北京大学经济学院工作论文系列
Peking University School of Economics Working Paper Series

**E-2025-12-7**

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

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# Crops, Insects, and Diseases: Unintended Consequences of Straw-burning Ban on Ecosystem and Human Health*

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August 2025

**Abstract**

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***JEL Classification:*** Q57, Q51, Q10, Q50

*We are grateful to Shiyu Bo, Xiaomeng Cui, Donald R. Davis, Shanjun Li, Yuanning Liang, Sen Ma, Lina Meng, Yongwei Nian, Yu Qin, Julie Shi, Qu Tang, Ye Yuan, Ning Zhang, Chen Zhuang, seminar participants at Peking University, Shandong University and Jinan University, and conference participants at Duke Kunshan, Annual International Conference of China and Development Studies Development, Asian Economic Development Conference for their helpful comments.

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# 1 Introduction

Environmental regulations can save lives by reducing pollution, but by reshaping ecosystems and altering species dynamics, they can create new health risks that offset their intended benefits—an important yet underexplored dimension in both academic research and policy design. Understanding how policies can trigger ecological disturbances with health consequences is essential, given substantial evidence that changes in biodiversity, species interactions, and ecosystem services can have profound and lasting effects on human well-being (Pecl et al., 2017; Frank and Sudarshan, 2024; Frank et al., 2024). This paper makes two contributions. First, it identifies a previously overlooked mechanism: a widely adopted environmental policy—the straw-burning ban, designed to improve air quality—inadvertently created conditions that favored insect survival and reproduction, facilitating the spread of insect-borne diseases. Second, it shows that effective straw recycling substantially mitigates these effects, advocating for complementary ecological safeguards to preserve environmental gains while preventing unintended harm.

We exploit the staggered rollout of China's straw-burning ban—a top-down air pollution control policy—as a natural experiment to causally identify the health impacts of policy-induced ecological change. The ban is among China's most stringent national measures to combat air pollution.[1] While prior studies have examined the effects of straw burning on air quality, the ban's ecological consequences have been largely overlooked.

Figure 1 illustrates the influencing channel of our novel finding: how the ban may affect human health indirectly by altering land use and insect ecosystems. The straw-burning ban disrupted an ecological equilibrium in which seasonal cropland fires suppress insect populations. By banning burning and allowing crop residues to accumulate, the policy also enhanced overwintering habitats, increased insect survival and reproduction, and contributed to a rise in vector-borne diseases.[2] These diseases, closely tied to insect population dynamics, account for 17% of all infectious diseases globally and cause over 700,000 deaths annually (WHO, 2024), posing a significant threat to public health.[3]

Figure 1 about here.

This study draws on multiple data sources, including a representative database of hospitalization records from public hospitals across China, biodiversity monitoring data, remote sensing imagery of fires and land cover, and web search indices for related terms. For health outcomes,

[1] The rollout sequence was primarily determined by regional economic and social importance, rather than by health, climate, or other regional characteristics, as discussed in Section 4.1.

[2] Natural science research shows that changes in land management influence vector populations, including ticks and other arthropods (Allan, 2009; Samish and Alekseev, 2001; Gleim et al., 2014; Gallagher et al., 2022). Vector-borne diseases are caused by pathogens—such as parasites, viruses, and bacteria—transmitted to humans and animals through bites or contact with infected fluids from blood-feeding arthropods. We use the terms *arthropod* and *insect* interchangeably for ease of exposition. Additional details are provided in Section 2.2.

[3] Vector-borne diseases also impose significant economic burdens on healthcare systems, labor productivity, and public budgets. For example, the annual cost of Lyme disease in the U.S. is estimated at \$345–\$968 million (2016 USD), with average treatment costs of approximately \$3,000 per patient (Hook et al., 2022).

we focus on vector-borne diseases, identified using ICD-10 codes (listed in Table C1–C2) and validated through medical and epidemiological literature (WHO, 2024). We further examine the policy's effects on a subset of more severe conditions—tick-borne diseases—such as Lyme disease, tick-borne encephalitis, and severe fever with thrombocytopenia syndrome (SFTS), which are among the most common vector-borne diseases in farmland activities.

We employ a Difference-in-Differences (DID) framework exploiting the staggered implementation of the straw-burning ban in China.[4] The unit of analysis is the county-by-year-quarter level. To address potential confounding effects from unobserved time-varying factors correlated with both policy rollout and hospitalization outcomes, we incorporate fixed effects at the county, year-quarter, and province-by-quarter levels. We also control for observable factors that may affect both insect survival and hospitalization outcomes, including hospital characteristics, weather conditions, forest fire incidence, economic conditions, medical infrastructure, and cropland scale.

We conduct several validation tests to support the causal interpretation of our results. First, pre-trend analyses show that treated and untreated groups followed parallel trends prior to the policy's implementation. Second, we provide evidence for the exogeneity of the straw-burning ban, which was imposed as a top-down air pollution control policy determined by administrative hierarchies (Barwick et al., 2024). The rollout of the ban is strongly correlated with that of the Air Pollution Monitoring and Disclosure Program but shows no correlation with local health infrastructure. Moreover, air pollution levels are uncorrelated with the prevalence of vector-borne diseases. Third, we find no evidence of concurrent ecological, health, or agricultural policies that could confound the analysis. Finally, our results are robust to subsamples that exclude regions potentially affected by spatial spillovers or periods confounding the COVID-19 pandemic.

**Main Findings** Our findings indicate that the straw-burning ban led to an unintended rise in hospitalizations and medical expenditures for vector-borne diseases, amounting to roughly 50% and 173% of the sample means, respectively. These effects persist for up to four years after the policy's implementation, indicating a long-term ecological shift affecting human health. The results remain robust across alternative model specifications and sub-samples. A back-of-the-envelope calculation suggests that the additional hospitalization costs attributable to the policy exceed $388 million annually. This estimate represents a lower bound of the related economic burden, as it excludes outpatient care and indirect costs such as productivity losses, implying substantial social impacts.

Importantly, our analysis shows that the ecological feedback mechanisms triggered by the policy are not trivial. While the policy reduces medical expenditures for respiratory and cardiovascular diseases because of improved air quality, our estimates suggest that increased vector-borne disease costs offset 11% of these savings. These findings highlight the trade-offs embedded in environmental regulation: neglecting ecosystem feedbacks can undermine policy effectiveness and

[4] We apply multiple methods for estimation, such as Borusyak et al. (2024), Callaway and Sant'Anna (2021), Sun and Abraham (2021), and de Chaisemartin et al. (2022), obtaining similar results.

generate secondary risks to public health and social welfare.

To validate our findings and empirically confirm the mechanism, we integrate multiple data sources to trace the causal pathway: reduced agricultural burning $\rightarrow$ increased insect activity $\rightarrow$ greater human infections of vector-borne diseases.

We separately test the impact of straw-burning ban on cropland fire, insect population, and people's behavior responses. Using high-resolution remote sensing data on land cover and fire records, we construct county-level measures of straw-burning incidence and burned area. Applying the same DID specification, we find that the policy reduced the frequency of cropland fires by 58% and burned area by 50% per county-year, equivalent to a decline of 45.8 $km^2$, confirming a substantial reduction in straw-burning activity. In addition, using taxonomic observation data, we document a significant increase in reported sightings of arthropod species—including insects and non-insect arthropods—groups frequently linked to agricultural ecosystems. This suggests increased insect abundance post-intervention.

Furthermore, to capture behavioral responses and exposures not reflected in hospitalization records, we analyze Baidu Search Index data for terms related to insect bites and sightings. The results reveal sharp increases in search activity for insect-related queries and protective measures—such as bite-related medical information and vaccination—following the policy's implementation. These findings likely reflect a rise in non-severe insect bites, heightened public awareness, and increased household defensive investment. Taken together, these patterns offer further support for the ecological pathway underlying the policy's unintended health consequences.

We also conduct various heterogeneity analyses to corroborate the proposed channel of impact. We find that the hospitalization effects of the policy are more pronounced: (1) among rural residents, although some spillover is observed in urban areas; (2) in wheat-producing counties, where straw burning was historically more common due to the lower economic value of wheat straw; (3) in warm regions, where environmental conditions are more favorable for insect survival and disease transmission; and (4) during harvest seasons, when human exposure to fields increases. These findings align with our hypothesized mechanism of impact.

**Policy Implications** Notably, we find that such unintended effects are not inevitable. Our results show that regions with strong straw-recycling policies—including subsidies, enforcement, or infrastructure—do not experience statistically significant increases in vector-borne diseases. This indicates that complementary ecological safeguards can effectively mitigate unintended consequences while preserving environmental gains. Thus, while straw burning should not be resumed, policies that recycle or reuse crop residues can reduce both air pollution and ecological health risks.

Overall, our findings highlight that the overlooked ecological channels can undermine intended policy goals. Improving straw management would not only mitigate ecological and health risks but also support agricultural productivity and rural livelihoods. These lessons are broadly applicable to other countries where straw-burning bans have been or will be implemented.[5]

**Related Literature** This paper contributes to the literature on the effects of biodiversity change. A growing body of research examines how disruptions to biodiversity impact human health. Frank and Sudarshan (2024) documents how the functional extinction of vultures in India increased human mortality through deteriorated sanitation, while Frank et al. (2024) finds that sparrow eradication during China's Four Pests Campaign reduced crop yields and increased mortality rates. Extending this strand of work, we provide one of the first empirical evidence on the unintended biological consequences of public policies: straw-burning bans, an environmental policy intended to improve air quality, can disrupt insect populations and, in turn, generate unintended health consequences.

Second, we contribute to the literature on the ecological effects of socioeconomic activities. Existing research has examined how transportation and energy infrastructure, environmentally oriented place-based policies, economic production, improved market access, trade and agricultural productivity affect ecological outcomes (Asher et al., 2020; Garg and Shenoy, 2021; **?**; Taylor and Mayer, 2023; Abman and Lundberg, 2024; Carreira et al., 2024; Costa et al., 2025). While most studies focus on direct ecological consequences such as deforestation or declines in bird biodiversity and their effects (Du et al., 2024; Meng et al., 2025), we broaden this scope by tracing impacts through habitat-driven species changes and investigating how policy-induced habitat alterations affect insect dynamics within agricultural and vector ecosystems.

Third, this paper contributes to the literature on ecosystems and human health (Garg, 2019). Some literature shows that invasive species can disrupt local ecosystems, affecting human wellbeing (Jones, 2019, 2023).[6] Our setting is distinct: the pathogen vectors in our study—arthropods—are native species that have historically coexisted with humans without causing widespread harm. This perspective advances understanding of how policy-induced ecological change can disrupt native species dynamics and destabilize longstanding human-nature equilibria, unintentionally amplifying public health risks.

Finally, this paper complements the literature on the health and labor market effects of agricultural fires. Existing studies show that agricultural fires worsen health outcomes, including increased mortality (He et al., 2020; Garg et al., 2024),[7] higher risks of hypertension (Pullabhotla and Souza, 2022), adverse birth outcomes (Rangel and Vogl, 2019), and cognitive impairments (Zivin et al., 2020; Lai et al., 2022), primarily due to increased $PM_{2.5}$. In terms of air pollution

[5]For example, in the United States, straw burning has been increasingly restricted since the 1990s to improve air quality, with exceptions for fields affected by disease (see United States Department of Agriculture). In India, the National Green Tribunal has imposed bans and penalties on straw burning across several states (see The Times of India). Brazil's Law 11.241, enacted in 2002, aimed to phase out sugarcane straw burning, initially covering 20% of mechanized areas and reaching 100% by 2021 (Paraiso and Gouveia, 2015).

[6]Jones (2023) shows that deforestation driven by the emerald ash borer increased obesity and reduced physical activity, while Jones (2019) finds that improved water quality following the die-off of zebra mussels increased birth weight and gestation length.

[7]Garg et al. (2024) finds that rural roads cause movement of workers out of agriculture and induce farmers to use fire, increasing infant mortality rate.

control, prior research has shown that providing economic incentives for straw recycling and payments for ecosystem services can significantly reduce pollution from agricultural burning (He et al., 2020; Cao and Ma, 2023; Nian, 2023; Jack et al., 2025). However, this literature has overlooked how reduced agricultural fires from policies can alter arthropod populations and introduce new health risks unrelated to air pollution and how straw recycling can reduce this unintended health risk.

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

## 2 Straw Burning, Ecosystem, and Vector-Borne Diseases

### 2.1 Straw-Burning Ban Policy

On-site straw burning, a traditional agricultural practice used to clear crop residues after harvest, has long been recognized as a major source of air pollution in China, particularly during the harvest season in rural areas (He et al., 2020). To address its environmental and public health consequences, China launched the straw-burning ban as part of a broader strategy to control air pollution (Barwick et al., 2024). The policy was implemented in a staggered manner across regions. Figure 2 shows the cumulative number of counties that adopted the ban over time. By the year 2022, more than 1,400 counties had enacted formal straw-burning bans.[8] This staggered rollout provides a quasi-experimental setting that enables causal identification of the policy's effects using a difference-in-differences (DID) framework.

Two features of the policy design are crucial for our empirical strategy. First, the timing of policy adoption was not driven by local health trends but instead reflected a top-down administrative hierarchy. Areas surrounding Beijing and other provincial capitals were prioritized in the early stages of the rollout due to their political importance and alignment with national performance targets (detailed in Appendix D). As illustrated in Figure D1, the ban was initially concentrated in the North China Plain and gradually expanded to northeastern and other northern regions. We show in Section 4.1 that the adoption timing is uncorrelated with pre-treatment health facility characteristics, reinforcing the plausibility of our identification strategy.

Figure 2 about here.

Second, we focus on bans that included performance evaluations to ensure the measurement of effective implementation. These evaluations, such as assessment criteria and reward-punishment

[8] The construction of the policy rollout measure is described in Section 3.

frameworks, have significantly improved local compliance.[9] In addition, beginning in 2011, the central government introduced a set of reforms to enhance compliance, including the use of satellite-based remote sensing to monitor fire hotspots and the introduction of formal performance metrics with reward–punishment mechanisms for local officials.[10] These measures increased the credibility and consistency of enforcement, allowing for a more accurate assessment of policy impacts.

Following the policy rollout, cropland fires in China declined significantly. Figure F1 in the appendix compares the distribution of cropland fires at the beginning and end of our study period, illustrating a notable reduction in cropland fire incidents, particularly in regions that adopted the ban earlier.[11]

### 2.2 Arthropods and Vector-Borne Diseases

Arthropods, such as mosquitoes, flies, and ticks, are closely linked to human populations due to their role as vectors of infectious pathogens including viruses, bacteria, and parasites.[12] Many arthropods thrive in warm, vegetated environments characterized by leaf litter, grasses, and dense undergrowth. Post-harvest crop residues create such microhabitats, providing shelter, moisture, and food that allow arthropod populations to survive through winter.

**Arthropod-Related Health Outcomes** Our primary health outcome variables are hospitalizations and medical expenditures associated with vector-borne diseases. Specifically, they include infectious diseases transmitted by arthropods, along with allergic or toxic reactions resulting from arthropod bites. The diseases included in our analysis were selected based on authoritative medical textbooks and peer-reviewed literature explicitly focused on arthropod-related illnesses. The full list is presented in Table C1.

We further distinguish tick-borne diseases as a separate category due to their distinct epidemiological profile, characterized by severe health outcomes and their prominence as a representative vector-borne disease in agricultural environments.[13] Tick-borne diseases are particularly sensitive to ecological changes, such as those caused by post-harvest straw retention, as many tick species

[9] Effective enforcement requires significant human and financial resources. For example, official reports from Henan Province document the high cost of policy enforcement (see the official website of Chinese Government, in Chinese).

[10] 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, implying formal monitoring was already in use by then (see the technical specification, in Chinese).

[11] We observe limited increase in straw recycling and biomass power plants following the policy (**??**). These developments are accounted for using fixed effects and further examined in our heterogeneity analysis (Table 8).

[12] The phylum *Arthropoda* includes multiple classes, most notably *Insecta* (e.g., flies, mosquitoes, beetles) and *Arachnida* (e.g., ticks, spiders, mites). Arthropods can transmit pathogens among livestock and wildlife, facilitate zoonotic transmission to humans, and, in some cases, enable direct human-to-human transmission of diseases such as dengue fever, malaria, and Zika virus. See Appendix B for details.

[13] Ticks feed on the blood of mammals, birds, and reptiles, often remaining attached to hosts for several days. Because tick bites are typically painless, early detection is difficult; delayed identification can lead to serious illness or death. Vaccines are unavailable for most tick-borne diseases, and hospitalization may be necessary for tick removal or treatment of complications.

overwinter in their adult stage rather than as eggs. The list of tick-borne diseases analyzed is provided in Table C2, with representative examples including SFTS, Lyme disease, rickettsiosis, tick-borne encephalitis, and tick paralysis.

**The Lethal Risk of Vector-Borne Diseases: Evidence from SFTS** SFTS is a highly virulent tick-borne viral illness that exemplifies the severe health risks associated with ecological changes affecting tick populations.[14] While the primary mode of transmission is through the bite of an infected tick, there is also a documented risk of human-to-human transmission via direct contact with infected blood. Among older adults, the case fatality rate can reach up to 50% (Chen et al., 2025), making it one of the most lethal vector-borne diseases currently circulating around the world. In May 2022, in Xinyang, Henan Province, four elderly individuals were infected following a single tick bite incident; all subsequently died.[15]

# 3 Data

We construct a county-level panel dataset by integrating multiple sources, including hospitalization records, administrative policy documents, satellite-based detections of straw burning, insect biodiversity observations, web search activity, agricultural land use, and environmental characteristics. To ensure relevance to the policy context, we exclude remote counties with minimal human presence or agricultural activity, particularly those that have never recorded any fire incidents. Table 1 presents summary statistics for the main variables used in the analysis. Columns (2) through (4) report sample size, time horizon, and data frequency; columns (5) and (6) summarize the mean and standard deviation of key outcomes. Additional details on data sources and variable construction are provided below and in Appendix A.

Table 1 about here.

## 3.1 Data Sources

**Hospitalization Data** We use inpatient medical records from public hospitals across China from 2015 to 2022, obtained from the Data Center for High-Quality Hospital Management at Peking University's Institute for Global Health and Development. It was collected by an independent anonymous third-party company for the purpose of monitoring electronic medical records. To our knowledge, this dataset represents the most comprehensive collections of inpatient medical records from public hospitals nationwide after 2015, covering approximately 21% of tier-2 and

[14]Caused by the SFTS virus, the disease typically presents with high fever, thrombocytopenia, and gastrointestinal symptoms such as vomiting and diarrhea.
[15]See Sina News for details.

tier-3 hospitals across 30 provinces.[16] The data quality is reliably high, as hospitals have strong incentives to maintain accurate and complete digital records.[17] The dataset includes hospitalization records from all departments within each hospital. So we construct different disease categories, such as vector-borne diseases, tick-borne diseases, and diseases commonly associated with air pollution, such as respiratory and cardiovascular conditions.

Panel (a) in Figure 3 illustrates the distribution of vector-borne diseases in our dataset from 2015 to 2022. Because the data was not collected for administrative purposes, it is unlikely that they are subject to selection bias. We show in Appendix A that there is no evidence the selection in county, hospital, duration in sample, and having an infectious disease department correlates to the timing of straw-burning ban policies, or city administrative hierarchy, as shown to be correlated with the straw-burning ban rollout.

Each hospitalization record contains admission and discharge dates, ICD-10 codes of primary and secondary diagnoses, patient demographics (gender, age, and insurance type), and hospital characteristics, tier—2 and 3, class—A, B, and C, and type- general and specialized.[18] We aggregate these records to the county-by-year-quarter level, allowing for seasonal variation in disease transmission. More details on the data source, variable construction, and age distribution of vector-borne disease patients are provided in Appendix A.1.

**Policy Data** We construct the policy treatment variable using official government documents from the Peking University Law Database, the most comprehensive and authoritative archive of Chinese policy texts.[19] We begin by retrieving all local regulatory documents containing the keyword "straw-burning ban." Each document is manually reviewed and coded to identify whether it includes clearly defined performance assessment measures and whether it is accompanied by straw recycling measures or subsidies. Based on these classifications, we group policies into two categories: (1) straw-burning prohibition policies with assessment mechanisms, which form the basis of our benchmark analysis, and (2) policies that additionally include straw recycling measures, which are used in our heterogeneity analysis. Appendix Figures Figure A1 to Figure A3 provide examples of these different policy types from a city in China.

To construct a county-level treatment variable consistent with the hospitalization data, we define a county as subject to the straw-burning ban beginning in the first year that either the county

[16]In China, public hospitals are the primary providers of inpatient care, whereas private hospital coverage is highly limited in China. The number of hospitalizations in private hospitals accounts for less than 24% of that in public hospitals (National Health Commission of the People's Republic of China, 2022). Public hospitals are classified under a three-tier system, where tiers (1, 2, 3) indicate ascending levels of capacity, service scope, and administrative oversight—with tier 3 being the highest. Hospitalizations of tier-1 hospitals accounts for only 5.7% of all public hospitals (National Health Commission of the People's Republic of China, 2023).

[17]Medical records serve as the foundation for both public and private insurance reimbursements. Hospitals risk financial losses if patients are misclassified to inaccurate diagnoses. In addition, participation in the digital reporting system is mandated by the National Health Commission. See more details in Appendix A.

[18]Hospitals in each tier is further divided into three classes (A, B, C), with class A representing the highest quality in terms of facilities, staffing, and performance. There are two types of hospitals in China: general hospitals and specialized hospitals.

[19]https://www.pkulaw.com.

itself or its governing prefecture-level city implemented a ban.[20] Specifically: (1) if a county-level government issued a ban, we assume it remains in effect from that year onward; (2) if no county-level policy exists, we assign the policy date of the corresponding prefecture-level city. Given that enforcement relies heavily on local capacity (He et al., 2020; Cao and Ma, 2023), national and provincial-level policies are not treated as binding unless followed by concrete implementation at the city level.[21]

In practice, some regions may issue multiple straw-burning ban directives. These typically fall into two categories: repeated emergency notices and detailed implementation plans outlining supporting measures, such as personnel deployment and resource allocation. As a result, the number of repeated policy issuances may reflect the intensity of enforcement. We therefore use the cumulative number of straw-burning ban policies issued by a county as a proxy for policy intensity in our robustness checks. More details of the variable construction are provided in Appendix A.2.

**Straw Burning** To measure straw-burning activity with high spatial and temporal precision, we combine two satellite products: the MODIS Burned Area Product and the MODIS Land Cover Type Product (MCD12Q1), covering 2001–2022. These datasets provide consistent and reliable measurements for fire detection.[22] We identify straw-burning events by overlaying MODIS fire detections with cropland classifications from MCD12Q1, following Assunçãoa et al. (2019) (see Appendix A.3 for details). This method minimizes misclassification from forest fires and ensures high-resolution coverage over our study period. We aggregate the number and area of cropland fires to the county-year level. As a robustness check, we also construct analogous measures for forest fires and include them as controls to isolate the effects of agricultural burning.

In our empirical analyses, we control for the quarterly/annual frequency and burned area of forest wildfires. This mitigates measurement errors from the expansion of wildfires and enhances the robustness of our results.

**Insect observations** We obtain species observation data across various taxonomic categories from iNaturalist, an online social network and biodiversity platform. Specifically, we collect insect biodiversity data for China between 2015 and 2022. iNaturalist provides one of the most comprehensive sources of science-based species observations available nationwide. The platform enables users to share geotagged observations of organisms, thereby contributing to a collaborative database that supports scientific research, conservation efforts, and public education. This community-generated dataset offers a valuable resource for analyzing ecological patterns across

[20] For simplicity, we refer to prefecture-level cities as "cities" throughout the paper.

[21] Costs include dispatching personnel to patrol fields and prevent burning; for example, a major agricultural county in northeastern China incurred over 100,000 CNY (approximately 13,700 USD) in meal expenses for field personnel during enforcement periods (Xinhua News).

[22] MODIS data are provided by NASA's Land Processes Distributed Active Archive Center. The two products are collected independently of Chinese administrative reporting and are widely used in remote sensing applications to detect both fire events and burned areas, offering high spatial and temporal resolution.

taxonomic groups.

Each iNaturalist record corresponds to a single observation of a species and includes information on the observation date, geographic coordinates (latitude and longitude), a unique observer ID, and the kingdom and phylum of the observed species.[23] From 2015 to 2022, we compile a total of 99,814 individual-by-species observations.

Although observation data may be subject to sampling bias due to spatial and temporal variations in observer effort and site accessibility, we address this concern by aggregating records to the county-year level and controlling for observation effort using the number of unique contributors per county-year as a proxy (**?**). This approach allows us to mitigate sampling bias and leverage the dataset to investigate ecological changes following policy interventions, especially in regions where systematic ecological monitoring is limited or unavailable.

We focus on observations of taxonomic groups relevant to vector-borne disease transmission, including *Arthropoda*, *Insecta*, *Arachnida*, *Chilopoda*) (see Appendix B for more details). Our primary outcome variables are constructed as the number of observation trips involving species from each taxonomic group at the county-year level.[24]

**Web Searches** We measure public awareness and residents' behavioral responses using the Baidu Search Index, which provides city-level daily search data from 2009 onward. We track search intensity for terms related to straw-burning ban, insect bites, ticks, symptoms or treatment of insect bites, protective behavior, and related vaccination. We calculate the quarterly indices by averaging the daily indices and then summing the search intensities of all keywords within each category to construct a composite index. Because search data are available only at the city level, we aggregate the treatment variable to the city level to capture behavioral responses and public awareness in later analysis, following an approach consistent with existing research using Baidu data. The detailed lists of search terms for each category are provided in Appendix Table A4.

