Adulterated Spice: Lead Poisoning, Conflicts, and Fertility*

Xinming Du† Shan Zhang‡

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Abstract

We estimate the impacts of foodborne lead exposure on human outcomes. Despite the extensive literature on lead from water, traffic, and industrial sources, foodborne lead remains little studied or regulated. We focus on turmeric, a spice from the ginger family, often coated with lead chromate to enhance its color. Our identification strategy exploits Bangladesh's 2018 lead ban that successfully removed lead from turmeric. Comparing villages near the border of India and Bangladesh, conflicts in Bangladesh decreased by 11% per village-month following the 2018 policy for at least three years. Using trade and consumer expenditure data, we find US counties with higher historical exposure of imported turmeric exhibit higher blood lead levels and lower fertility rates. Bangladesh's removal of lead from turmeric corresponds to 1,750 additional births annually across the entire US.

JEL Classifications: Q56, Q18, J13, I18

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†Department of Economics, National University of Singapore. Email: xdu@nus.edu.sg

‡Department of Economics, Old Dominion University. Email: s2zhang@odu.edu

1 Introduction

Food safety remains a major concern worldwide. Every year, one out of ten people falls ill from eating contaminated food, and 420,000 die. Children under 5 years of age are at particularly high risk, with 125,000 children dying from foodborne diseases each year (WHO, 2014). This issue is especially severe in developing countries and disadvantaged regions where food safety is often compromised, raising concerns about injustice. Despite recent progress in reducing pollution from industries and transitioning to cleaner energy sources, food safety challenges have intensified, likely due to inadequate monitoring, non-binding regulations, and limited public awareness. This paper studies the impact of one specific type of food safety concern: foodborne lead contamination.

Lead is harmful to human health, fertility, and cognitive functions, with a larger estimated elasticity compared to other pollutants (Reyes, 2015). Once absorbed, lead is difficult to eliminate from the human body, unlike other non-metal pollutants. Although lead has detrimental effects during early childhood, lead exposure can cause short-term effects on the human body, as confirmed by laboratory experiments and empirical evidence (e.g. Dobrakowski et al., 2017; Simões et al., 2011; Fioresi et al., 2014). This highlights the need for regulatory policies to address lead pollution, which would benefit public health and social stability, the latter being particularly important in developing countries. Additionally, as the human body cannot distinguish lead from calcium, countries with lower nutrient levels may be more vulnerable to the harmful effects of lead pollution.

Our focus is on foodborne lead exposure from turmeric, a popular spice in South Asian cuisine. Turmeric is a key ingredient in curry products, renowned for its distinct flavor, vibrant color, and medicinal properties. However, a hidden danger exists as producers often coat turmeric with lead chromate to make it look brighter yellow. This practice has been common in India and Bangladesh, which together produce 75% of the world's turmeric. The widespread use of lead-contaminated turmeric has significantly contributed to the high rates of lead poisoning observed across South Asia.[1]

This paper studies the impact of lead contamination on conflict and fertility in South

[1]Lead contamination in turmeric has been reported in mainstream media, for example: How to stop turmeric from killing people. (2023, November 2) The Economist. https://www.economist.com/leaders/2023/11/02/how-to-stop-turmeric-from-killing-people

Asia, and fertility in the US. For the former, our variation in lead exposure comes from the 2018 Bangladesh lead ban. In response to the alarming levels of lead contamination, the Bangladeshi government launched a strong campaign against turmeric adulteration at the start of 2018, which intensified in 2019. The government enforced strict laws against adulteration and conducted high-profile raids on wholesalers who ignored these rules. Authorities tested blood samples from workers at turmeric mills to show how lead was affecting people who handled the spice, and they publicized these findings to increase awareness and compliance. Legal actions were taken against those breaking the law, with substantial fines and the confiscation of contaminated products. These actions have been shown to reduce lead-adulterated turmeric, from 47% of market samples with detectable levels of lead to 0% within two years.[2] In contrast, India, as the other country with the highest turmeric consumption and export, has yet to implement policies to combat the issue.

We exploit the Bangladeshi lead ban as our identification strategy and start with a local analysis in South Asia. We use conflict incidents in India and Bangladesh as outcome variables. Focusing on areas within 25km of the border, a difference-in-difference analysis shows that Bangladesh's conflict incidents decreased by 0.1 per village-month relative to India's after the 2018 policy. Using an event study specification, we confirm that areas on both sides of the border shared a common trend of conflict incidents prior to the policy. In the post-period, decreases in conflict incidents become more pronounced after a year, with the magnitude of the difference continuing to increase the year after. Heterogeneity analysis shows that the reduction in conflict incidents is primarily driven by decreases in protests and riots. Using the same difference-in-difference specification, we find that the turmeric lead policy coincides with an increase in the fertility rate in Bangladesh. The magnitude of this increase is 4.55 additional births per 1,000 women, equivalent to 6.56% of the average fertility rate.

Then, we explore how lead contamination from Bangladesh affects other countries via the food trade channel. We focus on the US due to its diverse population profile — which

[2]The impact of turmeric lead contamination on blood lead has been supported by the literature (e.g. Forsyth et al., 2019) and reported in the news: Death by turmeric: Bangladesh strikes a blow against lead poisoning. (2023, November 2). The Economist. https://www.economist.com/asia/2023/11/02/bangladesh-strikes-a-blow-against-lead-poisoning.

naturally leads to the popularity of Indian cuisine, as well as the crucial role of the US in the international turmeric market as a major importer. We use two datasets to construct a turmeric exposure measure at the county-month level: (i) historical curry-related spice consumption,[3] and (ii) trade data on turmeric exports from India and Bangladesh to the US. Using a two-way fixed-effects model, we find that for every one percent increase in turmeric exposure (imported from India/Bangladesh), the fertility rate in the US decreases by 0.027-0.037 per 1,000 women, suggesting a 0.52-0.71% decrease relative to the average US monthly fertility rate. The reduction in fertility rates is more striking in counties with a larger share of the Asian population, low nutrition rates, and severe food security issues. For the latter two, our findings are consistent with the biological mechanism that poor nutrition and food insecurity compromise human health and immunity, making people more vulnerable to lead exposure. Additionally, we verify our turmeric exposure measure using blood lead data in Massachusetts and confirm that counties with high turmeric exposure have 0.0003-0.0005 higher rates of blood lead.[4]

Using the same turmeric lead ban policy as a natural experiment, we study how the removal of lead from turmeric in Bangladesh affects fertility in the US. We find that counties with higher levels of turmeric exposure observe greater increases in fertility rates after 2018. Holding turmeric exposure constant, the US fertility rate increases by 0.0267 per 1,000 women following the policy. Aggregating the policy effect across the entire US, the removal of lead from turmeric in Bangladesh results in 1,750 additional births annually. An event study analysis shows that the policy's impact on US fertility rates grows larger over time. Our findings highlight that contamination regulation in the producer country generates positive spillover effects via food trade and benefits international consumers.

Our paper contributes to three aspects of the existing literature. First is the impact of lead exposure on conflict and fertility. Medical literature supports that lead pollution harms human cognitive and reproductive functions (e.g. Pant et al., 2014; Clifford et al., 2016; Collin et al., 2022), which may lead to both changes in violence and fertility reductions. Empirical evidence also shows that high lead pollution from water (Ferrie et al., 2012;

[3] We also use foot traffic as a proxy for consumption, using historical visits to Indian-Bangladesh cuisine restaurants.

[4] The outcome variable of interest is the rate of high blood lead levels above 5μg/dL per 1,000 tested kids at the county-year level.

Clay et al., 2014; Grossman and Slusky, 2019; Dave and Yang, 2022; Marcus, 2023), traffic (Aizer and Currie, 2019; Grönqvist et al., 2020; Hollingsworth et al., 2020; Hollingsworth and Rudik, 2021; Clay et al., 2021; Du and Taylor, 2024), or industrial sources (Clay et al., 2022; Tanaka et al., 2022) causes more conflicts, worse health outcomes, and lower fertility rates. However, less is known about how lead contamination from food sources affects human outcomes. Food contamination is critical as food is the key energy source, and its quality is naturally tied to the quality of human performance. It is also important, given the international connectivity of the food market, to understand how one region's food contamination can affect other regions. Our paper contributes to the literature by providing the first evidence on the impact of food lead contamination on human outcomes.

The second related literature is the spillover effect of environmental externalities on non-local areas. Existing empirical studies on spillovers have shown how local events can affect remote regions through human migration (Ehrlich and Kim, 2015), alumni networks (Enikolopov et al., 2020), supply chains (Giroud, 2013), and traffic connections (Schlenker and Walker, 2016). Focusing on environmental stressors, local pollution or temperature can generate non-local effects via wind (Anderson, 2020; Deryugina et al., 2019), water flow (Do et al., 2018; Garg et al., 2018), and social media platforms (Almond et al., 2022; Du, 2023). Our work adds another channel — food product trade — through which externalities can propagate and result in non-local changes.

Third, our paper contributes to understanding the global decline in fertility. This trend now also extends to developing countries, where, in recent decades, fertility rates have converged with those of developed countries. While there has been a secular decline that is driven primarily by economic and social changes, in many places there has emerged a gap between desired and attained fertility (Beaujouan and Berghammer, 2019). This paper sheds some light on potential environmental factor that may contribute to this fertility gap by impairing fecundity, one area of research with relatively little quasi-experimental evidence.

From a policy perspective, our evidence connecting food safety and health impacts emphasizes the importance of food quality regulation. Diligent monitoring and inspections are needed for food safety regulations to ensure compliance with existing hazardous chemical limits and safety standards. These regulations should cover not only domestic food products

but also imported foods and ingredients.

In addition, we highlight a potential direction to prevent conflict in developing countries — mitigating environmental contamination especially lead. Reducing conflicts is a primary policy emphasis in these countries. Policies aimed at tackling environmental degradation will have co-benefits in reducing conflict, which is crucial for enhancing social stability and promoting development.

The rest of the paper is organized as follows. Section 2 provides a brief description of the background and related literature, and Section 3 describes the data sources. Section 4 details the empirical strategy and results for lead contamination and outcomes in Bangladesh. Sections 5 and 6 present lead contamination and outcomes in the US, with the latter focusing on the international impact of Bangladesh lead ban. Section 7 concludes.

2 Background

2.1 Turmeric and lead contamination

Turmeric is an important spice in South Asian and Middle Eastern cuisine. It adds bittersweet flavors and bright yellow colors to curry. It is also integral to India's culture, used in religious observances, as a cosmetic, a dye, and in traditional remedies. Apart from India, other major producers of turmeric include Bangladesh, Pakistan, Myanmar, and countries in the Caribbean and Latin America.

