# Yaxuan You

Ph.D. Candidate in Agricultural Economics, Peking University
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September 13, 2026

Dear Professors Breza, Viviano, and Chandrasekhar,

I am writing to apply for the NBER Workshop on Development Economics and Networks for Early-Career Researchers, to be held in Cambridge on December 5, 2026. I am a Ph.D. candidate in Agricultural Economics at Peking University, and am **currently a visiting Ph.D. student at Stanford University**. My research lies primarily in development, environmental, and agricultural economics, with a focus on how public policies and climate change affect rural households, local economies, and population well-being in developing countries.

My research agenda is centered on development policy, environmental change, and rural transformation. My published work in the *American Journal of Agricultural Economics* evaluates the impact of a large-scale poverty alleviation program in China. In ongoing work, I study the consequences of environmental regulation, energy transition, and migration for households and communities in developing settings. My work on China's spatial livestock production bans, which examines their effects on pollution, agricultural production, and rural household income, is currently at the Revise and Resubmit stage at *PNAS*. Another project studies how renewable energy expansion affects infant mortality across 54 developing countries. Together, these projects reflect my broader interest in the distributional and welfare consequences of development policies and structural change.

My research is also strongly informed by field experience. I have participated in and led several large-scale rural surveys in China. These experiences have helped me connect empirical research with the institutional realities faced by rural households and have shaped the development questions I hope to pursue in my future work.

I am particularly attracted to this workshop because many of the development questions I study involve interactions across households, producers, and locations. My current research examines how economic and environmental shocks generate spatial spillovers and broader adjustments in population, employment, and economic activity. I am especially interested in learning how network-based empirical approaches can help formalize these interactions and open new directions for my research on rural development, policy spillovers, and structural transformation.

At this stage of my Ph.D., I would greatly value the opportunity to receive feedback on work in progress, learn from senior researchers working at the frontier of empirical development and network economics, and engage with other early-career researchers whose work approaches related questions from complementary perspectives. I would be grateful for the opportunity to participate in the workshop.

Thank you very much for considering my application.

Sincerely,

**Yaxuan You**

**Faculty member available to provide a recommendation if I am shortlisted:**

**Kaixing Huang**
Research Fellow and Ph.D. Supervisor
China Center for Agricultural Policy, Peking University
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# Statement of Motivation and Current Research Interests

Yaxuan You

My research lies at the intersection of development, environmental, and agricultural economics. I study how public policies, environmental change, and structural transformation affect rural households, local economies, and population well-being in developing countries. Across my research, I use administrative, household, and spatial data to examine how economic and environmental shocks shape behavior, resource allocation, and local development.

My research agenda centers on three interconnected themes. First, I study how environmental and agricultural policies affect rural economic activity and household welfare. In ongoing work on China's spatial livestock production bans, currently at the **Revise and Resubmit stage at *PNAS***, I examine how environmental regulation reshapes agricultural production, pollution, and rural household outcomes. Second, I study the broader development consequences of environmental change, including the effects of energy transition on human development. Third, my research examines how development policies affect local welfare, building on my published work in the *American Journal of Agricultural Economics* on poverty alleviation in China.

My research interests are also shaped by extensive field experience in rural China. I have participated in and led field surveys on agricultural production, groundwater over-extraction, and rural development, and most recently served as a research team leader for a randomized controlled trial on AI-assisted rural education. These experiences have strengthened my interest in how policies interact with local institutions, household decisions, and differences across communities.

I am motivated to attend this workshop because many of the development questions I study involve interactions across households, producers, and locations. Environmental and economic shocks can generate spatial spillovers and broader adjustments in population, employment, and economic activity. I am particularly interested in learning how network-based empirical methods can help formalize and study these interactions, and in developing new research questions at the intersection of development and networks.

As I develop my dissertation and longer-term research agenda, I hope to build a program of research on development policy, environmental change, and rural transformation, with greater attention to how shocks and policies propagate across economic agents and communities. This workshop would provide a valuable opportunity to receive feedback on my work, learn from researchers at the frontier of empirical network and development economics, and engage with other early-career researchers working on related questions.

# YAXUAN YOU

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## EDUCATION

**Stanford University (present)** *September 2026 - 2027*
Visiting graduate student
Stanford Center on China's Economy and Institutions (SCCEI)

**Peking University** *September 2023 - Present*
Ph.D. candidate in Agricultural Economics
China Center for Agricultural Policy (CCAP, PKU)

**Nankai University** *2019-2023*
BA in Economics
Department of Economics, School of Economics

## PUBLICATIONS

Huang, Kaixing, and **Yaxuan You**. "Evaluating the impact of the fourth round of China's poverty alleviation program." ***American Journal of Agricultural Economics*** 107.2 (2025): 583-610.

Yan, W., Huang, K.*, Lin, F., **You, Y.**, Hao, X. (2024). "Infrastructure construction, shipping capacity improvement and firm export: A quasi-natural experiment based on the impoundment and navigation of the Three Gorges Dam." ***China Economic Quarterly***, 24(06), 1798-1815.

## WORKING PAPERS

Hui Mao, **Yaxuan You**, Kaixing Huang*.(Co-first authors) *"Spatial Livestock Production Bans in China: Evidence of Impacts on Livestock-Related Emissions and Farm Household Income."* **R&R (Revise and Resubmit) in PNAS.**

**Yaxuan You**, and Kaixing Huang*. *"From Wind and Sun to Fewer Funerals: How Renewable Energy Reduces Infant Mortality in the Developing World."* **Under review in JAERE**

**Yaxuan You**, and Kaixing Huang*. *"The Unexpected Impact of Genetically Modified Crops on Global Carbon Emissions."*

Shuhui Dong, **Yaxuan You***, and Kaixing Huang. *"Internal migration barriers and rural social order: Evidence from China's Hukou reform"* **Under review in JDS**

**Yaxuan You**, and Kaixing Huang*. *"How Could Climate Change Reshape Criminal Activity in a Developing Country: Evidence from China"*

**Yaxuan You**, and Kaixing Huang*. *"Synchronization of rain and heat and agricultural civilization."*

## CONFERENCE EXPERIENCE

**32nd International Conference of Agricultural Economists (ICAE 2024)** (oral presentation; Awarded Official Travel Grant) *Summer 2024 in Delhi, India*
**The 15th CAER-IFPRI Annual Conference** (oral presentation) *Autumn 2023 in Nanjing, China*

## RURAL SURVEY RESEARCH EXPERIENCE

**Rural Education AI RCT** *May 2026*
Research Team Leader in *Shaanxi Province*

**Cash Crop Agglomeration and Livestock Production Survey** *October 2025*
Researcher in *Hebei Province*

**China Rural Revitalization Data Platform 2024 (SAAS, PKU)** *January 2024*
Research Team Leader & Data Cleaner in *Shaanxi Province*

**Groundwater Over-mining Research (SAAS, PKU)** *August 2023*
Research Team Leader in *Hebei Province*

**Rural Revitalization Research (CCAP, PKU)** *March 2023*
Researcher & Data Cleaner in *Beijing*

**Land Hosting Research (SAAS, PKU)** *July 2022*
Researcher & Data Cleaner in *Shandong Province*

## HONORS

**Outstanding Scientific Research Award, Peking University** *Autumn 2025*
**Kangde Outstanding Research Scholarship, Peking University** *Autumn 2025*
**Okamatsu Scholarship, Peking University** *Autumn 2024*
**Award for Academic Excellence, Peking University** *Autumn 2024*
**National College Student Mathematical Modeling Competition, First Prize** *Autumn 2021*
Academic Excellence Scholarship in Nankai University *Autumn 2020-2021*
Comprehensive Scholarship in Nankai University *Autumn 2022*
Outstanding Completion of National Innovation Project for College Students *Spring 2023*

## SKILLS

| | |
|---|---|
| **Programming Languages** | Stata, Python, MATLAB |
| **Software & Tools** | Arcgis, LaTeX |
| **Language Proficiency** | English (IELTS-7.0, CET6-591); Chinese (native language) |

## PH.D. COURSEWORK

Development Economics; Advanced Microeconomics I; Advanced Microeconomics II; Advanced Econometrics I; Advanced Econometrics II; Applied Microeconometric Research Methods; Advanced Agricultural Economics; Advanced Natural Resource Economics and Policy Analysis; Frontiers and Evolution of Agricultural Economics; Research Design and Academic Writing in Agricultural Economics; Agricultural Product Markets and Trade; Quantitative Research on the History of Agricultural Economics; English Academic Writing in Economics: From Topic Selection to Publication; Chinese Marxism and Contemporary China; Graduate English I; Botany on the Tip of the Tongue; The Science and Culture Behind Wine.

# How Could Climate Change Reshape Criminal Activity in a Developing Country: Evidence from China

Yaxuan You Kaixing Huang*

September 14, 2026

China Center for Agricultural Policy, Peking University

**Abstract**

This paper provides the first evidence that climate change induces a spatial redistribution of crime between rural and urban areas. Using geocoded judicial records from China, we show that while short-term temperature shocks increase crime in both areas, whereas the long-term relationship differs sharply across space. Specifically, a 1°C increase in average temperature reduces rural crime by 0.53% and increases urban crime by 2.48%, implying a 1.96% net rise in aggregate crime. The evidence suggests that this redistribution is linked to climate-induced economic stress in agriculture, accompanied by population and employment reallocation away from agricultural environments. Projections indicate that climate change will further reduce rural crime but substantially increase urban crime, leading to an overall rise of 3.4% to 8.69% by the end of the century. Finally, we show that policies such as agricultural subsidies, monitoring procurement, and free trade zone designation are associated with a weaker urban temperature response and may help mitigate this spatial divergence.

**Keywords:** Climate change; Crime; Adaptation Policy; Urban–rural divergence; Economic adjustment
**JEL:** Q54, K42, R12, O13, R23

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# 1 Introduction

Climate change is reshaping socioeconomic conditions across the world, with mean temperatures projected to rise by 1.39°C to 5.8°C over the coming century (Nakicenovic *et al.*, 2000; IPCC, 2023). A large literature has documented the consequences of climatic shocks for aggregate output (Burke *et al.*, 2015b; Dell *et al.*, 2014), agricultural productivity (Deschênes & Greenstone, 2007), and human health (Gasparrini *et al.*, 2015). By contrast, much less is known about how climate change affects the spatial distribution of criminal activity. Existing work has linked extreme weather to broad forms of social disruption, including civil conflict (Burke *et al.*, 2009; Hsiang *et al.*, 2011) and political instability (Harari & Ferrara, 2018), but the local and spatial dimensions of the temperature–crime relationship remain less well understood, especially in developing countries undergoing rapid structural transformation and urbanization.

This paper addresses three critical gaps in the literature. Despite recent evidence linking climatic conditions to criminal behavior (Ranson, 2014), several critical questions remain unresolved.First, how does climate change affect crime in developing economies, and do these effects differ systematically between rural and urban areas? Second, beyond the behavioral responses emphasized in prior work, to what extent are temperature effects on crime related to economic pressures and broader spatial adjustment? Third, how do long-term temperature effects compare with short-term responses, which have been the main focus of the existing literature?

Answering these questions requires spatially disaggregated crime data that can distinguish rural from urban crime within the same administrative unit. Such data are rarely available, particularly in developing countries. We address this challenge using a novel dataset of geocoded judicial records from China, a setting characterized by a pronounced urban–rural divide. Following a 2013 transparency mandate, Chinese courts made large numbers of criminal judgment documents publicly available. We use these records to extract the geographic coordinates of crime incidents and match them to the Global Human Settlement Layer (GHSL) Settlement Model grid (GHS-SMOD). This high-resolution matching allows us to measure rural and urban crime separately and to study how temperature affects crime across space within counties.

This paper makes four main contributions. First, by disaggregating crime into urban and rural components, we uncover a clear spatial divergence: while short-term heat shocks are associated with higher crime in both settings, long-term temperature

increases are associated with lower rural crime and higher urban crime. This suggests that aggregate estimates in prior research may mask important spatial differences in how climate change affects criminal activity. Second, we provide evidence consistent with an economic mechanism operating through agriculture and broader spatial adjustment, shifting the focus away from purely behavioral heat responses toward differential impacts across agricultural and non-agricultural environments. Third, our comparison across time horizons shows that the long-term urban–rural divergence is concentrated in property crime rather than violent crime, which helps distinguish longer-term adjustment from short-term behavioral responses. Finally, we identify the types of counties in which crime is more sensitive to climate conditions, and show that variation across policy environments provides useful guidance on which interventions may help moderate these effects.

Our empirical analysis provides, to our knowledge, the first evidence of the how climate change is associated with differences in rural and urban crime. Leveraging a high-resolution panel of county-level crime rates in China from 2013 to 2018, we identify a we identify a sharp temporal and spatial contrast. In the short term, transitory temperature shocks are associated with higher crime in both rural and urban areas. However, our baseline long-term specification reveals a clear divergence: a 1°C increase in average temperature is associated with a 0.53% decline in rural crime and a 2.48% increase in urban crime, implying a 1.96% net increase in aggregate crime. These results are robust to a broad set of checks, including different definitions of rural areas, different crime-rate constructions, specifications without additional controls, more flexible functional forms, and alternative ways of measuring climatic exposure. In particular, the baseline pattern remains similar when temperature is captured using agro-climatic indices such as Growing Degree Days (GDD) and Harmful Degree Days (HDD), as well as temperature shocks, temperature bins, and intra-annual temperature variation. Estimates from the long-difference specification are also directionally consistent with the baseline results. Taken together, these checks suggest that the urban–rural divergence is not driven by a particular specification or temperature measure.

The mechanism evidence is more consistent with economic and spatial adjustment than with a purely behavioral response to heat. The long-term urban–rural divergence is concentrated in property crime rather than violent crime, while the spillover estimates indicate that temperature effects extend across nearby counties but decay quickly with distance. At the micro level, higher temperatures are associated with

a higher probability of urban residence, lower agricultural employment, and higher non-agricultural employment. At the county level, they are associated with lower output and income and with shifts in firm entry away from agricultural sectors and toward non-agricultural sectors. We also find that higher temperatures worsen self-reported emotional well-being, but this psychological channel appears more relevant for short-term responses than for the long-term divergence between rural and urban crime. Taken together, these results suggest that climate-related differences in crime across space are linked to differential impacts across agricultural and non-agricultural environments, accompanied by broader population, employment, and economic adjustment.

Finally, we examine how the temperature–crime relationship varies across local conditions, policy environments, and future warming scenarios. The heterogeneous effects show that the urban crime response to temperature is more pronounced in economically weaker, less diversified, and more densely populated counties. The policy results further indicate that this urban response is weaker in places with stronger agricultural subsidies, free trade zone designation, and monitoring procurement. Looking ahead, projections based on future climate scenarios imply that warming is likely to reduce rural crime but increase urban crime more sharply, leading to a net increase in aggregate crime by 2100. Together, these findings suggest that the social costs of climate change depend not only on the degree of warming itself, but also on local economic structure, policy support, and public safety capacity.

This paper contributes to three interconnected strands of literature. First, we extend the literature on climate and crime from short-run responses to longer-run spatial adjustment. Existing studies show that high temperatures and adverse weather conditions increase crime in both developed and developing economies (Ranson, 2014; Heilmann *et al.*, 2021; Blakeslee & Fishman, 2018; Iyer & Topalova, 2014). These effects have been linked to immediate heat-induced behavioral responses (Anderson, 1989), weather-driven income shocks (Mehlum *et al.*, 2006), and other environmental stressors such as air pollution (Bondy *et al.*, 2020; Herrnstadt *et al.*, 2021); more broadly, climate variability increases interpersonal and intergroup conflict (Hsiang *et al.*, 2013; Burke *et al.*, 2015a). Yet this literature largely focuses on transitory shocks, whereas persistent climatic stress can reshape the economic conditions under which crime occurs. A large climate-economy literature documents effects on growth and output (Dell *et al.*, 2009, 2012; Hsiang, 2010; Somanathan *et al.*, 2021), labor productivity and income (Graff Zivin & Neidell, 2014; Lai *et al.*, 2023; Andersen *et al.*, 2016), health (Carleton *et al.*, 2022), and especially agricultural productivity and rural livelihoods (Schlenker &

Roberts, 2009; Lobell *et al.*, 2011; Deschênes & Greenstone, 2007; Burke *et al.*, 2015b), with longer-run consequences for human capital and social stability (Angrist *et al.*, 2024; Fishman *et al.*, 2019; Carleton & Hsiang, 2016; Hsiang *et al.*, 2013; Burke *et al.*, 2015a). Such shocks can also induce migration and labor reallocation (Munshi, 2003; Marchiori *et al.*, 2012; Jessoe *et al.*, 2018), thereby reshaping the spatial distribution of population and economic activity (Costinot *et al.*, 2016; Desmet & Rossi-Hansberg, 2015). What remains unclear is whether these longer-run adjustment margins also reshape the spatial distribution of crime. We address this gap by distinguishing short-run weather responses from longer-run temperature relationships and documenting a sharp divergence in crime across the rural–urban divide.

