. Consequently, observation counts in Columns [1] and [2] (and [3] and [4]) are not additive. We report estimates for subsamples where average biomass power plants is below and above the national median (8.5 plants per county), respectively. The analysis spans four years (sixteen quarters) before and after policy implementation. The model includes county, province–quarter, and year–quarter fixed effects. Control variables include hospital characteristics, weather conditions (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

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