**Other Control Variables** Weather data (temperature and precipitation) are obtained from the Global Summary of the Day (GSOD) dataset.[25] We compute county-level weighted averages using nearby stations, weighting by the inverse distance to the county centroid, and aggregate the data to the county-quarter level for analysis. These controls account for climatic influences on both fire activity and disease dynamics. Land cover data are drawn from Yang and Huang (2021), which provide high-resolution cropland and forest coverage from 1985 to 2022. We aggregate these measures to the county-year level. Land slope is calculated using the ASTER Digital Elevation Model, sourced from China's National Earth System Science Data Center, and serves as a time-

[23]iNaturalist records do not include counts of individuals observed during a single trip.

[24]To reduce the influence of extreme values, we winsorize the top 5% of arthropod observations. Since Insecta, Arachnida, and Chilopoda are all subgroups of the phylum Arthropoda, we winsorize their observations separately to ensure that the value of each subgroup variable does not exceed the maximum value of the overall arthropod observation distribution.

[25]The GSOD database provides daily weather characteristics from over 9,000 weather stations worldwide, covering the period from 1928 to the present.

invariant control for geographic suitability for agriculture. Other control variables—including county GDP, population, total number of hospital beds, and cropland area—are obtained from the China County Yearbooks.

### 3.2 Data Visualization and Descriptive Evidence

We present visualization of data and their descriptive patterns before causal analysas. In Figure 3, Panel (a) displays the distribution of the number of hospitalizations of vector-borne diseases across counties from 2015 to 2022. Panel (b) illustrates a negative correlation across regions: areas with more agricultural fires, such as northeastern China, tend to report fewer vector-borne disease hospitalizations, whereas central, southern, and northwestern regions, with fewer fires, show more hospitalization. Panel (c) classifies vector-borne disease hospitalizations, with insect allergies, fly-borne diseases, and insect toxicity as the most common categories; tick-borne diseases account for 5.6% of cases. Panel (d) displays the monthly trends in hospitalizations, with seasonal pattern and peaks during the second and third quarters, consistent with insect ecology and transmission cycles.

Figure 3 about here.

Figure F1 shows substantial reduction in cropland fires during 2011-2021. Biodiversity observations show an increase in insect abundance over time (**??**). **??** show that search activity related to insect bites and ticks rose sharply, particularly in areas with strong policy enforcement (Figure D1). These descriptive patterns provide preliminary evidence supporting the proposed ecological and health impact pathway. Building on this, we turn to our empirical strategy to identify the causal effects of the policy rigorously.

## 4 Empirical Strategy

We exploit the staggered implementation of China's straw-burning ban using a difference-in-differences (DID) framework to estimate its causal impact on hospitalizations and medical expenditures related to vector-borne diseases. Traditional two-way fixed effects (TWFE) estimators are known to yield biased estimates in settings with treatment effect heterogeneity across cohorts or over time (Goodman-Bacon, 2021; Sun and Abraham, 2021). To address this issue, we adopt the imputation-based estimator developed by Borusyak et al. (2024), which delivers well-defined causal parameters that are robust to such heterogeneity.

Following Borusyak et al. (2024), our estimation proceeds in three steps. First, we estimate unit and time fixed effects using only data from untreated observations—i.e., counties that are never treated or not yet treated at a given time. Second, we use the estimated fixed effects to impute the counterfactual untreated outcome for each treated observation. Third, we compute the treatment effect as the difference between the observed and imputed counterfactual outcome and obtain the final estimate by averaging these effects across treated units using pre-specified weights.

This approach allows us to compare outcomes in counties affected by the straw-burning ban with outcomes in counties that are never or not yet treated, while controlling for a rich set of fixed effects and time-varying characteristics. Specifically, we control for county-level covariates, county-by-year fixed effects, and province-by-year-quarter fixed effects. This estimator avoids the negative weighting and "forbidden comparisons" problems that distort TWFE estimates, and under standard DID assumptions, yields unbiased and efficient estimates even in the presence of treatment effect heterogeneity across cohorts and over time.

We now formalize the estimation procedure. Let $D^{gt}$ be a binary treatment indicator and $Y^{gt}$ the outcome for group $g$ in period $t$. In our context, group $g$ denotes a set of counties with the same policy adoption time, and $D^{gt} = \mathbf{1}[t \geq E^g]$, where $E^g$ is the period in which group $g$ first adopts the straw-burning ban. For never-treated groups, $E^g = \infty$. The set of treated observations is defined as $\Omega_1 = \{(g,t) : D^{gt} = 1\}$, with cardinality $N_1 = |\Omega_1|$.

Let $Y^{gt}(0)$ denote the potential outcome in the absence of treatment. The treatment effect for treated observations is $\tau^{gt} = \mathbb{E}[Y^{gt} - Y^{gt}(0)]$. Given a vector of non-random weights $w = (w^{gt})_{(g,t)\in\Omega_1}$, the estimand is:

$$\tau_w = \sum_{(g,t)\in\Omega_1} w^{gt}\tau^{gt}.$$

In our dataset, each observation is indexed by county $c$, province $p$, year $y$, and quarter $q$. To make the notation explicit, we extend the indexing to include these components. The first step involves estimating the untreated potential outcome model:

$$Y^{gt}_{cpyq}(0) = \mathbf{X}'^{gt}_{cpyq}\alpha + \eta^{gt}_{cy} + \delta^{gt}_{pyq}, \tag{1}$$

where $Y^{gt}_{cpyq}$ denotes the outcome of interest (hospitalizations or medical expenditures from vector-borne diseases), and $\mathbf{X}_{cpyq}$ includes county-level time-varying controls such as hospital characteristics, weather conditions, and forest fires. The fixed effects $\eta^{gt}_{cy}$ and $\delta^{gt}_{pyq}$ absorb unobserved shocks at the county-year and province-year-quarter level, respectively. This regression is estimated using only untreated observations.

In the second step, we impute the untreated counterfactual outcome for treated observations:

$$\hat{Y}^{gt}_{cpyq}(0) = \mathbf{X}'^{gt}_{cpyq}\hat{\alpha} + \hat{\eta}^{gt}_{cy} + \hat{\delta}^{gt}_{pyq}. \tag{2}$$

The estimated treatment effect for each treated observation is then given by:

$$\hat{\tau}^{gt}_{cpyq} = Y^{gt}_{cpyq} - \hat{Y}^{gt}_{cpyq}(0).$$

Finally, we compute the average treatment effect on the treated (ATT) using equal weights:

$$\hat{\tau}_w = \sum_{(g,t)\in\Omega_1} w^{gt}_{cpyq}\hat{\tau}^{gt}_{cpyq}, \quad \text{where} \quad w^{gt}_{cpyq} = \frac{1}{N_1} \quad \forall (g,t,c,p,y,q) \in \Omega_1.$$

This yields:

$$\hat{\tau}_{\text{ATT}} = \frac{1}{N_1} \sum_{(g,t,c,p,y,q)\in\Omega_1} \hat{\tau}^{gt}_{cpyq}.$$

To assess the robustness of our findings, we implement three complementary estimation strategies. First, we apply alternative methods including (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021), showing consistent estimates. Second, we apply the Poisson pseudo-maximum likelihood (PPML) model as hospitalization numbers are count outcomes. Results from the PPML method align with our benchmark estimates. Third, we explore the effect of treatment intensity, measured by the accumulative number of straw-burning ban insurances. We estimate this effect using the approach developed by de Chaisemartin et al. (2022) to accommodate continuous treatment within a staggered DID framework. Further details on these robustness checks are provided in Section 5.2.

## 4.1 Identification

The identification of the policy's effects leverages the staggered rollout of the program across counties. The key identification assumption is that, in the absence of the straw-burning ban, outcomes in treated and untreated counties would have followed parallel trends. While this assumption is not directly testable, we outline below a series of validation strategies that address potential sources of bias—including policy endogeneity, omitted time-varying confounders, spillovers, and concurrent policies—and demonstrate that they are unlikely to undermine our causal interpretation.

**Pre-treatment Trend** We assess the plausibility of parallel trends using event-study specifications (Figure 4). Results indicate no significant pre-treatment differences between treated and untreated counties. Robustness checks using alternative specifications for health outcomes, as well as regressions for other outcomes—such as fires, insect populations, and residents' responses—also confirm the parallel trends assumption.

**Assignment to Straw-Burning Ban Policy** A central concern is that the policy may be endogenously implemented in response to unobserved factors correlated with vector-borne disease outcomes. To address this concern, we present evidence suggesting that the policy rollout was plausibly exogenous to insect-related health trends and that potential confounders are unlikely to drive our results. First, the straw-burning ban was part of China's broader effort to mitigate air pollution. As shown in Figure D2, the rollout pattern of the straw-burning ban closely mirrors that of the Air Pollution Monitoring and Disclosure Program, which has been shown to follow an administrative sequence (Barwick et al., 2024).

We further confirm that the rollout pattern is not correlated with local health infrastructure. Table D1 and Table D2 examine socioeconomic and infrastructural characteristics across different policy adoption waves. Earlier-treated counties tend to have higher GDP and larger populations, consistent with prioritization of higher-level administrative regions. However, other potentially confounding factors—such as cropland area and healthcare infrastructure—do not explain the timing of policy adoption, conditioning on administrative hierarchies. To address concerns that air quality improvements induced by the policy may confound the estimated health effects, we examine the relationship between $PM_{2.5}$ concentrations and vector-borne disease hospitalizations. Table D3 shows no statistically significant relationship between $PM_{2.5}$ levels and vector-borne disease hospitalizations, suggesting that our health outcomes are unlikely to be driven by coincident improvements in air quality.

**Fixed Effects and Time-Varying Controls** Our empirical specification includes county, year-quarter, and province-by-quarter fixed effects to account for time-invariant regional characteristics, macroeconomic trends, and regional seasonal patterns. These fixed effects absorb variations related to changes in, for example, population age structure, industrial composition, agricultural activities, and public health or climate policies.

To further mitigate concerns about potential confounding from quarterly-varying county-level factors, we include a comprehensive set of controls grouped into four categories: First, we control for hospital operational characteristics, as the recorded incidence of vector-borne diseases may be affected by local healthcare capacity. Specifically, we include the number of hospitals by tier, class, type, and total number of hospitals in each quarter, as well as the the average number of annual hospitalization. Second, we control for weather conditions, including temperature and precipitation, which can influence insect activity and human exposure. Third, we include socioeconomic characteristics that may affect health outcomes, such as GDP, population, cropland area, and the total number of hospital beds. Finally, we control for forest fire incidence and area to distinguish the effects of straw burning from broader ecological disturbances.

**Concurrent Policies** Several concurrent agricultural and health reforms overlapped with the implementation period of the straw-burning ban. However, it is unlikely that these policies confound our results for two main reasons. First, most were national in scope or implemented as provincial pilot programs, which can be captured by the province-by-year-quarter fixed effects in our empirical model. Second, none of these concurrent policies directly increase insect populations. Appendix D provides additional details. To rule out the potential influence of the COVID-19 pandemic (2020–2022) on our results, we exclude these three years from the analysis and confirm that the main findings remain robust (Table E10).

The study period coincides with several national and local initiatives that could potentially confound the estimated effects of the straw burning ban. While the central government launched the Sloping Land Conversion Program —these programs were broadly awarded across .... and not explicitly linked to environmental objectives. In contrast the straw burning ban was a punitive policy focused on environmentally .... To mitigate confounding, all regressions include ... and year fixed effects. We further account for the influence of concurrent environmental regulations

—such as provincial $SO_2$ reduction targets, national energy conservation campaigns, and clean air mandates—by excluding affected regions and sectors in a battery of robustness checks (Appendix Table xxx). The estimated effects remain consistent in both magnitude and significance. These identification strategies collectively reinforce that our results are not driven by contemporaneous policy interference.

**Spillover Effects** Within-county spillovers (i.e., rural-to-urban exposure) are captured in our aggregated county-level measures. However, inter-county spillovers remain a potential concern if treatment in one county affects outcomes in neighboring untreated counties. Due to the cumulative and dynamic nature of spillovers under staggered adoption, conventional parametric spillover estimators are inapplicable in our framework. To address this, we conduct a robustness check in Section 5.2, where we exclude geographically adjacent treatment and control counties to find the direct effect. The results support the validity of our identification.

### 4.2 Pathway Analyses

We conduct two efforts to verify the impact pathway. First, we apply the same DID specification to a range of related outcomes, including agricultural fires, insect populations, and responses in awareness and defensive investment to insect exposure. Second, if the impact operates through changes in agricultural fires and insect population dynamics, we would expect to see heterogeneity along closely related dimensions. To test this, we examine whether the policy's effects vary by rural versus urban populations, by major crops that differ in pre-ban straw burning practices, by climate patterns that affect insect populations, and by harvest versus non-harvest seasons that shape human exposure to agricultural fields. Together, these analyses substantiate the proposed mechanism of impact.

## 5 Result

### 5.1 Straw-Burning Ban and Vector-Borne Diseases

We first examine the impact of the straw-burning ban on the incidence of vector-borne diseases. Table 2 presents the results. Panel A reports the effects on all vector-borne diseases, while Panel B focuses specifically on tick-borne diseases—a medically severe subset that includes illnesses such as Lyme disease and SFTS. The dependent variables are the inverse hyperbolic sine (IHS) transformations of hospitalization counts and expenditures. Columns (1)–(5) use the number of hospitalizations as the dependent variable. Column (1) includes county and year-quarter fixed effects and shows that the ban significantly increases hospitalizations for vector-borne diseases. Column (2) adds province-by-quarter fixed effects, and Columns (3)–(5) progressively incorporate additional controls. The results remain robust across specifications. In Column (5), the estimated effect implies a 50.2% increase relative to the sample mean, corresponding to 12 additional cases per county per quarter (23.812 × 0.502). Columns (6)–(10) examine medical expenditures, revealing that the ban leads to a 173.2% increase relative to the sample mean, or approximately 203,365 yuan (117,461 × 1.732, approximately 0.28 million U.S. dollars) per county per quarter. The estimates for tick-borne diseases also show statistically significant effects, albeit with smaller magnitudes.

Table 2 about here.

To assess the economic impact, a back-of-the-envelope calculation suggests that, across the 1,403 counties where the ban was implemented, the annual increase in hospitalization costs for vector-borne diseases amounts to 2.81 billion CNY (approximately 388 million U.S. dollars).[26] Of this amount, 69.3 million CNY is attributable to tick-borne diseases (7,569 × 0.703 × 4 × 1,403 × 2.32 = 69.3 million, approximately 9.6 million U.S. dollars). Our estimates likely represent a lower bound on the total economic burden, as outpatient data is unavailable.

**Medical Burden Compared to Benefits from Air Pollution-related Diseases Reduction** Although we do not have outpatient data and thus cannot directly assess the absolute magnitude of the health costs, we leverage our dataset to estimate the impact of the straw-burning ban on diseases known to be sensitive to air pollution. This allows for a meaningful comparison with findings from prior literature. Existing studies have identified respiratory and cardiovascular diseases—corresponding to ICD-10 codes J00–J99 and I00–I99 —as major categories affected by air pollution.

We estimate the effect of the ban on these diseases. As shown in Table F1 in the Appendix, hospitalizations and medical expenditures for respiratory and cardiovascular diseases declined following the ban. The reduction in medical expenditures attributable to improved air quality is approximately 1.86 million yuan per county per quarter for respiratory diseases and 1.67 million yuan for cardiovascular diseases (the latter being statistically insignificant).

Comparing these savings with the estimated increase in vector-borne disease-related expenditures, we find that the additional cost offsets about 10.96% of the respiratory benefits. This unintended health cost is nontrivial and warrants serious consideration in future policy design.

**Event Study** We implement an event study framework to test for parallel trends prior to the policy and examine its dynamic effects post-implementation. The upper and lower panels of Figure 4 display estimates for vector-borne disease-related hospitalizations and medical expenditures, respectively. The x-axis shows quarters relative to the policy rollout, with the vertical dashed line

[26] The calculation proceeds in two steps. First, since our dataset does not cover all hospitals within each county, we extrapolate our estimates to the national level by applying a multiplier based on hospital coverage. Specifically, we use the ratio of the full national system (14,668 tier-2 and tier-3 hospitals across 2,843 counties) to the hospitals covered in our data (2,788 tier-2 and tier-3 hospitals across 1,252 counties), as reported by National Health Commission of the People's Republic of China (2023), yielding a multiplier of 2.32. Total medical expenditure is calculated as 203,365 × 4 × 1,403 × 2.32 = 2.65 billion CNY. Second, since total hospitalizations of tier-1 hospitals accounts for 6.2% of those in tier-2 and tier-3 hospitals, we calculate the hospitalization cost for tier-1 hospitals as 2.65 × 6.2% billion = 0.16 billion CNY. The combined total is 2.81 billion CNY.

marking the quarter of implementation. The y-axis reports estimated treatment effects relative to untreated counties, along with 95% confidence intervals.

Figure 4 about here.

The insignificant pre-treatment coefficients support the parallel trend assumption and the persistently positive post-treatment coefficients indicate a sustained rise in hospitalization and medical expenditures post policy implementation. Figure E1 shows similar patterns in the policy's dynamic effects on tick-borne diseases, Figure E2 shows consistent results from using the CSDID estimator (Callaway and Sant'Anna, 2021), and Figure E3 shows the results using (Sun and Abraham, 2021), further validating the persistence and magnitude of the policy's unintended health consequences.

## 5.2 Alternative Concerns and Robustness Checks

To ensure the robustness of our results, we conduct a series of robustness checks. For brevity, we present the detailed regression results are reported in Figure E2 and Figure E3, as well as Table E3 through Table E10 in the appendix.

**Spillover Effects** We recognize that DID estimates may be biased when spillover effects occur across county borders: adjacent treatment and control counties may lead to biased treatment effects if they are indirectly affected through the ecological spread of insects.[27] To mitigate these concerns, we exclude geographically adjacent treatment and control counties.[28] Figure F2 illustrates the spatial and temporal distribution of treated counties after removing adjacent counties across treatment waves and between treatment and control groups. We then re-estimate our baseline models using this restricted sample.

The results, presented in Table E3, remain substantial and statistically significant, and are comparable in magnitude to the average effects reported in Table 2.

**Alternative Estimation Models** To validate the robustness of our two-stage staggered DID estimates, we employ two widely used alternative approaches. First, we implement the methods proposed by Callaway and Sant'Anna (2021) and Sun and Abraham (2021), which address treatment effect heterogeneity and correct for potential bias in staggered adoption settings. As shown in Table E5 and Table E6, the results closely align with those from our benchmark model, while the event study plots (Figure E2 and Figure E3) further confirm the persistence of the treatment effects for up to four years after the ban.

[27] It is worth noting that our analysis is conducted at the county level, and we are therefore unable to directly observe or disentangle potential spillover effects occurring within counties. However, in Section 6.4, we perform a heterogeneity analysis comparing urban vs. rural health outcomes, which further implies the existence of within county spillovers.

[28] Explicitly estimating spillover effects under a staggered adoption model is challenging due to the cumulative nature of spillovers and the inapplicability of parametric approach for staggered model.

Second, although the inverse hyperbolic sine (IHS) transformation is suited for the outcome variables, we also present results using alternative specifications, specifically $log(1 + x)$ transformations for robustness check. We also use a PPML model which provides efficient estimator for count data (Correia et al., 2020). The results, reported in Table E7 and Table E8, remain consistent with our baseline findings.

**Alternative Policy Measurement: Treatment Intensity** A potential concern in evaluating policy effects is variation in treatment intensity across regions and over time. To account for this, we construct a measure for policy intensity as the cumulative number of straw-burning ban documents issued.[29] Table E9 presents the estimation results using this intensity-based measure. We use the method proposed by de Chaisemartin et al. (2022) to integrate treatment intensity within a staggered DID framework. The findings remain consistent with our baseline estimates.

**Alternative Sample** As an additional robustness check, we re-estimate our main models using a subsample from 2015 to 2019, which excludes the period of the COVID-19 pandemic. The results, reported in Table E10, remain consistent with our baseline estimates and continue to show significant effects of the straw-burning ban on hospitalizations of vector-borne diseases.

# 6 Pathway of Impact

To empirically validate the mechanism through which the straw-burning ban affects insect population and the associated health outcomes, we trace the full causal pathway linking environmental policy to disease outcomes.

## 6.1 Straw Burning

We begin by examining the policy's impact on agricultural burning. Using county–year-level data on cropland fires, we apply the difference-in-differences imputation estimator of Borusyak et al. (2024). The primary dependent variables are the frequency and total burned area of cropland fires during the harvest season. To ensure consistency with the main analyses on hospitalization data, we restrict the sample period to 2015–2022. The specification includes county and year fixed effects, as well as controls for weather conditions, wildfire characteristics, grain planting area, GDP, and population. Estimation results are reported in Table 3, and the corresponding event-study plots are presented in Figure 6.

Table 3 indicates substantial annual reductions in both the frequency of agricultural fires (-0.21 fires, 119.8% of the sample mean) and total burned area (-0.496 $km^2$, 91.2% of the sample mean)

[29] Local governments sometimes issue repeated documents—such as emergency notices and enforcement announcements—to signal increased urgency and stronger implementation efforts. The cumulative number of such documents serve as a meaningful proxy for government engagement and enforcement intensity.

per county following the straw-burning ban.[30] These findings remain consistent across alternative estimation strategies (Table E12).

Table 3 about here.

Panels (a) and (b) of Figure 6 suggest that the parallel trends assumption holds and that the ban's effect on fire incidence persists for at least six years after implementation. As a robustness check, we replicate the event-study analysis using fire data from 2001–2022. Panels (c) and (d) of Figure 6 confirm both the validity of the parallel trends assumption and the persistence of the policy's impact.

Figure 6 about here.

### 6.2 Insect Observations

We next examine whether the straw-burning ban led to insect proliferation. To assess changes in the abundance of disease-relevant species, we use species observation data and apply an inverse hyperbolic sine (IHS) transformation to account for the skewed distribution in the number of species and observers. We evaluate the policy's effect across multiple arthropod taxonomic categories.

First, we estimate the impact of the straw-burning ban on the total number of *Arthropoda* observations. Second, since *Insecta* contains the largest number of species within the *Arthropoda*, we examine the effect of the policy on the total number of *Insecta* observations.[31] Third, since non *Insecta* species certain arthropods linked to severe health risks such as ticks, we also estimate the effect of the policy on observations of non-*Insecta* species such as *Arachnida* and *Chilopoda*.

Table 4 about here.

Our DID model includes county and year fixed effects and time-varying controls such as the number of unique observers, GDP, weather controls, and forest fire characteristics. As shown in Table 4, we find significant increases in *Arthropoda* observations following policy implementation, including both insect and non-insect species. The increase is especially pronounced for *Insecta* observations that are closely associated with disease transmission. Figure 7 presents the event study estimates of the ban's impact on insect populations. The results show no significant pre-trends, supporting the parallel trend assumption, and reveal a persistent increase in insect

[30] Agricultural fires are detected using remote sensing data, counting any burning activity within a 1 km $\times$ 1 km cropland grid in a given month as one event. This approach reduces measurement error arising from variation in cropland size and from the possibility that residues are removed through multiple burns or spatially scattered burning within the same plot. In our estimation sample, the average annual county-level values are 0.178 fire events and 0.648 $km^2$ of burned area.

[31] For instance, within *Insecta*, insect orders such as *Diptera* (e.g., flies, mosquitoes, horseflies), *Lepidoptera* (e.g., stinging caterpillars), *Hymenoptera* (e.g., bees), and *Coleoptera* (e.g., rove beetles) widely recognized as disease vectors or as species associated with dermatological, allergic, or toxicological health conditions via bites or stings (see Appendix B for more details). Thus, species in *Insecta* are known to be linked to vector-borne health outcomes.

abundance following the policy implementation. These patterns are consistent with ecological literature suggesting that reduced fire activity results in lower mortality of insect eggs and improves overwintering conditions for arthropods, thereby increasing their survival rates.

Figure 7 about here.

We also test robustness using alternative empirical specifications and controls such as using log transformation of the number of species observation trips and controlling for weather characteristics in the last period or the number of unique bird observers (see Table E13).

**Discussing Magnitude of Impact** We find that insect populations increased by less than 5%, yet hospitalizations rose by over 50% and medical expenditures by 173%. This seemingly striking pattern can be explained by epidemic theory, drawing on insights from Kilpatrick and Randolph (2012) and Smith et al. (2012), which show that even modest increases in vector abundance can trigger disproportionately large rises in human infections due to nonlinear exposure dynamics. Once vector density exceeds a critical threshold—causing the basic reproductive number ($R_0$) to surpass 1—the frequency of human–vector contact can rise sharply (Anderson and May, 1991), thereby amplifying disease transmission even in response to seemingly minor ecological changes.

Several mutually reinforcing mechanisms help explain this nonlinearity. First, even without a large increase in the overall vector population, insects may become more spatially concentrated near human activity zones, such as cropland edges or residential areas. This spatial redistribution raises the effective exposure rate. Our later finding that the policy's impact is more pronounced during harvest seasons—when people interact more frequently with fields—supports this mechanism (see **??**). Second, the accumulation of straw residues may improve insect survival, extend lifespans, or increase biting frequency, potentially enhancing the proportion of vectors carrying pathogens and thereby intensifying transmission efficiency, even if total insect counts remain relatively stable. Third, there may be a behavioral lag in protective responses. Because the straw-burning ban was designed primarily for air quality improvement, the public likely did not anticipate heightened vector-borne disease risks. As a result, individuals may have lacked timely and adequate protective behaviors—such as using insect repellents, protective clothing, or vaccines—leading to concentrated outbreaks in the early stages of policy enforcement.