Second, we contribute to the economics of crime by linking economic incentives to the spatial environment in which criminal activity occurs. Crime generates substantial social costs beyond direct victim losses, including criminal-justice expenditures, private protection and avoidance, residential responses, and persistent economic consequences for victims (Anderson, 1999, 2021; Cullen & Levitt, 1999; Linden & Rockoff, 2008; Bindler & Ketel, 2022). Building on the economic model of crime (Becker, 1968; Ehrlich, 1973), empirical research shows that criminal behavior responds to labor-market opportunities and unemployment (Raphael & Winter-Ebmer, 2001; Gould *et al.*, 2002), liquidity and income support (Foley, 2011; Deshpande & Mueller-Smith, 2022), and other determinants of the relative returns and costs of crime, including education, inequality, criminal returns, and law enforcement (Lochner & Moretti, 2004; Fajnzylber *et al.*, 2002a; d'Este, 2020; Levitt, 1996; Draca *et al.*, 2011). At the same time, social interactions, urban structure, and neighborhood exposure make crime strongly spatially dependent (Glaeser *et al.*, 1996; Glaeser & Sacerdote, 1999; Damm & Dustmann, 2014). These economic and spatial margins, however, are generally studied separately. We connect them by showing that higher temperatures are associated with changes in income, sectoral employment, and population location, alongside opposing long-run rural and urban crime responses concentrated primarily in property offenses. This provides an economic and spatial interpretation of the climate–crime relationship beyond the immediate heat–aggression channel.

Third, we contribute to the literature on climate adaptation by showing that adjustment may redistribute social costs across sectors and locations rather than simply eliminate them. Existing work documents adaptation to climate damages in economic activity, mortality, and agriculture (Burke *et al.*, 2015a; Carleton & Hsiang, 2016; Carleton *et al.*, 2022; Barreca *et al.*, 2016; Deschênes & Greenstone, 2011; Mendelsohn

*et al.*, 1994; Schlenker *et al.*, 2006; Burke & Emerick, 2016; Cui, 2020), including through changes in production, technology, labor allocation, and migration (Auffhammer, 2018; Fisher *et al.*, 2012; Feng *et al.*, 2010; Cattaneo & Peri, 2016; Huang & Sim, 2021; Cui & Feng, 2021; Huang *et al.*, 2020). Because such adjustment is often incomplete and may shift damages across sectors or locations (Deryugina & Hsiang, 2014; Graff Zivin & Neidell, 2014; Carleton & Hsiang, 2016), evaluating adaptation requires looking beyond aggregate losses. We add a public-safety dimension by showing that climate-related adjustment is associated with lower rural crime but greater urban crime pressures, and that these responses vary across rural support and land policies (Jayne & Rashid, 2013; Huang *et al.*, 2024; Besley & Burgess, 2000; Galiani & Schargrodsky, 2010), urban–rural integration and economic policies (Ngai *et al.*, 2019; Huang & You, 2025; Ma *et al.*, 2025), and deterrence infrastructure (Ma *et al.*, 2026). More broadly, our findings suggest that adaptation can change not only the magnitude of climate damages but also where their social consequences are borne.

The remainder of the study proceeds as follows. Section 2 provides the stylized facts and our conceptual framework. Section 3 describes the data and the empirical strategy. Section 4 presents the main results and robustness checks. Section 5 examines the mechanisms of the effect. Section 6 discusses the heterogeneous effects, policy implications, and projected impacts. Section 7 concludes.

# 2 Background

## 2.1 Stylized facts

The landscape of criminal activity in China exhibits substantial spatial heterogeneity. As illustrated in Figure 1, rural and urban crime not only display uneven spatial distributions but also manifest markedly different patterns of geographic concentration. Rural crime rates are disproportionately higher in western regions—areas typically characterized by lower levels of economic development, constrained fiscal capacity, and limited public service provision. In contrast, urban crime is concentrated in the southeastern coastal provinces, particularly within densely populated municipalities and economically vibrant counties. This spatial divergence suggests that urban and rural crimes are embedded in fundamentally different socioeconomic contexts and, consequently, may exhibit heterogeneous elasticities to external shocks such as climatic stress.

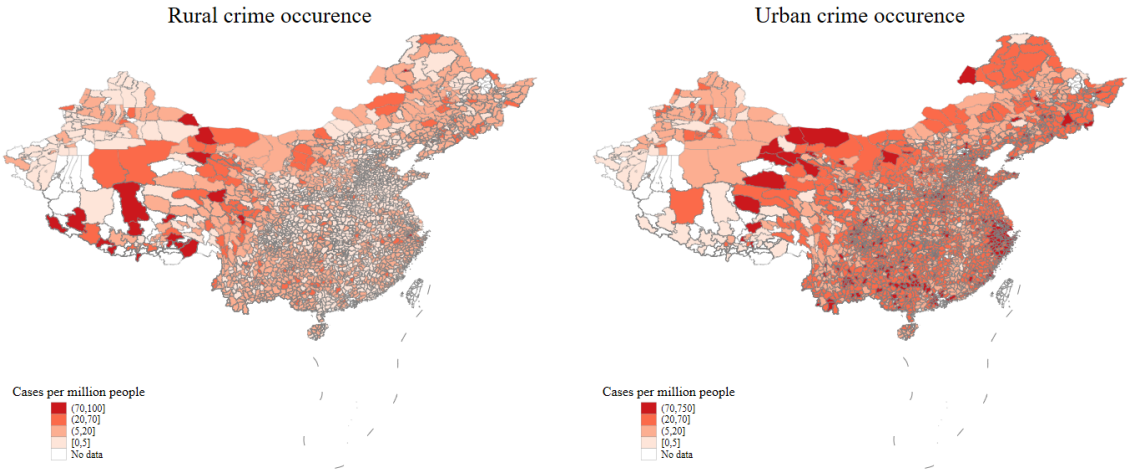



**Figure 1:** Mean crime occurrence distribution

*Notes:* This figure maps county-level average crime rates per million people separately for rural and urban areas. Crime incidents are classified as rural or urban based on the Global Human Settlement Layer (GHSL) Settlement Model grid (GHS-SMOD). County-level crime rates are then constructed by aggregating geocoded crime incidents within county boundaries and dividing by the corresponding county population.

Beyond static geographic distributions, Figure 2 illustrates the changes in the distribution of crime in urban and rural areas from 2013 to 2018. During this period, we observed that the overall change in rural areas was less pronounced, while the distribution of crime in urban areas increased. Meanwhile, urban and rural crime follow distinct temporal trajectories across China's seven macro-regions as Appendix Figure

A2 shown. Such regional variation suggests that the underlying structural drivers of criminal activity differ systematically across the urban–rural divide.

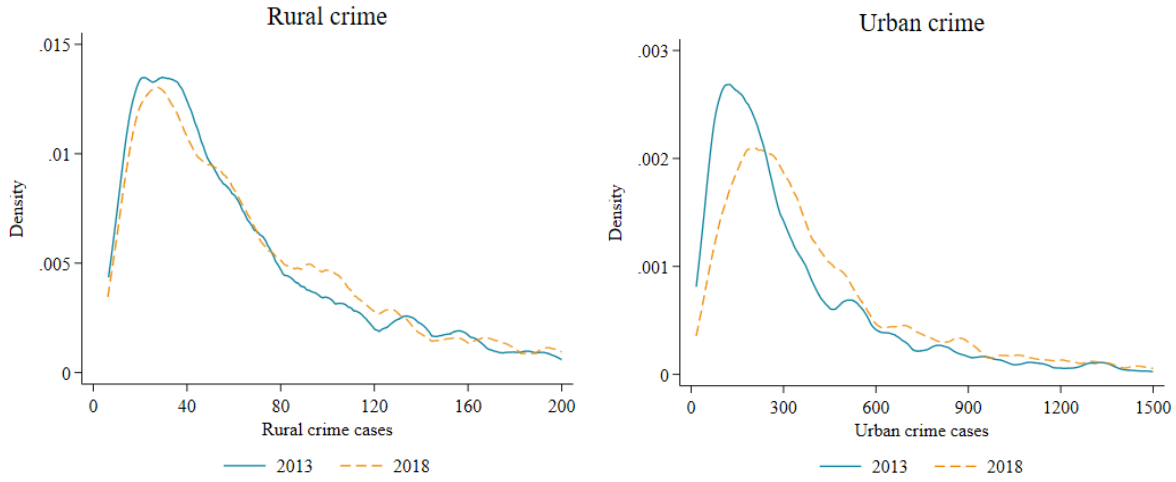



**Figure 2:** Changes in county-level crime incidents in rural and urban areas

*Notes:* This figure maps county-level changes in the number of crime incidents from 2013 to 2018, separately for rural areas (left panel) and urban areas (right panel).

Crucially, the relationship between temperature and crime differs across rural and urban settings, as shown in Figure 3. In rural areas, crime exhibits a U-shaped association with temperature, with higher rates observed at both thermal extremes. In contrast, the relationship in urban areasis more strongly increasing, with crime rates rising as temperatures increase. This contrast suggests that the temperature–crime relationship is unlikely to operate through a single, spatially uniform channel. If temperature affected crime only through a common physiological or behavioral response to heat, one might expect a more similar functional form across rural and urban areas. Instead, the difference in patterns is more consistent with the view that temperature also interacts with broader economic conditions, including the greater climate sensitivity of agricultural livelihoods and the resulting differences in population and employment adjustment across the urban–rural divide.

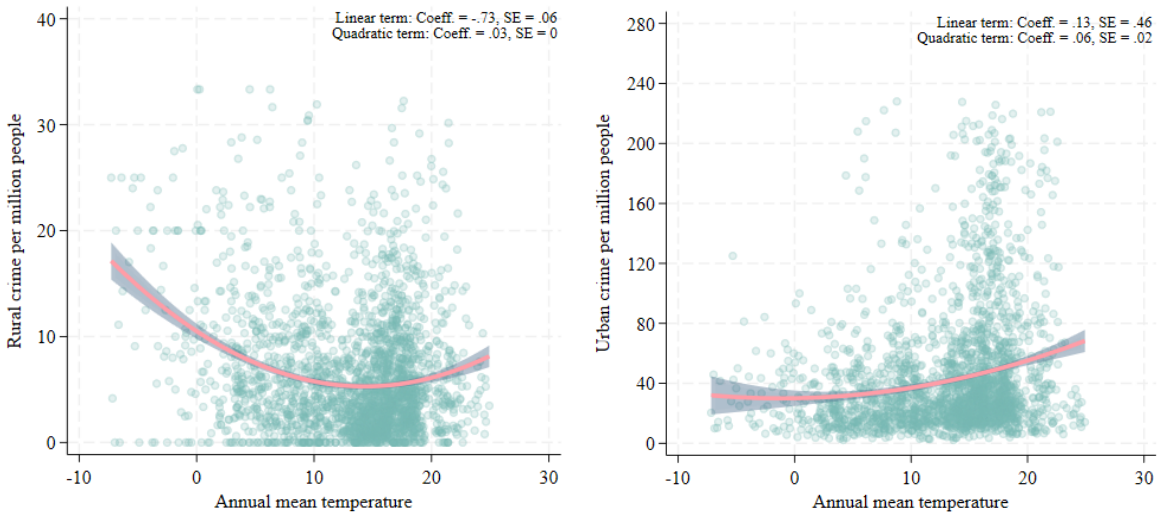



**Figure 3:** Scatter plots of temperature and crime rates in rural and urban areas

*Notes:* This figure presents scatter plots of rural and urban crime rates against annual mean temperature using county-year observations. The solid lines show quadratic fitted values, and the shaded areas denote 95% confidence intervals.

Collectively, these stylized facts—spatial concentration, divergent temporal trends, and opposing temperature associations—underscore that aggregating urban and rural crime may obscure the complex dynamics through which climate change reshapes social order. Characterizing these differences is therefore a prerequisite for accurately identifying the mechanisms of climate-induced crime and designing targeted policy interventions.

## 2.2 Conceptual framework

To understand the divergent impact of climate change on urban and rural crime, we combine the economic theory of crime (Becker, 1968) with climate-induced population and labor reallocation. We hypothesize that temperature influences criminal activity through three related channels: a direct behavioral channel, an indirect income channel, and a broader spatial adjustment channel.

**Direct Behavioral Channel.** The most immediate link is physiological. Extreme heat can increase irritability and aggression while impairing self-control (Anderson, 1989; Ranson, 2014). Beyond biology, environmental stressors—including air pollution (Bondy *et al.*, 2020; Herrnstadt *et al.*, 2021) and temperature shocks (Cohen & Gonzalez, 2024)—can alter behavior in ways that increase criminal opportunity or impulsive

conduct. For example, favorable weather may increase outdoor activity and interaction, expanding the pool of potential victims and targets. This channel is most likely to operate in the short term and, absent other forces, would be expected to increase crime in both rural and urban settings, especially for impulsive or violent offenses.

**Indirect Income Channel.** The second channel operates through economic incentives. In the Beckerian framework, individuals engage in crime when the expected return to illegal activity exceeds the opportunity cost of legal work (Becker, 1968). Climate change can affect these trade-offs by reducing productivity, earnings, and household resources. In urban areas, higher temperatures lower productivity and output (Graff Zivin & Neidell, 2014; Deryugina & Hsiang, 2014). At the aggregate level, productivity peaks at moderate temperatures and declines as heat increases (Burke *et al.*, 2015b; Dell *et al.*, 2014). Such losses may tighten household budgets and lower the opportunity cost of crime (Davis, 1988).

In rural areas, these pressures may be stronger because agriculture is especially climate sensitive (Mendelsohn *et al.*, 1994; Wing *et al.*, 2021; Miller *et al.*, 2021). Thermal stress and climate variability reduce crop yields and farm profits (Schlenker *et al.*, 2006; Chen *et al.*, 2016; Carter *et al.*, 2018; Ray *et al.*, 2015). In isolation, these losses could increase local criminal incentives (Blakeslee & Fishman, 2018). However, their net effect on observed crime may differ from that prediction if households respond by adjusting where and how they work.

**Spatial Adjustment Channel.** Unlike transitory weather shocks, long-term climatic shifts may induce broader structural adjustment. When agricultural productivity declines, may reallocate labor toward non-farm sectors (Huang *et al.*, 2020) or migrate in response to income pressures (Jessoe *et al.*, 2018; Marchiori *et al.*, 2012; Bohra-Mishra *et al.*, 2014; Black *et al.*, 2011). These responses need not imply that crime itself is directly transported across space. Instead, they can change the environments in which crime occurs by altering where people live, work, and face economic stress.

In rural areas, out-migration and reduced agricultural activity may lower the local incidence of crime by shrinking the pool of economically active and mobile individuals most exposed to these shocks. In urban areas, inflows of labor and greater pressure on jobs, wages, and public services may strengthen the conditions under which crime increases. While the direct link between migration and crime remains unclear (Leiva

*et al.*, 2020; Kang, 2016), our framework focuses more broadly on how climate-induced population and employment adjustment may contribute to differences in crime across rural and urban settings.

**Synthesis and Empirical Implications.** Taken together, these mechanisms imply that the relationship between climate change and crime is not spatially or temporally uniform (Fajnzylber *et al.*, 2002b; Bignon *et al.*, 2017; Foley, 2011). Short-term temperature shocks may increase crime in both rural and urban areas through immediate behavioral responses. By contrast, long-term climatic stress may generate divergent effects if economic losses and subsequent adjustment differ across agricultural and non-agricultural environments. Under this interpretation, rural crime may decline if climate stress is accompanied by reduced agricultural activity and population outflows, while urban crime may rise if economic pressure and population concentration increase in urban areas. Because these longer-term effects are more closely tied to incentives and economic adjustment than to impulsive behavior, they may be more pronounced for property crime than for violent crime. This framework motivates our empirical strategy and helps organize the distinction between short-term behavioral effects and long-term spatial divergence.

