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Xinming Du Lei Li

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Xinming Du[‡] Lei Li[§]

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Abstract

This paper studies the short-term trade-off between economic growth and environmental governance from the perspective of political incentives. In the context of international trade conflicts, we use the U.S.-China trade war as a natural experiment and find that higher U.S. tariffs worsen air quality in China. The city-level analysis shows that a 1% increase in the tariff burden leads to 0.9% and 0.7% increases in SO_2 and $PM_{2.5}$, respectively. Firm-level emission data generate similar results. Interestingly, the hourly monitor-level air quality data suggests that the pollution increases are concentrated at night. We hypothesize that the surprising findings can be largely attributed to the lenient environmental policies adopted by local governments when faced with the risks of economic downturn. We provide suggestive evidence that cities more exposed to the U.S. tariffs attach less emphasis on environmental regulations in local government reports and charge fewer fines on firms violating environmental regulations. Cities with native and older party secretaries and areas closer to province boundaries experience a less severe increase in pollution during the trade war. Our findings are relevant as China scrambles to maintain growth in the face of economic headwinds.

JEL Classifications: Q53, Q56, F14, F18
Keywords: Trade conflict, air quality, firm emissions, political incentive, China

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[‡]Department of Economics, National University of Singapore. Email: xd2197@columbia.edu

[§]Department of Economics, University of Mannheim. Email: lei.li@uni-mannheim.de

1 Introduction

How do political incentives affect the trade-off between economic growth and environmental enforcement? Many politicians face a challenging trade-off between short-term economic growth and environmental protection, a conundrum that becomes more vexing during economic downturns. Despite its importance, there is a lack of comprehensive research on this topic. This paper investigates how politicians and firms respond to adverse economic shocks by providing compelling evidence on a novel channel, namely lenient environmental regulations.

Our rationale is intuitive. A key concern for government officials is balancing economic growth and environmental regulation. Economic growth is associated with a range of activities, such as pollutant emission and natural resource exploitation, which can lead to adverse environmental consequences. However, the implementation of stringent environmental regulations may cause economic slowdowns, job losses, and social unrest in the short run. This trade-off highlights the need to balance short-term economic gains and long-term sustainable development. Under the pressure of economic downturn risk, political unrest (Campante et al., 2023), and short-term performance evaluation (Li and Zhou, 2005), government officials tend to sacrifice long-term sustainable development and give firms tacit permission to excess pollutant emissions to offset the negative impacts of adverse economic shocks.

The U.S.-China trade war provides a good setting to test this trade-off. China has experienced remarkable economic growth since 1978. However, there are concerns about the slowdown in economic growth. 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 U.S. tariffs across a diverse range of products, which provides exogenous shocks on the heightened risks of economic downturns. Moreover, despite the growing literature on the trade war (e.g., Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021; Jiao et al., 2021; Feng et al., 2023), less is known about its environmental consequences in terms of environmental enforcement and pollution emission.

In this paper, we study the impact of trade protectionism on pollution emissions and explore the trade-off between economic growth and environmental enforcement. Using hourly air quality data and firm-level pollution emission 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 difference-in-difference design, we observe that cities with high exposure, characterized as being in the top quartile of U.S. tariff increases, experience more pronounced air pollution after July 2018. In comparison to cities with low exposure, those burdened with tariffs witness a 10.3% increase in SO_2, a 7.1% increase in $PM_{2.5}$, and a 6.5% increase in PM_{10} levels. To address the dynamic effect of evolving trade patterns over time, we conduct a first difference estimation and obtain a similar increase in pollution. Specifically, a 1% increase in U.S. tariffs corresponds to 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 productions, the greater magnitude of the increase in SO_2

compared to other pollutants suggests the great contribution of industrial productions. The findings are surprising because reduced economic activities due to adverse economic shocks are supposed to generate fewer pollution emissions. 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 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. Similar to the monitor-level analysis, China's retaliatory tariffs do not have any notable impacts on firm emission intensities. Our findings show that firms in cities more exposed to the U.S. tariffs exhibit higher emission intensities, suggesting a citywide rollback of environmental regulations by local governments.

To demystify the puzzling findings on increased pollution, we explore the mechanism in three ways. First, we complement the above analysis by investigating the impact of the trade war on Chinese exports. We find that a one percent increase in U.S. tariffs leads to a 0.6% decline in exports to the U.S. Meanwhile, China's exports to the rest of the world increase accordingly, which almost offset the negative impact of the U.S. tariffs on China's exports to the U.S. The estimation of trade elasticity requires precisely measuring the changes in tariffs. During the trade war, China lowered the Most-Favored-Nation (MFN) tariffs to boost imports from other countries and had several regional trade agreements that granted preferential tariffs to some trade partners, who accounted for 43% of China's total imports in 2017. To account for these changes, we hand-collected the daily announcement of Chinese tariff schedules by HS-8 instead of using the annual MFN tariffs by HS-6, apart from collecting data on punitive tariffs.

Second, we provide evidence of the stringency of environmental policy. To test whether the worsening of air quality is driven by the relaxation of environmental policies, 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 regulations in response to trade escalation. Another measure of lenient environmental policies lies in the manipulation of air quality data. We show that the bunching of pollution data reported by firms becomes more pronounced after the trade war, suggesting an elevated prevalence of data manipulation. It potentially reflects a decrease in regulatory oversight or inspections.

Third, 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. Further evidence using the environmental fine data shows that local environmental agencies in more trade-exposed cities didn't conduct inspections and charged smaller amounts of fines on firms violating environmental regulations. 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 and periods 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 regulations and enforcement during the trade war.

This paper is among the first to report evidence on local governments' trade-off between short-term economic growth and long-term substantial development. Despite its importance, there is a lack of comprehensive research on this topic. In the context of trade protectionism, we investigate how politicians and firms respond to adverse economic shocks. We show that government officials tend to sacrifice long-term sustainable development and give firms tacit permission to emit excess pollutant emissions.

This paper is related to the existing literature that studies the enforcement and effectiveness of environmental regulations. Jia (2017) finds that gaining connections with key officials in the central government increases pollution. China's recent tightening of environmental regulation and enforcement has been shown to decrease heavily polluting industries' emission intensity and production (Shi and Xu, 2018), generate substantial health benefits (Pope III and Dockery, 2013), and obtain efficiency gain (Wang et al., 2018). Regarding the latest environmental regulations, Wong and Karplus (2017) provides a detailed review of the policies and argues that the misalignment of incentives between the local and central governments is still present. Low enforcement in local areas induces gaming activities in emissions and high pollution levels (Zhang and Mu, 2018). Similar evidence is documented by Ghanem and Zhang (2014) that shows local governments have suspicious air quality data especially when the anomaly is least detectable. Karplus et al. (2018) compares ground-based firm emission data and remotely-sensed satellite products to show that, after emission standards became stricter in 2014, firms in regions with tougher standards are more likely to manipulate their emissions data. These studies highlight the challenges posed by low environmental enforcement in China and the resulting gaming activities in pollution. They shed light on the detrimental effects of weak enforcement, such as increased pollution levels, corruption, and pollution offshoring. Relative to the literature, our paper provides empirical evidence on the trade-off between long-term sustainable development and short-run economic growth. We find that local officials have incentives to relax environmental regulations when the region is at a higher risk of economic downturn.

Another related literature is on decentralization and political tournament. Li and Zhou (2005) find that the likelihood of promotion of provincial leaders in China increases with their economic performance. Jia and Nie (2017) use China's coal mine deaths to show collusion between regulators and firms affects workplace safety because decentralization makes collusion more likely. Li et al. (2019) proposes a Tullock contest model in a multi-layered tournament-based organization, which predicts a top-down amplification of economic growth targets along the jurisdiction levels.

Our paper contributes to the literature that studies the impact of trade on pollution. Despite the growing literature on the impacts of the trade protectionism 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), night light (Chor and Li, 2021; Feng et al., 2023), employment (Flaaen and Pierce, 2019; Beck et al., 2023), politics (Blanchard et al., 2019), and stock returns (Amiti et al., 2021; Feng et al., 2023; Han et al., 2023), little is known about its impact on the environment.

Beyond trade conflicts, there are researches on the impact of trade on the environment. Poncet et al. (2015) find that export has a positive effect on pollution in China, mostly attributable to foreign firms in processing trade. Bombardini and Li (2020) shows that Chinese cities that had high export growth in "dirty" industries between 1990 and 2010 experienced a bigger increase in SO_2 concentration and infant mortality. Cherniwchan (2017) find that the trade liberalization following NAFTA reductions can explain about two-thirds of the reductions in PM_{10} and SO_2 emissions among U.S. manufacturing firms between 1994 and 1998. Shapiro and Walker (2018) uses plant-level data to show that the decline in air pollution produced by U.S. manufacturers is mainly due to changes in environmental regulations instead of trade. While the previous literature mainly focuses on pollution content and export expansion channels, our paper studies the impact of unexpected adverse economic shocks on pollution by exploring a novel channel, namely the lenient environmental policy.

The rest of the paper is organized as follows. Section 2 introduces the U.S.-China trade war and highlights key data patterns. Section 3 describes the data and variable construction. Section 4 illustrates the econometric specification and displays empirical evidence of the impact of the trade war on China's air pollution. Section 5 explores the export effect as a potential channel of pollution change. Section 6 tests the mechanism. Section 7 discusses the health effect due to increased air pollution and concerns about environmental injustice. Section 8 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 trade partners. 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 aluminum 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.

From mid-2018, the U.S. government shifted its focus to China, as shown in Figure A1. 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 A1 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 A2) and import structure (Figure A3), 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 A2, 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 A3). 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 Environmental regulation in China

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 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, signified 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.

Central policies serve as the foundational basis for environmental regulations, while local governments are responsible for their implementation and governance enforcement. Both types of governments play roles in the process of environmental regulation. The effectiveness of environmental policies primarily hinges on the enforcement efforts of local governments. This depends on local governments' resources, management level, and willingness to implement environmental policies. When local governments have low incentives to enforce environmental regulations, rational polluting firms may choose not to undertake pollution control measures. The stronger the enforcement by local governments, the greater the effectiveness of environmental policies, and the more obvious the regulatory effects.

In the process of environmental regulation, local governments do not always make choices in line with the goal of maximizing social welfare (Fischer et al., 2003) or prioritizing environmental regulation. Due to the obvious differences in social, economic, and other aspects among provinces, local governments may exhibit different behavioral preferences when implementing environmental policies, influenced by varying environmental regulation motivations. Due to other incentives such as economic outputs and social stability, local governments may have different preferences when implementing environmental policies. Consequently, China's environmental enforcement and implementation remain at a relatively low level.

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.[1]

Apart from annual firm-level data, we also acquire monthly product-level 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 country-HS-8 product level and ranges from January 2017 to December 2019. It contains over 7,000 HS-8 products and over 200 trade partners. 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 A31 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 export variety (product-country) composition at the city-level; and (ii) differences in the U.S. tariff changes over time at product-level, $\Delta USTariff_{it}$. A location specializing in exporting targeted products to the U.S. market would experience a huge drop in external demand when U.S. tariffs hike.

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

[1]We assign each firm to a city based on the city's administrative boundary in 2000.

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

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 A31. 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 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 heavy environmental regulation.

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 in industrial air 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 City-level air quality

4.1.1 Event study

We start by exploring monthly changes in U.S. tariffs and air pollution. There was a sharp jump in the U.S. tariffs in July 2018 in high-exposure cities, as shown in Figure A4. In contrast, low-exposure cities experienced modest changes in tariff rates during the same period. This discrepancy highlights the differentiated impact of U.S. tariffs across locations. As for air quality, the pollution level measured in SO_2 and $PM_{2.5}$ experienced decreasing trends before the trade war. However, the improvements rolled back and the slopes became positive after July 2018. The flipped trends were primarily driven by high-exposure cities grappling with the augmented burden of U.S. tariffs. In contrast, low-exposure cities experienced a smaller change in pollution trends. This suggests that the escalated tariff burdens in high-exposure cities have evidently hampered their progress in mitigating air pollution.