Given its importance, turmeric is extensively tested for adulteration and has been identified as a major source of lead (Pb) exposure in South Asia (e.g. Forsyth et al., 2019, 2023). The use of lead chromate can enhance the golden color of turmeric, generating economic profits, especially in regions where turmeric yield is low and natural coloration is poor. This has raised concerns about the safety of the spice. The lead pigment enhances the color of the spice but harms anyone who comes into contact with it or consumes the tainted turmeric.

Lead contamination in turmeric products was first detected in Bangladesh, where turmeric adulteration is part of a larger, more prevalent issue that also affects India and Pakistan.

Nearly thirteen brands of lead-contaminated turmeric have been voluntarily recalled since 2011 (Cowell et al., 2017). The public health literature has documented sources of lead contamination due to lead chromate in pigment (Lee et al., 2016; Forsyth et al., 2024). Studies in Bangladesh have shown that turmeric is a critical source of public lead exposure. A high percentage of children were found with elevated blood lead levels, linked to the consumption of lead-adulterated turmeric (Gleason et al., 2014; Forsyth et al., 2019). Additionally, these studies have highlighted regulatory gaps. Despite widespread exposure to lead contamination via trade in food products, turmeric has not been extensively monitored for adulteration, emphasizing the need for stricter regulatory oversight and better enforcement of food safety standards (Cowell et al., 2017).

2.2 Lead ban in Bangladesh

Much evidence has emerged of turmeric being adulterated with lead in Bangladesh over the past few decades. Scientists from Stanford University and the Bangladeshi nonprofit organization ICDDR,B identified that turmeric polished with lead is the main cause of lead poisoning among women in rural Bangladesh based on their research from 2014 to 2018 (Forsyth et al., 2019). In July 2017, the research team shared their findings with governmental and non-governmental organizations in a workshop, and a series of six meetings with major turmeric businessmen and community leaders were held from March to September 2019 to discuss feasible ways to stop lead chromate adulteration (Forsyth et al., 2024). It was urgent to inform the public about the risk of using lead chromate in turmeric.

In the following months, the Bangladesh Food Safety Authority and the research team took a set of actions to draw people's attention. Two studies presenting lead adulteration in turmeric in Bangladesh were published in September 2019. Additionally, ICDDR,B published an article on its official website later, revealing that lead in turmeric is the main source of the rising blood lead levels for people in the region. International and local mainstream media also successively reported on this news. Following media publicity, the Bangladesh Food Safety Authority released an official public notice on September 25, confirming that the lead adulteration of turmeric violated the Safe Food Law of 2013.

This declaration created a legal deterrent against the adulteration of turmeric with lead. Furthermore, in October, ICDDR,B researchers held meetings with major turmeric producers and processors to emphasize the health and legal risks of using lead chromate pigments (Forsyth et al., 2024).

Over the next few years, researchers reached out to market vendors to conduct sample assessments of lead and chromium concentrations three times: in January 2020, September 2020, and January 2021 (Forsyth et al., 2024). The test results showed a large, gradual decrease in the percentage of turmeric samples testing positive for lead. In our study, we define the year of policy shock as 2018, as it marks the first year that research on lead exposure in turmeric was officially informed and discussed at the government, business and community levels.

In contrast to Bangladesh, which has implemented open and pragmatic measures to tackle the adulteration of turmeric, India, the world's largest producer of turmeric, has not yet taken significant action on the issue. India has been reported to have one of the highest incidences of lead poisoning worldwide, with turmeric adulteration contributing to the problem. The country's spice supply chain is highly complex, involving numerous small-scale producers and intermediaries, making effective regulation and monitoring of contamination particularly challenging. India's lack of comprehensive and transparent national policies to address turmeric adulteration provides a unique opportunity to evaluate the effectiveness of Bangladesh's lead ban as a natural experiment.

2.3 Turmeric and curry trade

India and Bangladesh are major exporters in the international spice trade. India has a rich history of spice cultivation dating back to ancient times. Thanks to their diverse climate and soil conditions, advanced farming techniques, strong international demand, and strict quality control measures, these two countries are top producers worldwide of a wide variety of spices. In 2023, India exported spices worth $692.5 million. Among all spices, turmeric accounts for 10% of India and Bangladesh's spice exports.

Turmeric is a key component of Indian curry powder, the quintessential spice blend that defines numerous Indian dishes. With its distinct earthy and slightly bitter taste, turmeric

not only contributes to the flavor profile of curry powder but also imports a rich yellow color to curries and other dishes.

The US, with its diverse population, has large imports of Indian spices. The global popularity of South Asian dishes further underscores the influence of Indian spices and ingredients. The demand for South Asian spices in the US continues to grow by 35% per year on average over the past five years (Grand View Research, 2023), making the US one of the largest importers of these products.

2.4 US import food safety policy

In the US, only 1-2% of imported food is inspected at the ports of entry (Keener, 2019). According to the US Federal Food, Drug, and Cosmetic Act, importers of food are responsible for ensuring their products are safe, sanitary, and properly labeled according to US standards. This creates an opportunity for food exporters to bypass safety requirements. The Food & Drug Administration (FDA) inspects imported food, gambling on detection at US ports of entry, and may detain shipments of products that are found not to be in compliance with US requirements. However, due to the low inspection rate, some contaminated food may enter the US market and be consumed by customers.

Contamination with lead, together with other hazardous chemicals, remains a safety concern in the US due to the generally low level of food safety regulation. There is no federal requirement for testing lead in foods, and the FDA does not set limits on heavy metals in most foods. Due to budget constraints, the FDA often relies on food manufacturers to conduct their own testing for heavy metal or lead levels. High lead exposure has been frequently identified in products such as cinnamon applesauce, chocolate, candy, and juice, posing public health risks in recent years. In April 2024, the FDA recently began to urge Congress to pass legislation mandating that food manufacturers test for lead in products imported to the US.

Even with regulation and inspection, lead-contaminated food products, like turmeric, can still enter the US due to the complexity of global supply chains. Food ingredients, especially spices, often pass through multiple stages of processing and handling, involving numerous suppliers and manufacturers. This complexity makes it difficult to trace contamination

sources and ensure consistent safety standards. Different countries have varying levels of enforcement and standards for agricultural and manufacturing practices. South Asian and African countries face the greatest food safety concerns and the highest burden of foodborne diseases (WHO, 2014). The diverse profiles of food ingredients lead to inconsistencies, making it challenging to hold accountable the manufacturers who provide the initial ingredients.

2.5 Related literature on lead impacts

The human body responds rapidly to lead exposure. Existing studies show blood lead levels change quickly in response to acute lead intake or environmental exposure (Ara et al., 2015; World Health Organization, 2024). After exposure, lead contamination can affect cognition, health, birth outcomes, and fertility. Historical records in the US from the late 19th to early 20th century show a 39% higher infant mortality rate in areas with leaded water pipes compared to those without (Troesken, 2008). Analyzing data from 172 cities between 1900 and 1920, Clay et al. (2014) find the average water lead content in regions with leaded pipes increased infant mortality by 19% relative to the mean mortality rate. Recent years have seen a notable decrease in fugitive lead emissions from 1980s to 2018 due to policies like the elimination of leaded gasoline and toxic release inventories. This decline has led to a consequential reduction in infant deaths (Clay et al., 2022).

In terms of fertility, the Flint water crisis, which involved lead exposure, reduced the number of births by 7.5 per 1,000 women, constituting 12% of the average fertility rate (Grossman and Slusky, 2019). The elimination of lead from gasoline has been linked to increased fertility in the US: the observed reduction in airborne lead corresponds to a 4-birth increase per 1,000 women, accounting for 6% of the mean fertility rate (Clay et al., 2021). Furthermore, lead exposure affects birth outcomes. The Flint water crisis is associated with a reduction in birth weights by 32-49 grams (Abouk and Adams, 2018; Wang et al., 2021). Additionally, a change in US policy stringency regarding ambient airborne lead pollution, leading to the relocation of lead battery recycling from the US to Mexico, resulted in a 24-gram decrease in birth weight for infants born within two miles of Mexican recycling plants (Tanaka et al., 2022).

Apart from health, lead exposure also affects education and learning performance. Empirical

evidence has shown the detrimental effects of lead on diminished IQ, reduced educational attainment, and labor outcomes (Ferrie et al., 2012; Reyes, 2015; Aizer and Currie, 2019; Grönqvist et al., 2020). Early-life exposure to lead has also been investigated as a potential factor contributing to changes in violent conflict trends and antisocial behaviors (Reyes, 2007, 2015; Aizer and Currie, 2019).

While most studies focus on the long-term effects of lead exposure during early life, lead pollution could also affect contemporaneous outcomes. Medical literature indicates that lead poisoning can affect protein and oxidative functions within a month (Dobrakowski et al., 2017). Similar rapid responses due to short-term lead exposure are observed in endocrine functions (Doumouchtsis et al., 2009), hormone levels (Aminian et al., 2013), blood pressure (Simões et al., 2011; Fioresi et al., 2014), and memory loss (Fenga et al., 2016), which could naturally affect behaviors. Our paper contributes to the literature by focusing on the contemporaneous and short-term effects of lead exposure on conflict and fertility.

Anthropogenic sources serve as the primary contributors to environmental lead. Various sources have been employed as natural experiments. In the context of water, studies have exploited the presence of lead pipes (Ferrie et al., 2012; Clay et al., 2014), examined lead-related drinking water crises in places like Flint and Newark (Grossman and Slusky, 2019; Dave and Yang, 2022), and explored the effects of lead pipeline replacement (Marcus, 2023). Others have focused on lead paint in a school context: studies have identified lead impacts using classroom-level lead variation (Sauve-Syed, 2023) and comparing within-sibling performance (Gazze et al., 2021). Focusing on industrial sources, studies have examined locations in proximity to plants with toxic release inventories (Clay et al., 2022) or near battery recycling sites (Tanaka et al., 2022) to explore lead impacts. Another major source of lead pollution lies in the traffic sector. Some studies have taken advantage of regulatory changes in NASCAR gasoline content (Hollingsworth and Rudik, 2021; Hollingsworth et al., 2020) or proximity to airports (Zahran et al., 2017) as sources of variation. Other papers concentrate on the phase-out of leaded gasoline in developed nations like the US (Aizer and Currie, 2019; Clay et al., 2019, 2021) and Sweden (Grönqvist et al., 2020). In contrast, our paper is the first to explore a foodborne source of lead pollution and how it affects fertility and conflict.

3 Data

3.1 Fertility

Fertility data in Bangladesh comes from the annual report by the country's Sample Vital Registration System. National-level data are extracted from the section "Key Findings of the Sample Vital Registration System", while division-level (equivalent to US state) data is sourced from Chapter 3 for the years 2012 to 2021 and from Chapter 5 for 2010 to 2011.[5]

Fertility data in India is extracted from its annual Sample Registration System Statistical Reports, under Chapter 3. We obtain fertility rates at the state level.[6]

Fertility data for the US is obtained from the National Vital Statistics System (NVSS). We aggregate individual-level birth records at the county-month level from 2014 to 2020. Our outcome of interest is the fertility rate per 1,000 women, defined as the total number of births divided by the female population aged 15-49, multiplied by 1,000. The female population data are obtained from NIH SEER database.