# 3 Data and empirical strategy

## 3.1 Data

### 3.1.1 Crime data

**Crime Records and Geocoding.** Our primary source of criminal incidents is a novel database constructed from China Judgments Online (CJO), the official national repository managed by the Supreme People's Court. As of late 2023, the CJO has archived over 140 million judicial documents, including approximately 10 million criminal judgments, averaging one million cases per year. While a 2013 transparency mandate established a general principle of public disclosure, certain cases remain unreleased due to statutory exceptions involving national security, juvenile delinquency, or mediation-based settlements.[1] We focus on the 2013–2018 period to ensure data

[1]For instance, internal reports from local courts (e.g., Haixi Mongol and Tibetan Autonomous Prefecture Intermediate People's Court in 2018) suggest a non-disclosure rate of approximately 15%.

integrity and avoid the structural confounding effects of the COVID-19 pandemic.

To ensure a high-resolution spatial analysis and maintain the integrity of our monthly panel, we apply three stringent filters to the universe of public criminal judgments between 2013 and 2018. First, we restrict the sample to cases with explicitly disclosed incident dates (month and year). Second, we focus on offenses that are most suitable for spatial analysis, especially property-related offenses such as theft and robbery, which constitute approximately 15% of all criminal indictments according to prosecutorial statistics (see Appendix Figure A3). These offenses are particularly well suited to spatial analysis because they typically occur at fixed, reportable physical locations. The resulting geocoded sample is therefore dominated by property-related cases, although some of these cases also involve violent elements and a smaller number of other offense categories can likewise be retained when sufficiently precise incident locations are available. In contrast, many other categories—such as cybercrime, trafficking, or disorderly conduct—are often unsuitable for this purpose because of reporting conventions, confidentiality requirements, or their cross-jurisdictional nature.[2] Third, a case must contain a geocodable address to allow for urban-rural classification. We utilize an unstructured-to-structured data pipeline, leveraging Large Language Models (LLMs) to extract precise textual descriptions of crime locations (at the community or street level) from millions of documents, which are then converted into latitude and longitude coordinates via the Geocoding API.

Following these criteria, our final dataset comprises approximately 520,000 geocoded criminal incidents, most of them are property crimes (see Figure 4). Considering that not all crime records contain precise, geocodable street-level addresses (with many reporting only district-level administrative units), our final sample represents a substantial and reliable subset of the eligible population. This high-resolution approach allows us to move beyond administrative aggregates to a granular, monthly county-level panel. Crucially, our estimates remain unbiased as long as the judicial disclosure rate and the availability of precise geocoded information are not systematically correlated with short-term temperature fluctuations or decadal climate shifts. Under this identifying assumption, our data provide a consistent and reliable proxy for the relative changes in criminal activity across space and time.

[2]Many such cases either lack a single verifiable location or only report administrative-level information.

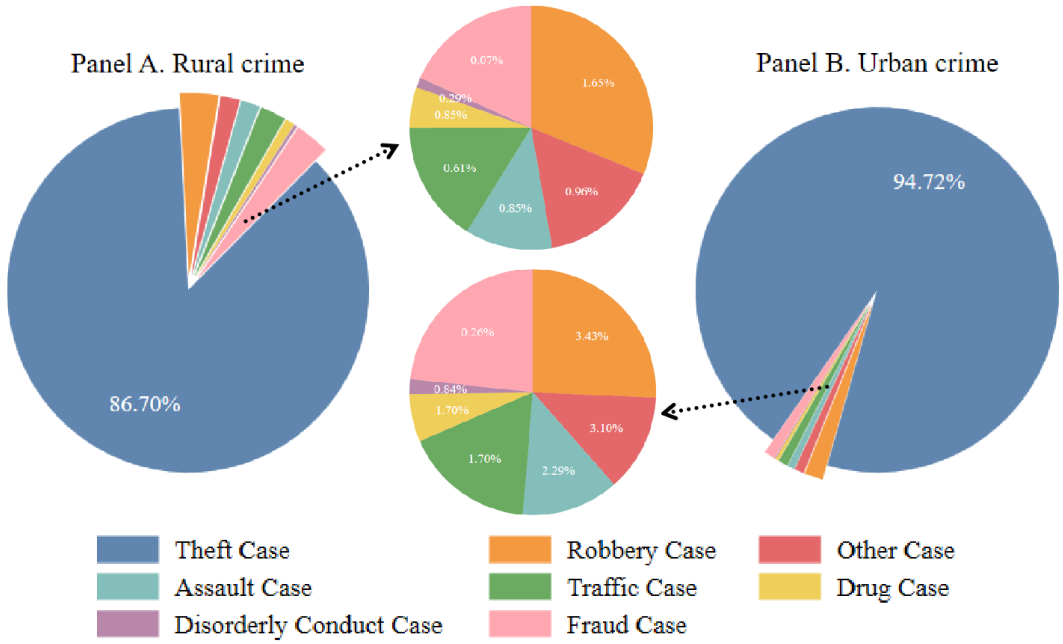



**Figure 4:** Distribution of criminal indictments by offense category

*Notes:* This figure shows the distribution of offense categories separately for rural and urban geocoded crime incidents. Incidents are classified as rural or urban using the Global Human Settlement Layer (GHSL) Settlement Model grid (GHS-SMOD).

**Classification of Urban and Rural Crimes.** A central innovation of this study is the decoupling of urban and rural criminal activity within the same administrative unit. Rather than relying on coarse administrative designations, we classify each geocoded incident based on its immediate physical and demographic context using the Global Human Settlement Layer (GHSL) Settlement Model (GHS-SMOD) (Pesaresi *et al.*, 2024).

Produced by the European Commission's Joint Research Centre, GHS-SMOD provides a global spatial raster at a 1 km resolution[3]. We assign each crime incident the settlement class of its corresponding grid cell. Specifically, cells identified as "urban centers" or "urban clusters" are categorized as urban, while the remaining cells are designated as rural. This high-resolution approach allows us to trace the spatial redistribution of crime across the urban–rural boundary with unprecedented precision.

[3]The GHS-SMOD data are publicly available at https://ghsl.jrc.ec.europa.eu/download.php. It classifies each grid cell into categories such as 'urban centre', 'urban cluster', and 'rural grid cells' based on population density, contiguity, and built-up area share.

**Construction of Urban and Rural Crime Rates.** We construct our core dependent variables—the urban and rural crime rates—at the county-year-month level. For each county $c$, year $y$, and month $m$, we separately aggregate the number of crimes classified as urban ($Crime_{cmy}^{Urban}$) and rural ($Crime_{cmy}^{Rural}$) based on their geocoded coordinates. A defining feature of our empirical approach is the choice of the denominator for these rates. Specifically, both urban and rural crime counts are normalized by the county's total resident population ($Pop_{cy}^{Total}$), sourced from official county statistical yearbooks, to represent the number of incidents per million residents.[4]

The rationale for using a unified, county-wide denominator is to facilitate a consistent comparison of sectoral crime dynamics across the urban-rural divide. This approach ensures that the dependent variables are mathematically additive, allowing us to evaluate the relative shift in the spatial distribution of social risks within a given administrative unit. By maintaining a stable population baseline at the county level, we can effectively characterize the asymmetrical sensitivity of different economic sectors—specifically the climate-sensitive agricultural sector versus the urban non-agricultural sector—to climatic shocks, while minimizing the statistical noise introduced by sub-regional population fluctuations. To ensure the robustness of this specification, we also perform alternative analyses as a complementary check, where rural and urban crimes are normalized by their respective base-period (2012) sub-regional populations to account for the initial distribution of the population at risk.

### 3.1.2 Temperature data

Our primary meteorological variables are derived from the China Meteorological Data Sharing Service System (CMDSSS), the most authoritative repository of historical weather observations in China. The dataset provides daily records of mean temperature and total precipitation from 677 national-level stations maintained by the China Meteorological Administration (CMA).

To aggregate these station-level observations into county-level monthly measures, we employ a multi-step interpolation procedure. For counties containing meteorological stations, we apply the inverse-distance weighting (IDW) method to calculate spatially representative averages. For counties without internal stations, we extend the spatial search to all stations within a 100-kilometer buffer of the county centroid—a radius

[4]Total resident population data are typically reported annually; we assign the same annual value to each month within a given year.

consistent with the spatial autocorrelation range of temperature in China. This procedure allows us to cover the full sample of counties while maintaining high data accuracy. Finally, daily values are aggregated to the monthly level to smooth high-frequency noise and align with our crime data, resulting in a robust monthly panel of local climatic conditions.

### 3.1.3 Socioeconomic and Survey Data

To examine the economic mechanisms and potential heterogeneities, we integrate county-level administrative data with individual-level micro-survey data. Our primary source for county-level indicators is the *China County Statistical Yearbooks*. This comprehensive dataset provides annual information on a wide range of socioeconomic factors, including sectoral GDP (primary, secondary, and tertiary), industrial output, fiscal capacity, employment structures, and household income levels. We utilize these data to test the mediating roles of agricultural productivity and non-farm employment in our theoretical framework, as well as to investigate how the climate–crime relationship varies across regions with divergent development trajectories.

To probe individual-level behavioral responses and labor reallocation, we incorporate microdata from the China Family Panel Studies (CFPS) (Xie & Hu, 2014). Conducted by the Institute of Social Science Survey (ISSS) at Peking University, the CFPS is a biennial, nationally representative longitudinal survey covering 25 provinces and representing approximately 95% of the Chinese population. Using waves from 2014, 2016, and 2018, we leverage its multi-stage probability sampling design and panel structure to track households over time. These data provide critical micro-evidence for two specific channels: (i) the structural labor reallocation from agricultural to non-agricultural sectors in response to climatic stress, and (ii) the psychological pathways, including emotional distress and social attitudes, that may complement economic incentives. The integration of high-quality administrative and survey data allows us to bridge the gap between macro-level climate shocks and micro-level adaptive behaviors, providing a robust empirical foundation for our findings.

## 3.2 Empirical strategy

To examine how temperature affects crime over different horizons, we estimate a short-term panel model and a long-term model, with the latter serving as our baseline

specification for the main analysis. The short-term specification captures the response to transitory temperature fluctuations within counties over time, while the long-term specification exploits persistent cross-county differences in temperature within provinces.

**Short-term Specification.** We first estimate the short-term effect of transitory temperature fluctuations on criminal activity using a monthly panel:

$$y_{cpmy} = \alpha + \beta_1 \text{Temperature}_{cpmy} + \mu_c + \lambda_{my} + \mathbf{X}_{cpmy}\theta + \varepsilon_{cpmy} \tag{1}$$

where $y_{cpmy}$ denotes the crime rate for county $c$ in province $p$, month $m$, and year $y$. To maintain comparability across specifications, we annualize monthly crime counts by dividing the number of incidents by the county's total resident population (in millions) and multiplying by 12. The key independent variable, $\text{Temperature}_{cpmy}$, is the monthly mean temperature.

This model identifies $\beta_1$ using within-county temporal fluctuations. County fixed effects ($\mu_c$) absorb time-invariant local characteristics, such as historical, geographic, and persistent economic factors, while month-by-year fixed effects ($\lambda_{my}$) absorb common seasonal patterns and nationwide shocks in each month-year. The vector $\mathbf{X}_{cpmy}$ includes additional meteorological controls, specifically monthly wind speed, and latent heat flux. Standard errors are clustered at the province $\times$ year level.

**Long-term Specification.** While Equation (1) captures short-term responses to temperature fluctuations, it is less informative about whether crime differs systematically across locations with different long-term climatic conditions. We therefore estimate a second specification:

$$y_{cpmy} = \alpha + \beta_1 \text{Temperature}_{cpmy} + \tau_p + \lambda_{my} + \mathbf{X}_{cpmy}\theta + \varepsilon_{cpmy} \tag{2}$$

where province fixed effects ($\tau_p$) replace county fixed effects. Under this specification, $\beta_1$ is identified from cross-county differences in temperature within the same province, after accounting for common month-by-year shocks and observable weather controls.

We use this specification as our baseline model for the long-term temperature–crime relationship. By exploiting persistent spatial variation in temperature, it captures how crime differs across locations facing different long-term climatic conditions. This makes it particularly suitable for our main question, namely whether the relationship between

temperature and crime differs systematically across rural and urban environments over longer horizons. Although we do not interpret this specification as isolating a fully causal adaptation effect, it provides our primary empirical framework for studying long-term spatial differences in the temperature–crime relationship.

# 4 Main results

## 4.1 Baseline estimates

We begin by examining the relationship between temperature and criminal activity across different time horizons, as reported in Table 1. In the short term (Panel A), transitory temperature shocks exert a heterogeneous upward pressure on crime. A 1°C increase in monthly mean temperature significantly raises rural crime by 0.09 incidents per million residents (Column 1a), while the effect on urban crime, though positive (0.04), remains statistically insignificant (Column 2a). Aggregated at the county level, the net effect is a significant increase of 0.13 incidents per million in total crime (Column 3a). This suggests that the immediate behavioral responses to thermal stress—often characterized as the "heat-aggression" effect (Ranson, 2014)—are primarily driven by the rural population in our context[5]. While the heat-aggression hypothesis predicts that physiological discomfort universally increases impulsive behavior, the translation of this impulse into criminal acts depends critically on opportunity structures. In China urban environments, characterized by air conditioning, indoor economic activities, and denser formal surveillance, attenuate the behavioral consequences of thermal stress despite higher population density. In contrast, rural residents face greater direct heat exposure through outdoor agricultural labor, with fewer mitigating infrastructure resources, amplifying the per-capita behavioral response to temperature shocks.

However, when shifting from transitory weather anomalies to long-term climatic norms (Panel B), the rural and urban responses undergo a striking divergence and a qualitative sign reversal. For rural areas, a 1°C increase in the long-term average

[5]The magnitude of our crime estimate is comparable to existing evidence from developed countries. Using U.S. data, Ranson (2014) finds that a 1°C temperature increase raises violent crime by approximately 0.2–0.4% and property crime by 0.1–0.2%. Our total crime elasticity of 0.23% falls within a similar range, particularly given that our measure mainly includes property offenses. This alignment corroborates the external validity of our findings while highlighting a key distinction: prior U.S.-based studies, constrained by aggregate data, could not detect the opposing rural response in developing world we uncover.

temperature reduces rural crime by 0.30 incidents per million (Column 1a)—a 0.53% decline relative to the total mean.[6] Conversely, urban areas experience a robust and highly significant escalation, with a 1°C increase raising urban crime by 1.41 incidents per million (Column 2a), representing a 2.48% increase relative to the total mean. The opposing signs across settings are consistent with our conceptual framework: temperature shocks generate heterogeneous economic pressures that differentially shape criminal incentives in rural versus urban areas. While aggregate total crime shows a net increase of 1.96% (Column 3a), this headline figure masks a profound redistribution of social risk across the urban–rural boundary.

We also examine our results to the inclusion of quadratic terms for temperature, as shown in Columns (1b), (2b), and (3b). Across both short-term and long-term horizons, the primary patterns of rural reduction and urban escalation remain robust. Collectively, the results from these three time horizons deliver three key insights. First, the effect of temperature on crime is not spatially uniform—aggregate analyses mask stark urban–rural disparities. Second, the short-term and long-term impacts differ qualitatively, suggesting that behavioral responses and structural adaptations operate in opposite directions in rural settings. Third, the persistent decline in rural crime over the long term suggests mechanisms beyond the psychological pathways emphasized in prior work, motivating our investigation of economic channels.

[6]To evaluate the systemic weight of these sector-specific fluctuations, we normalize all estimated coefficients against the aggregate district-wide mean (comprising both urban and rural sectors). This provides a uniform benchmark to assess the marginal contribution of localized changes to the county's overall crime landscape. Consequently, all percentage changes reported hereafter are calculated relative to this global baseline unless otherwise specified.

