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Abstract

We analyze the impact of a rise in protectionism on environmental regulation. Using the 2018 US-China trade war as a quasi-natural experiment, we find that higher exposure to tariffs leads to less stringent regulation targets in China, increasing air pollution and carbon emissions. Politically motivated changes in environmental policies rationalize our results: the central government and local party secretaries relax environmental regulations to mitigate the negative consequences of tariffs for polluting industries. We find heterogeneous effects depending on politicians' characteristics: younger, recently appointed, and more connected local politicians are more likely to ease environmental regulation. This policy reaction benefits politicians: prefectures with the most considerable easing in environmental regulation manage to curb the negative economic consequences of the trade war, while their mayors have a relatively larger probability of promotion. This paper presents the first empirical evidence of political incentives to manipulate environmental regulation to curb negative economic shocks.

JEL Classifications: Q50, Q56, F13, F18, E32, D72.

Keywords: Political Cycles, Environmental Regulation, Trade Protection, US-China Trade War

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1 Introduction

Since Nordhaus (1975)'s pioneering model, economists have considered manipulating economic policies for electoral motives as an essential determinant of macroeconomic fluctuations. According to this theory, political leaders aim to hold office opportunistically. For this reason, they have incentives to implement policies to expend the economy and promote political stability (Acemoglu and Robinson, 2005). In this paper, we are the first to systematically investigate how politicians use environmental regulation to curb the effects of a negative income shock.

Environmental protection can be highly costly for firms because it might require significant expenditures to complain to regulations while distorting firms' investment and production decisions (Pizer and Kopp, 2005). Several empirical studies show that environmental regulation affects firm productivity in developed (e.g., Greenstone, 2002) and developing countries (e.g., He et al., 2020). For this reason, politicians can be incentivized to ease environmental regulation to obtain economic benefits at the expense of people's health.

Anecdotal evidence points to environmental regulation as one tool to smooth the business cycle for both China and the United States. For instance, in June 2020, President Trump signed an executive order to waive long-standing environmental laws in the aftermath of the outbreak of the COVID-19 crisis. The idea behind this change in legislation was that "unnecessary regulatory delays will deny our citizens opportunities for jobs and economic security, keeping millions of Americans out of work and hindering our economic recovery from the national emergency."[1] As another example, following the 2018 Trade War, Chinese officials publicly declared that "external elements, such as the Sino-US trade war, have brought negative impacts and increasing uncertainties to the global economy, which has also made it more difficult for China to tackle climate change [...] With the economy under downward pressure, the country has to take more measures to guarantee employment and the people's livelihood [...] Some of those measures may not fit our effort to tackle climate change."[2]

To test this mechanism, we investigate how governments react to worsening economic conditions using the 2018 US-China trade war as a quasi-natural experiment. The trade war upended a decades-long trend toward reducing global trade barriers, with many escalated tariffs persisting beyond 2021 (Fajgelbaum et al., 2021). In addition, it induced a steep

[1] Executive Order 13927 of June 4, 2020. Accelerating the Nation's Economic Recovery From the COVID-19 Emergency by Expediting Infrastructure Investments and Other Activities.

[2] Muyu Xu and David Stanway, "China CO2 emission targets at risk from US trade war," *Reuters*, August 30, 2019.

increase in trade barriers between the two major world economies and caused a negative impact on both the Chinese and the US economy (Chor and Li, 2021).

To answer our research question, we build a novel database on environmental regulations for China's central and local governments. Taking into account both levels of executive authority in the analysis is crucial because, in China, top-down governance administrates environmental regulation with shared competencies between the central government and the local administration (Kahn et al., 2015; He et al., 2020).[3] In particular, we measure national environmental regulation using discretionary data on annual air pollution density targets from 2016 to 2020. We focus on $PM_{2.5}$ targets that is considered the main air pollution density target according to Chinese environmental laws as in force during the trade war.[4] At the same time, we assess the local government's efforts in implementing environmental regulations in two ways. First, we collect data on the number of local environmental penalties targeting Chinese firms. Second, we analyze the word counts relating to environmental regulations in the prefectures' annual government work reports.

In our paper, we focus on China for four main reasons. First, the United States has been the most important export destination for Chinese firms since China joined the WTO. Indeed, exports to the United States account for 6% of China's GDP. Thus, Trump Tariffs represent a significant demand shock for Chinese firms. Second, there has been increasing attention towards pollution in China since 2003 (He et al., 2020; Greenstone et al., 2022), and the success in achieving environmental goals is crucial for the advancement to higher political positions of local party secretaries (Kahn et al., 2015; He et al., 2020). Third, granular official data allow us to directly measure the general targets of local air quality from the upper-layer government and the the level of local regulations' enforcement. Finally, each prefecture in China reports its air pollution for $PM_{2.5}$ daily. $PM_{2.5}$ refers to particulate matter in the atmosphere with a diameter equal to or smaller than 2.5 micrometers.[5] These

[3] Usually, the central government sets a general pollution removal target to be implemented by local authorities. Success in achieving environmental goals becomes a criterion for promoting local politicians (Kahn et al., 2015).

[4] $PM_{2.5}$ refers to particulate matter in the atmosphere with a diameter equal to or smaller than 2.5 micrometers. Particles resulting from industrial emissions, vehicle exhausts, coal combustion, and wood burning can be harmful when inhaled. These inhalable particles can penetrate the human respiratory system, lodging deep within the respiratory tract and alveoli, potentially leading to diseases. Prolonged exposure to such particles is associated with cardiovascular and respiratory ailments, including lung cancer. Since 2018, the "Three Year Action Plan to Wing the Blue Sky Defense War" defines the $PM_{2.5}$ targets as the main pollutant for regulation.

[5] Particles resulting from activities such as industrial emissions, vehicle exhausts, coal combustion, and wood burning can be harmful when inhaled. These inhalable particles can penetrate the human respiratory system, lodging deep within the respiratory tract and alveoli, potentially leading to diseases. Notably, the smaller the particle's diameter, the deeper its penetration into the respiratory system. For instance, particles

data allow us to measure precisely air pollution dynamics.

Our identification strategy relies on a differences-in-difference model. Using a shift-share research design, we measure the prefecture exposure to US import tariff shocks according to the initial industry specialization across Chinese prefectures before the trade war, while the timing of the trade war represents the variation across time, the year 2018. In particular, the initial industry specialization is measured using the prefectures' exports to the United States across industries before the trade war.[6] The intuition is that aggregate changes in tariffs across industries can affect different Chinese prefectures differently according to the weight of the US market in the prefecture's economy.

Our baseline estimates suggest that the trade war significantly reduced the stringency of environmental regulation in China. A one-standard-deviation increase in tariffs exposure induces an increase in $PM_{2.5}$ density limits by 62%. Furthermore, the trade war significantly reduces the local enforcement of environmental regulation by looking at the textual analysis and the number of environmental administrative actions. According to the literature (He et al., 2016; Greenstone, 2002), stringent environmental regulations can increase costs for firms, potentially constraining their production and leading to reduced air pollution. Conversely, easing these regulations might result in increased air pollution. Our paper also estimates the trade war's impact on air pollution and carbon emission. We find that prefectures with substantial exposure to US import tariffs experience a more robust rise in the air density of $PM_{2.5}$ and CO_2. This evidence suggests that the trade war had adverse effects on the health of Chinese citizens and constitutes a negative global externality provided by the increase in carbon emissions.

In our study, we address potential endogeneity concerns in several ways. First, our identification strategy assumes that treated and not treated prefectures had similar trends for environmental regulation before the trade war. To test this assumption, we conduct an event study and found no significant evidence for a pre-trend. A second concern is that the export structure of a prefecture could be endogenous if the US administration sets tariffs targeting a specific prefecture because of its characteristics. Furthermore, industries are not randomly exposed to Trump tariffs as some unobservable industry characteristics could drive

with diameters less than 2.5 microns ($PM_{2.5}$) can infiltrate entirely into the bronchioles and alveoli. Due to their small size and large surface area, these particles remain suspended in the air for extended periods, often carrying harmful substances like toxins, heavy metals, and microorganisms. Their prolonged atmospheric presence and potential to travel long distances make them especially detrimental to human health, impacting air quality and visibility. Prolonged exposure to such particles is associated with cardiovascular and respiratory ailments, including lung cancer.

[6]According to our data, around 90% of the Chinese prefectures had been affected by the trade war as they host firms exporting to the United States.

both tariffs and environmental regulation. To address these concerns, we always include a set of a prefecture's initial characteristics that are interacted with year dummies.