3.2 Conflict

Conflict data for Bangladesh and India are sourced from the Armed Conflict Location & Event Data Project (ACLED). This is a publicly available tracking project that maps geo-referenced conflict event locations and covers a total of 49 countries from 1997 to 2023. This dataset includes details for each conflict event, including date, location, scale, and type of conflict event. Nine different event types are coded in the dataset: violence against civilians; battle-no change of territory; remote violence; riots/protests; strategic development; battle-government regains territory; non-violent transfer of territory; headquarters or base established; and battle-non-state actor overtakes territory.

We focus on conflict events from 2016 to 2020 and end up with 147,417 and 26,261 conflict events in India and Bangladesh, respectively. We aggregate the event-level data into village(the third level of administrative unit)-month counts as outcome variables to

[5]Data for the division of "Mymensingh" is only available from 2018 onwards, and that for the division of "Rangpur" is not available for 2010.

[6]Statistics for the states of "Telangana" and "Uttarakhand" are available from 2014 onwards only.

study changes in conflict in these two countries before and after the ban on lead being added to turmeric.

3.3 Blood lead

Blood lead information is available only in the US and is obtained from the Department of Public Health of Massachusetts, where the state mandates reporting of blood lead testing results (105 CMR 460.070) under its Childhood Lead Poisoning Prevention Program. The department conducts annual testing on a representative sample of children aged from 9-12 months to 47 months. Specimens are analyzed at laboratories operating under Clinical Laboratories Improvement Act standards for blood lead analyses. In cases where children either test above a specified threshold or reside in high-risk communities, an additional follow-up test is conducted at the age of four.

Our analysis focuses on the detection rate of high blood leads, defined as the number or proportion of cases with confirmed blood lead levels exceeding 5μg/dL or 10μg/dL. This threshold is also used by the department to identify high-risk sub-counties. Geolocations are recorded as census tracts.

3.4 Turmeric trade

We use US trade data at the national and state levels sourced from the US Census Bureau's USA Trade Online. Our analysis focuses on US imports of turmeric products from India and Bangladesh from 2014 to 2020. The specific products of interest are the 4-digit commodity code 0910 ("Ginger, Saffron, Turmeric, Thyme, Bay Leaves, etc.") and specifically the 4-digit commodity code 091030 ("Turmeric/Curcuma").

3.5 Consumption of turmeric via curry-related products

To measure the consumption of curry-related products in the US, we use the Nielsen consumer panel. This dataset consists of a representative panel of households that consistently provide information about their purchases in a longitudinal study. Panelists remain part of

the study as long as they continue to meet Nielsen's criteria. Nielsen consumer panelists use in-home scanners to record all purchases made for personal, in-home use from any outlet. Consumers provide details about their households, the products they purchase, and specifics regarding when and where they make these purchases.

The dataset spans 2004-2020 and covers 40,000-60,000 panelists each year. These panelists are representative of the total US population using household projection factors. For each household, we observe demographic details including household income, composition, and racial makeup. Geographic data such as zip code and county are recorded, along with product ownership variables. Additionally, select demographics for the heads of households and other members are included. For each purchase, we obtain data on the date, retailer code, product UPC code which can be linked to the brand and detailed product description, product quantity, and total expenditure.

We identify 290 curry products (UPCs) from 141 brands using keyword searches within product names and descriptions. Among these products, 18 brands are predominantly supplied by Indian or Bangladeshi importers and may be subject to potential turmeric-related lead exposure. Focusing on products from these Indian/Bangladeshi importers, we aggregate trip-level purchase data into county-month levels to measure exposure to Indian/Bangladeshi curry products. Additionally, we aggregate county-month panel data from 2004-2017 into county-level data to create a cross-sectional share measure before the Bangladesh lead ban.

3.6 Exposure to curry via visits to restaurants

Apart from consumer purchases, we use US visits to Indian/Bangladeshi-cuisine restaurants as an alternative method to measure lead exposure from imported curry products. Visit data are obtained from Safegraph, a cell phone-based human mobility measurement that aggregates anonymized location data from various mobile applications to track people's movements to each point of interest (POI). In the raw data, there were 32.1 million visits to 3.9 million POIs recorded daily from 2018 to 2019. For each POI, we observe its location recorded as coordinates, county, zip code, top and subcategory, and parent company. Under the restaurant category, we also capture cuisine types such as Indian, Mexican,

Chinese, etc.

Among these POIs, our focus is on restaurants categorized as the top category. We then filter cuisine through name and subcategory searches, resulting in 10,622 restaurants located in 1,183 counties that serve Indian/Bangladeshi food. We use two measures to assess curry exposure: the count of restaurants at the county level and the number of visits at the county-month level.

4 Turmeric lead ban, conflict, and fertility in Bangladesh

We start by estimating the impact of the Bangladesh turmeric lead ban on local conflict and fertility. We use conflict incidents and fertility rates in the border area between Bangladesh and India as outcome variables. We use 25km as a distance cutoff to ensure comparable characteristics in both countries, and alternative cutoffs as robustness checks. Figure S5 shows the Bangladesh and India border map and locations of conflict incidents. Assuming villages near the Bangladesh-India boundary share similar characteristics other than religion, the only difference between them over time is the turmeric lead removal policy by the Bangladesh government.

4.1 Empirical strategy

We use a difference-in-difference model that compares the number of conflict incidents in the Bangladesh-India border area, before and after the turmeric lead removal in January 2018. The econometric specification is as follows:

$$Y_{it} = \beta \cdot Bangladesh_i \times Post_t + Village_i + \tau_t + \epsilon_{it} \tag{1}$$

where i denotes village (adm3) and t is year-month. Outcome variable Y_{it} is the number of conflict incidents in village i in year-month t. On the right-hand side, $Bangladesh_i$ is an indicator for the treated group, and $Post_t$ indicates this year-month is after January 2018 when Bangladesh started the policy intervention on lead in turmeric. We control for

village fixed effects in the main results, and district (adm2) fixed effects for robustness check, to address village-specific time-invariant characteristics such as religion. We also add year and month fixed effects to address regional changes over time that are the same for both countries. Standard errors are clustered at the village level to control for the within-village across-time serial correlation.

Coefficient of interest is β, which captures the average treatment effect of Bangladesh's policy on Bangladesh's conflict incidents. If the turmeric lead removal policy decreases lead exposure and in turn decreases conflict incidents, we expect δ to be negative. The identifying assumption is that Bangladesh's conflict incidents have similar trends to India's in the absence of treatment. We test this assumption by showing parallel pre-trends before the policy in a dynamic difference-in-differences analysis:

$$Y_{it} = \sum_{k=Jan2016}^{Dec2020} \left(\beta^k \cdot Bangladesh_i \times \mathbf{1}[Time_t = k]\right) + Village_i + \tau_t + \epsilon_{it} \tag{2}$$

where the sample is the same as that in Equation (1). December 2017 is dropped and serves as the baseline period. The policy effect in each period (year-month) t is captured by β^k, the relative change in conflict incidents relative to December 2017. We expect β^k to be small and imprecise in year-months prior to the policy change, and β^k to be negative in year-months following the policy change.

4.2 Results on conflict

Figure S2 shows the raw time series of conflict incident counts within 25km of the border, with data for India in red and for Bangladesh in green. The data coverage is increasing over time for both countries, as indicated by the increases in reported conflict incidents, so we control for time trends in the regression. Before the Bangladesh turmeric lead policy in January 2018, the total incidents within 25km of the border area followed similar trends. After January 2018, conflict incidents in Bangladesh were lower than those in India. The graphical evidence supports our hypothesis that lead removal in Bangladesh should decrease conflict incidents.

Table 1 reports the regression results from estimating Equation (1). Column (1) presents the simplest diff-in-diff specification with $Bangladesh$, $Post$, and their interaction term. Column (2) adds village fixed effects, Column (3) adds year and month fixed effects, Column (4) adds year-month fixed effects, and Column (5) adds a quadratic time trend to control increasing reporting rate in conflict data over time. All the five columns show negative and significant estimates on $Bangladesh \times Post$, implying in Bangladesh boarder area, the conflict incidents decreased significantly after the turmeric lead policy relative to conflict change in India boarder. The magnitude of conflict reduction is 0.075 per village month, equivalent to 11% decrease in the standard deviation of the conflict count.

Since the conflict event count is a discrete variable and right-skewed, Columns (6) and (7) use a Poisson model. We find robust, negative, and precise estimates on $Bangladesh \times Post$. After the lead ban in Bangladesh, the coefficient of $Bangladesh \times Post$ is -1.005, which corresponds to a 9.5% decrease in the standard deviation of the conflict count. These results show that the turmeric lead policy has a significant reduction in conflict incidents in Bangladesh.

Our event study figure is reported in Figure S3. We estimate Equation (2), place the number of conflict incidents at the village-month level on the Y-axis, control for village, year, and month fixed effects, and plot point estimates and confidence intervals for each month. In the pre-period, estimates of conflict changes are not statistically different from zero. This confirms our identifying assumption in Equation (1) that the timing of Bangladesh's turmeric lead policy is plausibly exogenous and the two countries' conflict trends are parallel before the policy. In the post-period, Bangladesh's conflict differences with India are negative and statistically significant relative to differences in December 2017. The magnitude of the effect is about 0.075 events per village-month. The effect begins to emerge right after the policy is implemented, increases gradually over time, and remains stable after a year of the policy. This suggests it may take time for lead from turmeric exposure to transfer through human bodies and affect behavior.

We also test how each of the six types of conflicts is affected. In Table S1, the observed conflict reductions are mainly driven by protests and riots. In contrast, turmeric lead removal has little effect on battles, violence against civilians, explosions, and remote violence. One potential explanation is the severity of conflicts. By intuition, protests are civil expressions

of dissent that may not necessarily turn violent. In contrast, battles usually involve more direct violence and chaos than protests, potentially leading to injuries and property damage. Violence against civilians, explosions and remote violence are even more severe, potentially causing high casualties and widespread destruction. Our findings suggest that food lead contamination has larger effects on less-severe types of violence.

4.3 Robustness

We conducted several robustness checks. First, instead of aggregating the data on conflict incidents at the village-month level, we aggregate incidents at the district-month level (admin2). We add district fixed effects and cluster standard errors at the district level. Re-estimating Equation (1), Table S3 shows similar results to those in Table 1. The turmeric lead policy significantly reduced conflict incidents in Bangladesh by 2.5 per district-month. The event study figure in Figure S4 also shows robust patterns, with no pre-trend, negative changes in conflicts in the post-period, and gradually increased magnitudes after 12 months.

