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

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Abstract

Environmental regulations aim to reduce pollution, yet they can also reshape ecological systems in ways that affect human health. We study China's ban on burning crop straw, introduced to reduce air pollution from agricultural fires. Combining nationwide inpatient records with the staggered rollout of the policy in a difference-in-differences design, we find that the ban raised hospitalizations for vector-borne diseases by about 38% and inpatient spending by about 37%. The evidence points to an ecological mechanism: crop residue left unburned provides habitat for insects and ticks that transmit disease, with effects concentrated among populations with greater agricultural exposure. We estimate the additional hospitalization burden at about $108 million annually, offsetting close to 6% of the health gains from cleaner air. The cost is not unavoidable. Where the ban was paired with subsidies for straw recycling, the increase in disease was substantially attenuated, suggesting that complementary residue-management policies can preserve air-quality benefits while reducing unintended health costs.

Keywords: Environmental regulation, Ecological feedback, Crop residue burning, Vector-borne diseases, Environmental health

JEL Classification: Q57, Q51, Q50, Q10

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1 Introduction

Environmental policies designed to reduce air pollution can act on more than the air. They can reshape ecological systems by altering vegetation, habitat, and species interactions, generating unintended health consequences beyond their intended environmental benefits. However, the magnitude of these ecological feedbacks, who bears their costs, and whether they can be mitigated remain poorly understood, even as biodiversity and species interactions 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). Exploring these feedbacks is therefore essential for understanding and assessing environmental policy.

We study one such ecological feedback in the context of China's ban on burning crop straw, one of the country's largest air-pollution control policies. After the harvest, farmers traditionally burn crop residue to clear fields quickly, creating severe seasonal air pollution. To improve air quality, China progressively prohibited this practice across counties. The policy substantially reduced agricultural fires, but the straw did not disappear. Left in the field, crop residue provides habitat for insects and ticks that transmit disease.[1] This ecological change provides a natural setting to study how environmental regulation can affect human health through ecological pathways.

This mechanism is not unique to China's straw-burning ban. Policies that alter vegetation, residue management, or land use are common and often implemented at large scales. Such interventions can change the habitat and activity of disease vectors, even modest ecological responses may generate meaningful public-health consequences. Vector-borne diseases account for roughly 17% of infectious diseases worldwide and impose substantial medical and productivity costs (WHO, 2024; Hook et al., 2022). Therefore, it speaks to a broader policy problem: environmental regulation may improve one dimension of health while inadvertently worsening another through changes in ecological conditions.

The phenomenon is ecological, but its impacts and implications are economic. By increasing disease risk, the accumulation of unburned residue creates costs that partially offset the health gains from cleaner air. It is not that more or fewer insects are intrinsically desirable, nor does it diminish the importance of controlling agricultural air pollution. Rather, a natural mitigation question to complete the policy: are these ecological costs an unavoidable consequence of environmental intervention? As the mechanism begins with straw residue, policies that promote straw recycling provide a potential way to mitigate the disease burden while preserving environmental benefits.

Answering the above questions requires observing each stage of the ecological pathway from environmental regulation to human health. We do so by combining nationwide inpatient records with satellite measures of fires and land cover, arthropod observations, internet search activity,

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

and records of agricultural machinery adoption. These data allow us to trace how the straw-burning ban changed burning activity, vector abundance, and ultimately human health and cost.[2]

Identification exploits the staggered rollout of China's straw-burning ban across counties. Because the rollout was driven primarily by national administrative priorities rather than local disease conditions or ecological trends, it provides plausibly exogenous variation in exposure to the policy. We estimate the effects using a staggered difference-in-differences design following Borusyak et al. (2024). The identifying assumptions are supported by parallel pre-policy trends, evidence that rollout tracked national air-pollution priorities rather than local disease conditions, robustness to alternative specifications and concurrent policies, and placebo tests on diseases unrelated to arthropod exposure. This design allows us to ask three linked questions: whether the ban increased vector-borne diseases, which populations the burden was concentrated among, and whether complementary residue-management policies mitigated the effect. We find evidence on all three margins.

First, the straw-burning ban increased the burden of vector-borne diseases. Hospitalizations rose by about 38%, and associated inpatient spending rose by about 37% relative to pre-ban levels. The effects persist for several years after adoption, consistent with a sustained ecological response rather than a short-lived adjustment. A back-of-the-envelope calculation values the additional hospitalization burden at roughly $108 million annually, likely a lower bound because it excludes outpatient care, lost productivity, and private avoidance costs. The evidence points to an ecological pathway: satellite data show large declines in agricultural fires after the ban; the health effects are larger in places where winter temperatures favor vector survival; internet searches indicate greater public attention to insect bites and defensive products; and arthropod observations rise after the ban. Comparing across disease categories in the same data, the added vector-borne disease burden is equivalent to about 6.1% of the reduction in hospitalization spending for pollution-related diseases.[3] Such morbidity effects can be persistent and recurrent. The underlying ecological response also appears durable and spatially diffuse: the event-study estimates remain elevated for several years after policy adoption, and related ecological changes extend beyond the immediately treated area. Incorporating spatial adjustment raises the estimated offset above 6%.

Second, the health costs are concentrated among populations with greater agricultural exposure. The effects are larger in cropland-intensive counties, where suppressing fire most directly changes field ecology. They are also larger among farmers, who face more frequent contact with fields and disease vectors. These patterns suggest that the ecological costs of environmental regulation are not borne evenly: they fall disproportionately on the people and places most exposed to the ecological changes created by the policy.

[2]Following standard epidemiological practice (WHO, 2024), we identify vector-borne diseases using ICD-10 diagnosis codes and distinguish a severe subset of tick-borne diseases, including Lyme disease, tick-borne encephalitis, and severe fever with thrombocytopenia syndrome (SFTS). See Table C1 and Table C2.

[3]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, the additional health costs can be mitigated. As the mechanism begins with residue left in the field, residue management provides a natural complementary policy. We show that straw-recycling subsidies increased the adoption of straw-collection equipment and substantially attenuated the rise in vector-borne disease. Complementary residue management can therefore preserve the air-quality benefits of burning restrictions while reducing their unintended health costs. This finding is directly relevant for the many countries that restrict, or are considering restrictions on, open-field crop-residue burning.

Related Literature These findings contribute to three strands of research. First, the paper adds to a growing literature on the economic and health consequences of ecological change. Recent work shows that biodiversity loss and ecological imbalance can have large effects on human welfare: vulture declines in India increased mortality through deteriorating sanitation (Frank and Sudarshan, 2024); sparrow eradication during China's Four Pests Campaign reduced agricultural output and increased mortality (Frank et al., 2024); afforestation in Beijing improved air quality but increased pollen exposure and allergy-related emergency visits (Xing et al., 2023); and ecological shocks such as cicada emergence and bat declines can affect infant health through changes in pesticide use (Taylor, 2021; Frank, 2024). Related work in ecology emphasizes that biodiversity loss can weaken ecosystem services and public-health resilience (Cardinale et al., 2012; Pecl et al., 2017; Blowes et al., 2019). We contribute by showing that environmental regulation itself can generate an ecological feedback: a policy aimed at reducing air pollution altered field ecology in ways that increased vector-borne disease. The result links environmental policy to biodiversity and health through a mechanism that is typically outside conventional evaluations of air-pollution regulation.

Second, the paper contributes to the literature on agricultural fires and crop-residue policy. Existing studies show that exposure to agricultural burning, primarily through elevated $PM_{2.5}$ (Guo, 2021) and reduced water quality (Hong and Chen, 2026), worsens health outcomes including mortality (He et al., 2020; Garg et al., 2024), hypertension (Pullabhotla and Souza, 2022), birth outcomes (Rangel and Vogl, 2019), and cognition (Zivin et al., 2020; Lai et al., 2022). A related literature studies policies that reduce burning, including bans, payments for ecosystem services, straw-recycling subsidies, and biomass energy infrastructure (He et al., 2020; Jack et al., 2025; Cao and Ma, 2023; Nian, 2023). These studies document important benefits from reducing fires. We show that fire reduction can also create a countervailing ecological channel by leaving crop residue in the field, increasing vector activity and vector-borne disease. The paper therefore complements existing evidence on the benefits of reducing agricultural fires by measuring an unintended health cost and showing that residue-management policies can mitigate it.

Third, the paper speaks to research on the design and distributional impacts of environmental policy. A large literature shows that environmental risks and policy impacts differ across groups because exposure, vulnerability, and adaptive capacity are unequally distributed (Banzhaf et al., 2019; Fowlie et al., 2020; Currie et al., 2023). We show that ecological feedbacks can create a similar

form of disproportionate distribution. The health costs of the straw-burning ban are concentrated in cropland-intensive areas and among farmers, while they are attenuated where adaptive capacity and residue-management options are stronger. This evidence suggests that the design of environmental regulation should account not only for direct pollution benefits, but also for ecological responses and the populations most exposed to them.

The rest of the paper proceeds as follows. Section 2 describes China's straw-burning ban and the epidemiological background on vector-borne diseases. Section 3 presents the data, and Section 4 develops the empirical strategy. Section 5 reports the main effects on vector-borne and tick-borne diseases, examines the ecological pathway, and presents robustness checks. Section 6 studies the role of straw-recycling policies as a mitigating strategy and discusses policy implications. Section 7 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).[4] This staggered rollout provides a quasi-experimental setting that enables causal identification of the policy's effects using a DiD framework.

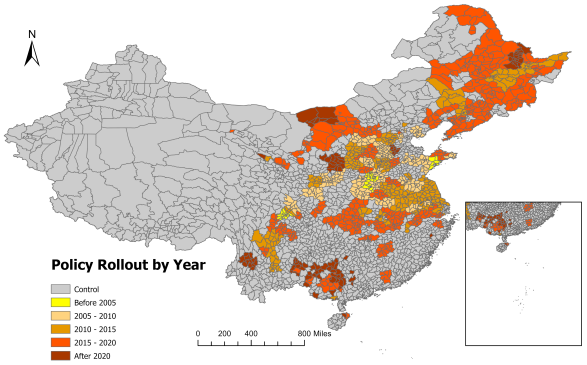
Two features of the policy design are central to our empirical strategy. First, we examine the effects of straw-burning bans with credible enforcement. In our setting, enforcement at the county level was generally well institutionalized. To ensure accurate policy measurements, we restrict the analysis 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-based remote sensing to detect fire hotspots and integrated this information into official performance evaluations.[5] These measures enhanced the credibility, traceability, and uniformity of policy enforcement, supporting reliable policy measurement and robust identification.[6]

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

[5]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).

[6]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

(a) Spatial Rollouts



(b) Temporal Rollouts

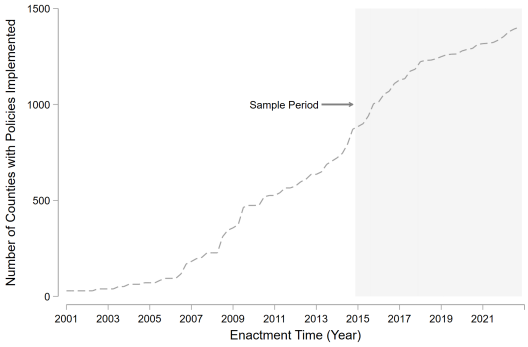


Figure 1: Rollout of China's Straw-Burning Ban Across Counties

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 shown in Figure 1 and detailed in Appendix F, 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.[7] In Section 4.2, we further document that, conditional on administrative hierarchy, the timing of adoption is uncorrelated with pre-policy health infrastructure 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 6, 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.

within-province heterogeneity in enforcement and agricultural practices, and leverages staggered county-level policy adoption for improved causal inference.

