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When Growth Stumbles, Pollute? Trade War, Environmental Enforcement, and Pollution

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When Growth Stumbles, Pollute?
Trade War, Environmental Enforcement, and Pollution[*†]

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Abstract

This paper studies how perceived risks of economic downturns affect pollution from the perspective of political incentives and environmental enforcement. In the context of the U.S.-China trade war, we find a 1% increase in the U.S. tariff leads to 0.9% and 0.7% increases in SO_2 and $PM_{2.5}$ in Chinese cities. Hourly data suggests the pollution increases are concentrated at night. The surprising findings can be largely attributed to lenient environmental policies enforced by local government officials who are politically motivated. Cities more exposed to tariffs place less emphasis on environmental issues in local government reports and impose fewer fines on firms violating environmental regulations.

JEL Classifications: Q53, Q56, F18

Keywords: Air pollution, environmental enforcement, political incentive, trade war

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1 Introduction

The impact of economic growth on the environment has always been a central topic for policymakers and academics. The Environmental Kuznets Curve (EKC) suggests that there is an inverted U-shaped curve between income and pollution driven by preference changes. As countries become richer, there is increased environmental awareness, and governments are better able to address environmental issues through stricter regulations and enforcement. This paper studies the impact of economic growth on the environment by exploring a novel channel, namely the political incentive channel. Faced with heightened risks of economic downturns, government officials tend to prioritize economic growth and assist firms in reducing costs by externalizing pollution externalities.

We investigate how politically motivated government officials respond to perceived risks of economic slowdowns by providing compelling evidence on lenient environmental enforcement. Government officials are usually faced with a challenging trade-off between fostering economic growth and enforcing environmental regulations. Economic growth can generate adverse environmental consequences through pollutant emissions, natural resource exploitation, and other economic activities. Therefore, the implementation of stringent environmental regulations can induce short-term economic slowdowns, job losses, and social unrest. This trade-off necessitates the balancing of short-term economic gains and long-term sustainable development. Facing the pressure of short-term performance evaluation and the possibility of social unrest (Campante et al., 2023), government officials tend to sacrifice long-term sustainable development and give firms tacit permission for excess pollutant emissions to offset the negative impacts of adverse economic shocks. The phenomena are observed in developed countries and developing countries alike.[1]

The U.S.-China trade war provides a good setting to test this trade-off. China has experienced remarkable economic growth since 1978 and transformed into an upper middle-income country in 2010. The trade war stands out as a remarkable economic event, intensifying the risk of economic disruptions. It is characterized by the sudden and substantial increases in the U.S. tariffs across a diverse range of products, which provides exogenous shocks on the heightened risks of economic downturns in China. Despite the growing literature on the economic consequences of the trade war (e.g., Chor and Li, 2023; Jiao et al., 2021), less is known about its environmental consequences. In this paper, we fill in the gap and reveal the hidden cost of the trade war.

This paper studies the unintended environmental consequences of trade protectionism. We

[1] To foster growth and help the auto industry, the Trump administration announced a new rule on automobile fuel efficiency in 2019, which rolls back a 2012 standard that had required automakers to cut planet-warming tailpipe pollution (https://www.nytimes.com/2020/03/31/climate/trump-pollution-rollback.html).
In Brazil, large-scale deforestation of the Amazon and the commercial exploitation of indigenous lands accelerated under Bolsonaro since 2019 (https://www.reuters.com/article/us-brazil-environment-idUSKBN22K1U1).
To fight the coronavirus pandemic, Indonesia passed the Omnibus Law in 2020, which introduced the deregulation of the environment and put less restraint on factories to help lift the economy (https://sites.lsa.umich.edu/mje/2020/11/16/indonesias-plan-to-fight-the-recession-from-the-pandemic/).

show that environmental enforcement functions as a special form of industrial policy used to subsidize firms and assist them in confronting adverse trade shocks. Using novel hourly firm-level pollution emission data and hourly monitor-level air quality data, we investigate the impact of tariff escalations on pollution emissions in China. We find that higher U.S. tariffs lead to worse air quality. Employing a first-difference design, we observe that cities with higher U.S. tariff escalation experience more pronounced air pollution since the trade war. Specifically, a 1% increase in U.S. tariffs results in a 0.9% increase in SO_2 and a 0.7% increase in $PM_{2.5}$. As SO_2 is mainly generated from power generation and manufacturing production, the greater magnitude of the increase in SO_2 compared to other pollutants suggests the great contribution of power and industrial production. The findings are surprising. During the trade war, there was growing concern about possible economic contractions. Indeed, higher U.S. tariffs lead to reduced economic activities (Chor and Li, 2023), which are supposed to generate fewer pollution emissions.[2] A further exploration of hourly pollution patterns reveals that the increase in air pollution is more pronounced after sunset and before sunrise, suggesting secret pollution emission and lenient environmental policies.

To answer the question of who generates additional pollutants, we use the data on firms' end-of-pipe emissions from the Continuous Emission Monitoring System (CEMS) to investigate pollution emission patterns. Firms that emit more pollutants could be those more exposed to the increased tariffs or those located in cities more negatively affected by the trade war. To disentangle the two, we incorporate both industry-level tariffs and citywide tariffs into the regression. Firm-level evidence suggests that it is citywide tariffs rather than industry-level tariffs that drive the results. Firms located in high-exposure cities in targeted or non-targeted industries experienced similar changes in emissions. In comparison, a 1% increase in city-level U.S. tariffs results in a 16.2% increase in particles and a 22.8% increase in SO_2 emissions among the major polluting firms monitored by the government. Similar to the monitor-level analysis, China's retaliatory tariffs do not have any notable impacts on firm emission intensities, consistent with the findings of Chor and Li (2023) that Chinese retaliatory tariffs don't exert much negative impact on economic activities. Our findings show that firms in cities more exposed to the U.S. tariffs exhibit higher emission intensities, implying a citywide rollback of environmental enforcement by local governments. The findings suggest that politically motivated local government officials care about the overall economic growth and employment rather than compensating firms adversely hit by the trade war.

To demystify the puzzling findings on increased pollution, we explore the mechanism in two ways. First, we show that the worsening air quality can be partly attributed to the lenient environmental enforcement by local governments. While environmental policies make

[2] In the context of international trade, the Pollution Haven hypothesis makes a similar prediction. Developing countries like China have less stringent environmental regulations than their developed trade partners. Consequently, China has experienced high pollution levels especially after its opening up of trade (Bombardini and Li, 2020; Gong et al., 2023). With increased trade barriers due to the U.S. tariff escalation, we should anticipate a reduction in China's air pollution.

firms internalize pollution externalities by raising their production costs, lenient environmental enforcement serves as a unique type of industrial policy used to subsidize firms. We begin by constructing a text-based stringency index based on annual reports from local governments. Our results indicate that high U.S. tariffs result in a decrease in the index, suggesting that local governments in high-exposure cities place less emphasis on environmental issues in response to tariff escalation. Further evidence using the environmental fine data shows that local environmental agencies in more trade-exposed cities conducted fewer inspections and charged smaller amounts of fines on firms violating environmental regulations. Another measure of lenient environmental policies lies in the manipulation of air pollution data. We show that the bunching of CEMS data near emission limits becomes less pronounced after the trade war. It reflects a decrease in firms' efforts to either carefully design production just below the emission standard or manipulate CEMS data, due to regulatory oversight or decreased enforcement during the trade war.

Second, we provide suggestive evidence that political incentives affect politicians' decisions. Cities with native or older party secretaries are less likely to experience worsened air pollution in response to U.S. tariff escalations. A likely explanation is that native officials care more about long-term sustainable development and older officials have less incentive for promotion. Furthermore, we leverage the heterogeneity across various locations as a proxy to examine variations in environmental enforcement. Our analysis reveals that the rise in air pollution is particularly prominent near regional boundaries. These areas typically experience reduced monitoring of emissions by inspectors and a general decline in environmental enforcement, which are likely to be the first areas affected by policy rollbacks. The above evidence implies that local government officials soften environmental enforcement during the trade war.

This paper contributes to the literature on economic growth and the environment (e.g. Grossman and Krueger, 1995; Brock and Taylor, 2005; Xepapadeas, 2005). There is an extensive literature documenting the inverted U-shaped relationship between economic growth and environmental quality in the long run, namely the environmental Kuznets curve. The key mechanism is the changes in citizens' environmental awareness. Our paper contributes to the literature by studying the short-term impact of economic growth on pollution from the perspective of political incentives and lenient policy enforcement. We find that there is an ease in policy enforcement in times of increased risks of economic downturns. Specifically, we investigate local government officials' regulatory responses to the trade war and show that they tend to sacrifice environmental sustainability for economic growth and give firms tacit permission to emit excess pollutants.

This paper is also related to the literature on the enforcement of environmental regulations. There are large variations in the implementation of environmental policies within and between countries (Shimshack, 2014; Greenstone and Jack, 2015), depending on economic conditions (Greenstone et al., 2012), local officials' political incentives (Ghanem and Zhang, 2014; Wong and Karplus, 2017; Jia, 2017; Karplus et al., 2018; Zou, 2021; Buntaine et al., 2022), and firms and citizens' responses (Zhang and Mu, 2018; Shimshack and Ward, 2022). Regarding the literature on government officials' political incentives, Buntaine et al. (2022) find that social media appeals to regulators have been shown to substantially reduce violations and pollution emissions, while private appeals yield more modest environmental improvements. Jia (2017) finds that the establishment of connections with key officials in the central government increases pollution. Suspicious air quality data by local governments, especially when anomalies are least detectable, have also been documented (Ghanem and Zhang, 2014). These studies shed light on the detrimental effects of weak enforcement, such as increased pollution and corruption. Our paper contributes to the literature by exploring the impact of exogenous adverse economic shocks in the context of trade protectionism. Local officials have incentives to relax environmental enforcement when faced with negative trade shocks triggered by the trade war.

Our paper also contributes to the literature on the impact of trade on the environment (e.g. Poncet et al., 2015; Cherniwchan, 2017; Shapiro and Walker, 2018; Bombardini and Li, 2020). Bombardini and Li (2020) shows that Chinese cities that had high export growth in "dirty" industries between 1990 and 2010 experienced a greater increase in SO_2 concentration and infant mortality. Moreover, they also examine a temporary "trade war" in 2002 when the U.S. government announced a tariff increase in 272 different steel product categories. There was a small but significant improvement in air quality. While the previous works focus on the production and income channels, our paper contributes to literature by exploring the political incentive channel.

Moreover, our paper relates to the literature on the trade war by exploring the hidden cost of the trade war. Despite the growing literature on the economic consequences of trade protectionism, such as its impact on trade flows and prices (Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021; Fajgelbaum et al., 2021; Jiao et al., 2021; Feng et al., 2023; Jiang et al., 2023), nightlight and economic activities (Chor and Li, 2023; Han et al., 2023), employment (Flaaen and Pierce, 2019; Beck et al., 2023), elections and politicians' responses (Blanchard et al., 2019; Li et al., 2023), and stock returns (Amiti et al., 2021; Huang et al., 2023; Li et al., 2023; Han et al., 2023), little is known about its impact on the environment.

The rest of the paper is organized as follows. Section 2 introduces the background on the U.S.-China trade war and China's environmental policies before and during the trade war. Section 3 describes the data and variable construction, while Section 4 illustrates the econometric specification and presents empirical evidence of the impact of the trade war on China's air pollution. Section 5 tests the mechanism of pollution change from the perspectives of lenient environmental enforcement and political incentives. Section 6 discusses the health effects due to increased air pollution and concerns about environmental injustice. Section 7 concludes.

2 Background

2.1 The U.S.-China trade war

The U.S. government initiated a series of tariffs on imports from trade partners starting in early 2018, as described in Table A1. Punitive tariffs were unexpectedly raised on a large scale for a wide range of products in a short time window and induced a set of tit-for-tat tariff measures from several trade partners including China. Specifically, the Trump administration imposed global safeguard tariffs on \$8.5 billion worth of solar panel imports and \$1.8 billion worth of washing machine imports on February 7, which triggered WTO disputes initiated by China and South Korea. Furthermore, additional tariffs on steel and aluminium were enforced under Section 232 on March 23, with temporary exemptions granted to seven trade partners. In response, trade partners, such as Canada, China, European Union, India, Mexico, and Turkey, imposed retaliatory tariffs on U.S. goods. At the onset of the trade war, extensive discussions took place concerning its potential duration and severity due to considerable associated policy uncertainty.

Starting in mid-2018, the U.S. government shifted its focus to China, as shown in Figure B1. On June 16, the U.S. announced a list of \$50 billion of goods imported from China at a rate of 25%. Among the list, imports worth \$34 billion were taxed from July 6 (wave 1), and the remaining \$16 billion were taxed from August 23 (wave 2). As a countermeasure, China released retaliation lists targeting U.S. imports amounting to \$50 billion, set to take effect on July 6 (wave 1) and August 23 (wave 2). These goods were subject to 25% punitive tariffs. At the end of 2019, about 86% of the HS-10 products imported from China in 2017 were subject to the U.S. punitive tariffs, accounting for around 54% of its total imports from China. Figure B1 plots the dynamics of U.S. punitive tariffs on Chinese products (solid blue line) and its baseline tariffs, namely the Most-Favored-Nation (MFN) tariffs (dashed blue line). It also displays the Chinese retaliatory tariffs on the U.S. products (solid red line) and its MFN tariffs (dashed red line). By adding the punitive tariffs with the baseline tariffs, we learn that the import-weighted average U.S. tariffs rose from 2.7% in January 2018 to 13.8% in December 2019. Meanwhile, the Chinese tariffs on U.S. products increased from 5.3% to 16.2%.

From the U.S. trade policy (Figure B3) and import structure (Figure B2), we learn that the main target of the U.S. is the future competition from China in high-tech sectors rather than manipulating the terms of trade and reducing the trade deficit. As shown in Figure B3, the first few waves of punitive tariffs targeted high-tech products from China, such as aircraft, railways, and optical instruments. Most of these were listed in China's five-year plan "Made in China 2025". Their import values were relatively small compared to labor-intensive products that the U.S. imported heavily from China, such as textiles and electronics (Figure B2). Feng et al. (2023) further show that the U.S. tariffs were negatively correlated with U.S. imports from China. Apart from high-tech sectors, the U.S. government was also preoccupied with product substitutability, and the economic interest of U.S. importers and consumers, and political elections (Fajgelbaum et al., 2020; Feng et al., 2023).

2.2 The economic consequences of the trade war

During the trade war, gloomy shadows loomed over the prospect of economic growth, casting doubt and stirring a rising tide of pessimism. The ominous specter of impending economic downturns and pervasive pessimism swiftly infiltrated the stock market, triggering a plunge in the stock market returns for affected firms (Huang et al., 2023; Li et al., 2023). Furthermore, the surge in tariff raised the trade policy uncertainty faced by Chinese firms, especially for smaller and less capital-intensive firms, and reduced investment, R&D expenditures, and profits (Benguria et al., 2022). Indeed, the U.S. tariffs reduced economic activities in China, measured with night-time luminosity (Chor and Li, 2023).

Regarding exports, the dynamic effect of the U.S. tariffs on China's exports to the U.S. is shown in Figure 1 based on the following econometric specification. We find that there is a sharp decline in exports with the imposition of U.S. punitive tariffs.[3]

$$\Delta Y_{pt} = \sum_{t=-6}^{t=6} \beta^t \Delta USTariff_{pt} + D_p + D_{sm} + D_t + \varepsilon_{pt}^X$$

where ΔY_{pt} denotes the year-to-year log change in export value or export quantity of HS-8 product p. $\Delta USTariff_{pt}$ measures the year-to-year log change in tariffs on product p imposed by the U.S. government. β captures the dynamic effect of the U.S. tariffs on China's exports to the U.S. measured in value and quantity, respectively. D_p is the HS-8 product fixed effect. D_{sm} controls for shocks that vary by month within broad HS categories m. D_t controls for the year-month fixed effects that address time-varying macroeconomic shocks.

2.3 Environmental regulations and policy enforcement before and during the trade war

Since the 1990s, China has become a predominant recipient of international industrial transfers and a pivotal global manufacturing hub. Following China's accession to the World Trade Organization in 2001, developed nations, especially its trade partners, increasingly outsourced labor-intensive and capital-intensive industries to China, resulting in severe pollution problems (Liu and Diamond, 2005). With rapid industrial expansion, China incurred a substantial environmental toll, leading to its recognition as one of the most environmentally compromised nations globally (Li and Ramanathan, 2018). The concerns regarding severe air pollution affect

[3]Perceived risks of future economic downturns compel local officials to take actions to mitigate the looming threat on economic growth and social unrest posed by the trade war. The increase in China's exports to the rest of the world (Table A18) is likely to result from the joint efforts of the governments and exporting firms.

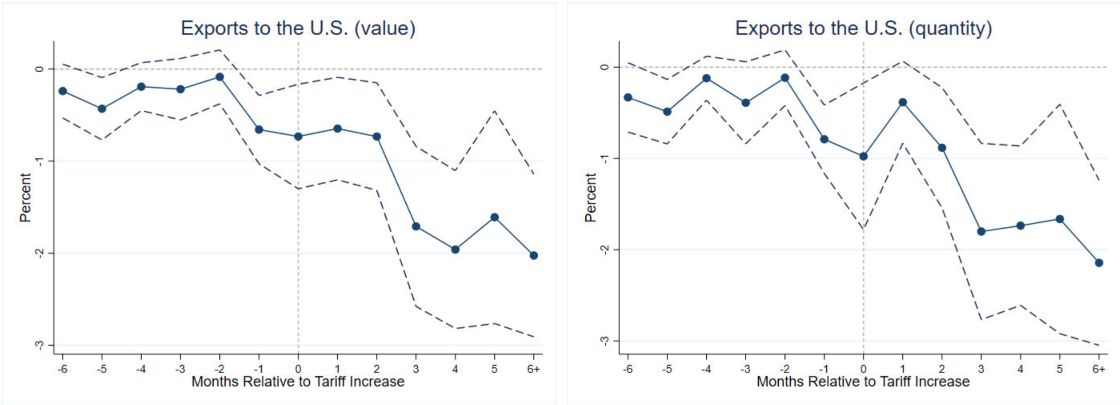


Figure 1: **Dynamic effects of U.S. tariffs on Chinese exports to the U.S.**

Notes. The figures report the estimated coefficients (solid line) and the 95% confidence intervals (dashed line), with standard errors clustered by HS-2 product. The figure on the left shows the impact of U.S. tariffs on China's export values to the U.S. The figure on the right shows the impact of U.S. tariffs on China's export quantity to the U.S. We use China's monthly HS-8-product-level export from January 2017 to December 2019.

not only China but also the environments of neighboring countries and even the whole world (Liu and Diamond, 2005).