Motivated by the stylized facts, we employ a difference-in-difference empirical approach to ascertain the causal impact of the trade war on local air pollution. We define high-exposure cities as those that bore the heaviest tariff burden between July 2018 and December 2019. We calculate the sum of tariff escalation at the city level, and we assign cities into quartiles. Cities in the top quartile are categorized as high-exposure cities, while the remaining three quartiles are regarded as low-exposure cities. We use the start of China-specific trade tariffs in July 2018 as the event time. Our regression model is specified as follows:

$$\ln P_{it} = \beta \ \mathrm{Post}_t \times \mathrm{Treated}_i + City_i + YearMonth_{it} + \eta_t + \epsilon_{it} \tag{3}$$

where $\ln P_{it}$ is the logarithm of the average air pollution concentration in city i in month t. Our independent variables include $Treated_i$, a binary variable indicating whether city i is categorized as a high-exposure city affected by U.S. tariffs, and $Post_t$ that equals to 1 for the months from July 2018 onwards and 0 otherwise. We also add city fixed effects to account for city-specific time-invariant characteristics and year-month fixed effects to control for national monthly differences. The coefficient of interest is β, the coefficient on the interaction between $Post_t$ and $Treated_i$. In other words, β estimates the impact of the trade war shock on the level of pollution of cities with high exposure relative to other cities, using their difference in pollution before the trade war as the baseline.

Our identification strategy relies on the assumption that our treatment assignment based on $\Delta USTariff_{it}$ is as good as random conditional on the controls. In other words, we assume that in the absence of the trade war, high-exposure cities would have exhibited a similar trajectory of pollution levels compared to other cities. To examine this parallel trend assumption, we employ a dynamic difference-in-difference design and estimate the following regression model:

$$\ln P_{it} = \sum_{q=-8}^{16} \beta_m I\left(\text{event}_t = m\right) \times \text{Treated}_i + City_i + YearMonth_{it} + \eta_t + \epsilon_{it} \tag{4}$$

The dynamic specification focuses on an event window spanning 8 months before and 16 months after the initiation of the trade war in July 2018. The variables $I\left(\text{event}_t = m\right)$ 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_m. It represents the estimated difference in average log air pollution between the treatment high-exposure cities and the control cities during the specific event time period m, relative to their difference before the trade war. Similar to equation (3), we include the same set of control variables to account for city-specific time-invariant patterns and national monthly differences.

In Figure 1, we compare cities that are in the top quartile and bottom quartile based on total U.S. tariff burdens in the post period. The event study figure serves to validate our identification strategy by examining the pre-trends in air pollution levels before the initiation of the trade war in July 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, high-exposure cities and other cities exhibited similar pollution trajectories. In the post period, there were minimal changes in air pollution levels during the latter part of 2018. However, starting in 2019, we observe a significant positive effect of the U.S. tariff shocks on high-exposure cities' levels of SO_2. This finding suggests that the trade war had a notable impact on air pollution dynamics four months after the tariff enactment.

We further explore the heterogeneity across U.S. tariff quartiles. As is shown in Figure A11, our effects are mainly driven by the difference between the fourth and the first quartile. In other

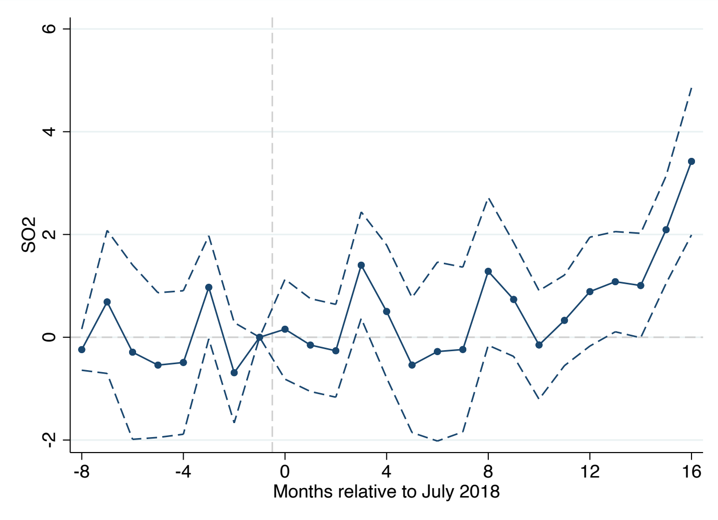


Figure 1: **Event study of city-level air quality**

Note: The figures plot the impact of U.S. tariffs on citywide air quality. We compare SO_2 in the top quartile and that in the bottom quartile. Figures using all four quartiles are displayed in Figure A11. We plot point estimates and their 95% confidence intervals in each month, with month negative 1 dropped. We control for city, year-month, and prov-month fixed effects. Standard errors are clustered at the station-month level.

words, cities subjected to the most substantial tariff increase experience a significantly larger increase in air pollution levels, compared with control cities with minor tariff changes. As the tariff decreases, the green and blue lines exhibit a diminishing magnitude. This suggests that cities falling within the second and third quartiles do not display significantly different pollution responses in comparison to the highest impacted group. This motivates our next empirical design to study the intensive margin, whether the pollution responds to an additional increase in U.S. tariff.

Table 1 Panel A shows a similar pattern to the patterns observed in Figure 1. In Column (1), we observe that the air quality index in high-exposure cities is approximately 4.294 units higher compared to low-exposure cities. This difference represents an increase of around 6.0% relative to the average AQI across all cities. In Column (3), we find a significant increase of $1.997\mu g/m^3$ in SO_2 levels in high-exposure cities, which corresponds to a relative increase of 10.3% compared to the mean. As SO_2 emissions are primarily associated with power plants and manufacturing productions, the larger magnitude observed in Column (2) suggests that the trade war had a more pronounced effect on air pollution in these industries. Columns (4) and (5) show an increase in $PM_{2.5}$ and PM_{10} of $3.11\mu g/m^3$ (7.1%) and $5.19\mu g/m^3$ (6.5%) respectively. These findings conclude that the trade war increased air pollution, especially SO_2 and $PM_{2.5}$.

4.1.2 Dynamic tariff exposure

Next, we show the impact of tariff changes over time 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 controls. Our econometric specification is as follows:

$$\Delta ln(P_{it}) = \beta \Delta USTariff_{it} + \alpha \Delta CHNTariff_{it} + \gamma_t + \eta_i + \varepsilon_{it} \tag{5}$$

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, $\Delta CHNTariff_{it}$ captures the year-on-year log change in China tariffs for the same city and time period. The two Bartik-style shift-share instruments $USTariff_{it}$ and $_{it}$ 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_i includes city fixed effects to account for time-invariant factors specific to each city that may influence air pollution levels. 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 China tariffs on air pollution changes.

Table 1: **Tariff effects on citywide air quality**

	Panel A: Event study				
	AQI	SO_2	NO_2	$PM_{2.5}$	PM_{10}
	(1)	(2)	(3)	(4)	(5)
High exposure × Post	4.294***	1.997***	1.322***	3.107***	5.192***
	(1.334)	(0.488)	(0.485)	(1.065)	(1.687)
Observations	39970	39970	39970	39970	39970
R-square	0.857	0.816	0.844	0.846	0.845
Y-mean	71.453	19.366	30.366	43.792	79.553
Y-sd	31.606	16.885	15.268	25.758	41.623
	Panel B: Dynamic tariff exposure				
	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
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
Year-Month FEs	Y	Y	Y	Y	Y

Notes: Sample period is from 2017:1 to 2019:12. In Panel A, Columns (1) to (5) report air pollution regressed the double difference interaction term. All columns include year-month, prov-month, and monitor fixed effects. Variable *High exposure* is absorbed by monitor fixed effects. *Post* is absorbed by year-month fixed effects. In Panel B, 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.

The identifying assumption relies on the exogenous changes in U.S. tariffs and China tariffs over time. As shown in Figure 1, 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 regression results for dynamic tariff exposures from equation (5). 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 1.0% increase in SO_2 and 0.7% increase in $PM_{2.5}$. Like the results of the static difference-in-difference estimate in Table 1 Panel A, 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.

However, as indicated by the coefficients on $\Delta CHNTariff_{it}$, China's retaliatory tariff shocks do not have a significant impact on air pollution. Estimates are small and statistically imprecise when we use AQI, SO_2 and PM_{10} as dependent variables. One potential explanation is that China's retaliatory tariffs may be targeted toward final goods or intermediate goods. In the former case, the imposition of protectionist measures could potentially benefit local firms, resulting in positive effects on air pollution. In contrast, if tariffs increase the cost of imported intermediate goods, it could lead to higher production costs for local firms and potentially negative effects on air pollution. It is possible that both channels exist and have similar magnitudes, leading to an ambiguous overall impact on air pollution.

To test the robustness of our results, we conducted several additional analyses. Firstly, we dropped the year 2017 from our analysis, as most tariff changes during that year were zero. Results in Table A2 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. In the second robustness check, we replaced year-on-year changes with month-on-month changes in both tariff and pollution variables. Results in Table A3 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. 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 A4 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 A5 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 A6 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, specifically from the National Meteorological Information

Centre (CMA). Results in Table A7 indicate that U.S. tariff burdens do not exhibit any effects on the observed weather variables.

Besides, we show dynamic effects in each quarter in Table A13. In Column (1), we observe that AQI decreases in the third quarter of 2018, indicating improved air quality during that period. However, AQI increases in the winter quarters of 2018-2019, suggesting a deterioration in air quality during those months. Similar patterns are found in the case of SO_2 and $PM_{2.5}$. The negative responses in air pollution during the first quarter may be attributed to transaction costs associated with trade diversion from the U.S. to other countries. This could lead to a decrease in production and subsequently lower air pollution levels. After the first quarter, the higher responses in air pollution during the winter quarters may be due to higher emission potentials and more intensive pollution regulations in winter before the trade war. There is a higher emission potential during winter due to increased energy consumption for heating purposes. As a result, governments often enforce more stringent pollution regulations during the winter season to mitigate the impact of heating-related emissions. Manufacturing firms may be required to operate at lower levels to compensate for higher emissions from power plants and heating facilities. However, with the onset of the trade war, these enforced regulations may have been relaxed initially, resulting in higher pollution increases during the winter quarters.

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. It's noteworthy that the World Health Organization (WHO) suggests $PM_{2.5}$ should not exceed $15\mu g/m^3$ to avoid health harms, whereas the U.S. EPA set a standard of $12\mu g/m^3$. We use air quality values and code dummies for each air pollutant that is considered non-excellent air quality. This dummy aligns with the definition of unhealthy air quality according to WHO standards. We use dummies at the monitor-day level and re-estimate equation (3). Results in Table A8 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 A9 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.

4.1.3 Heterogeneity across hours

Using detailed hourly data, we find that additional pollutants are emitted at night, providing direct evidence of lenient environmental regulations and softening enforcement. In Table A14 Panel A, we use the air quality data at 2 pm to calculate city-month level pollution. Estimates on $\Delta USTariff_{it}$ are positive but small and statistically insignificant. This suggests that the change in air pollution at 2 pm in response to tariff changes is minimal. In contrast, Panel B reveals significant increases in pollution levels at 10 pm. These effects are consistent across different pollutants and are more pronounced than in Table 1. Specifically, when the U.S. tariff increases by 1%, SO_2 and $PM_{2.5}$ at 10 pm significantly increase by 1.12% and 0.58%, respectively. These findings indicate that the effects of tariff changes on air pollution are more pronounced during the late evening hours.