[7] 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).

2.2 Ecological Dynamics and Vector-Borne Diseases

Figure C4 illustrates the underlying transmission mechanism. Straw-burning ban increased post-harvest residue accumulation, affecting vector populations and leading to related health risks. Arthropods such as mosquitoes and ticks are important vectors of many diseases.[8] Their populations are highly sensitive to local ecological conditions, favoring humidity, vegetation, and the presence of organic crop residue. When straw is burned after harvest, these materials are largely removed from the field. By contrast, when straw burning is prohibited and residues remain on agricultural land, the resulting environment can provide favorable conditions for insects and ticks to survive and reproduce.

We examine health risks associated with increased 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.[9] Tick populations are highly sensitive to ecological conditions, particularly vegetation 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

[8] 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 C provides additional biological and disease-related background.

[9] 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 hospitalization 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.

blood. For example, in May 2022, a cluster of four deaths in Xinyang, Henan Province, followed a single suspected tick exposure.[10] 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.[11] 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.[12] The dataset 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.[13]

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

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

[11] 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).

[12] 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 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.

[13] 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.

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.[14] 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.[15] 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 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.[16] A county is coded as treated beginning in the first year–quarter during which the ban was enforced for all three months. 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).[17] We identify straw-burning events by overlaying fire detections with cropland classifications following Assunçãoa et al. (2019). This pro-

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

[15] 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.

[16] 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.

[17] 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.

cedure 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.[18]

Insect Observations and Web Searches We assemble two complementary sources to trace the ecological and behavioral responses to the ban. First, to quantify ecological change, we use arthropod occurrence records from the Global Biodiversity Information Facility (GBIF), an international network that aggregates species occurrence data worldwide.[19] Each record includes geolocation, observation date, taxonomic classification, and observer identity. For the period 2015–2022, we compile 99,814 arthropod observations in China, including taxa such as *Insecta* and *Arachnida* (see Appendix C for taxonomic definitions and their relevance to vector-borne disease transmission). Our measure is the annual count of observations per county for the relevant taxa, and we control for the number of unique observers per county-year to account for spatial and temporal variation in sampling effort, following Liang et al. (2025). Second, to capture public awareness, the non-hospitalized medical burden, and defensive behavior, we use the Baidu Search Index, which reports daily keyword search frequencies at the city level from 2009 onward.[20] We track searches for insect bites and for defensive behaviors such as pest control (see Appendix A.3 for keyword lists), geocoded at the city level and matched to policy exposure using the same specification. Because these species records and search indices proxy for broad ecological and behavioral responses rather than clinical outcomes, we treat them as suggestive evidence on the mechanism.

Procurement of Straw Recycling Equipment To assess straw management, we construct a novel dataset from China's nationwide registry of agricultural machinery subsidy reimbursements.[21] 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 fo-

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

[19] GBIF compiles data from diverse sources, including DNA barcodes and smartphone photographs, under standardized protocols such as Darwin Core. It is widely used in ecological and conservation research (GBIF, 2025) and enables analysis of ecological change where systematic monitoring is otherwise limited.

[20] Baidu is China's dominant search engine, and its Search Index is a well-established measure of public attention among Chinese internet users; see Barwick et al. (2024) for recent applications. Quarterly indices sum daily search counts across keywords in each category, averaged over the quarter.

[21] 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 E2 for examples of straw management equipment.

cus 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.[22] Additional controls include GDP, value added of the primary industry, population, hospital bed availability, and cropland area, sourced from the China County Statistical Yearbooks.

3.2 Summary Statistics

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. Figure E1 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.

4 Empirical Strategy

The straw-burning ban generated environmental benefits by reducing open-field burning and improving local air quality (He et al., 2020; Cao and Ma, 2023; Nian, 2023). However, the policy design did not adequately account for potential ecological consequences. We address the following questions: First, what causal effect does the straw-burning ban have on ecological health risks, and what are its underlying mechanisms? Second, how are the resulting costs distributed across populations with varying levels of exposure? Furthermore, we will explore the policy implications of these findings by assessing whether complementary residue-management policies can effectively mitigate the unintended costs of the ban.

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

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	27.954	72.474	0	752
Tick-borne diseases	1.494	5.105	0	45
Inpatient expenditure (1,000 CNY)				
Vector-borne diseases	147.023	471.830	0	5,548.714
Tick-borne diseases	6.464	24.922	0	227.824
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

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.

4.1 Baseline Causal Design

To estimate the causal effect of China's straw-burning ban, we exploit its staggered rollout across counties and implement a difference-in-differences design using county-by-year-quarter data. The policy was introduced over multiple years, creating quasi-experimental variation in treatment timing. Our baseline estimating equation is

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

where c indexes counties, p indexes provinces, and yq denotes year-quarters. $Y_{c,yq}$ represents the outcome of interest, including hospitalizations and inpatient expenditures for vector-borne diseases as well as ecological and behavioral outcomes such as agricultural fires, vector populations, web-search intensity, and straw-management equipment procurement. $BAN_{c,yq}$ is an indicator equal to one after the straw-burning ban is implemented in county c. County fixed effects η_c absorb time-invariant local characteristics, year-quarter fixed effects δ_{yq} absorb common shocks, and province-by-quarter fixed effects $\gamma_{p,q}$ flexibly capture province-specific seasonal shocks. The vector $\mathbf{X}_{c,yq}$ includes weather conditions, forest fire activity, local healthcare capacity, socioeconomic characteristics, and other time-varying controls. Standard errors are clustered at the county level.

Because treatment timing is staggered, our preferred estimator follows Borusyak et al. (2024). This imputation-based approach avoids the negative-weighting and forbidden-comparison problems that can arise in conventional two-way fixed-effects settings with heterogeneous treatment effects (Goodman-Bacon, 2021; Sun and Abraham, 2021). Let D^{gt} denote treatment status and Y^{gt} the observed outcome for group g in period t, where counties are grouped by adoption timing. Let $\Omega_1 = \{(g,t) : D^{gt} = 1\}$ denote the set of treated observations, with cardinality $N_1 = |\Omega_1|$. Following Borusyak et al. (2024), we first estimate untreated potential outcomes using never-treated and not-yet-treated observations, then impute counterfactual untreated outcomes for treated observations. The average treatment effect on the treated is

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

where the imputed untreated outcome is

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

Our primary treatment variable is an indicator for whether a county has adopted the straw-burning ban. As shown in Figure 1, implementation was staggered across counties over time, making this setting well suited to a staggered-DiD design.

4.2 Identification and Validity

Identification requires that, absent the ban, treated and untreated counties would have followed similar trends in the outcomes of interest. Although this assumption is ultimately untestable, we provide several forms of evidence supporting its plausibility.

First, we examine pre-treatment dynamics using event-study specifications. As shown in Figure 2, we find no evidence of differential pre-trends in vector-borne disease outcomes before policy adoption. Similar patterns hold for related outcomes such as agricultural fires, insect populations, and equipment adoption, providing additional support for the parallel-trends assumption.

Second, we consider the possibility that adoption timing is endogenous to local ecological or health conditions. Institutional evidence suggests otherwise. The rollout of the ban closely tracked national air-pollution-control priorities and administrative sequencing rather than local disease conditions, resembling the rollout logic documented for other environmental monitoring programs such as the Air Pollution Monitoring and Disclosure Program (Barwick et al., 2024). Consistent with this interpretation, Table D1 shows no systematic relationship between adoption timing and baseline healthcare capacity, while Table D2 indicates that adoption correlates with economic and administrative characteristics rather than pre-policy health conditions or disease burdens.

Third, our baseline specification includes a rich set of fixed effects and time-varying controls. County fixed effects absorb time-invariant differences across counties, year-quarter fixed effects capture common macro shocks and national seasonality, and province-by-quarter fixed effects absorb province-specific seasonal patterns. We further control for weather conditions, forest fire activity, healthcare infrastructure, GDP, value added of the primary industry, population, cropland area, and related observables to reduce concerns about time-varying confounders.

Fourth, we address the possibility that concurrent policies drive our results. The study period overlaps with greening initiatives, the Sponge City program, healthcare reforms, and agricultural support policies.[23] These policies were either implemented nationally, followed different rollout patterns, or are unlikely to affect vector ecology through the same channel. We show that our estimates remain stable when controlling for vegetation dynamics using NDVI, excluding Sponge City pilot cities, and restricting attention to the pre-pandemic period (Table E3 and Table E7).

Fifth, we conduct placebo tests using outcomes unlikely to respond to arthropod exposure, including non-arthropod-related dermatoses, neoplasms, and bone fractures. As shown in Table E2, we find no statistically significant effects for these placebo outcomes. These results make it less likely that the estimated effects reflect broad changes in healthcare utilization, income, or general health demand rather than an ecological channel. They also help rule out the alternative possibility that improvements in air quality affect our outcomes through non-ecological pathways.[24]

[23] See Appendix F for details.

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

Finally, we consider spatial spillovers. If ecological changes extend across county borders, untreated neighboring counties may be indirectly affected by nearby treated counties. To address this possibility, we re-estimate the baseline specification after excluding geographically adjacent treated-control county pairs. The estimates remain similar in magnitude and significance, suggesting that cross-county spillovers are unlikely to drive the main results.

In addition to these core validity checks, we assess robustness using alternative outcome definitions, alternative staggered-DiD estimators (Callaway and Sant'Anna, 2021), and PPML models for count outcomes (Correia et al., 2020). These results are consistent with the baseline findings and are reported in the Appendix.

4.3 Mechanism and Distributional Incidence

Having established the baseline causal effect and the validity of the research design, we next examine the mechanism through which the ban affects health outcomes and the extent to which the resulting burden is concentrated among more exposed and vulnerable groups.

We assess the ecological mechanism in three complementary ways. First, we estimate the effects of the ban on intermediate outcomes along the proposed transmission chain, including agricultural fires, insect observation, public awareness related to insect exposure, and defensive responses. These analyses trace whether the policy changes the ecological conditions under which vector-borne disease risk rises. Second, we use policy rollout as an instrument for fire activity to estimate the causal effect of reduced agricultural burning on disease outcomes. Third, we examine heterogeneity along dimensions predicted by the mechanism, mainly climatic conditions favorable to vector survival.

We then study the distributional incidence of these ecological costs. The central idea is that a common ecological shock may generate unequal health burdens because exposure, healthcare access, and adaptive capacity differ across populations. Accordingly, we examine whether the policy's adverse health effects are larger in counties and populations with greater agricultural exposure, more limited access to healthcare, and weaker capacity to avoid or mitigate vector contact. This analysis allows us to distinguish between average treatment effects and the incidence of those effects across demographic and socioeconomic groups. The resulting heterogeneity is informative not only about mechanism, but also about the distributional consequences of environmental regulation when ecological risks interact with pre-existing vulnerability.