To address the pollution problem, the central government of China declared a "war against pollution" in March 2014 (Greenstone et al., 2021). The timing of this declaration, made at the outset of a nationally televised conference typically reserved for discussing pivotal economic targets, underscored a significant departure from the country's longstanding policy of prioritizing economic growth at the expense of environmental protection. Furthermore, it marked a notable shift in the official rhetoric of the government concerning the nation's air quality. Historically, state media had sought to downplay concerns about air quality. However, the government now places a heightened emphasis on environmental responsibility, unequivocally stating that the nation cannot afford to pollute first and clean up later. The central government is committed to combating pollution with unwavering resolve.

Amidst the tumultuous landscape of the trade war, however, there was a relaxation of policy implementation. To combat the headwinds of the trade war and alleviate the perceived risk of economic downturn, the Chinese local governments eased the enforcement of environmental regulations.[4] This is because local government officials' promotions largely depend on the economic performance and social stability of the respective regions. Faced with elevated risks of economic disruptions, politically motivated politicians shift policy priorities. They are reluctant to enforce stringent environmental policies and are less inclined to levy environmental penalties, fearing the potential repercussions of further exacerbating short-term economic sluggishness, job losses, and social unrest. In response, polluting firms found themselves emboldened to forgo pollution control measures. There are numerous anecdotes suggesting secret pollution at night. For example, Figure B9 displays the nighttime emissions of a Chinese paper mill plant in 2019.

[4]https://www.icis.com/explore/resources/news/2018/10/04/10263657/china-relaxes-environmental-rules-as-trade-war-bites/.

3 Data and variable construction

3.1 Import and export

To capture each city's exposure to tariff shocks, we draw on Chinese Customs data in 2015 to calculate the initial import weights. The data is at the firm-HS-8 product-country level and covers the universe of Chinese importers and exporters. It provides information on each firm's customs declaration zone, based on which we can infer the city in which the firm is located.[5]

Apart from annual firm-level data, we also acquire monthly product-level aggregate export data from the Customs General Administration of China to study the impact of the trade war on Chinese exports. The data records export values (in USD) and quantities at the destination-HS-8 product level and ranges from January 2017 to December 2019. It contains over 7,000 HS-8 products and nearly 200 export destinations.[6] The tariff-exclusive unit value is calculated as the ratio of export value to quantity.

3.2 Tariff

To construct the local exposure to the tariff shocks for each Chinese city, we collect four data sets on monthly product-level tariff lines for China and the U.S. First, the annual baseline tariff schedule. For the U.S., the data are available at the country-HS-8 product level and released by the United States International Trade Commission (USITC). For China, the data are available at the country-HS-10 product level and released by the Customs General Administration of China. Second, punitive tariffs. For the U.S. punitive tariffs imposed on goods imported from China, the data are available at the country-HS-10 product level and are from the United States Trade Representative (USTR). For China, its retaliatory tariffs on US goods are available at the HS-8 level released by the Ministry of Finance of China. Third, tariff exemptions, available at the country-HS-10 product level for the U.S. and HS-8 product level for China. Fourth, China's adjustments in MFN tariff schedule and Free Trade Agreement (FTA) preferential rates, available at the country-HS-8 product level. When aggregating the data to the monthly level, we scale the punitive tariffs by the number of days of the month in effect following Fajgelbaum et al. (2020). Table A19 displays the summary statistics.

Based on the above product-level tariffs, we construct city i's exposure to the U.S. tariffs:

$$\Delta USTariff_{it} = \sum_k \frac{X_{ik0}^{US}}{X_{i0}} \Delta USTariff_{kt} \tag{1}$$

where $\frac{X_{ik0}^{US}}{X_{i0}}$ denotes city i's export of product k as a share of city i's total export in 2015 prior to the U.S.-China trade war. The variation in $\Delta USTariff_{it}$ stems from: (i) differences in initial

[5] We assign each firm to a city based on the city's administrative boundary in 2000. The Customs data provides information on the location of production and the location of export. We use the former one in the analysis.

[6] Export data at city level is not available.

export variety (product-country) composition at the city level; and (ii) differences in the U.S. tariff changes over time at the product level, $\Delta USTariff_{kt}$. A city specializing in exporting targeted products to the U.S. market would experience a huge drop in external demand when U.S. tariffs hike.[7]

Similarly, a city's exposure to Chinese tariff shocks is calculated as:

$$\Delta CHNTariff_{it} = \sum_{k \in \mathcal{K}, j} \frac{M_{ikj0}}{M_{i0}} \Delta CHNTariff_{kjt} \tag{2}$$

where K is the set of products k which are defined as intermediate inputs based on Broad Economic Codes (BEC). $\frac{M_{ikj0}}{M_{i0}}$ denotes the import share of product k of city i from country j, relative to total city-level imports in 2015. As constructed, the variation in $\Delta CHNTariff_{kjt}$ stems from: (i) differences in initial import variety (product-country) composition at the city-level; and (ii) differences in China's import tariff changes over time at variety-level, $\Delta CHNTariff_{kt}$. The summary statistics are shown in Table A19. Because we use the data in 2015, the initial export and import composition at the city level in 2015 ($\frac{X_{ik0}^{US}}{X_{i0}}$ and $\frac{M_{ikj0}}{M_{i0}}$) and variety-specific tariff at national-level ($\Delta USTariff_{it}$ and $\Delta CHNTariff_{kjt}$) are arguably not correlated with unobserved shocks u_{it} to pollution, conditional on a set of observables.

3.3 Air pollution

To measure local air quality, we obtain hourly pollution data from China's air quality monitoring stations from 2013 to 2019. Due to increasing public concerns about air pollution, the Chinese government built the National Urban Air Quality Real-Time Publishing Platform, which mandates regular recordings of local pollution levels at each monitoring station. The platform is required to report six primary pollutants — SO_2, NO_2, CO, O_3, PM_{10}, $PM_{2.5}$ — and Air Quality Indexes (AQI) since 2013. By the end of our study period, the reporting system covers 341 prefecture-level cities and 2,016 monitors across China.

We collect data from official monitor reports and restrict our sample to monitor stations built before 2015 that have consecutive monthly observations during our sample period. To exclude outliers, we winsorize the pollution concentrations that are above the 99^{th} percentile or below the 1^{st} percentile. While the monitor stations measure six major pollutants and the air quality index, we focus our analysis on $PM_{2.5}$ and SO_2. $PM_{2.5}$ is a mixture of solid and liquid particles suspended in the air, consisting of various chemical species such as sulfate, nitrate, ammonium, organic compounds, and elemental carbon. $PM_{2.5}$ particles are small enough to be inhaled deep into the respiratory system, posing health risks to exposed individuals. Among all common air pollutants, $PM_{2.5}$ is associated with the greatest proportion of adverse health effects related to

[7]For simplicity, we refer to $\Delta USTariff_{it}$, the change in weighted tariffs across products and importers, as the U.S. tariffs. $\Delta USTariff_{it}$, the change in tariffs imposed by all importers, is much smaller than the change in tariffs imposed by the U.S. government on Chinese goods (Figure B1), as non-US countries barely changed their tariffs on China during the trade war.

air pollution (Collaborators et al., 2015). SO_2, on the other hand, primarily originates from the combustion of fossil fuels, particularly coal, and industrial activities such as power generation and manufacturing processes. Given its association with industrial emissions, SO_2 serves as an indicator of the environmental impacts of energy production and industrial activities. Due to the long-standing acid rain problem, these two pollutants are also key targets of China's National Environmental Protection Plans, and hence face stringent environmental regulations.

We complement our city-wide air pollution measures with firm-level emission data, which were scraped from China's Continuous Emission Monitoring Systems (CEMS), initially constructed by Karplus et al. (2018). The systems include firms operating in various high-polluting industries, including thermal power generation and manufacturing, which collectively contribute to 65% of the total air pollution in China. To ensure compliance with emission standards, these firms were mandated to install devices that automatically measure and upload hourly emission data to the local environmental bureau's website. For each firm, pollution intensity sensors are placed to monitor the flow rate and strength of many pollutants. A firm may have more than one sensor as they have different end-of-pipe emission tunnels. If multiple sensors, CEMS would include all the reports at the sensor-hour level. CEMS data is automatically uploaded to government agencies. It allows officials to monitor emissions and detect any violations of the prescribed standards. The CEMS data we utilize in our analysis are at the firm-hour level and encompass the emissions of particles, SO_2, and NO_x. For subsequent analyses, we consider the entire population of firms in the CEMS system, as well as a subset of balanced firms that have reported data for each quarter.

4 Trade war and air pollution

4.1 Air quality: evidence from monitoring stations

4.1.1 Event study

We visualize the effect of the trade war on local air pollution using an event-study framework and ascertain the causal impact. We use tariff escalation in June 2018 relative to that in June 2017 as a cross-sectional treatment measure and set June 2018 as the event time. Our regression is specified as follows:

$$\ln P_{ist} = \sum_{q=-8}^{16} \beta_q I\left(\text{event}_q\right) \times \Delta USTariff_i + \gamma_{ym} + \eta_{isy} + \eta_{ism} + t_p + \epsilon_{ist}$$

where $\ln P_{ist}$ is the logarithm of the average air pollution concentration in the monitor station s of city i in time t, namely in year y month m. The dynamic specification covers an event window spanning 42 months before and 16 months after the initiation of the US-China trade war.[8] The

[8] The coefficient of for the period -8 captures the joint effect of all periods prior to November 2017.

variables $I\left(\text{event}_q\right)$ are a set of time dummy variables for each month in the event window. To establish a baseline, we omit the month immediately preceding the start of the trade war (June 2018). The coefficients of interest are the set of β_q. By taking the first-difference of the dependent and independent variables, we are able to control for city-station time-invariant characteristics. Furthermore, we add station-year and station-month fixed effects to account for station-specific time-variant characteristics. We also control for province time trends t_p and year-month fixed effects γ_{ym}. Standard errors are clustered at the station-month level. Our identification strategy relies on the assumption that our treatment assignment based on $\Delta USTariff_i$ is as good as random conditional on the controls. In other words, we assume that in the absence of the trade war, cities with higher trade exposures would have exhibited a similar trajectory of pollution levels compared to other cities.

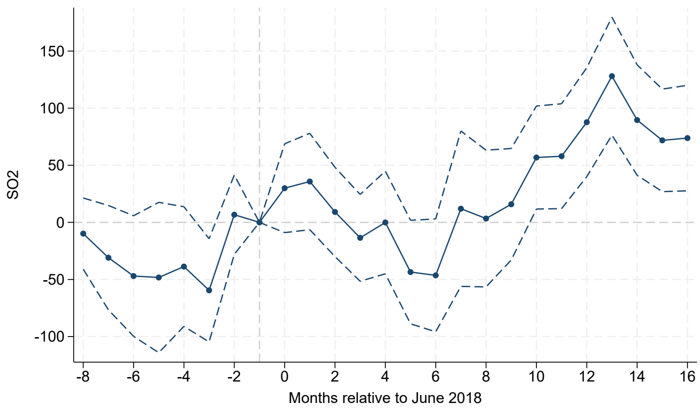


Figure 2: **Event study: trade war and air pollution**

Notes: The figure plots the impact of U.S. tariffs on air quality. We use tariff escalation from June 2018 compared to that of June 2017 as the continuous treatment variable, and SO_2 as the outcome variable. Coefficients are estimated for each month using a dynamic difference-in-difference design. We plot point estimates and their 95% confidence intervals in each month, with month negative 1 dropped. We control for year-month, station-year, and station-month fixed effects. Standard errors are clustered at the station-month level.

Figure 2 validates our identification strategy by examining the pre-trends in air pollution levels before the initiation of the trade war in June 2018. We find no discernible pre-trends in air pollution levels in the pre-periods, which supports our assumption that prior to the trade war, cities exhibited similar pollution trajectories. In the post-period, SO_2 in cities more exposed to the U.S. tariffs first experienced a modest decline and the coefficients are not statistically significant. A likely explanation is that the air quality improved slightly due to the reduction in production activities before any government intervention. Half a year later, however, cities more exposed to the U.S. tariffs witnessed a continuous and significant increase in SO_2. These findings suggest that it takes some time for local government officials to respond. One explanation is that it takes time to make decisions and take actions. Another reason could be local government officials are not sure whether the trade war is going to end very soon and whether they need to take actions.[9]

[9]There were numerous policy discussions in the beginning of the trade war with regard to its duration and

4.1.2 Baseline results

Motivated by the graphical evidence, we investigate the impact of tariff changes on air pollution. To do so, we use year-on-year changes in air pollution as dependent variables and year-on-year changes in tariff as the main independent variables of interest. Our econometric specification is as follows:

$$\Delta ln(P_{ist}) = \beta \Delta ln(USTariff_{it}) + \alpha \Delta ln(CHNTariff_{it}) + \gamma_t + \eta_{is} + t_p + \varepsilon_{ist} \tag{3}$$

where $\Delta USTariff_{it}$ represents the year-on-year log change in U.S. tariffs for city i in month t relative to one year ago. Similarly, $\Delta ln(CHNTariff_{it})$ captures the year-on-year log change in Chinese tariffs for the same city and time period. The trade exposures $USTariff_{it}$ and $CHNTariff_{it}$ are constructed following equations (1) and (2), where we calculate the monthly tariff exposures for each city by weighting product-level tariffs with city-product level import or export shares. γ_t captures year-month fixed effects to control for common time-specific factors that may affect air pollution changes. η_{is} includes city-monitor fixed effects to account for time-invariant factors specific to each monitor station that may influence air pollution levels. t_p accounts for province-specific time trends. The coefficient of interest β measures the effect of changes in U.S. tariffs on air pollution changes. α quantifies the impact of changes in Chinese tariffs on air pollution changes.

The identifying assumption relies on the exogenous changes in U.S. tariffs and Chinese tariffs over time. As shown in Figure 2, there are no significant pre-trends in air pollution changes before the trade war period, supporting the assumption of exogenous tariff changes. Table 1 shows the first-difference regression results from estimating equation (3). In Column (1), a 1% increase in U.S. tariffs leads to a 0.596% increase in city-month AQI. This suggests that higher U.S. tariffs are linked to worsened overall air pollution levels. Disentangling different pollutants, in Column (2) and (4), a 1% increase in U.S. tariff leads to a 0.95% increase in SO_2 and 0.71% increase in $PM_{2.5}$. Increases in SO_2 levels exhibit a larger magnitude compared to the overall increases in AQI. This pattern suggests that the trade war has had a more substantial impact on the pollution originating from power generation and manufacturing production.

As indicated by the coefficients on $\Delta CHNTariff_{it}$, China's retaliatory tariff shocks do not have a similar significant positive impact on air pollution. Estimates are small and statistically imprecise when we use AQI, SO_2 and PM_{10} as dependent variables. These findings are consistent with the findings of Chor and Li (2023) that Chinese retaliatory tariffs don't exert much negative impact on economic activities. One potential explanation is that the effects of China's retaliatory tariffs on different Chinese firms cancel each other out. With the increase in tariffs, the imposition of protectionist measures could potentially reduce import competition and benefit

severity, given the significant uncertainty involved. As decribed in the background section, a number of countries, such as Canada, European Union, and Mexico, raised retalitory tariffs. Unlike China, they managed to reach resolutions with the U.S. shortly after the rise of the U.S. tariffs.

domestic firms producing similar products, resulting in positive effects on air pollution. In contrast, it could lead to higher production costs for local firms that used to import these products as intermediate inputs, which would potentially reduce production and air pollution. It is possible that both channels exist and have similar magnitudes, leading to an ambiguous overall impact on air pollution.

Table 1: **Trade war and air pollution**

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
	(1)	(2)	(3)	(4)	(5)
Δln(USTariff)	0.596***	0.951**	0.914***	0.711**	0.662***
	(0.184)	(0.436)	(0.261)	(0.279)	(0.237)
Δln(CHNTariff)	-0.096	-0.115	0.430***	-0.633***	-0.031
	(0.134)	(0.272)	(0.149)	(0.182)	(0.158)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.169	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. Columns (1) to (5) report logged difference in air pollution regressed logged difference in tariffs. All columns include year-month and monitor fixed effects. Standard errors are clustered at the station-month level. Significance: * 0.10, ** 0.05, *** 0.01.

One concern is the potential confounding policy occurring simultaneously with tariff changes. The Chinese government began placing more emphasis on environmental regulation since 2014, and there are subsequent waves of new regulations or revisions after 2014. To address this concern, we reviewed the central government's environmental policies during our study period and identified two potential confounders: the three-year blue-sky plan and the central government's national environmental inspections. Regarding the former, the central government announced blue-sky plan on June 13, 2018, to combat air pollution in key regions. 84 prefecture-level cities were specified as key regions, and the plan concluded on February 25, 2021. To address this concern, we add an interaction term $KeyRegion_i \times Plan_t$ into our equation (3) to control for pollution changes in key regions during the post-plan period. Results in Table C1 demonstrate stable estimates on $\Delta USTariff_{it}$, suggesting that our identified link between US tariff changes remains unaffected.

For national inspections, the central government dispatched environmental inspection teams randomly to certain province-months to detect suspicious pollution activities. Existing literature has shown that inspections improve air quality, but only temporarily, with pollution rebounding after the inspectors leave (e.g. Karplus and Wu, 2023; Wang et al., 2021). To address this potential confounding factor, we include an $Inspection_{it}$ dummy variable, which equals one if the province or city i is inspected by the central government in month t, and zero otherwise. Results in Table C2 indicate that our main findings are robust.

To test the robustness of our results, we conducted several additional analyses. Firstly, we replaced year-on-year changes with month-on-month changes in both tariff and pollution variables. Results in Table C3 continue to show a positive relationship between higher U.S. tariffs and increased air pollution. However, the magnitudes are smaller, possibly due to lower variability across months compared to years or the influence of seasonality effects. In the second robustness check, we dropped the year 2017 from our analysis, as most tariff changes during that year were zero. Results in Table C4 using a two-year sample period with more tariff variations demonstrate positive and significant estimates for $\Delta USTariff_{it}$, with magnitudes stronger than those in Table 1. For the third exercise, we tested the sensitivity of our sample by using air quality at the city-month level as the dependent variable. Results in Table C5 are consistent with the main findings, although the magnitudes are somewhat reduced. Importantly, we still do not find significant effects of China's tariffs on air pollution. Furthermore, we employed weighted regression for the city-month level analysis, assigning weights based on city GDP in 2017. Results in Table C6 indicate that the increases in air pollution are primarily driven by small cities with lower economic outputs, as estimates on $\Delta USTariff_{it}$ become smaller.

Additionally, we conducted a falsification exercise by examining the matching of tariff changes with air pollution changes in the following year. Results in Table C7 reveal that U.S. tariff changes do not have significant effects on future air pollution levels. Estimates are small, statistically imprecise, and even exhibit a flipped sign. Another placebo test is to examine the tariff impact on weather conditions. We obtain temperature, wind speed, and humidity data from the Climatic Data Centre's National Meteorological Information Centre (CMA). Results in Table C8 indicate that U.S. tariff burdens do not exhibit any effects on the observed weather variables.