Second, we use alternative distance cutoffs to define the Bangladesh-India border. Results using 10km to 50km are reported in Table S4. Estimates on $Bangladesh \times Post$ remain negative and large, confirming the reduction effects of turmeric lead removal on conflict incidents in Bangladesh. Precision is lower when using 10km as distance cutoff due to smaller sample sizes. The magnitudes become slightly smaller as the distance increases, possibly because locations further from the Bangladesh-India border become less comparable.

Third, we use the conflict rate rather than conflict count as the outcome variable. We calculate the conflict rate by dividing conflict counts by the average population of the village. Population data is obtained from the Gridded Population of the World 2015, organized by the NASA Socioeconomic Data and Applications Center (SEDAC). Table S5 shows strongly robust results. After the removal of lead from turmeric in Bangladesh, the conflict rate decreased by 0.18%, equivalent to a 38% reduction in the standard deviation of the conflict rate at the village-month level.

Fourth, to rule out the potential contamination of the control group — policy spillovers from Bangladesh to India especially near the border area, we classify border villages by

percentiles based on their road intensity.[7] The intuition is that residents near villages with more roads tend to be more mobile and move to other places, which raises more spillover concerns than others. However, this test is not perfect, since villages with more roads also tend to be more developed and may naturally have a different effect on the lead ban than others. In Table S2, we find no statistically significant differences in $Bangladesh \times Post$ when excluding high road intensity villages above the 90th, 75th, and 50th percentiles, confirming that the spillover concern is less likely to be severe in our setting.

4.4 Mechanism

Our findings suggest that the removal of lead from Bangladesh's turmeric products results in a reduction in conflict events. This is consistent with existing empirical evidence and medical papers documenting the effects of lead poisoning on conflict. Lead exposure induces biological changes in nerve conduction, brain development, and hormone production (e.g. Aminian et al., 2013; Dobrakowski et al., 2017; Doumouchtsis et al., 2009; Simões et al., 2011; Fioresi et al., 2014). As reviewed in Section 2.5, these effects not only occur at young ages but also during the same period and immediate responses. These biological changes tend to lead to increased aggressiveness and a propensity to engage in conflict. As a result, lead removal and the associated reduction in exposure could mitigate conflict incidence in Bangladesh.

Apart from biological responses, another potential explanation for the higher incidence of conflict in India after the policy lies in the product supply-side effect. Turmeric in India that still contains lead becomes less competitive after the Bangladesh lead-removal policy. Since the two products are highly substitutable, global consumers may prefer Bangladesh's turmeric over India's after the policy takes effect. This supply-side change is observed in turmeric prices. In Figure S5, the turmeric price in Bangladesh shows an increasing trend over time, while the price in India experiences a significant drop after 2018. A similar pattern could be seen in Figure S6 when examining the US import price of turmeric products from India and Bangladesh. Thus, the growing reputation and

[7] Road intensity data comes from the Global Roads Open Access Data Set (gROADSv1), created by the Center for International Earth Science Information Network (CIESIN) at Columbia University. It records cross-sectional road locations that represent road networks 1980-2010. We calculate the length of road segments in each village polygon to determine road intensity.

profitability of Bangladeshi turmeric could potentially improve economic well-being and reduce conflicts in Bangladesh.

4.5 Results on fertility

Apart from conflict, we also study the effect of the ban on lead in turmeric on fertility outcomes in Bangladesh, because lead is an important environmental factor affecting human reproductive function and fertility. We use the same difference-in-differences specification as in Equation (1). The outcome variable is fertility in India and Bangladesh at the state(the first level of administrative unit)-year levels, defined as the number of new births per 1,000 women. We use state and year fixed effects and cluster standard errors at the state level.

Estimation results are reported in Table 2. Columns (1) and (2) present results with year fixed effects and state fixed effects separately, and Column (3) adds both fixed effects. All three columns show positive and statistically significant estimates on $Bangladesh_i \times Post_{it}$, suggesting the turmeric lead policy coincides with an increase in the fertility rate in Bangladesh. The magnitude of the increase is 4.55 more new birth per 1,000 women, equivalent to 6.56% of the average fertility. Our findings are consistent with existing literature that lead pollution harms fertility rates (Grossman and Slusky, 2019; Clay et al., 2021).

5 Lead exposure and fertility in the US

5.1 Empirical strategy

In this section, we study the effect of turmeric exposure on fertility rates in the US. To measure exposure, we construct the exposure to turmeric across US counties over time by interacting (i) the whole US's turmeric import from India and Bangladesh with (ii) each county's tendency to purchase turmeric products, similar to a shift-share measure. The time-series shift takes place turmeric imports by the US from India and Bangladesh. The cross-sectional share comes from each county's historical consumption of turmeric products.

Focusing on the cross-sectional share variable, we first use Nielsen consumer panel data to calculate the proportion of curry (turmeric)-related purchases in each US county relative to the total product purchases in that county. We calculate this share by both quantity and expenditure. As an alternative measure, we also use Safegraph data to calculate the share of Indian/Bangladeshi-cuisine restaurants in a county relative to the total number of such restaurants in the US, divided by the county population. This share was calculated by both the number of restaurants and the number of visits to these restaurants.[8]

Then we use the entire US' turmeric import from Bangladesh and India in each month to construct the shift variable. We multiply this import with the cross-sectional share at the county level. Our turmeric lead exposure for each county i month t is calculated as:

$$Turmeric_{it} = \frac{\sum_{t=2010}^{2018} Exposure_{i,j=curry}}{\sum_{t=2010}^{2018} \sum_{j}^{j=J} Exposure_{ij}} \times TurmericImport_{US,t} \tag{3}$$

where $\frac{\sum_{t=2010}^{2018} Exposure_{i,j=curry}}{\sum_{t=2010}^{2018} \sum_{j}^{j=J} Exposure_{ij}}$ denotes either Nielsen consumption share, the share of county i's curry purchases relative to all products purchases, measured by quantity or expenditure; or Safegraph foot traffic share, the share of county i's visits to Indian/Bangladeshi-cuisine restaurants divided by the county population, using either the number of restaurants or the number of visits. In other words, we use four share variables to code each county's tendency to consume turmeric products.

The time-series shift term, $TurmericImport_{US,t}$ captures the total monthly imports of turmeric (curry) from India/Bangladesh to the US from 2014 to 2020. To rule out the concern that the exposure variable $Turmeric_{it}$ itself is affected by the Bangladesh lead ban, we use a single difference model and find no change in $Turmeric_{it}$ before and after the policy change, as shown in S6.

Figure S7 shows the distribution of pre-policy turmeric exposure at the county level.

[8]Both share variables, derived from Nielsen and Safegraph data, are calculated as averages across years, providing a cross-sectional data set at the county level.

Due to the small number of Indian/Bangladeshi curry products and Indian/Bangladeshi cuisine restaurants, we have non-missing exposure data for 473 counties using Nielsen and 1,188 counties using Safegraph food traffic data. Covered counties are well-distributed across the country, with more coverage in the East and West coastal areas. Within each state, there are large variations across counties, suggesting we are less likely to capture regional effects but focus on turmeric exposure effects. We focus on non-missing counties as our sample and compare high and low exposure counties. That said, we focus on the intensive margin rather than the extensive margin of lead exposure impacts.

We then estimate the impact of imported turmeric exposure on US fertility using the following equation:

$$Y_{it} = \delta \cdot \log(Turmeric_{i,t-9}) + County_i + \tau_t + \epsilon_{it} \tag{4}$$

where Y_{it} represents the fertility rate in county i in year-month t. On the right-hand side, $\log(Turmeric_{i,t-9})$ represents average turmeric exposure in the conceiving month, namely 9 months prior to the birth month. We add county, year, and month fixed effects, and cluster standard errors at the county level. δ is the coefficient of interest, measuring the average effect of turmeric exposure on fertility. If higher turmeric exposure leads to increased lead exposure and a lower fertility rate, we would expect δ to be negative.

5.2 Lead exposure via imported turmeric and fertility

Table 3 reports the estimation results. In Columns (1) and (2), we use the Nielsen curry purchase data as measures of historical consumption. We use purchase quantity and total curry expenditure to calculate share. In Columns (3) and (4), we use Safegraph data to construct alternative turmeric exposure variables, using the number of restaurants or the number of visits. All columns show negative and statistically significant estimates on $log(Turmeric_{i,t-9})$, indicating that turmeric exposure imported from India/Bangladesh decreases the fertility rate in the US. For every additional percent of turmeric exposure, the fertility rate decreases by 0.027 to 0.037 , equivalent to 0.52% to 0.71% decreases in the

mean fertility rate.

5.3 Lead exposure via imported turmeric and blood lead

To verify human exposure to turmeric lead, we test if blood lead levels in the US are also affected by Bangladesh turmeric exposure. We use blood lead data from Massachusetts and employ the same specification as in Equation (3). The outcome variable is the rate of high blood lead levels (above 5μg/dL) per 1,000 tested kids at the county-year level. On the right-hand side, we control for both $Turmeric_{i,t}$ and $Turmeric_{i,t-1}$, to study the immediate and lagged effects of turmeric exposure on blood lead levels. If imported turmeric contains lead that can be absorbed into the human body, we would expect a positive estimate on δ.

Table S7 displays the regression results. Columns (1) and (2) use the Nielsen consumption data, and Columns (3), (4), (5) use Safegraph number of restaurant numbers, visits, and visitors. All five columns include county and year fixed effects. Positive and significant estimates on $Turmeric_{i,t}$ and $Turmeric_{i,t-1}$ suggest that counties with one additional unit of turmeric exposure have 0.0009 higher rates of high blood lead levels per 1,000 persons. These results validate our turmeric exposure variable and confirm that turmeric lead contamination leads to high blood lead levels.

How much could turmeric exposure explain the high blood lead levels? Using Nielsen data and share measured by purchase quantity, the average turmeric exposure value is 17,020 among counties in Massachusetts. From our point estimates, current exposure results in an increase of 15.3 per thousand in the high blood lead rate per county-year. On average, there are 1062 children tested per county each year from 2012-2020. Scaling up linearly, a total of 16.2 high blood lead incidences per county-year, or 227 incidences per state-year, could be avoided by eliminating turmeric exposure from current levels to zero.

5.4 Heterogeneity and placebo tests

We expect that the fertility rate response to turmeric exposure may vary across socioeconomic characteristics. Different effect elasticities have been found across income and nutrition levels with the same level of ambient lead (Clay et al., 2023). Therefore, we test for additional heterogeneity across racial composition, food insecurity levels, and nutrition levels. Results of subsample analyses are presented in Figure S8. Fertility rates in counties with a higher Asian population respond more negatively to turmeric exposure. In contrast, counties with a higher White population are more resilient to turmeric exposure. We find no significant effect of turmeric exposure in areas with a larger Black population. These results align with the fact that Asian people, especially South Asians, are more likely to be exposed to food or products containing turmeric as part of their regular diet. Therefore, with the same county-level of turmeric exposure, counties with a larger Asian population are more likely to consume more turmeric products and are likely to see bigger reductions in fertility.