**Table 1:** Effects of monthly mean temperature on crime

| | Rural crime | | Urban crime | | Total crime | |
|---|---|---|---|---|---|---|
| | (1a) | (1b) | (2a) | (2b) | (3a) | (3b) |
| | | | *Panel A. Short-term effect* | | | |
| $Temperature_{cym}$ | 0.09*** | 0.09*** | 0.04 | 0.04 | 0.13** | 0.13** |
| | [0.03] | [0.03] | [0.08] | [0.09] | [0.09] | [0.09] |
| $Temperature^2_{cym}$ | | -0.00*** | | 0.00** | | -0.00 |
| | | [0.00] | | [0.00] | | [0.00] |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year × Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 166,080 | 166,080 | 166,080 | 166,080 | 166,080 | 166,080 |
| R-squared | 0.114 | 0.114 | 0.543 | 0.543 | 0.503 | 0.503 |
| | | | *Panel B. Long-term effect* | | | |
| $Temperature_{cym}$ | -0.30*** | -0.26*** | 1.41*** | 1.19*** | 1.11*** | 0.93*** |
| | [0.05] | [0.05] | [0.17] | [0.14] | [0.14] | [0.12] |
| $Temperature^2_{cym}$ | | -0.01*** | | 0.03*** | | 0.03*** |
| | | [0.00] | | [0.00] | | [0.00] |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year × Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 165,492 | 165,492 | 165,492 | 165,492 | 165,492 | 165,492 |
| R-squared | 0.024 | 0.025 | 0.142 | 0.144 | 0.139 | 0.140 |
| Independent variable mean | 6.73 | 6.73 | 50.01 | 50.01 | 56.75 | 56.75 |

*Notes:* Panel A presents the short-term effect estimated based on model (1), while Panel B presents the long-term effect estimated based on model (2). We estimate these effects respectively for rural (columns 1a and 1b), urban (columns 2a and 2b), and the whole sample (columns 3a and 3b). The only difference of column b from column a is that the former additionally includes the square term of the temperature measure. Standard errors reported in square brackets are clustered at the province×year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

## 4.2 Robustness checks

We next assess the robustness of the baseline long-term estimates in Table 1. In particular, we consider alternative definitions of urban and rural areas, alternative crime-rate constructions, specifications without additional controls, an alternative long-difference specification, more flexible functional forms, and alternative temperature measures. Unless otherwise noted, all specifications in this subsection are based on the long-term model in equation (2). The results are stable throughout: higher temperature is associated with lower rural crime and higher urban crime.

#### 4.2.1 Alternative urban–rural classification

Our baseline classification relies on the GHSL settlement categories. A potential concern is that the results may depend on this particular classification rule. To address this concern, we adopt an alternative classification based on land cover rather than settlement structure and re-estimate the baseline long-term specification. Specifically, we classify each geocoded crime incident according to the characteristics of its immediate geographic environment using the global land cover and land use change dataset (GLCLUC2020) produced by the GLAD laboratory (Potapov *et al.*, 2022). This dataset provides global raster data at a 30-meter resolution.[7] For each crime incident, we identify the raster cell containing its coordinates and assign the incident to that cell's land-use category. Incidents located in cells classified as "impervious surfaces" are coded as urban, while all remaining incidents are coded as rural.

This alternative measure is intentionally conservative and serves only as a robustness check. Unlike the baseline GHSL-based classification, which is designed to capture broader settlement structure, the impervious-surface measure identifies built-up land at a very fine spatial scale. As a result, it may over-classify some rural locations as urban, since impervious surfaces such as paved roads, village streets, or hardened farmyards can also appear in rural areas. Although this issue is unlikely to systematically affect large contiguous rural areas, it could introduce some misclassification at the margin.

Panel A of Table 2 shows that the results remain very similar under this alternative definition. A 1°C increase in temperature reduces rural crime by 0.33 incidents per million and increases urban crime by 1.53 incidents per million, with a positive effect of 1.20 incidents per million on total crime. The similarity of these estimates to the baseline results suggests that our main findings are not driven by the specific way we classify urban and rural incidents.

#### 4.2.2 No control variables

Our baseline specification includes weather controls. To show that the results are not sensitive to these controls, Panel B of Table 2 reports estimates from the same long-term model without additional controls. The coefficients are nearly unchanged relative to

[7]The GLCLUC2020 dataset is publicly available at https://glad.umd.edu/dataset/GLCLUC2020. It quantifies annual land cover and land use change globally from 2000 to 2020. In our application, the category "impervious surfaces" corresponds to built-up surfaces such as buildings and roads.

the baseline. A 1°C increase in temperature reduces rural crime by 0.32 incidents per million, increases urban crime by 1.40 incidents per million, and raises total crime by 1.08 incidents per million. This suggests that the urban–rural divergence is not driven by the inclusion of other weather variables.

#### 4.2.3 Alternative crime-rate measure

Another potential concern is that our baseline crime-rate construction may mechanically affect the estimated urban–rural contrast, because both urban and rural crime counts are normalized by the contemporaneous total county population. To assess whether the results are sensitive to this denominator choice, we construct an alternative crime-rate measure in which urban and rural crime counts are normalized by their respective 2012 sub-regional populations. Panel C of Table 2 shows that the results remain qualitatively unchanged: higher temperature continues to reduce rural crime and increase urban crime. This finding suggests that our baseline results are not driven solely by the choice of denominator.

The coefficients from this specification are not directly comparable to those in the baseline because the dependent variables are defined differently. In the baseline, both urban and rural crime counts are normalized by the same county-wide population, which facilitates comparison of crime redistribution within a county. Here, each crime count is normalized by its own fixed 2012 sub-regional population, so the measure instead captures crime incidence relative to the initial urban and rural population sizes. We therefore interpret this specification as a robustness check on the denominator choice, rather than as our preferred measure of spatial redistribution.

#### 4.2.4 Long-difference model

As an additional check on the empirical specification, we estimate a long-difference model following Burke *et al.* (2015b) and Moore & Lobell (2014). Unlike the baseline long-term specification, which exploits cross-sectional variation in temperature levels across counties, this specification relates changes in crime to changes in long-term local climate within counties over time. It therefore serves as a complementary validation.

Specifically, we estimate

$$y_{cpy} = \alpha + \beta_1 \overline{\text{Temperature}}_{cpy} + \mu_p + \lambda_y + \mathbf{X}_{cpy}\theta + \varepsilon_{cpy} \tag{3}$$

where $\overline{\text{Temperature}}_{cpy}$ is the 30-year rolling average temperature preceding year $y$. We construct this variable by averaging temperature over the 30 years prior to each sample year; for example, the 2013 observation is matched with the 1983–2012 climate norm. By construction, this measure filters out short-term weather fluctuations and captures slow-moving variation in local climate. With province fixed effects ($\mu_p$) included, identification comes from cross-county differences in long-term temperature norms after absorbing time-invariant provincial heterogeneity.

Panel D of Table 2 reports the results. The estimates are consistent with the baseline long-term pattern: a higher 30-year temperature norm is associated with lower rural crime and higher urban crime. Quantitatively, a 1°C increase in the long-term temperature norm reduces rural crime by 0.803 incidents per million and increases urban crime by 3.077 incidents per million, implying a net increase of 2.274 incidents per million in total crime. These results suggest that the baseline findings are not solely driven by static cross-sectional correlates.

#### 4.2.5 Agro-climatic temperature measures

We next examine whether the baseline pattern is robust to alternative temperature measures that more directly capture agricultural conditions. The motivation is that, if the long-term temperature effect partly operates through agricultural stress, then measures tailored to crop growth and harmful heat exposure should produce a similar urban–rural pattern.

Specifically, we replace mean temperature with three agro-climatic indices: growing degree days (GDD), harmful degree days (HDD), and growing-season total precipitation (GTP). We estimate

$$y_{cpy} = \alpha + \beta_1 \overline{\text{GDD}}_{cpy} + \beta_2 \overline{\text{HDD}}_{cpy} + \beta_3 \overline{\text{GTP}}_{cpy} + \text{FE} + \mathbf{X}_{cpy}\theta + \varepsilon_{cpy} \tag{4}$$

where the agro-climatic indices are constructed for the primary growing season (April–September) using the sinusoidal interpolation method of Schlenker & Roberts (2009).[8] GDD measures cumulative exposure to temperatures conducive to crop growth between 8°C and 32°C, whereas HDD measures cumulative exposure to temperatures

[8]This approach moves beyond simple daily averages by using daily minimum ($T_{min}$) and maximum ($T_{max}$) temperatures to approximate the within-day temperature path. Specifically, temperature is assumed to follow a sine curve over a 24-hour period, which allows us to estimate the fraction of time spent within different temperature thresholds.

above 32°C, which is harmful to agricultural yields and labor productivity.[9] GTP captures cumulative precipitation over the same growing season. Daily measures are then aggregated to the county-year level.

Panel E of Table 2 reports estimates from the long-term specification using these agro-climatic measures. The results are consistent with the interpretation that the baseline temperature effect is related to agricultural stress. Higher GDD is associated with lower rural crime and higher urban crime, while HDD has no statistically significant effect on rural crime but significantly increases both urban and total crime. Quantitatively, a 100-unit increase in GDD reduces rural crime by 0.417 incidents per million and increases urban crime by 1.817 incidents per million. By contrast, a 100-unit increase in HDD raises urban crime by 1.277 incidents per million and total crime by 1.266 incidents per million. Taken together, these results suggest that the main findings are not specific to the use of average temperature and are consistent with an agricultural economic channel.

[9]For each day, we integrate the implied temperature curve to calculate degree-days in each category: GDD is the integral between 8°C and 32°C, and HDD is the integral above 32°C.

**Table 2:** Robustness checks of long-term effects on crime

| | Rural crime (1) | Urban crime (2) | Total crime (3) |
|---|---|---|---|
| | *Panel A. Alternative urban–rural classification* | | |
| $Temperature_{cym}$ | -0.33*** | 1.53*** | 1.20*** |
| | [0.11] | [0.19] | [0.14] |
| Observations | 165,492 | 165,492 | 165,492 |
| R-squared | 0.102 | 0.163 | 0.140 |
| | *Panel B. No control variables* | | |
| $Temperature_{cym}$ | -0.32*** | 1.40*** | 1.08*** |
| | [0.06] | [0.16] | [0.13] |
| Observations | 165,492 | 165,492 | 165,492 |
| R-squared | 0.024 | 0.142 | 0.139 |
| | *Panel C. Alternative crime-rate measure* | | |
| $Temperature_{cym}$ | -0.54*** | 4.17*** | 0.91*** |
| | [0.10] | [0.56] | [0.14] |
| Observations | 169,176 | 166,272 | 168,564 |
| R-squared | 0.023 | 0.098 | 0.142 |
| | *Panel D. Long difference model* | | |
| $Temperature_{cym}$ | -0.803*** | 3.077*** | 2.274*** |
| | [0.089] | [0.338] | [0.352] |
| Observations | 13,791 | 13,791 | 13,791 |
| R-squared | 0.149 | 0.214 | 0.219 |
| | *Panel E. Agro-climatic temperature measures* | | |
| GDD | -0.417*** | 1.817*** | 1.400*** |
| | [0.047] | [0.184] | [0.189] |
| HDD | -0.011 | 1.277*** | 1.266*** |
| | [0.050] | [0.481] | [0.528] |
| Observations | 13,804 | 13,804 | 13,804 |
| R-squared | 0.138 | 0.218 | 0.223 |
| Province FE | Yes | No | No |
| Year FE | Yes | Yes | Yes |

*Notes:* This table reports robustness checks for the baseline long-term estimates in Table 1, Panel B. Columns (1)–(3) report estimates for rural crime, urban crime, and total crime, respectively. Panel A presents estimates using an alternative urban–rural classification. Panel B presents estimates from the baseline specification without control variables. Panel C presents estimates using an alternative crime-rate measure, in which urban and rural crime rates are defined using the 2012 urban and rural populations, respectively. Panel A–C are based on model (2). Panel D presents estimates from the long-difference specification based on model (3). Panel E presents estimates using growing degree days (GDD) and harmful degree days (HDD) using equation (4). Standard errors reported in square brackets are clustered at the province×year level. Significance levels are $p < 0.01$, $p < 0.05$, and $p < 0.1$.

#### 4.2.6 Alternative functional form

We next examine whether the baseline long-term results are sensitive to the assumed functional form of temperature. To this end, we re-estimate the relationship using increasingly flexible polynomial specifications. Specifically, we consider second- and third-order polynomials in monthly mean temperature, and then augment the third-order specification by additionally controlling for county-level GDP per capita to account for potential confounding from local economic development. Appendix Figure A4 plots the estimated relationships across these specifications. The results remain consistent with the baseline pattern: higher temperatures are associated with lower rural crime and higher urban crime. Adding GDP per capita does not materially affect this divergence. These findings suggest that the baseline results are not driven by the linearity assumption or by restricting the relationship to a quadratic form. We provide further evidence using annual data in Appendix Table A2 and Appendix Figure A5.

#### 4.2.7 Various other Temperature Measures

We further examine whether the baseline results are sensitive to how temperature exposure is measured. To do so, we consider three alternative measures: positive temperature shocks, temperature bins, and intra-annual temperature variation.

**Heat Shocks.** We first test whether extreme temperature realizations, rather than average temperature itself, generate a similar urban–rural divergence. Following Ashraf & Michalopoulos (2015) and Miller *et al.* (2021), we define a positive temperature shock as a month in which mean temperature exceeds its long-term monthly mean by at least one standard deviation. We then construct an annual shock measure as the number of such months in a county-year, which ranges from 0 to 12, and estimate:

$$y_{cpy} = \alpha + \sum_{j=1}^{12} \gamma_j \mathbb{1}(Shock_{cpy} = j) + \mu_{py} + \mathbf{X}_{cpy}\theta + \varepsilon_{cpy} \tag{5}$$

Appendix Figure A7 shows that more frequent positive temperature shocks are associated with lower rural crime and higher urban crime, consistent with the baseline results.

**Temperature Bins.** To relax functional form assumptions more directly, we next adopt a non-parametric bin specification following Schlenker & Roberts (2009). Using

daily data, we calculate the number of days in a county-year falling into seven 6°C intervals: below 0°C, 0–6°C, 6–12°C, 12–18°C, 18–24°C, 24–30°C, and above 30°C. We estimate:

$$y_{cpy} = \alpha + \sum_{j \neq 2} \beta_j Bin^j_{cpy} + \mu_{py} + \mathbf{X}_{cpy}\theta + \varepsilon_{cpy} \tag{6}$$

where the 0–6°C bin is omitted. As shown in Appendix Figure A8, exposure to hotter days is associated with higher urban crime and lower rural crime. This pattern is again consistent with the baseline results.

**Temperature Variation.** Finally, we examine whether intra-annual temperature volatility matters independently of mean temperature (Ray *et al.*, 2015). We measure temperature variation as the standard deviation of monthly temperatures within a county-year:

$$Variation_{cpy} = \sqrt{\frac{1}{12}\sum_{m=1}^{12}(T_{cpmy} - \bar{T}_{cpy})^2} \tag{7}$$

where $T_{cpmy}$ is the mean temperature in month $m$ and $\bar{T}_{cpy}$ is the annual mean temperature in county $c$ and year $y$. We then estimate:

$$y_{cpy} = \alpha + \Gamma f(Variation_{cpy}) + \mu_{py} + \mathbf{X}_{cpy}\theta + \varepsilon_{cpy} \tag{8}$$

where $f(\cdot)$ is a third-order polynomial. Appendix Figure A9 shows that greater temperature variation is also associated with lower rural crime and higher urban crime. Taken together, these results indicate that the baseline urban–rural divergence is robust to alternative measures of temperature exposure.

# 5 Mechanisms

The results above point to different channels operating over different horizons. While the short-term estimates are consistent with behavioral responses to heat, the long-term divergence between rural and urban crime suggests that temperature may also affect crime through broader economic and spatial adjustment. In this section, we examine several pieces of mechanism evidence, focusing on crime type, spatial spillovers, population and employment reallocation, local economic impacts, and psychological responses.

## 5.1 Crime-type evidence

To help distinguish between behavioral and economic channels, we next examine whether the temperature effect differs by crime category. Figure 5 reports the estimated effects separately for property crime, violent crime, and other crime categories in the short-term and long-term specifications. In the short term (Panel A), higher temperatures increase violent crime in both rural and urban areas, while the effects on property crime are small and statistically insignificant. This pattern is consistent with a behavioral channel in which heat exposure increases impulsive or aggressive behavior over short horizons.

In the long term (Panel B), the pattern differs markedly across crime categories. Higher temperatures are associated with declines in both rural property crime and rural violent crime, while urban property crime rises substantially. By contrast, the long-term effect on urban violent crime is small and statistically insignificant. The fact that the urban–rural divergence is concentrated in property crime, rather than violent crime, is more consistent with an economic channel than with a purely behavioral one. In particular, it suggests that the long-term redistribution of crime is linked to changes in economic opportunities and population allocation across space. At the same time, these results should be interpreted as suggestive rather than definitive evidence on mechanisms, which is why we turn next to more direct evidence on population, employment adjustment, and related channels.