### 6.3 Web Search for Insect Awareness and Defensive Investment

To examine behavioral responses, we complement the health data with Baidu Search Indices, which proxy for public concern and non-hospitalized health impacts. Using a DID specification at the city-quarter leve, we analyze search activity for keywords related to straw-burning ban, awareness of insect bites, and defensive investment.[32] The regressions include city and province-by-year-quarter fixed effects to account for regional and seasonal variation in media attention,

[32]Although Baidu data are only available at the city level and may be influenced by media coverage, they represent the best available measurements for non-hospitalized health outcomes and individual risk perception of vector-borne diseases.

internet access, and socioeconomic conditions. We also control weather patterns and forest fires in the regressions. As shown in Column (1) in Table 5, the policy led to significant increases in search activity related to the straw-burning ban, suggesting that the Baidu Search Index effectively captures real-world responses. Columns (2)–(4) examine public awareness using three categories of keywords: insect bites, ticks, and seeking help after being bitten. The results indicate that search volumes increased by 40% to 110% relative to the sample means, with particularly sharp increases in searches related to ticks. Although indirect, these search patterns reflect heightened public concern and exposure, supporting that the observed ecological changes were salient.

Table 5 about here.

We further assess policy-induced defensive behavior and preventive investment. Since not all insect-related illnesses lead to hospitalizations, our baseline estimates likely understate the full economic burden. The analysis of Baidu search activity thus complements the hospitalization data by capturing broader public responses and potential non-severe cases. We classify search activity into two categories: protective measures (e.g., mosquito nets, coils, repellents), and vaccines for vector-borne diseases (e.g., tick-borne encephalitis, yellow fever). Columns (5) and (6) in Table 5 show that the policy significantly increased search activity in both domains, indicating additional health-related costs and behavioral responses beyond hospitalizations.

We also present event study analyses for all six keyword categories in Figure 8. We observe parallel pre-trends for most measures of public awareness and defensive investment. A slight pre-trend appears for searches related to the "straw burning ban," which may reflect anticipatory responses to policy implementation. These findings indicate that heightened exposure prompted behavioral responses and greater demand for protective measures. Yet, the persistence of health effects over time suggests that such measures were insufficient to fully offset the associated risks.

Figure 8 about here.

### 6.4 Supporting Evidence from Heterogeneity Analysis

To further corroborate the channel analysis, we investigate heterogeneity in the policy's effects along three dimensions: (i) rural and urban residents, (ii) the type of major grain cultivated, (iii) regional climate characteristics, and (iv) human exposure to farmland activities captured by harvest and non-harvest seasons. These factors capture variation in population affected, crop-specific ecological interactions, and environmental conditions that influence vector-borne disease transmission, providing additional evidence on the mechanisms underlying our results.

**Rural and Urban Residents** The straw-burning ban policy naturally has a direct impact on rural residents who work in agricultural fields. However, increased insect populations may also spill over into urban areas, either through migration or via infected animals, potentially exposing urban residents to similar health risks. To examine this possibility, we conduct a heterogeneity analysis based on each hospitalized individual's health insurance type. We use two categories: the New Rural Cooperative Medical Scheme (NCMS), which covers rural residents, and those under the Urban Employee Basic Medical Insurance (UEBMI), which covers urban employees.[33]

Table E1 presents the heterogeneous effects of the straw-burning ban on hospitalizations for vector-borne and tick-borne diseases. Columns (1) and (2) show significant increases in vector-borne diseases hospitalizations for individuals covered by NCMS and UEBMI, with similar magnitude of impact. Columns (3) and (4) shows the impact on tick-borne diseases is more significant and of larger magnitude for rural residents. This can be intuitively explained by the ecological characteristics of ticks, since ticks are incapable of flight and have a limited range of activity, typically only several tens of meters. These findings suggest that the straw-burning ban has spillover effects beyond rural areas, potentially affecting urban populations as well.

**Heterogeneity by Major Grain** The effects of the straw-burning ban are expected to manifest primarily in regions where open-field burning of straw residues was common prior to the policy. Such variation is largely driven by differences in post-harvest straw management practices across crop types. Two representative cases are wheat and corn. Wheat straw—owing to its low market value and high collection costs—was almost always burned on-site before the ban. In contrast, corn straw has higher economic value and is frequently collected for use as fodder or fuel, making open-field burning relatively rare.[34] **??** presents the heterogeneous effects of the ban across counties with different dominant grain types. Column (1) reports the baseline results for all counties. Column (2) shows that the effect is significantly stronger in wheat-producing regions. In contrast, column (3) indicates no discernible impact in corn-dominated regions.

**Heterogeneity by Climate** **??** examines heterogeneity in the health effects of the straw-burning ban across counties with different climatic conditions—specifically precipitation and temperature—both of which are ecologically relevant to vector-borne disease transmission.[35] We classify counties by median of their average annual precipitation or temperature during 2015–2022.

The results show that the straw-burning ban significantly increases hospitalizations in both high- and low-precipitation areas, as well as in warm regions. In contrast, the estimated effects are smaller and statistically insignificant in low-temperature counties. These findings provide indirect support for the proposed mechanism: the policy's impact on insect-related health outcomes is more pronounced in warmer regions, where unburned straw likely improves insect habitats

[33] Before 2016, urban non-employed residents were covered by the Urban Resident Basic Medical Insurance (URBMI). After 2016, to reduce disparities in healthcare access between urban and rural populations, the NCMS and URBMI were gradually integrated into the Urban and Rural Resident Basic Medical Insurance (URRBMI). Therefore, we do not use URBMI to identify urban residents. See Appendix A.1 for details.

[34] Wheat straw is typically returned to the field, whereas corn straw is often collected for further utilization (Wu et al., 2021).

[35] Wet and warm environments are well-documented to enhance vector survival, reproduction, and activity. See Tanaka and Tanaka (1982), Bale and Hayward (2010), Miao et al. (2019), França et al. (2020), Ma et al. (2025) for references.

and increases vector abundance. In colder regions, vector survival and activity are naturally constrained, weakening the ecological and health effects of the ban. The lack of differential effects by precipitation may reflect offsetting forces—while humid conditions favor insect survival, drier regions tend to experience more open burning prior to the policy, potentially mitigating the contrast.

**Heterogeneity by Human Exposure** If the ban affects disease incidence by increasing insect populations, then human exposure should be a key factor amplifying health risks. One period of particularly high exposure is the harvest season, when people spend more time working in the fields. We test this implication by comparing the ban's effects between harvest and non-harvest seasons, using data aggregated at the county-month level. As shown in the results (see **??**), the impact of the ban on vector-borne diseases is significantly larger during harvest months. This finding suggests that increased human exposure plays an important role in translating ecological changes into health risks, further supporting our proposed mechanism.

# 7 Role of Straw Residue Management and Policy Implications

The results above reveal an unintended ecological and health consequence of China's straw-burning ban: an increase in vector-borne diseases with substantial medical costs. A critical question, then, is how to avoid these negative health impacts while still achieving the air pollution reductions that the ban targets. Given that open-site straw burning remains widespread in many developing countries—and similar bans may be implemented elsewhere for environmental reasons—it is important to draw policy implications for designing effective and balanced interventions in comparable contexts.

An important but often overlooked aspect in practice is how straw residues are managed after burning bans are implemented. As illustrated in Figure F3, regions in China varied widely in their post-ban handling of straw residues. In some areas, straw was left to accumulate on cropland and later crushed and buried into the soil before the next planting season. In other regions, however, local capacity enabled more effective removal or recycling of straw. The primary methods involve baling and collecting straw for use as livestock feed or as fuel for biomass power plants. Because the cost of collection and processing often exceeds the market value of recycled straw, the extent of recycling is highly dependent on government subsidies (He et al., 2020) and industrial demand, particularly from biomass energy facilities (Cao and Ma, 2023; Nian, 2023). Since accumulated straw residues improve overwintering conditions for insects, regions where straw was not removed are more likely to experience negative health consequences. To test this hypothesis, we examine whether improved straw management practices—such as removal or recycling—can mitigate these unintended effects.

Figure F3 about here.

We construct multiple measures to capture the extent of straw residue removal and recycling. First, for straw recycling subsidies, we use two approaches. Following He et al. (2020), we consider the central government's 2016 incentive-based policy that subsidized individuals and enterprises to recycle straw from fields. Under this policy, ten provinces received subsidies totaling 1.3 billion RMB (approximately 186 million USD). We treat counties within these provinces as part of the subsidized group. As an alternative measure, we identify counties covered by straw-burning prohibition policies that explicitly mention subsidies for straw recycling in their policy documents.[36] Second, we use the number of biomass power plants per county as a proxy for recycling capacity. Biomass power plants incentivize farmers to collect straw residues for electricity generation, thereby reducing residue accumulation in fields (Cao and Ma, 2023; Nian, 2023). These measures capture institutional and infrastructural efforts to reduce straw residues, which may mitigate ecological conditions conducive to vector-borne disease transmission.[37]

Table 8 presents the heterogeneous effects of the straw-burning ban based on straw recycling measures. Columns (1) and (2) examine the role of recycling subsidies as province level policy, finding that the effect is statistically insignificant in counties receiving such support, while the effect is significantly larger in counties that did not receive support. Columns (3) and (4) compare the effects of the ban in counties with and without formal recycling policies. The estimated health effects are significantly smaller in regions with recycling policies, suggesting that straw removal mitigates disease risks. Consistent with these findings, columns (5) and (6) show that counties with greater recycling capacity—measured by the number of biomass power plants—also exhibit statistically insignificant policy effects on vector-borne disease hospitalizations.

Table 8 about here.

We plot event studies for groups classified using all three recycling measures. Across specifications, we find no significant differences in pre-trends between the two groups. After the policy implementation, however, counties without recycling subsidies, without explicit recycling policies, or with fewer biomass power plants show a clear increase in vector-borne diseases, while the impact is much smaller in counties with stronger recycling capacity.

Figure 10 about here.

These results confirm that effective straw recycling reduces exposure to disease vectors by removing crop residues and thus limiting favorable ecological conditions for insect survival. As such, straw recycling and biomass utilization represent a promising dual-benefit strategy: they not only reduce air pollution, as documented in the literature, but also mitigate the unintended public

[36]See Appendix A.2 for details of policy definition.

[37]These recycling indicators are plausibly exogenous to insect-related health outcomes, as their adoption was primarily driven by straw management needs (He et al., 2020), rather than concerns about insect-borne diseases. To further address potential endogeneity related to government responsiveness or local socioeconomic factors, all specifications include controls for hospital characteristics, weather conditions, and forest fire frequency, along with county, year-quarter, and province-by-quarter fixed effects to absorb jurisdiction-specific policy and environmental trends.

health costs of straw-burning bans. Existing studies have shown that the health benefits from air pollution reduction due to straw recycling subsidies exceed the subsidy costs. Our findings further demonstrate that these subsidies also substantially reduce the harm from vector-borne diseases caused by the straw-burning ban.

Therefore, our results do not imply a recommendation to reintroduce straw burning. Instead, they point to the need for more comprehensive and context-sensitive straw management strategies that reconcile environmental goals with ecological and public health outcomes. Providing targeted subsidies and incentives for farmers to adopt these alternatives could help reduce both ecological and public health risks.

## 8 Conclusion

This paper examines unintended health consequences of China's straw-burning ban, which was originally implemented to reduce air pollution but has increased insect populations and the prevalence of vector-borne diseases. The medical costs are substantial, amounting to roughly 11% of the health benefits gained from air pollution reduction. We provide evidence on how this occurs by showing that while the ban effectively reduced cropland fires, it also increased insect abundance and heightened public concern and defensive investment related to insect bites and vector-borne diseases. Importantly, we find that these health harms can be largely mitigated when straw residues are removed from croplands—such as in regions with effective straw recycling policies or widespread biomass power plants.

These findings offer important insights for future straw-burning bans in developing countries. While such policies have clear environmental benefits, they can unintentionally disrupt ecosystems and harm human health. However, these negative impacts can be avoided with well-designed policies that manage straw residues effectively. At the individual level, low-cost protective measures—such as using insect repellents, bed nets, and wearing protective clothing—can reduce exposure to insect bites. At the government level, strengthening public health education, improving disease surveillance, and expanding healthcare access are essential. Moreover, our results show that a one-size-fits-all approach is suboptimal. The harm is especially pronounced in wheat-producing regions and warmer areas. Therefore, straw-burning regulations should be crop-sensitive and climate-responsive, with policies tailored to local agricultural practices and ecological risks.

As a broad general insight, this paper illustrates the complex and often overlooked interactions between human interventions and ecological systems. Our findings call for a more integrated approach to environmental policy design—one that considers ecosystem feedback loops to avoid merely shifting health and environmental risks elsewhere.

## References


**Abman, Ryan and Clark Lundberg**, "Contracting, market access and deforestation," *Journal of Development Economics*, 2024, *168*, 103269.

**Allan, Brian F**, "Influence of prescribed burns on the abundance of Amblyomma americanum (Acari: Ixodidae) in the Missouri Ozarks," *Journal of Medical Entomology*, 2009, *46* (5), 1030–1036.

**Anderson, Roy M and Robert M May**, *Infectious diseases of humans: dynamics and control*, Oxford university press, 1991.

**Asher, Sam, Teevrat Garg, and Paul Novosad**, "The ecological impact of transportation infrastructure," *The Economic Journal*, 2020, *130* (629), 1173–1199.

**Assunçãoa, Juliano, Clarissa Gandoura, and Eduardo Souza-Rodriguesd**, "The forest awakens: Amazon regeneration and policy spillover," *CPI/PUC-Rio, Working Paper*, 2019.

**Bale, JS and SAL Hayward**, "Insect overwintering in a changing climate," *Journal of Experimental Biology*, 2010, *213* (6), 980–994.

**Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Yongchen Zou**, "From fog to smog: The value of pollution information," *American Economic Review*, 2024, *114* (5), 1338–1381.

**Borusyak, Kirill, Xavier Jaravel, and Jann Spiess**, "Revisiting event-study designs: robust and efficient estimation," *Review of Economic Studies*, 2024, *91* (6), 3253–3285.

**Callaway, Brantly and Pedro HC Sant'Anna**, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

**Cao, Jing and Rong Ma**, "Mitigating agricultural fires with carrot or stick? Evidence from China," *Journal of Development Economics*, 2023, *165*, 103173.

**Carreira, Igor, Francisco Costa, and Joao Paulo Pessoa**, "The deforestation effects of trade and agricultural productivity in Brazil," *Journal of Development Economics*, 2024, *167*, 103217.

**Chen, Tao, Meng Zhang, Qian Liu, Wensi Li, Zhilin Zeng, Chuanwen Chen, Yi Zhou, Tiantong Zhou, Yaping Li, Wei Wang et al.**, "Development and validation of a novel mortality risk stratification simplified scoring scale for severe fever with thrombocytopenia syndrome," *Clinical Microbiology and Infection*, 2025.

**Correia, Sergio, Paulo Guimarães, and Tom Zylkin**, "Fast Poisson estimation with high-dimensional fixed effects," *The Stata Journal*, 2020, *20* (1), 95–115.

**Costa, Francisco, Dimitri Szerman, and Juliano Assunção**, "The environmental costs of political interference: Evidence from power plants in the Amazon," *Journal of Public Economics*, 2025, *242*, 105314.

**de Chaisemartin, Clement, Xavier d'Haultfoeuille, Félix Pasquier, and Gonzalo Vazquez-Bare**, "Difference-in-Differences for continuous treatments and instruments with stayers," *Available at SSRN 4011782*, 2022.

**Dong, Jie, Yangyang Fu, Jingjing Wang, Haifeng Tian, Shan Fu, Zheng Niu, Wei Han, Yi Zheng, Jianxi Huang, and Wenping Yuan**, "Early-season mapping of winter wheat in China based on Landsat and Sentinel images," *Earth System Science Data*, 2020, *12*, 3081–3095.

**Du, Xinming, Lei Li, and Eric Zou**, "Trade, trees, and lives," *National Bureau of Economic Research*, 2024.

**Fang, Meiyu, Lihui Lin, and Jianwei Liu**, *Vector-Borne Diseases*, Military Medical Science Press, 2005.

**França, Leonardo Fernandes, Victória Helen Figueiredo-Paixão, Thales Afonso Duarte-Silva, and Kamila Barbosa dos Santos**, "The effects of rainfall and arthropod abundance on breeding season of insectivorous birds, in a semi-arid neotropical environment," *Zoologia (Curitiba)*, 2020, *37*, e37716.

**Frank, Eyal and Anant Sudarshan**, "The social costs of keystone species collapse: Evidence from the decline of vultures in India," *American Economic Review*, 2024, *114* (10), 3007–3040.

_ **, Shaoda Wang, Xuebin Wang, Qinyun Wang, and Yang You**, "Campaigning for extinction: Eradication of sparrows and the Great Famine in China," *Working Paper*, 2024.

**Gallagher, Michael R, Jesse K Kreye, Erika T Machtinger, Alexis Everland, Nathaniel Schmidt, and Nicholas S Skowronski**, "Can restoration of fire-dependent ecosystems reduce ticks and tick-borne disease prevalence in the eastern United States?," *Ecological Applications*, 2022, *32* (7), e2637.

**Garg, Teevrat**, "Ecosystems and human health: The local benefits of forest cover in Indonesia," *Journal of Environmental Economics and Management*, 2019, *98*, 102271.

_ **and Ajay Shenoy**, "The ecological impact of place-Based economic policies," *American Journal of Agricultural Economics*, 2021, *103* (4), 1239–1250.

_ **, Maulik Jagnani, and Hemant K Pullabhotla**, "Rural roads, farm labor exits, and crop fires," *American Economic Journal: Economic Policy*, 2024, *16* (3), 420–450.

**Gleim, Elizabeth R, L Mike Conner, Roy D Berghaus, Michael L Levin, Galina E Zemtsova, and Michael J Yabsley**, "The phenology of ticks and the effects of long-term prescribed burning on tick population dynamics in southwestern Georgia and northwestern Florida," *PLoS One*, 2014, *9* (11), e112174.

**Goodman-Bacon, Andrew**, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, 2021, *225* (2), 254–277.

**He, Guojun, Tong Liu, and Maigeng Zhou**, "Straw burning, PM2.5, and death: Evidence from China," *Journal of Development Economics*, 2020, *145*, 102468.

**Hook, Sarah A, Seonghye Jeon, Sara A Niesobecki, AmberJean P Hansen, James I Meek, Jenna KH Bjork, Franny M Dorr, Heather J Rutz, Katherine A Feldman, Jennifer L White et al.**, "Economic burden of reported Lyme disease in high-incidence areas, United States, 2014–2016," *Emerging Infectious Diseases*, 2022, *28* (6), 1170.

**Jack, B Kelsey, Seema Jayachandran, Namrata Kala, and Rohini Pande**, "Money (not) to burn: payments for ecosystem services to reduce crop residue burning," *American Economic Review: Insights*, 2025, *7* (1), 39–55.

**Jiang, Zhikuan, Zhimin Zheng, and Zhongcan Wang**, *Management of hygienic pest*, People's Medical Publishing House, 2011.

**Jones, Benjamin A**, "Infant health impacts of freshwater algal blooms: evidence from an invasive species natural experiment," *Journal of Environmental Economics and Management*, 2019, *96*, 36–59.

_ , "Can invasive species lead to sedentary behavior? The time use and obesity impacts of a forest-attacking pest," *Journal of Environmental Economics and Management*, 2023, *119*, 102800.

**Kilpatrick, A. Marm and Sarah E. Randolph**, "Drivers, dynamics, and control of emerging vector-borne zoonotic diseases," *The Lancet*, 2012, *380* (9857), 1946–1955.

**Lai, Wangyang, Shanjun Li, Yanan Li, and Xiaohui Tian**, "Air pollution and cognitive functions: evidence from straw burning in China," *American Journal of Agricultural Economics*, 2022, *104* (1), 190–208.

**Ma, Chun-Sen, Bing-Xin Wang, Xue-Jing Wang, Qing-Cai Lin, Wei Zhang, Xue-Fang Yang, Joan van Baaren, Daniel P Bebber, Sanford D Eigenbrode, Myron P Zalucki et al.**, "Crop pest responses to global changes in climate and land management," *Nature Reviews Earth & Environment*, 2025, *6* (4), 264–283.

**Meng, Lina, Pengfei Liu, Yinggang Zhou, and Yingdan Mei**, "Blaming the wind? The impact of wind turbine on bird biodiversity," *Journal of Development Economics*, 2025, *172*, 103402.

**Miao, Jin, Jianrong Huang, Yuqing Wu, Zhongjun Gong, Huiling Li, Guoyan Zhang, Yun**

**Duan, Tong Li, and Yueli Jiang**, "Climate factors associated with the population dynamics of Sitodiplosis mosellana (Diptera: Cecidomyiidae) in central China," *Scientific Reports*, 2019, *9* (1), 12361.

**National Health Commission of the People's Republic of China**, *2022 Statistical Bulletin on the Development of China's Health Care Industry* 2022.

—, *China Health Statistics Yearbook 2023*, Peking Union Medical College Press, 2023.

**Nian, Yongwei**, "Incentives, penalties, and rural air pollution: Evidence from satellite data," *Journal of Development Economics*, 2023, *161*, 103049.

**Paraiso, MLS and Nelson Gouveia**, "Health risks due to pre-harvesting sugarcane burning in São Paulo State, Brazil," *Revista Brasileira de Epidemiologia*, 2015, *18*, 691–701.

**Pecl, Gretta T, Miguel B Araújo, Johann D Bell, Julia Blanchard, Timothy C Bonebrake, I-Ching Chen, Timothy D Clark, Robert K Colwell, Finn Danielsen, Birgitta Evengård et al.**, "Biodiversity redistribution under climate change: Impacts on ecosystems and human well-being," *Science*, 2017, *355* (6332), eaai9214.

**Peng, Qiongyan, Ruoque Shen, Xiangqian Li, Tao Ye, Jie Dong, Yangyang Fu, and Wenping Yuan**, "A twenty-year dataset of high-resolution maize distribution in China," *Scientific Data*, 2023, *10*, 658.

**Pullabhotla, Hemant K and Mateus Souza**, "Air pollution from agricultural fires increases hypertension risk," *Journal of Environmental Economics and Management*, 2022, *115*, 102723.

**Rangel, Marcos A and Tom S Vogl**, "Agricultural fires and health at birth," *Review of Economics and Statistics*, 2019, *101* (4), 616–630.

**Samish, Michael and Evgeny Alekseev**, "Arthropods as predators of ticks (Ixodoidea)," *Journal of Medical Entomology*, 2001, *38* (1), 1–11.

**Smith, David L, Katherine E Battle, Simon I Hay, Christopher M Barker, Thomas W Scott, and F Ellis McKenzie**, "Ross, Macdonald, and a theory for the dynamics and control of mosquito-transmitted pathogens," *PLoS pathogens*, 2012, *8* (4), e1002588.

**Sun, Liyang and Sarah Abraham**, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

**Tanaka, LK and SK Tanaka**, "Rainfall and seasonal changes in arthropod abundance on a tropical oceanic island," *Biotropica*, 1982, pp. 114–123.

**Taylor, M Scott and Fruzsina Mayer**, "International trade, noise pollution, and killer whales," Technical Report, National Bureau of Economic Research 2023.

**WHO**, "Vector-borne diseases," https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases 2024. Accessed: 2025-04-22.

**Wu, Juanjuan, Jian Zhang, Weiming Yi, Hongzhen Cai, Zhanpeng Su, and Yang Li**, "Economic analysis of different straw supply modes in China," *Energy*, 2021, *237*, 121594.

**Yang, Jie and Xin Huang**, "30 m annual land cover and its dynamics in China from 1990 to 2019," *Earth System Science Data Discussions*, 2021, pp. 1–29.

**Zivin, Joshua Graff, Tong Liu, Yingquan Song, Qu Tang, and Peng Zhang**, "The unintended impacts of agricultural fires: Human capital in China," *Journal of Development Economics*, 2020, *147*, 102560.

# Tables and Figures

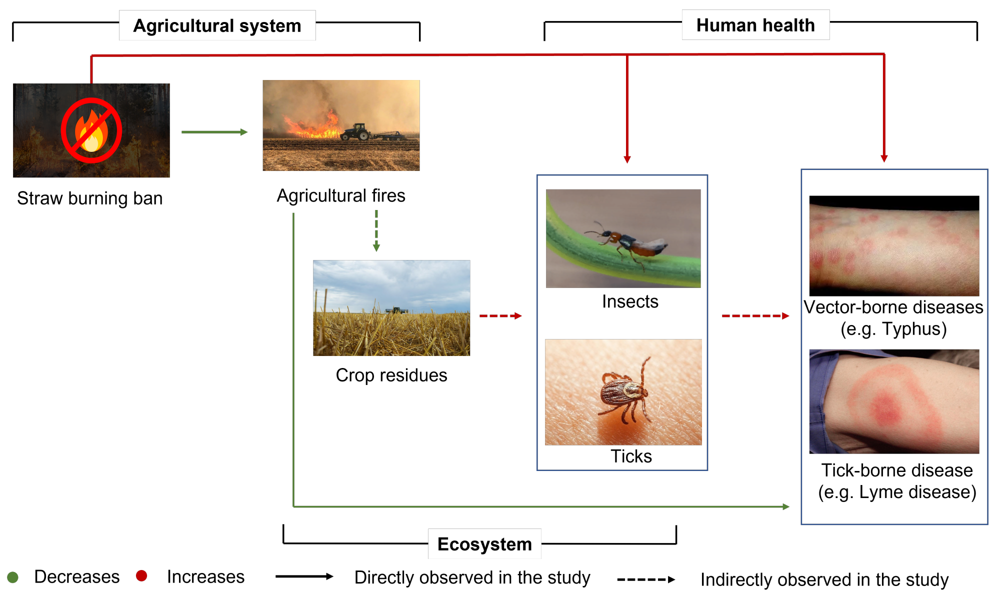



Figure 1: Ecological Framework Linking Straw-Burning Bans with Human Health

*Notes*: This figure illustrates the key mechanism linking the straw-burning ban to unintended health outcomes: (i) the ban reduces the incidence of agricultural fires, resulting in the accumulation of crop residues; (ii) these residues create favorable habitats for arthropods, including insects and non-insect species such as ticks; and (iii) the increased vector populations contribute to a rise in vector-borne infectious diseases, including a severe subset—tick-borne diseases.