In addition, we consider the incidence of pollution levels exceeding established standards as a binary outcome variable. In China, an AQI below 50 corresponds to "excellent" air quality, while AQI levels between 50 and 100 are classified as "good". The corresponding threshold values for excellent air quality for SO_2, NO_2, $PM_{2.5}$, and PM_{10} stand at $50\mu g/m^3$, $80\mu g/m^3$, $35\mu g/m^3$, and $50\mu g/m^3$, respectively. We use air quality values and code dummies for each air pollutant that is considered non-excellent air quality. We use dummies at the monitor-day level and re-estimate equation (3). Results in Table C9 Panel A show positive and statistically significant estimates on $\Delta USTariff_{it}$. Specifically, a 1% increase in U.S. tariffs results in a 0.93% increase in the likelihood of the city's air quality being categorized as non-excellent. Delving into different air pollutants, we find the elasticity of U.S. tariffs to non-excellent SO_2 and $PM_{2.5}$ is 0.349 and 0.314, respectively.

In a similar vein, we use non-good standards to code our outcome variables. Table C9 Panel B shows the likelihood of AQI exceeding 100 is not significantly affected by U.S. tariffs, though the point estimate is positive. This implies that tariff increases result in a small rise in air pollution from excellent to good, but pollution levels are not above the second-tier threshold. Regarding specific air pollutants, Column (2)-(5) shows statistically significant increases of 0.157% and

0.295% in the probability of SO_2 and $PM_{2.5}$ surpassing the designated good thresholds, for every 1% increase in U.S. tariffs. In contrast, the impact on PM_{10} is small and imprecise.

Besides, we show dynamic effects in each quarter in Table A3. In Column (1), we observe that AQI decreased in the third quarter of 2018, indicating improved air quality. As time went by, however, AQI started to increase, suggesting a deterioration in air quality. Similar patterns are found in the case of SO_2 and $PM_{2.5}$. The improvement in air pollution during the first quarter is likely due to the fact that it takes time for government officials to take actions to curb the negative economic consequences of the trade war. It can also be attributed to switching costs associated with producing for the U.S. to producing for other countries, which could lead to a decrease in production and subsequently lower air pollution levels. After the first quarter, air pollution worsened in more trade-war exposed cities during the subsequent quarters. In the next section, we will provide a set of comprehensive evidence to show that it is mainly due to the lenient environmental enforcement.

4.1.3 Excess night emission: heterogeneity across hours

In this section, we study the impact of tariff escalation on air pollution at different hours. In Table 2, we use same-day pollution differences as dependent variables. We collect daily sunset times for each city in our sample and link it to our hourly pollution data reported by local pollution monitors. Specifically, a 1% increase in U.S. tariff leads to an 11.1% increase in AQI, 3.2%, 6.4% and 15% increase in SO_2, $PM_{2.5}$ and PM_{10} respectively. The larger magnitudes observed suggest that secret pollutant discharges, which occur during the actual sunset hour rather than clock hours, have a more pronounced response to U.S. tariff changes.[10] Pollution emitted at night is less visible, which reduces the likelihood of environmental regulators being on patrol. Besides, emissions during nighttime pose a lower risk in terms of public outcry. With pollutants shrouded in darkness, surrounding residents and media coverage are less likely to file complaints or write reports. The existence of emissions during unwatched periods has been documented by previous studies in both China and the U.S. (e.g. Zou, 2021; Agarwal et al., 2023).

Table 2: **Pollution before vs. after sunset**

	Dark hour - daytime hour				
	$\Delta\Delta\ln(AQI)$	$\Delta\Delta\ln(SO_2)$	$\Delta\Delta\ln(NO_2)$	$\Delta\Delta\ln(PM_{2.5})$	$\Delta\Delta\ln(PM_{10})$
	(1)	(2)	(3)	(4)	(5)
$\Delta\ln(USTariff)$	11.058***	3.173**	1.250	6.404***	15.003***
	(2.260)	(1.352)	(0.935)	(1.918)	(2.503)
$\Delta\ln(CHNTariff)$	-4.959***	0.738	0.912*	-2.809**	-5.264***
	(1.380)	(0.892)	(0.466)	(1.103)	(1.771)
Observations	48847	48847	48847	48847	48847

[10]For example, Figure B9 displays the nighttime emissions of a paper mill plant in 2019.

R-square	0.048	0.066	0.088	0.051	0.048
Y-mean	-0.105	0.119	0.054	0.012	-0.033
Y-sd	2.032	1.213	0.915	1.717	2.345
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: The sample period is from 2017:1 to 2019:12. Columns (1) to (5) report the impact of the log-difference in tariffs on log-difference in excess dark air pollution. All columns include year-month and monitor fixed effects. Standard errors are clustered at the station-month level. Significance: * 0.10, ** 0.05, *** 0.01.

We plot the estimated coefficients using each hour's pollution in Figure 3, with the X-axis representing the relative hour compared to the sunset hour and the Y-axis representing the estimated coefficients β. Before sunset, estimates are small and statistically insignificant, indicating a minimal impact. However, pollution increases become more pronounced starting from hour 3 and continue to rise until hour 7. These findings suggest that the identified pollution increases are primarily driven by secret nighttime discharges. Because the CEMS real-time on-site monitors have been shown to be effective in detecting and preventing disguised pollution behaviors (Agarwal et al., 2023), excess pollution at night is very likely due to the less stringent policy enforcement. We will provide additional evidence on lenient environmental regulations and softening enforcement in Section 5.

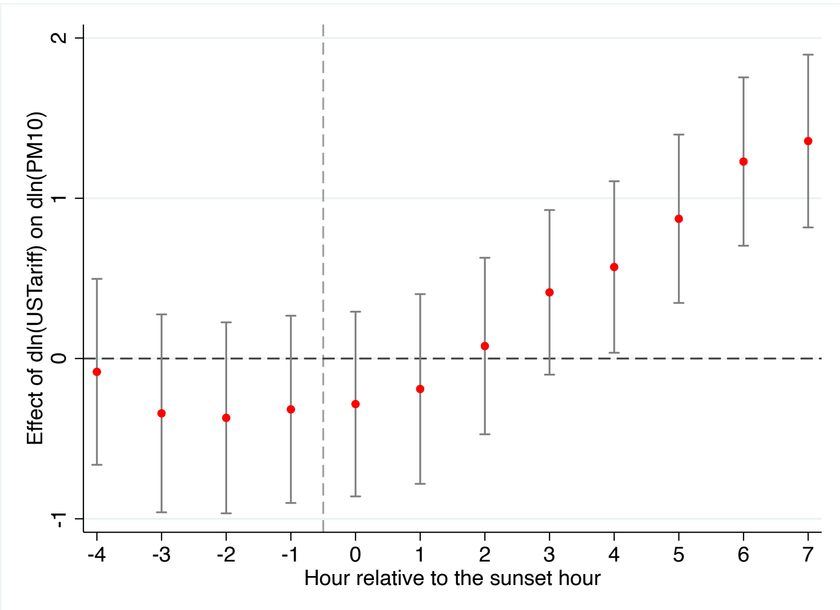


Figure 3: **Pollution before vs. after sunset**

Notes: This figure displays coefficients on $\Delta\ln(\text{USTariff})$. We separately estimate coefficients at each sunset hour.

Furthermore, we do a similar practice by using clock hours that are the same across time and cities. Following the econometric specification of equations (2), we examine the event studies in the morning (9 a.m.) and at night (9 p.m.), respectively. As shown in Figure 4, the change in air pollution in the morning (9 a.m.) in response to tariff changes is modest. In comparison, there is a significant increase in pollution at 9 p.m. The effects are larger in magnitude compared to those in the morning in most of the periods. The stronger effect during night suggests the presence of secret dark-time emissions. We find a pattern similar to that in Table A2.

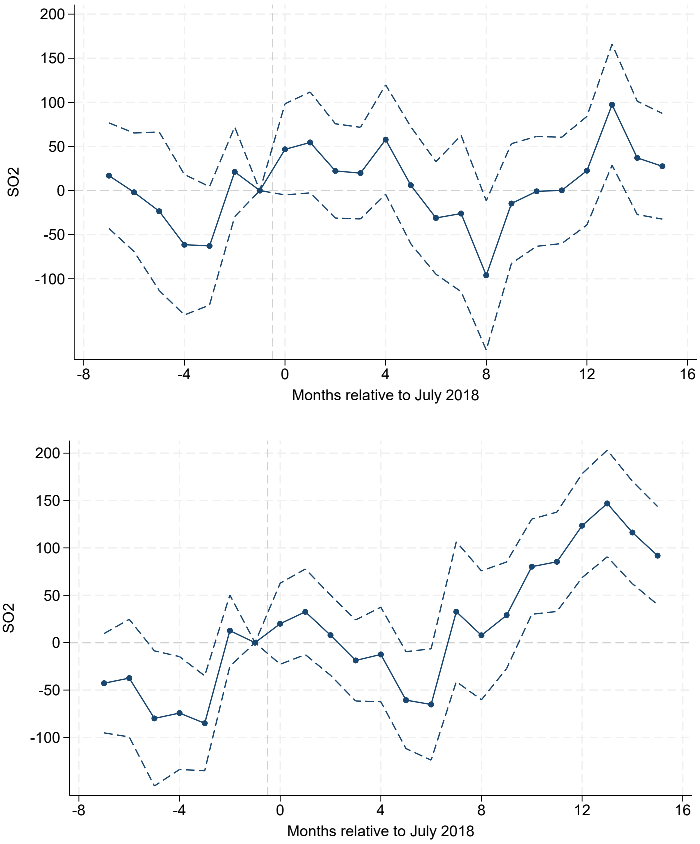


Figure 4: **Event study: morning (9 a.m.) vs. night (9 p.m.)**

Notes: The figures plot the impact of U.S. tariffs on air quality at 9 a.m. and 9 p.m., respectively. We use the tariff increase from June 2018 compared to that of June 2017 as the continuous treatment variable, and SO_2 as the outcome variable. Coefficients are estimated for each month using a dynamic difference-in-difference design. We plot point estimates and their 95% confidence intervals in each month, with month negative 1 dropped. We control for year-month, station-year, and station-month fixed effects. Standard errors are clustered at the station-month level.

We confirm the above findings in Table A2. Specifically, we use pollution difference after and before working hours — 8 a.m. to 6 p.m. — to examine if there are significant differential responses. Estimates show positive and significant effects of $\Delta USTariff_{it}$ on the pollution differences. Specifically, as the U.S. tariff burden increases by 1%, the pollution differences increase by 9.8%, 2.3%, and 6.3% when using AQI, SO_2, and $PM_{2.5}$ as dependent variables, respectively. In contrast, estimates on $\Delta CHNTariff_{it}$ remain small and have inconsistent signs across pollutants, suggesting that China's tariff burdens do not have a significant impact on pollution differences during working hours.

4.2 Firm-level pollution emission

4.2.1 City-level tariff exposure

We complement the above city pollution measures with firm-level end-of-pipe emission data from China's Continuous Emission Monitoring Systems (CEMS). The econometric specification is set as follows:

$$\Delta ln(E_{it}) = \beta_1 \Delta USTariff_{it} + \beta_2 \times \Delta CHNTariff_{it} + \gamma_t + \eta_i + \varepsilon_{it}, \quad (4)$$

where $\Delta \ln E_{it}$ represents the year-on-year change in emissions for firm i in month t. Variables $\Delta\ USTariff_{it}$ and $\Delta CHNTariff_{it}$ capture the changes in U.S. and Chinese tariffs in the city where firm i is located during month t. The coefficient of interest is β_1, which indicates the impact of U.S. tariff changes on the year-on-year changes in emissions, and the coefficient β_2 represents the effect of Chinese tariff changes. To account for firm-specific time-invariant unobserved factors, we include firm fixed effects denoted by η_i.

Table 3 shows our regression results. In Column (1), there is a significant increase in firms' end-of-pipe particle emissions. A 1% increase in U.S. tariffs leads to a 16.2% increase in particle emissions. Column (2) shows a similar pattern, with a 22.8% increase in SO_2 emissions linked to U.S. tariff changes. However, no significant change is observed in firms' NO_x emissions, as shown in Column (3). The magnitudes of the effects on SO_2 and particle emissions are notably larger than those reported in Table 1. This aligns with expectations, as city-wide air quality represents a steady state resulting from a combination of firm emissions, pollutant transportation, and settlement. Among these activities, firms' end-of-pipe emissions are more directly influenced by tariff changes, so they exhibit larger effects. In the second row, the coefficient on $\Delta CHNTariff_{it}$ is statistically imprecise. This suggests that China's retaliatory tariffs did not have a significant effect on firms' air pollutant emissions. These findings, together with the results in Table 1, provide evidence that China's tariffs had minimal influence on China's air pollution levels.

We investigate the heterogeneity of firm emissions across different hours of the day by using local sunset hours and running separate estimates during daytime and after sunset. In Table A6, we find higher levels of Particles and SO_2 emissions in both panels in response to higher U.S. tariffs, indicating a consistent increase in emissions throughout the day. In Panel A, a 1% increase in U.S. tariffs leads to a 15.9% rise in daytime particle emissions and a 12.6% increase in SO_2 emissions. In Panel B, the impact of U.S. tariff increases is slightly more pronounced during dark hours. SO_2 experiences a 23% increase as the U.S. tariff increases. This disparity in emissions before and after sunset aligns with our observations on nighttime emissions in Table 2.

Table 3: **Tariff and firms' emissions**

	Δln(Particles) (1)	Δln(SO_2) (2)	Δln(NO_x) (3)	Δln(Particles) (4)	Δln(SO_2) (5)	Δln(NO_x) (6)
Δln(USTariff)	16.158*	22.830**	-9.710	15.501*	23.022**	-9.852
	(8.854)	(8.268)	(7.900)	(8.818)	(8.399)	(7.857)
Δln(USTariff_Ind)				13.519*	7.878	-7.764
				(7.046)	(9.125)	(11.218)
Δln(CHNTariff)	2.572	-10.210	-0.619	2.741	-8.850	-0.754
	(3.302)	(7.846)	(2.686)	(3.145)	(7.165)	(2.430)
Observations	3965	3689	3705	3829	3561	3554
R-square	0.515	0.522	0.514	0.514	0.528	0.515
Y-mean	-0.271	-0.276	-0.155	-0.274	-0.269	-0.160
Y-sd	1.111	1.300	1.035	1.106	1.295	1.042
Firm FEs	Y	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y	Y

Notes: The sample period is from 2018:1 to 2019:12. Columns (1) to (3) report the log-difference in firms' air pollutant emissions regressed logged difference in city-level tariffs. Columns (4) to (6) report log-difference in firms' air pollutant emissions regressed log-difference in both industry-level and city-level tariffs. All columns include year-month and firm-fixed effects. Standard errors are clustered at the provincial level. Significance: * 0.10, ** 0.05, *** 0.01.

Given the identified evidence of increased emission intensity, what are firms' actual behaviors in response to tariff escalations and relaxed environmental enforcement? It is likely that firms curtailed marginal abatement costs by turning off pollution control equipment like scrubbers. A sample pollution scrubber is shown in Figure B10. The waste air undergoes sulfur and nitrogen removal processes before being discharged into the atmosphere. The marginal cost of running scrubbers is estimated to be \$84-265 per ton of abated SO_2 (Stoerk, 2018) and \$80-89 per ton for CO_2 abatement (Du et al., 2015). That said, the marginal cost of pollution abatement is still high, which motivates firms to avoid the costs of operation and maintenance (Xu, 2011). This marginal cost avoidance is supported by empirical findings. For instance, Karplus and Wu (2023) shows that China's environmental inspections conducted by the central government prompt power plants to operate their existing scrubbers. Though the abatement equipment has been installed prior to the arrival of inspectors, running a scrubber requires variable inputs of labor and materials. Plants with SO_2 scrubbers show a statistically significant additional decrease in SO_2 pollution during the onsite period.

We obtained data from Karplus and Wu (2023) which includes firm-level scrubber dummies, and merged firm names with our CEMS firm sample. Only 1,112 firms exist in both datasets, 14.6% of our CEMS firm list. We replicate our first-difference estimates by introducing interaction terms of $\Delta USTariff_{it}$ and the scrubber dummy. Results using the merged sample are summarized in Table A4 Panel A. Our estimation precisions are reduced compared with those in Table 3 due to the smaller sample size. Point estimates on $\Delta USTariff_{it} \times Scrubber$ have positive values when using Particles and SO_2 as dependent variables. This suggests that firms equipped with scrubbers experienced a more substantial increase in pollution emission intensity compared to other non-scrubber firms.

In Panel B, we extend our analysis to encompass the entire CEMS sample, coding the *Scrubber* dummies as zeros for firms without available scrubber information. In Panel B, we still observe positive point estimates for $\Delta USTariff_{it} \times Scrubber$, despite smaller magnitudes and lower precisions. This practice using scrubber indicators provides suggestive evidence that firms are likely to turn off scrubbers in response to lenient environmental enforcement so as to avoid high marginal abatement costs.

Furthermore, we analyze the heterogeneity across firm ownership by categorizing firms into three groups: state-owned, foreign-financed, and private firms. Results of subsample analysis are presented in Table A5. We find the observed increase in emission intensities is primarily attributed to private firms, which exhibit big point estimates and high statistical precision. In comparison, foreign-financed firms show a slightly smaller effect, while state-owned enterprises exhibit the smallest impact. This pattern suggests that when firms are more susceptible to trade shocks and associated economic costs, they are more inclined to increase their pollution levels and avoid incurring abatement expenses. Our findings align with this hypothesis, as private firms, often more exposed to market dynamics, display more pronounced effects. Conversely, state-owned enterprises, characterized by relatively stable profits and limited exposure to trade conflicts, lack strong incentives to elevate their emission intensities.

Since the CEMS data has missing values and strategic reporting concerns, we conduct a robustness check by requiring firms with complete data in each quarter between 2017 and 2019. This leads to a smaller sample size in Table C10. Estimates on $\Delta USTariff_{it}$ remain positive and significant when using firm-level particles and SO_2 as dependent variables. This suggests that the positive effect of U.S. tariffs on firms' emissions holds when considering a more restricted sample. In addition, we also use relative emissions compared with emission standards as dependent variables. Results in C11 remain stable, indicating that U.S. tariffs are associated with higher emissions at the firm-month level relative to the emission standards.

Moreover, we test whether the number of firms with non-zero emission data is affected by tariff burdens. We hypothesize that due to the imposition of rigorous environmental regulations and pollution abatement costs, polluting firms may have refrained from operating prior to the trade war but started operations afterwards. To test this hypothesis, we use the count of firms at the city-month level that have reported at least one particle, NO_x, and SO_2 values as dependent variables. We also add province-specific time trends into the estimation to account for potential improvements in data quality over time.