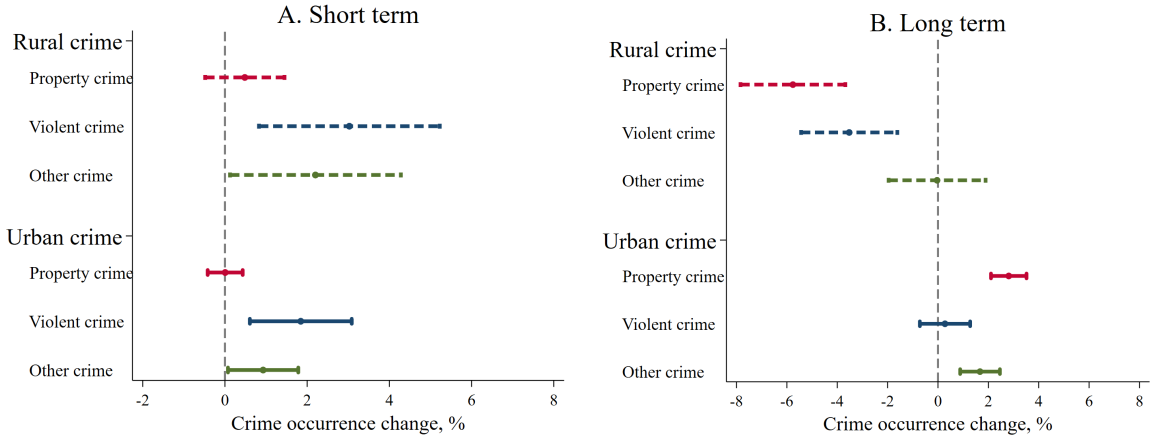



**Figure 5:** Temperature effects by crime category

*Notes:* This figure reports the estimated effects of temperature on crime by category. The left panel uses the short-term specification in equation (1), and the right panel uses the long-term specification in equation (2). Property crime includes theft and robbery. Violent crime includes intentional injury, picking quarrels and provoking trouble, and rape. All remaining offenses are grouped as other crimes. Horizontal lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

## 5.2 Spatial spillovers

We next examine whether temperature in surrounding areas affects local crime. This exercise provides additional evidence on the spatial scope of the long-term temperature–crime relationship and helps assess whether the estimated effects are purely local or partly reflect broader regional adjustment. We do so by replacing local temperature with area-standardized average temperatures in a series of concentric distance rings around each county. We estimate the following empirical model:

$$y_{cpmy} = \alpha + \sum_{n=1}^{4} \beta_n \text{TempStd}_{cpmy}^{(n)} + \mu_p + \lambda_{my} + \mathbf{X}'_{cpmy}\theta + \varepsilon_{cpmy} \tag{9}$$

where $y_{cpmy}$ is the crime rate in county $c$ in month $m$ and year $y$. We include province fixed effects ($\mu_p$) and month-by-year fixed effects ($\lambda_{my}$). The key regressors, $\text{TempStd}_{cpmy}^{(n)}$, measure area-standardized temperature in the $n$-th ring around county $c$. These rings correspond to counties whose centroids lie within $<100$ km, 100–200 km, 200–300 km, and 300–400 km of county $c$, excluding county $c$ itself. Formally,

$$\text{TempStd}_{cpmy}^{(n)} = \frac{A_c^{(n)}}{\bar{A}} \sum_{j \in \mathcal{R}_c^{(n)}} \text{Temp}_{jpmy}, \tag{10}$$

where $\mathcal{R}_c^{(n)}$ denotes the set of counties in ring $n$, $A_c^{(n)}$ is the total area of those counties, and $\bar{A}$ is the average county area in the sample. This scaling makes the coefficients comparable across rings of different total sizes.

Figure 6 reports the estimates. Two patterns stand out. First, temperature in the nearest ring (within 100 km) has a positive effect on urban crime and a negative effect on rural crime, in the same direction as the baseline local estimates. This suggests that the temperature–crime relationship is not purely local and extends to geographically proximate areas. Second, the spillover pattern weakens rapidly with distance. For rural crime, the estimates outside the nearest ring are small and statistically insignificant. For urban crime, temperature in the 100–200 km ring is associated with a decline in crime, while estimates beyond 200 km are close to zero and statistically insignificant. Overall, the spillover effects appear geographically limited, with little evidence of meaningful effects beyond roughly 200 km. Taken together, these results are consistent with the view that temperature affects crime through spatially connected local environments rather than through diffuse nationwide shocks. At the same time, because the spillover

estimates do not identify the precise channel, we interpret them as suggestive evidence of localized spatial adjustment.

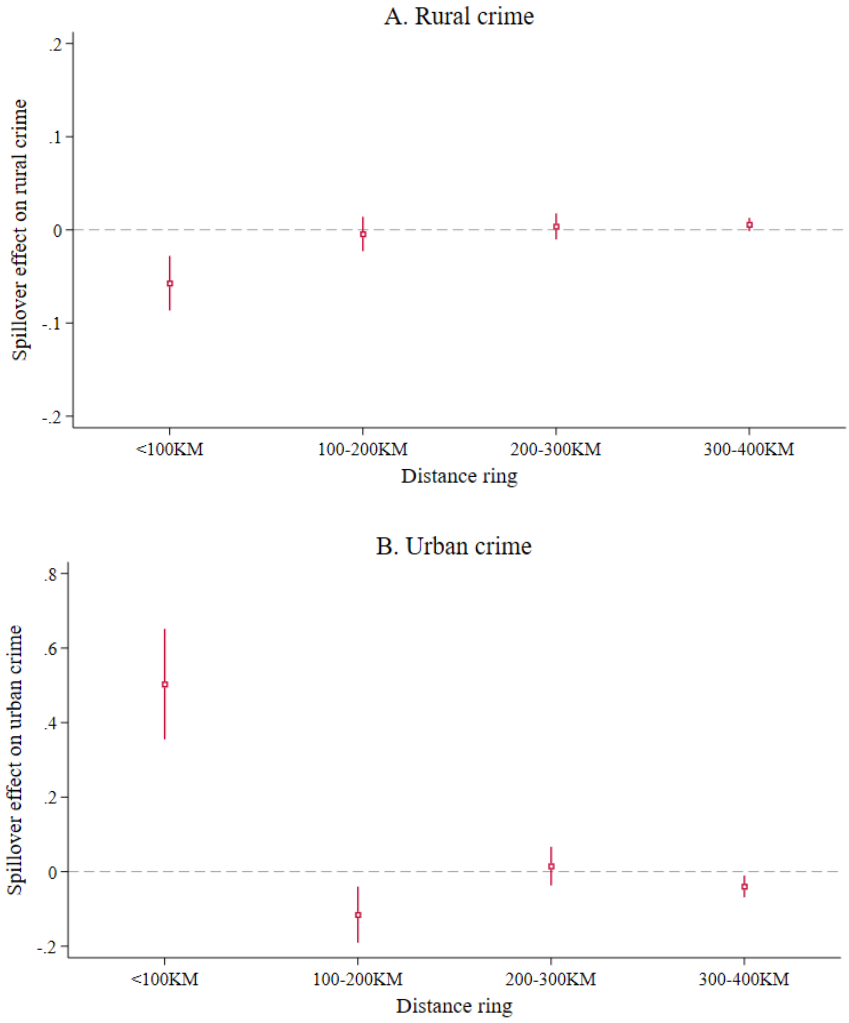



**Figure 6:** Spillover of long-term effects on crime

*Notes:* This figure reports coefficient estimates from equation (9) for temperature in surrounding distance rings (< 100 km, 100–200 km, 200–300 km, and 300–400 km). The coefficients are area-standardized using the average county area, which makes them comparable across rings of different sizes. Horizontal lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

## 5.3 Population and employment reallocation

We next examine whether higher temperatures are associated with changes in individuals' residential location and employment status. This exercise does not identify the movement of offenders directly, but it provides micro-level evidence on whether thermal stress is accompanied by shifts away from agriculture and toward urban and non-agricultural activities. Using multiple waves of the CFPS, we estimate the following individual-level

panel specification:

$$y_{icy} = \alpha + \beta_1 Temperature_{cy} + \mu_i + \lambda_y + X_{icy}\theta + \varepsilon_{icy} \tag{11}$$

where $y_{icy}$ denotes the outcome of interest for individual $i$ in county $c$ and year $y$, including indicators for urban residence and sectoral employment. $Temperature_{cy}$ is the annual mean temperature in the respondent's county of residence. We include individual fixed effects ($\mu_i$) and year fixed effects ($\lambda_y$), along with time-varying individual and local controls.

Table 3 reports the results. Higher temperatures are associated with a higher probability of residing in urban areas (Column 1), a lower probability of working in agriculture (Column 2), and a higher probability of working in non-agricultural and business activities (Columns 3–4). Quantitatively, a 1°C increase in annual mean temperature raises the probability of urban residence by 2.7 percentage points, reduces agricultural employment by 2.8 percentage points, and increases non-agricultural and business work by 3.1 and 1.2 percentage points, respectively.

Taken together, these results point to population and employment reallocation away from agriculture and toward urban and non-agricultural activities. While they do not directly show that crime is transferred across space through migration, they are consistent with the broader interpretation that temperature shocks reshape the environments in which criminal activity occurs by changing where people live and work.

**Table 3:** Population and employment reallocation

| | Urban resident | Agriculture work | Non-agriculture work | Business work |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $Temperature_{cy}$ | 0.027*** | -0.028*** | 0.031*** | 0.012*** |
| | [0.007] | [0.007] | [0.008] | [0.004] |
| Year FE | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes |
| Observations | 31,117 | 31,365 | 24,220 | 31,365 1 |
| R-squared | 0.936 | 0.777 | 0.756 | 0.662 |

*Notes:* This table reports individual-level estimates from equation (11). The dependent variables are indicators for urban residence, agricultural work, non-agricultural work, and business work. Standard errors, reported in brackets, are clustered at the individual level. Significance levels are *** p < 0.01, ** p < 0.05, and * p < 0.1.

## 5.4 Economic impacts and sectoral reallocation

We next examine whether temperature affects local economic outcomes in ways that are consistent with the long-term divergence between rural and urban crime. To do so, we study sector-specific output, wages, household income, and firm entry at the county level. These results speak to two related margins: the direct effect of temperature on economic conditions, and the extent to which temperature shifts the composition of local economic activity across sectors.

Table 4 shows that higher temperatures reduce both agricultural and non-agricultural GDP per capita (Columns 1a–1b). They also lower wages and household income (Columns 1c–1e), with particularly pronounced declines in rural income. These results indicate that temperature imposes broad economic costs, especially in climate-sensitive settings. In a Beckerian framework (Becker, 1968), such income losses may reduce the opportunity cost of crime, particularly for property offenses.

At the same time, temperature is associated with changes in the sectoral composition of local economic activity. Columns 2a–2b show that higher temperatures are associated with greater net entry of non-agricultural firms and lower net entry of agricultural firms. This pattern is consistent with the idea that thermal stress weakens agricultural activity while shifting economic activity toward non-agricultural sectors.

Taken together, these findings suggest that temperature affects crime also through economic pressures and sectoral reallocation. More importantly for our interpretation, they indicate that the long-term urban–rural divergence in crime is accompanied by systematic differences in how temperature affects agricultural and non-agricultural environments.

**Table 4:** Economic impacts and sectoral reallocation

| | Log value per capita | | | | | Firm net entry (sd) | |
|---|---|---|---|---|---|---|---|
| | Agricultural GDP | Non-agricultural GDP | Wage | Urban income | Rural income | Non-agriculture firm | Agriculture firm |
| | (1a) | (1b) | (1c) | (1d) | (1e) | (2a) | (2b) |
| $Temperature_{cy}$ | -0.051*** | -0.135*** | -0.032*** | -0.014*** | -0.031*** | 0.063*** | -0.078*** |
| | [0.006] | [0.008] | [0.004] | [0.003] | [0.002] | [0.013] | [0.026] |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17,476 | 17,478 | 7,030 | 13,195 | 15,833 | 14,917 | 14,917 |
| R-squared | 0.957 | 0.962 | 0.926 | 0.971 | 0.978 | 0.754 | 0.294 |

*Notes:* This table reports county-level estimates of the effects of temperature on sector-specific output, income, and firm entry. Columns (1a)–(1e) report outcomes in logs. Columns (2a)–(2b) report standardized firm net entry in non-agricultural and agricultural sectors. All specifications use the annual version of the baseline model with county and year fixed effects. Standard errors, reported in brackets, are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

## 5.5 Psychological responses

Finally, we examine whether temperature affects psychological states that may be related to impulsive or aggressive behavior. This channel is a plausible explanation for short-term crime responses to heat, but it is less obviously consistent with the long-term divergence between rural and urban crime documented above. Table 5 shows that higher temperatures are associated with increases in self-reported depression, nervousness, and impetuousness. The estimated effects are statistically significant, but modest in magnitude[10]. These findings are consistent with a behavioral channel through which heat exposure worsens emotional well-being.

At the same time, this evidence is less well aligned with the long-term spatial pattern of crime. If psychological distress were the primary mechanism, one would expect temperature to affect rural and urban crime in a more similar way. Instead, the long-term estimates show a clear divergence between the two. We therefore interpret psychological responses as a complementary channel, particularly for short-term effects, rather than as the main explanation for the long-term urban–rural divergence.

[10]Because the psychological measures are available only in a single survey wave, we estimate this relationship using cross-sectional OLS rather than the individual fixed-effects specification used above.

**Table 5:** Psychological responses to temperature

| | Depressed (1) | Nervousness (2) | Impetuous (3) |
|---|---|---|---|
| $Temperature_{cy}$ | 0.012*** | 0.007*** | 0.007*** |
| | [0.003] | [0.003] | [0.003] |
| Observations | 5,088 | 5,088 | 5,088 |
| R-squared | 0.009 | 0.009 | 0.007 |

*Notes:* This table reports individual-level estimates of the effects of temperature on self-reported emotional states. The dependent variables are indicators for feeling depressed, nervous, and impetuous. All specifications are based on the OLS version of equation (11). Standard errors, reported in brackets, are clustered at the county level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

# 6 Policy Implications

## 6.1 Implications from heterogeneous analyses

We next examine whether the long-term temperature effect varies systematically across counties with different economic structures, locations, and baseline conditions. The purpose of this exercise is to identify the types of places in which the urban–rural divergence is most pronounced, and to draw policy implications from that pattern. For each moderating variable, we construct a dummy equal to one if the county's 2013 value is above the sample median and zero otherwise. We then interact this dummy with temperature in the baseline long-term specification:

$$y_{cpmy} = \alpha + \beta_1 Temperature_{cpmy} + \beta_2 Temperature_{cpmy} \times Dummy_c + \mu_p + \lambda_{my} + \mathbf{X}_{cpmy}\theta + \varepsilon_{cpmy} \tag{12}$$

where $\beta_1$ captures the temperature effect for the low group and $\beta_1 + \beta_2$ gives the corresponding effect for the high group. Figure 7 plots these subgroup estimates.

Several patterns emerge. First, the positive temperature effect on urban crime is larger in economically less advantaged counties. The estimated effect is stronger in counties with lower GDP per capita, higher agricultural GDP shares, lower non-agricultural labor shares, weaker industrial and service sectors, and lower export values. This pattern is consistent with the idea that urban areas with less diversified local economies are less able to absorb the social costs of climate stress. Second, the urban effect also varies with geography and initial local conditions. The temperature-induced increase in urban crime is larger in western counties than in non-western counties, larger in city districts than in non-city districts, and larger in counties with lower baseline temperature, lower baseline crime rates, and higher population density. Taken together, these results suggest that the urban crime response to warming is particularly strong in places with weaker economic buffers or greater pressure on urban public services. By contrast, the negative temperature effect on rural crime is present across most subgroups and shows less variation in magnitude. The rural decline is somewhat larger in counties with lower baseline temperature and in western counties, but overall the heterogeneity is more limited than for urban crime.

These heterogeneous patterns yield two policy implications. First, the rise in crime associated with warming is not uniform across space: it is concentrated in urban areas that are economically less diversified and more exposed to structural adjustment.

This suggests that adaptation policies should place greater weight on vulnerable urban destinations, rather than focusing only on the rural origins of climate stress. Second, because the urban response is stronger in places with weaker non-agricultural development and higher population density, climate adaptation policy should pay particular attention to urban areas with limited economic buffers and greater pressure on public services.