In terms of nutrition, we find counties with higher levels of food insecurity and very low nutrition show more striking reductions in fertility rates. This may be due to the low nutrition levels causing lower health resilience, making individuals more vulnerable to the effects of lead in turmeric.

We conduct a placebo check by testing how exposure to non-turmeric spices affects fertility rates. Non-turmeric exposure is constructed using a similar shift-share intuition based on the Nielsen purchase data. We identified 3,581 products that are categorized as spices but are not related to turmeric or curry. We use the same specification as Equation (3) and replace the treatment variable with $log(NonTurmeric_{i,t-9})$. Table S10 indicates that exposure to non-turmeric spices has no significant effect on fertility rates.

5.5 Two-stage least square

One potential concern is the validity of our turmeric exposure. We use historical data to calculate the intent-to-purchase curry products imported from India and Bangladesh. It is unclear whether this intent-to-purchase could reflect the actual purchase of curry products. To verify our turmeric exposure measure, we use trade data at the state-month

level, focusing on turmeric import quantity and import value from India and Bangladesh as the first-stage outcome variables. Here we assume states with high turmeric imports also purchase more turmeric. This assumption is likely to be true given the large number of turmeric importers in the US, making the market competitive. Consequently, a cost-minimizing firm tends to cater more to local consumers.

The first stage results by regressing import on turmeric exposure measure are displayed in Table S8. In Column (1), we use turmeric import value as the dependent variable and consumer expenditure in the Nielsen data to construct the exposure measure. Positive and significant estimate on $Exposure\ expenditure$ suggests our turmeric exposure measure significantly increases turmeric import. In Column (2)-(4), we use turmeric import quantity or purchase quantity as alternative variables to code the exposure measure and import. The first stage coefficients remain positive and precise, confirming our constructed measure could capture changes in turmeric imports from India and Bangladesh.

We then test if turmeric import affects fertility using the constructed exposure measure as an instrument variable. The two-stage least square results are reported in Table S9. In Column (1), we use turmeric import value as the endogenous regressor, turmeric exposure using consumption expenditure as the instrument, and fertility as the outcome. Estimate on $Import\ value$ is negative and significant, suggesting high turmeric import from India/Bangladesh leads to lower fertility rate. Results remain stable if we replace the instrument variable with purchase quantity from Nielsen, and replace regressor with turmeric import quantity, as shown in Column (2)-(4).

F-statistics in Table S9 are around 8 in Column (1) and (2), and over 30 in Column (3) and (4). This indicates our turmeric exposure measuring the intent-to-purchase a high quantity turmeric is a strong instrument of the actual turmeric import. The instrument is weaker if we use intensity to purchase a high dollar value of turmeric. The potential bias lies in turmeric price. Compared with expenditure value, using purchase quantity to construct turmeric purchase intent has a higher predicting power to explain actual turmeric import. Therefore, we conclude that our turmeric exposure variable is valid and our reduced form estimates in Section 5 and 6 capture how imported turmeric after the Bangladeshi ban affects fertility in the US.

6 Turmeric lead ban and fertility in the US

6.1 Empirical strategy

With the same level of turmeric exposure, the reduction in the fertility rate in the US should be smaller after the 2018 policy change, as turmeric is less lead-contaminated following the Bangladesh ban. To test this hypothesis, we use a continuous difference-in-difference specification that compares fertility rates before and after the policy, in counties with different levels of turmeric exposure. The regression specification is as follows:

$$Y_{it} = \gamma \cdot log(Turmeric_i) \times Post_t + County_i + \tau_t + \epsilon_{it} \tag{5}$$

where the sample is at the county-month level. Outcome variable Y_{it} is the fertility rate per 1,000 women in county i in year-month t. $log(Turmeric_i)$ is a continuous treatment variable at the county level. The cross-sectional value is generated using the **pre-policy** average turmeric exposure $log(Turmeric_{it})$ from 2014 to 2018. This approach ensures that the turmeric exposure treatment itself should not be affected by the policy. $Post_t$ is a dummy for the year-month after January 2018 when Bangladesh initiated the policy intervention on turmeric lead, and is the same for all counties. We add county, year, and month fixed effects, and cluster standard errors at the county level.

γ is the coefficient of interest, capturing how Bangladesh's lead removal affects US fertility, hypothesized to be positive. The identifying assumption lies in the exogenous timing of the Bangladesh lead ban, which is validated by the pre-trend test in Section 4.2. Additionally, even if the policy implementation decision in Bangladesh is correlated with other local factors, it is less likely to be correlated with US factors.

6.2 Results

Table 4 reports the estimation results. We use the Nielsen data to construct turmeric exposure in Columns (1) and (2) based on curry consumption quantity, and in Columns

(3) and (4) based on curry consumption expenditure. Estimates on $log(Turmeric_i) \times Post_t$ are positive and precise, suggesting that higher levels of turmeric exposure result in a greater increase in fertility rates post-policy than pre-policy. This could be interpreted as the policy potentially mitigating the negative effects of lead in turmeric, as we found in Section 5, leading to higher fertility rates in areas with higher turmeric exposure once the lead content is reduced. In terms of magnitude, for each 1% increase in turmeric exposure, the fertility rate increases by an additional 0.018-0.032 per 1,000 women after the policy compared to before the policy.

We also present an event study figure to show the dynamics of impacts and to test the pre-trends. Here, we estimate a modified version of Equation (5) and interact $Turmeric_i$ with indicators for each time period (Quarter). The interaction term for Q4 2017 is omitted as the reference period. We plot point estimates of the interaction terms and their 95% confidence intervals in Figure 1.

Before Q1 2018, we do not observe any pre-trends, suggesting turmeric's impacts on fertility rates are similar in Q4 2017 and previous quarters. In other words, high turmeric exposure decreases fertility in the US, and the magnitude is similar over time before 2018.

After the policy, estimated coefficients are positive and statistically different from zero. This indicates that turmeric's impact on fertility rates is positive after Q1 2018 compared to previous periods. In other words, high turmeric exposure no longer decreases US fertility rates as much after 2018, which confirms that the lead removal policy by the Bangladeshi government has positive spillovers on the US fertility rate. The magnitude of effects becomes slightly larger over time, likely due to the lagged effects of international food trade and the local food market.

How large is the effect size? Using our point estimate and the exposure measure in each county, aggregating the policy effect across the entire US shows that the removal of lead from turmeric in Bangladesh results in 1,750 additional births annually. This overall effect could be significantly larger, considering that the turmeric lead ban applies only to turmeric from Bangladesh, which accounts for less than 1% of total U.S. turmeric imports. Although imported turmeric constitutes only a small part of the diet, our estimate suggests that a significant fertility decline could be avoided if foodborne lead is regulated. Furthermore, more fertility benefits could be realized if domestic food products and other

imported foods and ingredients are regulated. Besides, our estimated number is smaller than the induced birth increase from the US leaded gasoline ban, which is estimated at 95,000 annually for the entire country (Clay et al., 2021).

7 Discussion and conclusion

This paper uncovers an important yet underexplored externality due to foodborne lead contamination. Using the removal of lead in turmeric as a natural experiment, we observe an increase in fertility and a reduction in conflict incidents in Bangladesh. Our findings corroborate existing biological mechanisms and empirical studies on the impacts of lead pollution. The results suggest that removing lead from turmeric could reduce conflict incidents by 0.08, equivalent to an 11% decrease per village-year-month. Political parties and local governments seeking to enhance social stability will find these insights valuable for conflict prevention, especially in developing countries.

Beyond local effects, we document the transboundary externality of lead contamination through food trade to other countries. Results from the US indicate that counties with a 1% increase in consumption of Indian/Bangladeshi curry products experience a decrease in the fertility rate of 0.027 to 0.03 per 1,000 women, suggesting a 0.52% to 0.71% decrease based on the baseline fertility rate of 5.204 per 1,000 women. Furthermore, counties with higher percentages of food insecurity and very low nutrition levels exhibit greater negative effects on fertility. This may be attributed to the low nutrition levels compromising health immunity, thereby making individuals more susceptible to the effects of lead in turmeric. A key policy implication involves destination regulation and consumer scrutiny as potential strategies to compel polluters to ensure food safety. This is crucial given the enhanced monitoring and environmental awareness in developed countries.

The impact of removing lead from food on conflict and fertility proves to be large and significant. This could pave the way for another policy direction in lead regulation, following the global elimination of leaded gasoline and the increasingly stringent regulation of industrial emissions. Our paper highlights the need for future policies addressing lead regulation in food sources.

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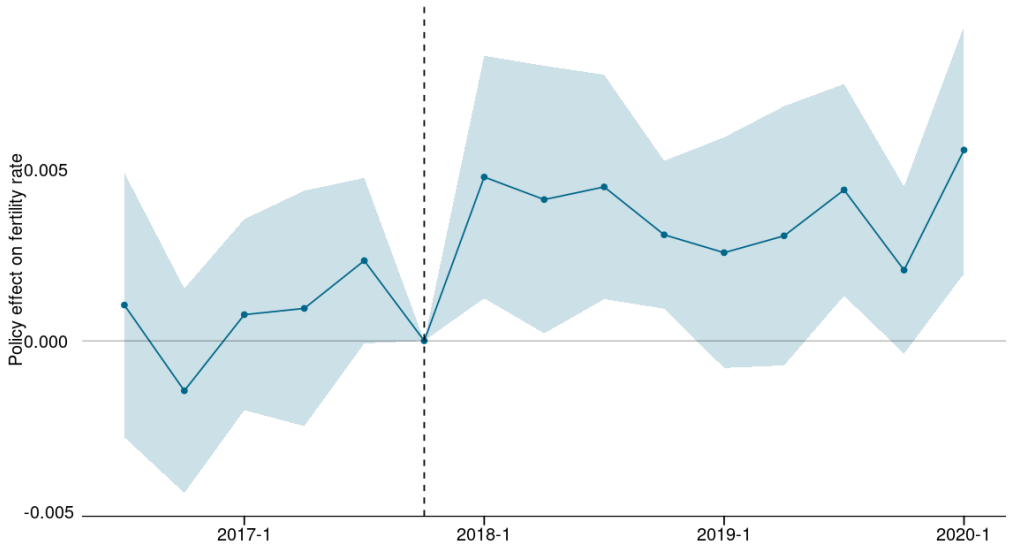
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Figures and tables

Figure 1: Impact of Bangladesh turmeric lead policy on US fertility rate



Note: Fertility rate data are from US NVSS (Natality) and NIH (Population). The model sample is at the county-quarter level from Q3 2016 to Q4 2020. Q4 of 2017 is omitted as the reference period. County, year, and quarter fixed effects are included, with standard errors clustered at the county level. The figure displays the point estimates and 95% confidence intervals (in blue shades) for the policy effect in each quarter.