This framework implies that the incidence of policy-induced health costs may be uneven even if average environmental quality improves. Groups that spend more time near cropland, face greater direct contact with residues, have weaker access to healthcare, or possess fewer resources to avoid exposure may bear a disproportionate share of the unintended burden.

4.4 Mitigation and Policy Design

Finally, we examine whether complementary residue-management policies mitigate the unintended health costs of the ban. Because residue accumulation is central to the proposed mechanism, policies that promote straw collection, recycling, or related equipment adoption may weaken the ecological conditions that facilitate vector exposure while preserving the air-quality benefits of reduced open burning. We therefore exploit regional variation in straw-recycling subsidies and infrastructure to test whether better residue management attenuates the adverse effects of the ban on vector-borne disease outcomes. This final step links the empirical findings to policy design by asking not only whether the straw-burning ban had unintended consequences, but also whether those consequences can be reduced through complementary interventions.

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. Columns (1) and (3) report effects on hospitalizations and medical expenditures per 100,000 population, which makes magnitudes comparable across counties of different size. Columns (2) and (4) report Poisson pseudo-maximum-likelihood (PPML) estimates on outcome levels, which accommodate zeros and skewness without a transformation-specific interpretation.[25]

Panel A examines the impact of the straw-burning ban on vector-borne diseases. Column (1) shows that the ban increases hospitalizations by 38.2% relative to the pre-treatment mean, equivalent to approximately 11 additional cases per county per quarter (0.382×27.954).[26] Columns (3) and (4) present effects on medical expenditures. Column (3) implies a 37.2% increase in total expenditures, or approximately 54,693 CNY (147,023 $\times$ 0.372, about 7,813 U.S. dollars) per county per quarter. Columns (2) and (4) show that PPML model produce similar results.[27] Panel B focuses on tick-borne diseases, the clinically severe subset of vector-borne illnesses. Here the effects are proportionally larger: hospitalizations rise by 57.8% and expenditures by 80.3% in the per-100,000-population specification, and by 37.7% and 35.5% under Poisson estimation. That the

[25] Results based on the inverse hyperbolic sine (IHS) transformation and other alternative specifications are reported in Appendix 5.4 and are consistent in sign and significance.

[26] 27.954 is the mean quarterly hospitalizations before treatment for treated counties in our sample.

[27] The Poisson count models in Columns (2) and (4) imply increases of 27.3% and 27.4%, respectively.

severe subset rises more than the broad aggregate indicates the additional burden is not driven by minor bite or allergic reactions alone.

Table 2: Effects of Straw-Burning Bans on Vector-borne Disease

	Hospitalizations		Medical Expenditures	
	Per 100,000 pop.	PPML	Per 100,000 pop.	PPML
	(1)	(2)	(3)	(4)
Panel A. Vector-Borne Diseases				
Straw-burning ban	1.500**	0.241***	6.740**	0.242***
	(0.623)	(0.092)	(2.894)	(0.091)
Implied effect	38.2%	27.3%	37.2%	27.4%
Panel B. Tick-Borne Diseases				
Straw-burning ban	0.166**	0.320**	0.993***	0.304*
	(0.070)	(0.151)	(0.314)	(0.182)
Implied effect	57.8%	37.7%	80.3%	35.5%
County FE	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Province-quarter FE	✓	✓	✓	✓
Hospital controls	✓	✓	✓	✓
Weather and forest-fire controls	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓
Observations: Panel A	4,570	5,779	4,570	5,779
Observations: Panel B	4,570	4,408	4,570	4,408

Notes: This table reports baseline estimates of the effects of county-level straw-burning bans on vector-borne and tick-borne disease outcomes using the Borusyak et al. (2024) staggered difference-in-differences estimator. The unit of observation is the county-year-quarter, and the sample covers 2015–2022. Columns (1) and (3) use hospitalizations and medical expenditures (1,000 CNY) per 100,000 population as the dependent variables. Columns (2) and (4) report Poisson pseudo-maximum-likelihood estimates using outcome levels. For the per-100,000 specifications, the implied effects are calculated relative to the pre-treatment mean among treated counties. For the PPML specifications, the implied effects are calculated as $100[\exp(\widehat{\beta}) - 1]$. All specifications include county, year-quarter, and province-quarter fixed effects, hospital-capacity controls, weather and forest-fire controls, and additional socioeconomic controls. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 2 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. The post-treatment dynamics exhibit a

pronounced seasonal pattern, in line with established evidence on tick phenology (Gleim et al., 2014).

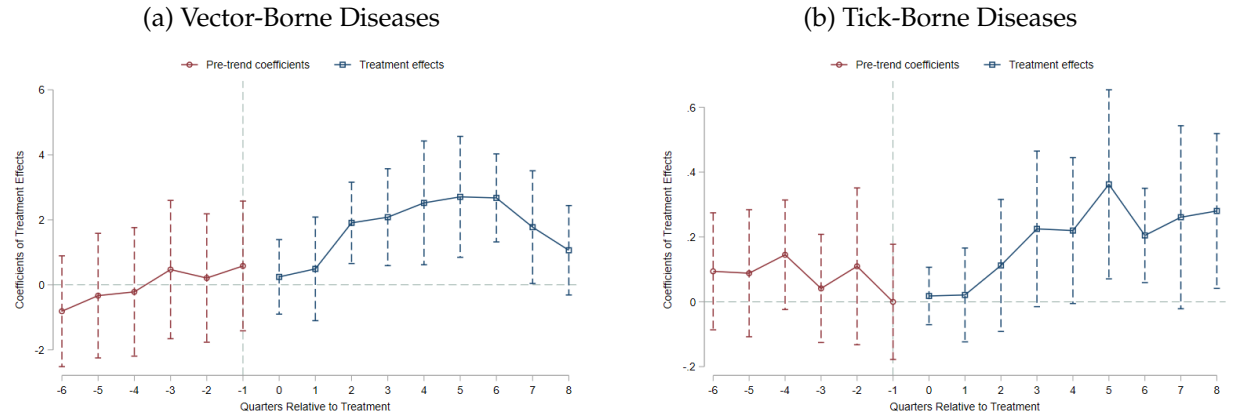


Figure 2: Event Study: Effects of Straw-burning Bans on Hospitalizations

Notes: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne and tick-borne disease hospitalizations. Panels (a) reports the effects on hospitalizations for vector-borne diseases, while Panel (b) reports the corresponding effects for tick-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. The x-axis is quarters relative to treatment. The y-axis displays estimated treatment effects relative to never-treated counties, with 95% confidence intervals clustered at the county level.

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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 (2) indicates that the ban increases the total length of stay for vector-borne diseases by 33.6%, and column (4) shows an increase of 28.2% for tick-borne diseases.

Aggregate Medical Expenditure 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 756.1 million CNY (approximately 108 million USD).[28] Of

[28]This calculation proceeds as below. Starting with the estimated effect on vector-borne disease expenditures reported in Table 2 ($147{,}023 \times 0.372 = 54{,}693$ CNY per county per quarter, or approximately 0.055 million CNY), we scale the county-quarter estimate to the 1,403 counties in which the ban was implemented and adjust for the incomplete coverage of hospitals in our sample. Our sample contains 2,788 secondary and tertiary hospitals in 1,252 counties, whereas the national hospital system contains 14,668 such hospitals in 2,843 counties. The resulting coverage adjustment is 2.32. Applying this adjustment, the implied annual increase in expenditures at secondary and tertiary hospitals is $54{,}693 \times 4 \times 1{,}403 \times 2.32 = 712.1$ million CNY. Primary hospitals account for an additional 6.2% of hospitalizations relative to secondary and tertiary hospitals (National Health Commission of the People's Republic of China, 2022). Including these facilities yields a total annual inpatient expenditure increase of $712.1 \times 1.062 = 756.1$ million CNY, or approximately 108 million U.S. dollars. Hospital counts are from National Health Commission of the People's Republic of China (2023). The U.S.-dollar conversion uses an exchange rate of 7 CNY per U.S. dollar. This calculation assumes that the proportional expenditure effect estimated in our hospital sample applies to otherwise comparable hospitals outside the sample.

this, approximately 51.7 million CNY, or 7.4 million U.S. dollars, is attributable to tick-borne diseases, the clinically more severe subset of the vector-borne disease category.[29]

This calculation captures only the burden incurred within counties that implemented the ban and may therefore omit costs arising from the spatial diffusion of vector exposure. To incorporate such geographic dispersion, we use a conservative spatial adjustment of 1.25, under which indirect effects outside treated counties equal one-quarter of the direct effect.[30] This adjustment raises the implied annual broader-area burden of vector-borne diseases to be 945.1 million CNY, or approximately $135 million.

Comparison with inpatient savings for air-pollution-sensitive diseases To contextualize the magnitude of the ecological health costs, we compare these ecological health costs with the policy-induced reduction in inpatient expenditures for respiratory and cardiovascular diseases. 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.[31] As shown in Table E10, both hospitalizations and medical expenditures decline following the straw-burning ban. Combining the estimated proportional effects with the corresponding pre-treatment means, the estimates imply quarterly expenditure reductions of approximately 0.97 million CNY per county for respiratory diseases and 1.34 million CNY per county for cardiovascular diseases. The combined quarterly inpatient saving is therefore approximately 2.31 million CNY per county.

Relative to these benefits, the estimated 0.055 million CNY quarterly increase in vector-borne disease expenditures offsets 6.1% ($= 6.740/(50.802 + 60.296)$)) of the combined reduction in respiratory and cardiovascular inpatient expenditures: 13.3% ($= 6.740/50.802$) of the benefits attributable to respiratory conditions and 11.2% ($= 6.740/(50.802 + 60.296)$ of those from cardiovascular conditions. Taken account of the spatial adjustment, vector-borne disease expenditures offsets approximately 6% of the reductions from respiratory and cardiovascular inpatient expenditures.

These comparisons should be interpreted as a partial accounting of inpatient medical expenditures rather than as a comprehensive benefit–cost analysis. On the benefit side, they exclude reductions in mortality, outpatient treatment, and productivity losses associated with improved air quality. On the cost side, they exclude mortality, outpatient care, behavioral adaptation, produc-

[29] The corresponding calculation is $6{,}464 \times 0.578 \times 4 \times 1{,}403 \times 2.32 \times 1.062 = 51.7$ million CNY, where 6,464 CNY is the pre-treatment quarterly mean and 0.578 is the estimated proportional increase in tick-borne disease expenditures reported in Table 2.

[30] This adjustment is extrapolated from evidence on spatial externalities from malaria-control interventions rather than estimated directly in our setting, we treat it as a sensitivity exercise rather than as our preferred estimate. Jarvis et al. (2019) find that the indirect effect associated with distance from a bed-net intervention household is approximately one-tenth of the estimated direct effect. Binka et al. (1998) report an indirect effect approximately four-tenths as large as the direct effect. The adjustment of 0.25 is the midpoint of these two estimates. Differences between malaria transmission and the diseases studied here imply that this calculation should be interpreted cautiously.

[31] 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).

tivity losses, and other consequences of increased vector exposure.[32] Nevertheless, the inpatient comparison establishes that ecological responses generate measurable health costs that partially offset the policy's gains for air-pollution-sensitive conditions. These offsetting effects highlight a broader insight for environmental policy: even when regulations successfully improve environmental quality, neglecting ecological feedbacks may generate unintended health risks that partially reverse intended gains.