The stronger effect of tariff changes on pollution during night hours suggests the presence of secret dark-time emissions. Pollution emitted at night is less visible, which reduces the likelihood of environmental regulators being on patrol and decreases the chances of residents filing complaints. This phenomenon is supported by Figure A12, which displays the nighttime emissions of a paper mill plant in 2019. 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).

We use pollution difference after and before working hours — 8 am-6 pm — to code outcome variables. Results are reported in Table A15. 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.

In Table 2, we do a similar practice by using pollution difference as dependent variables. Instead of using clock hours that are the same across time and cities, we collect daily sunset times for each city in our sample and link it to our hourly pollution data reported by local pollution monitors. We find a pattern similar to that in Table A15, and the point estimates in $\Delta USTariff_{it}$ become larger. Specifically, a 1% increase in U.S. tariff leads to 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.

We plot the estimated coefficients using each hour's pollution in Figure 2, 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, which are associated with less stringent environmental enforcement during those hours.

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

	Dark hour - daytime hour				
	ΔAQI diff	ΔSO_2 diff	ΔNO_2 diff	$\Delta PM_{2.5}$ diff	ΔPM_{10} diff
	(1)	(2)	(3)	(4)	(5)
Δ US Tariff	11.058***	3.173**	1.250	6.404***	15.003***
	(2.260)	(1.352)	(0.935)	(1.918)	(2.503)
Δ China Tariff	-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
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
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.

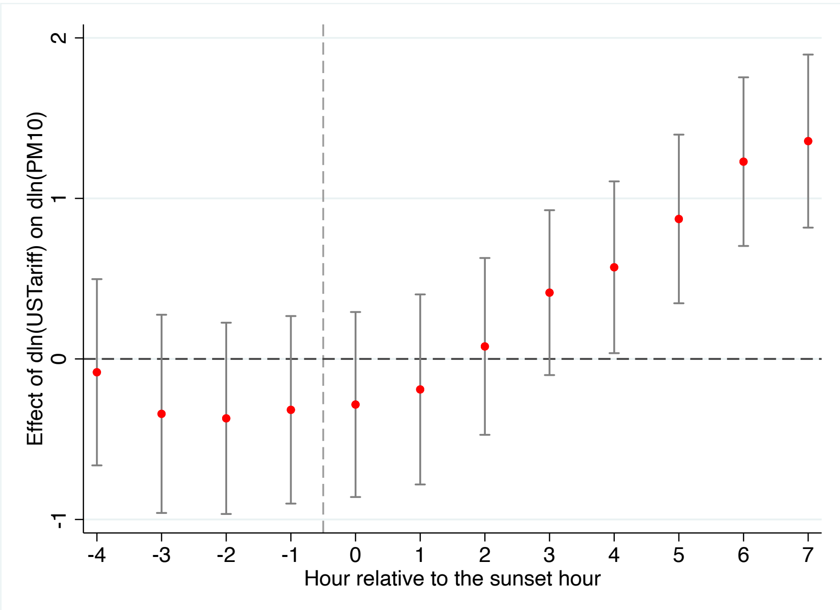


Figure 2: **Pollution before vs. after sunset**

Note: This figure display coefficients on ΔUS Tariff. We separately estimate coefficients at each sunset hour.

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:

$$\Delta ln(E_{it}) = \beta_1 \Delta USTariff_{it} + \beta_2 \times \Delta CHNTariff_{it} + \gamma_t + \eta_i + \varepsilon_{it}, \tag{6}$$

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 China 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 γ represents the effect of China 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. On the other hand, 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 insignificant. 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 A16, 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_x 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 using citywide air quality data in Table 2.

Given the identified evidence of increased emission intensity, what are firms' actual behaviors in response to tariff escalations and relaxed environmental regulations? It is likely that firms curtailed marginal abatement costs by turning off pollution control equipment. A sample pollution scrubber is shown in Figure A13. 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 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.

Table 3: **Tariff effects on firms' emissions**

	ΔParticles (1)	ΔSO_2 (2)	ΔNO_x (3)	ΔParticles (4)	ΔSO_2 (5)	ΔNO_x (6)
Δ US Tariff	16.158*	22.830**	-9.710	15.501*	23.022**	-9.852
	(8.854)	(8.268)	(7.900)	(8.818)	(8.399)	(7.857)
Δ US Tariff_Industry				13.519*	7.878	-7.764
				(7.046)	(9.125)	(11.218)
Δ China Tariff	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
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.

Since the CEMS data has many 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 A10. 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 A11 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 afterward. 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 A12 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.

4.2.2 Firm-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 5.2 and 5.3, we hypothesize that firms located in cities with high overall exposure, but operating in low-exposure industries, also emit more pollutants. We used the hourly end-of-pipe emissions at the firm level to test this hypothesis. To assign industry codes to the 7,639 firms in our CEMS sample, we scrape firms' basic information 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. Then we add the industry-level tariff as an additional control in equation (5) to examine whether city- or industry-level tariff drives the observed pollution increase.

The results in Table 3 Column (4) to (6) report positive and statistically significant estimates in $\Delta USTariff\_City_{it}$, similar to those observed in Column (1) to (3). This suggests that our observed citywide tariff impacts on firm emissions remain strongly robust. In the second row, we find positive but smaller estimates for $\Delta USTariff\_City_{it}$ when using particle emissions as the dependent variable. 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 (6), NO_x emissions are not significantly affected by U.S. tariffs at the city or industry level. 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 imposed by industrial tariffs. 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.

5 Mechanism

If local governments perceive that the trade war may have a significant adverse effect on the local economy, they tend to relax environmental regulations to alleviate the adverse shocks (Karplus et al., 2021). Previous sections show that higher U.S. tariffs indeed reduced China's exports to the U.S. However, it did not reduce China's total exports and even resulted in a reduction in SO_2 and $PM_{2.5}$ pollution levels. In this section, we provide suggestive evidence to show that tariff burdens lead to lenient environmental policies.

5.1 Trade war, export, and economic outputs

We begin by investigating the impact of the U.S. tariffs on China's exports to test the impact of the production channel following Equation 7:

$$\Delta X_{Ipct} = \alpha_0 + \beta_1 \Delta USTariff_{pt} + \beta_2 \Delta Tariff_{pct} + D_{p'I} + D_{p'c} + D_{ct} + \mu_{Ipct}, \tag{7}$$

where $\Delta USTariff_{pt}$ denotes the log change in tariffs imposed by the U.S. on product p compared to last year and $\Delta Tariff_{Ipct}$ denotes the log change in tariffs imposed by country c on product p compared to last year. $\Delta \ln X_{pct}$ denotes the log of Chinese exports (i.e., export values or duty-inclusive unit values) of product p from province I to country c at time t between January 2017 and December 2019. The regression includes HS-6 product fixed effects ($D_{p'I}$) to control for time-invariant heterogeneity at the product-province level, HS6-product-country fixed effects ($D_{p'c}$) to control for time-invariant heterogeneity at the product-country level and country-year-month fixed effects (D_{ct}) to take all country-specific time trends affecting Chinese exports into consideration. Under the assumption that the tariff changes imposed by exporting countries are exogenous and not correlated with unobserved shocks to Chinese exports, the estimated coefficients β_1 capture the causal impact of tariffs on Chinese exports.

The estimation results are reported in Table 4. Columns (1) and (2) of Table 4 examine China's export value and quantity to the U.S. in response to the exporting tariffs, respectively. As expected, the increased exporting tariffs reduce China's export values (quantities) to the U.S. with a β_1 elasticity of -0.6 (-0.58). Combined with the summary statistics for tariff changes in summary statistics in Table A31, we find that one percentage point increase in the U.S. tariffs was associated with a 0.7% decrease in export value and a 0.4% decrease in export quantity.

Columns (3) and (4) examine the trade diversion effect. Higher tariffs increase China's export value (quantity) to the rest of the world with a β_1 elasticity of 0.14 (0.1). Columns (5) and (6) examine the impact on China's total export. China's total export remains unchanged, as the positive trade diversion effects offsets the decline in exports to the U.S.

Table 4: **Tariffs and exports**

	(1)	(2)	(3)	(4)	(5)	(6)
	Export to the U.S.		to third countries		to the world	
	$\Delta ln(V)$	$\Delta ln(Q)$	$\Delta ln(V)$	$\Delta ln(Q)$	$\Delta ln(V)$	$\Delta ln(Q)$
$\Delta \ln(1+\tau\_us_{pt})$	-0.60***	-0.58***	0.14**	0.10**	0.10	0.06
	(0.12)	(0.12)	(0.06)	(0.05)	(0.07)	(0.05)
$\Delta \ln(1+\tau_{pct})$			-0.22	-0.07	-0.53***	-0.44**
			(0.29)	(0.28)	(0.20)	(0.20)
Observations	109,340	108,968	4,479,791	4,434,843	4,589,131	4,543,811
R-squared	0.31	0.29	0.19	0.18	0.20	0.19
HS-6 FE	YES	YES	NO	NO	NO	NO
HS-6 × Country FE	NO	NO	YES	YES	YES	YES
Country × Year-month FE	NO	NO	YES	YES	YES	YES
Year-month FE	YES	YES	NO	NO	NO	NO

Notes. Columns (1) - (6) report export values and export quantities regressed on the export tariff rates. Columns (1) and (2) include HS-6 product fixed effects and time fixed effects. Columns (3) - (6) include HS-6-product-country fixed effects and country-time fixed effects. Sample in Columns (1) - (2): China's monthly HS-8-product-level export data to the U.S. from 2017:1 to 2019:12. Sample in Columns (3) - (4): China's monthly HS-8-product-country-level export data to third countries from 2017:1 to 2019:12. Sample in Columns (5) - (6): China's monthly HS-8-product-country-level export data to all countries from 2017:1 to 2019:12. Variables are in twelve-month log change. Regressions in Columns (1) and (2) are weighted by HS-8 product-level export value last year. Regressions in Columns (3) - (6) are weighted by HS-8 product-country-level export value last year. Standard errors in Columns (1) and (2) are clustered by HS-6 product. Standard errors in Columns (3) - (6) are clustered by HS-6 product and country. Significance: * 0.10, ** 0.05, *** 0.01.

Figure 3 plots the dynamic effects. The top two figures show the impact of U.S. tariffs on China's exports to the U.S. measured in value and quantity, respectively. There is a sharp decline in export after the event. The two figures in the middle show the trade diversion effect, namely the third-country effect. Chinese exports to countries other than the U.S. increase in response to the U.S. tariffs. The bottom two figures show the overall effect of U.S. tariffs on China's total exports. The direct and third-country effects offset each other and the net impact is zero.

In addition, we use night light data as a proxy to assess firms' economic outputs. We use the Version 1 Nighttime Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band dataset provided by NOAA/NCEI. It is a radiance product after removing the impact of stray light, lightning, lunar illumination, and cloud cover, and is produced at the monthly level in 15 arc-second geographic grids. To construct our sample, we compute the average digital number at the firm-month level for each CEMS firm, using 1km and 5km buffers projected on the gridded night light product.