Our results survive a battery of additional robustness checks. First, in a critical robustness check, we show that our results are robust by controlling for unobservable product-level characteristics following Borusyak et al. (2021). Hence, their methodology allows us to rewrite our baseline model at the product level, controlling for product fixed effects. Then, we show that our benchmark results are robust to modifying our exposure shares using industry employment in a prefecture. We also show that our estimates are not statistically significant if we construct the prefecture's exposure using its exports to the European Union, indicating that US tariffs directly drive our results rather than potential spillovers of the trade war on other key trade partners such as the European Union. Next, we conducted a placebo test to examine the presence of anticipation effects. Specifically, we construct a sample before the trade war and use 2017 as a placebo time for the treatment. In this case, the estimates are insignificant and close to zero, so we do not have statistical differences in environmental regulation. Lastly, we verify if Chinese retaliatory tariffs drive our results. When we include retaliatory tariffs in our regression, we observe that retaliatory tariffs do not influence environmental regulation, suggesting that US demand shocks drive our estimates.

This research question is fundamental in the case of China for three main reasons. First, the local government also has incentives to implement these policies given that economic performance and social stability are essential criteria for promoting politicians (Li and Zhou, 2005; Campante et al., 2023; Chen and Zhang, 2021). Second, previous studies have shown that Chinese politicians have incentives to promote social stability through different types of policies (Wen, 2020). Third, environmental regulation is very costly for Chinese firms (He et al., 2020), and lifting those constraints will likely reduce their production costs. Relaxing environmental regulation is also motivated by the large share of SOEs in polluting industries (Wang and Jin, 2007). Thus, changing environmental policy could increase production for these firms.

We suggested a political economy mechanism to rationalize our results. Politicians relax environmental regulations to improve the competitiveness of Chinese firms facing a rise in US tariffs to boost their careers and promote social stability. This argument echoes previous studies that show how trade-induced economic distress raises the salience of economic issues in a society (Bez et al., 2023). To test this mechanism, we analyzed the impact of the trade war on GDP and the probability of promoting local Party secretaries to a higher level of government. Our estimates suggest that the rise in US tariffs negatively affects these two variables. However, prefectures with the most significant easing in environmental regulation manage to curb this negative impact on GDP, and their mayors have a larger probability of promotion. These results confirm that local politicians might have wanted to manipulate environmental policy for political purposes.

Our paper offers two main contributions. First, we present systematic evidence that environmental policy can potentially be used to smooth the business cycle. This has significant negative welfare implications, especially given the documented substantial adverse effects of pollution on life expectancy (Chen et al., 2013; Ebenstein et al., 2017). Second, our findings underscore the importance of governmental responses when analyzing the impact of protectionism on third-country policies. Specifically, our results suggest that trade protectionism leads to increased pollution due to politically-motivated shifts in environmental regulation.

The rest of the paper is organized as follows: Section 2 briefly discusses the related literature. Section 3 discusses the background of the US-China trade war. Section 4 introduces the identification strategy. Section 5 presents the empirical results. Section 6 discusses the possible mechanisms explaining our results. Finally, section 7 presents the robustness checks, and section 8 concludes the paper.

2 Related literature

Our paper contributes to the extensive literature that examines political cycles. Historically, this body of work has primarily centered on macroeconomic policies, specifically fiscal and monetary policies (Alesina et al., 1997; Drazen, 2000a,b).[7] Several studies underscore the endogenous political determination of environmental policy, influenced either by lobbying activities (e.g., Conconi, 2003) or electoral incentives (e.g., List and Sturm, 2006; Burgess et al., 2012; Colantone et al., 2023). A significant portion of influential research has been directed towards China due to its proactive stance against pollution. Zheng et al. (2014) and Kahn et al. (2015) demonstrate that incorporating environmental objectives as promotional criteria for local officials leads to notable strides in pollution mitigation. Notably, Chen et al. (2018) posits that a dip in GDP growth correlates with a decrease in pollution, suggesting a balancing act between China's environmental and economic aspirations. In a seminal work, He et al. (2020) posits that environmental regulations adversely impact firm productivity, with this effect being particularly pronounced in industries with high pollution. This shift became evident once the government overtly tied political promotions to water quality met-

[7]Nonetheless, research on the effects of political cycles on economic policy has expanded to encompass outcomes like trade policy (Conconi et al., 2014, 2017) and financial regulation (Dagher and Peria, 2018).

rics. Our study is pioneering in offering systematic causal evidence on the ramifications of economic shocks, especially those stemming from trade-induced economic challenges, on alterations in environmental policy.

Second, this paper contributes to the literature studying the cyclical patterns of environmental regulations. This literature has been based so far more on macroeconomic models (e.g., Dynamic Stochastic General Equilibrium models) rather than providing causal evidence using micro-data, as we do in our paper. Annicchiarico et al. (2021) provides an extensive review of this literature. Though these models provide some insights into the distributional and welfare implication of environmental policies,[8] the crucial question of whether environmental policies adjust to business cycles is still open. Compared to this literature, our paper provides the first empirical evidence of how economic shocks affect the decisions on environmental policy and ambient air pollution.

Third, this paper contributes to the extensive literature that studies trade policy effects on the environment.[9] Several studies show that trade liberalizations have positive effects for the environment (Cherniwchan, 2017; Shapiro and Walker, 2018). However, Bombardini and Li (2020) find that export specialization in polluting industries leads to a higher local infant mortality rate. Shapiro (2020) shows that tariffs and non-tariff barriers are substantially lower on polluted than on clean industries, inducing a global implicit subsidy to CO2 emissions in internationally traded goods. In this paper, we contribute to this literature by providing the first estimates on how a change in trade policy causes a shift in environmental regulation and its consequences for ambient air pollution. We differentiate from these papers along several lines. First, we consider a protectionist rather than a liberalization episode. Second, we document how protectionism against countries with weak environmental regulation might trigger undesirable policy responses. These results suggest that we must consider the political consequences of tariffs on the environment in designing commercial policies.

Finally, this paper also contributes to the literature on the US-China trade war by being the first paper to provide estimates on the causal effects of the trade war on environmental policy. This literature has mainly focused on estimating the negative impact of the trade war on the welfare of US consumers (e.g., Amiti et al., 2019; Fajgelbaum et al., 2020; Cavallo et al., 2021). Other papers study firm-level outcomes in China showing that US trade protectionism caused a decline in Chinese exports to the US, firm-level investment, and R&D

[8]In particular, as described by Annicchiarico et al. (2021), this literature highlights how environmental policy standards can vary over the business cycle, affecting the economy and welfare.

[9]See Copeland et al. (2021) and Cherniwchan et al. (2017) for extensive literature reviews on trade and environment

expenditures (Jiang et al., 2022; Benguria et al., 2022). A very related paper to our study is Lin et al. (2019), where they found that the US-China trade war could benefit health outcomes. Moreover, this study took a traditional view that the trade war would reduce the production or specialization in polluting industries of the affected countries without considering their policy reactions.

3 Background

3.1 The US-China trade war

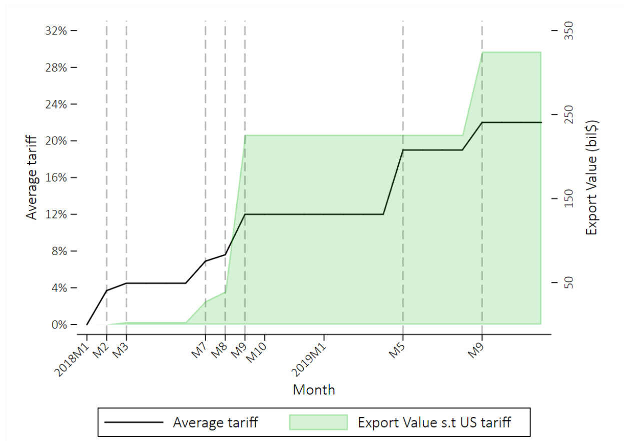
On August 18, 2017, the United States Trade Representative announced an investigation under Section 301 of the Trade Act of 1974 against the Chinese government for acts, policies, and practices related to technology transfer, intellectual property, and innovation. The US government initiated a trade war against China from this date by raising tariffs seven times in five months.

Figure 1 shows the dynamics of US import tariffs on Chinese products. From February to July, the average US import tariffs weighted by the Chinese export increased marginally from less than 0.04% to around 1.73%. These first three waves of import tariffs concentrate on products including washing machines, steel, aluminum, electrical equipment manufacturing, computers, and metal products. In total, over $34 billion of Chinese exports were affected.