Results presented in Table A8 demonstrate a significant increase in the number of emitting firms in response to U.S. tariff burdens. Specifically, with every 1% tariff increase, the number of CEMS firms significantly increases by 17.9% to 26.8%. This pattern is consistent across the three pollutants and the magnitudes are similar. As our main results in Table 3 include firm fixed effects, the estimation does not take account of newly reporting firms. New firms that started to report later would further increase the magnitude of pollution increase in response to tariff escalation. It is important to note that firms without positive emission reports could experience either non-operating hours or operating but non-reporting hours. The latter scenario is considered data manipulation when firms hide their emissions. We provide further discussion to disentangle pollution increase or manipulation decrease in response to U.S. tariff burdens in Section 5.1.3.

4.2.2 Industry-level tariff exposure

In this section, we investigate whether the rollback of environmental policies affects the entire city or if it is specifically targeted at affected industries. Based on our observations of local environmental enforcement in Sections 5.1 and 5.2, we hypothesize that firms located in cities with high overall exposure, but operating in low-exposure industries, also emit more pollutants. This is because politically motivated local government officials mainly care about the overall economic growth and employment rather than compensating firms adversely hit by the trade war.

We use the hourly end-of-pipe emissions at the firm level to test this hypothesis. The monitored firms are major polluters operating in various high-polluting industries. To assign industry codes to the 7,639 firms in our CEMS sample, we scrape firms' basic information including industry classification from the Tianyancha website. Our data set includes 76 industries. We merge the industry names with the HS-8 list and calculate the industry-month-level tariff burden.

Column (1) to Column (3) of Table 3 report the positive impact of city-level tariffs on pollution.[11] In Column (4) to (6), we add the industry-level tariff as an additional control in equation (3) to examine whether city- or industry-level tariff drives the observed pollution increase. We find that pollution is affected by both tariff exposures. As shown in Column (4), for firms located in the same cities, those operating in high-exposure industries exhibit higher particle emissions compared to those in industries with lower tariff escalation. Specifically, a 1% increase in industry-wide tariffs leads to a 13.5% increase in firms' particle emissions. In Column (5), the estimate on $\Delta USTariff\_Industry_{it}$ becomes smaller and statistically imprecise. This indicates that firms located in the same cities exhibit similar responses in terms of SO_2 emissions, regardless of the burden due to tariff escalation. In other words, non-targeted industries in treated cities also experience similar increases in SO_2 emissions, indicating a city-wide relaxation of environmental policies. A likely explanation is that local government officials primarily care about the overall economic growth and employment. That's why they adopt a city-wide lenient environmental enforcement rather than compensating firms in trade-war affected industries. We will elaborate on the political incentive channel in the next section.

[11] The estimated effect of $\Delta USTariff\_City_{it}$ is larger compared to that in our baseline regressions, as the firms with emission monitors are major polluting firms monitored by the government.

5 Mechanism

In the previous section, we learn that cities with higher exposure to the U.S. tariffs have worse air quality, especially at night. Polluting firms located in these cities, regardless of whether they are adversely affected by the trade war, generate excess pollution emissions. In this section, we provide a comprehensive set of evidence to show that the above findings can be rationalized by politically motivated environmental enforcement. Environmental policies make firms internalize pollution externalities by raising their production costs. Accordingly, lenient environmental enforcement serves as a unique type of industrial policy used to subsidize firms. If local governments perceive that the trade war may have a significant adverse effect on the local economy, they tend to relax environmental enforcement to alleviate the adverse shocks of trade protection on the economy (Karplus et al., 2021).

5.1 Environmental enforcement

5.1.1 Environmental stringency index

To directly measure how lenient environmental policies are, we use the text-based environmental stringency index, originally constructed by Chen et al. (2018). Based on local government reports, this index quantifies the extent to which environmental protection and emission reduction are emphasized at the city-year level. It relies on official documents where local authorities delineate their initiatives and strategies concerning various policies. The underlying assumption is that if local officials prioritize environmental concerns, the reports will contain more words and sentences related to the environment. We use 15 keywords and phrases related to environmental enforcement, including PM_{10}, $PM_{2.5}$, SO_2, CO_2, low carbon, emission reduction, COD, pollution, pollutant discharge, environmental protection, protect the environment, ecology, air, green, and energy efficiency. The environmental stringency index for each phrase p in city c in year y is calculated as:

$$\begin{aligned} ESI_{pcy} &= \frac{\#\text{words in phrase } p\text{-related sentences in city } c \text{ year } t\text{'s work report}}{\#\text{words in city } c \text{ year } t\text{'s work report}} \\ ESI_{cy} &= \sum_p \frac{\#\text{words in phrase } p\text{-related sentences in city } c \text{ year } t\text{'s work report}}{\#\text{words in city } c \text{ year } t\text{'s work report}} \end{aligned} \tag{5}$$

We use ESI as the dependent variable and re-estimate equation (3). In Table 4 Column (1), we find a negative and statistically significant effect on $\Delta\ln(\text{USTariff})$. Specifically, as the U.S. tariff increases by 1%, the environmental stringency index decreases by 0.77 units, equivalent to a decrease of 118% compared to the average index value of 0.652. In Column (2), we conduct a phrase-city-year level analysis with phrase fixed effects. Here, we find that a 1% increase in U.S. tariff leads to a 0.07 unit decrease in the phrase-specific stringency index, 1.7 times the mean and 85% of the standard deviation of the index. These results further support our previous findings, indicating that local officials diminish their focus on environmental priorities and pollution reduction in response to higher U.S. tariff burdens.

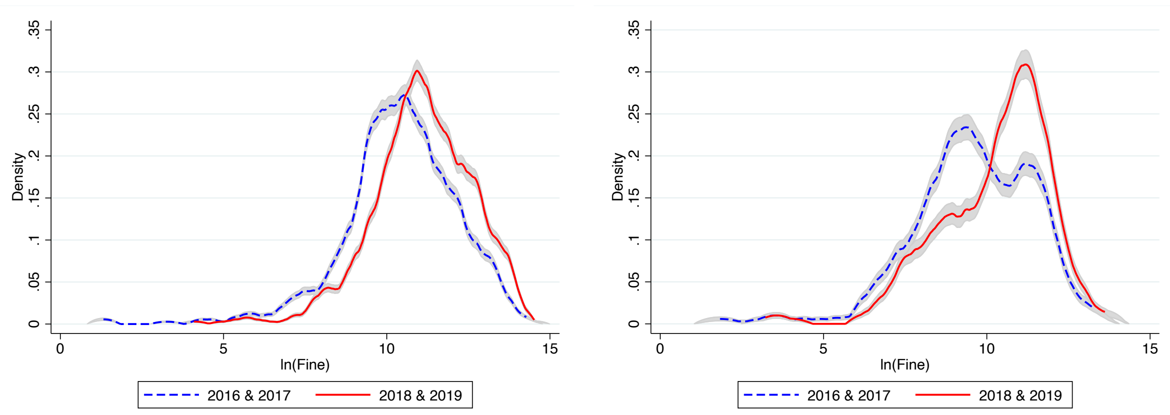
5.1.2 Fines

Apart from measuring environmental enforcement with text analysis, we also measure environmental enforcement using the novel data on environmental penalty. Local environmental agencies conduct inspections on illegal acts and impose fines on firms found to violate environmental regulations. The fines measure firms' opportunity costs of violating environmental rules and are documented and made available through annual releases on government websites. Each fine ticket includes the culpable firm's name, industry affiliation, location, details on illegal acts, fine amount, and environmental agency involved. Additionally, we have access to the release date — when the event is published online — and the event date. However, it is worth noting that the latter is inconsistently recorded, with only 18.9% of records containing the exact event dates. Therefore, we use release dates to determine the timing and aggregate the data at the city-year level.[12]

Figure B5 displays the amount of environmental fines at the city-year level before and after the trade war. The distribution of the whole sample shows an increase in fine amounts in each year in 2016-2019, indicating a rising trend of environmental penalties over time. We then separate cities into high-exposure and low-exposure groups using the classification in Section 4.1.2. In Figure 5, low-exposure cities experience a more pronounced increase in environmental fines. Meanwhile, cities more exposed to U.S. tariffs show mild increases in environmental fines. This graphical evidence suggests that high U.S. tariffs lead to a softening of environmental enforcement and a reduction of opportunity cost of violating environmental regulations, despite an increasing trend nationwide.

Using the fine data, we construct four measures for policy enforcement, namely the number of penalty events, events resulting in fines, total fine amount, and fine amount per event. Results of estimating equation (3) are presented in Table 4 Column (3) to (6). In Column (3), we find U.S. tariffs have negligible impacts on both the number of penalty tickets issued and tickets with fines. This suggests that the local government did conduct more environmental inspections in response to the U.S. tariff increases, despite the significant impact on the deterioration of air quality shown in Section 4.1.2. Under similar levels of policy enforcement, greater pollution levels would lead to more inspections and tickets. Our findings of no discernible effect provide suggestive evidence that local environmental agencies are not as stringent as they were before the trade shock.

[12]Table C12 displays first-difference estimation results using fine months to merge with tariff months. Results demonstrate qualitative consistency with our favored specification in Table 4 Columns (3) to (6). High exposure to U.S. tariffs leads to a reduction in both the overall sum of environmental fines and the fines incurred per individual event. This suggests less stringent penalties being imposed by local environmental agencies.



(a) High-exposure cities

(b) Low-exposure cities

Figure 5: **Environmental fine distribution before and after the trade war**

Notes: We calculate total environmental fine at the city-year level, and plot kernel density curves for high-exposure, and low-exposure cities in Panel (a) and (b) respectively. Grey areas denote the 95% confidence intervals.

In Columns (5) and (6), the estimates for $\Delta USTariff_{it}$ are negative, significant, and large. We find that a 1% increase in U.S. tariffs causes the total fine amount to decrease by 6.9%. We also find that the fine amount per event also decreases significantly by 8.5%. Condition on inspections taking place, higher exposure to U.S. tariffs corresponds to a decrease in financial penalties and a reduction in the opportunity cost of violating environmental regulations. In other words, local environmental agencies adopt less stringent enforcement when cities face elevated tariffs.

We further perform separate estimations of equation (3) using penalty classification in the data. Each event is flagged with serious violations or other violations. Results presented in Table A10 reveal that the decrease in tariff-induced fines is primarily driven by non-serious violations. In Panel B, a 1% increase in U.S. tariffs results in a significant 7.5% decrease in total environmental fines and an 8.9% decrease in the fine amount per event. However, the impact is notably smaller in Panel A, implying penalties for serious environmental violations remain largely unaffected. The relaxation of environmental policy appears to apply to less severe violations primarily.

We also use the number of firms that experienced environmental violations with and without fines as dependent variables. The same firm that was fined multiple times by local environmental agencies is counted once. As presented in Table A11, the estimates on $\Delta USTariff_{it}$ are negative but have low statistical significance. This suggests that there are no significant changes in the number of firms subjected to fines. The observed reduction in fines is less likely attributed to changes in firm composition but a result of behavioral changes from the local environmental agencies.

Since each fine event is coded with violation records, we explore heterogeneity across environmental fines for different pollutants. We separate events into air, water, and solid waste-related violations.

In Table A9 Panel A, we find similar estimates on $\Delta USTariff_{it}$ compared with those in Table 4. This implies that a substantial portion of the local environmental penalties are linked to air pollution violations. In Panel B, we do not observe any effects on water pollution-related fines. In Panel C, Columns (3) and (4) show negative and significant estimates on $\Delta USTariff_{it}$. There is a similar relaxation in solid waste regulation, and the magnitude is similar to air pollution fine decrease.

Table 4: **Tariff effects on environmental stringency index and environmental fine**

	ΔStringency index		Δln(#Events)	Δln(#Events with fine)	Δln(Total fine)	Δln(Fine per event)
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(USTariff)	-0.770**	-0.074***	0.311	0.785	-6.912**	-8.530**
	(0.331)	(0.017)	(0.769)	(0.800)	(3.130)	(3.815)
Δln(CHNTariff)	0.255	0.019	-3.590***	-4.094***	-9.622**	-2.729
	(0.189)	(0.012)	(0.639)	(0.591)	(4.483)	(4.581)
Observations	10008	150120	11880	11880	11880	11880
R-square	0.701	0.714	0.435	0.326	0.301	0.263
Y-mean	0.652	0.043	0.199	0.080	0.285	0.171
Y-sd	0.239	0.087	0.611	0.564	1.671	1.595
Phrase FEs		Y				
City FEs	Y	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. In Column (1) to (2), we stack our sample 12 times to merge city-year level stringency index with city-month level tariff. Column (1) sums all 15 environmental phrases together. Column (2) uses separate ESI for each phrase and adds phrase fixed effects. In Column (3) to (6), we stack our sample 12 times to merge city-year level fine with city-month level tariff. $\#Events$, $\#Events\ with\ fine$, and $Total\ fine$ are divided by 12, i.e. we assume fine events are equally distributed across the year. All six columns include year-month and city fixed effects. Column (2) also adds phrase fixed effects. Standard errors are clustered at the province-year level. Significance: * 0.10, ** 0.05, *** 0.01.

Moreover, we explore the heterogeneity across industries. As illustrated in Figure B6, the decline in environmental fines is particularly noteworthy in manufacturing.[13] Specifically, a 1% increase in U.S. tariffs results in a decrease in fines of 15.2% for computer and electronic equipment manufacturing. The effect size is 8.7% for automobile manufacturing, 8.7% for metal mining, and 21.5% for other manufacturing. Manufacturing and high-end goods industries bear a heavier burden of U.S. tariff escalation. They also experience the strongest decrease in environmental fines, indicating a considerable policy relaxation within these industries. In contrast, changes in environmental fines due to tariff burdens are not statistically significant for research and development, fishery, food production, and pharmaceutical industries.

As a placebo test, we examine the impact of tariff burdens on non-manufacturing industries' environmental fines. Non-manufacturing industries include dining and restaurants, sports, entertainment, insurance, education, hotels, and social work that primarily includes neighborhood committees and street offices. While these industries are subject to environmental fines, they are deemed less

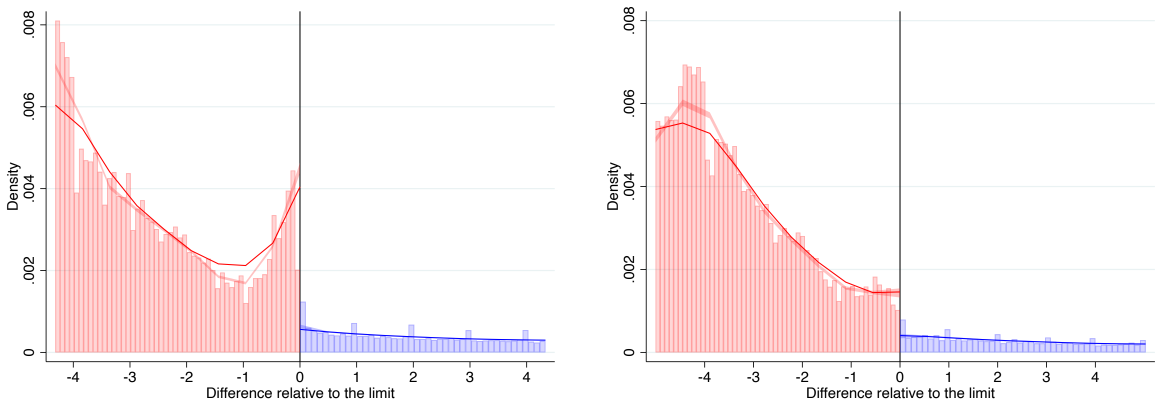
[13]The fines are defined as the total fines for each industry in each city. Alternatively, we also change the dependent variable to the fine per ticket and the results are very robust.

susceptible to the impact of tariff burdens. Results in Table C13 show estimates on $\Delta USTariff_{it}$ are negative but have low statistical significance, indicating no discernible effects of U.S. tariff burdens on these unrelated industries.

5.1.3 Bunching of pollution data

Another measure of lenient environmental policies lies in the manipulation of air pollution data. Both firms' and local officials' career advancements hinge on emission and air quality outcomes, which has been demonstrated to notably stimulate pollution reduction endeavors by local governments (Yin and Wu, 2022). Consequently, local administrations possess strong incentives to manipulate air pollution reports, a phenomenon that is documented by existing empirical studies (Chen et al., 2012; Ghanem and Zhang, 2014). We explore this issue by examining whether firms strategically emit pollutants right below the cutoff point.

We start by investigating the impact of tariff burdens on the tendency of local governments to manipulate firms' emission data. Given that production, emission, and scrubber operation are the result of a complex interplay within firms, the inherent data generation process is expected to exhibit a smooth pattern around the government-defined emission limits. The presence of discontinuities at this point could indicate deliberate efforts to manipulate data in order to attain compliance. Given the differences in emission limits across provinces, sectors, and pollutants, we calculate the difference between actual emission concentrations and the prescribed emission limits. We conduct similar statistical tests to determine the presence of bunching behavior in proximity to the zero difference point. The identification of significant bunching tendencies among negative values would substantiate our hypothesis, suggesting that firms may deliberately underestimate emission intensities in order to align with the stipulated emission limits.



(a) January 2017 - June 2018

(b) July 2018 - December 2019

Figure 6: **Bunching of CEMS data before and after the trade war**

Notes: We use firm-hour level reports of CEMS emissions for SO_2, NO_x, and Particles 2017-2019, and calculate emission concentrations relative to the limits. We test if there are discontinuities around $0\mu g/m^3$. McCrary test shows t-statistics are -52.4778 and -15.682 in the pre- and post-period respectively.

Figure B4 plots the proportion of relative values using each pollutant's regional emission standards. Panel A reveals a notable concentration of relative emissions of 0 from January 2017 to June 2018. During this period, there is a distinct spike in the distribution just below the emission intensity limit. However, Panel B shows a less pronounced spike in proportions from July 2018 to December 2019. The descriptive findings imply that most firms tend to cluster their emission intensities below cutoff points, although this pattern is less prevalent after July 2018.

In Figure 6, we find that bunching activities diminished after the trade war. The data exhibits concentration values towards negative, with conspicuous declines observed after the zero point. These observations imply strategic conduct by firms aimed at ensuring compliance with the emission threshold. Specifically, the density of bunching manifests a more pronounced reduction from 0.004 to 0.001 during the pre-trade war period, followed by a comparatively smaller decrease from 0.002 to 0.001 post the trade war. Corresponding McCrary discontinuity test statistics are -52.5 and -15.7 respectively, signifying diminished bunching endeavors subsequent to the trade war.

If the relaxation of environmental policies results from the combined efforts of firms and local governments, our findings indicate that it is predominantly the local governments that grant leeway to firms regarding their emission levels. Consequently, firms appear to have ceased their efforts to maintain emissions below the prescribed thresholds. Conversely, in a scenario where firms wield greater influence than local governments, one would anticipate an upsurge in data manipulation and an increased prevalence of bunching beneath the threshold in the CEMS data. Our results provide suggestive evidence that the primary authority for permitting elevated pollution emissions lies with local governments, granting polluting firms permission to do so.