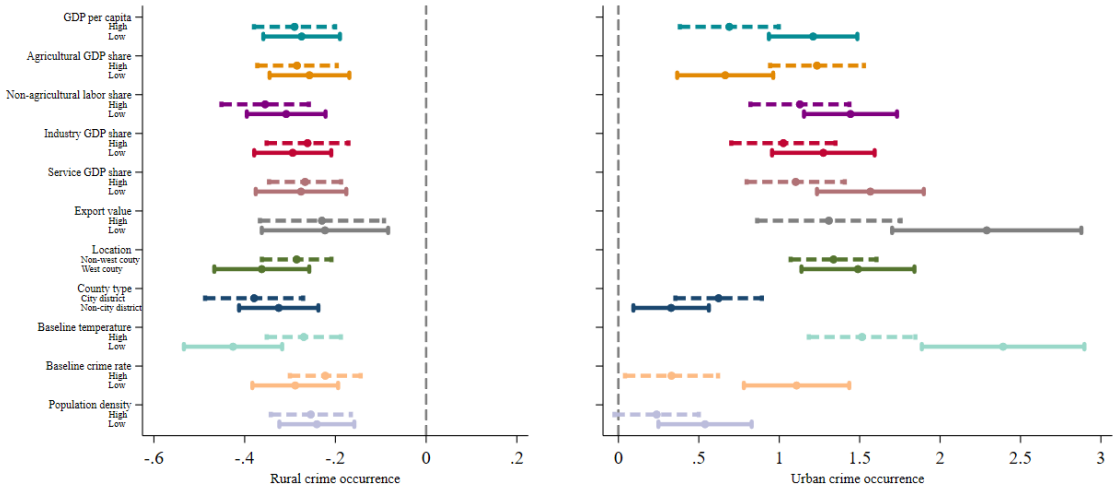



**Figure 7:** Heterogeneous long-term effects of temperature on rural and urban crime

*Notes:* This figure plots subgroup estimates from equation (12). For each moderating variable, counties are split at the median of the 2013 distribution. The figure reports the estimated temperature effect for the low group ($\beta_1$, solid line) and the high group ($\beta_1 + \beta_2$, dashed line), together with 95% confidence intervals. The left panel reports estimates for rural crime, and the right panel reports estimates for urban crime. Standard errors are clustered at the province×year level.

## 6.2 Moderating effects of various policies

We next examine whether the temperature–crime relationship differs across local policy environments. Figure 8 reports the estimated temperature coefficients for rural and urban crime under different policy groupings.

Several results are worth highlighting. Among agricultural support policies, agricultural subsidies show the clearest moderating role. In counties with higher subsidy intensity, the temperature effect on urban crime is notably smaller than in counties with lower subsidy intensity. This pattern is consistent with the view that direct income support in agriculture can partially ease the pressures associated with warming and thereby mitigate the increase in urban crime. By contrast, land-based interventions—including farmland construction investment, irrigation, and land titling—show much weaker heterogeneity. The estimated temperature coefficients

are broadly similar across policy groups, especially relative to the differences observed for agricultural subsidies. This suggests that these policies do not substantially alter the temperature sensitivity of crime.

The urban-side patterns are more pronounced for several non-agricultural policies. Free trade zone designation and monitoring procurement are both associated with smaller urban temperature coefficients, indicating that stronger local economic opportunities or deterrence capacity may help contain the rise in urban crime under higher temperatures. Hukou reform, however, displays the opposite pattern: counties with stronger reform intensity exhibit a larger urban temperature coefficient. This suggests that policies facilitating mobility do not necessarily dampen the urban consequences of climate stress and may instead coincide with a stronger urban crime response to warming.

Poverty alleviation presents a more nuanced case. The urban temperature coefficient is steeper in treated counties, indicating that this policy does not appear to weaken the marginal temperature effect on urban crime. At the same time, if the baseline level results reported elsewhere are taken into account, poverty alleviation may still contribute to lower overall crime even if it does not attenuate the temperature gradient itself. We therefore interpret its role as reducing underlying social vulnerability rather than directly weakening the temperature–crime link.

Across policies, the rural temperature coefficient remains negative and comparatively stable. Most of the policy-related heterogeneity is concentrated in urban crime. This pattern is consistent with the broader results of the paper: policy relevance lies less in changing the rural response and more in limiting the increase in urban crime associated with higher temperature.

Overall, the policy heterogeneity points to three main lessons. First, direct agricultural support appears more effective than land-based interventions in moderating the urban crime response to temperature. Second, policies that expand economic opportunities or strengthen monitoring capacity are also associated with a weaker urban response. Third, mobility-enhancing reforms need not reduce urban climate-related social pressure and may, in some settings, amplify it.

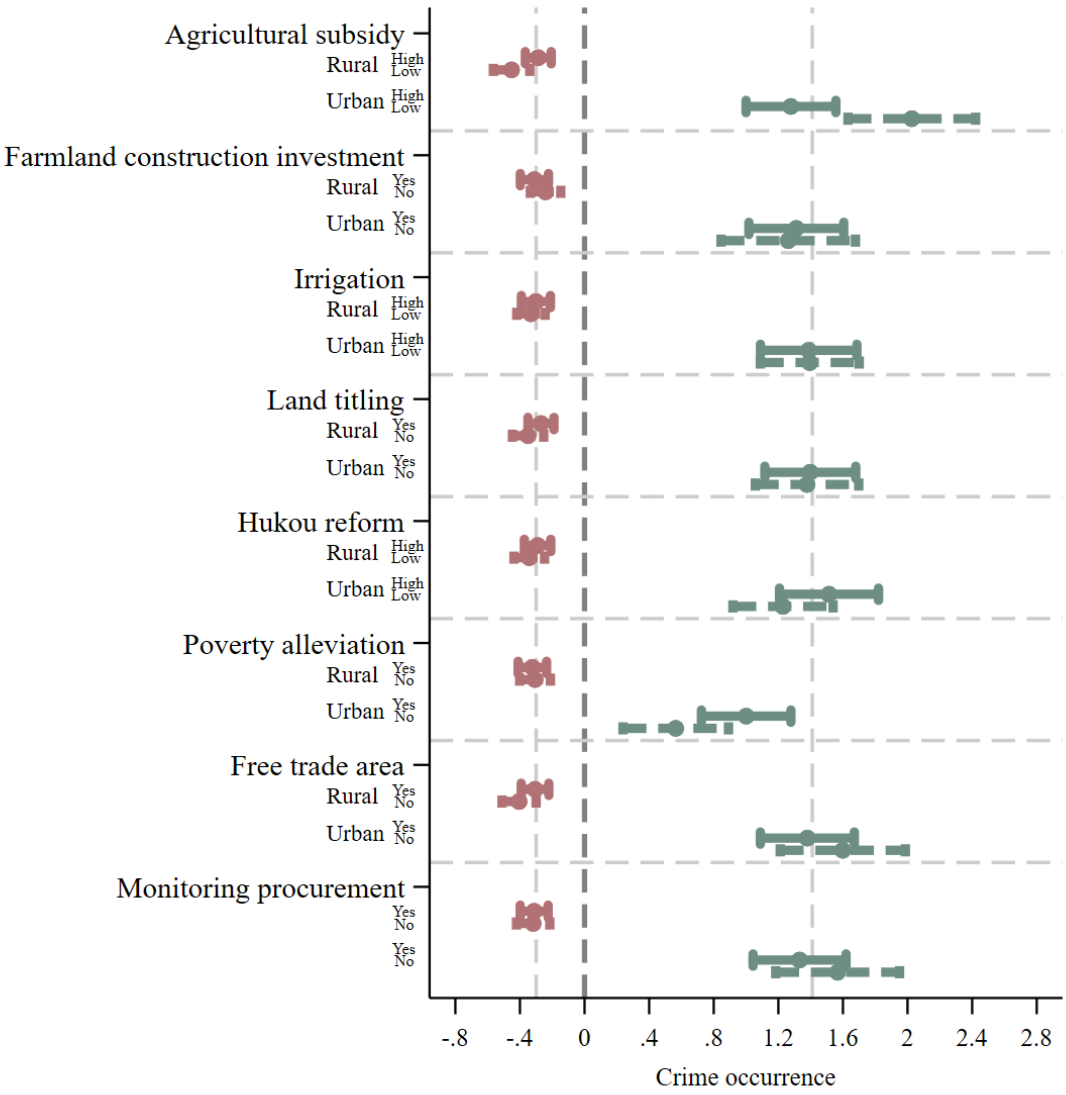



**Figure 8:** Interaction effects with other policies

*Notes:* This figure plots subgroup-specific temperature coefficients for rural and urban crime across different policy environments. For policies with explicit implementation status—including farmland construction, land titling, poverty alleviation, free trade zone designation, and monitoring procurement—counties are divided into implemented and non-implemented groups. For policies implemented more broadly—including agricultural subsidies, irrigation, and hukou reform—counties are divided into above-median and below-median intensity groups. Coefficients are estimated using the interaction specification in equation (12). Horizontal lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

## 6.3 Projected effects and welfare implications

We next illustrate the long-run implications of the estimated temperature–crime relationship under alternative climate scenarios. As shown in Table 6, a 1°C increase

in temperature is associated with a 0.53% decline in rural crime and a 2.48% increase in urban crime, implying a 1.96% increase in total crime. The spatial divergence becomes more pronounced under future warming. By the end of the century, total crime is projected to increase by 3.40% under RCP4.5 and by 8.69% under RCP8.5, with the aggregate increase driven by a substantially larger rise in urban crime than the accompanying decline in rural crime.

To gauge the potential economic significance of these projected crime effects, we conduct a simple back-of-the-envelope monetization exercise following Ranson (2014). We value each additional crime using the $3,523 tangible social cost of a larceny/theft offense estimated by McCollister *et al.* (2010). We use this relatively conservative benchmark because our geocoded sample is dominated by property offenses and the long-run urban–rural divergence is concentrated primarily in property crime, rather than applying the substantially higher costs associated with serious violent offenses. The resulting estimates are intended to indicate the approximate order of magnitude of the potential social costs, rather than to provide a precise welfare valuation.[11]

**Table 6:** Projected changes in crime and illustrative social costs

| | Change in crime (%) | | | Annual social cost | |
|---|---|---|---|---|---|
| Scenario | Rural | Urban | Total | Geocoded sample | All criminal cases |
| 1°C increase | -0.53 | 2.48 | 1.96 | 6 | 77 |
| RCP4.5 | -1.07 | 4.48 | 3.40 | 10 | 134 |
| RCP8.5 | -1.76 | 11.40 | 8.69 | 27 | 342 |

*Notes:* The first three columns report percentage changes in rural, urban, and total crime. The 1°C estimates are based on the baseline long-term specification, while the RCP4.5 and RCP8.5 estimates are obtained by applying projected end-of-century temperatures to the nonlinear long-term specification. The last two columns report approximate annual social costs in millions of 2008 U.S. dollars. Following Ranson (2014), additional crimes are monetized using the $3,532 per-offense social cost of larceny/theft estimated by McCollister *et al.* (2010). The "Geocoded sample" scenario assumes that the estimated proportional effects apply only to crimes represented in our geocoded sample, whereas the "All criminal cases" scenario assumes that the same proportional effects extend to all first-instance criminal cases in China. Monetary values are rounded to the nearest million and should be interpreted as rough order-of-magnitude illustrations rather than precise China-specific welfare estimates.

Under the narrower assumption that the estimated relationship applies only to crimes represented in our geocoded sample, the implied annual social cost is approximately $6

[11]For the narrower scenario, we apply the estimated proportional changes in total crime to approximately 520,000 geocoded incidents observed over 2013–2018, equivalent to about 86,667 incidents per year. For the broader scenario, we apply the same proportional changes to approximately 1.115 million first-instance criminal cases per year over the same period. The calculations use a 1.96% increase in total crime for a 1°C increase, and projected increases of 3.40% and 8.69% under RCP4.5 and RCP8.5, respectively. Annual social costs are calculated as the relevant annual crime baseline multiplied by the corresponding proportional change in crime and by $3,523 per additional offense. Monetary values are expressed in 2008 U.S. dollars.

million for a 1°C increase, rising to about $10 million under RCP4.5 and $27 million under RCP8.5. If the same proportional response is applied more broadly to all criminal cases, the corresponding figures are approximately $77 million, $134 million, and $342 million. These calculations are necessarily approximate and are intended to illustrate the potential order of magnitude rather than provide precise welfare estimates for China. In particular, they rely on a U.S.-based per-offense valuation, while the broader scenario additionally extrapolates the estimated crime response beyond the offenses represented in our geocoded sample.

Figure 9 maps the spatial heterogeneity in the projected effects of future warming across counties under the RCP8.5 scenario. The figure reports percentage changes relative to current crime levels. Projected rural crime declines and urban crime increases vary substantially across space, reflecting differences in baseline temperature, baseline crime levels, and the nonlinearity of the estimated temperature–crime relationship. Appendix Figure A10 reports the corresponding changes in crimes per million people.

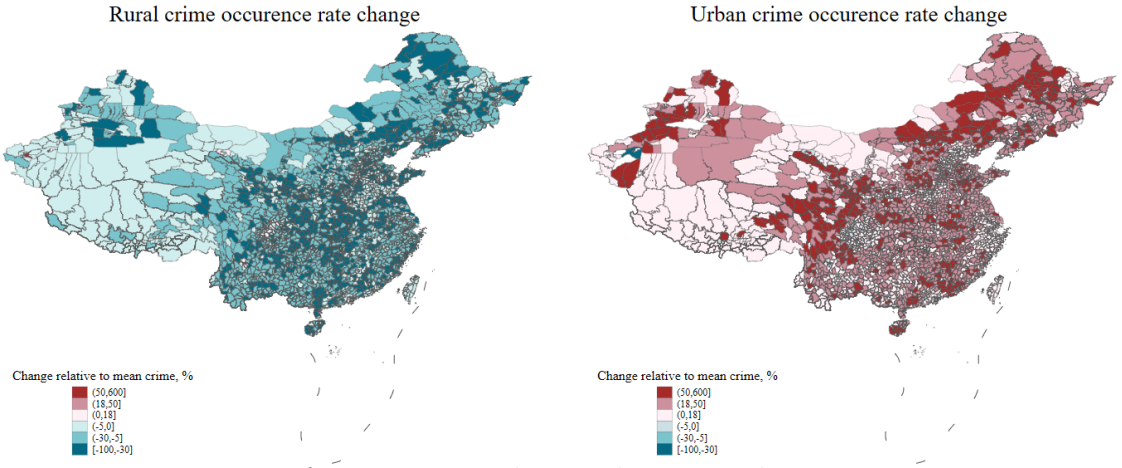



**Figure 9:** Impact of temperature changes by 2100 relative to present on crime

*Notes:* This figure maps projected percentage changes in rural and urban crime by 2100 under the RCP8.5 scenario, based on the annual third-order nonlinear long-term model.

# 7 Conclusion

This paper studies how temperature affects crime across rural and urban settings in China. Using geocoded judicial records matched to high-resolution settlement data, we document a clear difference between short-term and long-term temperature effects. In the short term, higher temperature is associated with higher crime in both rural and urban areas. In the long term, however, the effects diverge across space: a 1°C increase in temperature is associated with a 0.53% decline in rural crime and a 2.48% increase in urban crime, implying a net increase in total crime. These findings are robust to alternative functional forms, alternative definitions of urban and rural areas, alternative crime-rate measures, agro-climatic indices, and other temperature measures. Estimates from the long-difference specification are directionally consistent with the baseline results.

The evidence further suggests that this divergence is more closely related to economic and spatial adjustment than to a purely behavioral response to heat. The long-term urban–rural divergence is concentrated in property crime rather than violent crime, and the spillover results indicate that temperature effects extend across nearby counties but decay quickly with distance. At the micro level, higher temperature is associated with a lower probability of agricultural work and a higher probability of urban residence and non-agricultural employment. At the county level, temperature depresses output and income while shifting firm entry away from agriculture and toward non-agricultural sectors. We also find evidence that higher temperature worsens self-reported emotional well-being, but this psychological channel appears better suited to explaining short-term responses than the long-term divergence between rural and urban crime. Taken together, these results are consistent with the view that rising temperature affects crime through differential impacts across agricultural and non-agricultural environments, accompanied by broader population, employment, and economic adjustment.