The import tariff continued to rise from July 2018 and peaked in September 2019. In these two months, we observed the most significant wave of tariffs stroke, and nearly 200 billion dollars worth of Chinese exports received a massive rise in tariff. Across industries, over 92% of industries Chinese exporting industries have been affected. In total, the United States imposed tariffs on products from China worth about $250 billion. In the meantime, the breadth and depth of tariff increases have gradually peaked, and 48.8% of China's exports to the United States face an increase in tariffs Fajgelbaum et al. (2020). After the large tariff wave in September, economic and trade negotiations lasted for several months, but there was no new tariff rise until May 2019, and most Trump tariffs are still in force in 2023.[10]

[10] Chad P. Bown and Melina Kolb provide detailed information on the timeline of the trade war in "Trump's Trade War Timeline: An Up-to-Date Guide," Peterson Institute for International Economics, March 24, 2023.

Figure 1
The evolution of US import tariffs



The figure plots the average US import tariff and the affected export value throughout the course of the US-China trade war. The average tariff is calculated as the average duty in each wave weighted by the value of Chinese exports to the United States in 2015. The vertical dotted lines show the timing of introducing new tariffs, while the green area indicates the affected trade value.

3.2 Institutional background

As described by Chen and Zhang (2021), mayors in China face accountability from the upper administrative level and not from voters' interests. Hence, the Chinese cadre promotion system assigns mayors to higher offices based on performance. The way mayors are evaluated on an explicit range of indicators and showcase projects in which economic and environmental performance play an important role.

Economic performance has long been the critical promotion criterion for local party secretaries. However, since 2006, local economic performance and environmental quality have been used as key criteria for promoting local party secretaries (Kahn et al., 2015). The goal for the promising young local party secretary, who has a long political path ahead, is to take necessary actions to fulfill the central government's pollution removal standard. The party secretary is in the top position at the prefecture level, followed immediately by the mayor. In principle, party secretaries supervise the government, while the mayor decides on detailed government affairs. As pointed out by Li and Zhou (2005), the prefecture party secretaries are "just like the middle-level managers in a multi-divisional corporation responsible for their divisional performance."

During the last few years, environmental policy played an increasing role in politicians' careers in China as, in 2018, the Chinese government introduced the "Fighting for the Blue Skyline Plan" to improve air quality. To achieve the pollutant removal targets, the central government assigned pollutant removal targets to each province, and provincial governors were required to sign individual responsibility contracts with the central government. These documents contain detailed information on emission abatement plans. In addition, provincial governors further assign pollution removal mandates to prefecture and county leaders and incorporate these environmental targets as an essential criterion in determining their promotion cases (He et al., 2020).[11]

4 Data and measurement

This section introduces the data used in our analysis, for which we retrieve information at the prefecture level about environmental regulation, ambient air pollution, international trade participation, and economic development.

4.1 Environmental regulation data

The extensive collection of granular data on local environmental regulation in China represents one of the main contributions of this paper. In particular, we measure the actual level of regulation represented by information on the prefectures' air pollutants removal targets and the level of enforcement measured using information retrieved from the annual prefecture-level government work report and the administrative penalties database.

4.1.1 $PM_{2.5}$ density targets

First, we collect information on environmental regulations at the prefecture level under the supervision of the central government. In China, national environmental policy is based on two key indicators: pollutant removal targets and density limits. We hand-collected a discretionary database on local environmental regulation in China by directly contacting the provinces or prefectures' using an institutional tool named "Government information disclosed upon request." The Regulation on the Disclosure of Government Information of the People's Republic of China entitles citizens, legal entities, or other organizations the right apply to the State Council or to any local government to obtain relevant government

[11]Several studies highlight how decentralization of power is crucial to understanding economic policy in China. For instance, Jia and Nie (2017) finds that decentralization provoked an easing of workplace safety in China as provincial leaders have incentives to favor local firms.

information beyond the ordinary disclosure by administrative organs based on their unique professional or personal needs. Obtaining this information through the ecological and environmental bureaus' disclosure upon request was highly complex, and we spent approximately three months collecting and processing government information. In Appendix A, we provide additional information on the collection of data on pollution targets.[12]

Within the pollution density limit targets, a lower target for pollution reduction reflects a more stringent environmental regulation. It is important to highlight that, in 2018, the central government turned its air pollutant focus toward reducing the air density of $PM_{2.5}$, and the number of prefectures with a pollution target of PM_{10} reduced. This institutional change directed our empirical investigation to focus on $PM_{2.5}$ targets for which we managed to collect information for 246 over 298 prefectures from 2016 to 2020.[13]

4.1.2 Annual Government Reports

To complement the analysis, we collect information on the level of local environmental enforcement in China. First, we infer the level of enforcement from the prefectures' annual work report for 285 prefectures from 2014 to 2020.[14] To retrieve regulation information from the government report, we use the *jieba* python database to search for keywords related to environmental regulation in each report.

We adopt the text mining approach to measure the degree of attention paid to environmental strength using key expressions indicating the government's willingness to fight pollution. More specifically, we calculated the frequency of words such as "environmental quality", "environmental pollution", "pollution control", "air pollution", "pollution governance", "comprehensive governance", "environmental protection", and "environmental remediation" in each government work report.[15] Within these paragraphs, we have highlighted

[12] Figures A1 and A2 show some examples of government responses to our requests about the annual pollution density limits.

[13] The main reason for missing observation is the need for quantitative $PM_{2.5}$ targets to run our econometric analysis. Hence, of the 298 prefecture-level cities with $PM_{2.5}$ targets, 277 have specific concentration limits. However, 31 prefecture cities only have observational data for one year. Therefore, 246 cities have data for at least two years or more.

[14] These work reports are released in the first quarter of each year. They summarize different aspects of social development in the past year and deliver plans and proposals for the upcoming years. In total, only 286 prefectures provide a balanced panel of annual reports. Of these, one prefecture is dropped, considering the absence of the pollution control keywords in the text. For this reason, the sample consists of 285 prefectures for these measures of environmental action.

[15] For example, Figure A3 of the Appendix the shows us sample paragraphs of the government reports from Shijiazhuang prefecture for 2017 and 2018. The words in red refer belong to the key words categories in our sample.

keywords in red that pertain to pollution and its prevention.[16] Thus, we retrieve the level of stringency of environmental regulation at the local level by counting the number of keywords indicating the willingness of the local government to fight pollution.

4.1.3 Administrative Penalties Dataset

Finally, we measure the level of regulation enforcement by retrieving information about the administrative action on environmental regulation violations at the prefecture level using the Administrative Penalties Dataset constructed by the Law School of Bejing University.[17] These data collect administrative penalties for all legal persons in 264 Chinese prefectures. It contains information about who receives the penalty, reasons for the punishment, and their timing directly from the verdicts.

For the $\mathrm{PM}_{2.5}$ air density limits, we define the variables $\overline{\mathrm{PM}}_{2.5,p,t}$ as the target for pollution emissions for $\mathrm{PM}_{2.5}$ in prefecture p at year t. Furthermore, we construct the following variables capturing the level of environmental regulation enforcement: $\mathrm{Penalties}_{p,t}$ is the count of administrative actions enforcing environmental regulation in prefecture p at year t, Penalties Share $_{p,t}$ is the variable $\mathrm{Penalties}_{p,t}$ divided by prefecture GDP, $\mathrm{Count}_{p,t}$ is the count of words regarding environmental regulation enforcement in the prefecture's annual report, and $\mathrm{Share}_{p,t}$ is the variable $\mathrm{Count}_{p,t}$ divided by the total number of words contained in the annual report. We take the logarithm of all the environmental regulation enforcement variables to account for possible outliers.

4.2 Pollution data

Daily air quality data are collected from the records of 1,650 local monitoring stations reporting the intensity of air pollutants. The data are available from 2014 to 2020. This database reports the concentrations of SO_2, NO_2, PM_{10}, $\mathrm{PM}_{2.5}$, and O_3. In our analysis, we focus on fine particulate matter. We define the variable $\mathrm{PM}_{2.5,p,t}$, which is the log of the average hourly concentration data for a prefecture p in year t .[18]

A general concern is that local governments in China have incentives to manipulate air quality data because they affect the probability of promotion (Ghanem and Zhang, 2014).