We re-estimate the first difference model and report results in Table A18. Using night light as dependent variables, estimates on $\Delta USTariff_{it}$ remain small and imprecise. The U.S. tariff burdens exert no discernible impacts on the light signals around by CEMS firms. Results remain

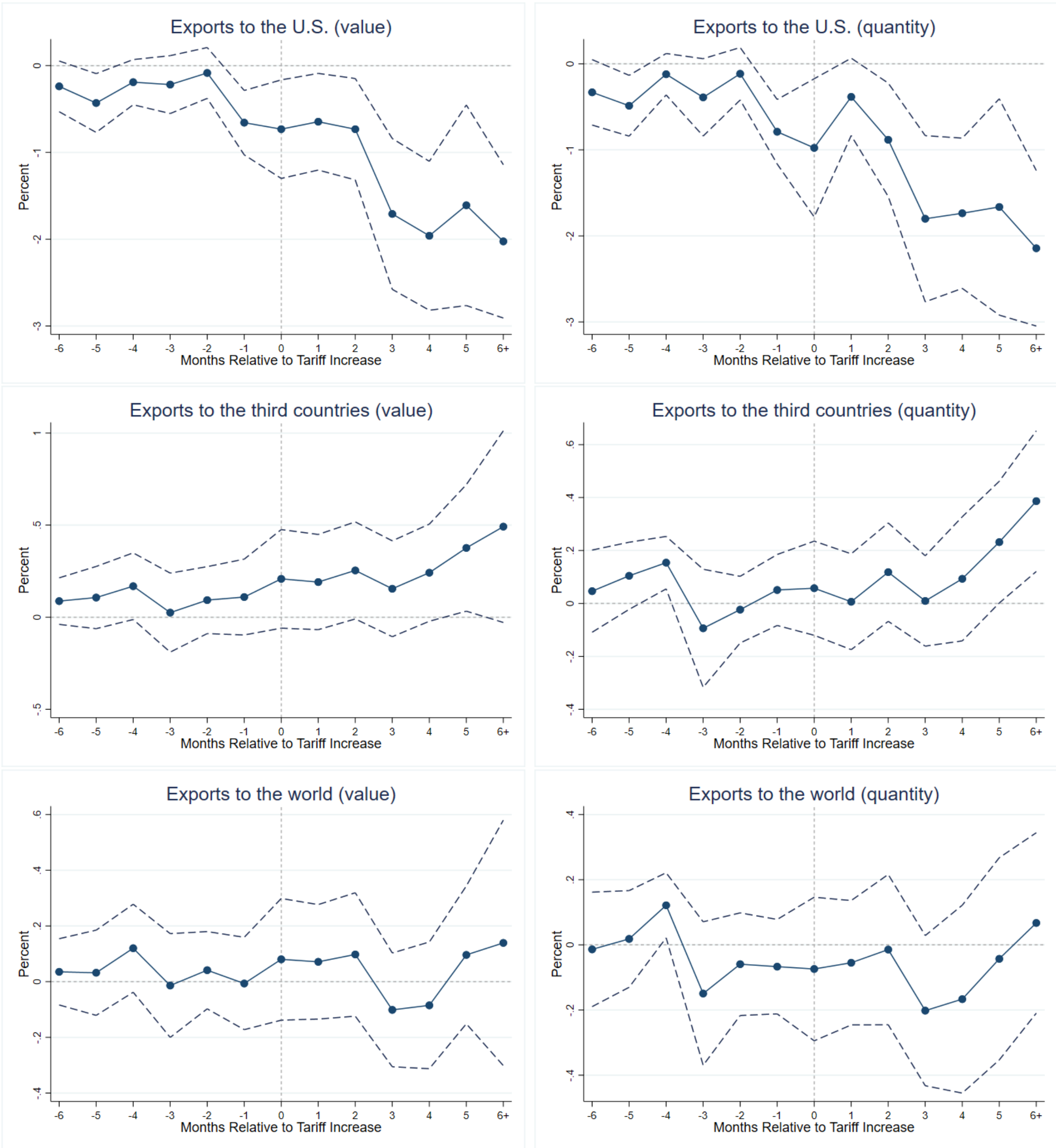


Figure 3: **Dynamic effects of tariffs on exports**

Notes. The three figures on the left show the impact of U.S. tariffs on China's export values to the U.S., other countries, and all the countries, respectively. The three figures on the right show the impact of U.S. tariffs on China's export quantities to the U.S., other countries, and all the countries, respectively. Sample for the top two figures: China's monthly HS-8-product-level export from 2017:1 to 2019:12. Sample for the two figures in the middle: China's monthly HS-8-product-country-level export to third countries from 2017:1 to 2019:12. Sample for the two figures in the bottom: China's monthly HS-8-product-country-level export to all trade partners from 2017:1 to 2019:12.

robust when employing alternative buffer zones for analysis. This suggests that earlier findings on increased emission intensities of CEMS firms are not likely to be driven by production changes.

5.2 Environmental regulation and enforcement

5.2.1 Environmental stringency index

We then measure how lenient environmental policies are by using 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 regulation, 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:

$$
\begin{aligned}
ESI_{pcy} &= \frac{\#\text{words in phrase } p\text{-related sentences in city } c \text{ year } t\text{'s work report}}{\#\text{words in city } c \text{ year } t\text{'s work report}} \\
ESI_{cy} &= \sum_p \frac{\#\text{words in phrase } p\text{-related sentences in city } c \text{ year } t\text{'s work report}}{\#\text{words in city } c \text{ year } t\text{'s work report}}
\end{aligned}
\tag{8}
$$

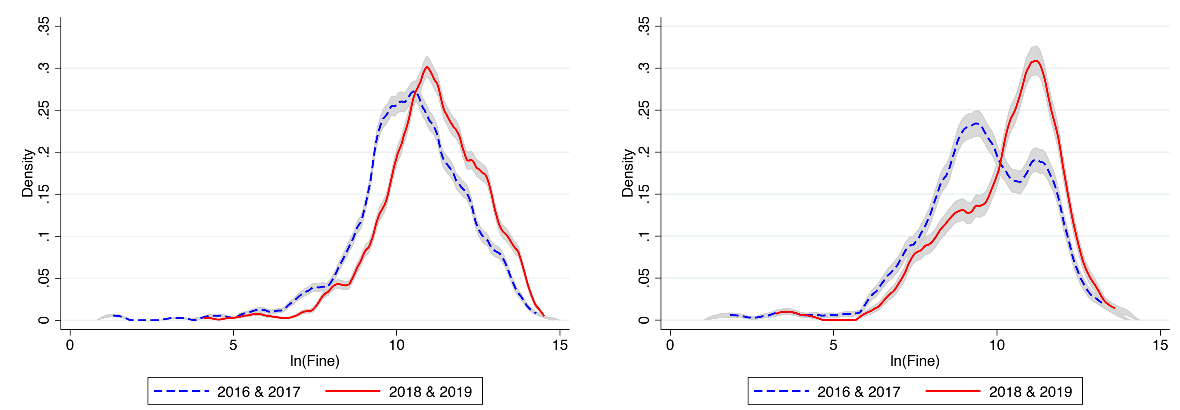
We use ESI as the dependent variable and re-estimate equation (5). In Table 5 Column (1), we find a negative and statistically significant effect on $\Delta USTariff$. Specifically, as the U.S. tariff increases by 1%, the environmental stringency index decreases by 0.77 units, equivalent to a decrease 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.

5.2.2 Fines

Apart from measuring environmental regulation, we also measure environmental enforcement using the environmental penalty data. Local environmental agencies conduct inspections on illegal acts and impose penalties on firms found to violate environmental regulations. These penalties are documented and made available through annual releases on government websites.

Each 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.[2]

Figure A5 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 4.1.1. In Figure 4, 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, despite an increasing trend nationwide.



(a) High-exposure cities

(b) Low-exposure cities

Figure 4: **Environmental fine distribution before and after the trade war**

Note: 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. Gray areas denote the 95% confidence intervals.

Using the fine data, we construct four measures for environmental enforcement, namely the number of penalty events, events resulting in fines, total fine amount, and fine amount per event. Results of estimating equation (5) are presented in Table 5 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 Sections 4.1.1 and 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

[2]Table A19 displays first-difference estimation results using fine month to merge with tariff months. Results demonstrate qualitative consistency with our favored specification in Table 5 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.

provide suggestive evidence that local environmental agencies are not as stringent as they were before the trade shock.

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. In other words, local environmental agencies adopt less stringent enforcement when cities face elevated tariffs.

Table 5: **Tariff effects on environmental stringency index and environmental fine**

	Stringency index		Δ#Events	Δ#Events with fine	ΔTotal fine	ΔFine per event
	(1)	(2)	(3)	(4)	(5)	(6)
Δ US Tariff	-0.770**	-0.074***	0.311	0.785	-6.912**	-8.530**
	(0.331)	(0.017)	(0.769)	(0.800)	(3.130)	(3.815)
Δ China Tariff	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 the 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.

We further perform separate estimations of equation (5) using penalty classification in the data. Each event is flagged with serious violations or other violations. Results presented in Table A20 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 A22, 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 A24 Panel A, we find similar estimates on $\Delta USTariff_{it}$ compared with those in Table 5. 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.

Moreover, we explore the heterogeneity across industries. As illustrated in Figure A6, the decline in environmental fines is particularly noteworthy in the manufacturing.[3] 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 susceptible to the impact of tariff burdens. Results in Table A23 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.

5.2.3 Bunching of pollution data

Another measure of lenient environmental policies lies in the manipulation of air quality data. In China, air quality is characterized as "excellent" when $PM_{2.5}$ levels are below $35\mu g/m^3$, and as "good" when $PM_{2.5}$ levels are below $75\mu g/m^3$. This critical threshold of $35\mu g/m^3$ also corresponds to the national objective outlined in the Air Pollution Prevention and Control Action Plan for long-term air quality targets[4]. Notably, local officials' career advancements hinge on air quality outcomes, which has been demonstrated to notably stimulate pollution reduction endeavors by local governments (Yin and Wu, 2022). Consequently, local administrations possess

[3]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.

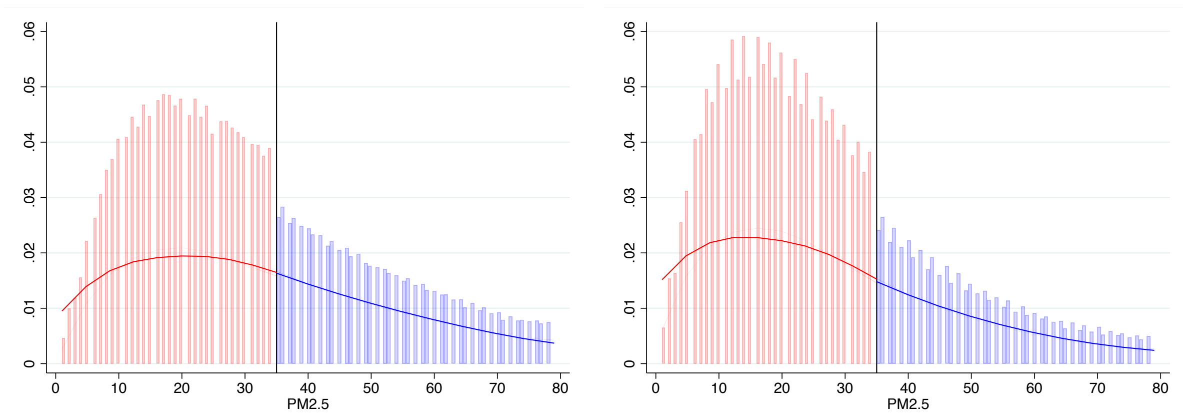
[4]State Council of China. http://www.gov.cn/zhengce/2018-06/24/content$_5$300953.htm.

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 investigate the impact of tariff burdens on the tendency of local governments to manipulate $PM_{2.5}$ data, as indicated by discontinuities around the threshold of $35\mu g/m^3$. Given that the citywide $PM_{2.5}$ levels are a result of a complex interplay between firm emissions, transportation and residential usage, wind patterns, and pollution deposition, the inherent data generation process is expected to exhibit a smooth pattern around the government-defined threshold of $35\mu g/m^3$. The presence of discontinuities at this point could indicate deliberate efforts to manipulate data in order to attain the classification of "excellent" air quality.