In Figure B8, we separately explore bunching patterns before and after the sunset, before and after the trade war. Both daytime and darktime bunching activities were severe before July 2018. Employing McCrary tests with cutoffs at 0, the t-statistics reveal significant values of -41.51 and -50.44 before and after sunset, respectively. Post-July 2018, although the severity of bunching behaviors diminishes, they are still statistically significant. The t-statistics have values of -7.82 prior to sunset and -14.04 thereafter. We conclude that the reduction in efforts to manipulate data in response to the relaxation of environmental enforcement exhibits uniformity across various hours.

As a robustness check, we conduct a falsification test employing a placebo cutoff of $10\mu g/m^3$. Figure B7 visually represents the absence of notable bunching behavior in the vicinity of this threshold. McCrary tests' t-statistics are -0.324 and 0.177 and are no longer statistically significant, further corroborating the robustness of our findings.

Discussion: data manipulation We investigate the possibility of data manipulation in the CEMS data by using satellite-derived pollution levels as a benchmark. The satellite pollution data is sourced from the MCD19A2 V6.1 product, which quantifies aerosol optical depth (AOD) at the grid-day level, with a spatial resolution of 1km. To measure firms' surrounding pollution, we make 15km buffers around firms and project them on the gridded AOD products. Then we calculate the mean AOD at the firm-day level. If correlations between CEMS particle emissions and AOD are different before and after the trade war, the tariff burden may have affected data manipulation efforts. To test this hypothesis, we use AOD as the dependent variable, CEMS particle data as the running variable, and add CEMS interaction with a post-event dummy.

Results in Table A7 Column (1) show a positive and statistically significant estimate for the variable $CEMS$, implying a positive correlation between the CEMS particle data and the satellite AOD measurements. A $1\mu g/m^3$ increase in firms' end-of-pipe emissions corresponds to a 0.07-unit rise in satellite AOD measurements. Focusing on the interaction term, we find a statistically insignificant estimate on $CEMS \times Post$, which implies that the correlation between satellite and CEMS data remains similar both before and after the trade war. The findings suggest that the data quality of the CEMS particle data is similar before and during the trade war and there is not much change triggered by the tariff escalations. Therefore, the main findings in Section 4 are unlikely to stem from the change in the emission data quality before and after the outbreak of the trade war.

Following a similar logic, we employ official air quality monitoring as a benchmark for firms' emissions. The potential of data manipulation is more substantial in firms' end-of-pipe emissions compared to air quality data reported by monitoring stations. Compared with government-owned monitors, firms have a relatively higher opportunity to alter CEMS readings or upload manipulated emission reports onto CEMS websites. To do so, we use the nearest city air quality monitor to merge with firms' emission data. We then employ a difference-in-difference model to estimate the correlation and whether this correlation has changed in the pre and post-trade war periods.

In Table A7 Column (2) and (3), we find positive and significant associations between firms' particle emissions and $PM_{2.5}$ and PM_{10} levels. This confirms a substantial contribution from manufacturing firms and power plants to the overall particulate matter levels within the city. The correlations are slightly stronger for PM_{10} than $PM_{2.5}$, consistent with the fact that manufacturing emissions tend to manifest as larger-sized particulates resembling dust, whereas $PM_{2.5}$ is more likely to originate from chemical conversions and represents an aggregated, steady-state measure of multiple emission sources.

In the second row, estimates on $CEMS \times Post$ are negative, consistent with the result in Column (1) when using satellite AOD serves as the benchmark. The interaction term is also negative and significant when using monitor PM_{10} as the dependent variable. These results provide suggestive evidence that a same-level increase in CEMS emissions corresponds to a proportionally smaller uptick in station-level pollution after the trade war. In other words, with the same magnitude of actual pollution change, CEMS reports had a relatively smaller increase before the trade war, suggesting the possibility of data manipulation and potential underreporting of CEMS emissions are more prevalent in the pre-period. This finding, together with lower bunching efforts after the trade war shown in Figure 6, suggests that firms may not consider it necessary to manipulate emission data if local governments no longer regulate emission activities that much.

5.1.4 Media exposure and public attention

An additional indication of soft environmental enforcement can be observed by analyzing how tariff burdens affect media attention and public awareness of environmental issues. Local government officials in cities facing high tariff burdens would have a reduced emphasis on environmental enforcement, resulting in fewer newspaper reports and web page coverages about environmental concerns. Consequently, this reduced media coverage can then lead to lower public awareness and distract attention from pollution issues.

We measure media coverage with Baidu media index and measure public attention with Baidu search index, where both indexes vary at the county-day level. Baidu is the most popular search engine in China. The Baidu media index is derived from the number of news articles reported by major Internet media and included in Baidu News. The index is calculated based on keywords found in the headlines. Baidu search index serves as an effective indicator of public interest in specific topics. Previous research has shown that this index can reflect public awareness of environmental problems (Barwick et al., 2019; Zheng et al., 2014). We use media and search index for the keyword 'smog' as dependent variables and estimate equation (3).

In Table A17, Column (1) shows a negative and significant estimate on $\Delta USTariff_{it}$, suggesting that the media index on 'smog' significantly decreases with U.S. tariff burdens. Specifically, a 1% increase in U.S. tariffs leads to a 2.1% decrease in the media index. This result is in line with Section 5.1 that local officials pay less attention to environmental issues in response to the escalation of U.S. tariffs. As media in China is subject to strict control by officials, the local media index serves as a reliable proxy for local officials' attention. This finding supports our hypothesis that U.S. tariffs result in an increase in pollution due to the influence of more lenient local environmental policies.

In Columns (2) to (4), we find negative and imprecise estimates on $\Delta USTariff_{it}$, indicating that U.S. tariff burdens have no significant impact on citizens' search behaviors of environmental topics. The decrease in local awareness is much smaller when compared to the decline observed in official media coverage. Despite higher levels of air pollution, citizens show little discussion or concern about environmental issues and their awareness remains unaffected. One potential explanation is the nighttime emissions discussed in Section 4.1.3. The increase in pollution due to tariffs predominantly occurs during dark hours, making it less likely for residents to witness secret pollutant discharges. Consequently, the reduced visibility of these emissions could be a contributing factor to the lack of public environmental concern.

5.2 Political incentives

5.2.1 Local officials' background

Local officials' place of birth, age, and political incentives can significantly influence local pollution emissions (Meng et al., 2019; Yu et al., 2019). To begin with, we test whether local officials are born in the current city using the background information data for party secretaries and mayors of prefecture-level cities between 2017 and 2019 to measure promotion incentives. In Table A12 Panel A, we interact $\Delta USTariff_{it}$ with $Native\ Party$ that equals one if the party secretary is from the same province. We also code $Native\ Mayor$ to indicate if the mayor is from the same province. We find negative estimates on both interaction terms when using AQI as the dependent variable. This implies that cities whose local officials are natives are less likely to experience worsened air pollution in response to the same level of U.S. tariff increases compared to cities with non-native party secretaries. For party secretaries, estimates on interaction terms are negative, large, and significant other pollution indicators as well, except for the $PM_{2.5}$ regression. For mayors, the results are similar. Estimates on $\Delta USTariff_{it} \times Native\ Mayor$ are negative for all pollutants except NO_2, and magnitudes and precision are smaller than party secretaries. A likely explanation for the above findings is that natives care more about cities' long-term sustainable development and personal reputation than short-run economic development and promotion. Therefore, they tend to stick to environmental regulations and are less likely to have rollbacks. Since party secretaries have the highest authority over other administrators on the same level, their political incentives dominate other local leaders, and we find stronger effects for party secretaries than mayors. These political incentives provide suggestive evidence for the trade-off between long-term sustainable development and short-run benefit.

We further assess the heterogeneous effect of age and political incentives. We interact $\Delta USTariff_{it}$ with variable $Old\ Party$ and $Old\ Mayor$ to indicate if the party secretary or city mayor is above the age of 68. This practice is to test whether senior leaders exhibit different responses to U.S. tariff increases compared to their younger counterparts. Table A12 Panel B shows negative estimates on $\Delta USTariff_{it} \times Old\ Party$ when using AQI, SO_2, $PM_{2.5}$ and PM_{10} as dependent variables. Results are not statistically significant when studying mayor age differences, consistent with Table A12 Panel A that party secretaries' incentives play a more important role in environmental policy. Our findings suggest that cities with senior local officials who will retire soon and have fewer chances for promotion have fewer pollution emissions.

In addition, we examine the potential impact of tenure length on local governments' decisions regarding environmental relaxations. When local positions feature shorter tenures, there tends to be a decreased emphasis on long-term environmental performance, with a heightened focus on short-term economic growth instead. In this context, local officials prioritize addressing immediate economic challenges such as tariff exposures, rather than the long-term environmental impact. To delve into this dynamic, we introduce an interaction term between U.S. tariffs and the average duration of tenures in each city. Results presented in Table A12 Panel C reveal negative and statistically significant coefficients on $\Delta USTariff_{it} \times Tenure$. This suggests that local party secretaries with shorter tenures tend to exhibit a more pronounced increase in pollution levels and a greater inclination towards relaxed environmental implementation.

5.2.2 Public budget

In the realm of economic policy, local governments often resort to subsidies or tax relief measures to counterbalance the adverse effects of tariffs, thereby reducing production costs for firms, helping them explore new trade partners, and making trade diversions easier. Our results highlight an alternative approach: the possibility of substituting traditional subsidies with the relaxation of environmental enforcement to mitigate the negative costs of tariff burdens. The environmental relaxation is hypothesized to be prominent in cities facing budget deficits, where financial constraints limit the provision of direct subsidies. In such scenarios, local governments may opt to ease environmental policies as a strategic response to their fiscal challenges. To assess these political incentives, we perform a heterogeneity test of pollution levels in cities with different levels of public budgets.

We obtain local public finance data from the China City Statistical Yearbook. This dataset provides city-year level public expenditure, revenue, and tax collection. To establish the pre-period public budget, we compute the average budget for 2015 and 2016 as the baseline public budget. To explore heterogeneity in local public financing concerning the impact of U.S. tariff escalation, we introduce an additional interaction term on the right-hand side between tariff escalation and cross-sectional budget. This allowed us to test variations in the effects across different levels of local public financing.

The estimation results are presented in Table A13. We find negative and significant estimates on $\Delta USTariff_{it} \times Budget$ when using SO_2 and PM_{10} as dependent variables. This suggests that pollution increases are more pronounced in cities with lower budgets or higher financial deficits. The findings align with our hypothesis, supporting the notion that the provision of public subsidies and the relaxation of environmental enforcement act as substitutions in the face of fiscal constraints.

Furthermore, we examine the impact of U.S. tariffs on government revenues, aiming to ascertain whether local governments reduce tax burdens on local firms to mitigate the adverse effects of trade shocks. We use the actual government revenue, expenditure, and fiscal surplus data in 2017-2019 as dependent variables. As is shown in Table A14, higher U.S. tariffs result in a decrease in government revenue and an increase in expenditure, resulting in a significant reduction in the fiscal surplus. These results affirm that local governments actively adjust their budgets in response to trade shocks.

5.2.3 Heterogeneity across locations

For political incentives, we provide further evidence on how pollution emissions vary across locations. Due to pollution externality, areas closer to administrative boundaries may receive fewer complaints from citizens, and less monitoring and inspection from local governments, leading to more lenient environmental enforcement. To make matters worse, due to the transboundary pollution, local governments may have lower incentives to regulate air quality near boundaries (Gray and Shadbegian, 2004; Du et al., 2020). With full enforcement, all polluters may be regulated in the same way. When enforcement is relaxed, polluters far away from administrative centers may be relaxed first. To test this hypothesis, we geocode the locations of pollution monitors and calculate the distances between each monitor and the nearest administrative boundary. We then interact these distance variables with the tariff burdens to explore whether the pollution increases in response to the tariff burdens are more severe for polluters that are farther away from administrative centers.

Results in Table A15 Panel A and B show positive and significant estimates on $\Delta USTariff_{it}$, indicating a robust relationship between tariff burdens and pollution increases. Estimates on the interaction terms, $\Delta USTariff_{it} \times Dist$ are negative and significant. Monitors located closer to provincial and city boundaries observe a stronger pollution increase in response to the tariff burdens compared to monitors situated closer to administrative centers. These results support our hypothesis that environmental leniency is more prevalent in remote areas near administrative boundaries, where enforcement may be relatively relaxed.

6 Health effects of air pollution rollback

In this section, we examine the mortality effects of increased air pollution by using the identified pollution increases from Section 4.1.2 to construct a counterfactual baseline pollution level in the absence of trade shocks. Focusing on SO_2 pollution, the marginal contribution of U.S. tariff changes is calculated as: *trade shock-free* SO_2 = *observed* SO_2 − *identified* SO_2 increases due to tariffs. We follow a similar procedure for the case of $PM_{2.5}$. The marginal contribution of tariffs is calculated as: *trade shock-free* $PM_{2.5}$ = *observed* $PM_{2.5}$ − *identified* $PM_{2.5}$ increases due to tariffs.

The next step is to estimate air pollution deaths associated with the marginal contribution of tariff burdens. We adopt the methodology outlined by Cropper et al. (2021) to calculate baseline deaths caused by air pollution from anthropogenic sources:

$$\sum_i M_i = \lambda_i \times RR(Pollution_i) \times Population_i \tag{6}$$

where M_i represents deaths in city i. λ_i denotes the death rate at the background level. While λ_i is not observable, we estimate λ_i using mortality caused by baseline air pollution, 4.5 million per year documented by HEI (2020). $RR(Pollution_i)$ is the relative risk of death at the exposure level. $Population_i$ is the population size at the city level. Air pollution deaths without the contribution of tariff changes ($\sum_i \Delta M_i$) can then be estimated as:

$$\sum_i \Delta M_i = \lambda_i \times RR(Pollution_i - TradePollution_i) \times Population_i \tag{7}$$

where $TradePollution_i$ is the identified SO_2 or $PM_{2.5}$ pollution increases in city i.

We separately estimate effects of SO_2 and $PM_{2.5}$ using dose-response functions from Orellano et al. (2021) and Burnett et al. (2018). $PM_{2.5}$ exhibits a concave relationship with mortality risk, with hazard ratios ranging from 1 to 1.8. On the other hand, Orellano et al. (2021) conduct a meta-analysis to aggregate individual results on SO_2 exposure and death risks. They find that an increase of $10\mu g/m^3$ in the 24-hour average exposure to SO_2 is associated with a 1.0059 relative risk for all-cause mortality. Consequently, we employ a linear relative risk function for $PM_{2.5}$ estimates based on its levels, while a constant relative risk is utilized for SO_2 estimates.

Our findings reveal that a 1% increase in U.S. tariffs corresponds to a 1% increase in SO_2 levels and a 0.7% increase in $PM_{2.5}$ levels when considering all city-months collectively. Considering the dose-response function, the elevated levels of SO_2 resulting from tariff burdens are associated with a 1.1% increase in health risks or approximately 39.2 thousand additional air pollution-induced deaths from 2017 to 2019. Similarly, for $PM_{2.5}$, a 1.4% increase or approximately 49.9 thousand additional deaths can be attributed to pollution stemming from environmental rollbacks. It is important to note that air pollution encompasses the accumulation of various pollutants, and as such, we do not attempt to combine these two values, as the effects are not mutually exclusive. Consequently, we consider the estimate of 1.4% additional deaths to be the lower bound for mortality resulting from intensified air pollution.

Earlier studies on the health effects of anthropogenic air pollution vary to a large degree. Vohra et al. (2021) documents 10.2 million global excess deaths per year are due to $PM_{2.5}$ from fossil fuel combustion. In the U.S., 350,000 premature deaths are attributed to emissions from the fossil industry. The number in India is 2.5 million people per year, representing over 30% of all-cause deaths. Penney et al. (2009) estimates 6,000 to 10,700 annual deaths are attributed to 88 publicly-financed coal power plants worldwide. Cropper et al. (2021) conclude that 112,000 deaths are attributable annually to coal-fired power plants in India. Lueken et al. (2016) finds between 7,500 and 52,000 people in the U.S. could be saved if switching from all coal plants to gas, equivalent to between \$20 billion and \$50 billion in monetized benefits. In Europe, Kushta et al. (2021) identifies 18,400-105,900 deaths are avoided from the phase-out of coal power plants' emissions. In Africa, Marais et al. (2019) show 48,000 premature deaths due to fossil fuel electricity generation. Results in our paper per unit pollution increase lie in the wide range of previous estimates. Our findings indicate the significant impact of tariff-induced policy relaxation on air pollution-caused deaths.

The health effects are not evenly distributed across Chinese cities. Cities with high exposure experience greater increases in U.S. tariffs, higher levels of air pollution, and more severe health burdens. The relationship between each city's health burden and socioeconomic variables is presented in Table A16. Our findings indicate that high-income cities with larger populations and higher export values bear the brunt of health burdens. This aligns with our calculation of tariff exposure based on export structures. In summary, our analysis does not reveal evidence of environmental injustice concerns resulting from the pollution increases or mortality effects caused by trade shocks.

7 Conclusion

This paper studies the impact of economic growth on the environment. The Environmental Kuznets Curve (EKC) suggests that there is an inverted U-shaped curve between income and pollution. This relationship is mainly driven by citizens' preferences. As countries become richer, there is growing environmental awareness among citizens, and governments are better able to address environmental issues through stricter regulations and enforcement. In this paper, we contribute to the literature on economic growth and environment by exploring a novel channel, namely political incentive.

The trade war offers a good setting to study how politicians respond to perceived risks of economic downturns. The U.S. tariffs have triggered protectionism worldwide and there has been a growing literature studying the economic consequences of the trade war. The U.S. tariffs have been found to reduce imports from China, increase U.S. import prices, reduce affected firms' market value, and hinder China's economic growth. Nevertheless, little is known about the environmental consequences.

In this paper, we seek to reveal the hidden cost of the trade war and study the impact of tariff escalation on pollution. Politicians are usually confronted with a difficult trade-off, as they need to balance economic growth with environmental protection. When faced with perceived risks of economic slowdown, politically motivated politicians opt to ease the enforcement of environmental regulations. Despite the importance of this channel, there is limited empirical evidence. We fill the gap and explore this trade-off in the context of the U.S.-China trade war, where the series of protective tariffs were raised unexpectedly.

We find that cities exposed to higher U.S. tariffs had worse air quality. In the main analysis, we use the air quality monitor data to explore the environmental consequences of the tariff increase. As the tariff burden increases by 1%, SO_2 and $PM_{2.5}$ increase by 0.9% and 0.7%, respectively. The additional pollutants are mostly emitted after sunset and before sunrise, suggesting that local officials soften environmental enforcement during the trade war. To further explore the mechanism, we find that high-exposure cities also place less emphasis on environmental enforcement based on a text-based stringency index from local government reports.