[16] For instance, the keywords relating to environmental regulation include expressions such as pollution control, air pollution, environment protection, air quality, and environmental quality.

[17] The data are available at the following website: www.pkulaw.com/penalty/.

[18] For the scope of this study, it is crucial to highlight that pollution is mainly driven by industrial production in China. According to the data released by the "China Environmental Statistics Yearbook", industrial emissions of particulate matter and SO_2 account for 85% of the total between 2016 and 2018. Therefore, the production choices of Chinese firms drive our results.

However, this concern has been significantly alleviated as China upgraded its air quality monitoring system by gathering pollutant samples automatically and, at the same time, reporting the results. This newly adopted system significantly improved the air quality, as shown by Greenstone et al. (2022), because this monitoring system makes it very difficult for the local government to manipulate data.

In our paper, we also construct information on carbon emissions at the prefecture level. Following Wu and Guo (2006), we retrieve data on CO_2 emissions by combining different sources of direct energy consumption (e.g., gas and liquefied petroleum, electricity, and heat generation) and emissions from transportation. First, CO_2 emissions from energy consumption are calculated with the emission intensity coefficient from IPCC2006. We follow Glaeser and Kahn (2010) and multiply a prefecture's grid baseline emission factor by its electricity consumption. Second, to measure CO_2 emissions from within-prefecture transportation, we combine information on energy consumption intensity (energy consumption of Unit passenger traffic (10,000 kilometers) and freight traffic (10,000 kilometers) for each type of transportation and the actual passenger and cargo traffic. Third, the information on energy consumption intensity comes from the "China Statistical Yearbook," and the information on the actual passenger and cargo traffic comes from the "China Urban Statistical Yearbook." A prefecture's heat consumption includes Boiler room heating and thermal power plant heating, which rely heavily on coal. The "China Urban Construction Statistical Year" provides a panel dataset on a prefecture's central heating statistics. By summing up the CO_2 emission from electricity, direct energy consumption, transportation, and heat consumption, we can define the variable $\mathrm{CO}_{2,p,t}$ measuring the carbon emission for prefecture p in year t.

4.3 Tariffs and trade data

Data about Trump tariffs at the HS8 level are provided by Fajgelbaum et al. (2020). Their data contain two crucial pieces of information: the applied duty and the implementation date published by the US International Trade Commission. We calculate the average tariff at the HS6 level to match this information with Chinese custom data.

Data about Chinese exports to the United States are retrieved from the Chinese Custom Database. It covers the universe of Chinese firms' export and import values at the transaction level. The General Administration of Customs compiles and maintains the data and provides detailed statistics on the origin and destination of imports and exports.

4.4 Local development data

We retrieve information on the GDP of Chinese prefectures and municipal districts ($\text{GDP}_{p,t}$) from the "China City Statistical Yearbook." This annual publication comprehensively contains essential statistics on cities' social and economic development, including information about population, labor, land resources, and comprehensive economy. Since 2017, the China City Statistical Yearbook only contains GDP data for municipal districts. Furthermore, we retrieve GDP data for prefecture-level cities from the statistical yearbooks of provinces and cities. After matching the GDP data of each city with the tariff exposure, we obtain a sample of 273 cities from 2016 to 2018.

As a robustness check, we also collect information about nightlights to measure economic performance. In our study, the average values of DN nighttime light for 329 prefectures are calculated with the NPP-VIIRS nightlight data on NASA satellite images. We define the variable $\text{Nightlight}_{p,t}$ as the total DN value of prefecture p at time t divided by the total area of the corresponding prefecture-level city. This variable can be considered an alternative measure of economic development at the prefecture level. Since the US National Oceanic and Atmospheric Administration's official website does not provide global nighttime light-maps for June 2018 and January 2019, there is no current data for these two months.

In this paper, we retrieve information on a large set of city characteristics to construct control variables. First, we control for a prefecture city's linear distance to the nearest port. We identify the major ports in China as in Baum-Snow et al. (2017) and we define the variable Port Distance_p the linear distance between prefecture cities and significant ports using ArcGIS. We also define a dummy variable Highspeed Rail_p equal to one if a prefecture has a connection with the high-speed railway before the trade war according the National Railway Administration and related statistics. Finally, we define a dummy Heating_p equal to one if a prefecture p is located in the northern part of China consider as regions with an intensive use of heating in the winter as in Chen et al. (2013).

4.5 Local politicians careers

We manually collected information for 602 Party Secretaries in 312 prefectures from 2016 to 2020 through websites such as China Economic Net and People's Daily Online. The collected information includes their names, ages, dates of assuming office, tenure, and previous and subsequent positions. Following Persson and Zhuravskaya (2016) and Campante et al. (2023), we examine the Chinese Communist Party's Secretary changes in these prefectures as the

Party's Secretary holds the highest administrative position in prefectures, with ultimate authority and significant discretion over local fiscal, regulatory, and personnel policies. We classify the following changes in the Secretary positions: first, we define the dummy variable $\text{Promotion}_{p,t}$ equal to one if a secretary in prefecture p in year t is promoted from a prefecture-level position to sub-province level or above.

5 Identification strategy

To study the impact of a rise in trade barriers on China's environmental regulations, we develop the following difference-in-differences (diff-in-diff) model:

$$\text{Regulation}_{p,t} = \alpha_0 + \alpha_1 \Delta\tau_p \times I_{(t\geq 2018)} + \alpha_p + X_p \times \alpha_t + \alpha_r \times \alpha_t + \epsilon_{p,t}, \tag{1}$$

where $\text{Regulations}_{p,t}$ represents the level of local environmental regulation in prefecture p for year t, $\Delta\tau_p$ captures the exposure to US-China trade for prefecture p, and we construct the prefecture's tariff exposure using the US tariff changes during 2018 and 2019. $I_{(t\geq t_0)}$ is a dummy variable equal to one if year t is after 2018. In our empirical model, we always include prefecture fixed effects (α_p) and region-year fixed effects ($\alpha_r \times \alpha_t$). Prefecture fixed effects account for any time-invariant prefecture characteristics. In contrast, the region-year fixed effects allow us to control for any aggregate shocks across Chinese regions during our sample period. We also control for predetermined prefecture-level characteristics (such as the prefecture's distance to the nearest international port, export flows, and heating provision in winter) interacted with the year fixed effects, $X_i \times \alpha_t$. These controls eliminate potential confounding factors which could bias our estimates in α_1. In the regression, we cluster the standard errors at the regional level to account for serial correlation over time and space within the same region.[19] In conclusion, we always weigh our regression by the prefecture population in 2017 to obtain the average effect for any person residing in China. [20]

To analyze the dynamics of the relationship between regulation and trade tariffs, we

[19]Our baseline results are robust to clustering at the province level for the variables $\text{PM}_{2.5,p,t}$, $\text{Share}_{p,t}$, and Penalties $\text{Share}_{p,t}$. The results are available upon request.

[20]The population in 2017 is retrieved from the "China City Statistical Yearbook" and is available for 296 prefectures.

extend our empirical model to develop a non-parametric regression:

$$\text{Regulation}_{p,t} = \beta_0 + \sum_{t=-T}^{T} \beta_1^t \Delta\tau_p \times I_{(t\geq 2018)} + \beta_p + X_p \times \beta_t + \beta_r \times \beta_t + \epsilon_{p,t}, \tag{2}$$

The event study approach allows us to affirm the hypothesis that prefectures, with varying exposures to Trump tariffs, exhibit similar dynamics in the pre-treatment period, specifically before 2018. This is vital, as the diff-in-diff estimator becomes biased if the parallel trend assumption is not upheld. In our context, the parallel trends assumption posits that the evolution of environmental policy across different prefectures would have remained consistent in the absence of the trade war.