5.2 Mechanism

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 the intermediate outcomes along the proposed transmission chain, including straw burning, insect awareness, and behavioral responses. Second, we validate the mechanism using an instrumental variable approach. Lastly, we further examine heterogeneity along climate conditions which are favorable to vector survival.

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 3 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 E11).[33] We also find corresponding declines in key pollutants associated with the straw-burning ban, including $PM_{2.5}$ and PM_{10} (Table E12).[34]

[32] Appendix E shows the way of calculating the policy's effect on mortality of vector-borne diseases.

[33] 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.

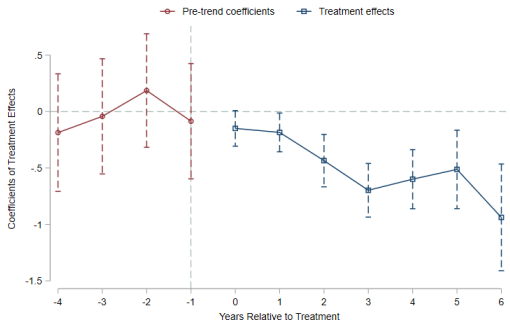
[34] These pollutants, released directly during combustion, are primary emissions associated with straw burning.

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

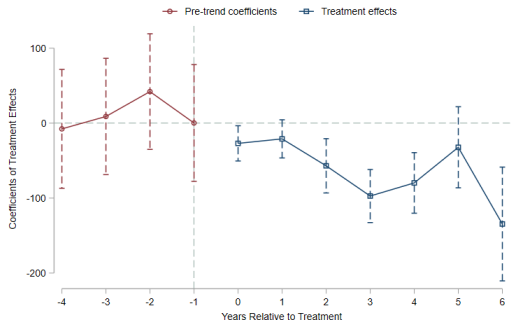


Figure 3: Effects on Cropland Fires: Event Study Plots

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.

Insect Awareness and Defensive Measures 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 different keyword categories: general insect bites and treatment and pest control (see Table A3 for detailed keyword lists).[35] 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.

Table 4 shows significant increases in searches related to public awareness and defensive behaviors after the ban. Search volumes for general insect bites rose by 24.1% (Column 1), and

[35]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.

searches for defensive behaviors, such as bite treatment and pest control, rose by 17.7% (Column 2), relative to their pre-treatment means. 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.

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

	Insect Bite	Defensive Behavior
	(1)	(2)
Straw-Burning Ban	0.545***	0.592***
	(0.109)	(0.121)
Pre-treatment mean	2.264	3.340
City FE	✓	✓
Province-Year-Quarter FE	✓	✓
Controls	✓	✓
Observations	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 A3.

Suggestive Evidence from Species Observations The behavioral responses above are consistent with rising human exposure to insects. As more direct, though still suggestive, evidence, we apply the same design to county-level arthropod occurrence records from GBIF. A large agronomic and ecological literature shows that retaining crop residue on fields raises the abundance of soil-dwelling arthropods (Xie et al., 2022; Kautz et al., 2006; Yang et al., 2023), so suppressing burning should leave more habitat for vectors. Consistent with this, observed arthropod counts rise by about 3.0% and insect counts by about 2.6% after the ban, with no differential pre-trends, whereas the effect on non-insect arachnids is small and imprecise (Appendix Appendix B and Figure B3). The increase is robust to controlling for a proxy for outdoor activity, indicating that it is not merely an artifact of greater time spent outdoors after the ban. We read these ecological measures as corroborative rather than definitive: species records are sparse and noisy, and disease transmission is highly nonlinear, so small shifts in vector activity can elevate infection risk before they become detectable in aggregate occurrence data (Anderson and May, 1991; Kilpatrick and Randolph, 2012; Smith et al., 2012). Appendix B provides the full analysis and taxonomic detail.

Cropland Fire and Vector-Borne Diseases 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 E13 presents the two-stage least squares results. The first stage confirms that the ban significantly reduced fires. In the second stage, this instrumented reduction in fire translates into a significant increase in hospitalizations for vector-borne diseases, consistent in direction and magnitude with the baseline estimates in Table 2. Together, these results reinforce our conclusion that fire suppression directly contributes to adverse health outcomes.

Mechanism Validation through Heterogeneity If vector proliferation drives the health effects, the ban's impact should concentrate where the local environment favors vector survival. We examine two climatic dimensions that govern arthropod overwintering and habitat suitability: winter temperature and annual precipitation. Table 5 reports the results.

Panel A splits counties by whether the average temperature in the coldest month exceeds 0°C, a critical threshold for arthropod overwintering and survival. The effect is large and significant in warmer counties, where hospitalizations rise by 2.211 per 100,000 population, but small and statistically insignificant in colder counties ($\leq$ 0°C). Panel B splits counties by annual precipitation. The effect is concentrated in wetter counties (above 800 mm), where humid ground cover favors vector habitats, and is smaller and insignificant in drier counties. These patterns align with the hypothesized mechanism: warmer and wetter climates enhance the suitability of local environments for vector survival and reproduction.[36]

The disruption is also expected to be largest where open-field burning was historically prevalent, which reflects post-harvest straw management practices that differ across crops. Wheat provides a clear illustration: its low-value straw was usually burned on-site due to high collection costs, whereas higher-value straw from crops such as corn, sorghum, and sesame was more often collected for fodder or fuel, implying lower pre-ban burning intensity (Wu et al., 2021). We further confirmed such distribution in Table 6.

5.3 Distributional Effects

Our baseline results show that the straw-burning ban unintentionally increased hospitalizations for vector-borne diseases on average. This aggregate effect, however, may conceal substantial differences in exposure and vulnerability across populations. A growing literature in environmental justice emphasizes that environmental risks and the costs of environmental regulation are rarely distributed uniformly. In China, rural populations may be especially vulnerable to infectious and vector-borne diseases because they face greater contact with agricultural environments,

[36] 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).

Table 5: Pathway-Based Heterogeneity in Vector-Borne Hospitalizations

Panel A. Winter Temperature	(1) Coldest-month temp.	(2)
	$> 0°C$	$\leq 0°C$
Straw-burning ban	2.211**	0.068
	(0.932)	(0.729)
Observations	3,284	1,286
Panel B. Humidity	Annual Precipitation	
	$>$ 800 mm	$\leq$ 800 mm
Straw-burning ban	1.596**	0.738
	(0.751)	(0.844)
Observations	3,631	939

Notes: This table reports heterogeneous effects of county-level straw-burning bans on hospitalizations for vector-borne diseases using the Borusyak et al. (2024) staggered difference-in-differences estimator. The dependent variable is the county-level hospitalization counts per 100,000 patients. Panel A divides counties according to whether their average temperature in the coldest month during 2015–2022 is above 0°C. Panel B divides counties according to whether average annual precipitation is above 800 millimeters. All specifications include county, year-by-quarter, and province-by-quarter fixed effects, as well as hospital-capacity, weather, forest-fire, and socioeconomic controls. The socioeconomic controls include cropland area, GDP, value added of the primary industry, and population. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

more limited access to healthcare, and less generous insurance coverage (Liu et al., 1999; Anand et al., 2008; Jiang et al., 2012; Chen and Jin, 2012; Yang et al., 2014; Lu et al., 2019). Consistent with this concern, farmers account for a disproportionately large share of reported cases (Liu et al., 2025). The ecological costs generated by environmental regulation may therefore fall more heavily on populations with both greater exposure and fewer resources to avoid or manage the resulting risks. We examine whether the unintended health burden of the straw-burning ban is concentrated among agriculturally exposed and socioeconomically vulnerable groups.

The distributional results are consistent with this concern. Table 6 reports heterogeneity by rural status and cropland exposure. Panel A compares patients covered by the New Cooperative Medical Scheme (NCMS), which primarily serves rural residents, with those covered by Urban Employee Basic Medical Insurance (UEBMI). The estimated increases in hospitalizations and medical expenditures are larger for the NCMS group: hospitalizations rise by 0.470 per 100,000 population and expenditures by 2.112, compared with 0.263 and 1.492 for the UEBMI group. Panel B reveals a similarly pronounced exposure gradient. In counties with above-median cropland area, the ban increases hospitalizations by 2.253 and medical expenditures by 7.716 per 100,000 population. In counties with below-median cropland area, the hospitalization estimate is smaller and statistically indistinguishable from zero. Taken together, these patterns indicate that the unintended burden is concentrated in places and populations more closely connected to agricultural production, suggesting that the policy may reinforce existing socioeconomic disparities rather than distribute its ecological costs uniformly.[37]

[37] Appendix Table E9 further shows that the increase in disease burden spans age groups, suggesting that the ecological pathway is not confined to working-age adults directly engaged in farming.

The broader economic burden extends beyond hospital care. Appendix Table E14 shows that searches for insect bites and defensive measures increased primarily in high-cropland cities, where residue accumulation is most likely to alter vector habitat. Insect-bite searches also rose more in areas with limited healthcare access, suggesting that weaker medical capacity may leave households more reliant on private avoidance and information seeking. These responses reveal an additional dimension of vulnerability: households bear costs not captured by inpatient expenditures, further concentrating the policy's unintended burden.

Table 6: Heterogeneous Effects by Rural Status and Cropland Exposure

Panel A. Rural–Urban Status				
	Hospitalizations		Medical Expenditure	
	(1)	(2)	(3)	(4)
	NCMS	UEBMI	NCMS	UEBMI
Straw-burning ban	0.470**	0.263***	2.112**	1.492***
	(0.191)	(0.100)	(0.843)	(0.534)
County FE	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Province-quarter FE	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓
Observations	4,618	5,038	4,001	4,328
Panel B. County-Level Cropland Area				
	Hospitalizations		Medical Expenditures	
	(5)	(6)	(7)	(8)
	High	Low	High	Low
Straw-burning ban	2.253***	0.821	7.716**	6.649*
	(0.692)	(0.957)	(3.693)	(4.005)
County FE	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Province-quarter FE	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓
Observations	2,514	2,052	2,514	2,052

Notes: This table reports heterogeneous effects of county-level straw-burning bans on disease outcomes. Panel A compares patients covered by the New Cooperative Medical Scheme (NCMS), which primarily serves rural residents, with patients covered by Urban Employee Basic Medical Insurance (UEBMI). Columns (1)–(2) report hospitalizations for vector-borne diseases, and columns (3)–(4) report medical expenditures. Panel B divides counties into high- and low-cropland groups and reports effects on vector-borne disease hospitalizations and medical expenditures. The dependent variables are county-level outcomes per 100,000 population. All specifications include county, year-quarter, and province-quarter fixed effects, together with hospital-capacity controls, weather and forest-fire controls, and additional socioeconomic controls. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.4 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.Detailed results are reported in Appendix Table E2 through Table E8.

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.

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). The results, reported in Table E4, are consistent with our baseline estimates. We also consider alternative outcome transformations and estimation frameworks. Specifically, we estimate models using $\log(1+x)$ or inverse hyperbolic sine (IHS) transformations as alternative specifications for count data (Correia et al., 2020). As shown in Table E5 and Table E6, the estimated effects remain positive and statistically significant, indicating that our findings are not driven by functional form assumptions.