More substantial pollution increases near provincial boundaries using hourly monitor-level air quality data. The above evidence suggests that local government officials adopt lenient environmental policies to mitigate the negative effect on economic activities when the economy is at a heightened risk of economic downturn.

To sum up, the trade war provides us with an exogenous source of perceived economic risks, which allows us to investigate how local officials' political incentives affect firms' pollution emissions. Our findings suggest that local officials tend to ease the enforcement of environmental regulations in an effort to confront the challenges posed by the trade war and mitigate the looming threat of economic downturn.

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A Appendix: Tables

Background

Table A1: Timeline

Wave	Date of implementation	Event
Panel A. United States		
Prelude 1	2018-02-07	The U.S. imposes 30% tariffs on solar panels and 20% on washing machines under two Section 201 cases.
Prelude 2	2018-03-23	The U.S. imposes 25 % Section 232 tariffs on steel and 10 % Section 232 tariffs on aluminum imported from China and other countries, temporarily exempting Argentina, Australia, Brazil, Canada, Mexico, the European Union, and South Korea.
Wave 1	2018-07-06	The U.S. imposes 25% Section 301 tariffs on $34 billion of imports from China.
Wave 2	2018-08-23	The U.S. imposes 25% Section 301 tariffs on $16 billion of imports from China.
Wave 3	2018-09-24	The U.S. imposes 10% Section 301 tariffs on $200 billion of imports from China.
Wave 4	2019-06-15	The U.S. raises Section 301 tariffs from 10% to 25% on $200 billion of imports from China.
Wave 5	2019-09-01	The U.S. imposes 15% tariffs on $101 billion of imports from China.
Panel B. China		
Prelude 1	2018-04-02	China imposes 15% or 25% retaliatory tariffs on $2.4 billion of imports from the U.S. in response to U.S. Section 232 tariffs on steel and aluminum tariffs.
Wave 1	2018-07-06	China imposes 25% retaliatory tariffs on $34 billion of imports from the U.S. in response to U.S. Section 301 tariffs imposed on July 6, 2018.
Wave 2	2018-08-23	China imposes 25% retaliatory tariffs on $16 billion of imports from the U.S. in response to U.S. Section 301 tariffs imposed on August 23, 2018.
Wave 3	2018-09-24	China imposes 5% or 10% retaliatory tariffs on $60 billion of imports from the U.S. in response to U.S. Section 301 tariffs imposed on September 24, 2018.
Wave 4	2019-06-01	China imposes an additional 5%, 10%, or 15% tariffs on a subset of the existing product list implemented on September 24, 2018, in response to the U.S. Section 301 tariff increase imposed on June 15, 2019.
Wave 5	2019-09-01	China imposes an additional 5% or 10% tariffs on $75 billion of imports from the U.S. in response to the U.S. Section 301 tariff increase imposed on September 1, 2019.

Table A2: Before vs. after working hours (8 a.m.-6 p.m.)

	Off hour - working hour				
	$\Delta\Delta\ln(AQI)$	$\Delta\Delta\ln(SO_2)$	$\Delta\Delta\ln(NO_2)$	$\Delta\Delta\ln(PM_{2.5})$	$\Delta\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	9.801***	2.279	1.151	6.250***	11.583***
	(2.343)	(1.440)	(1.089)	(1.780)	(2.425)
$\Delta\ln$(CHNTariff)	-2.744**	-0.018	1.691***	-1.804*	-2.329
	(1.383)	(1.056)	(0.437)	(0.990)	(1.793)
Observations	48855	48855	48855	48855	48855
R-square	0.066	0.078	0.124	0.064	0.055
Y-mean	-0.169	0.068	0.073	-0.012	-0.034
Y-sd	2.057	1.353	0.955	1.597	2.284
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table A3: Dynamic effects by quarter

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)$\times$ 2018q3	-2.851***	-4.270***	-1.955**	-4.981***	-3.573***
	(0.588)	(1.646)	(0.936)	(1.083)	(0.728)
$\Delta\ln$(USTariff)$\times$ 2018q4	1.959***	0.135	3.924***	2.611***	2.018***
	(0.627)	(0.988)	(0.623)	(0.861)	(0.743)
$\Delta\ln$(USTariff)$\times$ 2019q1	1.507**	-0.687	2.486***	0.986	2.713***
	(0.590)	(0.929)	(0.623)	(0.830)	(0.651)
$\Delta\ln$(USTariff)$\times$ 2019q2	0.267	-2.643***	1.048*	1.278**	0.226
	(0.342)	(0.869)	(0.545)	(0.619)	(0.481)
$\Delta\ln$(USTariff)$\times$ 2019q3	.124	1.61***	.538	.0703	.124
	(.226)	(.612)	(.421)	(.363)	(.306)
$\Delta\ln$(USTariff)$\times$ 2019q4	.689**	2.81***	-.454	.976**	.724*
	(.311)	(.716)	(.426)	(.432)	(.416)
$\Delta\ln$(CHNTariff)	-.124	-.0974	.35**	-.673***	-.0633
	(.135)	(.275)	(.15)	(.183)	(.158)
Observations	48868	48868	48868	48868	48868
R-square	0.277	0.187	0.195	0.234	0.280
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
FEs	Monitor, Prov-Month, Year-Month; $\Delta\ln$(USTariff) $\times$ 2017q1 to 2018q2				

Notes: Standard errors are clustered at the monitor-month level.

Firm-level pollution emission

Table A4: Heterogeneity across firms with and without scrubbers

	Δln(Particles)	Δln(SO_2)	Δln(NO_x)
	Panel A: Merged sample		
Δln(USTariff)	21.660	-8.399	-18.725*
	(16.854)	(21.583)	(11.113)
Δln(USTariff)× SO2 scrubber	14.494	33.278*	-0.744
	(16.429)	(18.152)	(9.943)
Δln(CHNTariff)	9.715**	-12.550**	-4.960
	(4.747)	(5.797)	(3.276)
Observations	1363	1241	1317
R-square	0.425	0.526	0.407
Y-mean	-0.391	-0.339	-0.134
Y-sd	1.186	1.179	0.897
	Panel B: All CEMS sample		
Δln(USTariff)	13.612	22.819	-7.950
	(8.351)	(14.601)	(8.677)
Δln(USTariff)× SO2 scrubber	9.653	0.066	-9.815
	(11.214)	(11.600)	(7.885)
Δln(CHNTariff)	2.584	-10.210**	-0.703
	(3.037)	(4.442)	(2.210)
Observations	3965	3689	3705
R-square	0.515	0.522	0.515
Y-mean	-0.271	-0.276	-0.155
Y-sd	1.111	1.300	1.035
Firm FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Sample period is 2018-2019. Firms are required to report data every quarter. Standard errors are clustered at the province level.

Table A5: Heterogeneity across firm ownership

	Panel A: Private firms		
	Δln(Particles)	Δln(SO_2)	Δln(NO_x)
Δln(USTariff)	16.171*	25.612*	-9.124
	(9.069)	(13.015)	(9.376)
Δln(CHNTariff)	2.784	-9.347*	0.284
	(2.988)	(5.073)	(2.520)
Observations	3851	3595	3614
R-square	0.514	0.523	0.515
	Panel B: Foreign financed firms		
Δln(USTariff)	23.085	75.669	52.079
	(26.080)	(51.650)	(31.407)
Δln(CHNTariff)	0.737	8.128	18.050
	(12.098)	(13.859)	(17.156)
Observations	609	575	567
R-square	0.712	0.565	0.423
Y-mean	-0.139	-0.182	-0.134
Y-sd	1.076	1.244	1.110
	Panel C: State owned enterprises		
Δln(USTariff)	9.021	19.075	-7.951
	(26.543)	(43.362)	(19.098)
Δln(CHNTariff)	30.038*	4.327	-10.686
	(16.087)	(30.051)	(35.472)
Observations	319	266	253
R-square	0.679	0.706	0.808
Firm FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Sample period is 2018-2019. Firms are required to report data every quarter. Standard errors are clustered at the province level.

Table A6: Firm emissions before vs. after sunset

	Panel A: Daytime		
	$\Delta\ln$(Particles)	$\Delta\ln(SO_2)$	$\Delta\ln(NO_x)$
$\Delta\ln$(USTariff)	15.909*	12.566*	-14.479**
	(9.197)	(6.878)	(6.288)
$\Delta\ln$(CHNTariff)	3.431	-8.838	-0.382
	(4.129)	(8.536)	(2.807)
Observations	3058	2935	3006
R-square	0.489	0.483	0.410
Y-mean	-0.284	-0.293	-0.132
Y-sd	1.036	1.160	0.879
	Panel B: Nighttime		
$\Delta\ln$(USTariff)	18.340	22.953**	-10.737*
	(16.451)	(10.912)	(5.828)
$\Delta\ln$(CHNTariff)	3.248	-12.100	0.850
	(4.047)	(7.758)	(3.554)
Observations	2627	2607	2643
R-square	0.508	0.463	0.456
Y-mean	-0.340	-0.292	-0.116
Y-sd	0.959	1.291	0.932
Firm FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Sample period is 2018-2019. Firms are required to report data every quarter. Standard errors are clustered at the province level.

Table A7: Correlation: CEMS vs. satellite AOD vs. station-level air quality data

	Satellite AOD	Monitor station PM_{10}	Monitor station $PM_{2.5}$
CEMS	0.070*	0.029***	0.014***
	(0.037)	(0.007)	(0.005)
CEMS × Post	-0.139	-0.028*	-0.014
	(0.090)	(0.015)	(0.011)
Observations	27983	26481	26406
R-square	0.662	0.750	0.745
Y-mean	626.941	72.864	40.816
Y-sd	208.329	32.779	20.668
Firm FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Sample period is 2017-2019. Standard errors are clustered at the province-month level.

Table A8: Number of firms in the CEMS data

	Δln(#Firms with Particles data)	Δln(#Firms with SO_2 data)	Δln(#Firms with NO_x data)
Δln(USTariff)	17.884***	21.189***	26.785***
	(5.261)	(6.049)	(7.338)
Δln(CHNTariff)	0.137	0.791	1.194
	(2.368)	(1.831)	(1.837)
Observations	2090	1979	1974
R-square	0.625	0.624	0.601
Y-mean	0.219	0.215	0.227
Y-sd	1.260	1.260	1.222
City FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Standard errors are clustered at the province level.

Mechanism

Table A9: Tariff and environmental fine: separate by pollution types

	Δln(#Events)	Δln(#Events with fine)	Δln(Total fine)	Δln(Fine per event)
	(1)	(2)	(3)	(4)
Panel A: Air pollution				
Δln(USTariff)	0.298	0.768	-6.751**	-8.370**
	(0.769)	(0.798)	(3.134)	(3.823)
Δln(CHNTariff)	-3.557***	-4.058***	-9.620**	-2.794
	(0.638)	(0.591)	(4.484)	(4.581)
Observations	11880	11880	11880	11880
R-square	0.434	0.326	0.301	0.263
Y-mean	0.199	0.081	0.286	0.171
Y-sd	0.612	0.565	1.668	1.595
Panel B: Water pollution				
Δln(USTariff)	0.050	0.075	4.689	6.267
	(0.104)	(0.103)	(3.528)	(4.415)
Δln(CHNTariff)	-0.054*	-0.022	-1.894	-3.115
	(0.030)	(0.027)	(1.634)	(2.165)
Observations	11880	11880	11880	11880
R-square	0.451	0.446	0.140	0.134
Y-mean	-0.002	-0.003	0.078	0.102
Y-sd	0.090	0.086	2.549	3.279
Panel C: Solid waste pollution				
Δln(USTariff)	0.043	-0.097***	-6.319***	-9.040***
	(0.047)	(0.022)	(1.588)	(2.210)
Δln(CHNTariff)	0.013	0.012	1.196	1.738
	(0.019)	(0.010)	(0.855)	(1.169)
Observations	11880	11880	11880	11880
R-square	0.044	0.098	0.152	0.159
Y-mean	0.000	0.000	0.008	0.014
Y-sd	0.032	0.019	0.776	1.038
City FEs	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. We stack our sample 12 times to merge city-year level fine with city-month level tariff. *#Events*, *#Events with fine*, and *Total fine* are divided by 12, i.e. we assume fine events are equally distributed across the year. All columns include year-month and city fixed effects. Standard errors are clustered at the province-year level.

Table A10: Tariff and environmental fine: serious and other violation

	Panel A: Serious violation			
	Δln(#Events)	Δln(#Events with fine)	Δln(Total fine)	Δln(Fine per event)
	(1)	(2)	(3)	(4)
Δln(USTariff)	0.606***	0.526***	3.692	-0.635
	(0.189)	(0.140)	(5.789)	(7.173)
Δln(CHNTariff)	-0.159	-0.160	-8.090**	-9.531**
	(0.190)	(0.147)	(4.018)	(4.838)
Observations	11880	11880	11880	11880
R-square	0.309	0.260	0.264	0.261
Y-mean	0.019	0.010	0.545	0.672
Y-sd	0.127	0.089	3.982	4.895
	Panel B: Other violation			
Δln(USTariff)	0.087	0.694	-7.533**	-8.887**
	(0.775)	(0.811)	(3.151)	(3.798)
Δln(CHNTariff)	-3.621***	-4.096***	-9.329**	-2.423
	(0.660)	(0.588)	(4.489)	(4.579)
Observations	11880	11880	11880	11880
R-square	0.432	0.326	0.298	0.261
Y-mean	0.195	0.078	0.272	0.164
Y-sd	0.614	0.565	1.678	1.592
City FEs	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. We stack our sample 12 times to merge city-year level fine with city-month level tariff. *#Events*, *#Events with fine*, and *Total fine* are divided by 12, i.e. we assume fine events are equally distributed across the year. All columns include year-month and city fixed effects. Standard errors are clustered at the province-year level.

Table A11: Tariff and the number of firms with environmental violations

	Δln(#Firms)	Δln(#Firms with fine)
	(1)	(2)
Δln(USTariff)	-0.934	-0.863
	(1.154)	(1.249)
Δln(CHNTariff)	-5.684***	-6.953***
	(1.096)	(1.469)
Observations	11880	11880
R-square	0.471	0.333
Y-mean	0.301	0.121
Y-sd	0.904	0.871
City FEs	Y	Y
Province time trends	Y	Y
Year-Month FEs	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. We stack our sample 12 times to merge city-year level firm count with city-month level tariff. Both columns include year-month and city fixed effects. Standard errors are clustered at the province-year level.

Table A12: Heterogeneity across local leader characteristics

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
	Panel A: Native provinces or not				
Δln(USTariff)	1.033***	3.107***	3.347***	0.466	1.265***
	(0.275)	(0.619)	(0.405)	(0.416)	(0.354)
Δln(USTariff)$\times$ Native Party	-0.475*	-3.492***	-3.252***	0.129	-0.760**
	(0.288)	(0.636)	(0.416)	(0.425)	(0.362)
Δln(USTariff)$\times$ Native Mayor	-1.672*	-0.715	2.432*	-1.599	-1.188
	(0.941)	(1.817)	(1.283)	(1.350)	(1.368)
Δln(CHNTariff)	-0.018	-0.380	0.323**	-0.578***	0.156
	(0.138)	(0.257)	(0.147)	(0.188)	(0.159)
Observations	44375	44375	44375	44375	44375
R-square	0.231	0.170	0.173	0.192	0.243
Y-mean	-0.047	-0.195	-0.027	-0.073	-0.062
Y-sd	0.218	0.403	0.269	0.293	0.270
	Panel B: Above or below 68				
Δln(USTariff)	0.662***	0.471	0.905***	0.564*	0.701***
	(0.198)	(0.441)	(0.288)	(0.298)	(0.253)
Δln(USTariff)$\times$ Old Party	-1.032	-8.443***	0.855	-2.827	-2.959*
	(1.235)	(2.258)	(1.678)	(1.960)	(1.564)
Δln(USTariff)$\times$ Old Mayor	0.905	9.644**	2.248	0.575	0.395
	(2.202)	(4.243)	(2.425)	(3.244)	(2.888)
Δln(CHNTariff)	-0.020	-0.405	0.230	-0.549***	0.163
	(0.138)	(0.259)	(0.147)	(0.192)	(0.159)
Observations	44375	44375	44375	44375	44375
R-square	0.231	0.170	0.171	0.192	0.243
Y-mean	-0.047	-0.195	-0.027	-0.073	-0.062
Y-sd	0.218	0.403	0.269	0.293	0.270
	Panel C: Local leaders' tenure length				
Δln(USTariff)	1.169***	0.103	2.450***	3.391***	0.572
	(0.448)	(1.051)	(0.675)	(0.655)	(0.566)
Δln(USTariff)$\times$ Tenure Party	-0.132	0.068	-0.471**	-0.896***	0.086
	(0.131)	(0.298)	(0.207)	(0.193)	(0.165)
Δln(CHNTariff)	-0.112	0.033	0.440***	-0.620***	-0.056
	(0.136)	(0.274)	(0.152)	(0.183)	(0.160)
Observations	45182	45182	45182	45182	45182
R-square	0.230	0.172	0.175	0.193	0.241
Y-mean	-0.047	-0.196	-0.027	-0.073	-0.063
Y-sd	0.218	0.404	0.270	0.292	0.270
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table A13: Heterogeneity across local government budgets

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
Δln(USTariff)	0.581***	0.586	0.929***	0.823***	0.530**
	(0.191)	(0.455)	(0.273)	(0.293)	(0.243)
Δln(USTariff)$\times$ Budget	-0.004	-0.088***	0.003	0.027**	-0.032***
	(0.009)	(0.019)	(0.010)	(0.011)	(0.010)
Δln(CHNTariff)	-0.096	-0.114	0.430***	-0.633***	-0.031
	(0.134)	(0.272)	(0.149)	(0.182)	(0.158)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.170	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table A14: Tariff and local government budgets

	Δln(Revenue)	Δln(Expenditure)	Δln(Fiscal surplus)
Δln(USTariff)	-11.592	95.376	-106.968**
	(38.870)	(69.073)	(52.433)
Δln(CHNTariff)	-92.575***	-152.126***	59.551**
	(10.949)	(29.615)	(26.714)
Observations	9264	9264	9264
R-square	0.996	0.994	0.955
Y-mean	246.752	471.445	-224.693
Y-sd	365.770	429.102	136.699
City FEs	Y	Y	Y
Province time trends	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: We stack our sample 12 times to merge city-year level public budgets with city-month level tariff. Standard errors are clustered at the province-month level.