We use $PM_{2.5}$ data at the hourly-monitor level and perform separate discontinuity tests for both pre- and post-trade war periods. As shown in Figure 5, significant instances of bunching around the threshold of $35\mu g/m^3$ are evident in both periods under consideration. Specifically, a high density of data points is observed preceding the 35 thresholds, followed by a distinct and abrupt drop beyond this point. This pattern remains consistent across both periods, and aligns with the anticipated outcome of data manipulation efforts and previous empirical evidence.

Separating data into pre- and post-periods, we find more bunching after the trade war. In Panel A of Figure 5, the density of bunching experiences a modest decrease from 0.04 to 0.03, while in the post-trade war period, this density shows a substantial drop from 0.04 to 0.25. McCrary discontinuity tests show t-statistics of 9.1 for the pre-period and 11.5 for the post-period. This suggests that the incidence of bunching becomes more pronounced after the trade war. There is an elevated prevalence of manipulations in the air quality data, potentially reflecting a decrease in regulatory oversight or inspections aimed at curbing such manipulation efforts.



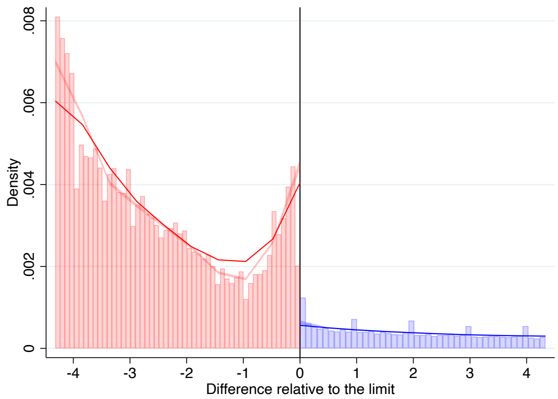
(a) January 2017 - June 2018

(b) July 2018 - December 2019

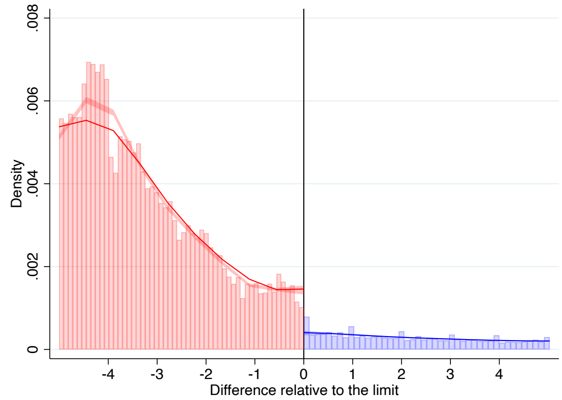
Figure 5: **Bunching of $PM_{2.5}$ data before and after the trade war**

Note: We use monitor-hour level reports of $PM_{2.5}$ 2017-2019, and test if there are discontinuities around $35\mu g/m^3$. McCrary test shows t-statistics are 9.0949 and 11.5437 in the pre- and post-period respectively.

In a similar idea, we investigate the potential bunching in firms' emission data. 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**

Note: 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.

We identify significant instances of bunching activities both before and after the trade war, as illustrated in Figure 6. 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.

This change in the bunching pattern is the opposite with the trend observed in citywide air quality data in Figure 5. 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 manipulate data in order 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 A8, 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 regulations exhibits uniformity across various hours.

We also test whether this bunching reduction arises from changes within individual firms or a decrease in the number of firms engaging in bunching. To do so, we calculate the emission differences relative to limits, add firm fixed effects, and estimate the residuals. We then employ a McCrary test using residuals as the dependent variables. In Figure A9, the existence of bunching near the limit cutoffs is not statistically different from zero. This implies that the observed changes in bunching behavior are predominantly attributable to firm compositions. There is a reduction in the number of firms attempting to manipulate emissions data rather than changes within firms before and after the trade war.

As a robustness check, we conduct a falsification test employing a placebo cutoff of $10\mu g/m^3$. Figure A10 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.

Apart from bunching, we also investigate the potential manipulation of 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 post event dummy.

Results in Table A17 Column (1) show a positive and statistically significant estimate on $CEMS$, implying a positive correlation between 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 consistent both before and after the trade war. We conclude there is no evidence of data manipulation efforts triggered by the tariff escalations. The findings in Section 4 likely stem from actual increases in pollution levels rather than stemming from reductions in the manipulation of emission data.

In a similar idea, we employ citywide 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 citywide air quality reports. 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 similar difference-in-difference model to estimate the correlation, and whether this correlation has changed in the pre and post-trade war periods.

In Table A17 Column (2) and (3), we find positive and significant associations between firms' particle emissions and citywide $PM_{2.5}$ 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 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 citywide pollution levels 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.

5.2.4 Media exposure and public attention

In this section, we investigate the impact of tariff burdens on media attention and public awareness of environmental issues. To measure public attention, we utilize the Baidu search index and media index at the county-day level and merge them with U.S. and China tariffs. Baidu is the most popular search engine in China, and its 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). 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. We hypothesize that cities facing high tariff burdens would have a reduced emphasis on environmental regulation by local governments. They would exhibit lower newspaper and web page coverage, leading to a decrease in the media index. We use media and search index for the keyword 'smog' as dependent variables and estimate equation (5).

In Table A21, 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 5.2 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.

5.3 Political incentives

5.3.1 Local officials' background

Local officials' place of birth, age, and political incentive can significantly influence local pollution emission (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 A25, 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 A26 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 A25 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 duration of city-level tenures. Results presented in Table A27 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 regulations.

5.3.2 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 lower 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 A28 and A29 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:

$$\sum_i M_i = \lambda_i \times RR(Pollution_i) \times Population_i \tag{9}$$

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:

$$\sum_i \Delta M_i = \lambda_i \times RR(Pollution_i - TradePollution_i) \times Population_i \tag{10}$$

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 A30. 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

Politicians are usually confronted with a difficult trade-off, as they need to balance economic growth with environmental protection. Despite its importance, there is limited empirical evidence. In this paper, we fill the gap and explore this trade-off in the context of international trade conflicts. The U.S.-China trade war provides a good setting as it can be used as a quasi-natural experiment to test this trade-off. Between 2018 and 2019, the U.S. government implemented a series of protective tariffs, which provoked a cascade of retaliatory tariffs from China and other trade partners. The trade war provides us with a source of adverse economic shocks, which allows us to investigate how local officials' political incentives affect firms' pollution emissions.

Adverse economic shocks are supposed to reduce production activities and thus reduce pollution emissions. Interestingly, 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 regulations during the trade war. To further explore the mechanism, we find that high-exposure cities also place less emphasis on environmental regulations 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. Using detailed export data, we provide additional evidence that the U.S. punitive tariffs reduce Chinese exports to the U.S. but barely affect China's total exports due to trade diversion. 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.

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A Appendix: Tables

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: **Robustness: Dropping 2017**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.733***	1.845***	0.900***	1.053***	0.696***
	(0.202)	(0.459)	(0.299)	(0.309)	(0.268)
Δ China Tariff	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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A3: **Robustness: Month-on-month change in pollution**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	3.402***	0.980	0.149	5.030***	1.920
	(0.978)	(1.176)	(0.973)	(1.277)	(1.176)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A4: **Robustness: City-month level pollution**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.629**	1.649**	0.482	0.853*	0.571
	(0.309)	(0.683)	(0.337)	(0.437)	(0.393)
Δ China Tariff	-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 A5: **Robustness: Weighted regression using city GDP**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	1.102**	0.289	0.600	1.529**	0.966
	(0.558)	(0.905)	(0.490)	(0.739)	(0.649)
Δ China Tariff	-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 A6: **Placebo: effect of the current tariff on last year's pollution**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	-0.788*	-0.314	-0.338	-1.028*	-0.772
	(0.420)	(0.627)	(0.451)	(0.580)	(0.501)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A7: **Placebo: effect of the tariff on weather conditions**

	ΔTemperature	ΔWind speed	ΔHumidity
Δ US Tariff	-0.192	-0.077	-0.056
	(0.570)	(0.278)	(1.416)
Δ China Tariff	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 A8: **Effect on air pollution non-attainment for excellent standards**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.929***	0.349***	0.258***	0.314**	0.870***
	(0.122)	(0.102)	(0.083)	(0.136)	(0.128)
Δ China Tariff	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
Monitor FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A9: **Effect on air pollution non-attainment for good standards**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.153	0.157**	0.258***	0.205*	0.058
	(0.107)	(0.080)	(0.083)	(0.107)	(0.091)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A10: **Restricting firms with observations every quarter**

	ΔParticles	ΔSO_2	ΔNO_x
Δ US Tariff	25.717***	30.882**	-12.692
	(8.629)	(14.268)	(8.894)
Δ China Tariff	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 A11: **Emission concentration relative to limits**

	(Concentration - limit) / limit		
	ΔParticles	ΔSO_2	ΔNO_x
Δ US Tariff	26.817***	24.209	-10.608
	(7.903)	(27.569)	(17.314)
Δ China Tariff	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 A12: **Number of firms in the CEMS data**

	Δ#Firms with Particles data	Δ#Firms with SO_2 data	Δ#Firms with NO_x data
Δ US Tariff	17.884***	21.189***	26.785***
	(5.261)	(6.049)	(7.338)
Δ China Tariff	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
Year-Month FEs	Y	Y	Y

Notes: Standard errors are clustered at the province level.

Table A13: **Dynamic effects by quarter**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff × 2018q3	-2.851***	-4.270***	-1.955**	-4.981***	-3.573***
	(0.588)	(1.646)	(0.936)	(1.083)	(0.728)
Δ US Tariff × 2018q4	1.959***	0.135	3.924***	2.611***	2.018***
	(0.627)	(0.988)	(0.623)	(0.861)	(0.743)
Δ US Tariff × 2019q1	1.507**	-0.687	2.486***	0.986	2.713***
	(0.590)	(0.929)	(0.623)	(0.830)	(0.651)
Δ US Tariff × 2019q2	0.267	-2.643***	1.048*	1.278**	0.226
	(0.342)	(0.869)	(0.545)	(0.619)	(0.481)
Δ US Tariff × 2019q3	.124	1.61***	.538	.0703	.124
	(.226)	(.612)	(.421)	(.363)	(.306)
Δ US Tariff × 2019q4	.689**	2.81***	-.454	.976**	.724*
	(.311)	(.716)	(.426)	(.432)	(.416)
Δ China Tariff	-.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; Δ US Tariff × 2017q1 to 2018q2				

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

Table A14: **Effects by hour**

	Effects at 2pm				
	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.036	0.650	0.097	0.306	-0.248
	(0.217)	(0.447)	(0.365)	(0.327)	(0.285)
Δ China Tariff	0.063	-0.498*	-0.205	-0.355*	0.048
	(0.159)	(0.298)	(0.216)	(0.212)	(0.200)
Observations	48811	48811	48811	48811	48811
R-square	0.226	0.149	0.109	0.177	0.214
Y-mean	-0.037	-0.188	-0.049	-0.076	-0.065
Y-sd	0.243	0.423	0.347	0.331	0.310
	Effects at 10pm				
Δ US Tariff	0.742***	1.118**	1.177***	0.575*	0.834***
	(0.209)	(0.492)	(0.313)	(0.301)	(0.265)
Δ China Tariff	-0.298**	-0.134	0.759***	-0.839***	-0.377**
	(0.144)	(0.297)	(0.165)	(0.192)	(0.167)
Observations	48813	48813	48813	48813	48813
R-square	0.201	0.152	0.171	0.180	0.209
Y-mean	-0.054	-0.192	-0.024	-0.077	-0.068
Y-sd	0.237	0.442	0.293	0.313	0.295
Monitor FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A15: **Before vs. after working hours (8am-6pm)**