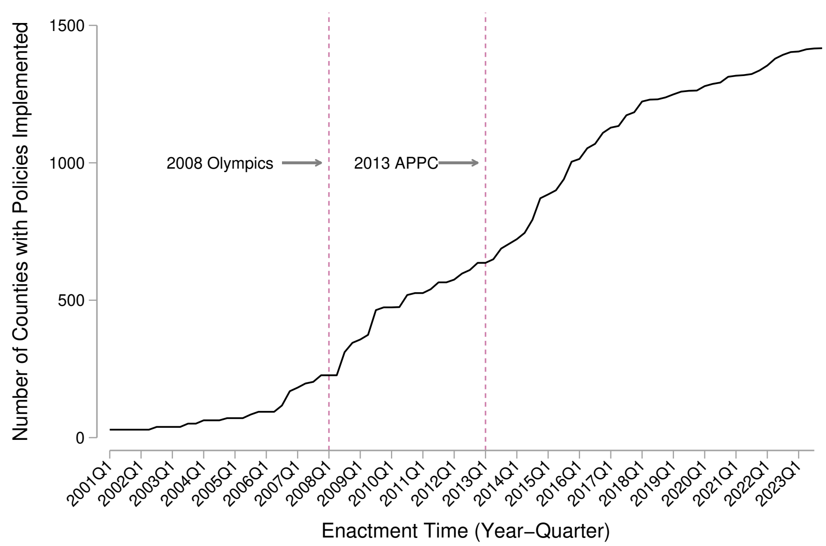



Figure 2: Rollout of the China's Straw-Burning Ban Across Counties

*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.

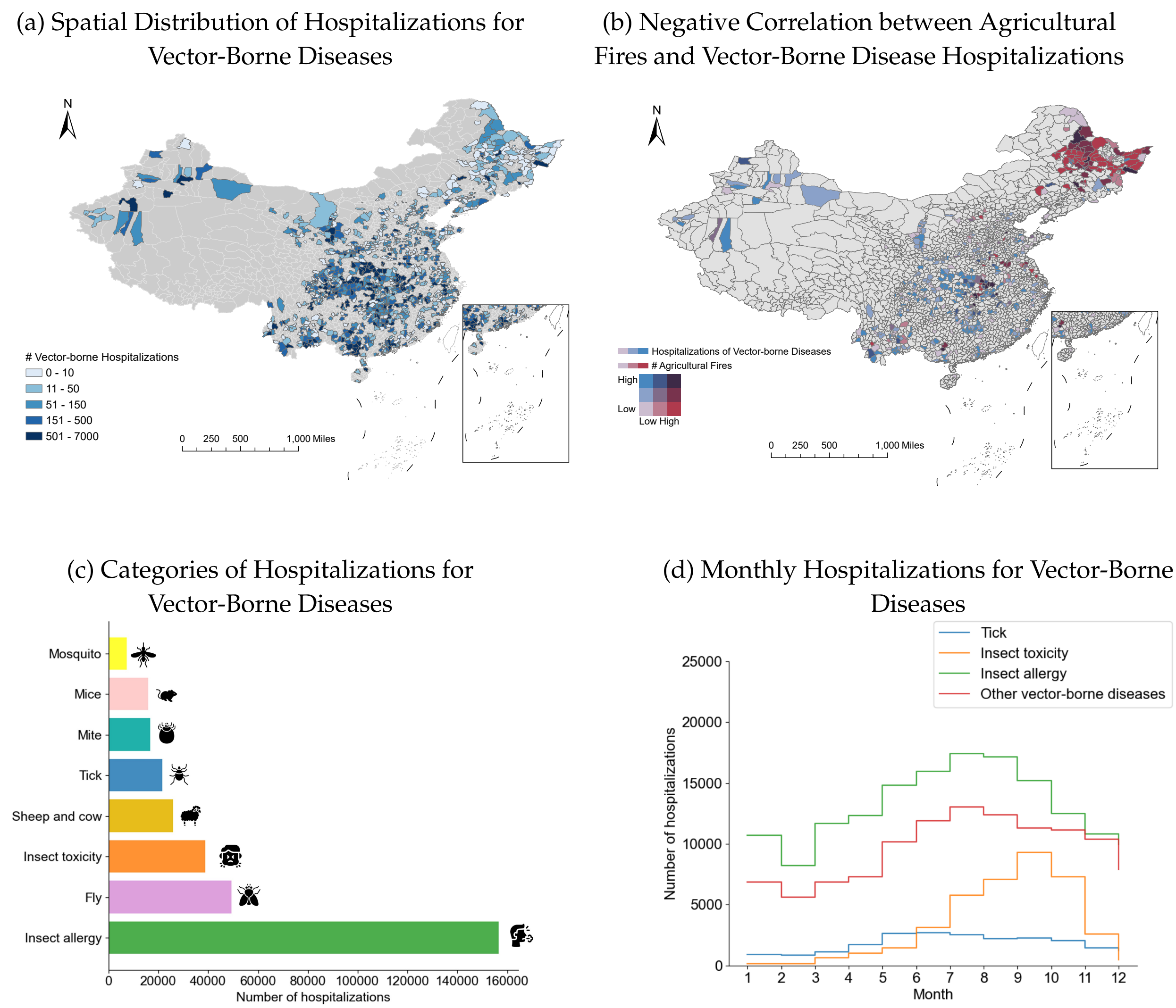
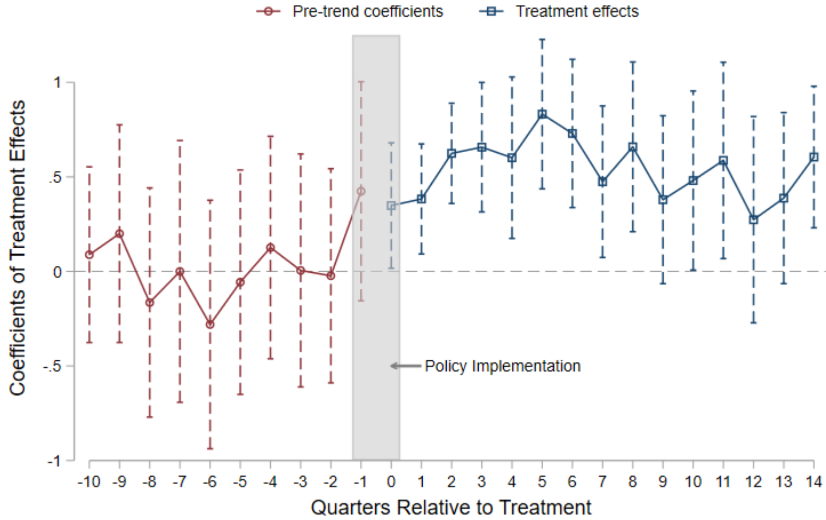



Figure 3: Distribution of Vector-Borne Disease Hospitalizations

*Notes*: Panel (a) displays the spatial distribution of hospitalizations for vector-borne diseases from 2015 to 2022. Panel (b) illustrates the negative spatial correlation between agricultural fire incidents and vector-borne disease hospitalizations in 2022. Panel (c) categorizes vector-borne disease hospitalizations by primary transmission vector. Panel (d) shows the total number of vector-borne disease hospitalizations by month.

(a) Event Study of Hospitalizations for Vector-Borne Diseases




(b) Event Study of Medical Expenditure for Vector-Borne Diseases

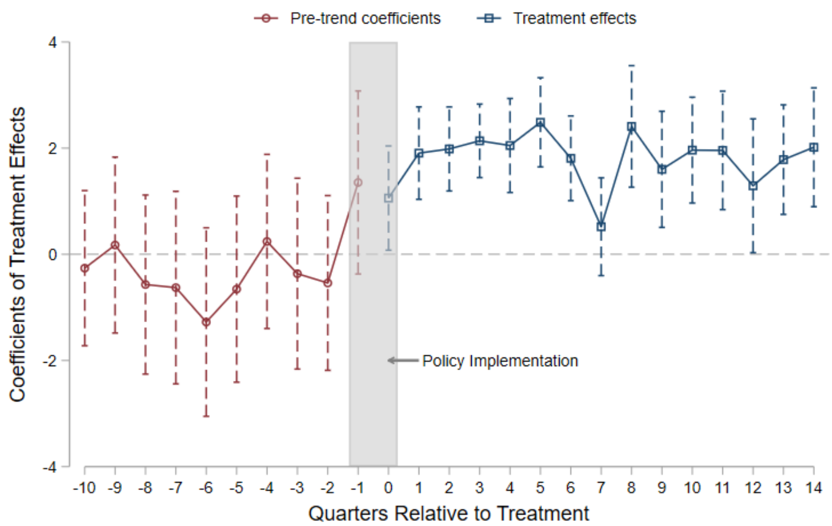



Figure 4: Effects on Vector-Borne Diseases: Event Study Plots

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

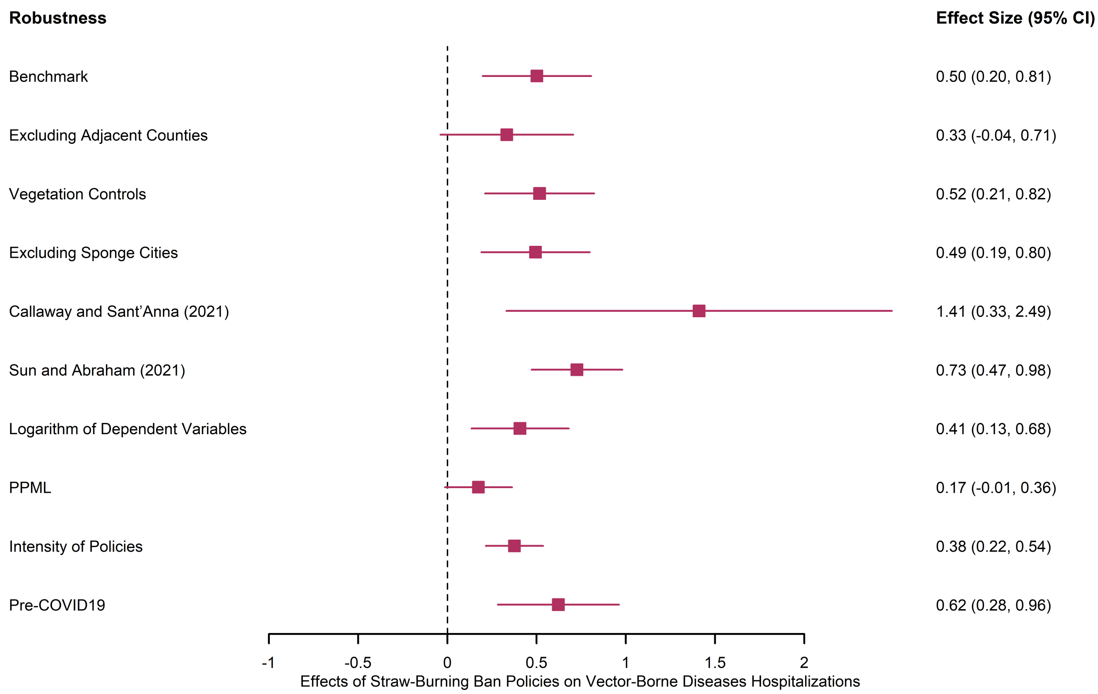
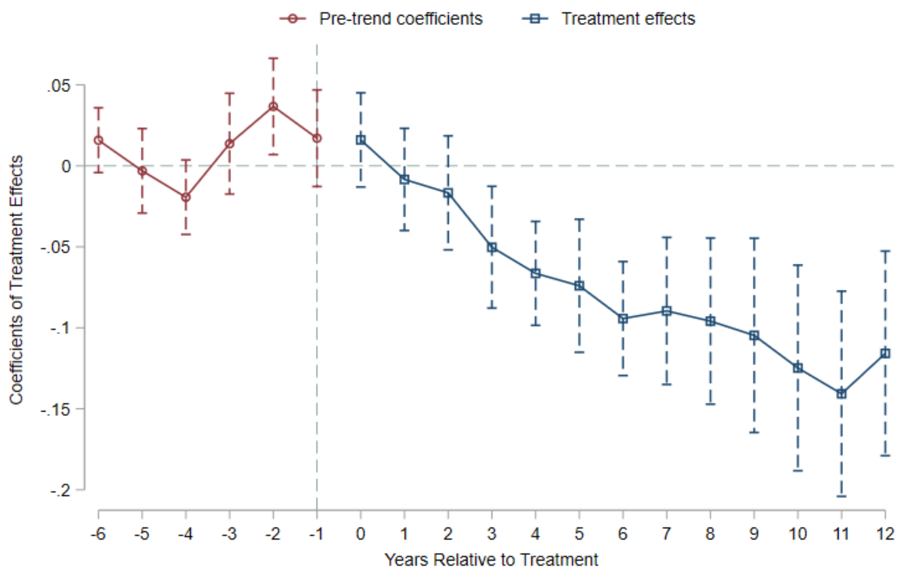



Figure 5: Robustness Checks

*Notes*: This figure presents results from various robustness checks on the impact of the straw-burning ban on hospitalizations for vector-borne diseases. Squares represent point estimates, and lines indicate 95% confidence intervals. The regression results are detailed in Table E1 through Table E10. The coefficient from the PPML model is interpreted as the marginal effect of the policy on the percentage change in the outcome variable, calculated as $(e^{\hat{\beta}} - 1) * 100\%$ from the point estimate reported in Table E8. For the effect of policy intensity, the reported estimate in Table E9 reflects the impact of one additional policy document. To compute the average effect for treated observations, this estimate is multiplied by the average cumulative number of policies (1.74) in those regions.

(a) Event Study of Cropland Fire Frequency




(b) Event Study of Cropland Fire Burned Area

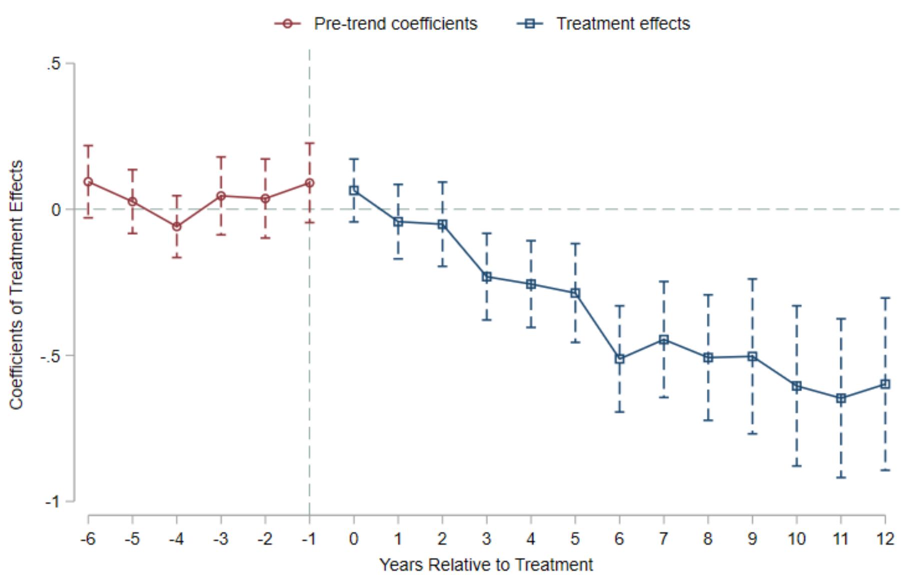
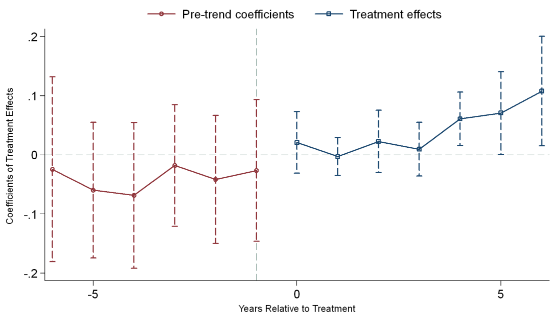


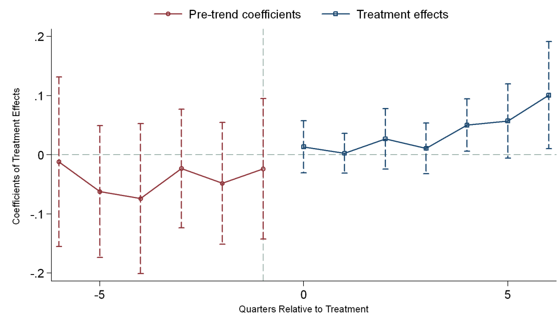

Figure 6: Effects on Cropland Fires: Event Study Plots

*Notes*: This figure illustrates the dynamic effects of the straw-burning ban on frequency and burned area of cropland fires using the imputation difference-in-differences event-study approach (Borusyak et al., 2024). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the frequency of cropland fire in harvest seasons (Panel a) and the IHS transformation of burned area of cropland fires in harvest seasons (Panel b), measured at the county-year level. The analysis uses data from 2001 to 2022. The regression includes county and province-by-year fixed effects. Control variables include average temperature and precipitation, the frequency and burned area of forest wildfires, lagged wheat and corn areas, log GDP, and log population. The x-axis is years relative to treatment. The y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

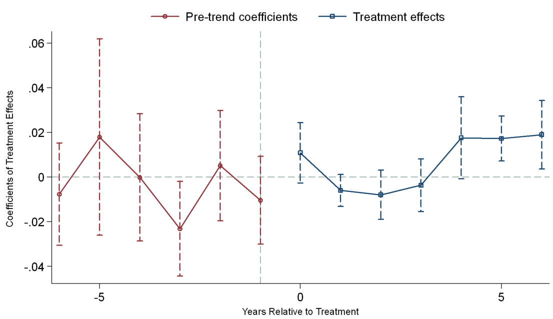
(a) Event Study of Arthropoda Population




(b) Event Study of Insecta Population




(c) Event Study of Arachnida Population




(d) Event Study of Chilopoda Population

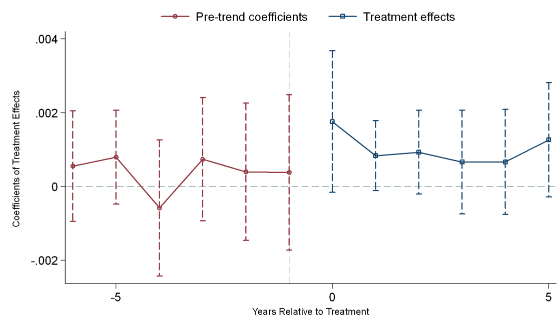
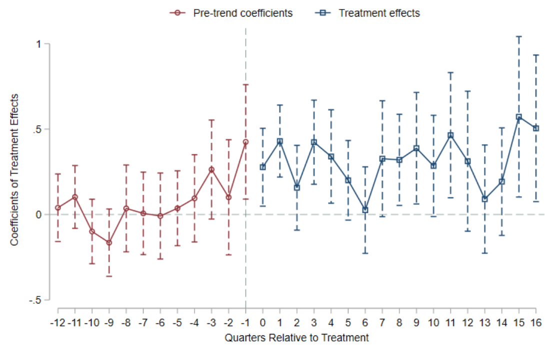


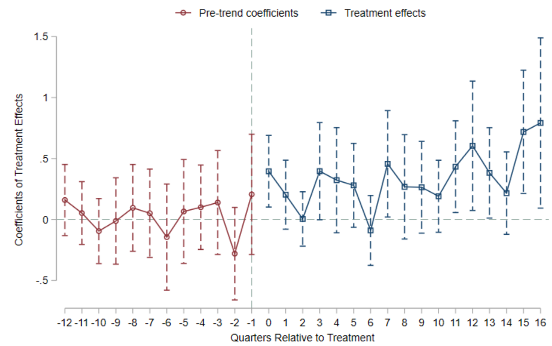

Figure 7: Effects on Insect Population: Event Study Plots

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

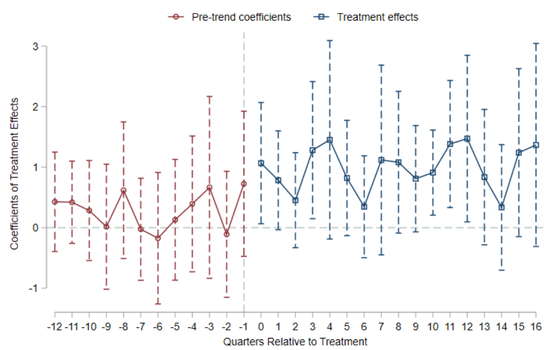
(a) Event Study of Straw-Burning Ban Searches



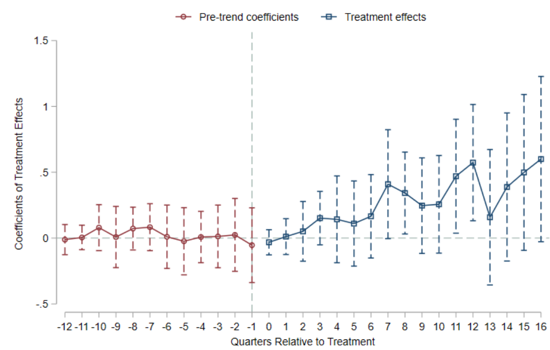

(b) Event Study of Insect Bite Searches



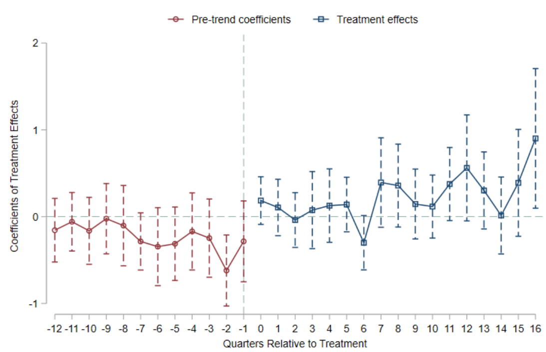

(c) Event Study of Tick Searches




(d) Event Study of Bite-Related Inquiries Searches




(e) Event Study of Pest Control Searches




(f) Event Study of Vaccination Searches

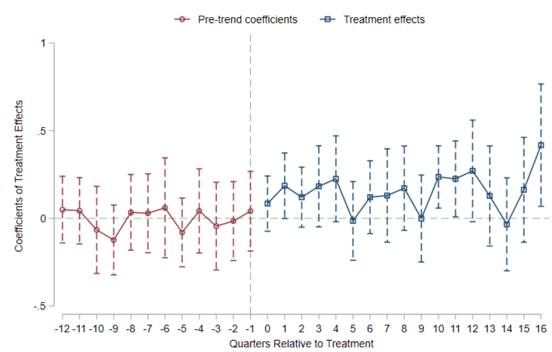
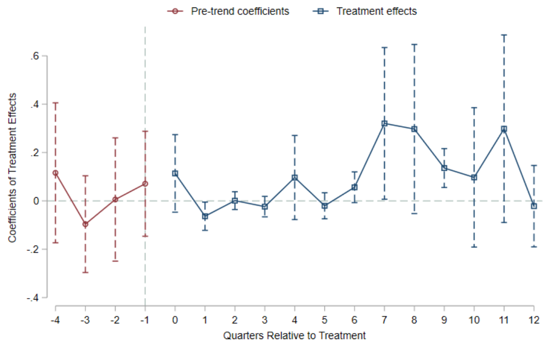


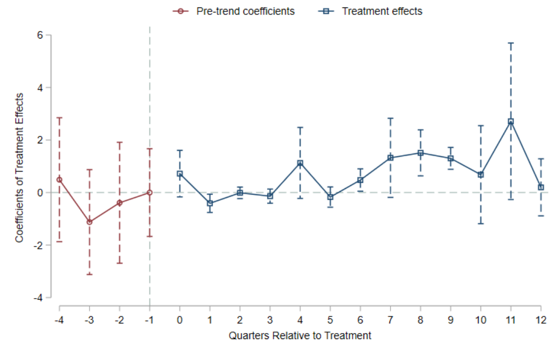

Figure 8: Effects on Baidu Search Index: Event Study Plots

*Notes*: This figure illustrates the dynamic effects of the straw-burning ban on Baidu Search Index of various terms, a proxy for public attention and concerns. The examined terms include straw-burning ban, insect bites, ticks, insect bite-related inquiries, pest control, and relevant vaccinations. The detailed words for search terms are listed in Table A4. The unit of observation is at the city-by-year-quarter level. The regression includes city fixed effects and province-by-year-quarter fixed effects. Control variables include average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. The x-axis is quarters relative to treatment. The y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

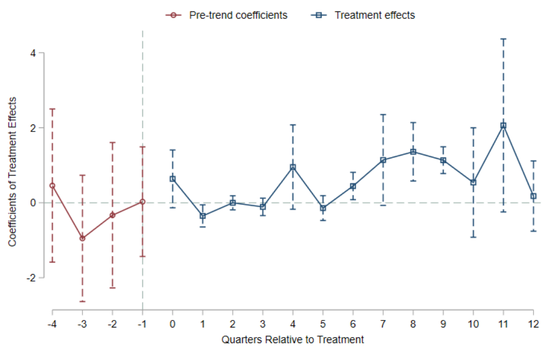
(a) Event Study of Number of Machine Procurements