The policy analysis points to three broader implications. First, the heterogeneous effects show that the urban crime response to temperature is stronger in counties with weaker economic buffers, including places with lower income, less diversified non-agricultural sectors, and higher population density. Second, the policy interaction results suggest that this urban response is weaker in some policy environments than in others: agricultural subsidies, free trade zone designation, and monitoring procurement are associated with smaller urban temperature effects, whereas land-based interventions show more limited heterogeneity. Third, the projection exercise implies that future

warming is likely to increase aggregate crime mainly through rising urban crime, even as rural crime declines. Taken together, these findings suggest that the social costs of climate change will depend importantly on local economic structure, policy support, and public safety capacity.

We conclude by acknowledging two primary limitations. First, our crime data are derived from judicial records with identifiable incident locations, which makes the analysis better suited to offenses with fixed physical locations and likely tilts the sample toward property crime. Second, while the evidence is consistent with spatial and economic adjustment, our data do not allow us to directly trace the movement of offenders across space. Future research with richer individual-level mobility and crime data could help further distinguish among the channels linking climate stress, economic adjustment, and the spatial distribution of crime.

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# A Appendix for Online Publication

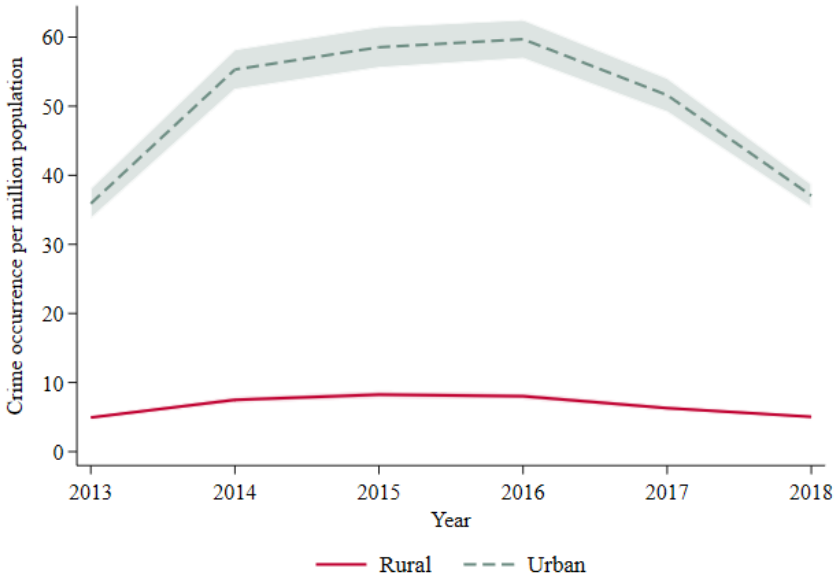



**Figure A1:** Crime occurrence trend

*Notes:* This figure plots crime trends in rural and urban areas over the sample period. The shaded areas denote 95% confidence intervals. Crime incidents are classified as rural or urban using the Global Human Settlement Layer (GHSL) Settlement Model grid (GHS-SMOD).

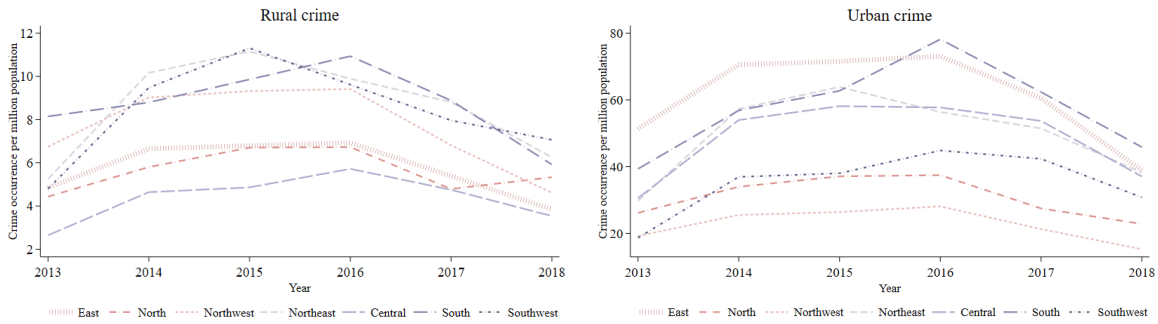



**Figure A2:** Crime occurrence trends across regions

*Notes:* This figure plots regional crime trends over the sample period, separately for rural areas (left panel) and urban areas (right panel). Crime incidents are classified as rural or urban using the Global Human Settlement Layer (GHSL) Settlement Model grid (GHS-SMOD). Provinces and municipalities are grouped into seven conventional geographic regions.[a]

[a]East China includes Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong; North China includes Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia; Northwest China includes Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang; Northeast China includes Liaoning, Jilin, and Heilongjiang; Central China includes Henan, Hubei, and Hunan; South China includes Guangdong, Guangxi, and Hainan; Southwest China includes Chongqing, Sichuan, Guizhou, Yunnan, and Tibet.

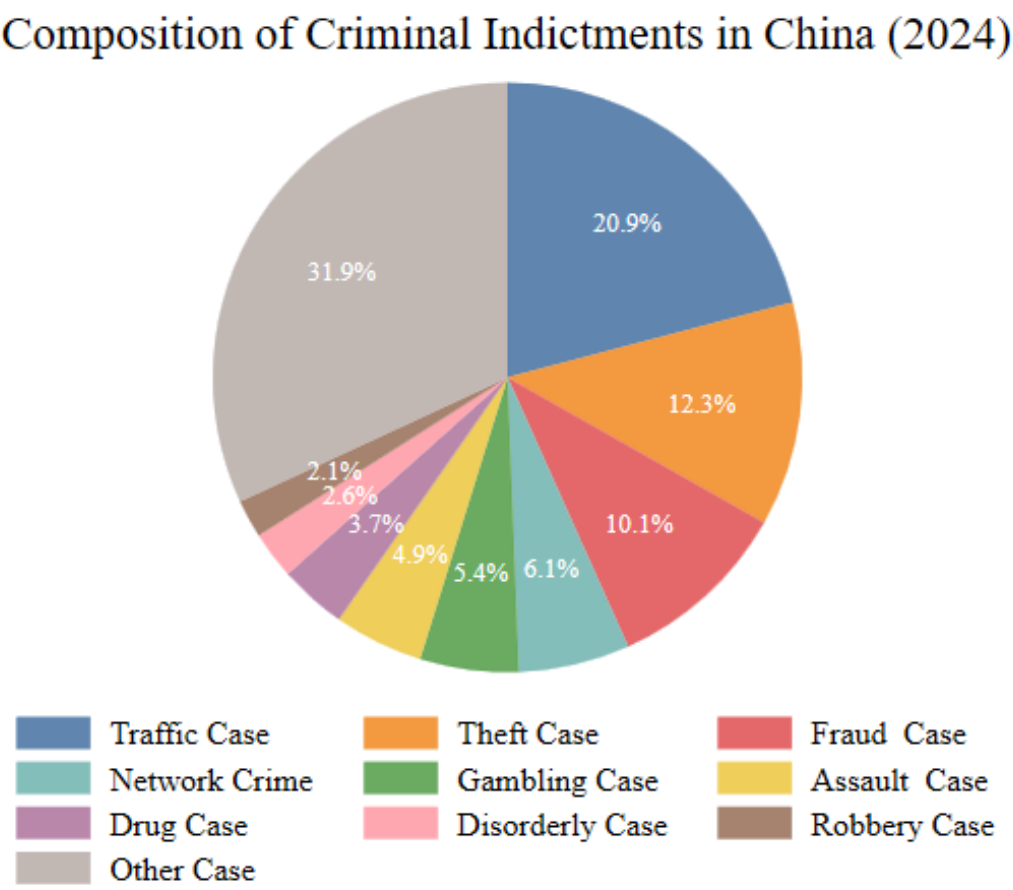



**Figure A3:** Composition of criminal indictments in China, 2024

*Notes:* This figure shows the composition of criminal indictments in China in 2024, based on the Supreme People's Procuratorate Work Report.

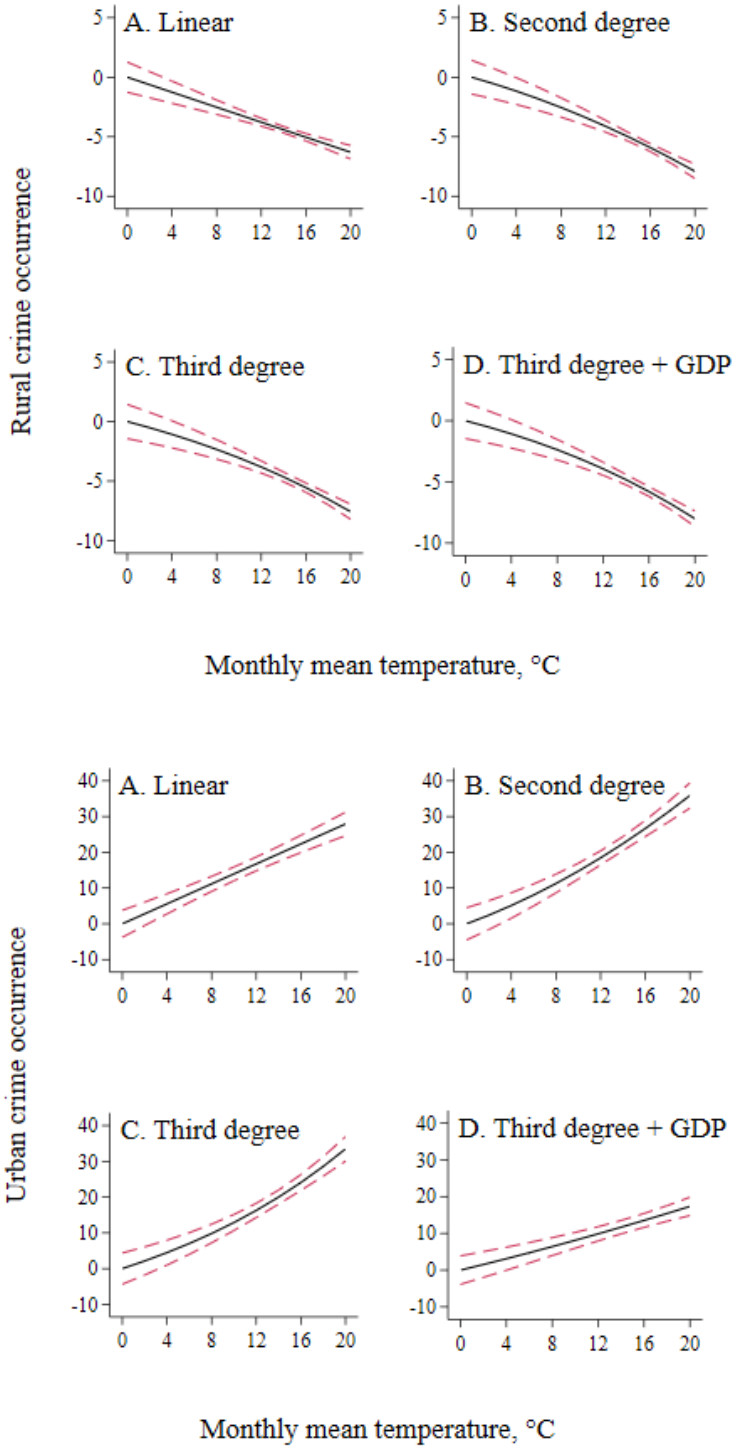



**Figure A4:** Nonlinear long-term effects of monthly mean temperature on crime

*Notes:* This figure reports the estimated long-term effects of monthly mean temperature on crime using nonlinear versions of equation (2). It provides a robustness check for Table 1, Panel B. Panels A–D correspond to first-, second-, and third-order polynomial specifications, and a third-order specification that additionally controls for per capita GDP. The 95% confidence intervals (dash lines) are computed using standard errors clustered at the province×year level.

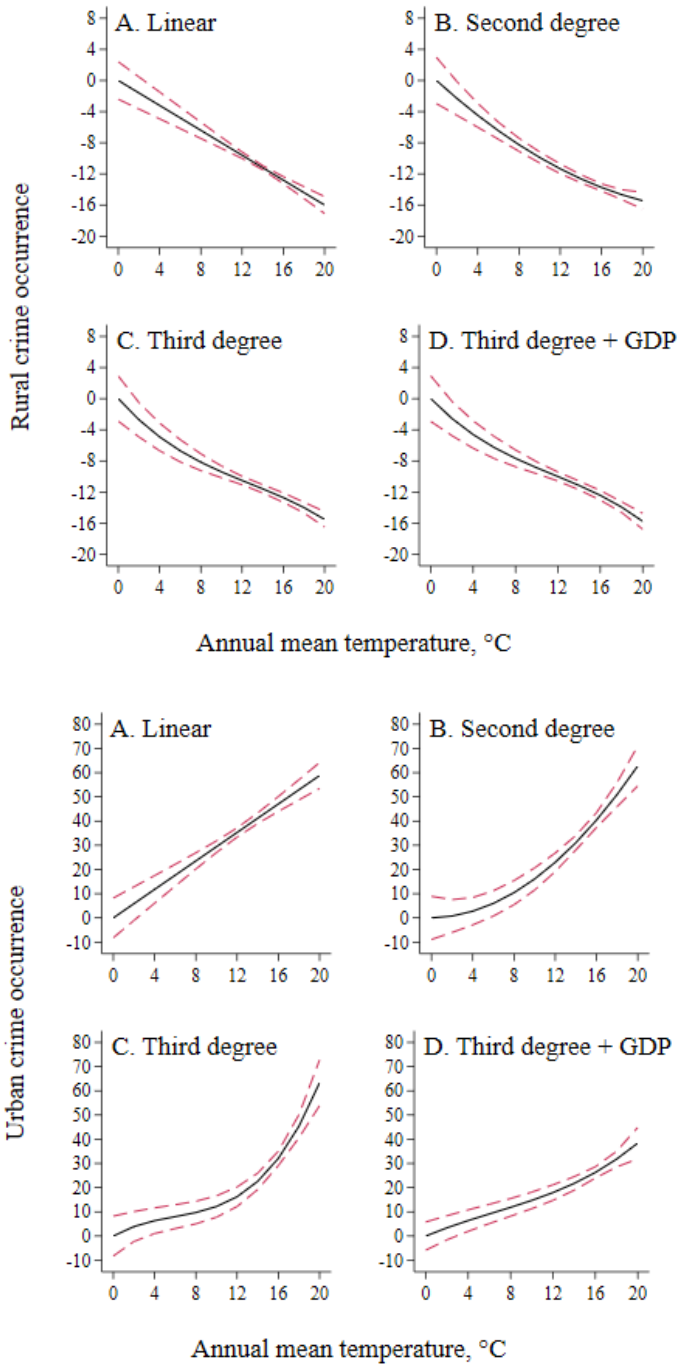



**Figure A5:** Nonlinear long-term effects of annual mean temperature on crime

*Notes:* This figure reports the estimated effects of annual mean temperature on crime using nonlinear versions of equation (2). The 95% confidence intervals (dash lines) are computed using standard errors clustered at the province×year level.