Table A15: Heterogeneity across distances to local boundaries

	Panel A: Provincial boundaries				
	$\Delta\ln(\text{AQI})$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	1.018***	1.496**	1.417***	1.701***	0.893**
	(0.279)	(0.606)	(0.382)	(0.422)	(0.349)
$\Delta\ln$(USTariff)$\times$ Dist	-0.006**	-0.008	-0.007	-0.014***	-0.003
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)
$\Delta\ln$(CHNTariff)	-0.095	-0.113	0.432***	-0.629***	-0.031
	(0.134)	(0.272)	(0.149)	(0.182)	(0.158)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.169	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
	Panel B: City boundaries				
$\Delta\ln$(USTariff)	0.956***	-0.911*	0.553*	1.413***	1.165***
	(0.245)	(0.528)	(0.328)	(0.372)	(0.308)
$\Delta\ln$(USTariff)$\times$ Dist	-0.014**	0.072***	0.014	-0.027***	-0.020**
	(0.007)	(0.013)	(0.009)	(0.010)	(0.009)
$\Delta\ln$(CHNTariff)	-0.104	-0.077	0.437***	-0.647***	-0.042
	(0.134)	(0.273)	(0.150)	(0.181)	(0.158)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.170	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table A16: Mortality effects and city covariates

	$PM_{2.5}$-induced mortality increase		
GDP	0.405		
	(0.603)		
Population		8.579	
		(5.797)	
Export value added			0.001
			(0.001)
Observations	288	329	329
R-square	0.002	0.007	0.005
Y-mean	0.442	0.416	0.416
Y-sd	0.332	0.337	0.337

Notes: Sample period is average effect at the city level in 2017-2019.

Table A17: Tariff and media and search index on “smog”

	Media index	Search index		
		Overall	PC	Mobile
Δln(USTariff)	-2.128***	-0.334	-0.001	-0.177
	(0.591)	(1.541)	(1.661)	(1.384)
Δln(CHNTariff)	1.090***	-0.224	-0.622	-0.555
	(0.245)	(0.681)	(0.952)	(0.763)
Observations	10656	10656	10656	10656
R-square	0.917	0.863	0.788	0.833
Y-mean	2.434	3.812	2.658	3.358
Y-sd	1.849	1.422	1.427	1.476
County FEs	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y

Notes: Standard errors are clustered at the province-month level.

Table A18: Tariffs and exports

	(1)	(2)	(3)	(4)
	Export to the U.S.		to third countries	
	$\Delta ln(V)$	$\Delta ln(Q)$	$\Delta ln(V)$	$\Delta ln(Q)$
Δln(USTariff)	-0.60***	-0.58***	0.14**	0.10**
	(0.12)	(0.12)	(0.06)	(0.05)
Δln(Tariff_world)			-0.22	-0.07
			(0.29)	(0.28)
Observations	109,340	108,968	4,479,791	4,434,843
R-squared	0.31	0.29	0.19	0.18
HS-6 FE	YES	YES	NO	NO
HS-6 $\times$ Country FE	NO	NO	YES	YES
Country $\times$ Year-month FE	NO	NO	YES	YES
Year-month FE	YES	YES	NO	NO

Notes. Columns (1) - (4) report the impact of year-to-year log change of U.S. tariff on year-to-year log change of export values and quantities. Columns (1) and (2) include HS-6 product fixed effects and time fixed effects. Columns (3) - (4) include HS-6-product-country fixed effects and country-time fixed effects. For Columns (1) and (2), we use China's monthly HS-8-product-level export data to the U.S. from January 2017 to December 2019. For Columns (3) and (4), we use China's monthly HS-8-product-country-level export data to third countries from January 2017 to December 2019. Regressions in Columns (1) and (2) are weighted by last year's HS-8 product-level export value. Regressions in Columns (3) - (4) are weighted by last year's HS-8 product-country-level export value. Standard errors in Columns (1) and (2) are clustered by HS-6 product. Standard errors in Columns (3) - (4) are clustered by HS-6 product and country. Significance: * 0.10, ** 0.05, *** 0.01.

Table A19: **Summary statistics**

	Obs	Mean	SD	Min	Max	P1	P5	P10	P25	P75	P90	P95	P99
Panel A. China													
$\Delta lnp^*_{igt}q_{igt}$	2,127,210	0.00	0.71	-14.89	14.81	-1.86	-0.82	-0.50	-0.19	0.20	0.50	0.82	1.87
Δlnq_{igt}	2,127,210	0.00	0.76	-18.66	18.73	-1.91	-0.83	-0.52	-0.19	0.20	0.51	0.83	1.90
Δlnp^*_{igt}	2,127,210	0.00	0.39	-17.39	16.11	-1.14	-0.34	-0.17	-0.05	0.06	0.17	0.33	1.13
Δlnp_{igt}	2,127,210	0.00	0.39	-17.39	16.11	-1.14	-0.34	-0.17	-0.05	0.06	0.17	0.33	1.13
$\Delta ln(1+\tau_{igt})$	2,127,210	0.00	0.01	-0.37	0.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B. United States													
$\Delta lnp^*_{igt}q_{igt}$	3,318,350	-0.00	0.66	-11.04	11.57	-1.96	-0.78	-0.48	-0.19	0.19	0.46	0.76	1.93
Δlnq_{igt}	3,318,350	-0.00	0.73	-16.75	16.61	-2.24	-0.86	-0.52	-0.20	0.19	0.50	0.83	2.20
Δlnp^*_{igt}	3,318,350	0.00	0.52	-15.60	15.47	-1.60	-0.47	-0.22	-0.06	0.07	0.23	0.46	1.62
Δlnp_{igt}	3,318,350	0.00	0.52	-15.60	15.47	-1.60	-0.46	-0.22	-0.06	0.07	0.24	0.46	1.63
$\Delta ln(1+\tau_{igt})$	3,318,350	0.00	0.01	-0.44	0.40	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06

Notes. All the statistics are weighted by the country-product-level import data in 2017. For China and the U.S., product codes are defined at the HS-8 level and HS-10 level, respectively. Sample in Panel A: China's monthly country-HS-8-product-level import data from all countries from 2017:1 to 2019:12. Sample in Panel B: U.S. monthly country-HS-10-product-level import data from all countries from 2017:1 to 2019:12.

B Appendix: Figures

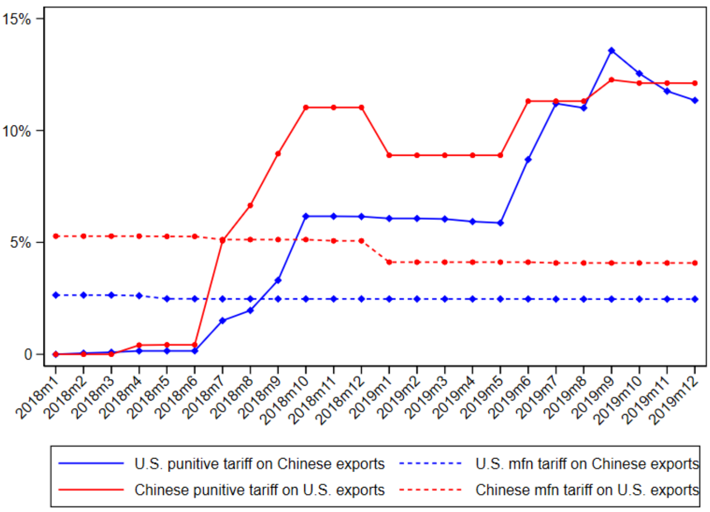


Figure B1: U.S. and Chinese tariffs

Notes: The figure presents the U.S. punitive tariffs on Chinese products (solid blue) and its MFN tariffs (dash-dotted blue), as well as the import-weighted average Chinese retaliatory tariff rates on U.S. products (solid red) and its MFN tariffs (dash-dotted red). U.S. tariffs are weighed by the U.S. country-HS-10-product-level imports in 2017. Chinese tariffs are weighed by China's country-HS-8-product-level imports in 2017.
Source: Authors' calculations based on data from China's Ministry of Commerce, Customs General Administration of China, the United States Census Bureau, United States Trade Representative (USTR), and United States International Trade Commission.

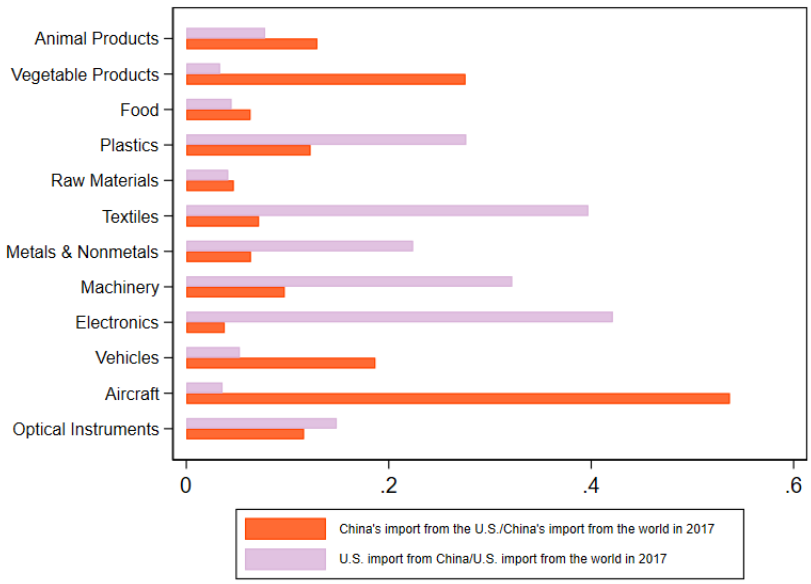
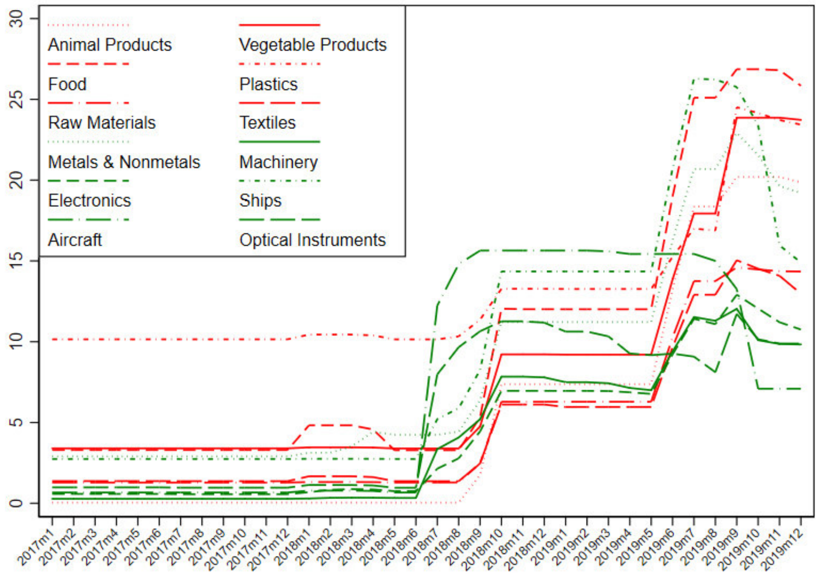
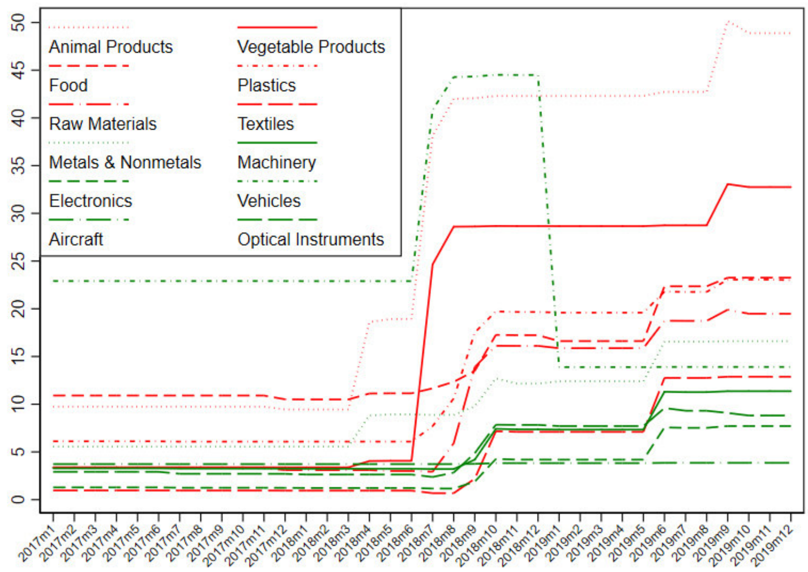


Figure B2: Import share by products

Notes: The figure presents China's imports from U.S. as a share of its total imports from the world (orange) and U.S. import share from China in 2017 (pink) by product category. Food refers to cooking oil, sugar, drinks, and tobacco. Plastics refers to plastics, leathers, wood, and paper. Raw Materials refers to chemicals, crude oil, and mineral products. Textiles refers to textiles and footwear, toys, and furniture. Electronics includes electronics and equipment. Vehicles includes motor vehicles, ships, and boats. Aircraft includes aircraft, railways, and weapons.
Source: Authors' calculations based on data from UN Comtrade.



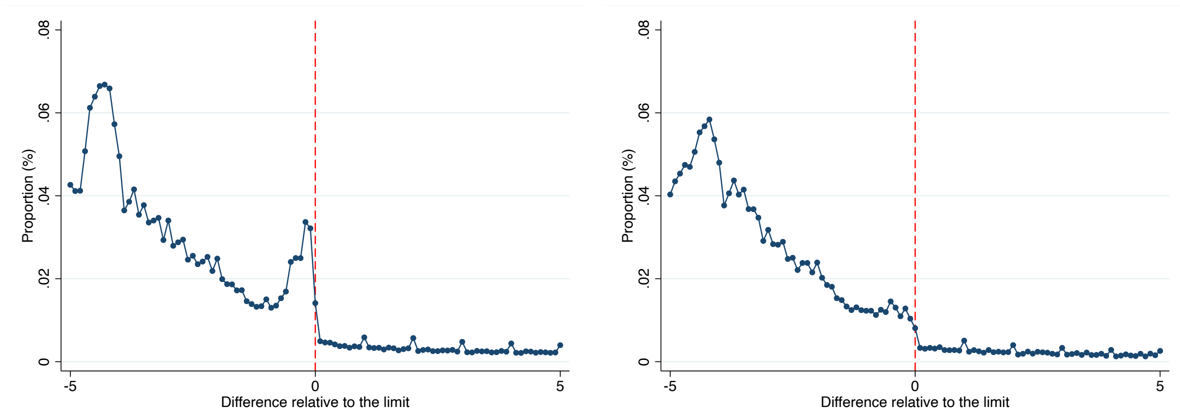
(a) U.S. statutory tariffs (%)



(b) Chinese statutory tariffs (%)

Figure B3: U.S. and Chinese statutory tariffs by products

Notes: Panel A presents the import-weighted U.S. tariff on Chinese products by industry, where weights are U.S. HS-10 imports from China in 2017. Panel B presents the import-weighted Chinese tariff rates on U.S. products by industry, where weights are China's imports from the U.S. in 2017 varying by HS-8. Food refers to cooking oil, sugar, drinks, and tobacco. Plastics refers to plastics, leathers, wood, and paper. Raw Materials refer to chemicals, crude oil, and mineral products. Textiles refer to textiles and footwear, toys, and furniture. Electronics refers to electronics and equipment. Vehicles refer to motor vehicles, ships, and boats. Aircraft refers to aircraft, railways, and weapons.
Source: Authors' calculations based on data from China's Ministry of Commerce, Customs General Administration of China, the United States Census Bureau, the United States Trade Representative (USTR), and the United States International Trade Commission (USITC).

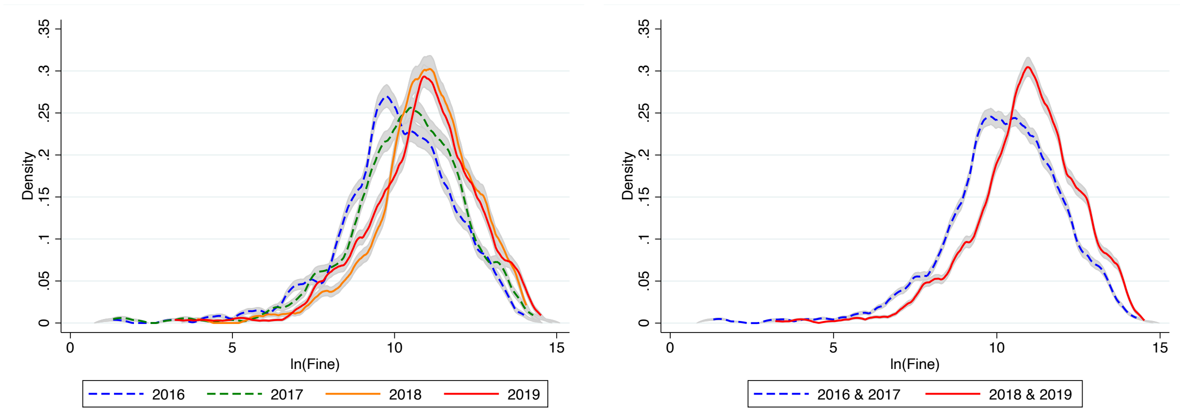


(a) January 2017 - June 2018

(b) July 2018 - December 2019

Figure B4: Distribution of CEMS data using emission relative to standard

Notes: We use firm-hour level reports of CEMS emissions for SO_2, NO_x, and Particles 2017-2019, and calculate emission concentrations relative to the limits. The connected dots show the proportion of relative values for each 0.1 interval. The reductions in bunching behaviors before and after the trade war are consistent with the results on the reduction in the opportunity cost of pollution emission in Table C12.



(a) All cities, histogram in each year

(b) All cities

Figure B5: Environmental fine distribution

Notes: We calculate total environmental fine at the city-year level, and plot kernel density curves for all cities. Grey areas denote the 95% confidence intervals.