Table 1: Lead ban and conflict in Bangladesh

	Conflict Incidents						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) Poisson	(7) Poisson
Bangladesh	0.024***						
	(0.009)						
Post	0.123***	0.122***					
	(0.007)	(0.028)					
Bangladesh × Post	-0.075***	-0.075***	-0.075***	-0.075***	-0.075***	-1.005***	-1.005***
	(0.012)	(0.029)	(0.029)	(0.029)	(0.029)	(0.199)	(0.199)
Fixed-effects							
Village		Yes	Yes	Yes	Yes	Yes	Yes
Year			Yes		Yes		Yes
Month			Yes		Yes		Yes
Year-month				Yes		Yes	
Time-trend					Yes		Yes
Outcome.mean	0.095	0.095	0.095	0.095	0.095	0.095	0.095
Outcome.sd	0.654	0.654	0.654	0.654	0.654	0.654	0.654
No. observations	54,360	54,360	54,360	54,360	54,360	54,360	54,360
R^2	0.006	0.434	0.435	0.438	0.436	0.404	0.394

Note: This table reports the regression results for Equation (1). The sample in all columns is at the village-month level from January 2016 to December 2020. Crime data is from ACLED. Column (1) presents the basic diff-in-diff specification; Column (2) adds village fixed effects; Column (3) adds year and month fixed effects; Column (4) adds year-month fixed effects; and Column (5) includes a quadratic time trend to control for the increasing reporting rate in crime data over time. $Post$ is absorbed by year fixed effects, as the treatment month is January 2018 and year 2018-2020 are coded as $Post = 1$ and year 2016-2017 are coded as $Post = 0$. Since crime counts are discrete and right-skewed, Columns (6) and (7) use a Poisson model instead of OLS. Standard errors are clustered at the village level in all models. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Lead ban and fertility in Bangladesh

	Fertility Rate Per 1000 Women		
	(1)	(2)	(3)
Bangladesh	-2.346***		
	(0.763)		
Post		-7.763***	
		(0.465)	
Bangladesh × Post	5.083***	5.083***	5.082***
	(1.001)	(1.563)	(1.585)
Fixed-effects			
State		Yes	Yes
Year	Yes		Yes
Outcome.mean	69.312	69.312	69.312
No. observations	300	300	300
R^2	0.023	0.947	0.962

Note: This table reports the estimates from the difference-in-differences specification in Equation (1), with the outcome variable being fertility rates in India and Bangladesh, defined as the number of new births per 1,000 women. Fertility data are from the Sample Vital Registration System. The sample in all columns is at the state-year level from 2011 to 2020. State and year fixed effects are used, with standard errors clustered at the state level. Columns (1) and (2) present results with year and state fixed effects separately, while Column (3) includes both. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Turmeric lead exposure and fertility in the US

	Fertility Rate			
	(1)	(2)	(3)	(4)
	Share by quantity	Share by expenditure	Share by # of restaurants	Share by # of visits
Nielsen				
Turmeric	-0.026**	-0.025**		
	(0.015)	(0.015)		
Safegraph				
Turmeric			-0.044***	-0.040***
			(0.016)	(0.016)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Outcome.mean	5.076	5.076	5.204	5.303
X.mean	9.121	9.184	6.108	5.298
No. observations	39,732	39,648	99,204	94,164
R^2	0.617	0.617	0.277	0.277

Note: This table estimates the effect of turmeric exposure on fertility rates in the US, defined as the monthly fertility rate per 1,000 women. Sample observations are at the county-month level from January 2014 to December 2020. Columns (1) and (2) use Nielsen data to construct shift-share measures based on the quantity of curry purchases, while Columns (3) and (4) use Safegraph data to construct shift-share measures based on number of Indian restaurants and number of restaurant visits. All models include county, year, and month fixed effects, with standard errors clustered at the county level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Lead ban and fertility rate in the US

	Fertility Rate Per 1,000 Women			
	(1)	(2)	(3)	(4)
	Share by quantity	Share by quantity	Share by expenditure	Share by expenditure
Post	-0.471***	-0.299***	-0.597***	-0.426***
	(0.102)	(0.114)	(0.089)	(0.102)
Turmeric × Post	0.019*	0.018*	0.033***	0.032***
	(0.011)	(0.011)	(0.010)	(0.010)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year		Yes		Yes
Month		Yes		Yes
Outcome.mean	5.0762	5.0762	5.0762	5.0762
No. observations	39,732	39,732	39,648	39,648
R^2	0.566	0.617	0.567	0.618

Note: This table reports the estimation of the impact of Bangladesh's lead policy on US fertility rates. Sample observations are at the county-month level from January 2014 to December 2020. Columns (1) and (2) use Nielsen shift-share measures based on quantity share, while Columns (3) and (4) use Nielsen shift-share measures based on expenditure. County, year, and month fixed effects are included, with standard errors clustered at the county level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendix

A Additional tables

Lead ban, conflicts, and fertility in Bangladesh

Table S1: Heterogeneity across crime types

	Crime Incidents					
	(1)	(2)	(3)	(4)	(5)	(6)
	Battles	Explosions Remote Violence	Protests	Riots	Strategic Developments	Violence Against Civilians
Bangladesh × Post	-0.0031***	-0.0014***	-0.0431**	-0.0308***	-0.0018***	0.0047**
	(0.0015)	(0.0004)	(0.0247)	(0.0051)	(0.0005)	(0.0026)
Fixed-effects						
Village	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Outcome.mean	0.0033	0.0006	0.0486	0.0295	0.0009	0.01175
No. observations	54,360	54,360	54,360	54,360	54,360	54,360
R^2	0.0206	0.0012	0.4462	0.1314	0.0045	0.0462

Note: Crime data by sub-type are from ACLED. The sample in all columns is at the village-month level from January 2016 to December 2020. Village, year, and month fixed effects are included, with standard errors clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S2: Lead ban and crime in Bangladesh

	Crime Incidents					
	(1) Length 90 percentile	(2) Length 75 percentile	(3) Length 50 percentile	(4) Count 90 percentile	(5) Count 75 percentile	(6) Count 50 percentile
Bangladesh × Post	-0.057*** (0.018)	-0.052*** (0.017)	-0.038*** (0.010)	-0.049*** (0.018)	-0.035*** (0.008)	-0.033*** (0.009)
Fixed-effects						
Village	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Outcome.mean	0.081	0.068	0.056	0.082	0.061	0.054
Outcome.sd	0.519	0.496	0.305	0.525	0.309	0.282
No. observations	48,900	40,740	27,120	48,960	40,920	30,720
R^2	0.422	0.449	0.171	0.432	0.160	0.127

Note: This table reports the robustness check regression results for Equation (1). The sample in all columns is at the village-month level from January 2016 to December 2020. Columns (1) to (3) present samples excluding villages that are above the 90th, 75th, and 50th percentiles with regard to road length, respectively. Columns (4) to (6) present samples excluding villages that are above the 90th, 75th, and 50th percentiles with regard to road counts, respectively. All columns include village, year, and month fixed effects. Standard errors are clustered at the village level in all models. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S3: Crime results at the district level

	Crime Incidents		
	(1)	(2)	(3)
Bangladesh	0.488***		
	(0.085)		
Post	2.143***	1.72***	
	(0.072)	(0.492)	
Bangladesh × Post	-1.718***	-1.299***	-1.298***
	(0.131)	(0.499)	(0.499)
Fixed-effects			
District		Yes	Yes
Year			Yes
Month			Yes
Outcome.mean	1.085	1.085	1.085
No. observations	4,740	4,740	4,740
R^2	0.060	0.431	0.438

Note: Crime data by district (admin2) are from ACLED. The sample in all columns is at the district-month level from January 2016 to December 2020. District, year, and month fixed effects are included, with standard errors clustered at the district level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S4: Lead ban and crime by distance cutoffs

	Crime Incidents				
	(1)	(2)	(3)	(4)	(5)
	10km	20km	30km	40km	50km
Bangladesh × Post	-0.057**	-0.078***	-0.074***	-0.061***	-0.059***
	(0.029)	(0.034)	(0.026)	(0.022)	(0.020)
Fixed-effects					
Village	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Outcome.mean	0.095	0.097	0.094	0.088	0.091
No. observations	32,100	48,420	61,860	74,640	85,620
R^2	0.459	0.441	0.430	0.415	0.415

Note: Alternative distance cutoffs around the Bangladesh-India border are used for a robustness check. Columns (1) to (5) use border distances ranging from 10km to 50km. The sample in all columns is at the village-month level from January 2016 to December 2020. Village, year, and month fixed effects are included, with standard errors clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S5: Crime rate results at the village level

	Crime Rate (percentage)		
	(1)	(2)	(3)
Post	0.023***		
	(0.004)		
Bangladesh × Post	-0.014***	-0.014***	-0.014***
	(0.005)	(0.005)	(0.005)
Fixed-effects			
Village	Yes	Yes	Yes
Year		Yes	
Month		Yes	
Year-month			Yes
Outcome.mean	0.017	0.017	0.017
No. observations	54,360	54,360	54,360
R^2	0.204	0.205	0.207

Note: The crime rate is defined as the ratio of crime counts to the average population of the village. Crime count data are from ACLED, and population data are obtained from the Gridded Population of the World 2015, organized by the NASA Socioeconomic Data and Applications Center (SEDAC). The sample is at the village-month level from January 2016 to December 2020 for all columns. Village, year, and month fixed effects are included, with standard errors clustered at the village level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S6: Single difference model of shift-share variable

	Turmeric$_{it}$			
	(1)	(2)	(3)	(4)
	Share by quantity	Share by expenditure	Share by # of restaurants	Share by # of visits
Post	0.0512	0.0512	-0.0080	-0.0080
	(0.0729)	(0.0729)	(0.0878)	(0.0878)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
Outcome.mean	8.9671	9.0305	6.0760	5.2664
No. observations	40,592	40,592	101,652	96,492
R^2	0.9664	0.9714	0.9727	0.9890

Note: Sample observations are at the county-month level from January 2014 to December 2020. Columns (1) and (2) use Nielsen data to construct shift-share measures based on the quantity of curry purchases, while Columns (3) and (4) use Safegraph data to construct shift-share measures based on the number of Indian restaurants and the number of restaurant visits. All models include county, year, and month fixed effects, as well as a linear time trend. All standard errors are clustered at the year level to account for potential correlations within the same year due to policy changes. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S7: Turmeric exposure and high blood lead level in Massachusetts