5.1 Measurement of tariff exposure

Following previous studies (e.g., Bombardini and Li, 2020; Handley et al., 2020), we adopt a Bartik research design (Bartik, 1991) to measure the Chinese prefecture's exposure to US import tariffs as follows:

$$\Delta\tau_p = \sum_{i\in I_p} \frac{Export_{ip,2015}^{US}}{Export_{ip,2015}} \Delta\tau_i, \tag{3}$$

Where I_p denotes the set of industries active in prefecture p, $Export_{ip,2015}$ is the aggregate export of prefecture p in product i, defined at the 6-digit HS level for the year 2015. $Export_{ip,2015}^{US}$ represents the total exports to the United States from prefecture p for product i in 2015. $\Delta\tau_i$ captures the change in US tariffs for industry i between t_0 and September 2019.[21] We define t_0 as the onset of the trade war in 2018 and t as any year subsequent to 2018. We utilize data from 2015 to construct our variable, as it is the most recent year available in the Chinese Custom Database prior to the trade war.[22] Descriptive statistics for $\Delta\tau_p$ and other variables discussed in this paper can be found in Table C1 in the Appendix.

he variation in $\Delta\tau_p$ arises from cross-prefecture differences in initial export compositions,

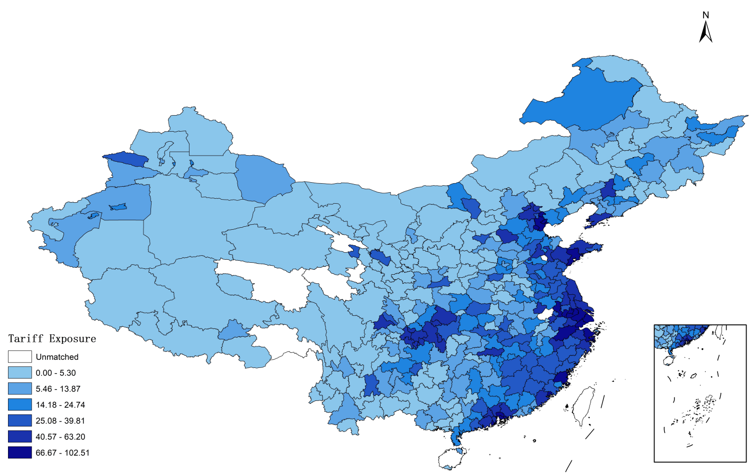
[21] As a control variable, we construct the variable $\Delta\tau_p^{SOE}$ by restricting the set of firms, used to construct the variable described in equation (3), to state-owned enterprises (SOE). This variable measures the prefecture's exposure to tariff shocks for SOEs.

[22] Ideally, we would prefer to use export data from 2017. However, due to data limitations, we use 2015 as our reference year. No systematic evidence exists regarding the export pattern at the industry level between 2015 and 2017.

the relative significance of the US market for Chinese exporters, and the product-level alterations in US import tariffs during 2018 and 2019. We interpret an increase in US import tariffs as a detrimental income shock to a given prefecture. By September 2019, nearly all prefectures in China had been subject to US import tariffs, as depicted in Figure (2). This figure also highlights the pronounced spatial variability in the extent to which different prefectures faced US import tariff shocks. Coastal provinces, including Guangdong, Fujian, Zhejiang, Jiangsu, and Shandong, bore the most significant brunt of the US import tariff shocks. The distribution of $\Delta\tau_{p,t}$ can be partially attributed to the concentration of Chinese production in coastal regions.

Figure 2

The spatial distribution of $\Delta\tau_p$



The figure illustrates the regional distribution of $\Delta\tau_p$. A darker shade of blue indicates a greater exposure of the prefecture to Trump Tariffs. Data for the prefectures Linzhi, Guoluo, Haibei, and Huangnan are unavailable.

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5.2 Identifying assumptions

To identify the causal effects of tariffs on environmental regulation, we must assume that our primary explanatory variable is uncorrelated with the error term:

$$\mathbb{E}(\Delta\tau_p \times I_{(t\geq 2018)}, \epsilon_{p,t}|W_{p,t}) = 0, \tag{4}$$

where $W_{p,t}$ represents the full set of controls in our regression model. This assumption holds if the following three conditions are met:

1. $\mathbb{E}(\sum_i \frac{Export^{US}_{ip,2015}}{Export_{ip,2015}}, \epsilon_{p,t}|W_{p,t}) = 0$,
2. $\mathbb{E}(\sum_i \Delta\tau_i, \epsilon_{p,t}|W_{p,t}) = 0$,
3. $\mathbb{E}(I_{(t\geq 2018)}, \epsilon_{p,t}|W_{p,t}) = 0$.

The first condition states that the export structure of a prefecture should be orthogonal to the error term. This condition is violated if prefectures are not randomly exposed to Trump tariffs. Hence, the US administration might set tariffs during the trade wars to target a specific prefecture because of its characteristics, which can be correlated with regulation. The second condition states that industries should be randomly exposed to Trump tariffs. If this is not the case, comparing industries according to their different exposure to the trade war is impossible because some unobservable industry characteristics drive tariffs and environmental regulation.

To mitigate these concerns, we incorporate a set of initial characteristics for each prefecture, which are interacted with year dummies. These characteristics could confound our main effect since they might influence environmental policy and have correlations with US tariffs. Such variables include distance to the nearest port, export values from state-owned enterprises, and total exports to the US preceding the trade war. Following Borusyak and Hull (2020) and Borusyak et al. (2021), we also adjust for the 2015 prefecture's total exports in targeted products, interacted with year dummies, to account for trends in prefectures more susceptible to shocks in international markets. Moreover, we account for the potential influence of past regulations on current ones by including the air quality of a prefecture from the preceding year.

Lastly, we tackle issues stemming from a breach of the third condition, which might arise if the trade war's timing was non-random. First, we always include the region-year fixed effects to control any macroeconomic shock correlated with the trade war. Second, it is essential to note that there was no indication of a tariff hike before 2018. To check for any expectation, we extended our baseline regression specification to develop an event-study regression model as described in equation (2).

6 Empirical results

6.1 Environmental regulation

In this paper, as described in Section 5, we have constructed three measures of local environmental regulations: the removal targets of local air pollutants, the count of environmental enforcement actions, and the number of words related to environmental protection, as mentioned in the prefectures' annual work reports. As a benchmark, we choose the removal targets because they capture the general stringency of environmental regulation (Greenstone et al., 2021). In this section, we first show the results of the event study regressions and then the standard diff-in-diff estimates.

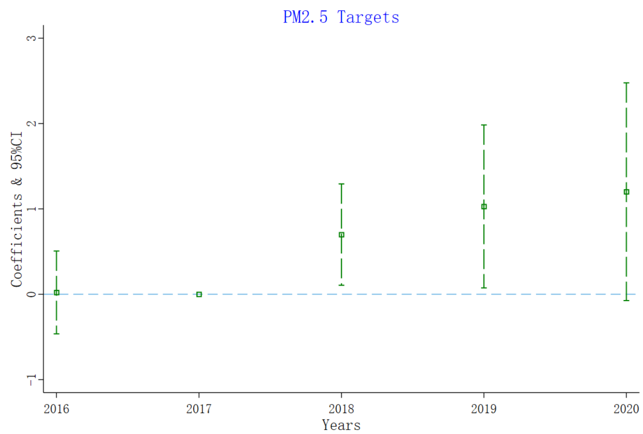
6.1.1 Event study

As mentioned in Section 5, an event-study approach is key for two reasons: showing the degree to which the trade war effects were dynamic and whether the parallel trend assumption holds in our empirical framework. Given the importance of this evidence for the unbiasedness of our estimation, we will first present the results of the event study. Then, we will present the estimates of the parsimonious diff-in-diff model presented in equation (1).

Figure 3 shows the point estimates with the 95% confidence intervals for the event study regressions described in equation (2). We find a significant increase in the $PM_{2.5}$ targets for prefectures more exposed to the tariff shock, indicating an easing of environmental regulation in China following the trade war. We next move to the local-level measures of environmental actions. Figure 4 reveals that the trade war also affected local politicians' enforcement of environmental regulations. Hence, panel (a) shows a significant decrease in the attention devoted to environmental regulation in the prefecture's annual work report, both in the count of keywords related to environmental protection and the share of keywords to the total number of words in the annual reports. Second, panel (b) exhibits a significant decrease in environmental actions against firms due to the US tariffs by measuring enforcement by the number of administrative penalties per 10 million RMB of local GDP and the measures on environmental regulations using word report.

Figure 3

The impact of trade protection on environmental protection



Notes. This figure plots the impact of the change in US tariffs on the local $PM_{2.5}$ pollution density limits. Our estimates always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level.