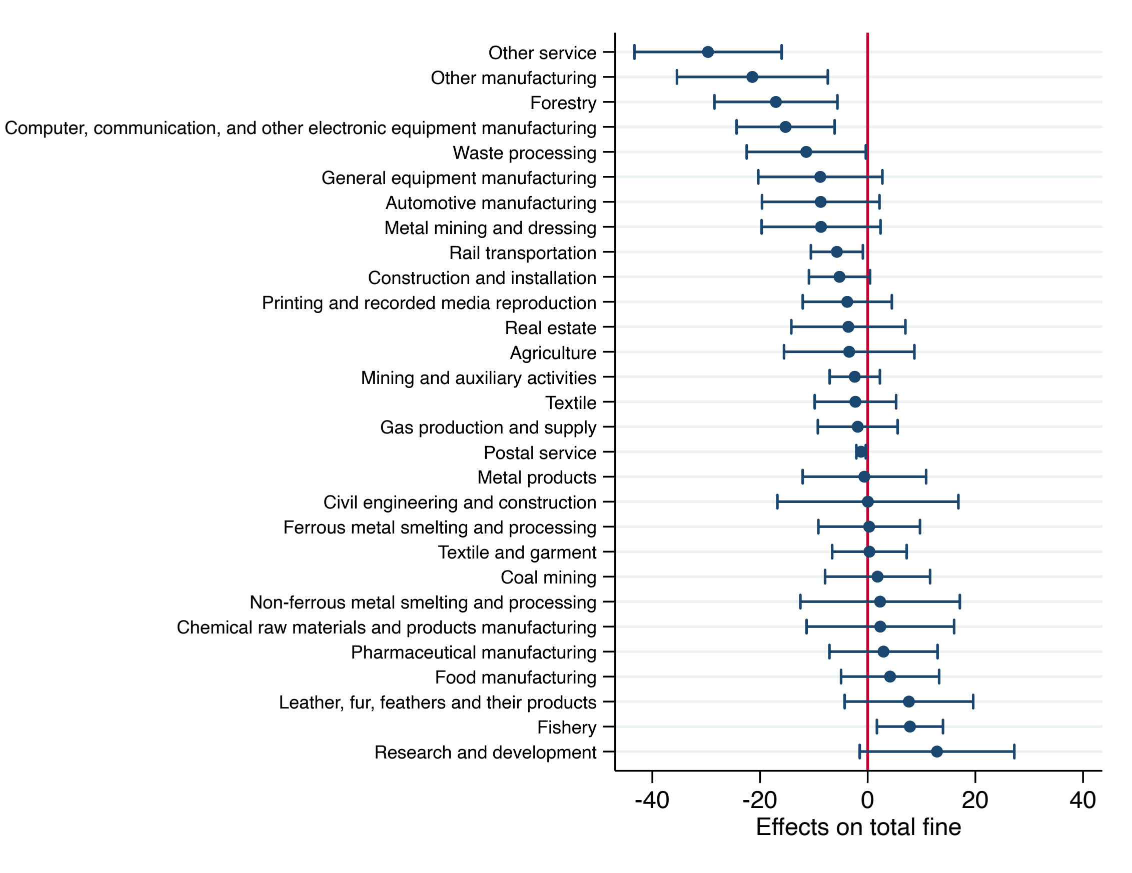
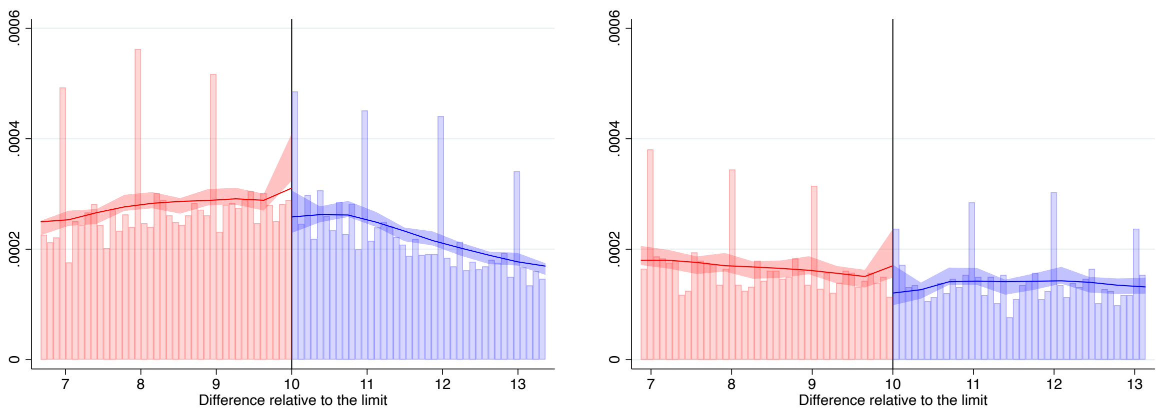


Figure B6: Tariff and environmental fine, heterogeneity across industries

Notes: This figure plots the estimated coefficients on $\Delta USTariff_{it}$ and 95% confidence intervals. We use the total fine of different industries as dependent variables. Sample and specifications are the same as Table 4 Column(5).

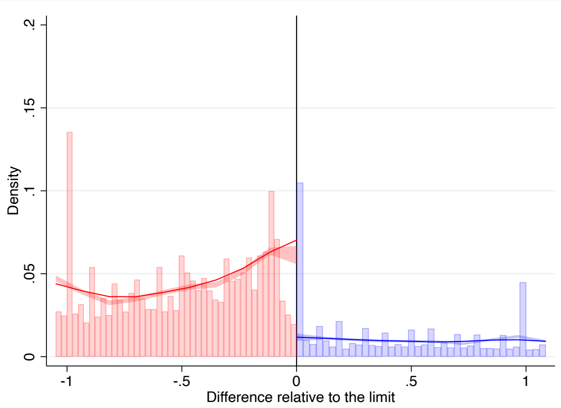


(a) January 2017 - June 2018

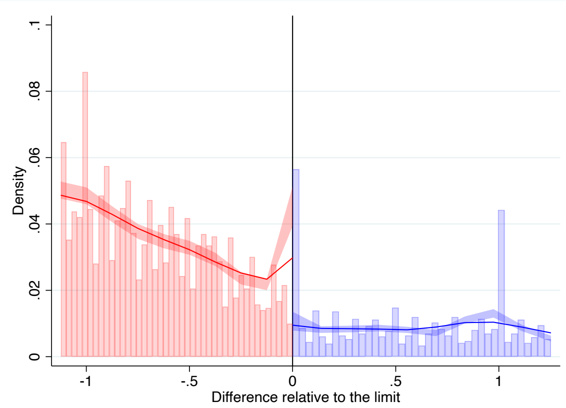
(b) July 2018 - December 2019

Figure B7: Bunching of CEMS data before and after the trade war using placebo cutoffs

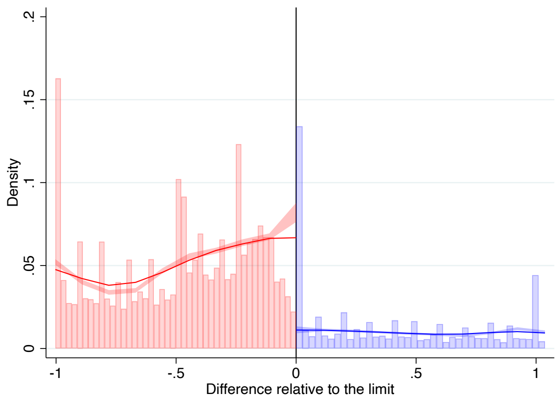
Notes: We use firm-hour level reports of CEMS emissions for SO_2, NO_x, and Particles 2017-2019, and calculate emission concentrations relative to the limits. We test if there are discontinuities around $10\mu g/m^3$. McCrary test shows t-statistics are -0.3242 and 0.1769 in the pre- and post-period respectively.



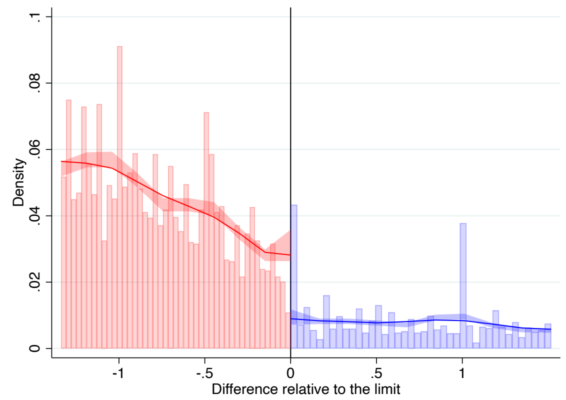
(a) Daytime emissions, January 2017 - June 2018



(b) Daytime emissions, July 2018 - December 2019



(c) Nighttime emissions, January 2017 - June 2018



(d) Nighttime emissions, July 2018 - December 2019

Figure B8: Bunching of CEMS data before and after the trade war, before and after sunset hours

Notes: We use firm-hour level reports of CEMS emissions for SO_2, NO_x, and Particles 2017-2019, and calculate emission concentrations relative to the limits. We test if there are discontinuities around $0\mu g/m^3$. McCrary test shows t-statistics are -41.5055 and -50.4410 in the pre-period before and after sunset hours respectively. After July 2018, t-statistics are -7.8167 and -50.4410 in the pre- and post-sunset hours, respectively. We also learn that the bunching behaviors are similar in the daytime and at night (a vs. c; b vs. d).

Figure B9: Night time emissions

Notes: Steel mill pollution during the night in Guangxi, June 2019.

Figure B10: Sulfur removal scrubber

Notes: This figure shows an example desulfurization equipment with the ammonia desalination method. The discharged gas is treated with cooling and a wet electrostatic precipitator to achieve the elimination of visible emissions at the chimney exit. The equipment is claimed to remove 99% of particulate matter, tar, aerosols, acid mist, and free water from the flue gas, and 80% of sulfur dioxide and 40% of nitrogen oxides. Source: Jufeng Environmental Protection Equipment Company, Guangdong, China, https://www.jfhuanbao.com/xinwenzhongxin/huanbaoxinwenzixun/2209.html.

C Appendix: Robustness

Table C1: Control for blue-sky plan

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
Δ US Tariff	0.604***	0.923**	0.974***	0.825***	0.703***
	(0.183)	(0.440)	(0.262)	(0.278)	(0.237)
Δ China Tariff	-0.097	-0.112	0.422***	-0.647***	-0.036
	(0.134)	(0.272)	(0.150)	(0.182)	(0.158)
KeyRegion $\times$ Plan	-0.002	0.008	-0.016**	-0.031***	-0.011
	(0.007)	(0.012)	(0.008)	(0.009)	(0.008)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.169	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. Columns (1) to (5) report logged difference in air pollution regressed logged difference in tariffs. All columns include year-month and monitor fixed effects. Standard errors are clustered at the station-month level. Significance: * 0.10, ** 0.05, *** 0.01.

Table C2: Control for environmental inspections

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
Δ US Tariff	0.597***	0.951**	0.914***	0.711**	0.662***
	(0.184)	(0.436)	(0.261)	(0.279)	(0.237)
Δ China Tariff	-0.096	-0.115	0.430***	-0.633***	-0.032
	(0.134)	(0.272)	(0.149)	(0.182)	(0.158)
Inspection	0.014**	-0.014	-0.002	0.006	0.008
	(0.006)	(0.014)	(0.009)	(0.009)	(0.008)
Observations	48868	48868	48868	48868	48868
R-square	0.228	0.169	0.178	0.192	0.239
Y-mean	-0.048	-0.193	-0.027	-0.075	-0.064
Y-sd	0.221	0.402	0.271	0.296	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. Columns (1) to (5) report logged difference in air pollution regressed logged difference in tariffs. All columns include year-month and monitor fixed effects. Standard errors are clustered at the station-month level. Significance: * 0.10, ** 0.05, *** 0.01.

Table C3: Robustness: Month-on-month change in pollution

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	3.402***	0.980	0.149	5.030***	1.920
	(0.978)	(1.176)	(0.973)	(1.277)	(1.176)
$\Delta\ln$(CHNTariff)	-1.612***	-1.017**	-0.183	-1.777***	-2.103***
	(0.354)	(0.472)	(0.459)	(0.567)	(0.463)
Observations	49044	49044	49044	49044	49044
R-square	0.400	0.211	0.444	0.409	0.438
Y-mean	-0.008	-0.021	-0.004	-0.009	-0.010
Y-sd	0.227	0.301	0.250	0.309	0.275
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the station-month level.

Table C4: Robustness: Dropping 2017

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	0.733***	1.845***	0.900***	1.053***	0.696***
	(0.202)	(0.459)	(0.299)	(0.309)	(0.268)
$\Delta\ln$(CHNTariff)	0.324**	0.330	0.794***	-0.158	0.477**
	(0.159)	(0.289)	(0.171)	(0.208)	(0.190)
Observations	32334	32334	32334	32334	32334
R-square	0.265	0.230	0.209	0.236	0.282
Y-mean	-0.065	-0.215	-0.061	-0.089	-0.089
Y-sd	0.217	0.383	0.251	0.291	0.271
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the station-month level.

Table C5: Robustness: City-month level pollution

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	0.629**	1.649**	0.482	0.853*	0.571
	(0.309)	(0.683)	(0.337)	(0.437)	(0.393)
$\Delta\ln$(CHNTariff)	-0.084	-0.077	0.669***	-0.658**	-0.140
	(0.229)	(0.432)	(0.207)	(0.295)	(0.265)
Observations	11844	11844	11844	11844	11844
R-square	0.241	0.209	0.239	0.206	0.257
Y-mean	-0.052	-0.193	-0.034	-0.081	-0.069
Y-sd	0.213	0.333	0.223	0.278	0.266
City FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the city-month level.

Table C6: Robustness: Weighted regression using city GDP

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	1.102**	0.289	0.600	1.529**	0.966
	(0.558)	(0.905)	(0.490)	(0.739)	(0.649)
$\Delta\ln$(CHNTariff)	-0.107	-0.910*	-0.244	-0.577	0.032
	(0.354)	(0.476)	(0.268)	(0.498)	(0.392)
Observations	10332	10332	10332	10332	10332
R-square	0.251	0.254	0.288	0.220	0.268
Y-mean	-0.050	-0.211	-0.035	-0.078	-0.065
Y-sd	0.202	0.283	0.186	0.257	0.240
City FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the city-month level.

Table C7: Placebo: effect of the current tariff on last year's pollution

	$\Delta\ln(AQI)$	$\Delta\ln(SO_2)$	$\Delta\ln(NO_2)$	$\Delta\ln(PM_{2.5})$	$\Delta\ln(PM_{10})$
$\Delta\ln$(USTariff)	-0.788*	-0.314	-0.338	-1.028*	-0.772
	(0.420)	(0.627)	(0.451)	(0.580)	(0.501)
$\Delta\ln$(CHNTariff)	-0.048	-0.003	0.036	-0.205	0.053
	(0.238)	(0.381)	(0.215)	(0.304)	(0.266)
Observations	48630	48630	48630	48630	48630
R-square	0.232	0.161	0.158	0.194	0.232
Y-mean	-0.051	-0.172	-0.010	-0.082	-0.057
Y-sd	0.233	0.433	0.306	0.308	0.287
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table C8: Placebo: effect of the tariff on weather conditions

	$\Delta\ln$(Temperature)	$\Delta\ln$(Wind speed)	$\Delta\ln$(Humidity)
$\Delta\ln$(USTariff)	-0.192	-0.077	-0.056
	(0.570)	(0.278)	(1.416)
$\Delta\ln$(CHNTariff)	0.313	0.009	0.732
	(0.357)	(0.153)	(0.576)
Observations	9306	9306	9306
R-square	0.275	0.223	0.218
Y-mean	-0.001	0.000	-0.047
Y-sd	0.286	0.124	0.475
Monitor FEs	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Standard errors are clustered at the city-month level.

Table C9: Effect on air pollution non-attainment relative to air quality standards

	Δln(AQI)	Δln(SO_2)	Δln(NO_2)	Δln($PM_{2.5}$)	Δln(PM_{10})
	Panel A: Excellent standards				
Δln(USTariff)	0.929***	0.349***	0.258***	0.314**	0.870***
	(0.122)	(0.102)	(0.083)	(0.136)	(0.128)
Δln(CHNTariff)	0.178***	0.035	0.079*	-0.106	0.271***
	(0.064)	(0.054)	(0.044)	(0.072)	(0.065)
Observations	52812	52812	52812	52812	52812
R-square	0.736	0.771	0.810	0.748	0.742
Y-mean	0.591	0.092	0.084	0.458	0.586
Y-sd	0.266	0.241	0.230	0.292	0.271
	Panel B: Good standards				
Δln(USTariff)	0.153	0.157**	0.258***	0.205*	0.058
	(0.107)	(0.080)	(0.083)	(0.107)	(0.091)
Δln(CHNTariff)	-0.015	0.098**	0.079*	0.012	0.057
	(0.057)	(0.045)	(0.044)	(0.054)	(0.054)
Observations	52812	52812	52812	52812	52812
R-square	0.750	0.833	0.810	0.743	0.767
Y-mean	0.201	0.068	0.084	0.173	0.141
Y-sd	0.267	0.228	0.230	0.262	0.247
Monitor FEs	Y	Y	Y	Y	Y
Province time trends	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Standard errors are clustered at the monitor-month level.

Table C10: Restricting firms with observations every quarter

	Δln(Particles)	Δln(SO_2)	Δln(NO_x)
Δln(USTariff)	25.717***	30.882**	-12.692
	(8.629)	(14.268)	(8.894)
Δln(CHNTariff)	0.347	-4.999	-2.744
	(3.125)	(5.251)	(3.511)
Observations	773	702	762
R-square	0.512	0.501	0.494
Y-mean	-0.115	-0.204	-0.106
Y-sd	1.066	1.228	0.745
Firm FEs	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Sample period is 2018-2019. Firms are required to report data every quarter. Standard errors are clustered at the province level.

Table C11: Emission concentration relative to limits

	(Concentration - limit) / limit		
	$\Delta\Delta\ln$(Particles)	$\Delta\Delta\ln(SO_2)$	$\Delta\Delta\ln(NO_x)$
$\Delta\ln$(USTariff)	26.817***	24.209	-10.608
	(7.903)	(27.569)	(17.314)
$\Delta\ln$(CHNTariff)	3.347	-7.400	2.419
	(7.570)	(17.809)	(10.377)
Observations	2868	2739	2711
R-square	0.489	0.478	0.328
Y-mean	-0.303	-0.309	-0.123
Y-sd	1.244	1.885	1.839
Firm FEs	Y	Y	Y
Year-Month FEs	Y	Y	Y

Notes: Standard errors are clustered at the province level.

Table C12: Tariff and environmental fine using fine month

	$\Delta\ln$(#Events)	$\Delta\ln$(#Events with fine)	$\Delta\ln$(Total fine)	$\Delta\ln$(Fine per event)
	(1)	(2)	(3)	(4)
$\Delta\ln$(USTariff)	-1.836	-2.132	-8.263	-7.224
	(1.915)	(1.831)	(10.657)	(9.926)
$\Delta\ln$(CHNTariff)	-4.451***	-4.729***	-26.203***	-23.055***
	(1.270)	(1.189)	(6.200)	(5.738)
Observations	11593	11593	11593	11593
R-square	0.187	0.159	0.100	0.086
Y-mean	0.103	0.078	0.390	0.330
Y-sd	1.248	1.181	5.943	5.451
City FEs	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. We use the inconsistently-recorded fine month to merge with city-month level tariff. All columns include year-month and city fixed effects. Standard errors are clustered at the province-year level.

Table C13: Tariff and environmental fine of unrelated sectors

	$\Delta\ln$(Total fine)	$\Delta\ln$(Fine per event)
	(1)	(2)
$\Delta\ln$(USTariff)	-10.948	-27.959
	(18.140)	(21.690)
Observations	5904	5904
R-square	0.169	0.168
Y-mean	0.069	0.109
Y-sd	3.999	5.182
City FEs	Y	Y
Year-Month FEs	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. We stack our sample 12 times to merge city-year level fine with city-month level tariff. Non-manufacturing industries include dining and restaurants, sports, entertainment, insurance, education, hotels, and social work, which primarily includes neighborhood committees and street offices. All columns include year-month and city fixed effects. Standard errors are clustered at the province-year level.