Pre-Pandemic Subsample We further assess robustness by restricting the analysis to the pre-pandemic period (2015–2019). As shown in Table E7, 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 E8, the results remain stable in both magnitude. This suggests that cross-county spillovers are unlikely to explain our main findings.[38]

6 Straw Residue Management and Policy Implications

The health effects documented above are not necessarily an unavoidable consequence of cleaner air. The straw-burning ban changed how crop residue was disposed of, but it did not remove the residue itself. This distinction raises a natural policy question: can the air-quality benefits of the ban be preserved while limiting the ecological risks created by leaving straw in the field?

We examine whether support for straw recycling helps address this policy gap. The results show a clear difference across regions. Where recycling support is limited, the ban is followed by substantial increases in vector-borne disease outcomes. Where recycling is more strongly supported, these effects are markedly smaller or statistically insignificant. This pattern is consistent with the proposed mechanism: removing or repurposing crop residue reduces the habitat changes that accompany fire suppression. The relevant policy choice is not between pollution control and public health, but between a stand-alone burning ban and a more complete approach to residue management.

6.1 Why Recycle, and Why Subsidize It?

Residue Disposal Burden 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.[39]

[38] 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.

[39] Figure E2 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.

Following the straw-burning ban, farmers faced growing residue disposal burdens due to the accumulation of untreated crop straw after harvest.[40] Due to the lack of effective infrastructure, collecting and transporting straw was mostly more costly than its market value, farmers frequently shredded and returned residues directly to the soil, increasing organic material left in fields. The crop residues impose substantial social and economic costs through increased disease burden, medical expenditures, and labor cost.

Recycling Subsidy 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 initiative allocated over 1 billion CNY (approximately 150 million USD) to support recycling machine procurement and incentivize collection, transportation, and storage.[41] 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 E3 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.

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.[42] Table 7 reports the results. Column (1) shows that the ban significantly increased both the number of machines procured (Panel A) and the total procurement value (Panel B). 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 response is much larger in subsidized regions, where machine procurement and total value rise sharply. Column (3) shows that unsubsidized regions also respond, but the effects are substantially smaller.

[40] The burden is concentrated among households and places with higher agricultural exposure and weaker capacity to adapt. See Table E15.

[41] 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).

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

Table 7: Straw-Burning Bans and Straw-Recycling Machine Procurement

	All counties	*With subsidy*	*Without subsidy*
Panel A. Number of Machines Procured			
Straw-burning ban	0.075***	0.103**	0.063*
	(0.026)	(0.042)	(0.034)
Panel B. Total Procurement Value			
Straw-burning ban	1,186.278***	1,693.729***	803.060**
	(283.392)	(477.755)	(369.931)
County FE	✓	✓	✓
Year-quarter FE	✓	✓	✓
Province-quarter FE	✓	✓	✓
Additional controls	✓	✓	✓
Observations	4,026	3,946	3,889

Notes: This table reports the effects of county-level straw-burning bans on straw-recycling machine procurement. Column (1) reports estimates for all counties. Columns (2) and (3) divide counties according to participation in the provincial straw-recycling subsidy program introduced in 2016. Panel A reports effects on the number of machines procured, and Panel B reports effects on total procurement value. The unit of observation is the county-year-quarter. All specifications include county, year-quarter, and province-quarter fixed effects, weather and forest-fire controls, and additional socioeconomic controls. The comparison group is held fixed across Columns (2) and (3) and consists of never-treated and not-yet-treated counties; their observation counts are therefore not additive. Standard errors clustered at the county level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.2 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 8 presents the results. Columns (1) and (2) show that counties with recycling subsidies experience no significant increase in vector-borne disease hospitalizations following the ban, whereas unsubsidized counties do. The subsidy program reduces the hospitalization effect by 77.0%. Columns (3) and (4) show a weaker pattern for medical expenditures: the effect among subsidized counties is 18.8% smaller but remains marginally significant. 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 4 support these findings: health outcomes diverge after the straw-burning ban between subsidized and unsubsidized counties.

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 E16 shows consistent patterns: areas with stronger recycling infrastructure experienced smaller and insignificant health effects from the ban.

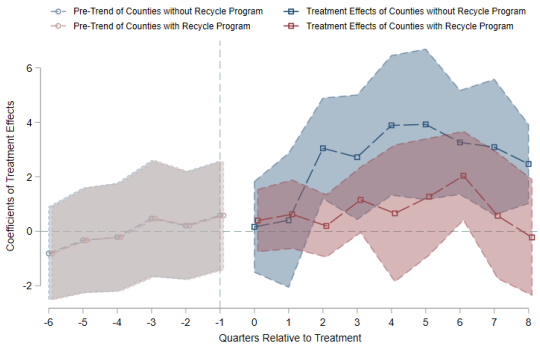
Together, the evidence reveals a clear inverse relationship between vector-borne disease outcomes and the intensity of straw recycling. These findings support the ecological mechanism and highlights the importance of pairing bans with effective residue management policies.

Table 8: Recycling Programs Mitigate the Health Effects of Straw-Burning Bans

	Hospitalizations		Medical Expenditures	
	(1) Without recycling	(2) With recycling	(3) Without recycling	(4) With recycling
Straw-burning ban	2.298***	0.529	7.363**	5.980*
	(0.855)	(0.769)	(3.659)	(3.449)
Implied effect	58.5%	13.5%	40.6%	33.0%
County FE	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
Province-quarter FE	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓
Observations	4,437	4,408	4,437	4,408

Notes: This table reports heterogeneous effects of county-level straw-burning bans on vector-borne disease outcomes by participation in provincial straw-recycling programs. Columns (1) and (3) report estimates for treated counties without a recycling program, while Columns (2) and (4) report estimates for treated counties with a recycling program. The dependent variables are hospitalization counts and medical expenditures per 100,000 patients. The treatment group is split based on participation in the provincial recycling subsidy program described in He et al. (2020), while the comparison group is held fixed across columns and consists of never-treated and not-yet-treated counties. Therefore, observation counts across the two treatment subsamples are not additive. All specifications include county, year-quarter, and province-quarter fixed effects, hospital controls, weather and forest-fire controls, and additional socioeconomic controls. 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

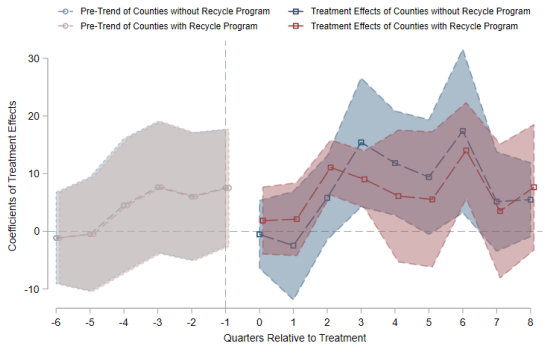


Figure 4: Heterogeneous Effects on Health Outcomes by Recycling Support: Event Study Plots

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 2. 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.

A natural concern is that recycling subsidies were not randomly assigned. We indicate that it won't mitigate our results. First, placement is predetermined and provincial: the 2016 pro-

gram covered ten provinces and was set at the provincial level before, and independently of, each county's own ban timing, so it cannot respond to county-quarter disease shocks. Second, the program deliberately targeted the most cropland-intensive, high-residue areas, precisely where the ban's health cost is largest. The finding that the disease increase nearly disappears in recycled crop-intensive areas evident that residue is the mechanism and that removing it is the remedy. Third, program placement is uncorrelated with pre-ban fire trends and with health infrastructure (Table D3), so treated and comparison counties are balanced on the dimensions that would otherwise confound the estimate. Because any remaining selection loads on higher-residue, higher-exposure counties, our estimate is a lower bound on how much residue management can offset the health cost.

6.3 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.

7 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. The burdens fall disproportionately on populations with greater agricultural exposure. 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.

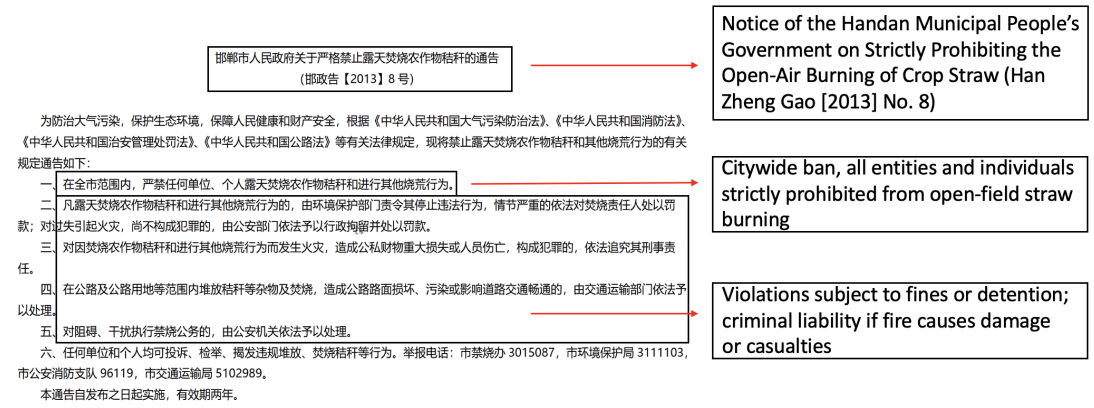
A.2 Policy Data Cleaning Details

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.

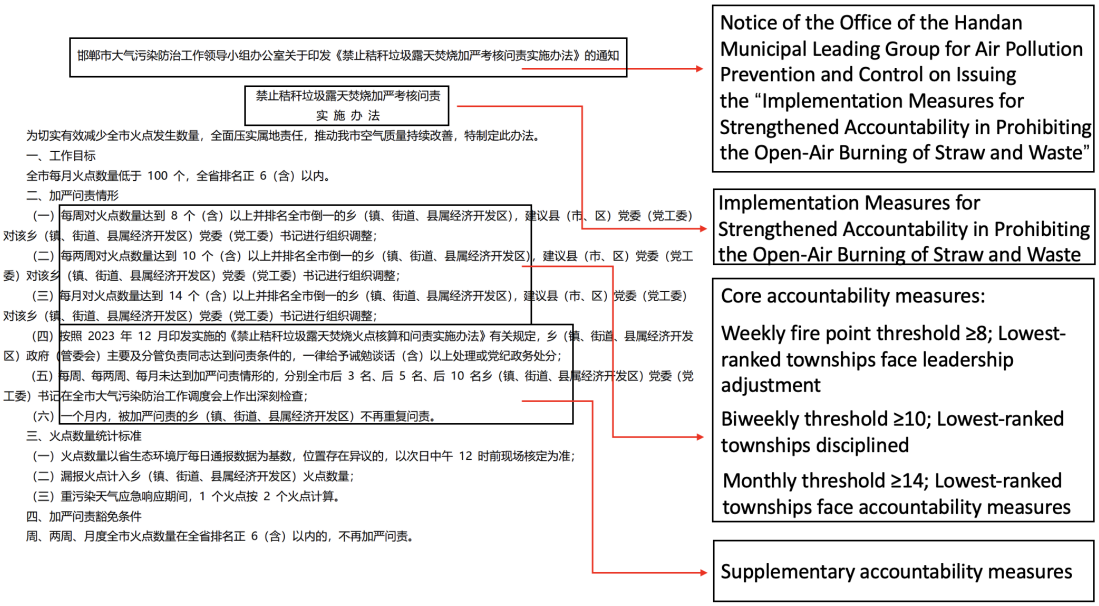
Illustrative Examples The following examples highlight how policy content varies in strictness across jurisdictions and over time. Figure A1 shows a basic straw-burning ban without assessment criteria, which states "*Across the entire city, all entities and individuals are strictly prohibited from burning 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.