(b) Event Study of Total Value of Machine Procurements




(c) Event Study of Subsidies of Machine Procurements




(d) Event Study of Unit Price of Machine Procurements

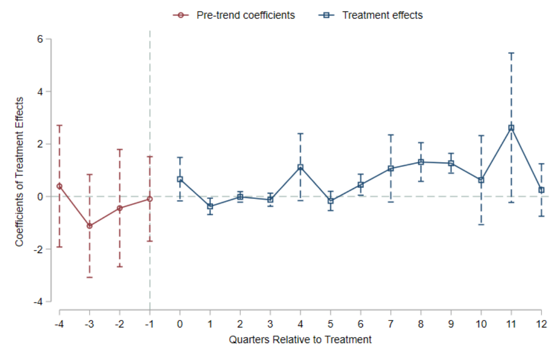
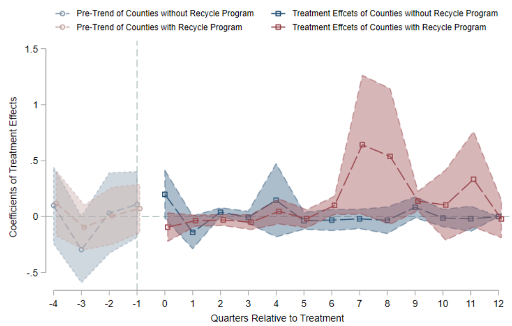


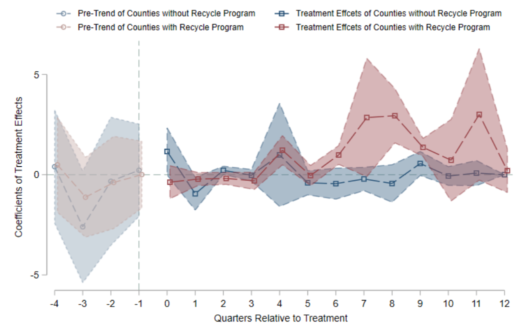

Figure 9: Effects on Machine Procurements: Event Study Plots

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

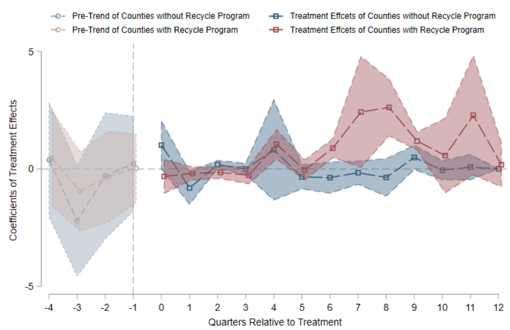
(a) Event Study of Number of Machine Procurements



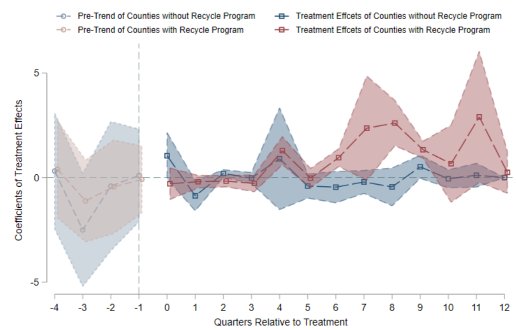

(b) Event Study of Total Value of Machine Procurements



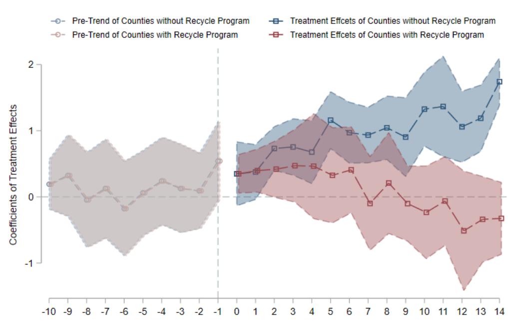

(c) Event Study of Subsidy of Machine Procurements




(d) Event Study of Unit Price of Machine Procurements




(e) Event Study of Vector-Borne Disease Hospitalizations




(f) Event Study of Vector-Borne Disease Medical Expenditure

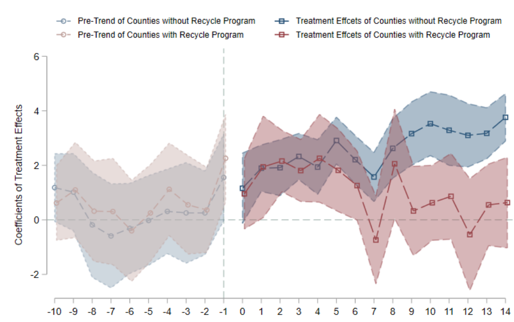



Figure 10: Event Study of Straw-Burning Ban by Recycling Program

*Notes*: This figure shows the dynamic effects of the straw-burning ban on straw-recycling machine procurement and vector-borne diseases, by the presence of recycling support. Panels (a)–(d) report event-study estimates for the inverse hyperbolic sine (IHS) of the number, total value, subsidy amount, and unit price of straw-recycling machine procurements, measured at the county–year–quarter level. Panels (e) and (f) report event-study estimates for the IHS of the number of inpatient admissions and medical expenditures for vector-borne diseases, also at the county–year–quarter level. In all panels, we compare the effects of the straw-burning ban between counties with and without the straw-recycling subsidy program described in He et al. (2020). The treatment groups consist of counties outside and inside the straw recycling subsidy program, respectively. In counties with a recycling program, the treatment group includes only observations with both a ban and a recycling program. The fixed effects and control variables are the same as in Figure 4, Figure 6, and Figure 9. 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.

Table 1: Summary Statistics

| | Observations | Years Available | Frequency | Mean | SD |
|---|---|---|---|---|---|
| *Panel A: Vector-Borne Diseases* | | | | | |
| Hospitalizations: Vector-Borne | 5,557 | 2015-2022 | Quarterly | 24.779 | 49.362 |
| Hospitalizations: Tick-Borne | 5,557 | 2015-2022 | Quarterly | 1.548 | 6.691 |
| Medical Expenditure: Vector-Borne *(1,000 CNY)* | 5,557 | 2015-2022 | Quarterly | 122.973 | 334.453 |
| Medical Expenditure: Tick-Borne *(1,000 CNY)* | 5,557 | 2015-2022 | Quarterly | 7.600 | 42.453 |
| *Panel B: Straw Burning* | | | | | |
| # Straw Burning | 17,218 | 2001-2022 | Yearly | 36.285 | 160.709 |
| Burned Area (*10,000 hectare*) | 17,218 | 2001-2022 | Yearly | 0.252 | 1.204 |
| *Panel C: Insect Observation* | | | | | |
| # obs. of species within Arthropoda | 10,288 | 2015-2022 | Yearly | 1.290 | 3.219 |
| # obs. of species within Insecta | 10,288 | 2015-2022 | Yearly | 1.204 | 3.126 |
| # obs. of species within Arachnida | 10,288 | 2015-2022 | Yearly | 0.162 | 1.063 |
| # obs. of species within Chilopoda | 10,288 | 2015-2022 | Yearly | 0.016 | 0.290 |
| *Panel D: Web Search Reactions (prefectural-level city level)* | | | | | |
| Baidu Index: Straw-burning ban | 12,849 | 2009-2022 | Quarterly | 2.246 | 3.041 |
| Baidu Index: Insect bites | 12,849 | 2009-2022 | Quarterly | 2.540 | 4.383 |
| Baidu Index: Tick | 12,849 | 2009-2022 | Quarterly | 8.479 | 10.964 |
| Baidu Index: Bite-related inquiries | 12,849 | 2009-2022 | Quarterly | 1.972 | 4.355 |
| Baidu Index: Pest control | 12,849 | 2009-2022 | Quarterly | 3.584 | 6.123 |
| Baidu Index: Vaccination | 12,849 | 2009-2022 | Quarterly | 1.127 | 2.214 |

*Notes:* Our data are nationally representative in scope. Health data are derived from hospitalization records. Agricultural data are obtained from satellite-based sources, including MODIS, MCD12Q1, and NDVI. Insect observation data are sourced from Global Biodiversity Information Facility (https://www.gbif.org). Baidu Search index data are sourced from https://index.baidu.com and data are available at the prefectural city level. The other datasets are constructed at the county level. We summarize the samples for our empirical analysis, excluding (i) remote areas with no fire records, (ii) regions that had already been treated with the straw-burning ban at the start of the study period, and (iii) outside the policy implementation window used in our analysis. See Section 3 and Appendix A for details. Column (2) reports sample size, while columns (3) and (4) summarize the temporal coverage and frequency. To reduce the influence of measurement errors and random factors, we aggregate health outcomes and Baidu search indices at the quarterly level and straw burning and insect observation variables at the annual level. Columns (5) and (6) present the mean and standard deviation.

Table 2: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Panel A: Vector-Borne Diseases** | | | | | | | | | |
| | Hospitalizations | | | | | Medical Expenditure | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Treatment (=1) | 0.552*** | 0.564*** | 0.460*** | 0.465*** | 0.502*** | 1.912*** | 1.956*** | 1.715*** | 1.731*** | 1.732*** |
| | (0.157) | (0.157) | (0.154) | (0.153) | (0.155) | (0.445) | (0.441) | (0.323) | (0.320) | (0.339) |
| Mean of Hosp./Exp. | | | 24.779 | | | | | 122,973 | | |
| S.D. of Hosp./Exp. | | | (49.362) | | | | | (334,453) | | |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-Quarter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Province-Quarter FE | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Hospital Characteristics | | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ |
| Weather and Forest Fire | | | | ✓ | ✓ | | | | ✓ | ✓ |
| Socio-economic Controls | | | | | ✓ | | | | | ✓ |
| Observations | 5,557 | 5,557 | 5,557 | 5,531 | 5,395 | 5,557 | 5,557 | 5,557 | 5,531 | 5,395 |
| | **Panel B: Tick-Borne Diseases** | | | | | | | | | |
| | Hospitalizations | | | | | Medical Expenditure | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Treatment (=1) | 0.252*** | 0.253*** | 0.217** | 0.213** | 0.212** | 0.898* | 0.909** | 0.721* | 0.701* | 0.703* |
| | (0.093) | (0.093) | (0.087) | (0.088) | (0.089) | (0.462) | (0.462) | (0.417) | (0.418) | (0.426) |
| Mean of Hosp./Exp. | | | 1.548 | | | | | 7,600 | | |
| S.D. of Hosp./Exp. | | | (6.691) | | | | | (42,453) | | |
| County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-Quarter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Province-Quarter FE | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Hospital Characteristics | | | ✓ | ✓ | ✓ | | | ✓ | ✓ | ✓ |
| Weather and Forest Fire | | | | ✓ | ✓ | | | | ✓ | ✓ |
| Socio-economic Controls | | | | | ✓ | | | | | ✓ |
| Observations | 5,557 | 5,557 | 5,557 | 5,531 | 5,395 | 5,557 | 5,557 | 5,557 | 5,531 | 5,395 |

*Notes:* This table presents the estimated effects of straw-burning ban policies on vector-borne disease hospitalizations using the imputation difference-in-differences estimator of Borusyak et al. (2024). The treatment variable is set to 1 for counties that have implemented a straw-burning ban with policy assessment. The dependent variables include the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions (Columns [1] to [5]) and medical expenditures (Columns [6] to [10]) for vector-borne (Panel A), and tick-borne diseases (Panel B). The relative effect (as a percentage of the sample mean) is calculated as $\left(\beta \cdot \sqrt{1+\bar{y}^2}/\bar{y}\right) \cdot 100\%$, where $\beta$ is the estimated coefficient on the treatment indicator and $\bar{y}$ is the sample mean of the number of hospitalizations or medical expenditure. The relative effects are discussed in detail in the main text. The regression sample spans from 2015 to 2022, covering four years (sixteen quarters) prior to and four years (sixteen quarters) after policy implementation. Hospital characteristics 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 characteristics include the average temperature and precipitation. Forest fire is measured by the occurrence and burned area of forest wildfires. Socio-economic controls include cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

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

| | Fires in Harvest Seasons | | All Fires | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | # Straw Burning | Burned Areas | # Straw Burning | Burned Areas |
| Treatment (= 1) | -0.270*** | -0.058*** | -0.347*** | -0.039** |
| | (0.060) | (0.012) | (0.094) | (0.018) |
| Effect relative to sample mean | -28.75% | -85.49% | -34.74% | -27.74% |
| Mean of # burning or burned area | 2.731 | 0.068 | 21.393 | 0.142 |
| S.D. of # burning or burned area | 14.735 | 0.508 | 122.075 | 0.891 |
| | County FE, province-year FE, control variables included | | | |
| Observations | 36,340 | 36,340 | 36,340 | 36,340 |

*Note:* This table presents the effects of straw-burning ban policies on the number and burned area of agricultural fires using the imputation difference-in-differences estimator of Borusyak et al. (2024). The dependent variables include the inverse hyperbolic sine (IHS) transformation of the number of agricultural fires and burned areas in harvest seasons in Columns (1) and (2), and the IHS transformation of the number of agricultural fires and burned areas in Columns (3) and (4). We use harvest seasons from He et al. (2020). Burned area is measured in *10,000 hectare*, and measured at the county-year level. The regression sample spans from 2001 to 2022, and covers ten years prior to and twelve years after policy implementation. The relative effect (as a percentage of the sample mean) is calculated as $\left(\beta \cdot \sqrt{1+\bar{y}^2}/\bar{y}\right) \cdot 100\%$, where $\beta$ is the estimated coefficient on the straw-burning ban policy variable, and $\bar{y}$ is the mean of the number or burned area of agricultural fires in the estimation sample. The model includes county and province-by-year fixed effects. Control variables include weather characteristics (average temperature and precipitation), wildfire characteristics (occurrence and burned areas of forest wildfires), lagged wheat and corn planting areas, GDP (in logarithmic form), and population (in logarithmic form). Standard errors (in parentheses) are clustered at the prefectural city level. *** p <0.01, ** p <0.05, * p <0.1.

Table 4: Effects of Straw-Burning Ban Policies on Insect Population

| | (1) Arthropoda | (2) Insecta | (3) Arachnida | (4) Chilopoda |
|---|---|---|---|---|
| Treatment (=1) | 0.030** | 0.027** | 0.004 | 0.001* |
| | (0.015) | (0.014) | (0.003) | (5.33e-04) |
| Effect relative to sample mean | 3.796% | 3.511% | 2.547% | 7.144% |
| Mean of # insect obs. | 1.290 | 1.204 | 0.162 | 0.016 |
| S.D. of # insect obs. | 3.219 | 3.126 | 1.063 | 0.290 |
| | County FE, year FE, control variables included | | | |
| Observations | 10,288 | 10,286 | 10,278 | 10,286 |

*Notes:* This table presents the effects of straw-burning ban policies on insect observation using the imputation difference-in-differences estimator of Borusyak et al. (2024). The dependent variable is the inverse hyperbolic sine (IHS) transformation of the number of recorded observations of species within each taxonomic category per county-year. The regression sample spans from 2015 to 2022, and covers six years prior to and six years after policy implementation. The relative effect (as a percentage of the sample mean) is calculated as $\left(\beta \cdot \sqrt{1+\bar{y}^2}/\bar{y}\right) \cdot 100\%$, where $\beta$ is the estimated coefficient on the straw-burning ban policy variable. $\bar{y}$ is the sample mean of the number of insect population. The model includes county and year fixed effects. Control variables include the number of unique observers (IHS-transformed), weather characteristics (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), and GDP (IHS-transformed). Standard errors (in parentheses) are clustered at the prefectural city level. *** p <0.01, ** p <0.05, * p <0.1.

Table 5: Effects of Straw-Burning Ban Policies on Insect Awareness and Defensive Investment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Baidu Search Index | | | | | |
| | Straw-Burning Ban | Insect Awareness | | | Defensive Investment | |
| | | Bite-Related Inquiries | Tick | Insect Bite | Pest-control | Vaccination |
| Treatment (=1) | 0.378*** | 0.413*** | 1.110** | 0.484*** | 0.358** | 0.191* |
| | (0.111) | (0.158) | (0.473) | (0.139) | (0.148) | (0.101) |
| Mean of index | 2.246 | 2.540 | 8.479 | 1.972 | 3.584 | 1.127 |
| S.D. of index | 3.041 | 4.383 | 10.964 | 4.355 | 6.123 | 2.214 |
| City FE, province-year-quarter FE, control variables included | | | | | | |
| Observations | 12,849 | 12,849 | 12,849 | 12,849 | 12,849 | 12,849 |

*Notes:* This table presents the effects of straw-burning ban policies on Baidu Search Index, a proxy for public attention and concerns, using the imputation difference-in-differences estimator of Borusyak et al. (2024). We examine the impact on multiple topics including the straw burning ban, insect bites, ticks, insect bite-related inquiries, pest control, and vaccination. The detailed words for search terms are listed in Table A4. The unit of observation is at the city-year-quarter level. The analysis spans four years (sixteen quarters) prior to and six years (twenty-four quarters) after policy implementation. The model includes city fixed effects and province-by-year-quarter fixed effects. Control variables include weather characteristics (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the prefectural city level. *** p <0.01, ** p <0.05, * p <0.1.

Table 6: Pathway-Based Heterogeneity: Straw Management, Winter Temperature, and Harvest Season

| | Vector-Borne Diseases Hospitalization | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | by Major Crop | | by Winter Temperature | | by Agricultural Season | |
| | Main Wheat | Others | $> 0°C$ | $< 0°C$ | Harvest | Non-Harvest |
| Treatment (=1) | 1.189*** | 0.389** | 0.813*** | 0.087 | 0.452*** | 0.312** |
| | (0.405) | (0.162) | (0.191) | (0.306) | (0.122) | (0.144) |
| | county, province-quarter, year-quarter FE and control variables included | | | | county, province-month, year-month FE and control variables included | |
| Observations | 1,222 | 4,173 | 3,876 | 1,519 | 7,508 | 7,445 |

*Notes:* This table reports the heterogeneous effects of straw-burning ban policies on hospitalizations for vector-borne diseases across counties with different characteristics. The dependent variable is the inverse hyperbolic sine (IHS) transformation of hospitalization counts. Columns (1) and (2) examine counties in China's major wheat-producing provinces versus the rest counties. According to the China Statistical Yearbook, the major wheat-producing provinces—Henan, Shandong, Anhui, Hebei, Jiangsu, Hubei, Sichuan, Shaanxi, Shanxi, and Chongqing—together accounted for 82.8% of China's total wheat planting area in 2015. Columns (3) and (4) present results for subsamples split by whether the average temperature in the coldest month (2015-2022) is above or below $0°C$, respectively. For Columns (1)–(4), the unit of observation is at the county–by-year–quarter level, covering four years (sixteen quarters) before and after policy implementation. Columns (5) and (6) examine harvest versus non-harvest months, with the unit of observation at the county–by-year–month level. Harvest months are defined as May–July and September–November, consistent with He et al. (2020). The sample spans four years (forty-eight months) before and after the ban. Control variables remain consistent with the baseline setting, including hospital characteristics, weather characteristics (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 7: Effects of Straw-Burning Ban Policies on Straw Recycle Machine Procurement

| | Straw Burning Ban | | | | | |
|---|---|---|---|---|---|---|
| | All counties | | With recycle program | | Without recycle program | |
| Machine Procurement | (1) Coefficient | (2) % Change (Mean) | (3) Coefficient | (4) % Change (Mean) | (5) Coefficient | (6) % Change (Mean) |
| Number of machines | 0.095*** | *27.6%* | 0.122*** | *35.0%* | 0.035 | *27.2%* |
| | (0.034) | (*0.367*) | (0.047) | (*0.372*) | (0.030) | (*0.130*) |
| Total procurement value | 0.652*** | *65.2%* | 0.909*** | *90.9%* | 0.146 | *14.6%* |
| | (0.212) | (*4,966.360*) | (0.281) | (*5,042.955*) | (0.268) | (*1,383.857*) |
| Subsidy amount | 0.551*** | *55.1%* | 0.758*** | *75.8%* | 0.134 | *13.4%* |
| | (0.175) | (*1,253.083*) | (0.229) | (*1,273.18*) | (0.226) | (*284.473*) |
| Average unit price | 0.603*** | *60.3%* | 0.852*** | *85.2%* | 0.118 | *11.8%* |
| | (0.198) | (*818.441*) | (0.258) | (*826.845*) | (0.267) | (*416.788*) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | | | |
| Observations | 4,022 | | 3,946 | | 2,412 | |

Notes: This table reports the effects of straw-burning ban policies on the procurement of straw recycle machines. The dependent variable in each row is the inverse hyperbolic sine (IHS) transformation of the corresponding outcome (number of machines, total procurement value in CNY, subsidy amount, or average unit price in CNY). "All counties" includes all treated counties; "with recycle program" and "without recycle program" split the sample according to participation in the provincial straw recycling subsidy program. The unit of observation is the county–year–quarter. All regressions control for wildfire characteristics, cropland area, log GDP, log population, and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Straw-burning Ban, Recycle Measures, and Vector-Borne Diseases

| | Vector-Borne Diseases | | | |
|---|---|---|---|---|
| | Hospitalizations | | Medical Expenditure | |
| | (1) without Recycle | (2) with Recycle | (3) without Recycle | (4) with Recycle |
| Treatment (=1) | 0.876*** | 0.001 | 2.372*** | 0.925*** |
| | (0.173) | (0.252) | (0.385) | (0.480) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 4,444 | 5,132 | 4,444 | 5,132 |

*Notes:* This table presents the heterogeneous effects of straw-burning ban policies on hospitalizations for vector-borne diseases across counties with and without straw recycling subsidy program. The dependent variable is the inverse hyperbolic sine (IHS) transformation of hospitalization counts at the county-by-year-quarter level. We compare counties outside and inside the provincial straw recycling subsidy program described in He et al. (2020); Columns (2) and (4) restricts the treatment group to counties that implemented a ban and participated in a provincial recycling program. The analysis spans four years (sixteen quarters) before and after policy implementation. The model includes county, province–quarter, and year–quarter fixed effects. Control variables include hospital characteristics, weather conditions (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

# Appendices

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

# A Data Cleaning

## A.1 Health Data

The data quality is reliably high, as hospitals have strong incentives to maintain accurate and complete digital records. First, medical records serve as the foundation for both public and private insurance reimbursements. For example, the National Healthcare Security Administration of China requires that patients be assigned to payment groups based on primary and secondary diagnoses and primary procedures recorded in their medical files. Each group receives standardized medical insurance payments, and hospitals risk financial losses if patients are misclassified due to inaccurate records. Second, participation in the digital reporting system is mandated by the National Health Commission. Local health commissions conduct regular performance evaluations of hospitals, which include assessments of their digital medical record systems. To ensure accuracy and consistency, medical records are typically completed by attending physicians and verified by clinical coders, who standardize diagnosis and procedure codes (Huang et al., 2023).

We aggregate these records to the county-by-year-quarter level, allowing for seasonal variation in disease transmission, following a three-step procedure. First, we extract all hospitalization records with a primary diagnosis of vector-borne diseases, excluding observations with implausibly low (below 100 RMB) or excessively high (above 8 million RMB) medical expenditures.[1] We then aggregate these records to the hospital-day level, summing inpatient admission counts and total medical expenditures. Second, for hospital-day combinations with missing values for vector-borne disease admissions, we differentiate between true zeros and missing data. If a hospital recorded at least one inpatient admission for any infectious disease during a given year, we treat unrecorded vector-borne disease hospitalizations as zeros; otherwise, we classify them as missing. Third, in order to reduce the influence of measurement errors and random factors, at the same time capture the seasonal variations in the vector-borne diseases, we aggregate the cleaned hospital-day level data to the county-by-year-quarter level for use in the main analysis. Hospitalizations for tick-borne diseases are constructed using the same procedure.

**Addressing Selection of Data** To assess potential concerns regarding sample selection, we conduct several tests. First, we construct a balanced county-year-quarter panel dataset and create an indicator variable for whether a county-year-quarter observation appears in our main estimation sample (i.e., the dataset used in Table 2). We then examine whether this indicator is affected by

[1] Such outliers are typically the result of data entry errors, such as misplaced decimal points.

the straw-burning ban policy or by the administrative level of a city. The results are presented in columns (1) and (2) of Appendix Table A1. In column (1), we control for county, year-by-quarter, and province-by-quarter fixed effects. In column (2), we omit county fixed effects because the administrative level of a city varies only at the city level.

Second, using the same balanced county-year-quarter panel dataset, we construct hospital-day counts, which serve as the basis for calculating the county-year-quarter measures of hospitalizations and medical expenditures in our main sample. We then test whether the inverse hyperbolic sine (IHS) transformation of this count variable is influenced by the straw-burning ban policy or the administrative level of a city. The results are shown in columns (3) and (4) of Appendix Table A1.

Third, we compile a balanced hospital-year-quarter panel dataset and examine whether the presence of an infectious disease department in a hospital is affected by the straw-burning ban policy or by the administrative level of a city. The results are reported in columns (5) and (6) of Appendix Table A1.

Across all specifications, the results indicate that neither the straw-burning ban policy nor the administrative level of a city has a statistically significant effect on any of the dependent variables in Appendix Table A1. These results suggest that selection issues are minimal.

Appendix Table A1: Examining the effects of straw-burning ban policy or city administrative level

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | county-year-quarter in main sample (0/1) | | IHS hospital-day counts in each county-year-quarter | | infectious department in hospital (0/1) | |
| 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-by-Quarter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year-by-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 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 hospital-day counts. In columns (5) and (6), the dependent variable is an indicator of whether a hospital contains an infectious disease department.