	Off hour - working hour				
	ΔAQI diff	ΔSO_2 diff	ΔNO_2 diff	$\Delta PM_{2.5}$ diff	ΔPM_{10} diff
Δ US Tariff	9.801***	2.279	1.151	6.250***	11.583***
	(2.343)	(1.440)	(1.089)	(1.780)	(2.425)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A16: **Firm emissions before vs. after sunset**

	Panel A: Daytime		
	ΔParticles	ΔSO_2	ΔNO_x
Δ US Tariff	15.909*	12.566*	-14.479**
	(9.197)	(6.878)	(6.288)
Δ China Tariff	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		
Δ US Tariff	18.340	22.953**	-10.737*
	(16.451)	(10.912)	(5.828)
Δ China Tariff	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
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 A17: **Correlation of CEMS and satellite AOD and citywide air quality data**

	Satellite AOD	Citywide PM_{10}	Citywide $PM_{2.5}$
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
Year-Month FEs	Y	Y	Y

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

Table A18: **Tariff effects night light around CEMS firms**

	Night light within 1km	Night light within 5km
Δ US Tariff	1.392	0.999
	(0.977)	(0.927)
Δ China Tariff	0.641	0.747*
	(0.436)	(0.388)
Observations	259416	259416
R-square	0.131	0.176
Y-mean	0.092	0.093
Y-sd	0.456	0.337
Firm FEs	Y	Y
Year-Month FEs	Y	Y

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

Table A19: **Tariff effects on environmental fine using fine month**

	Δ#Events (1)	Δ#Events with fine (2)	ΔTotal fine (3)	ΔFine per event (4)
Δ US Tariff	-1.836	-2.132	-8.263	-7.224
	(1.915)	(1.831)	(10.657)	(9.926)
Δ China Tariff	-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 A20: **Tariff effects on environmental fine: serious and other violation**

	Δ#Events	Δ#Events with fine	ΔTotal fine	ΔFine per event
	(1)	(2)	(3)	(4)
	Panel A: Serious violation			
Δ US Tariff	0.606***	0.526***	3.692	-0.635
	(0.189)	(0.140)	(5.789)	(7.173)
Δ China Tariff	-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			
Δ US Tariff	0.087	0.694	-7.533**	-8.887**
	(0.775)	(0.811)	(3.151)	(3.798)
Δ China Tariff	-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
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 A21: **Tariff effects on media and search index on "smog"**

	Media index	Search index		
		Overall	PC	Mobile
Δ US Tariff	-2.128***	-0.334	-0.001	-0.177
	(0.591)	(1.541)	(1.661)	(1.384)
Δ China Tariff	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
Year-Month FEs	Y	Y	Y	Y

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

Table A22: **Tariff effects on the number of firms with environmental violations**

	Δ#Firms	Δ#Firms with fine
	(1)	(2)
Δ US Tariff	-0.934	-0.863
	(1.154)	(1.249)
Δ China Tariff	-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
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 A23: **Tariff effects on environmental fine of unrelated sectors**

	ΔTotal fine	ΔFine per event
	(1)	(2)
Δ US Tariff	-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.

Table A24: **Tariff effects on environmental fine: separate by pollution types**

	Δ#Events	Δ#Events with fine	ΔTotal fine	ΔFine per event
	(1)	(2)	(3)	(4)
	Panel A: Air pollution			
Δ US Tariff	0.298	0.768	-6.751**	-8.370**
	(0.769)	(0.798)	(3.134)	(3.823)
Δ China Tariff	-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			
Δ US Tariff	0.050	0.075	4.689	6.267
	(0.104)	(0.103)	(3.528)	(4.415)
Δ China Tariff	-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			
Δ US Tariff	0.043	-0.097***	-6.319***	-9.040***
	(0.047)	(0.022)	(1.588)	(2.210)
Δ China Tariff	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
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 A25: **Local leaders are from native provinces or not**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	1.033***	3.107***	3.347***	0.466	1.265***
	(0.275)	(0.619)	(0.405)	(0.416)	(0.354)
Δ US Tariff $\times$ Native Party	-0.475*	-3.492***	-3.252***	0.129	-0.760**
	(0.288)	(0.636)	(0.416)	(0.425)	(0.362)
Δ US Tariff $\times$ Native Mayor	-1.672*	-0.715	2.432*	-1.599	-1.188
	(0.941)	(1.817)	(1.283)	(1.350)	(1.368)
Δ China Tariff	-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
Monitor FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A26: **Local leaders are above or below 68**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.662***	0.471	0.905***	0.564*	0.701***
	(0.198)	(0.441)	(0.288)	(0.298)	(0.253)
Δ US Tariff $\times$ Old Party	-1.032	-8.443***	0.855	-2.827	-2.959*
	(1.235)	(2.258)	(1.678)	(1.960)	(1.564)
Δ US Tariff $\times$ Old Mayor	0.905	9.644**	2.248	0.575	0.395
	(2.202)	(4.243)	(2.425)	(3.244)	(2.888)
Δ China Tariff	-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
Monitor FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A27: **Local leaders' tenure length**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	1.169***	0.103	2.450***	3.391***	0.572
	(0.448)	(1.051)	(0.675)	(0.655)	(0.566)
Δ US Tariff $\times$ Tenure Party	-0.132	0.068	-0.471**	-0.896***	0.086
	(0.131)	(0.298)	(0.207)	(0.193)	(0.165)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A28: **Heterogeneity across distances to province boundaries**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	1.018***	1.496**	1.417***	1.701***	0.893**
	(0.279)	(0.606)	(0.382)	(0.422)	(0.349)
Δ US Tariff $\times$ Dist	-0.006**	-0.008	-0.007	-0.014***	-0.003
	(0.003)	(0.006)	(0.005)	(0.004)	(0.004)
Δ China Tariff	-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
Monitor FEs	Y	Y	Y	Y	Y
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A29: **Heterogeneity across distances to city boundaries**

	ΔAQI	ΔSO_2	ΔNO_2	$\Delta PM_{2.5}$	ΔPM_{10}
Δ US Tariff	0.956***	-0.911*	0.553*	1.413***	1.165***
	(0.245)	(0.528)	(0.328)	(0.372)	(0.308)
Δ US Tariff $\times$ Dist	-0.014**	0.072***	0.014	-0.027***	-0.020**
	(0.007)	(0.013)	(0.009)	(0.010)	(0.009)
Δ China Tariff	-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
Year-Month FEs	Y	Y	Y	Y	Y

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

Table A30: **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 A31: **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

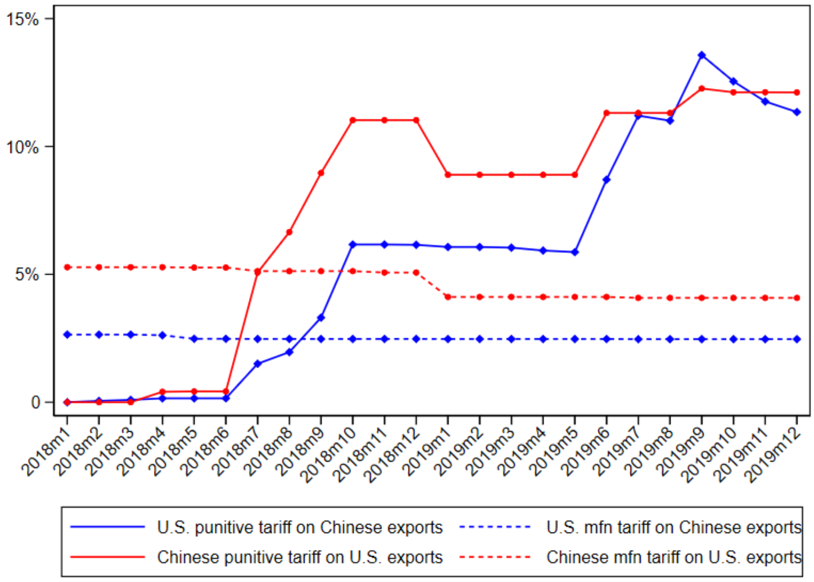
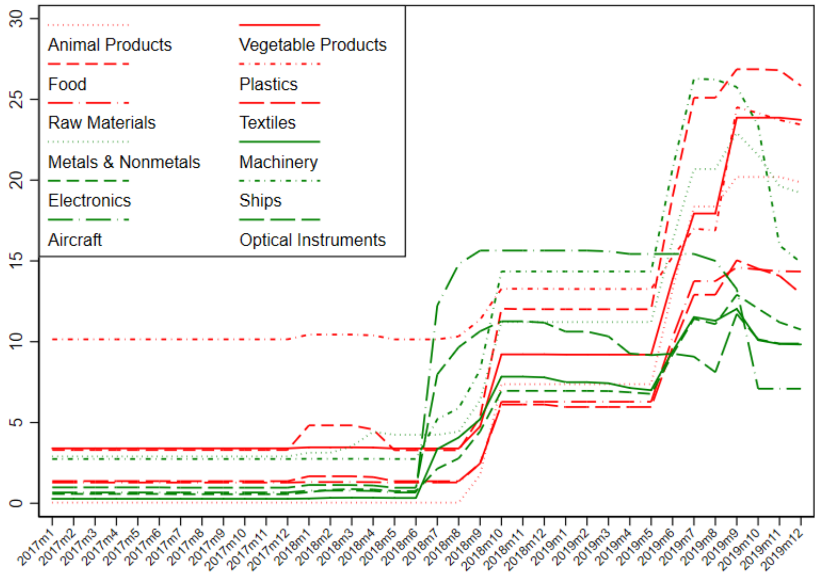
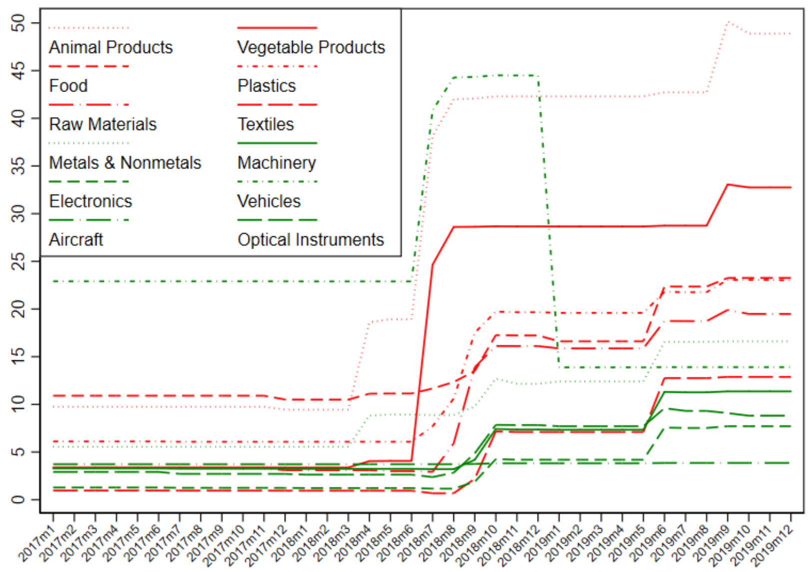


Figure A1: U.S. and Chinese tariffs

Note: The figure presents the U.S. punitive tariffs on Chinese products (solid blue line) and its MFN tariffs (dash-dotted blue line), as well as the import-weighted average Chinese retaliatory tariff rates on U.S. products (solid red line) and its MFN tariffs (dash-dotted red line). 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.



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



(b) Chinese statutory tariffs (%)

Figure A2: U.S. and Chinese statutory tariffs by products

Note: 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).