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



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



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.

Web Search Intensity (Baidu) 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 A3.

Appendix Table A3: 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
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

[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.

variation in local straw demand for power generation and serves as a proxy for alternative straw disposal options.

B Ecological Responses and Arthropod Exposure

The main text of the paper documents that straw-burning bans increased searches for insect bites and defensive behaviors. This appendix examines the ecological counterpart to those behavioral responses: whether the ban was followed by changes in recorded arthropod occurrences that are consistent with greater potential human exposure. We first describe the species-occurrence data and their limitations, then estimate the effects of the policy on broad arthropod groups, and finally examine whether the results can be explained by changes in outdoor activity or reporting intensity. Because the available data are not collected through a systematic population survey, we interpret this evidence as corroborative rather than as a direct measure of vector abundance or human–vector contact.

Species-Occurrence Data and Measurement Direct measures of arthropod populations in cropland and nearby residential environments are not available at the geographic and temporal scale of our analysis. We therefore use species-occurrence records from the Global Biodiversity Information Facility (GBIF), an international network that aggregates georeferenced biodiversity observations from a range of scientific and citizen-science sources.[3]

Each GBIF record reports the location and date of an observation, taxonomic classifications, and, when available, an observer identifier. For 2015–2022, we identify 99,814 arthropod observations in China, including observations classified as *Insecta* and *Arachnida*. We aggregate these records to the county-by-year level and construct annual occurrence counts for three taxonomic categories: all arthropods (*Arthropoda*), insects (*Insecta*), and arachnids (*Arachnida*). The following section, Appendix C, describes the medically relevant taxa contained within these broad classifications and their potential roles in vector-borne disease transmission.

An important limitation of occurrence data is that the number of recorded observations reflects both underlying ecological conditions and the intensity of observation. We therefore do not interpret the outcomes as census measures of arthropod populations. To account for spatial and temporal variation in sampling effort, all specifications control for the inverse hyperbolic sine transformation of the number of unique observers in each county-year, following Liang et al. (2025).

Ecological Response The ecological prediction follows directly from the policy-induced change in residue management documented in the paper. By suppressing open-field burning, the policy

[3]GBIF harmonizes records from sources including scientific collections, ecological surveys, DNA barcodes, and photographic observations using standardized data protocols such as Darwin Core. The database is widely used in ecological and conservation research and is particularly useful in settings where systematic ecological monitoring is unavailable (GBIF, 2025).

leaves a larger quantity of crop residue on or near agricultural fields. Agronomic and ecological studies show that retained crop residue can increase soil moisture, organic matter, and habitat availability, thereby increasing the abundance and diversity of soil-dwelling arthropods (e.g., Xie et al., 2022; Kautz et al., 2006; Yang et al., 2023). Accordingly, if the ban altered local ecological conditions in this direction, counties implementing the policy should experience an increase in recorded occurrences of arthropods, particularly insects.

This prediction does not require every arthropod group to respond uniformly. The taxonomic category *Arachnida*, for example, combines ticks and mites with many species that are not medically relevant and may respond differently to residue retention. Consequently, the class-level arachnid outcome is not a direct measure of tick abundance. The broader taxonomic analysis is instead intended to test whether the policy generated detectable ecological changes in the direction implied by the proposed mechanism.

Effects on Recorded Arthropod Occurrences We apply the staggered difference-in-differences design used elsewhere in the paper to the county-by-year species-occurrence outcomes. Table B5 reports the estimates, and Figure B3 presents the corresponding event-study results.

Panel A of Table B5 shows that the straw-burning ban increased the inverse hyperbolic sine transformation of recorded arthropod occurrences by 0.030 and recorded insect occurrences by 0.026. For these relatively small coefficients, the estimates correspond approximately to increases of 3.0 percent and 2.6 percent, respectively. Both estimates are statistically significant at the 5 percent level. In contrast, the estimated effect on the broad *Arachnida* category is small and statistically indistinguishable from zero.

The event-study estimates in Figure B3 provide no evidence of systematic differential trends before policy adoption. Following implementation, recorded arthropod and insect occurrences increase relative to untreated observations. Taken together, the regression and event-study results indicate that the increase in insect-related search activity documented in the main text was accompanied by ecological changes in the same direction.

Observation Effort and Outdoor Activity A remaining concern is that improvements in air quality following the ban may have encouraged residents to spend more time outdoors. Greater outdoor activity could mechanically increase the number of species observations even without a change in underlying ecological conditions. Our baseline control for the number of unique observers addresses general changes in reporting intensity, but it may not fully capture changes in the frequency with which individuals engage in outdoor activities.

To examine this possibility, we construct a city-level proxy for outdoor activity using the Baidu Search Index for terms related to outdoor recreation, parks, and camping. The detailed keyword list is reported in Table B4. Panel B of Table B5 adds this proxy to the baseline specification. The estimated effects on total arthropod and insect occurrences remain similar in magnitude and

statistical significance. These results make it less likely that the observed changes are driven solely by increased outdoor activity or mechanically greater opportunities to report species observations.

Appendix Table B4: 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.

Interpretation and Link to Health Outcomes The GBIF analysis should be interpreted with appropriate caution. Species-occurrence records are sparse, geographically uneven, and not collected according to a uniform sampling protocol. They do not measure arthropod abundance directly, identify the precise locations of human–vector contact, or establish that the observed organisms carried pathogens. The results therefore do not independently demonstrate the complete biological pathway from residue retention to disease transmission.

Nevertheless, three features make the evidence informative. First, the direction of the estimates is consistent with the ecological prediction that retaining agricultural residue creates more favorable habitats for arthropods. Second, the increases are concentrated among insects and remain after accounting for observer intensity and a proxy for outdoor activity. Third, the event-study estimates do not indicate differential pre-policy trends.

The relatively modest change in aggregate species observations is also not inconsistent with the larger estimated health response. Disease transmission is nonlinear: changes in vector survival, activity, location, or contact with humans may increase infection risk even when changes in aggregate ecological abundance are difficult to detect (Anderson and May, 1991; Kilpatrick and Randolph, 2012; Smith et al., 2012). Moreover, the relevant pathway may operate partly through changes in contact rather than only through changes in total populations. When farmers collect, shred, transport, or plow retained crop residue, they may come into closer contact with insects and other arthropods living within the residue. Consistent with this interpretation, the health effects are larger during harvest periods, when residue handling and human exposure are likely to be greatest (Table 5).

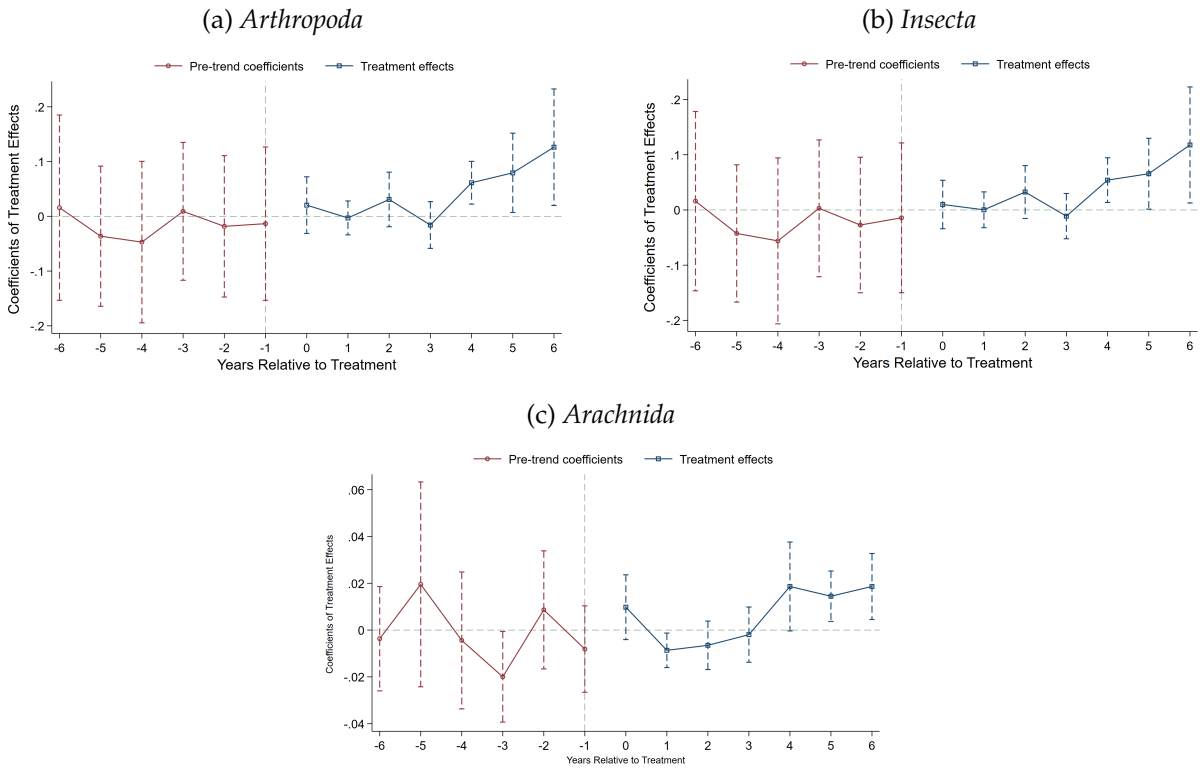
Thus, the GBIF evidence complements the Baidu search results in the main text. The search outcomes capture perceived exposure and defensive responses, while the occurrence records provide independent, albeit suggestive, evidence of ecological changes that could generate those re-

sponses. The next section provides the taxonomic and epidemiological background needed to connect these broad arthropod categories to the specific vector-borne and tick-borne diseases examined in the paper.

Appendix Table B5: Effects of Straw-Burning Bans on Recorded Arthropod Occurrences

	Arthropoda	*Insecta*	*Arachnida*
	(1)	(2)	(3)
Panel A. Baseline 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. Controlling for Outdoor Activity			
Straw-Burning Ban	0.032**	0.030**	0.004
	(0.015)	(0.014)	(0.003)
Outdoor-activity proxy	✓	✓	✓
County FE	✓	✓	✓
Year FE	✓	✓	✓
Controls	✓	✓	✓
Observations	9,805	9,804	9,796

Notes: This table reports the effects of straw-burning ban policies on recorded arthropod occurrences using the imputation difference-in-differences estimator of Borusyak et al. (2024). The dependent variable is the inverse hyperbolic sine transformation of the annual number of GBIF occurrence records in the indicated taxonomic category, measured at the county-by-year level. The sample covers 2015–2022. All specifications include county and year fixed effects. Controls include the inverse hyperbolic sine transformations of the number of unique observers and GDP, average temperature and precipitation, and the occurrence and burned area of forest wildfires. Panel B additionally controls for a proxy for outdoor activity constructed from the Baidu Search Index for terms related to outdoor recreation, parks, and camping. Standard errors, reported in parentheses, are clustered at the prefectural-level city level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.