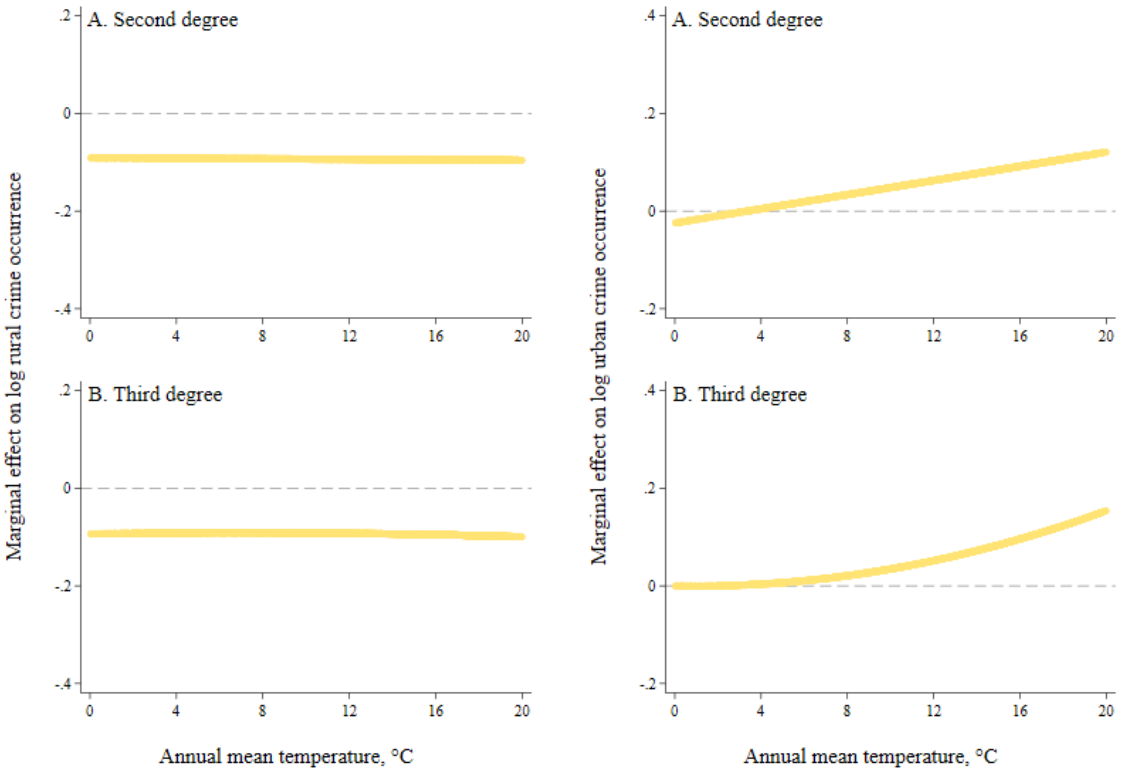



**Figure A6:** Marginal effects of annual mean temperature on crime

*Notes:* This figure plots the marginal effect of annual mean temperature on crime, evaluated using the estimated second- and third-order polynomial specifications. The left panel reports rural crime and the right panel reports urban crime.

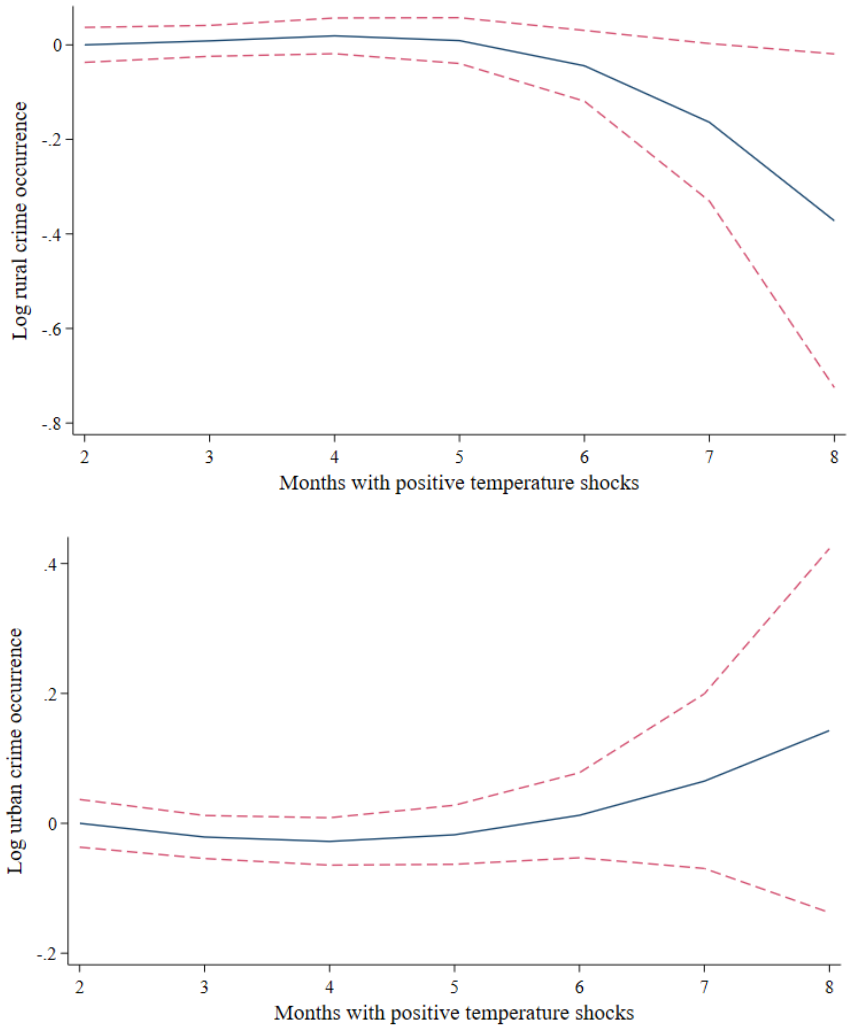



**Figure A7:** Effects of heat shocks on crime

*Notes:* This figure reports coefficient estimates from equation (5). The left panel reports rural crime and the right panel reports urban crime. Dash lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

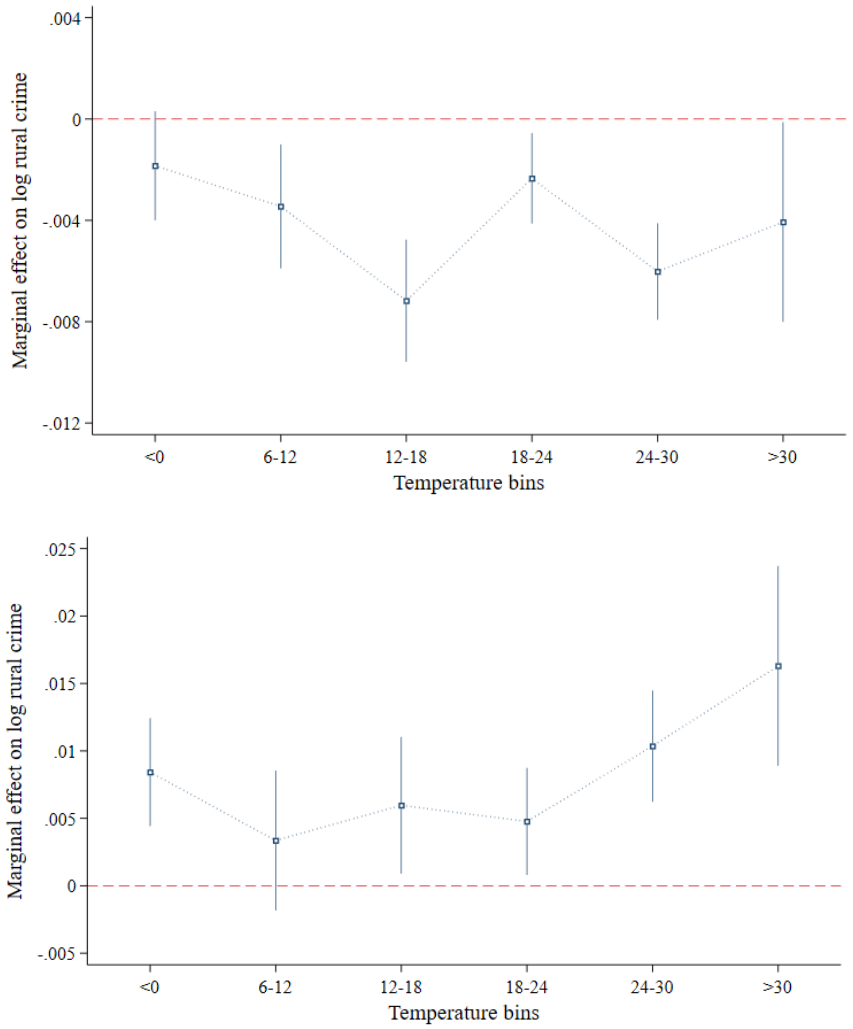



**Figure A8:** Effects of temperature bins on crime

*Notes:* This figure reports coefficient estimates from equation (6). The omitted category is the 0–6°C temperature bin. The left panel reports rural crime and the right panel reports urban crime. Horizontal lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

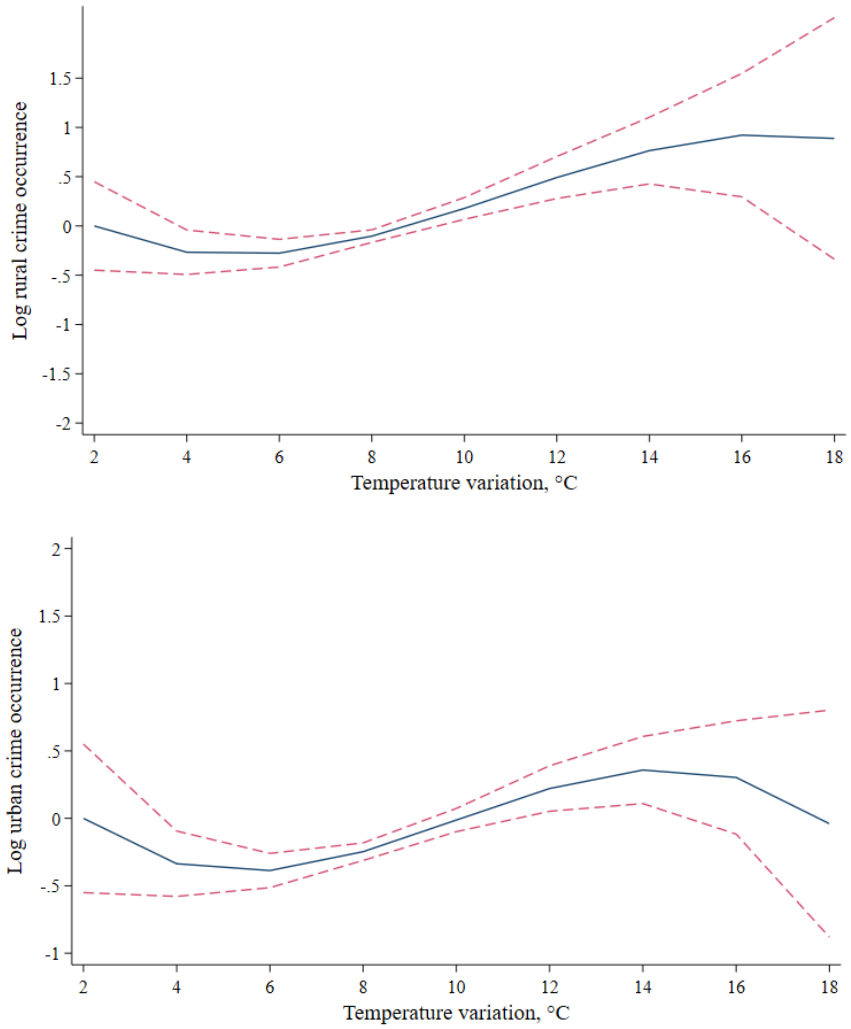



**Figure A9:** Effects of temperature variation on crime

*Notes:* This figure reports the estimated effects of intra-annual temperature variation on crime based on equation (8). The left panel reports rural crime and the right panel reports urban crime. Dash lines indicate 95% confidence intervals based on standard errors clustered at the province×year level.

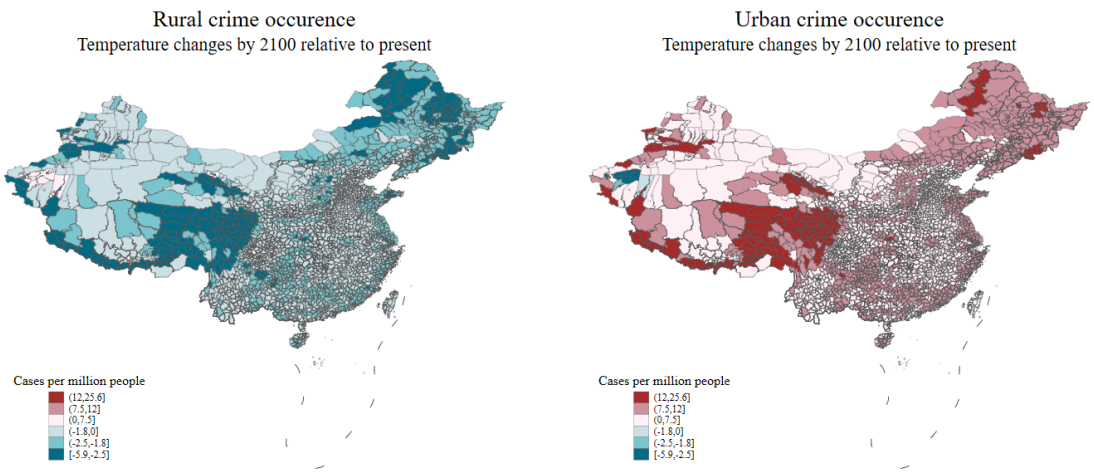



**Figure A10:** Impact of temperature changes by 2100 relative to present on crime

*Notes:* This figure presents the impact of temperature changes by 2100 (RCP8.5 model) relative to present on crime based on the annual third-order nonlinear model.

**Table A1:** Summary statistics

| | Mean | sd | Min | Max | N |
|---|---|---|---|---|---|
| Month level: county data | | | | | |
| Crime cases per million people per year | 56.75 | 84.95 | 0.00 | 1705.26 | 166685 |
| Rural rime cases per million people per year | 6.73 | 25.44 | 0.00 | 1200.00 | 166685 |
| Urban crime cases per million people per year | 50.01 | 80.47 | 0.00 | 1655.17 | 166685 |
| Monthly mean temperature | 13.01 | 10.97 | -28.32 | 32.83 | 204336 |
| Monthly total precitation | 3.35 | 3.45 | 0.00 | 31.44 | 204336 |
| Year level: county data | | | | | |
| Growing season degree-days | 2303.65 | 706.44 | 0.00 | 3576.77 | 16088 |
| Growing season harmful degree-days | 0.47 | 1.22 | 0.00 | 19.21 | 16088 |
| Growing season total precipitation | 32.75 | 14.97 | 0.00 | 133.15 | 16088 |
| Net entry of non-agricultural enterprises | 0.00 | 1.00 | -6.58 | 24.65 | 15050 |
| Net entry of agricultural enterprises | 0.00 | 1.00 | -22.01 | 24.06 | 15050 |
| Log primary sector GDP per capita | 8.15 | 0.94 | -4.44 | 11.07 | 12622 |
| Log second and third sector GDP per capita | 10.10 | 0.79 | 7.43 | 12.90 | 12713 |
| Log mean wage | 10.67 | 0.25 | 9.95 | 11.58 | 4950 |
| Log rural mean income | 9.17 | 0.38 | 7.66 | 10.34 | 11414 |
| Log urban mean income | 10.02 | 0.26 | 8.81 | 10.98 | 9799 |
| Year level: individual data | | | | | |
| Urban resident | 0.50 | 0.50 | 0.00 | 1.00 | 40124 |
| Engaged in agriculture | 0.47 | 0.50 | 0.00 | 1.00 | 40742 |
| Nonfarm employment | 0.51 | 0.50 | 0.00 | 1.00 | 32754 |
| Business work | 0.10 | 0.30 | 0.00 | 1.00 | 40742 |
| Log income | 10.62 | 1.17 | 0.00 | 16.25 | 39487 |
| Feeling easily discouraged | 4.17 | 1.03 | -8.00 | 5.00 | 13007 |
| Feeling tense | 4.35 | 0.95 | -8.00 | 5.00 | 13007 |
| Feeling unable to calm down | 4.42 | 0.94 | -8.00 | 5.00 | 13007 |

*Notes:* This table reports summary statistics for the main variables used in the analysis over 2013–2018. The first panel contains county-month variables; crime rates are measured as annualized incidents per million people. The second panel contains county-year variables, including growing-season agro-climatic measures (GDD, HDD, and precipitation) and standardized firm net entry. The third panel contains county-year individual-level variables from the CFPS.

**Table A2:** Effects of annual mean temperature on crime

| | Rural<br>(1) | Urban<br>(2) | Total<br>(3) |
|---|---|---|---|
| $Temperature_{cym}$ | -0.80*** | 2.94*** | 2.14*** |
| | [0.09] | [0.33] | [0.34] |
| Year FE | Yes | Yes | Yes |
| Province FE | Yes | Yes | Yes |
| Observations | 13,791 | 13,791 | 13,791 |
| R-squared | 0.150 | 0.214 | 0.218 |

*Notes:* This table presents the robustness check results of annual mean temperature, estimated based on the year-level version of model (1). The table includes rural crime (columns 1), urban crime (columns 2), and total crime (columns 3) per million population. Standard errors reported in square brackets are clustered at the province × year level. Significance levels are *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.