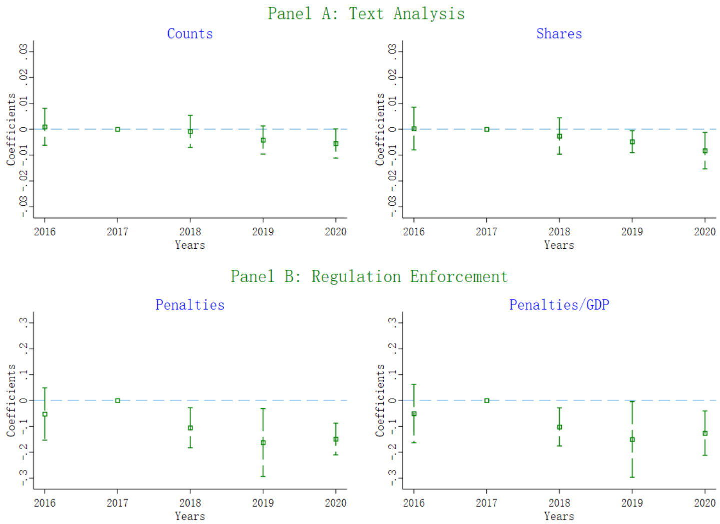
It is crucial to notice that figures 3 and 4 indicate no systematic difference in environmental regulation among prefectures before the trade war. Consequently, the absence of a significant pre-trend is indicative that there are no anticipation effects conditional to observable characteristics of a prefecture. Thus, we can consistently estimate our parsimonious diff-in-diff regression as described in equation 1.

6.1.2 Diff-in-Diff Estimates

In this subsection, we report the estimates of the parsimonious diff-in-diff model described in equation (1). The results are shown in Table 1. Column (1) reports the estimates for the local pollution targets. Our results show that increasing a prefecture's exposure to US tariffs leads to significantly higher pollution density limits. Columns (2) and (3) show the results using the textual analysis measures showing a significant decrease in the relative importance of local environmental protection after 2018 in treated prefectures. Columns (4) and (5) report the estimates about US tariffs on local government action to protect the environment and indicate that US tariffs reduce the number of punishments due to environmental law violations.

Figure 4

The Impact of trade protection on the enforcement of environmental protection



Notes. The figure plots the impact of the change in US tariffs on the level of local politicians' enforcement of environmental regulations. Panel (a) considers our measures of attention devoted to environmental regulation in the prefecture's annual work report, i.e., the log value of the number of keywords related to "environmental protection" (*Counts*) and the log of keywords over the total number of words contained in the annual work report (*Shares*). Panel (b) includes the log of the prefecture's administrative penalties due to environmental law violations (*Penalties*) and the log value of the ratio between the number of administrative penalties and the local GDP (*Penalties/GDP*). In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level.

To analyze the magnitude of our coefficients, we compare the effects of a one-standard-deviation tariff increase to the average of our outcome variables in 2017. According to our estimates, we find an increase of $PM_{2.5}$ air density limits by 62% (115% of its standard deviation), an increase in administrative penalties by 69% (133% of its standard deviation), and a decrease in the share of keywords about "environmental regulation" in the annual work reports by 5% (16% of its standard deviation). These findings show that US tariff changes substantially affect environmental regulation. Our empirical exercises show that US tariff has statistically significant and long-lasting effects on environmental regulations at the local and national levels.

Table 1

The impact of the trade war on environmental protection - Diff-in-diff estimates

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	1.140***	-0.011**	-0.006**	-0.149***	-0.139**
	(0.151)	(0.007)	(0.003)	(0.052)	(0.054)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	887	1411	1411	1156	1156
R^2	0.972	0.451	0.441	0.785	0.695

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

6.1.3 Robustness checks

This section shows the robustness of our baseline results to some essential robustness checks. First, we address potential concerns linked to using a Bartik-type research design. In particular, our reduced-form regressions rely on the implicit assumptions that shocks (the product-level change in tariffs), the exposure shares (the prefecture exposure to exports to the United States), or both are exogenous, i.e., they are orthogonal to unobservable shocks at the prefecture or product level.

In their pioneering paper, Borusyak et al. (2021) propose a new framework to ensure the estimates' consistency. According to their econometric model, the orthogonality between a shift-share instrument and an unobserved residual can be represented as the orthogonality between the underlying shocks and a shock-level unobservable. For this reason, they propose to redefine the estimated model at the level of shocks using exposure shares as weights to obtain shock-level aggregates. This empirical model allows us to control for any observable characteristics for the shock level aggregates, the 6-digit HS products in our empirical model, crucially including product-level fixed effects.

In alignment with Borusyak et al. (2021), we then proceed to compute the following regression:

$$\text{Regulation}^{\perp}_{i,t} = \alpha_0 + \alpha_1 \Delta\tau_i \times I_{(t\geq 2018)} + \alpha_i + \alpha_t + \epsilon_{i,t}, \tag{5}$$

where $\text{Regulation}^{\perp}_{i,t}$ are the average environmental regulation measures for product i at time t; τ_i is the change in US tariffs for product i due to the trade war, α_i and α_t refer to the product and year fixed effects.

Table (2) reports the results from the product-level regressions for the environmental regulations and other variables. Our baseline results are robust if we adopt the methodology proposed by Borusyak and Hull (2020). Interestingly, the estimated coefficient for our primary variable of interest ($\overline{\text{PM}}_{2.5,p,t}$) is not statistically different from the baseline estimates presented in Table 1. Thus, we can conclude that the assumption of exogeneity of the export shares is not crucial for the consistency of our estimates.

Table 2

Robust test: consistency under the methodology of Borusyak and Hull (2020)

	(1) $\overline{\text{PM}}^{\perp}_{2.5,i,t}$	(2) $\text{Count}^{\perp}_{i,t}$	(3) $\text{Share}^{\perp}_{i,t}$	(4) $\text{Penalties}^{\perp}_{i,t}$	(5) $\text{Penalties Share}^{\perp}_{i,t}$
$\Delta\tau_i \times I_{(t\geq 2018)}$	0.965***	-0.052**	-0.124***	-0.113**	-0.100*
	(0.189)	(0.021)	(0.039)	(0.057)	(0.057)
product FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
N	17,111	17,896	17,896	17,896	17,896
R^2	0.003	0.000	0.001	0.001	0.000

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. For these regressions, we use a HS-6 product measure to US tariffs. $\perp$ superscript refers to the suitably-transformed product-level analog of the variable in our baseline regression Table 1. The 2015 population weights observations. Standard errors are clustered at the HS-4 digit level. Significance levels: *: 10%; **: 5%; ***: 1%.

The econometric model defined in equation (5) allows us also to test an additional robustness test in which we omit one industry at a time. This robustness check broadly defines an industry as the corresponding HS section.[23] The point estimates and the 95% confidence

[23] We define 15 broad HS sections following Campante et al. (2023). The HS sections are: 1 - Animal & Animal Products; 2 - Vegetable Products; 3 - Foodstuffs; 4 - Mineral Products; 5 - Chemical & Allied Industries; 6 - Plastics/Rubbers; 7 - Raw Hides, Skins, Leather & Furs; 8 - Wood & Wood Products; 9 - Textiles;

intervals are shown in Figure B4 of the Appendix. Our benchmark measure of environmental regulation, PM25, is robust to dropping any industry. However, the text analysis results are not robust to the exclusion of sector 5, Chemicals & Allied Industries. At the same time, the measures of environmental actions are not robust to the exclusion of sectors 9 (Textiles) and 13 (Machinery & Electrical products). So crucially, the reaction of local politicians to the trade war depends on protectionism in critical industries.

Several other studies using a Bartik-type research design construct exposure share using employment in a geographical area (e.g., Autor et al., 2013). Relative to these studies, we prefer our current measure of exposure to Trump tariffs in our setting because it directly links prefecture exposure to export to the United States with the trade war. However, to reconcile our estimates with these studies, we test if our baseline estimates are robust by constructing the exposure share using employment at the prefecture-industry level ($L_{ps,2007}$) in 2007.[24] To run this exercise, we modify the exposure measure presented in equation (3) as follows:

$$\Delta\tau_p^L = \sum_{s \in S_p} \frac{L_{ps,2007}}{L_{p,2007}} \Delta\tau_s. \tag{6}$$

Data on employment are sourced from the 2007 Annual Survey of Industrial Firms (ASIF). Given the absence of product-level employment, we calculate for each sector s the average duty by matching each 6-digit HS product with a 4-digit CIC sector using the concordance table provided by Brandt et al. (2017). The correlation between $\Delta\tau_p$ and $\Delta\tau_p^L$ is 0.821. Table C5 of the Appendix presents the estimates for this robustness check. The results are qualitatively similar to our baseline results. However, the estimates are not statistically significant the variables $\text{Count}_{p,t}$ and $\text{Share}_{p,t}$.