Appendix Figure B3: Effects on Recorded Arthropod Occurrences: Event-Study Estimates

Notes: This figure presents the dynamic effects of straw-burning ban policies on recorded arthropod occurrences using the imputation difference-in-differences event-study estimator of Borusyak et al. (2024). The dependent variables are the inverse hyperbolic sine transformations of the annual numbers of GBIF occurrence records for *Arthropoda*, *Insecta*, and *Arachnida*, measured at the county-by-year level. All specifications include county and year fixed effects and control for the inverse hyperbolic sine transformations of the number of unique observers and GDP, average temperature and precipitation, and the occurrence and burned area of forest wildfires. The horizontal axis reports years relative to policy implementation. The vertical axis reports estimated treatment effects relative to untreated observations. Vertical bars indicate 95 percent confidence intervals.

C Arthropod Taxa and Vector-Borne Disease Risk

The preceding analysis documents an increase in broad arthropod and insect occurrence records following the straw-burning ban. This section clarifies how the taxonomic groups represented in those data relate to the health outcomes examined in the paper. Arthropods include both insect and non-insect taxa and encompass organisms that transmit pathogens biologically, carry pathogens mechanically, or cause direct health harm through bites and other forms of contact. The discussion below does not imply that every observed arthropod is a disease vector. Rather, it establishes the biological plausibility of the pathway by identifying medically relevant groups contained within the aggregate taxonomic outcomes.

Insects as Biological Vectors of Infectious Diseases Within the class *Insecta*, several orders contain established biological vectors of infectious diseases. A biological vector carries a pathogen that undergoes development or replication within the vector before being transmitted to a human or animal host (Laroche et al., 2018). Most prominently, the order *Diptera* includes mosquitoes in the family Culicidae, which transmit malaria, dengue, Zika virus, chikungunya, yellow fever, Japanese encephalitis, and lymphatic filariasis (WHO, 2024). Other medically relevant members of *Diptera* include sandflies, which transmit leishmaniasis and bartonellosis, and blackflies, which transmit onchocerciasis. Many of these organisms reproduce or survive more successfully in humid environments containing standing water, vegetation, or decomposing organic material. Such microenvironments may become more prevalent when crop residue remains on the ground rather than being removed through burning.

Other insect orders also contain important disease vectors. Fleas (*Siphonaptera*) can transmit plague and murine typhus, while lice (*Phthiraptera*) can transmit epidemic typhus, relapsing fever, and trench fever. These examples illustrate why changes in the local abundance, survival, or spatial distribution of insects can have health consequences even when the available occurrence data cannot identify individual vector species or pathogen carriage directly.

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.

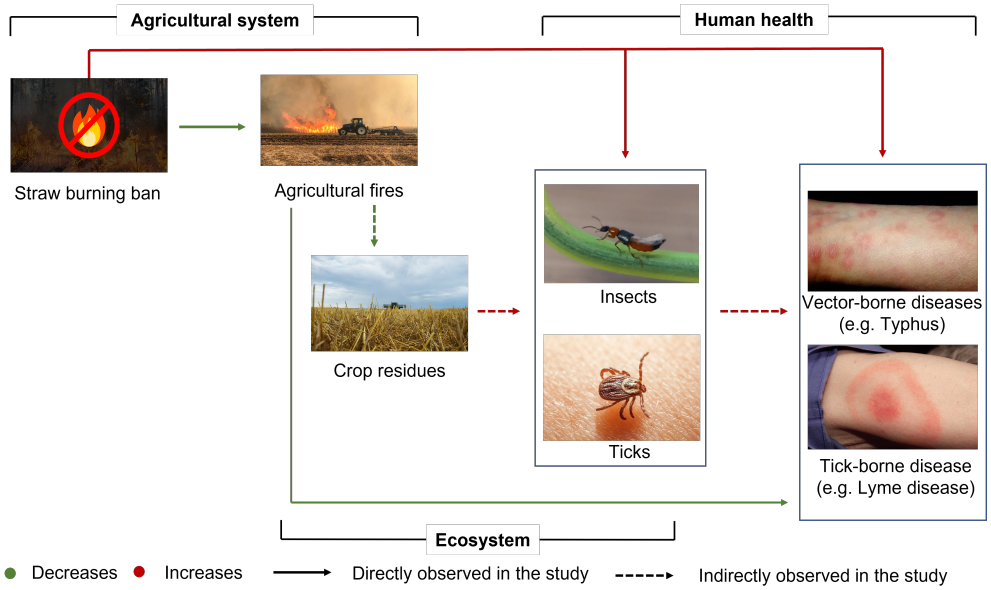
Non-insect Arthropods and Vector-Borne Diseases Outside the insect class, arthropods in *Arachnida* contribute to disease risks through envenomation, allergic reactions, and pathogen transmission.

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.



Appendix Figure C4: 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.

D 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 C 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 C for more details.

E Computing the Policy's Effects on Mortality of Vector-Borne Diseases

To translate the estimated effect of the straw-burning ban on vector-borne disease hospitalizations into an effect on the mortality rate, we combine the hospitalization estimates with disease-specific fatality probabilities. Let ΔH_j denote the estimated policy-induced change in hospitalizations for ICD-10 disease group j, measured per 100,000 population, and let f_j denote the share of hospitalized cases in group j that result in death. The implied change in the mortality rate is then

$$\Delta M = \sum_j \Delta H_j \times f_j.$$

This disease-specific calculation accounts for the difference in fatality risks across vector-borne diseases.[4]

However, hospitalizations for many specific vector-borne diseases are relatively scant in our data, which prevents reliable estimation of the policy's effect for hospitalizations of each individual ICD-10 disease group. Therefore, when disease-specific policy effects cannot be estimated, we approximate the mortality effect by multiplying the aggregate policy effect on vector-borne disease hospitalizations, ΔH, by a baseline hospitalization-weighted fatality rate:

$$\Delta M = \Delta H \times \bar{f}, \qquad \bar{f} = \sum_j s_j f_j,$$

where s_j is disease group j's share of vector-borne disease hospitalizations in the pre-policy period. This approach assumes that the policy-induced change in hospitalizations has the same disease composition as baseline hospitalizations.

F 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).

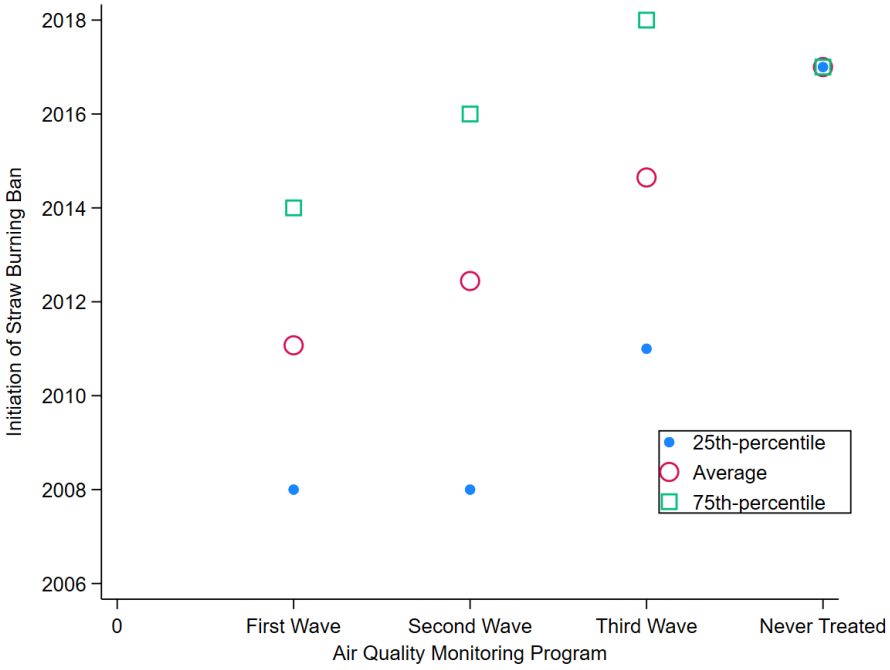
The early adoption concentrated in the North China Plain, followed by expansions into northeastern, northern, and southwestern regions. Figure D1 compares the rollout timing of the straw-

[4]For example, the case fatality rate in well-functioning cholera treatment centers should remain below 1%, whereas severe fever with thrombocytopenia syndrome has a case fatality rate of 17.4% (World Health Organization, 2024; Liu et al., 2013).

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.[5]

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: 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

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

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 eco-

nomic 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

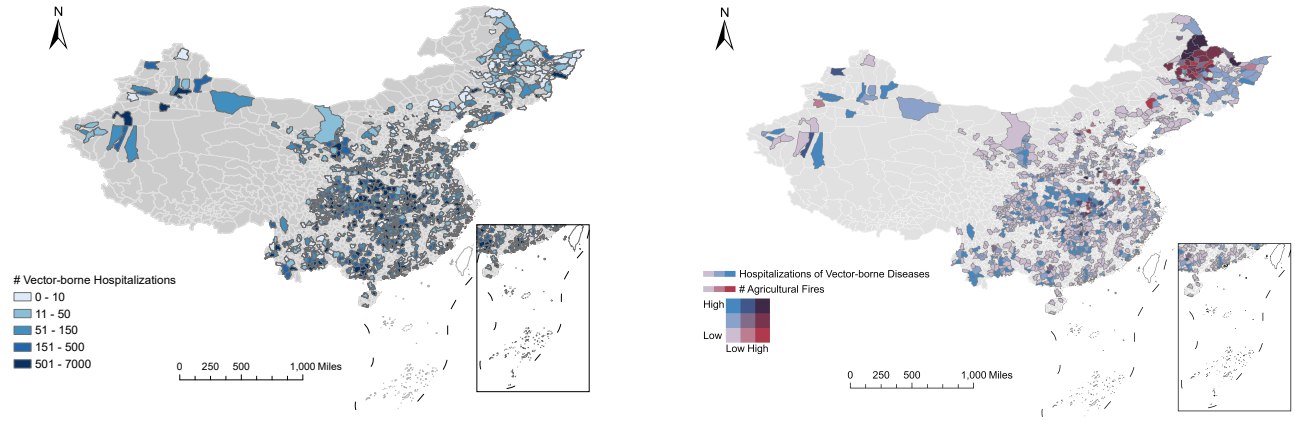
	Vector-Borne Hospitalizations			
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.007	0.136	0.130	0.130
	(0.126)	(0.116)	(0.116)	(0.116)
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls		✓	✓	✓
Weather Controls			✓	✓
Cropland and Forest Fire Controls				✓
Observations	15,927	15,927	15,800	15,800

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.

G Supplementary Figures and Tables

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

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



Appendix Figure E1: 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.