**Medical Insurance Distribution** China's public medical insurance system has historically comprised three main schemes: the Urban Employee Basic Medical Insurance (UEBMI) for formally employed urban residents; the New Rural Cooperative Medical Scheme (NCMS) for rural residents; and the Urban Resident Basic Medical Insurance (URBMI) for urban residents without formal employment. To reduce disparities in healthcare access between urban and rural populations, the NCMS and URBMI were gradually integrated, culminating in the establishment of the Urban and Rural Resident Basic Medical Insurance (URRBMI) at the end of 2016.

Currently, China's public insurance system is primarily composed of UEBMI for urban employees and URRBMI—which encompasses both former NCMS and URBMI participants—for all other residents. Since our data span 2011–2022, overlapping with the period of insurance integration, regional differences in classification limit our ability to consistently distinguish between NCMS and URBMI. As shown in Table A2, approximately 55% of hospitalizations for vector-borne diseases are covered by either NCMS or URBMI, 19% by UEBMI, and 16% involve patients without any insurance coverage. The remaining 10% are covered by other schemes, such as commercial medical insurance.

Appendix Table A2: Distribution of Hospitalizations: by Medical Insurance Type

| | Vector-Borne Diseases | | Tick-Borne Diseases | |
|---|---|---|---|---|
| | Freq. | Percent | Freq. | Percent |
| NCMS/URBMI | 170,170 | 54.79% | 12,475 | 60.59% |
| UEBMI | 59,010 | 19.00% | 3,142 | 15.26% |
| No insurance | 49,223 | 15.85% | 3,272 | 15.89% |
| Others | 32,183 | 10.36% | 1,701 | 8.26% |

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

**Age Distribution** Table A3 presents the age distribution of hospitalizations for vector-borne and tick-borne diseases. The results indicate that cases occur across all age groups, highlighting the broad population vulnerability to these illnesses.

Appendix Table A3: 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% |

### A.2 Policy Data Cleaning Details

The data on straw-related policy documents are sourced from the Peking University Law Database (https://www.pkulaw.com). We retrieved all local government regulatory documents containing the keyword "straw-burning ban," yielding a total of 1,381 policy documents issued between March 1993 and September 2024. Each document was manually reviewed and coded to identify whether it included assessment mechanisms for enforcement and whether it featured straw recycling subsidies. The initial coding underwent a second round of review and verification to ensure accuracy and consistency. Among these documents, 1,015 policies included assessment mechanisms for straw-burning prohibitions, and 741 policies also included straw recycling measures.

**Examples of Policy Documents** Figure A1 to Figure A3 show examples of different types of policies from one city in China. The straw-burning ban policy without assessment measures, as shown in Figure A1, 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 targets individuals directly involved in burning activities and assigns enforcement responsibilities to environmental protection departments.

In contrast, the policy with assessment measures (see Figure A2) outlines specific disciplinary actions for government officials. It stipulates demotions for township governments ranked among the bottom or those with more than 8 (weekly), 10 (biweekly), or 14 (monthly) fire spots. For example, the policy 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."

As shown in Figure A3, the policy with support measures explicitly includes provisions such as: "Subsidies will be provided for costs related to straw and weed removal, transportation, and straw return-to-field practices," and "Investments will be increased in the adoption of new agricultural machinery and practical technologies for comprehensive straw utilization."

邯郸市人民政府关于严格禁止露天焚烧农作物秸秆的通告
（邯政告【2013】8 号）

为防治大气污染，保护生态环境，保障人民健康和财产安全，根据《中华人民共和国大气污染防治法》、《中华人民共和国消防法》、《中华人民共和国治安管理处罚法》、《中华人民共和国公路法》等有关法律规定，现将禁止露天焚烧农作物秸秆和其他烧荒行为的有关规定通告如下：

一、在全市范围内，严禁任何单位、个人露天焚烧农作物秸秆和进行其他烧荒行为。

二、凡露天焚烧农作物秸秆和进行其他烧荒行为的，由环境保护部门责令其停止违法行为，情节严重的依法对焚烧责任人处以罚款；对过失引起火灾，尚不构成犯罪的，由公安部门依法予以行政拘留并处以罚款。

三、对因焚烧农作物秸秆和进行其他烧荒行为而发生火灾，造成公私财物重大损失或人员伤亡，构成犯罪的，依法追究其刑事责任。

四、在公路及公路用地等范围内堆放秸秆等杂物及焚烧，造成公路路面损坏、污染或影响道路交通畅通的，由交通运输部门依法予以处理。

五、对阻碍、干扰执行禁烧公务的，由公安机关依法予以处理。

六、任何单位和个人均可投诉、检举、揭发违规堆放、焚烧秸秆等行为。举报电话：市禁烧办 3015087，市环境保护局 3111103，市公安消防支队 96119，市交通运输局 5102989。

本通告自发布之日起实施，有效期两年。

Appendix Figure A1: A Typical Straw-burning Ban Policy

邯郸市大气污染防治工作领导小组办公室关于印发《禁止秸秆垃圾露天焚烧加严考核问责实施办法》的通知

禁止秸秆垃圾露天焚烧加严考核问责
实 施 办 法

为切实有效减少全市火点发生数量，全面压实属地责任，推动我市空气质量持续改善，特制定此办法。

一、工作目标

全市每月火点数量低于 100 个，全省排名正 6（含）以内。

二、加严问责情形

（一）每周对火点数量达到 8 个（含）以上并排名全市倒一的乡（镇、街道、县属经济开发区），建议县（市、区）党委（党工委）对该乡（镇、街道、县属经济开发区）党委（党工委）书记进行组织调整；

（二）每两周对火点数量达到 10 个（含）以上并排名全市倒一的乡（镇、街道、县属经济开发区），建议县（市、区）党委（党工委）对该乡（镇、街道、县属经济开发区）党委（党工委）书记进行组织调整；

（三）每月对火点数量达到 14 个（含）以上并排名全市倒一的乡（镇、街道、县属经济开发区），建议县（市、区）党委（党工委）对该乡（镇、街道、县属经济开发区）党委（党工委）书记进行组织调整；

（四）按照 2023 年 12 月印发实施的《禁止秸秆垃圾露天焚烧火点核算和问责实施办法》有关规定，乡（镇、街道、县属经济开发区）政府（管委会）主要及分管负责同志达到问责条件的，一律给予诫勉谈话（含）以上处理或党纪政务处分；

（五）每周、每两周、每月未达到加严问责情形的，分别全市后 3 名、后 5 名、后 10 名乡（镇、街道、县属经济开发区）党委（党工委）书记在全市大气污染防治工作调度会上作出深刻检查；

（六）一个月内，被加严问责的乡（镇、街道、县属经济开发区）不再重复问责。

三、火点数量统计标准

（一）火点数量以省生态环境厅每日通报数据为基数，位置存在异议的，以次日中午 12 时前现场核定为准；

（二）漏报火点计入乡（镇、街道、县属经济开发区）火点数量；

（三）重污染天气应急响应期间，1 个火点按 2 个火点计算。

四、加严问责豁免条件

周、两周、月度全市火点数量在全省排名正 6（含）以内的，不再加严问责。

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

邯郸市人民政府办公厅关于加大秸秆禁烧和综合利用工作县级财政资金支持力度的通知

邯政办字【2017】163 号

为进一步加大秸秆禁烧和综合利用工作县级财政资金支持力度，确保实现“不点一把火，不冒一股烟，不见一处灰"的任务目标，现将有关要求通知如下。

一、提高思想认识。市委、市政府高度重视秸秆禁烧工作，成效良好。但由于资金投入不足，秸秆综合利用程度不高，秸秆清运不到位，焚烧秸秆现象时有出现。近年来，我市大气污染防治形势日益严峻，秸秆禁烧和综合利用工作任务更加艰巨。在新形势下，突出源头治理，进一步强化秸秆综合利用和秸秆清除工作成为首要任务，需要大量人力、物力、财力保障相关工作的正常运转。因此，各县（市、区）政府要进一步提高思想认识，充分认清当前秸秆禁烧和综合利用工作的严峻形势，加大县级财政资金支持力度，全面保障禁烧工作顺利推进。

二、明确投入重点。一是加大“清秸秆、消隐患"活动投入。对清理秸秆、杂草的车辆运输、秸秆还田等费用进行补助；支持秸秆收储网点建设，引导有条件的企业开展秸秆收集储运；支持培育秸秆物流企业，加快建立“公司+农户"的秸秆收储模式。二是加大宣传工作投入。支持建立秸秆禁烧和综合利用宣传工作长效机制，通过科普下乡和广播、电视、报纸、网络、宣传片等多种形式，全方位多层次强化秸秆禁烧和综合利用工作宣传。三是加大引进、推广新型农机设备和秸秆综合利用实用技术方面的投入。

三、加强资金监管。各县（市、区）政府要将秸秆禁烧和综合利用专项资金纳入县级政府财政预算，建立完善专项资金使用办法等监管制度，规范专项资金的使用原则、范围、重点、部门职责、报批程序和监管要求，严明资金监管纪律责任，加强跟踪监督和绩效评价。

Appendix Figure A3: A Typical Straw-burning Ban Policy with Straw-Utilization Support

**Policy Documents of Different Levels of Government** Of the 1,015 identified policies with assessment mechanisms, 196 were issued at the provincial level, 705 at the prefecture-level city level, and 114 at the county level. Note that in the early stages, at the *national* level, the Chinese government issued 12 regulatory documents addressing straw burning controls between 1997 and 2012. These national-level policies had two main features. First, they were largely advisory in nature, lacking mandatory enforcement mechanisms. Second, most of these regulations did not target specific regions but instead focused on limiting straw burning in areas where smoke posed risks to transportation safety. For example, in 1999, the National Environmental Protection Agency (NEPA), the Ministry of Agriculture, and four other departments jointly issued the Regulations on the Management of Straw Burning Prohibition and Comprehensive Utilization, which explicitly defined prohibited zones. These included areas within a 15-kilometer radius of airports, a 2-kilometer buffer zone on both sides of highways and railways, and a 1-kilometer buffer zone along national and provincial roads.[2]

## A.3 Supplementary Datasets

**Straw Burning and Forest Wildfire** Satellite imagery is widely used to quantify agricultural burning and forest wildfires. Two remote sensing-based datasets capable of detecting fire and land use in China are the Moderate Resolution Imaging Spectroradiometer (MODIS) Burned Area product and the Land Cover Type Product (MCD12Q1).[3]

The MODIS Burned Area product is a widely used satellite dataset that records the presence of fire, the date of burning, and burned area extent. The dataset has been validated by comparison

[2] See Ministry of Ecology and Environment of China for details.

[3] Data sources: Up-to-date information on datasets, formats, and quality is available from the Land Processes DAAC at the Land Processes DAAC for MCD12Q1 and University of Maryland for the MODIS Fire and Burned Area products.

with Landsat 8 Operational Land Imager (OLI) imagery. According to the product guide, the standard errors of accuracy metrics are below 6% globally. Errors of omission and commission largely offset each other, as indicated by the coefficient of determination ($r^2 > 0.70$), slope ($> 0.79$), and intercept (-0.0030) of the regression between the MCD64A1 product and independent Landsat reference data. Full validation details can be found in Smith et al. (2016) and Roy et al. (2019).

To address a common limitation of burned area products—low reliability in detecting agricultural burning—we refine the identification of agricultural fires by overlaying burned area pixels with land cover classification data. By integrating MODIS burned area data with land cover products, we improve the accuracy of forest fire and agricultural burning estimates. Following the methodology of Assunçãoa et al. (2019) and using ArcGIS, we overlay land cover grid metrics with MODIS burned area data to distinguish between agricultural burning and forest wildfires. This integration enhances the precision of fire detection by associating burning events with specific land classifications.

**Web Searches** We track search intensity for terms related to straw-burning ban, insect bites, ticks, symptoms or treatment of insect bites, protective behavior, and related vaccination. The detailed lists of search terms for each category are provided in Table A4.

Appendix Table A4: Specific Search Terms on Baidu

| Category | Terms for Baidu Search Index |
|---|---|
| Straw utilization | jie2gan3li4yong4, jie2gan3da3bao1ji1, jie2gan3mei2cheng2xing2ji1, jie2gan3fen3sui4ji1, jie2gan3zong1he2li4yong4, jie2gan3ke1li4ji1, jie2gan3si4liao4ke1li4ji1 |
| Insect bites | chong2yao3, chong2yao3pi2yan2, chong2yao3xing4pi2yan2, wen2chong2ding1yao3, du2chong2 |
| Ticks | pi2, pi2chong2, pi2chong2ding1yao3, cao3pi2zi0, cao3pa2zi0, gou3dou4zi0, bi2shi1, niu2shi1, ying4pi2, bian3shi1 |
| Symptoms or treatment of insect bites | What medicine quickly reduces swelling and itching after insect bites; How to quickly reduce swelling and itching after a mosquito bite; What are the symptoms after a tick bite (in Chinese) |
| Protective behaviors | fang2wen2, fang2wen2sha1chuang1, fang2wen2tie1, wen2zhang4, wen3xiang1, bi4wen2an1, dian4wen2xiang1 |
| Vaccination | sen1lin2nao3yan2, yi3nao3yi4miao2, huang2re4bing4yi4miao2, deng1ge2re4yi4miao2, nao4yan2yi4miao2, liu2xing2xing4chu1xie3re4yi4miao2 |

**Crop Planting** We use crop planting information to support our heterogeneity analyses. The data are derived from high-resolution winter wheat and corn planting maps developed by Dong et al. (2020) and Peng et al. (2023), covering 11 provinces that account for over 98% and 99% of China's winter wheat and corn production, respectively. We aggregate both wheat and corn planting areas to the county-year level for the period 2011–2022. These measures capture regional variation in straw availability and burning pressure.

Dong et al. (2020) applied a phenology-based approach to distinguish winter wheat from other crops by comparing the seasonal variations of satellite-based NDVI across all croplands. This product enables large-scale early-season winter wheat mapping and generates high-resolution (30 m) maps for 2001–2023, covering 11 provinces that account for more than 98% of China's winter wheat production. Validation using survey samples yields producer and user accuracies of 89.30% and 90.59%, respectively. Peng et al. (2023) produced the annual corn planting map at 30m resolution for 2001–2023 across 22 provinces and municipalities, using a high spatiotemporal resolution fused dataset and a phenology-based method known as Time-Weighted Dynamic Time Warping. Validation based on field study samples showed average user and producer accuracies of 77.32% and 80.98%, respectively.

**Pollution and Biomass Power Plant** Monthly $PM_{2.5}$ concentrations are obtained from the Global Annual $PM_{2.5}$ Grids derived from satellite data by **?**. **?** estimate ground-level $PM_{2.5}$ by combining Aerosol Optical Dept (AOD) retrevals from the NASA MODIS, MISR, and SeaWiFS, which are subsequently calibrated to global ground-based observations of $PM_{2.5}$ using Geographically Weighted Regression (GWR). The raster grids of this ground calibrated $PM_{2.5}$ data have a high grid cell resolution of $0.01° \times 0.01°$. Several studies on air pollution have used this data and verified its validity (**??**). To identify biomass power plant activity, we obtain the list of registered companies in the biomass power industry from the Industrial and Commercial Firm Registry Database. Following Cao and Ma (2023), we retain firms whose business scope includes electricity generation through direct combustion or gasification of agricultural and forestry waste. Using this information, we construct a county-year measure of newly established biomass power plants.

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

Arthropods, including both insect and non-insect species, represent a diverse range of disease vectors. We provide an overview of key arthropod taxa and their associated health risks to illustrate how ecological changes—such as those triggered by straw-burning bans—can affect the incidence of vector-borne diseases.

**Insects and Vector-Borne Diseases** In the class of *Insecta*, several orders of insects are associated with vector-borne diseases. For instance, in the order *Diptera*, there are some of the most significant vectors of infectious diseases. Mosquitoes (Culicidae) are the primary vectors for malaria, dengue fever, Zika virus, chikungunya, yellow fever, Japanese encephalitis, and lymphatic filariasis—diseases responsible for substantial global morbidity and mortality (WHO, 2024). Similarly, houseflies (Musca domestica) and other dipteran species mechanically transmit pathogens causing dysentery, hepatitis A, typhoid, cholera, anthrax, and various parasitic infections (Förster et al., 2009). These insects thrive in environments with poor sanitation or accumulated organic waste, conditions potentially exacerbated by agricultural burning bans.

In the order *Lepidoptera*, stinging caterpillars—larval forms of butterflies and moths—pose medical risks primarily due to their venomous setae (bristles or spines), which can penetrate human skin. Exposure can lead to caterpillar dermatitis, characterized by erythematous rashes, itching, and occasionally systemic allergic reactions (Hossler, 2010). These dermatological and allergenic effects may strain local healthcare systems, especially in regions experiencing ecological changes that favor caterpillar proliferation.

Insects from the order *Hymenoptera*, including bees, wasps, and hornets, are widely recognized for their venomous stings. These stings can result in a spectrum of health outcomes ranging from localized pain, swelling, and irritation to systemic toxic effects and severe allergic reactions such as anaphylaxis, a potentially fatal condition (Golden, 2003).

The order *Coleoptera* contains several species of public health significance. Although beetles are not primary vectors of human pathogens, certain species, such as *Paederus*, cause irritant contact dermatitis through the toxin pederin, resulting in blistering and inflammation upon skin contact (Frank and Kanamitsu, 1987). Occupational exposure to beetles like *Tenebrio molitor* has been linked to allergic reactions, including asthma and dermatitis, particularly among agricultural and food-processing workers (Jeebhay et al., 2005). Additionally, ingestion of blister beetles (Meloidae) can lead to cantharidin poisoning, posing risks to both humans and livestock (Tagwireyi et al., 2000).

**Non-insect Arthropods and Vector-Borne Diseases** Non-insect arthropods, particularly ticks and mites within the class *Arachnida*, also significantly contribute to the transmission of vector-borne diseases. Ticks are second only to mosquitoes regarding global public health impact (Sonenshine and Roe, 2014), transmitting numerous bacterial, viral, and protozoal pathogens. For example, *Ixodes scapularis* (the black-legged tick) transmits *Borrelia burgdorferi*, the causative agent of Lyme disease, which incurs substantial healthcare costs and chronic morbidity (Adrion et al., 2015; CDC, 2022). Ticks also transmit pathogens causing babesiosis, anaplasmosis, ehrlichiosis, and tick-borne encephalitis (ECDC, 2025).

Mites, another arachnid group, transmit scrub typhus (*Orientia tsutsugamushi*) via chigger mites (*Trombiculidae*) and can cause allergic reactions through direct infestation (Koh et al., 2010). Additionally, some mite species mechanically transmit fungal spores or bacteria, particularly in agricultural settings.

In addition, another non-Insecta class of Arthropoda–Chilopoda–can cause local dermatological reactions, allergic responses, and envenomation-related symptoms due to their venomous bites although they are not vectors of pathogens such as viruses, bacteria, or protozoa (Undheim et al., 2015).

Ecological changes that enhance ground vegetation, moisture retention, or rodent populations—conditions likely resulting from accumulated straw residues—are known to improve habitat suitability and reproduction rates (Allan et al., 2003). Controlled burning practices have been shown to reduce tick and mite populations; thus, banning these practices may inadvertently create conditions favorable for their survival and pathogen transmission (Gleim et al., 2019).

Taken together, ecological changes resulting from straw-burning bans—including increased accumulation of crop residues and the preservation of arthropod eggs that would otherwise be reduced by fire—can substantially enhance habitats for insect and non-insect arthropods. Consequently, these habitat alterations may inadvertently amplify vector populations, elevating disease transmission risks and the associated healthcare burden.

## C Disease Categories for Empirical Analyses

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

| Disease name | ICD-10 codes |
|---|---|
| Relapsing fever, unspecified | A68.9 |
| Tularemia | A21 |
| Brucellosis | A23 |
| Arthropod-borne viral encephalitis, unspecified | A85.2 |
| Toxic effect of venom of other arthropods | T63.4 |
| Q fever | A78 |
| Bartonellosis | A44 |
| Typhus fever, unspecified | A75.9 |
| Unspecified viral encephalitis | A86 |
| Plague | A20 |
| Unspecified contact dermatitis due to other agents | L25.800x001 |
| Dengue | A90; A91 |
| Malaria | B50; B51; B52; B53; B54 |
| Mosquito-borne viral encephalitis | A83 |
| Chikungunya virus disease | A92.0 |
| Yellow fever | A95 |
| Zika virus disease | A92.8 |
| Myiasis | B87 |
| Onchocerciasis | B73 |
| Mansonelliasis | B74.4 |
| Gongylonemiasis pulchrum | B83.800x002 |
| Acanthocephaliasis | B83.800 |
| Typhus fever due to Rickettsia typhi | A75.2 |
| Teniasis | B68 |
| African trypanosomiasis | B56 |
| Loiasis | B74.3 |
| Leishmaniasis | B55 |
| Sandfly fever | A93.1 |
| Scabies | B86 |
| Acarine dermatitis | B88.000x004; B88.000x006 |

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

| Disease name | ICD-10 codes |
| --- | --- |
| Rickettsialpox due to Rickettsia akari | A79.1 |
| Hemorrhagic fever with renal syndrome (HFRS) | A98.5 |
| Paederus dermatitis | L24.800x002 |
| Epidemic louse-borne typhus fever due to Rickettsia prowazekii | A75.0 |
| Louse-borne relapsing fever | A68.0 |
| Trench fever | A79.0 |
| Typhoid and paratyphoid fevers | A01 |
| Shigellosis | A03 |
| Other bacterial intestinal infections | A04 |
| Other bacterial foodborne intoxications, not elsewhere classified | A05 |
| Cholera | A00 |
| Anthrax | A22 |
| Acute amebic dysentery | A06.0 |
| Ascariasis | B77 |
| Enterobiasis | B80 |
| Cysticercosis | B69 |
| Hookworm disease | B76 |
| Acute poliomyelitis | A80 |
| Acute hepatitis A | B15 |
| Trachoma | A71 |
| Pruritus | L29 |
| Rubella [German measles] | B06 |
| Allergic contact dermatitis, unspecific cause | L23.9 |
| Urticaria | L50 |
| Conjunctivitis | H10.1 |
| Papule | R23.800x001 |
| Typhus fever due to Rickettsia tsutsugamushi | A75.3 |
| Leptospirosis | A27 |
| Chlamydia psittaci infection | A70 |

*Note:* Vector-borne diseases include all diagnoses in this table and tick-borne diseases as listed in Appendix Table C2. This table is obtained from a cross-reference of relevant literature. See Fang et al. (2005), Jiang et al. (2011), WHO (2024), Bishopp (1915), Hu (1965), Norval et al. (1983), Wilson and Sutherst (1986), Xue (1988), Xue et al. (1989), Xue et al. (1990), Dryden and Broce (1991), Lawler and Dritz (2005), Lawler and Dritz (2006), Jia and Wu (2008), De Oliveira et al. (2012), Ke et al. (2013), Neoh and Bong (2017), and Wang et al. (2017).

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

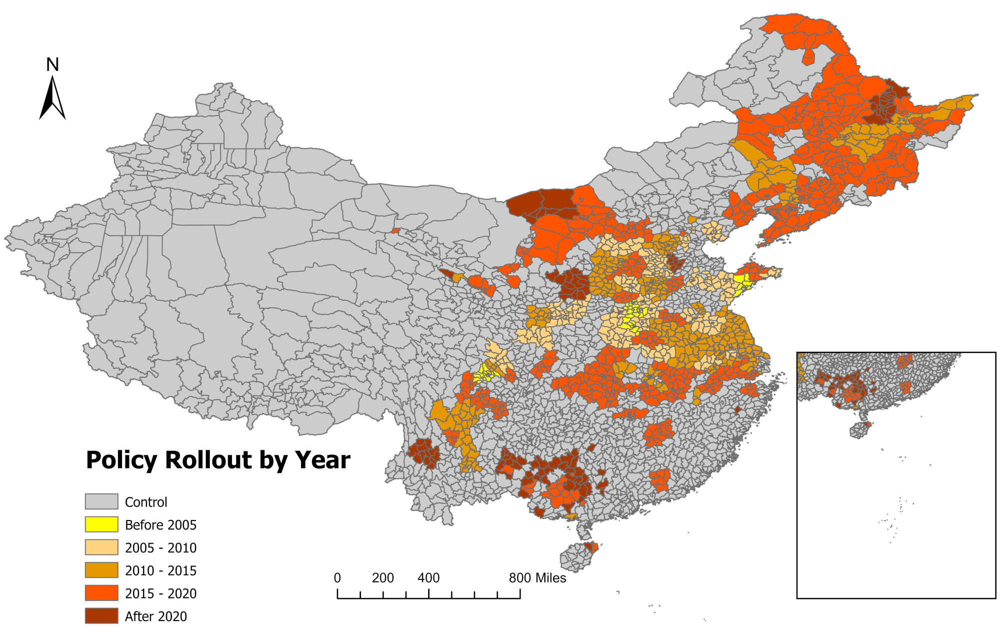
| **Disease name** | **ICD-10 codes** |
|---|---|
| Lyme disease | A69.2 |
| Human granulocytic anaplasmosis [HGA] | A93.8 |
| Tick-borne viral encephalitis [TBE] | A84 |
| Severe fever with thrombocytopenia syndrome [SFTS] | A93.8 |
| Crimean-Congo hemorrhagic fever | A98.0 |
| Rickettsiosis | A77; A79.9; A79.8 |
| Babesiosis | B60.0 |
| Omsk hemorrhagic fever | A98.1 |
| Kyasanur forest disease | A98.2 |

# D Supplementary Analyses Supporting Identification Strategy

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

Figure D1 plots the geographic sequence of policy rollout, revealing that early adoption concentrated in the North China Plain, followed by expansions into northeastern, northern, and southwestern regions. Figure D2 further compares the rollout timing of the straw-burning ban and the *APMD program*. The left panel shows a strong correlation between the two: counties that adopted the APMD program early also implemented the straw-burning ban early. The right panel isolates regions that never adopted the ban and shows that most were late adopters of air quality monitoring, supporting the notion of administrative inertia in environmental governance.