Furthermore, we run several robustness checks relative to our results' sensitivity to sample selection issues. Given the presence of missing observations in the employment data (used to construct the regression weights) and the control variables, we run two robustness checks. First, we verify that the results are qualitatively unchanged if we estimate unweighted regressions. The results are available in Table C2 of the Appendix. The baseline results are

10 - Footwear/Headgear; 11 - Stone/Glass; 12 - Metals; 13 - Machinery/Electrical; 14 - Transportation; and 15 - Miscellaneous.

[24] We decided to adopt employment data for 2007, given the general concerns about the data coverage for the ASIF data following this year. Indeed, after this year, there have been substantial changes in the sampling process so that a larger share of small firms are not included, and it is impossible to establish the representativeness of the data after 2007.

robust, but they are (weakly) insignificant if we consider the $\text{Count}_{p,t}$. Second, we remove all control variables from our benchmark regressions. Table C3 of the Appendix shows that our main results are robust apart from the variables the $\text{Count}_{p,t}$ and $\text{Share}_{p,t}$ that are weakly not significant with p-values of 0.117 and 0.102, respectively.

To conclude, we run three additional robustness checks. First, our benchmark estimates always include 2020 to test the persistence of our results. However, in 2020 the Chinese economy also faced an extensive shock, such as the outbreak of the Covid-19 pandemic. Consequently, it is important to highlight that our results are robust if we exclude 2020 from our sample (see Table C4 of the Appendix). Second, following Lu et al. (2017), we conduct a placebo test to investigate systematic differences in regulation among prefectures with different exposure to the US tariffs before the trade war. Specifically, we restrict our sample to the period before the tradewar from 2015 to 2017, using 2017 as a placebo treatment. For this placebo test, Table C6 shows that the estimates are not statistically different from zero, so we exclude the presence of an anticipation effect. Finally, as a falsification test, we substitute in equation 3 the exports to the United States with exports to the European Union. This robustness check aims to test if our results do not depend on potential spillovers of the trade war on other critical trade partners such as the European Union. Table C7 of the Appendix shows no significant changes in a prefecture's environmental regulations for all our baseline specifications. Furthermore, the estimates are quantitatively small in size. These findings suggest that changes in US tariffs do not impact local environmental regulations due to spillovers of the trade war to European countries.

6.1.4 Retaliatory tariffs

In response to the unprecedented increase in US trade protection due to Trump's tariffs, China implemented retaliatory tariffs targeting US products. These measures increased tariffs from 5% to 50% on approximately 3850 HS6 products. Given that both Trump's tariffs and the retaliatory measures could adversely impact the performance of Chinese firms, it becomes pertinent to examine whether China's retaliatory tariffs also influenced environmental regulation.

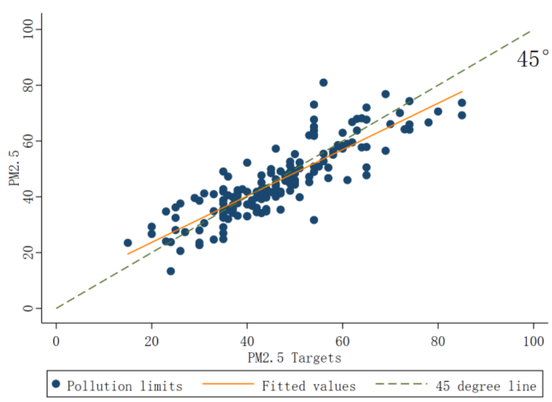
To this end, we define a prefecture's exposure to retaliatory tariffs, denoted as $\Delta\tau_p^{Ret}$, by substituting the change in US tariffs for product i with the change in Chinese tariffs during the trade war in the formula given by equation (3). We retrieved data on retaliatory tariffs from official documents published by the Chinese Ministry of Finance. The results detailing the effects of exposure to retaliatory tariffs on our five environmental regulation measures are presented in Table C8 of the Appendix. Our estimates show that including retaliatory tariffs in our analysis does not affect our baseline findings. However, it is worth noting that the variable Penalties Sharep,t becomes marginally significant (at the 15% level) upon incorporating the variable $\Delta\tau p^{Ret}$. This result supports the hypothesis that a political reaction favoring Chinese exporters drives our estimates.

6.2 Local air quality and carbon emissions

We have previously shown the damaging and persistent effects of US tariffs on local environmental regulations in China. Figure 5 shows a positive correlation between regulation and air pollution in China during the trade war. This evidence suggests analyzing US tariffs' impact on the local air quality and carbon emissions at the prefecture level.

Figure 5

Regulation and Pollution in China (2018-2020)



Notes. The panel plots the correlation between the air density limits for pollutants $PM_{2.5}$ and the actual air pollution for $PM_{2.5}$. The green dot line is the 45-degree line, and the solid red line is the fitted value.

To this extent, we introduce the variable $\text{Pollution}_{p,t}$ as the dependent variable in the model described in equation 1, where $\text{Pollution}_{p,t}$ is the log of the density of pollutants for prefecture p in year t. In particular, we focus on two key pollutants: fine particulate matter ($PM_{2.5}$) and carbon dioxide (CO_2). Figure B6 shows the event study estimates. We observe that prefectures more exposed to US tariffs experience a persistent rise in the density of air pollutants and carbon emissions compared with prefectures undergoing weak tariff exposure. Furthermore, we do not verify the presence of a significant difference in pollution among treated and non-treated prefectures before the trade war.

Table 3 reports the results for the diff-in-diff model. Our estimates suggest a worsening air quality in prefectures with considerable exposure to the US tariffs during the trade war for both $PM_{2.5}$ and CO_2. The results for $PM_{2.5}$ are robust by excluding 2020 from the sample, while data for 2020 are not yet available for CO_2. To evaluate the magnitude of our coefficients, we analyze the impact of a one-standard-deviation increase in the prefecture's exposure to US tariffs on pollution using the 2017 average in $PM_{2.5}$ and CO_2 as our benchmark. We find a 0.2% increase in $PM_{2.5}$ (30% of its standard deviation) equivalent to 1.03 $\mu g/m^3$. In addition, we find that a one-standard-deviation increase in exposure to US import tariff leads to an increase in CO_2 by 10 thousand tons (1.5% increase in its standard deviation). Our results are comparable to Bombardini and Li (2020), in which they find that a one-standard-deviation increase in export opportunities leads to a 16.6% standard deviation increase in $PM_{2.5}$ concentration.

Table 3

The Impact of Trade Protection on Pollution

	(1)	(2)	(3)
	$PM_{2.5,p,t}$	$PM_{2.5,p,t}$	$CO_{2,p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	0.006^{**}	0.007^{**}	0.005^{**}
	(0.002)	(0.002)	(0.002)
Prefecture FE	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes
Control	No	Yes	Yes
2020 Included	No	Yes	No
Observations	1,453	1,453	1,121
R^2	0.981	0.980	0.995

Notes. This table reports the estimates for α in equation 1 for $PM_{2.5}$ and CO_2. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

6.3 Political incentives and environmental regulation

The previous sections show that the trade war relaxed the local environmental regulation at the prefecture level and worsened pollution. Consequently, we have investigated three potential channels to better understand the political mechanisms behind our results. First, we examine whether it is much easier for the local government to fulfill the environmental target after the trade war. We then examine the impact of the trade war on the promotion probability of the local prefecture secretary and their adjustment to the GDP growth targets. We then extend our empirical analyses testing the presence of heterogeneous effects depending on local politicians' characteristics.

6.3.1 GDP targets

Parallel to data on environmental targets, we collect information on local GDP targets to how US trade protection affects the government's GDP targets ($\overline{\text{GDP}}_{p,t}$). Table C9 of the Appendix reports the results of this analysis. Our estimates suggest a reduction in the prefecture GDP target with strong exposure to the US tariffs during the trade war, and the results are robust by excluding 2020 from the sample. To evaluate the magnitude of our coefficients, we find that a one-standard-deviation increase in exposure to US import tariffs leads to a reduction in $\overline{\text{GDP}}_{p,t}$ by 143% in its standard deviation. These results confirm our political hypothesis that the political leadership in China had a less favorable economic outlook during the economic war; it might justify the relaxation in environmental regulations highlighted by this paper.[25]

6.3.2 Heterogeneous effects

Previous studies suggest that promotion incentives are vital in determining policy changes in China (e.g., Chen and Zhang, 2021; Campante et al., 2023). Therefore, we test if our results are heterogeneous depending on three specific political characteristics of local politicians. The first one is the age of the local secretary.