(a) Example for Straw Returning Machine

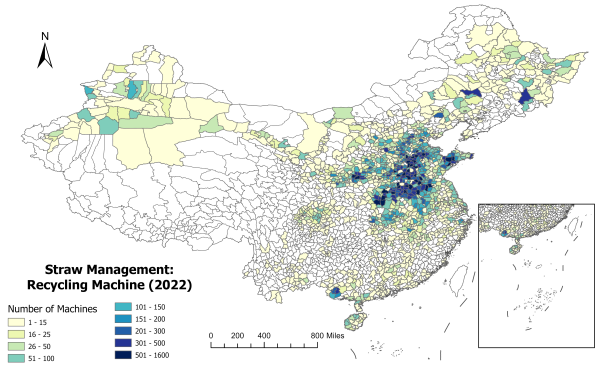
(b) Example for Straw Collecting Machine



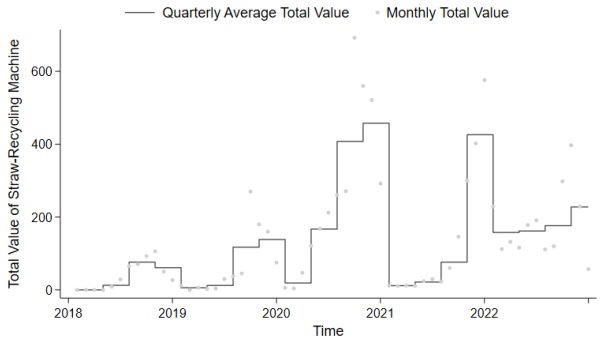
Appendix Figure E2: Straw Management Machines

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) Spatial Distribution of Straw Recycling Machine Procurement



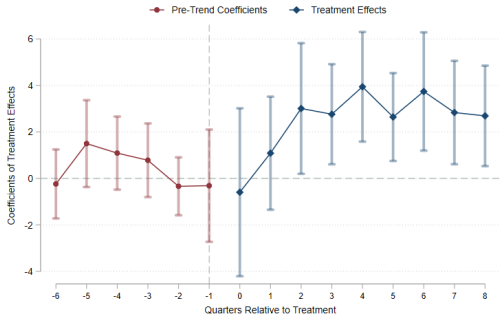
(b) Trend of Straw Recycling Machine Procurements



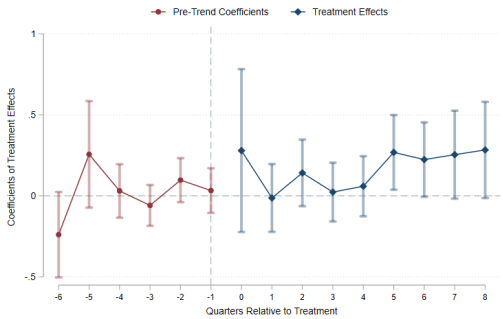
Appendix Figure E3: Straw Recycling Machine Procurement

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.

(a) Vector-Borne Diseases



(b) Tick-Borne Diseases



Appendix Figure E4: Event Study: Effects of Straw-burning Bans on Hospitalizations Using Callaway and Sant'Anna (2021)

Notes: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne diseases by different recycling measures. The dependent variable is number of inpatient admissions (Panel [a]) and the total medical expenditures (Panel [b]) for vector-borne diseases per 100,000 population, measured at the county-by-year-quarter level. Observations never treated and not yet treated are used as the control group. The fixed effects include county 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, burned area and frequency of forest wildfires, and GDP. 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)	(3)	(4)
Straw-Burning Ban	11.636***	8.227***	0.487*	0.277***
	(4.159)	(2.448)	(0.259)	(0.087)
Implied effect	47.47%	33.57%	49.54%	28.18%
No. Hospitalizations		✓		✓
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,570	4,570	4,570	4,570

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 hospitalization days per 100,000 population for vector-borne and tick-borne diseases. Columns (2) and (4) control for the number of hospitalizations. 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, value added of the primary industry, 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	-0.826	1.417	-0.999	-0.014	3.401	8.360
	(1.439)	(4.225)	(9.622)	(9.449)	(78.151)	(196.813)
Implied effect	-7.33%	3.48%	-1.73%	-0.02%	0.49%	0.95%
County FE	✓	✓	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	4,966	4,966	4,966	4,966	4,966	4,966

Notes: This table presents the impacts of straw-burning ban policies on hospitalizations for diseases unrelated to vectors. The dependent variables are hospitalizations and medical expenditures per 100,000 population 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, value added of the primary industry, 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	1.434**	1.542**	6.300**	6.950**
	(0.624)	(0.630)	(2.919)	(2.916)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,520	4,491	4,520	4,491

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, value added of the primary industry, 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	2.499***	7.702**	0.180**	0.580*
	(0.768)	(3.566)	(0.082)	(0.345)
County FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,953	5,953	5,953	5,953

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 hospitalizations and medical expenditure for vector-borne and tick-borne diseases per 100,000 population. 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, burned area and frequency of forest wildfires, and GDP. 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 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	0.449***	0.683***	0.155*	0.252**
	(0.151)	(0.186)	(0.081)	(0.128)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,570	4,570	4,570	4,570

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 disease outcomes per 100,000 patients. 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, value added of the primary industry, 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 E6: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Inverse Hyperbolic Sine (IHS) Estimation

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	0.548***	0.788***	0.180*	0.284*
	(0.170)	(0.204)	(0.100)	(0.153)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,570	4,570	4,570	4,570

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases estimated using the IHS estimator. 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 E7: 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	1.876**	10.638**	0.208**	1.413***
	(0.757)	(4.206)	(0.093)	(0.380)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	3,016	3,016	3,016	3,016

Notes: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases using data from 2015–2019, thereby excluding the COVID-19 pandemic period. The unit of observation is the county-by-year-quarter. The dependent variables are the inverse hyperbolic sine transformations of hospitalizations and medical expenditure for vector-borne and tick-borne diseases. Control variables include the total number of hospitals; the numbers of secondary, tertiary, Class B, Class C, and general hospitals; the average annual number of hospitalizations; average temperature and precipitation; the frequency and burned area of forest wildfires; cropland area; GDP; value added of the primary industry; population; and the number of hospital beds. Standard errors, reported in parentheses, are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Appendix Table E8: 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	1.250**	5.613**
	(0.529)	(2.855)
County FE	✓	✓
Province-Quarter FE	✓	✓
Year-Quarter FE	✓	✓
Controls	✓	✓
Observations	4483	4483

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 hospitalizations and medical expenditures for vector-borne diseases per 100,000 population. 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, value added of the primary industry, 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 E9: Effects on Vector-Borne Diseases for People of Different Age Groups

	Hospitalizations		Medical Expenditure	
	(1)	(2)	(3)	(4)
	Young	Old	Young	Old
Straw-Burning Ban	1.197**	0.369***	4.627**	2.532***
	(0.481)	(0.118)	(1.965)	(0.859)
Implied effect	41.32%	48.55%	40.27%	55.10%
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	4,570	4,570	4,570	4,570

Notes: This table presents the heterogeneous effects of straw-burning ban policies on hospitalizations and medical expenditures for vector-borne diseases by different age groups. The dependent variables are hospitalizations and medical expenditures per 100,000 population associated with vector-borne diseases. Columns (1) and (3) report results for individuals younger than 60, while columns (2) and (4) report results for those aged 60 and above. 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, value added of the primary industry, 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 Respiratory and Cardiovascular Diseases

	Respiratory Diseases		Cardiovascular Diseases	
	(1)	(2)	(3)	(4)
	Hospitalizations	Medical Expenditure	Hospitalizations	Medical Expenditure
Straw-Burning Ban	-12.601**	-50.802**	-7.939**	-60.296*
	(5.224)	(25.701)	(3.622)	(34.114)
Implied effect	-7.02%	-3.86%	-4.55%	-3.21%
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	5,722	5,722	5,722	5,722

Notes: This table presents the impacts of straw-burning ban policies on hospitalizations for respiratory and cardiovascular diseases. The dependent variables are the number of inpatient admissions and medical expenditures for respiratory and cardiovascular diseases per 100,000 population. 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, burned area of forest wildfires, 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 E11: 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 E12: 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 E13: 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 E14: Heterogeneous Effects on Defensive Responses

Panel A. County-Level Cropland Area

	Straw-Burning Ban		Insect Bite		Defensive Behavior	
	(1)	(2)	(3)	(4)	(5)	(6)
	High	Low	High	Low	High	Low
Straw-burning ban	0.425***	0.277***	0.249***	0.008	0.212**	-0.070
	(0.108)	(0.101)	(0.082)	(0.132)	(0.103)	(0.152)
City FE	✓	✓	✓	✓	✓	✓
Province-year-quarter FE	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Observations	4,977	6,190	4,977	6,190	4,977	6,190

Panel B. Healthcare Access

	Straw-Burning Ban		Insect Bite		Defensive Behavior	
	(7)	(8)	(9)	(10)	(11)	(12)
	High	Low	High	Low	High	Low
Straw-burning ban	0.443***	0.249**	0.035	0.220*	0.034	0.123
	(0.104)	(0.106)	(0.112)	(0.117)	(0.134)	(0.119)
City FE	✓	✓	✓	✓	✓	✓
Province-year-quarter FE	✓	✓	✓	✓	✓	✓
Additional controls	✓	✓	✓	✓	✓	✓
Observations	5,379	5,788	5,379	5,788	5,379	5,788

Notes: This table reports heterogeneous effects of county-level straw-burning bans on awareness and responses to ecological changes. Panel A divides cities into high- and low-cropland groups, and Panel B divides cities into high- and low-healthcare-access groups. High and Low indicate values above and below the sample median, respectively. The dependent variables are Baidu search indices for straw-burning bans, insect bites, and defensive behavior. The unit of observation is the city-year-quarter. All specifications include city and province-year-quarter fixed effects, weather and forest-fire controls, and additional socioeconomic controls. Standard errors clustered at the city level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table E15: Effects of Straw-Burning Ban Policies on Straw Recycling Machine Procurement by Cropland Area

	Number of Procurement		Value of Procurement	
	> median	< median	> median	< median
	(1)	(2)	(3)	(4)
Straw-burning Ban	0.092***	0.049	1554.298***	630.298
	(0.034)	(0.044)	(359.957)	(488.672)
County FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	2,100	1,926	2,100	1,926

Notes: This table reports the heterogeneous effects of county-level straw-burning bans on straw-recycling machine procurement by cropland area. The unit of observation is the county-by-year-quarter level. The dependent variables are (i) the number of machines procured, and (ii) total procurement value.Columns (1) and (3) report results for counties with larger cropland area than median, while columns (2) and (4) report results for counties with smaller cropland area than median. The ban indicator equals one for treated counties after policy implementation. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table E16: Straw-burning Ban, Recycle Measures, and Vector-Borne Diseases: Biomass Power Plants

	by Biomass Power Plants			
	Hospitalizations		Medical Expenditure	
	(1)	(2)	(3)	(4)
	< median	> median	< median	> median
Straw-Burning Ban	1.994**	0.290	7.299*	3.215
	(0.813)	(0.675)	(4.099)	(3.432)
County FE	✓	✓	✓	✓
Province-Quarter FE	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	2,260	2,310	2,260	2,310

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 hospitalization counts (columns [1] and [2]) and medical expenditure (columns [3] and [4]) per 100,000 patients at the county-by-year-quarter level. 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, value added of the primary industry, 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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