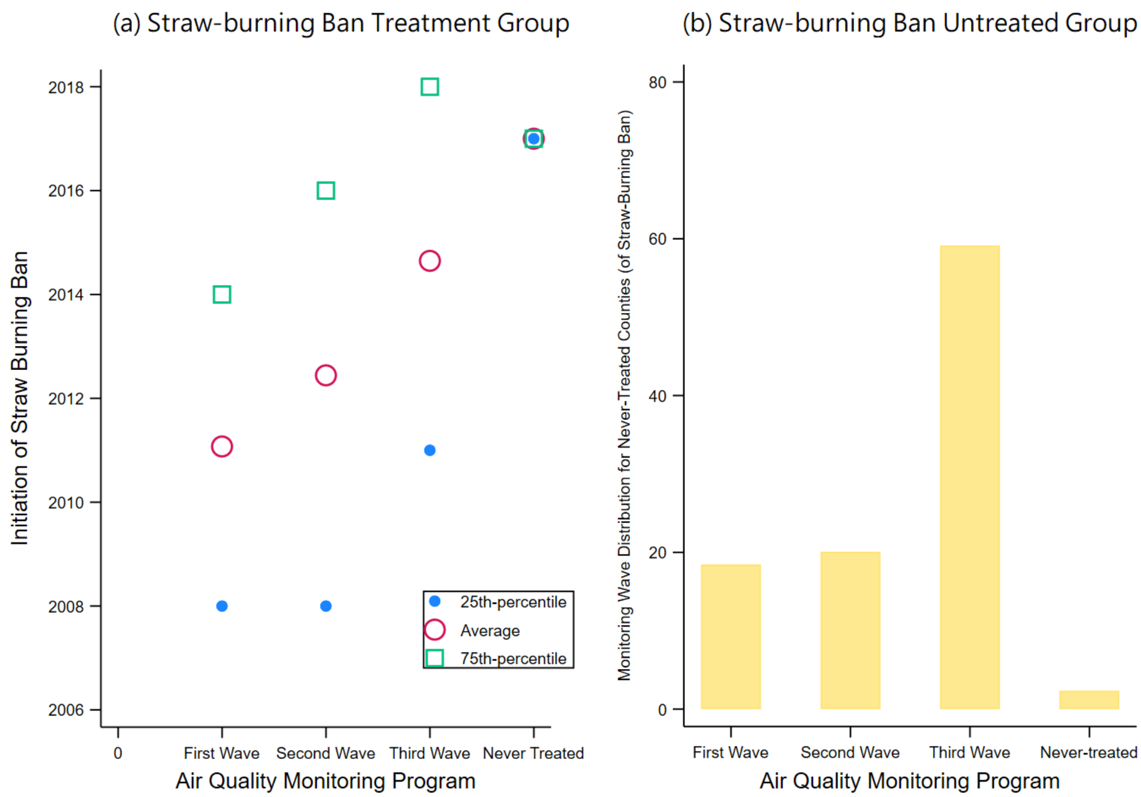
These patterns suggest that rollout timing was not driven by local health needs or ecological conditions but followed a national sequence of administrative hierarchy and political prioritization. This provides support for the plausibility of our identification strategy.




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

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

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




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

**Policy Rollout and Regional Covariates** Table D1 summarizes the economic and health facilities attributes of counties across different rollout waves of the straw-burning ban. First, since the rollout followed a top-down administrative hierarchy, earlier-adopting regions tend to have larger GDP and population. Second, while the policy targets agricultural burning, which may relate to cropland area, we find that although treated regions generally have more cropland, earlier adopters do not necessarily have larger cropland areas than later ones—suggesting that cropland size was not the primary determinant of rollout timing.

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

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

**Air Pollution Improvements as a Potential Confounder** One potential concern is whether observed health effects related to vector-borne diseases are confounded by improvements in air quality resulting from the ban. However, Table D3 presents placebo tests showing no significant relationship between $PM_{2.5}$ reductions and hospitalization rates for vector-borne diseases. This suggests that our estimated health effects are not simply driven by changes in general air quality.

**Concurrent Agricultural 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.

Our placebo tests on unrelated conditions—such as non-arthropod-related dermatoses, bone fractures (typically due to accidents), and neoplasms (linked to long-term biological processes). As shown in Table F2, we detect no significant treatment effects for these outcomes, confirming that the observed effects are not driven by concurrent health policies, concurrent changes in the health system or unrelated disease trends.

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 | 514 | 338 | 366 | 161 | 1379 | 1334 |
| GDP ($10^9$ *CNY*) | 36.21 | 24.54 | 23.20 | 12.20 | 27.05 | 19.79 |
| | (32.38) | (36.79) | (22.50) | (8.56) | (30.44) | (24.11) |
| Population ($10^3$) | 565.51 | 474.74 | 466.47 | 348.60 | 491.42 | 431.79 |
| | (327.85) | (300.83) | (278.85) | (249.65) | (307.49) | (379.23) |
| Cropland (*100 $km^2$*) | 671.10 | 914.15 | 930.37 | 709.09 | 804.94 | 575.90 |
| | (522.05) | (1,078.51) | (1,010.98) | (765.95) | (861.87) | (597.03) |
| Hospital Beds | 1,242.22 | 970.15 | 1,052.52 | 752.58 | 1,067.31 | 838.37 |
| | (720.61) | (597.66) | (644.69) | (533.33) | (669.48) | (695.13) |
| Hospital Beds per $10^3$ People | 2.66 | 2.64 | 2.86 | 2.76 | 2.72 | 2.37 |
| | (2.15) | (2.38) | (3.42) | (2.96) | (2.69) | (2.29) |
| 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, population, number of hospital beds, and hospital beds per 1000 people are measured by the 2001-2011 average. GDP is the average during 2013-2021 due to data availability. 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 Roll-out Waves

| | Roll-out Waves | | | Indicator for Treatment | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Wave | Wave | Wave | Ever-Treated | Ever-Treated | Ever-Treated |
| Administrative Level 1 | -0.753*** | -0.325*** | | 0.229*** | 0.120*** | |
| | (0.060) | (0.063) | | (0.023) | (0.025) | |
| Administrative Level 2 | -0.436*** | -0.219*** | | 0.268*** | 0.172*** | |
| | (0.069) | (0.065) | | (0.023) | (0.025) | |
| Hospital Beds ($10^3$) | | -0.025 | 0.012 | | -0.009 | -0.010 |
| | | (0.058) | (0.059) | | (0.021) | (0.021) |
| Cropland ($10^4$ $km^2$) | | -0.003 | -0.002 | | 0.010*** | 0.009*** |
| | | (0.002) | (0.002) | | (0.001) | (0.001) |
| GDP ($10^9$ $CNY$) | | -0.004*** | -0.006*** | | 0.000 | 0.001* |
| | | (0.001) | (0.001) | | (0.000) | (0.000) |
| $PM_{2.5}$ ($\mu g/m^3$) | | -0.024*** | -0.026*** | | 0.010*** | 0.011*** |
| | | (0.002) | (0.002) | | (0.001) | (0.001) |
| $R^2$ | 0.095 | 0.232 | 0.217 | 0.061 | 0.178 | 0.160 |
| Observations | 1,403 | 1,331 | 1,331 | 2,751 | 2,621 | 2,621 |

*Notes:* This table presents the determinants of the straw-burning ban roll-out. In Columns (1)–(3), the dependent variable is the roll-out wave, coded as a continuous variable taking values 1, 2, 3, or 4, corresponding to adoption before 2011, during 2011–2014, 2015–2018, and 2019–2022, respectively. In Columns (4)–(6), 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, number of hospital beds, and $PM_{2.5}$ are measured using the 2001–2011 averages. GDP is averaged over 2013–2021 due to data availability. Robust standard errors are reported in parentheses. *** p <0.01, ** p <0.05, * p <0.1.

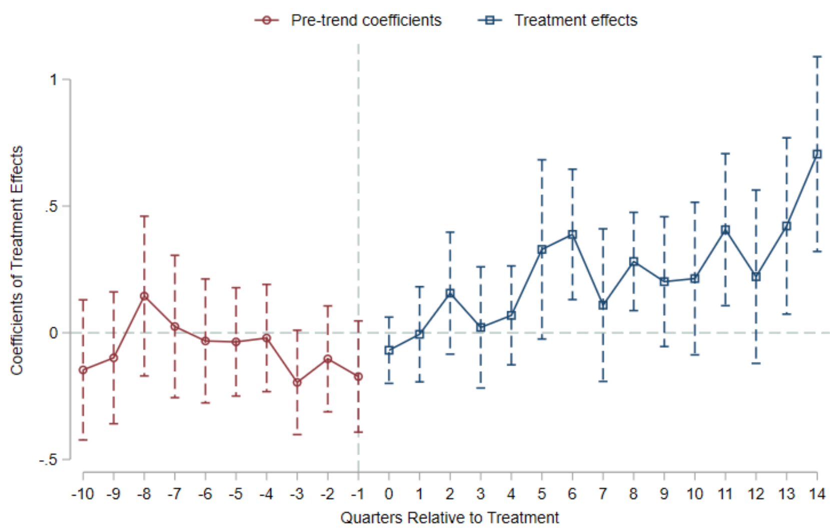
## Appendix Table D3: $PM_{2.5}$ and Vector-Borne Diseases

| | Vector-Borne Hospitalizations | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $PM_{2.5}$ | -0.178 | -0.178 | -0.174 | -0.175 |
| | (0.145) | (0.145) | (0.145) | (0.145) |
| County FE | ✓ | ✓ | ✓ | ✓ |
| Province-Year-Quarter FE | ✓ | ✓ | ✓ | ✓ |
| Hospital Controls | | ✓ | ✓ | ✓ |
| Weather Controls | | | ✓ | ✓ |
| Forest Fire Controls | | | | ✓ |
| Observations | 15,850 | 15,850 | 15,850 | 15,850 |

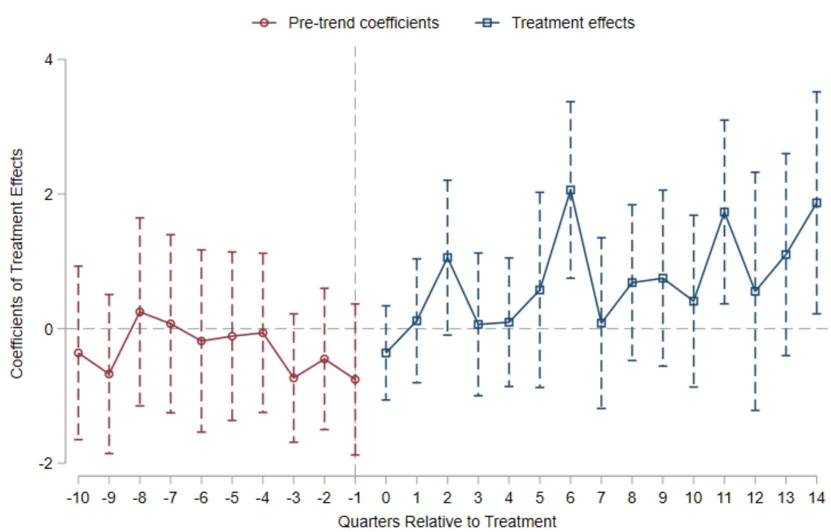
*Note:* This table presents the association between $PM_{2.5}$ and hospitalizations of vector-borne diseases. The model includes county and province-by-year-quarter fixed effects. Hospital controls include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general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

# E Robustness Checks and Heterogeneity Analysas

(a) Hospitalization of Tick-Borne Diseases



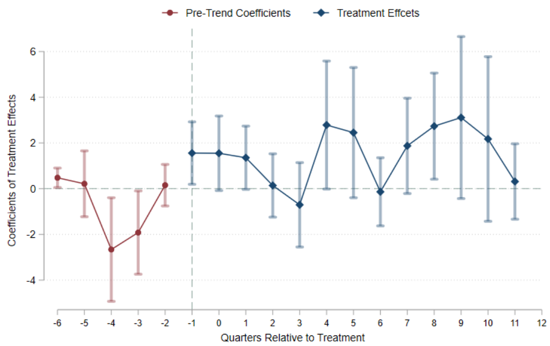

(b) Medical Expenditure of Tick-Borne Diseases



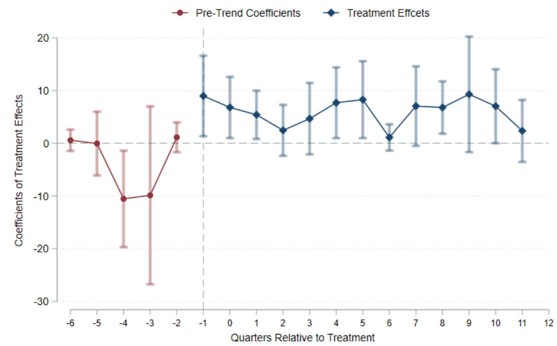

Appendix Figure E1: Effects on Tick-Borne Diseases: Event Study Plots

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

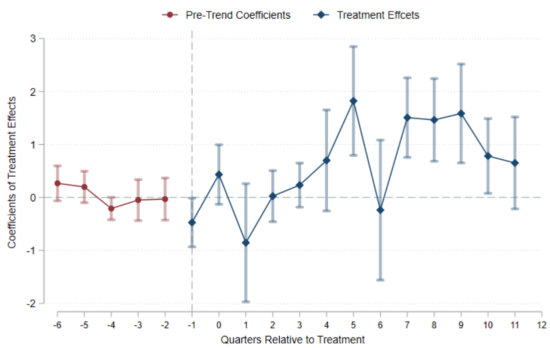
(a) Hospitalizations of Vector-Borne Diseases



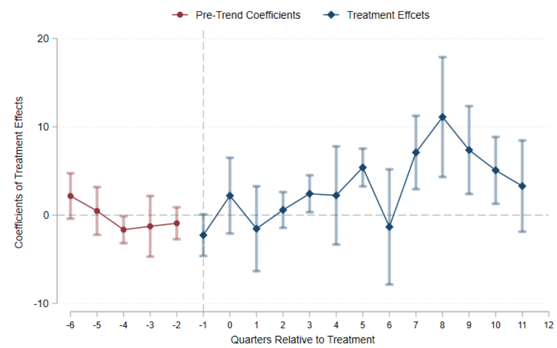

(b) Medical Expenditure of Vector-Borne Diseases




(c) Hospitalizations of Tick-Borne Diseases



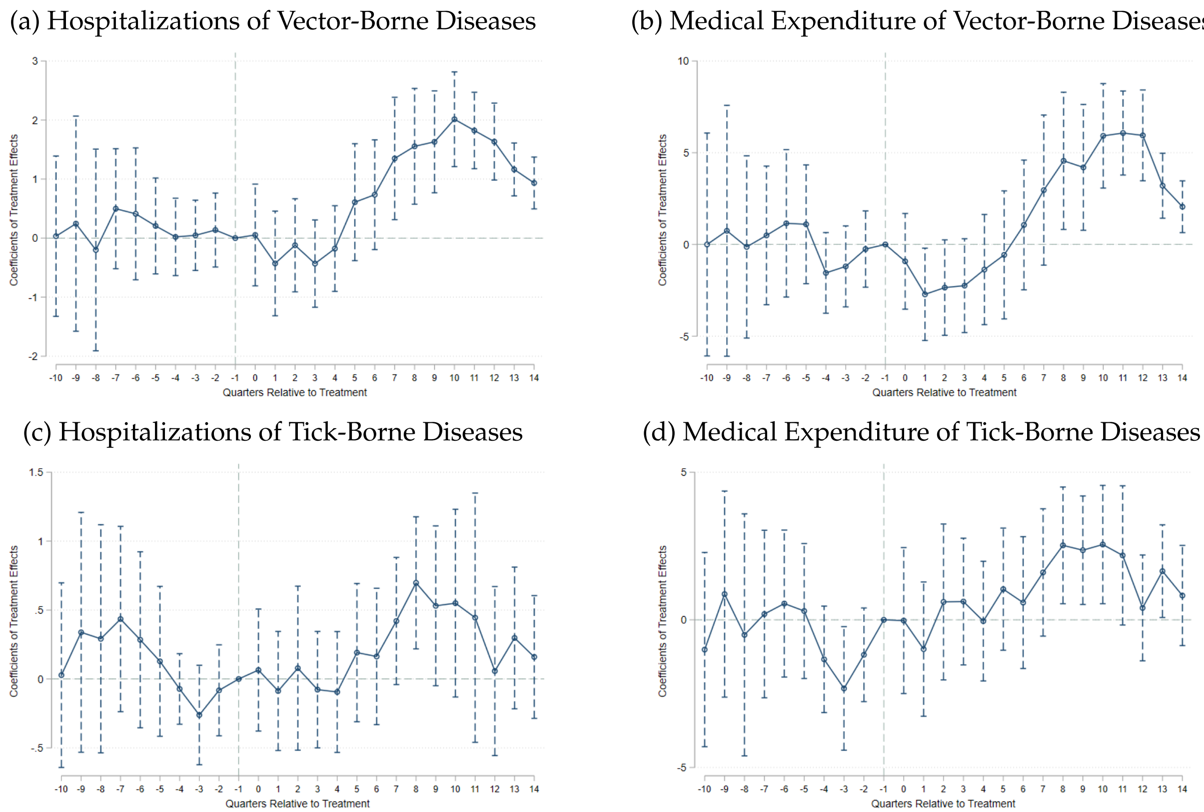

(d) Medical Expenditure of Tick-Borne Diseases




Appendix Figure E2: Effects on Vector-Borne Diseases and Tick-Borne Diseases: Event Study Using Callaway and Sant'Anna (2021)

*Notes*: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne and tick-borne diseases using the method of Callaway and Sant'Anna (2021). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions and total medical expenditures, with the unit of observation at the county-by-year-quarter level. The model includes county and province-by-quarter fixed effects.

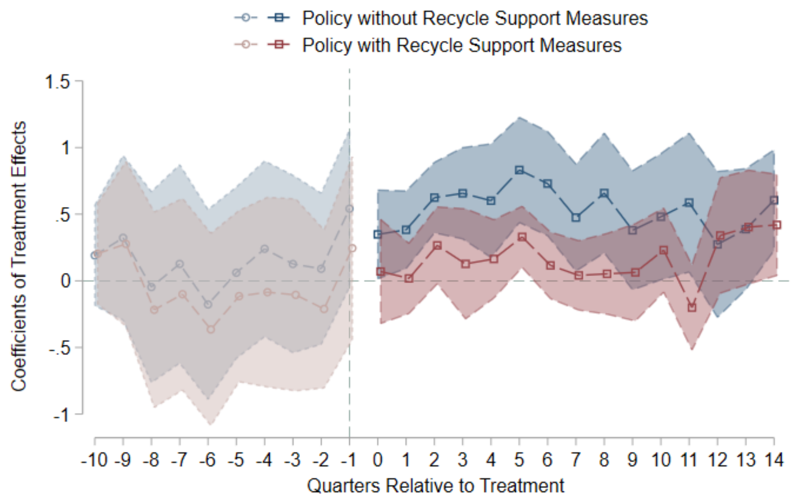
Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, and GDP. The x-axis is quarters relative to treatment. The y-axis presents the estimated treatment effects relative to never-treated and not-yet-treated counties, with 95% confidence intervals.



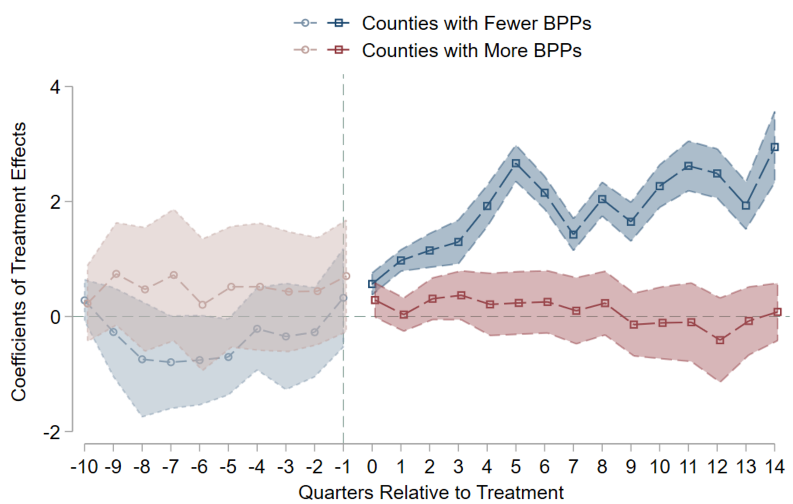

Appendix Figure E3: Effects on Vector-Borne Diseases and Tick-Borne Diseases: Event Study Using Sun and Abraham (2021)

*Notes*: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne and tick-borne diseases using the method of Sun and Abraham (2021). The dependent variables are the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions and total medical expenditures, with the unit of observation at the county-by-year-quarter level. The model includes county and province-by-year-quarter fixed effects. Control variables include the total number of hospitals, the counts of secondary, tertiary, Class B, Class C, and general hospitals, average number of annual hospitalizations, average temperature and precipitation, frequency and burned area of forest wildfires, cropland area, GDP, population, and the number of hospital beds. The x-axis is quarters relative to treatment. The y-axis presents the estimated treatment effects relative to never-treated and not-yet-treated counties, with 95% confidence intervals. This figure shows that significant effects emerge later than in Figure 4, which is estimated using the Borusyak et al. (2024) estimator. A potential reason lies in their different handling of "forbidden comparisons" in TWFE regressions between early- and late-treated cohorts. Specifically, Sun and Abraham (2021) construct interaction-weighted estimators that compare each cohort of treated units with appropriate never-treated or not-yet-treated controls. If some cohorts are observed only in the later post-periods, this method does not estimate early lags for them. As a result, early-period estimates rely heavily on a small subset of early adopters, and the early post-treatment coefficients are often imprecisely estimated and insignificant. As more treated cohorts accumulate in later periods, the estimates gain statistical power and often become significant. By contrast, Borusyak et al. (2024) predict untreated potential outcomes for each unit in every period and then average the treatment effect across all units in each relative period. This estimator "borrows strength" more directly across cohorts, often yielding smoother and more precise estimates in early periods even with fewer adopters.

(a) Heterogeneous Effects on Hospitalizations by County-level Recycling Support Measures




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




Appendix Figure E4: Event Study of Straw-Burning Ban by Alternative Recycling Measures

*Notes*: This figure illustrates the dynamic effects of the straw-burning ban on vector-borne diseases by different recycling measures. The dependent variable is the inverse hyperbolic sine (IHS) transformation of the number of inpatient admissions for vector-borne diseases, measured at the county-by-year-quarter level. Panel (a) estimates the effects of straw-burning ban policies with assessment criteria and with accompanying recycling support measures. In policies with support measures, the treatment group includes only observations with both a ban and accompanying recycling measures. Panel (b) divides the sample by the number of biomass power plants, comparing counties below and above the national median (two biomass power plants per county). The fixed effects and control variables are the same as in Figure 4. The x-axis shows quarters relative to treatment, and the y-axis displays estimated treatment effects relative to non-treated observations, with 95% confidence intervals.