	Rate of High Blood Lead				
	(1)	(2)	(3)	(4)	(5)
	Share by quantity	Share by expenditure	Share by # of restaurants	Share by # of visits	Share by # of visitors
Nielsen					
Turmeric$_{i,t}$	0.000944**	0.000774			
	(0.000439)	(0.000426)			
Turmeric$_{i,t-1}$	0.000922	0.000726			
	(0.000687)	(0.000653)			
Safegraph					
Turmeric$_{i,t}$			0.001430	0.001027*	0.000797*
			(0.000607)	(0.000607)	(0.000470)
Turmeric$_{i,t-1}$			0.001796	0.001308*	0.001004**
			(0.000737)	(0.000556)	(0.000556)
Fixed-effects					
County	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Outcome.mean	19.7716	19.7716	20.8624	20.8624	20.8624
No. observations	50	50	130	120	120
R^2	0.8342	0.8266	0.6682	0.5249	0.5248

Note: Rate of high blood lead is reported as the high blood lead level detection rate per 1,000 tested children. Blood lead data is from the Department of Public Health of Massachusetts Childhood Lead Poisoning Prevention Program. The sample is at the county-year level from 2012 to 2021. County, and year fixed effects are included, with standard errors clustered at the county level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S8: First stage

	Import value	Import weight	Import value	Import weight
	(1)	(2)	(3)	(4)
Exposure expenditure	0.0153***	0.0049***		
	(0.0054)	(0.0017)		
Exposure quantity			0.0747***	0.0202***
			(0.0127)	(0.0025)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Outcome.mean	57924.980	20884.475	57924.980	20884.475
No. observations	37114	37114	37114	37114
R^2	0.737	0.760	0.740	0.762

Note: Sample observations are at the county-month level from January 2014 to December 2020. Columns (1) and (2) use Nielsen data to construct shift-share measures based on the expenditure of curry purchases, while Columns (3) and (4) are based on the quantity of purchases. All models include county, year, and month fixed effects. All standard errors are clustered at the county level. Outcome variables are turmeric import value or weight, using data from USA Trade Online. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table S9: Two-stage least square

	Fertility			
	(1)	(2)	(3)	(4)
Import value	-0.0060*		-0.0022***	
	(0.0033)		(0.0008)	
Import weight		-0.0186*		-0.0083***
		(0.0098)		(0.0026)
Fixed-effects				
County	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Outcome.mean	5074.338	5074.338	5074.338	5074.338
No. observations	37114	37114	37114	37114
R^2	-0.425	-0.370	-0.061	-0.074
F-stat	8.105	8.485	34.312	63.009
Instrument	Exposure expenditure	expenditure	quantity	quantity

Note: Sample observations are at the county-month level from January 2014 to December 2020. Columns (1) and (2) use Nielsen data to construct shift-share measures based on the expenditure of curry purchases, while Columns (3) and (4) are based on the quantity of purchases. All models include county, year, and month fixed effects. All standard errors are clustered at the county level. Outcome variable, $Fertility$ is calculated as fertility rate (number of births per woman) $\times$ 1,000,000. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

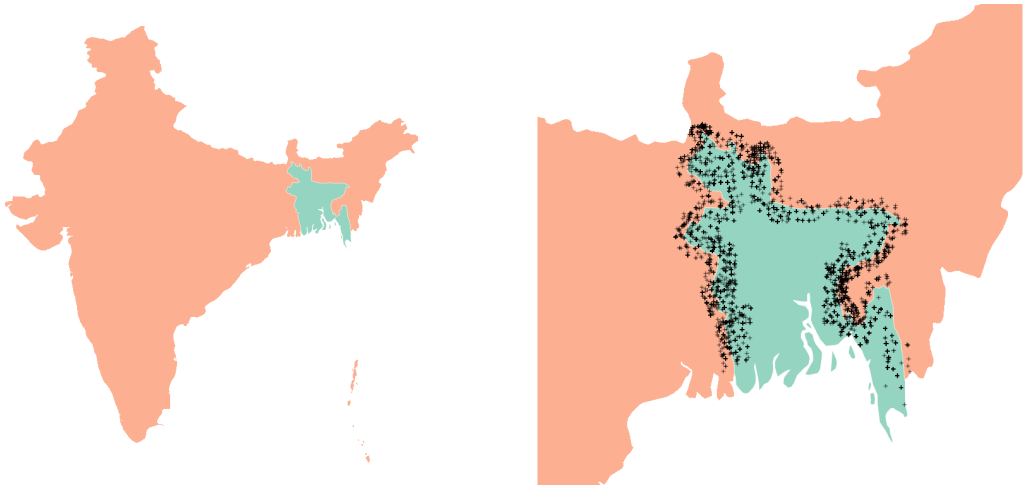
Table S10: Placebo test: non-turmeric exposure and fertility in the US

	Fertility Rate	
	(1)	(2)
	Share by quantity	Share by expenditure
Non-turmeric exposure	-0.0127	-0.0127
	(0.0142)	(0.014)
Fixed-effects		
County	Yes	Yes
Year	Yes	Yes
Month	Yes	Yes
Outcome.mean	5.4821	5.4821
No. observations	247,550	247,550
R^2	0.3216	0.3216

Note: Non-turmeric exposure is constructed using a similar shift-share method based on the Nielsen purchase data. Fertility rate is reported as the monthly fertility rate per 1,000 women. The sample is at the county-month level from January 2014 to December 2020 for both columns. County, year, and month fixed effects are included, with standard errors clustered at the county level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

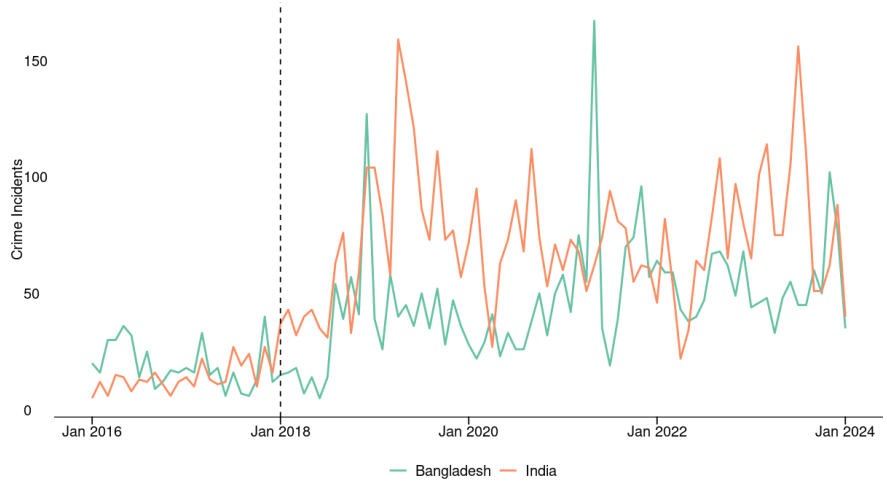
B Additional figures

Figure S1: India and Bangladesh map: border conflict incident villages



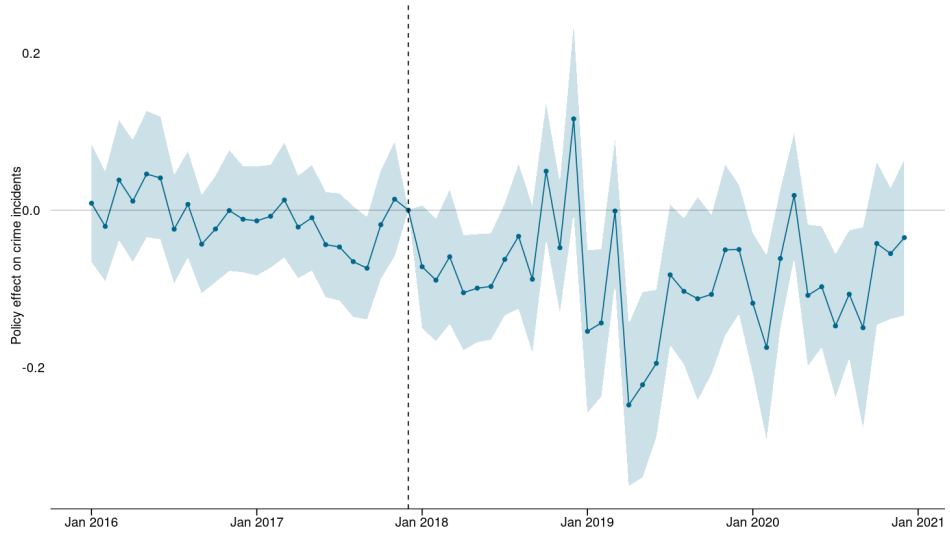
Note: The orange map represents the Indian territory, and the green map represents the Bangladeshi territory. The black cross marks indicate the unique geo-coordinates where conflicts occurred within a 25 km buffer of the India-Bangladesh border from January 2016 to December 2020. The geolocation data of conflict incidents is from ACLED.

Figure S2: Conflict incident trends: 25km across Bangladesh and India border



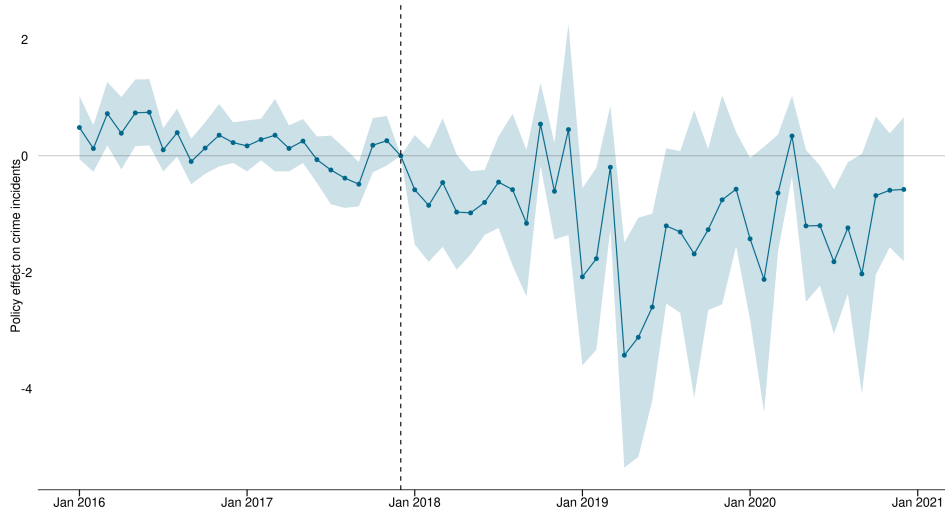
Note: The two trends represent the total monthly conflict incidents within 25km of the India-Bangladesh border from January 2016 to December 2020, with green representing Bangladesh and orange representing India. The conflict incident data is sourced from ACLED.