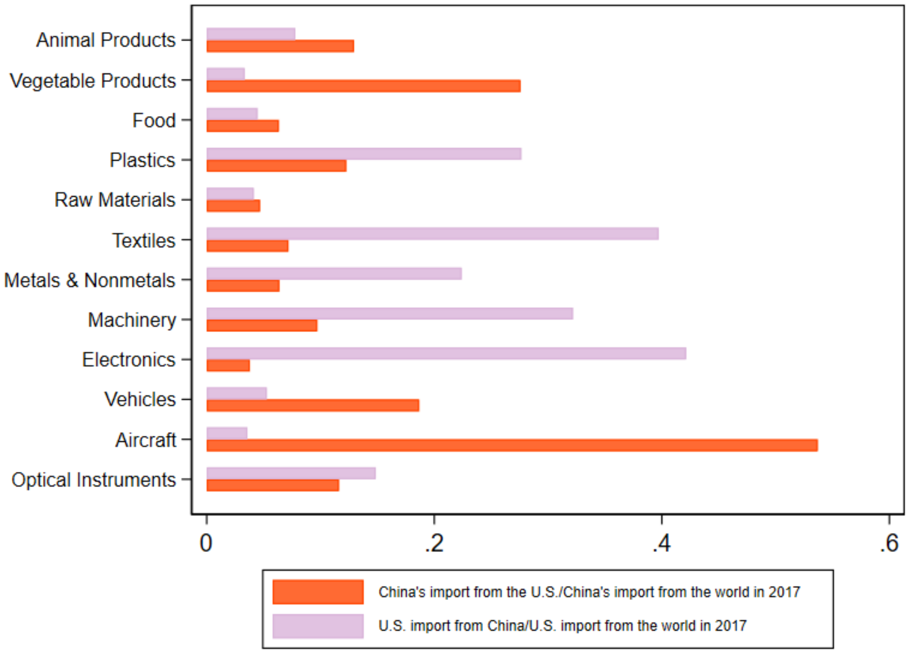
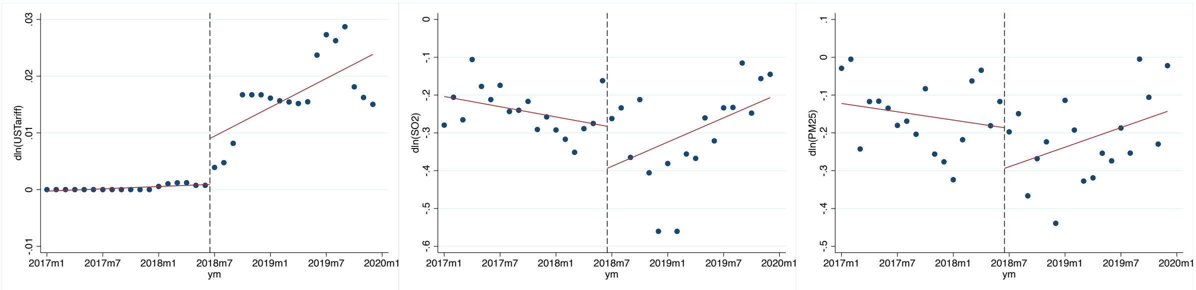


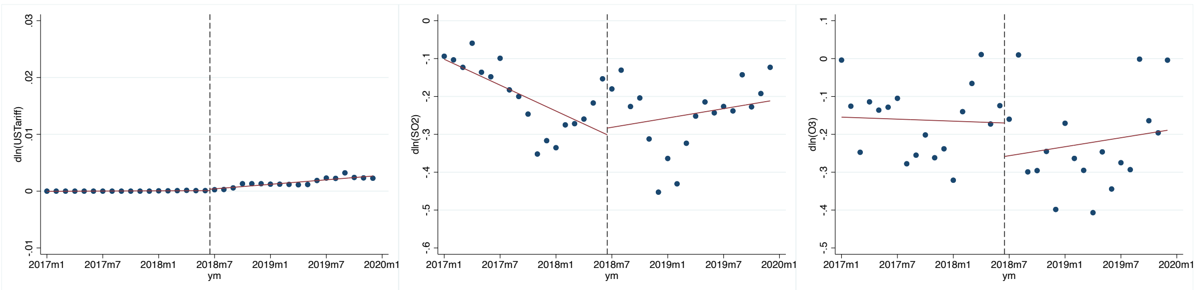
Figure A3: Import share by products

Note: The figure presents China's imports from the 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 refers to electronics and equipment. Vehicles refers to motor vehicles, ships, and boats. Aircraft refers to aircraft, railways, and weapons.

Source: Authors' calculations based on data from UN Comtrade.



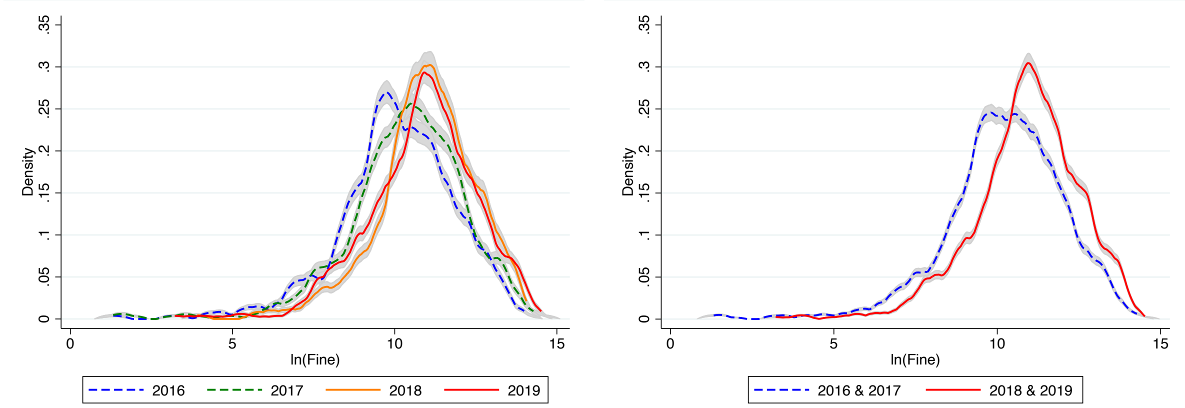
(a) High-exposure cities



(b) Low-exposure cities

Figure A4: U.S. tariff and air pollution over time

Notes: These figures display binscatter plots for the year-to-year monthly changes of U.S. tariffs, SO_2, and $PM_{2.5}$, where city-level tariffs are weighted by exports. Cities are classified into two groups based on their U.S. tariff exposure.



(a) All cities, histogram in each year

(b) All cities

Figure A5: Environmental fine distribution

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

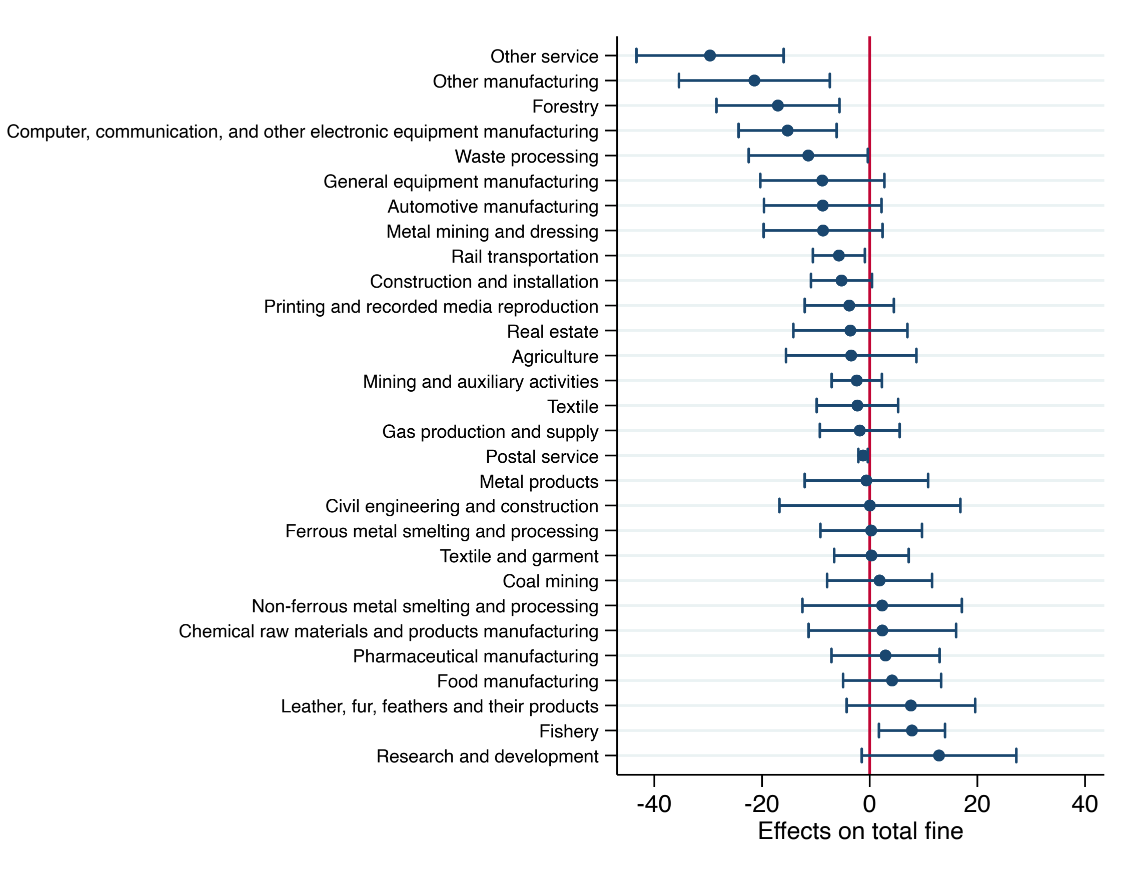
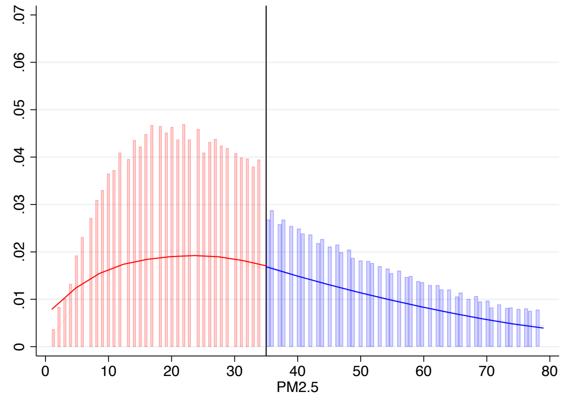
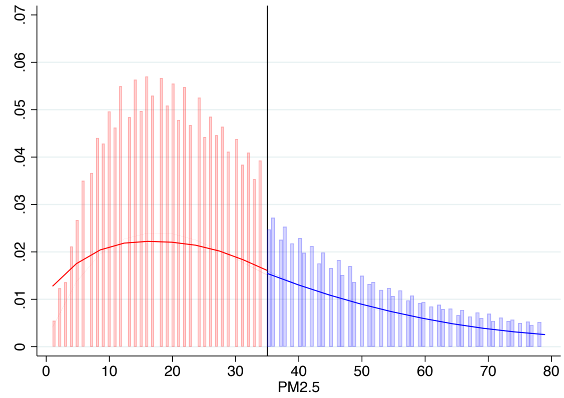


Figure A6: Tariff effects on environmental fine, heterogeneity across industries

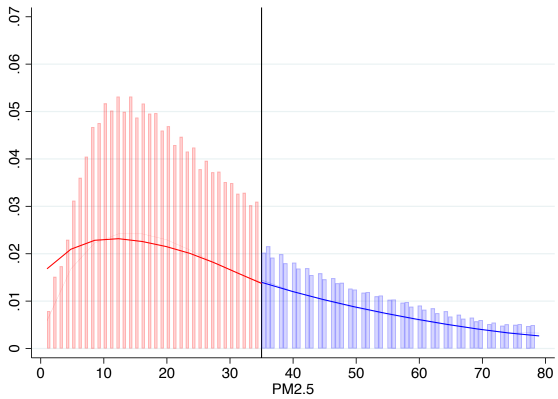
Note: This figure plots the estimated coefficients on $\Delta USTariff_{it}$ and 95% confidence intervals. We use the total fine of different industries as dependent variables. Sample and specifications are the same as Table 5 Column(5).