Appendix Table E1: Effects on Vector-Borne Diseases for Rural and Urban Residents

| | Hospitalization | | | |
|---|---|---|---|---|
| | Vector-Borne Diseases | | Tick-Borne Diseases | |
| | (1) | (2) | (3) | (4) |
| | Rural | Urban | Rural | Urban |
| Treatment (=1) | 0.362* | 0.359*** | 0.317*** | 0.051* |
| | (0.188) | (0.113) | (0.077) | (0.030) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 4,702 | 5,101 | 4,702 | 5,101 |

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

Appendix Table E2: Straw-burning Ban, Recycle Measures, and Vector-Borne Diseases: Alternative Recycle Measures

| | Vector-Borne Disease Hospitalization | | | |
|---|---|---|---|---|
| | by Policy Type | | by Biomass Power Plants | |
| | (1) | (2) | (3) | (4) |
| | Benchmark | With Recycle | $<$ median | $>$ median |
| Treatment (=1) | 0.502*** | 0.122 | 1.627*** | 0.050 |
| | (0.155) | (0.111) | (0.115) | (0.214) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 5,395 | 4,925 | 2,110 | 3,285 |

*Notes:* This table presents the heterogeneous effects of straw-burning ban policies on hospitalizations for vector-borne diseases across counties with different straw recycling policies. The dependent variable is the inverse hyperbolic sine (IHS) transformation of hospitalization counts at the county-by-year-quarter level. Columns (1) reproduces the results from the baseline analysis. Column (2) restricts the treatment group to counties with both a straw-burning ban and accompanying straw recycling support measures. Columns (3) and (4) report estimates for subsamples where the density of biomass power plants (per grain planting area) is below and above the national median (two plants per county), respectively. The analysis spans four years (sixteen quarters) before and after policy implementation. The model includes county, province–quarter, and year–quarter fixed effects. Control variables include hospital characteristics, weather conditions (average temperature and precipitation), wildfire characteristics (occurrence and burned area of forest wildfires), cropland area, GDP (in logarithmic form), population (in logarithmic form), and the number of hospital beds. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E3: 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 |
| Treatment (=1) | 0.333* | 1.285*** |
| | (0.190) | (0.344) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | |
| Observations | 5,267 | 5,267 |

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

Appendix Table E4: 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 |
| Treatment (=1) | 0.517*** | 0.494*** | 1.765*** | 1.664*** |
| | (0.156) | (0.155) | (0.342) | (0.332) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 5,328 | 5,296 | 5,328 | 5,296 |

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

Appendix Table E5: 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 |
| Treatment (=1) | 1.411** | 5.460*** | 0.849*** | 4.602*** |
| | (0.551) | (1.596) | (0.163) | (0.838) |
| | County FE, province-quarter FE, control variables included | | | |
| Observations | 6,772 | 6,772 | 6,772 | 6,772 |

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

Appendix Table E6: Effects of Straw-Burning Ban Policies Estimated Using Sun and Abraham (2021)

| | Vector-Borne Diseases | | Tick-Borne Diseases | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Hospitalizations | Medical Expenditure | Hospitalizations | Medical Expenditure |
| Treatment (=1) | 0.726*** | 1.466*** | 0.208 | 0.996** |
| | (0.130) | (0.475) | (0.137) | (0.392) |
| | County FE, province-year-quarter FE, control variables included | | | |
| Observations | 1,982 | 1,982 | 1,982 | 1,982 |

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

Appendix Table E7: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Log of the Dependent Variables

| | Vector-Borne | | Tick-Borne | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Hospitalizations | Medical Expenditure | Hospitalizations | Medical Expenditure |
| Treatment (=1) | 0.407*** | 1.634*** | 0.176** | 0.663* |
| | (0.139) | (0.321) | (0.071) | (0.397) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 5,395 | 5,395 | 5,395 | 5,395 |

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

Appendix Table E8: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Fixed-Effects PPML Estimation

| | Vector-Borne | | Tick-Borne | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Hospitalizations | Medical Expenditure | Hospitalizations | Medical Expenditure |
| Treatment (=1) | 0.160* | 0.157 | 0.338** | 0.440*** |
| | (0.092) | (0.098) | (0.133) | (0.136) |
| | County FE, province-quarter FE, control variables included | | | |
| Observations | 6,612 | 6,612 | 4,995 | 4,995 |

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

Appendix Table E9: Effects of Intensity of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases using de Chaisemartin et al. (2022)

| | Vector-Borne Diseases | | Tick-Borne Diseases | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Hospitalizations | Medical Expenditure | Hospitalizations | Medical Expenditure |
| ATT | 0.216*** | 0.349*** | 0.018 | 0.240* |
| | (0.047) | (0.123) | (0.028) | (0.144) |
| | County FE, year-quarter FE, control variables included | | | |
| Observations | 4,525 | 4,525 | 4,525 | 4,525 |

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

Appendix Table E10: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Alternative Sample Periods (2015-2019)

| | Vector-Borne Diseases | | Tick-Borne Diseases | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Hospitalizations | Medical Expenditure | Hospitalizations | Medical Expenditure |
| Treatment (=1) | 0.622*** | 1.816*** | 0.256** | 0.872 |
| | (0.173) | (0.474) | (0.123) | (0.572) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | |
| Observations | 3,030 | 3,030 | 3,030 | 3,030 |

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

Appendix Table E11: Effects of Straw-Burning Ban Policies on Straw Burning: Alternative Measures

| | Fire Points Orginal Value | | Aggregated Fire Points ($< 1km^2$) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | # Straw Burning | Burned Areas | # Straw Burning | Burned Areas |
| Treatment (=1) | -2.299*** | -0.086*** | -0.177*** | -0.053*** |
| | (0.804) | (0.024) | (0.046) | (0.012) |
| | County FE, province-year FE, control variables included | | | |
| Observations | 35,101 | 35,101 | 35,101 | 35,101 |

*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. The dependent variables are the original value of the number of agricultural fires in harvest seasons in Column (1) and the burned area in harvest seasons (10,000 hectares) in Column (2). In Columns (3) 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 province-by-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 city level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E12: Effects of Straw-Burning Ban Policies on Straw Burning Using Callaway and Sant'Anna (2021)

| | Fire in Harvest Seasons | | All Fire | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | # Straw Burning | Burned Areas | # Straw Burning | Burned Areas |
| Treatment (= 1) | -0.425*** | -0.064*** | -0.520*** | -0.075** |
| | (0.093) | (0.023) | (0.143) | (0.032) |
| | County FE, control variables included | | | |
| Observations | 39,655 | 39,655 | 39,655 | 39,655 |

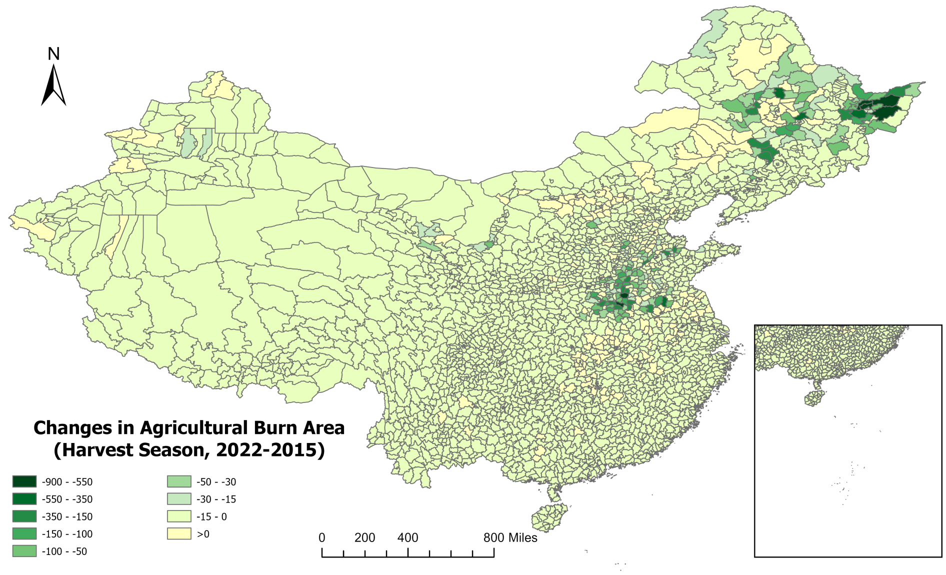
*Notes:* This table presents the effects of straw-burning ban policies on the number and burned area of agricultural fires using the method of Callaway and Sant'Anna (2021). The dependent variables include the inverse hyperbolic sine (IHS) transformation of the number of agricultural fires and burned areas in harvest seasons in Columns (1) and (2), and the IHS transformation of the number of agricultural fires and burned areas in Columns (3) and (4). Harvest seasons are defined following He et al. (2020). Burned area is measured in *10,000 hectare*, and measured at the county-year level. The regression sample spans from 2001 to 2022. Control variables include average temperature and precipitation, frequency and burned area of forest wildfires. Standard errors (in parentheses) are clustered at the city level. *** p <0.01, ** p <0.05, * p <0.1.

Appendix Table E13: Robustness Check: Effects of Straw-burning Ban on Insect Population

| | (1) Arthropoda | (2) Insecta | (3) Arachnida | (4) Chilopoda |
|---|---|---|---|---|
| | **Panel A: Log transformation of insect observation** | | | |
| Treatment (=1) | 0.023* | 0.021* | 0.003 | 0.001* |
| | (0.013) | (0.011) | (0.003) | (4.0e-04) |
| | County FE, year FE included<br>log observer No., other baseline control variables included | | | |
| Observations | 10,288 | 10,286 | 10,278 | 10,286 |
| | **Panel B: Alternative control variables: including bird observer No.** | | | |
| Treatment (=1) | 0.026* | 0.023* | 0.004 | 0.001* |
| | (0.015) | (0.014) | (0.004) | (5.1e-04) |
| | County FE, year FE, baseline control variables included<br>IHS bird observer No. included | | | |
| Observations | 9,922 | 9,920 | 9,913 | 9,921 |
| | **Panel C: Alternative control variables: including population** | | | |
| Treatment (=1) | 0.028* | 0.025* | 0.004 | 0.001* |
| | (0.015) | (0.014) | (0.003) | (5.5e-04) |
| | County FE, year FE, baseline control variables included<br>IHS population included | | | |
| Observations | 10,202 | 10,200 | 10,192 | 10,200 |

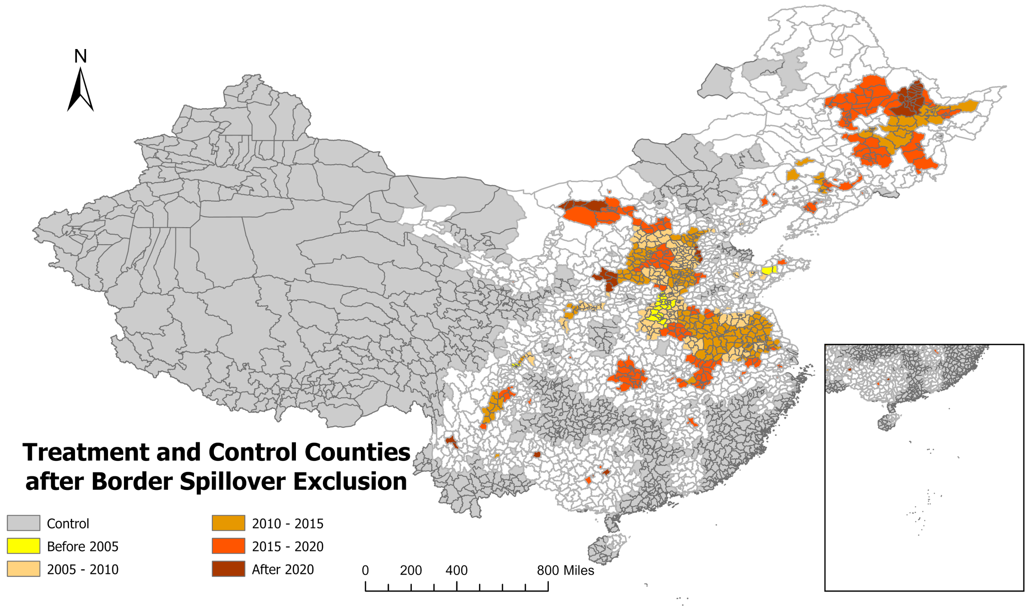
*Notes:* This table presents the effects of straw-burning ban policies on insect observations using data from 2015 to 2022. The dependent variable is the number of recorded observations for species within each taxonomic category per county–year, transformed using the logarithm in Panel A and the inverse hyperbolic sine (IHS) in Panels B and C. The log transformation takes the form log(variable+1). In Panel A, the number of unique observers and GDP are in logarithmic forms. Compared with the benchmark results, Panel B additionally includes the number of unique bird observers. Panel C additionally includes population. Standard errors (in parentheses) are clustered at the city level. *** p <0.01, ** p <0.05, * p <0.1.

# F Other Tables and Figures



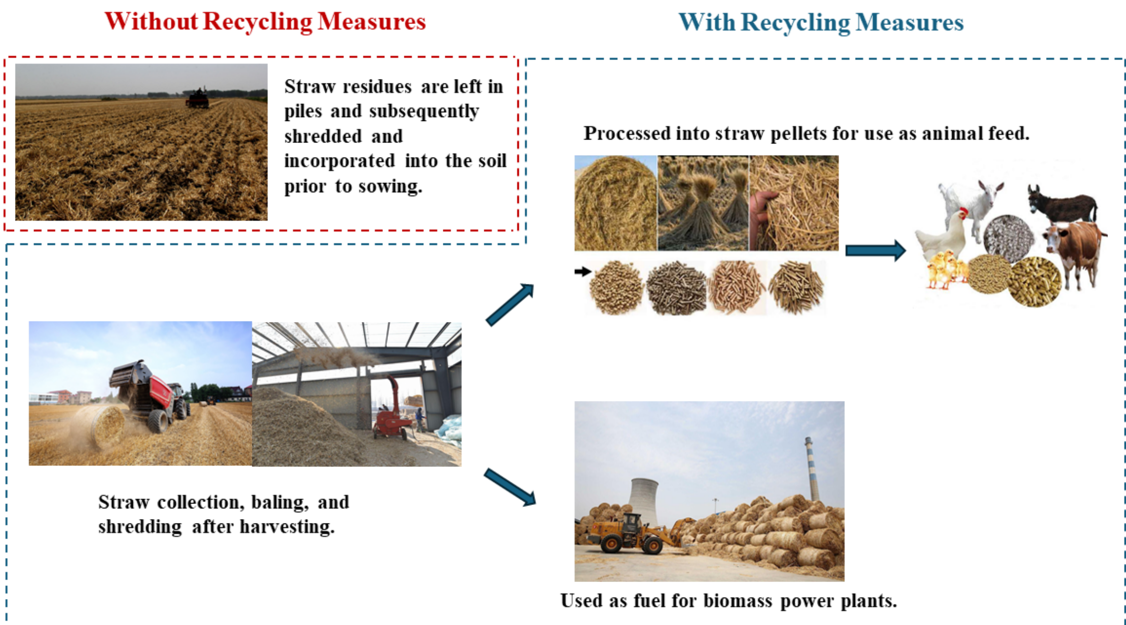

Appendix Figure F1: Changes in Cropland Fire 2015-2022

*Notes*: This figure illustrates the distribution of changes in cropland fire activity during the harvest season between 2015 and 2022 (the main sample period for our hospitalization analyses). A similar reduction in fires is observed when using the full fire data from 2001 to 2022.




Appendix Figure F2: Roll-out of China's Straw Burning Policies without across Borders Spillovers

*Notes*: This figure illustrates the distribution of roll-out of straw burning policies excluding geographically adjacent treatment and control counties. The data are obtained from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.




Appendix Figure F3: Illustration of Straw Residue Management After the Burning Ban

*Notes*: This figure illustrates different practices of straw residue management. After onsite burning is banned, the most common and economical practice is to leave straw residues to accumulate on cropland and later crush and incorporate them into the soil before the next planting season. In regions with stronger local capacity, residues are more effectively removed or recycled. Primary recycling methods include baling and collecting straw for use as livestock feed or as fuel for biomass power plants.

Appendix Table F1: 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 |
| Treatment (=1) | -0.113** | -0.077** | -0.114*** | -0.070* |
| | (0.046) | (0.033) | (0.044) | (0.070) |
| | County FE, province-year-quarter FE, control variables included | | | |
| Observations | 5,672 | 5,672 | 5,672 | 5,672 |

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

Appendix Table F2: Placebo Test on Unrelated Diseases

| | Hospitalizations | | | Medical Expenditure | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Other Dermatosis | Fracture | Neoplasm | Other Dermatosis | Fracture | Neoplasm |
| Treatment (=1) | -0.001 | -0.014 | 0.011 | 0.005 | -0.011 | 0.005 |
| | (0.009) | (0.021) | (0.026) | (0.006) | (0.038) | (0.036) |
| | County FE, province-quarter FE, year-quarter FE, control variables included | | | | | |
| Observations | 5,864 | 5,864 | 5,864 | 5,864 | 5,864 | 5,864 |

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

Appendix Table F3: Effects of Straw-Burning Ban Policies on Air Pollutants

| | (1) $PM_{2.5}$ | (2) $PM_{10}$ |
|---|---|---|
| Treatment (=1) | -1.247*** | -2.266*** |
| | (0.388) | (0.565) |
| | County FE, year FE, control variables included | |
| 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 F4: Effects of Cropland Fires on Vector-Borne Diseases Using Instrument Variable Method

| | Cropland Fires | Vector-Borne Diseases | |
|---|---|---|---|
| | First Stage | Hospitalizations | Medical Expenditure |
| Treatment (=1) | -0.051 ** | | |
| | (0.011) | | |
| Cropland Fires Area | | -8.680* | -18.115* |
| | | (4.783) | (10.920) |
| | County FE, year FE, control variables included | | |
| First stage $F$-stat | 6.455 | | |
| Observations | 2,461 | 2,461 | 2,461 |

*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 IHS transformation of the 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 F5: Effects of Straw-Burning Ban Policies on Agricultural Outcome

| | (1) Cropland | (2) Forest | (3) %Wheat Planting |
|---|---|---|---|
| Treatment (= 1) | -1,529.534*** | -1.594 | -0.012* |
| | (385.723) | (2.442) | (0.007) |
| | County FE, year FE, control variables included | | |
| Observations | 36,141 | 33,770 | 11,843 |

*Notes:* This table presents the effects of straw-burning ban policies on agricultural outcomes, including cropland area, forest area, and the percentage of land planted with wheat. Cropland and forest areas are measured in square kilometers (1 $km^2$ = 100 hectares). Wheat shares are defined as the proportion of wheat planted area relative to total cropland. Control variables include lagged wheat planting areas, average temperature and precipitation, frequency and burned area of forest wildfires. Standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

## Appendix References


**Adrion, Emily R, John Aucott, Klaus W Lemke, and Jonathan P Weiner**, "Health care costs, utilization and patterns of care following Lyme disease," *PloS One*, 2015, *10* (2), e0116767.

**Allan, Brian F, Felicia Keesing, and Richard S Ostfeld**, "Effect of forest fragmentation on Lyme disease risk," *Conservation Biology*, 2003, *17* (1), 267–272.

**Assunçãoa, Juliano, Clarissa Gandoura, and Eduardo Souza-Rodriguesd**, "The forest awakens: Amazon regeneration and policy spillover," *CPI/PUC-Rio, Working Paper*, 2019.

**Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Yongchen Zou**, "From fog to smog: The value of pollution information," *American Economic Review*, 2024, *114* (5), 1338–1381.

**Bishopp, F. C.**, *Fleas* number 248, US Department of Agriculture, 1915.

**Borusyak, Kirill, Xavier Jaravel, and Jann Spiess**, "Revisiting event-study designs: robust and efficient estimation," *Review of Economic Studies*, 2024, *91* (6), 3253–3285.

**Callaway, Brantly and Pedro HC Sant'Anna**, "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230.

**Cao, Jing and Rong Ma**, "Mitigating agricultural fires with carrot or stick? Evidence from China," *Journal of Development Economics*, 2023, *165*, 103173.

**CDC**, *Tickborne Diseases of the United States: A Reference Manual for Healthcare Providers*, Centers for Disease Control and Prevention, 2022.

**Correia, Sergio, Paulo Guimarães, and Tom Zylkin**, "Fast Poisson estimation with high-dimensional fixed effects," *The Stata Journal*, 2020, *20* (1), 95–115.

**de Chaisemartin, Clement, Xavier d'Haultfoeuille, Félix Pasquier, and Gonzalo Vazquez-Bare**, "Difference-in-Differences for continuous treatments and instruments with stayers," *Available at SSRN 4011782*, 2022.

**De Oliveira, R. D. F., L. C. De Almeida, D. R. De Souza, C. B. Munhae, O. C. Bueno, and M. S. de Castro Morini**, "Ant diversity (Hymenoptera: Formicidae) and predation by ants on different stages of the sugarcane borer life cycle, Diatraea saccharalis (Lepidoptera: Crambidae)," *European Journal of Entomology*, 2012, *109* (3), 381.

**Dong, Jie, Yangyang Fu, Jingjing Wang, Haifeng Tian, Shan Fu, Zheng Niu, Wei Han, Yi Zheng, Jianxi Huang, and Wenping Yuan**, "Early-season mapping of winter wheat in China based on Landsat and Sentinel images," *Earth System Science Data*, 2020, *12*, 3081–3095.

**Dryden, M. W. and A. B. Broce**, "Severe flea infestation in dairy calves," *Kansas Agricultural Experiment Station Research Reports*, 1991, (2), 25–30.

**ECDC**, *Tick-borne diseases*, European Centre for Disease Prevention and Control, 2025.

**Fang, Meiyu, Lihui Lin, and Jianwei Liu**, *Vector-borne Diseases*, Military Medical Science Press, 2005.

**Förster, Maike, Sven Klimpel, and Kai Sievert**, "The house fly (Musca domestica) as a potential vector of metazoan parasites caught in a pig-pen in Germany," *Veterinary Parasitology*, 2009, *160* (1-2), 163–167.

**Frank, JH and K Kanamitsu**, "Paederus, sensu lato (Coleoptera: Staphylinidae): natural history and medical importance," *Journal of Medical Entomology*, 1987, *24* (2), 155–191.

**Gleim, Elizabeth R, Galina E Zemtsova, Roy D Berghaus, Michael L Levin, Mike Conner, and Michael J Yabsley**, "Frequent prescribed fires can reduce risk of tick-borne diseases," *Scientific Reports*, 2019, *9* (1), 9974.

**Golden, David BK**, "Stinging insect allergy," *American Family Physician*, 2003, *67* (12), 2541–2546.

**He, Guojun, Tong Liu, and Maigeng Zhou**, "Straw burning, PM2.5, and death: Evidence from China," *Journal of Development Economics*, 2020, *145*, 102468.

**Hossler, Eric W**, "Caterpillars and moths: Part I. Dermatologic manifestations of encounters with Lepidoptera," *Journal of the American Academy of Dermatology*, 2010, *62* (1), 1–10.

**Hu, Rushen**, "Ecological habits and identification of major fly species in China," *People's Military Surgeon*, 1965, (Z1), 29–31.

**Huang, Jialin, Jianwei Xing, and Eric Yongchen Zou**, "(Re)scheduling pollution exposure: The case of surgery schedules," *Journal of Public Economics*, 2023, p. 104825.

**Jeebhay, Mohamed, Roslynn Baatjies, and Andreas Lopata**, "Work-related respiratory allergy associated with sensitisation to storage pests and mites among grain-mill workers: allergies in the workplace," *Current Allergy & Clinical Immunology*, 2005, *18* (2), 72–76.

**Jia, Desheng and Guanghua Wu**, "Fly control (II) — ecological habits and common species of flies," *Chinese Journal of Hygiene Insecticides and Equipments*, 2008, (02), 128–132.

**Jiang, Zhikuan, Zhimin Zheng, and Zhongcan Wang**, *Management of hygienic pest*, People's Medical Publishing House, 2011.

**Ke, J., D. D. Laskar, and S. Chen**, "Varied lignin-disruption mechanisms for different biomass substrates in lower termites," *Renewable Energy*, 2013, *50*, 1060–1064.

**Koh, Gavin CKW, Richard J Maude, Daniel H Paris, Paul N Newton, and Stuart D Blacksell**, "Diagnosis of scrub typhus," *The American Journal of Tropical Medicine and Hygiene*, 2010, *82* (3), 368.

**Lawler, Sharon P. and Deborah A. Dritz**, "Straw and winter flooding benefit mosquitoes and other insects in a rice agroecosystem," *Ecological Applications*, 2005, *15* (6), 2052–2059.

__ **and** __ , "Effects of rice straw and water management on riceland mosquitoes," *Journal of Medical Entomology*, 2006, *43* (5), 828–832.

**Neoh, Kok Boon and Lee Jin Bong**, "Factors driving Paederus outbreaks in human settings: climatic factors or human interventions?," *Proceedings of the Ninth International Conference on Urban Pests*, 2017.

**Norval, R. A. I., N. Tebele, N. J. Short, and J. N. Clatworthy**, "A Laboratory Study on the Control of Economically Important Tick Species with Legumes of the Genus Stylosanthes," *Zimbabwe Veterinary Journal*, 1983, *14*, 26–29.

**Roy, David P, Haiyan Huang, Luigi Boschetti, Louis Giglio, Lin Yan, Hankui H Zhang, and Zhongbin Li**, "Landsat-8 and Sentinel-2 burned area mapping-A combined sensor multi-temporal change detection approach," *Remote Sensing of Environment*, 2019, *231*, 111254.

**Smith, Alistair MS, Crystal A Kolden, Travis B Paveglio, Mark A Cochrane, David MJS Bowman, Max A Moritz, Andrew D Kliskey, Lilian Alessa, Andrew T Hudak, Chad M Hoffman et al.**, "The science of firescapes: achieving fire-resilient communities," *Bioscience*, 2016, *66* (2), 130–146.

**Sonenshine, Daniel E and R Michael Roe**, *Biology of Ticks Volume 2*, Vol. 2, Oxford University Press, 2014.

**Sun, Liyang and Sarah Abraham**, "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 2021, *225* (2), 175–199.

**Tagwireyi, D, DE Ball, PJ Loga, and S Moyo**, "Cantharidin poisoning due to "Blister beetle" ingestion," *Toxicon*, 2000, *38* (12), 1865–1869.

**Undheim, Eivind AB, Bryan G Fry, and Glenn F King**, "Centipede venom: recent discoveries and current state of knowledge," *Toxins*, 2015, *7* (3), 679–704.

**Wang, Chunfang, Zuqing Hu, Shutian Zhang et al.**, "Study on the life history and seasonal fluctuation of simulium in the lower reaches of the Irtysh river, Xinjiang," *Acta Parasitologica et Medica Entomologica Sinica*, 2017, *24* (03), 174–179.

**WHO**, "Vector-borne diseases," https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases 2024. Accessed: 2025-04-22.

**Wilson, L. J. and R. W. Sutherst**, "Acceptability of Stylosanthes scabra Vogel as a Substrate for Larvae of Boophilus microplus (Canestrini) (Acarina: Ixodidae)," *Australian Journal of Entomology*, 1986, *25* (4), 353–358.

**Xue, Ruide**, "Research progress on overwintering of Culex tritaeniorhynchus," *Journal of Medical Pest Control*, 1988, (02), 45–48.

__ **, Baolin Lu, and Maju Jing**, "Study on the Physiology and Ecology of Overwintering Anopheles sinensis," *Acta Entomologica Sinica*, 1990, (04), 444–449.

— , — , — , **and Jiguang Min**, "Preliminary study on overwintering and experimental overwintering of Culex tritaeniorhynchus," *Chinese Journal of Public Health*, 1989, (06), 321–323.