Figure S3: Impact of Bangladesh turmeric lead policy on conflict incidents



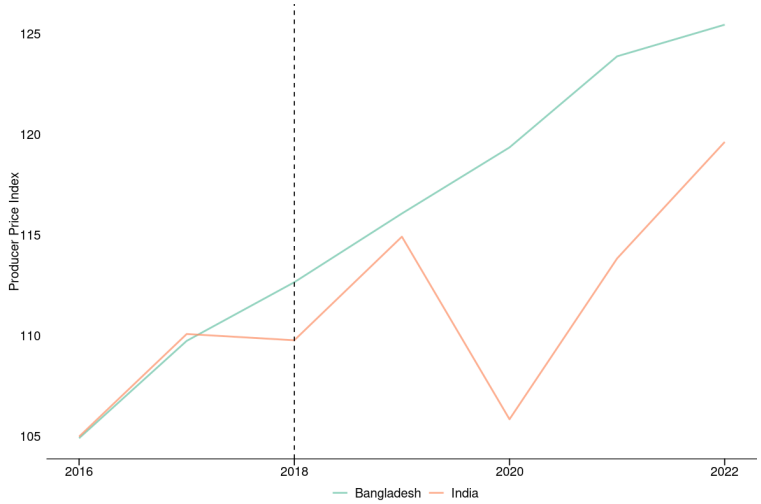
Note: Conflict incident data are from ACLED. The model sample is at the village-month level from January 2016 to December 2020. This figure shows the event study estimation of the impact of the lead policy on conflict incidents in Bangladesh. December of 2017 is omitted as the reference period. Village, year, and month fixed effects are included, with standard errors clustered at the village level. The figure displays both point estimates and 95% confidence intervals (in blue shades) for the policy effect in each month.

Figure S4: Conflict results at the district level



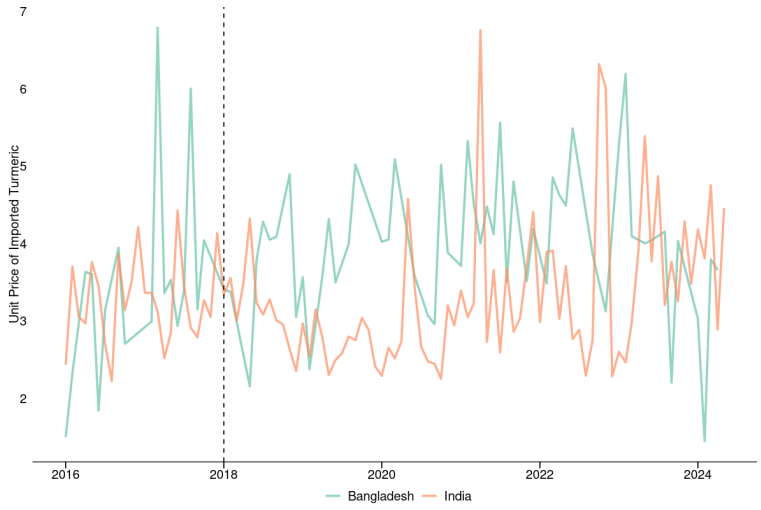
Note: Conflict incidents by district are from ACLED data. The model sample is at the district-month level from January 2016 to December 2020. The model includes district, year, and month fixed effects, with standard errors clustered at the district level. The figure displays point estimates and 95% confidence intervals (in blue shades) for the policy effect in each month.

Figure S5: Producer price index: other stimulant, spice and aromatic crops



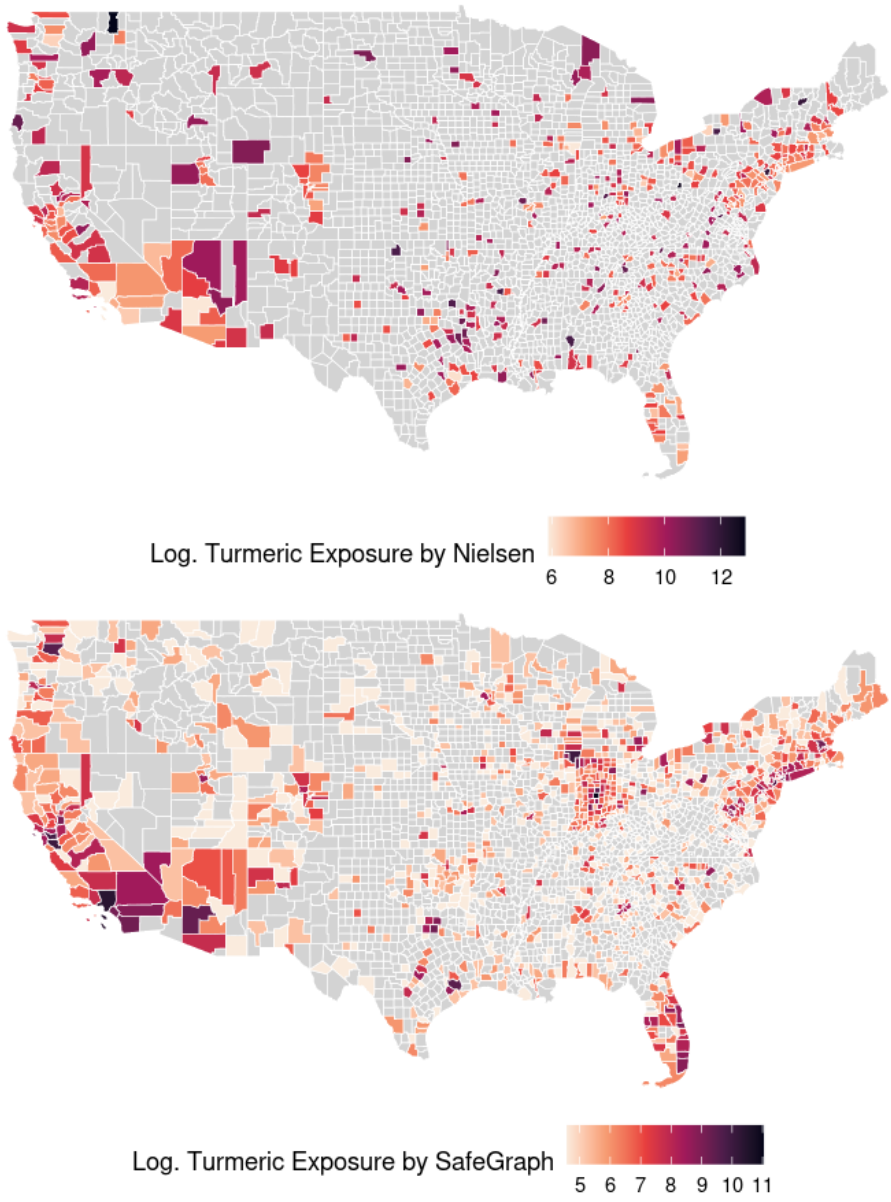
Note: The annual Producer Price Index (PPI) data for spices in India and Bangladesh are from the United Nations Food and Agriculture Organization (FAO) for the years 2014 to 2022. The green line represents Bangladesh's PPI for stimulant, spice, and aromatic crops, while the orange line represents India's PPI for the same category.

Figure S6: Unit price of US imported turmeric (USD/kg)



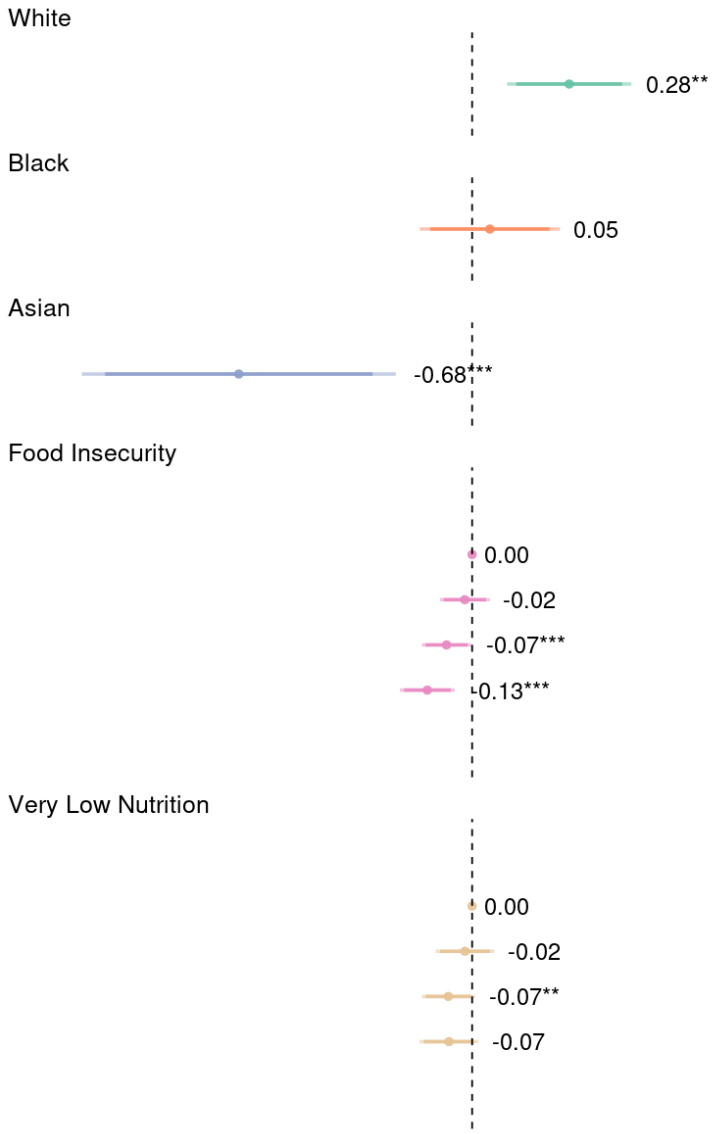
Note: The US imported turmeric data are from USA Trade Online for the period from January 2016 to April 2024. Unit price is calculated by trade value (USD) divided by weight (KG). The green line represents the unit price of turmeric imported from Bangladesh, and the orange line represents the unit price of turmeric imported from India.

Figure S7: Turmeric exposure across US counties



Note: There are 473 counties with turmeric exposure based on Nielsen curry purchases, and 1,188 counties with turmeric exposure based on Safegraph Indian/Bangladeshi cuisine restaurants. The cross-sectional exposure measurement is calculated by taking the average of turmeric exposure before 2018.

Figure S8: Heterogeneity: turmeric and fertility in the US



Note: All variables are measured as percentages and are cross-sectional at the county level, sourced from 2010 data. Racial composition is from the US Census American Community Survey (ACS) data. Food security and nutrition data are from the Current Population Survey (CPS) data. For food security and very low nutrition, percentages are divided into four groups as categorical variables. The first estimate (with standard deviation) is for variables under the 25th percentile and is omitted. The remaining estimates are for the 25-50th percentile, 50-75th percentile, and 75-100th percentile, in that order from top to bottom. The plot displays the point estimates of heterogeneous effects and their 90% and 95% confidence intervals.