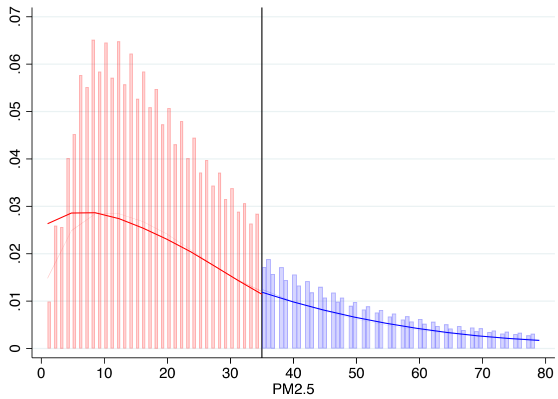
(a) High-exposure cities, January 2017 - June 2018



(b) High-exposure cities, July 2018 - December 2019



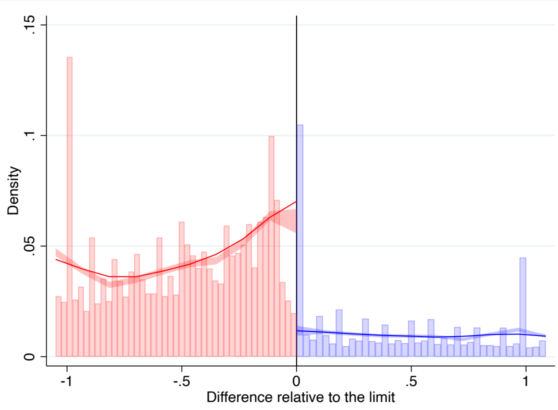
(c) Low-exposure cities, January 2017 - June 2018



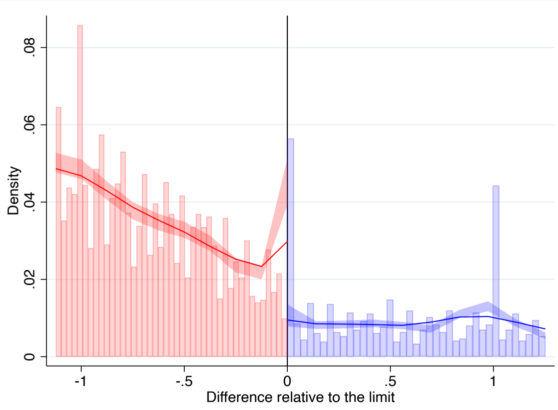
(d) Low-exposure cities, July 2018 - December 2019

Figure A7: Bunching of $PM_{2.5}$ in high- and low-exposure cities, before and after the trade war

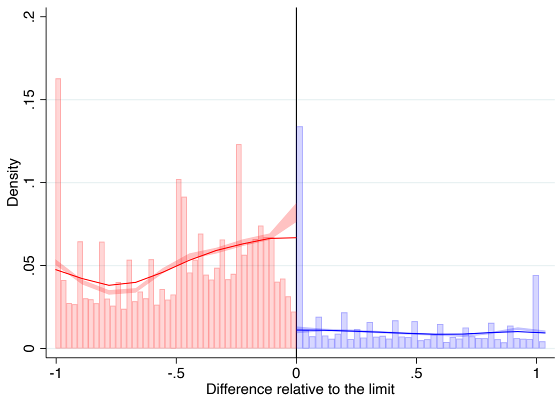
Note: We use monitor-hour level reports of $PM_{2.5}$ 2017-2019, and test if there are discontinuities around $35\mu g/m^3$. For high-exposure cities, McCrary test shows t-statistics are 9.1781 and 11.5564 in the pre- and post-period respectively. For low-exposure cities, McCrary test shows t-statistics are 1.5069 and 2.1768 in the pre- and post-period.



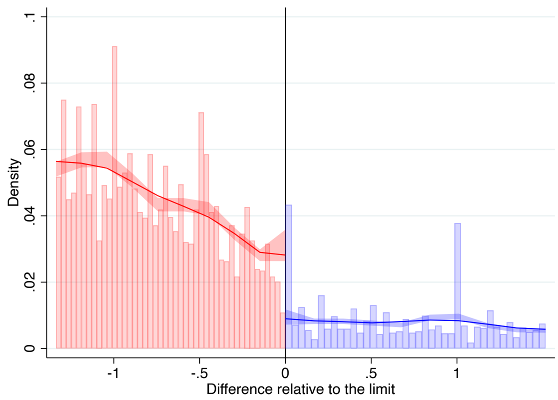
(a) Daytime emissions, January 2017 - June 2018



(b) Daytime emissions, July 2018 - December 2019



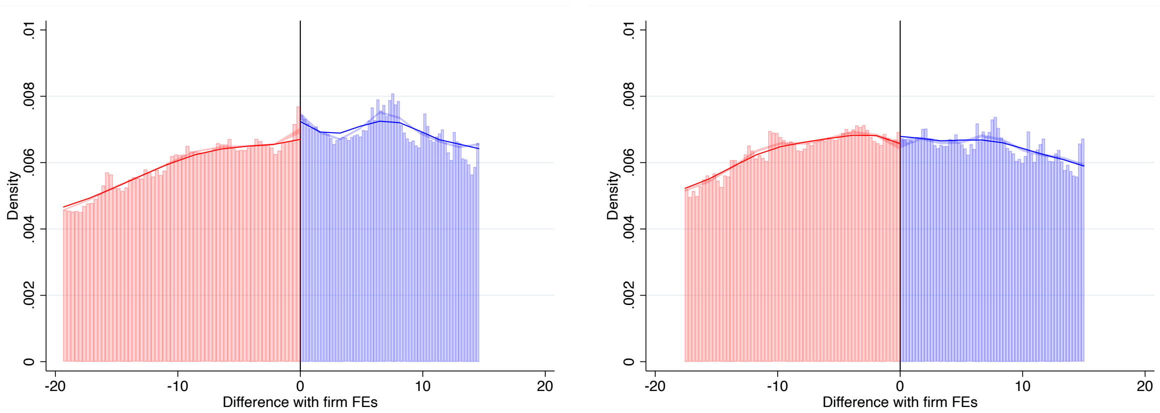
(c) Nighttime emissions, January 2017 - June 2018



(d) Nighttime emissions, July 2018 - December 2019

Figure A8: Bunching of CEMS data before and after the trade war, before and after sunset hours

Note: 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.

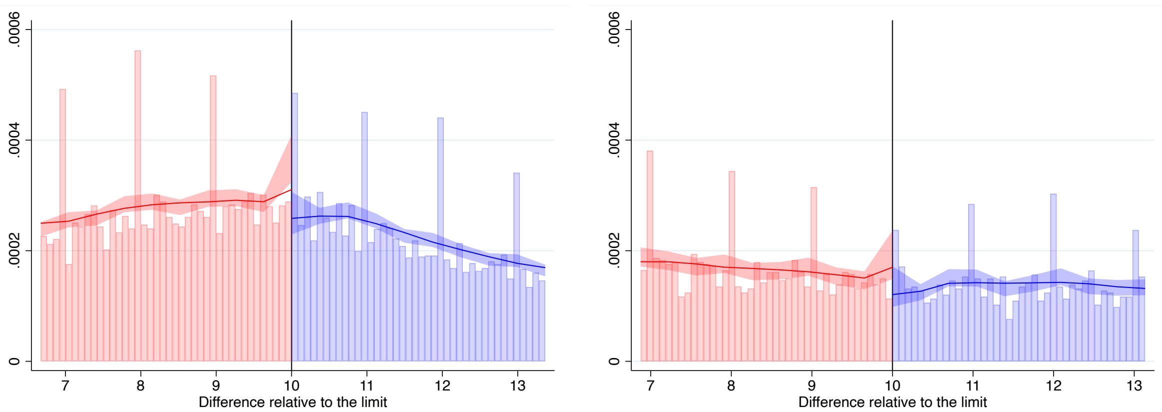


(a) January 2017 - June 2018

(b) July 2018 - December 2019

Figure A9: Bunching of CEMS data before and after the trade war with firm fixed effects

Note: We use firm-hour level reports of CEMS emissions for SO_2, NO_x, and Particles 2017-2019, calculate emission concentrations relative to the limits, and estimate residuals with firm fixed effects. We test if there are discontinuities around $10\mu g/m^3$. McCrary test shows t-statistics are 6.475 and 0.6251 in the pre- and post-period respectively.



(a) January 2017 - June 2018

(b) July 2018 - December 2019

Figure A10: Bunching of CEMS data before and after the trade war using placebo cutoffs

Note: 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.

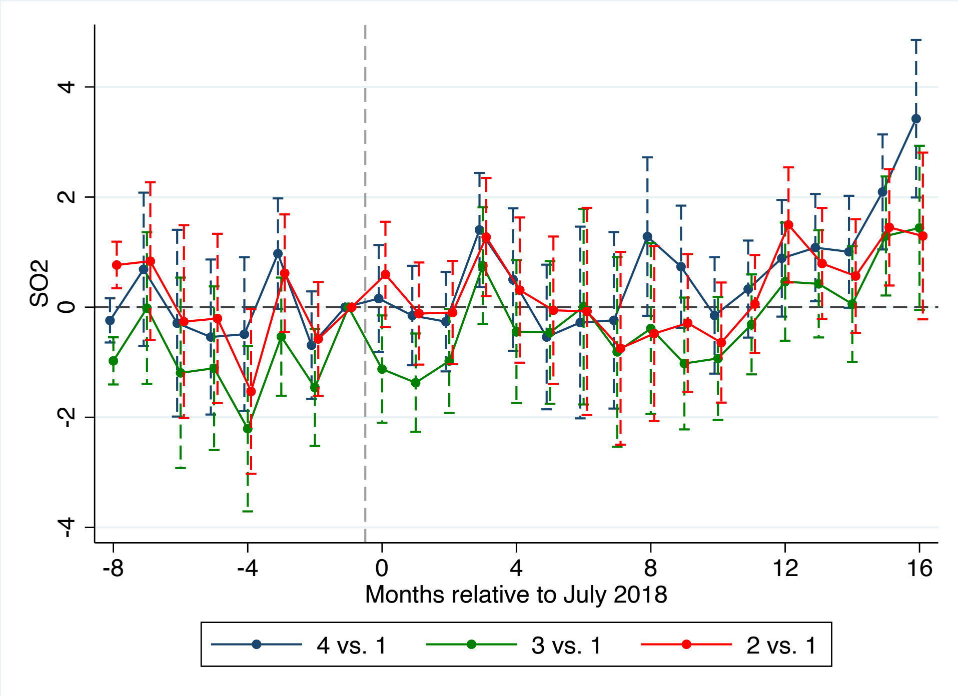


Figure A11: Event study of city-level air quality, separate by quartiles

Note: The figures plot the impact of U.S. tariffs on citywide air quality. We plot point estimates and their 95% confidence intervals in each months, with month negative 1 dropped. We control for city, year-month, and prov-month fixed effects. Standard errors are clustered at the station-month level.

Figure A12: Night time emissions

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

Figure A13: Sulfur removal scrubber

Note: 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.