According to Chinese laws, a prefecture leader can only be promoted to a higher level of government if younger than 57 years old. This rule affects the incentives of local leaders to undertake specific actions to boost their probability of promotions according to their age. Thus, we define the dummy $I_{age\leq 56,p}$ equal to one if the mayor's age is lower or equal to 56 in prefecture p before the trade war. The second one is the number of years working as prefecture leaders within the same prefecture because local leaders have more substantial political incentives if they are within the first three years of prefecture leader tenure.[26] We define dummy $I_{year\leq 3,p}$ equal to one if the local prefecture leader is within his/her first three years of prefecture office. The third one is the personal connection with the local provincial secretaries. We follow Jiang (2018) by considering a prefecture leader to be connected with

[25] Figure B5 of the Appendix shows the event study for the GDP targets. It confirms the trade war is associated with an increased concern for the Chinese leadership for the economic outlook following the trade war.

[26] Chen and Zhang (2021), the prefecture leaders will likely ensure tax cuts for local firms in the first several years of his/her tenure.

the provincial leader if he/she was promoted to the current position by this provincial leader and define dummy $I_{connect,p}$ equal to one if this leader promoted him/her.[27]

Table 4 reports the estimates. In column (1), we replicate our benchmark results for the sub-samples of prefectures for which we have data on local politicians. Columns (2), (3), and (4) show that prefectures with secretaries aged below 56 within the first three years of prefecture office and connected with the provincial leaders within the same province are more likely to have higher air density targets for $PM_{2.5}$, respectively. This finding suggests that prefectures with more substantial political promotion incentives are more likely to set laxer pollutant density limits.

Table 4

Heterogeneous Impacts of Trade Protection on environmental regulations and politician promotion

	(1)	(2)	(3)	(4)
	$\overline{\text{PM}}_{2.5,p,t}$	$\overline{\text{PM}}_{2.5,p,t}$	$\overline{\text{PM}}_{2.5,p,t}$	$\overline{\text{PM}}_{2.5,p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	1.140^{***}	1.179^{***}	1.092^{***}	1.055^{***}
	(0.151)	(0.139)	(0.179)	(0.132)
$\Delta\tau_p \times I_{(t\geq 2018)} \times I_{age\leq 56,p}$		0.014^{**}		
		(0.004)		
$\Delta\tau_p \times I_{(t\geq 2018)} \times I_{year\leq 3,p}$			0.017^{*}	
			(0.008)	
$\Delta\tau_p \times I_{(t\geq 2018)} \times I_{connect,p}$				0.032^{***}
				(0.006)
N	887	887	887	887
R^2	0.972	0.971	0.962	0.972

Notes. This table reports the estimates for α in equation 1 for the log of local GDP. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

[27] Jiang (2018) suggests that this connection induces the prefecture secretary to be more engaged in economic development and, hence, more likely to get further promoted.

6.4 Mechanism

In this section, we analyze the potential mechanism behind the change in environmental regulation due to the trade war. Previous studies show that GDP growth was an essential standard for local officer promotion in China (Li and Zhou, 2005) and that there is a trade-off between reaching environmental goals and GDP growth for Chinese local politicians as both are critical promotion criteria (e.g., Chen et al., 2018). Our previous evidence shows that during economic distress, the Chinese Communist Party might have given increased attention to economic rather than environmental performance, providing incentives for local politicians to relax environmental regulations.

Local politicians could relax environmental regulations to reduce the firms' production costs and curb the potential economic losses induced by US tariffs. Hence, previous studies provide mounting evidence that environmental regulation posits substantial costs on the manufacturing producers, reducing both the profit margins and the producers' productivity (He et al., 2020). If this mechanism is at play, two assumptions should be verified: first, the change in environmental action helped to smooth the negative effect of the trade war; second, mayors who relaxed the environmental regulation also experience a higher probability of promotion.

First, we analyze if changes in environmental regulations contributed to curbing the negative income shock induced by the trade war. Table 5 reports the effects on local GDP. In column (1), we find that the average effect of tariffs on GDP is negative and significant, confirming the findings of Chor and Li (2021) on the negative impact of the trade war on the Chinese economy. In columns (2) to (5), we analyze the presence of heterogeneous effects depending on the prefecture's policy response to the trade war. In particular, we divide prefectures in percentiles according to their changes in environmental regulations during the trade war, and we define a set of dummy variables $I_{X,p}$ equal to one if the prefecture p is the top $X\%$ in the increase in pollution targets. Columns (2) to (5) suggest that the more a prefecture eases environmental regulation, the less severe the contraction in GDP induced by the trade war.[28] To conclude, our results support our hypothesis that political economy reasons drive our benchmark results on policy responses to the trade war as both local and national level politicians may benefit from an improved economic outlook during the trade war.

[28] As a robustness check, we infer the impact of the US-China tariff war on China's economy using high-frequency satellite data on nighttime luminosity following the methodology proposed by Chor and Li (2021). Table C10 shows that our results are robust using a grid-level panel analysis.

Table 5
Heterogeneous Impacts of Trade Protection on Local GDP

	(1)	(2)	(3)	(4)	(5)
	$\text{GDP}_{p,t}$	$\text{GDP}_{p,t}$	$\text{GDP}_{p,t}$	$\text{GDP}_{p,t}$	$\text{GDP}_{p,t}$
$\Delta_p \times I_{t \geq t_0}$	-0.014*	-0.015**	-0.017**	-0.016**	-0.015*
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
$\Delta_p \times I_{t \geq t_0} \times I_{40\%,p}$		0.001			
		(0.001)			
$\Delta_p \times I_{t \geq t_0} \times I_{30\%,p}$			0.002*		
			(0.001)		
$\Delta_p \times I_{t \geq t_0} \times I_{20\%,p}$				0.003**	
				(0.001)	
$\Delta_p \times I_{t \geq t_0} \times I_{10\%,p}$					0.003***
					(0.001)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1148	1148	1148	1148	1148
R^2	0.972	0.972	0.972	0.972	0.972

Notes. This table reports the estimates for α in equation 1 for the log of local GDP. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

If local politicians manipulated environmental regulation to boost their careers, it is natural to verify the impact of the trade war on the probability of promotion. A caveat of this analysis is that we still have a short sample period following the trade war, and this is likely to underestimate the impact of the policy reaction to the trade war on promotions. To this purpose, we interact again with the variable $\Delta\tau_p$ by the top 40, 30, 20, and 10 percentiles according to their changes in environmental regulations during the trade war. Table 6 presents the estimates of the trade war's impact on the promotion probability. Consistently with the GDP estimates, column (1) shows that the trade war hurt the promotion probability.

However, as shown in columns (2) to (5), mayors located in prefectures that relaxed the environmental regulation during manage to relax environmental regulation also had a lower negative impact of the trade war on their probability of promotion. This effect is significant at 5% for prefectures in the top 10 percentile of easing environmental regulation. These results suggest that politicians that relaxed the environmental regulation during the trade war successfully smoothed the negative impact of Trump tariffs and obtained a relatively positive effect on their career paths.

Table 6

Heterogeneous Impacts of Trade Protection on Political Promotion

	(1)	(2)	(3)	(4)	(5)
	$\text{Promotion}_{p,t}$	$\text{Promotion}_{p,t}$	$\text{Promotion}_{p,t}$	$\text{Promotion}_{p,t}$	$\text{Promotion}_{p,t}$
$\Delta_p \times I_{t \geq t_0}$	-0.021*	-0.011	-0.011	-0.011	-0.011
	(0.008)	(0.014)	(0.014)	(0.014)	(0.014)
$\Delta_p \times I_{t \geq t_0} \times I_{40\%,p}$		0.000			
		(0.001)			
$\Delta_p \times I_{t \geq t_0} \times I_{30\%,p}$			0.002		
			(0.001)		
$\Delta_p \times I_{t \geq t_0} \times I_{20\%,p}$				0.000	
				(0.001)	
$\Delta_p \times I_{t \geq t_0} \times I_{10\%,p}$					0.003**
					(0.001)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1155	1155	1155	1155	1155
R^2	0.291	0.310	0.311	0.310	0.312

Notes. This table reports the estimates for α in equation 1 for the dummy $\text{Promotion}_{p,t}$. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

7 Conclusions

This paper analyzes how economic distress negatively affects environmental policy. We show this new empirical evidence by studying how the US-China trade war, the most significant episode of tariff increase since the ratification of the GATT, influenced environmental regulation and local air pollution in China. Using a unique dataset of environmental regulation in China, we find that the trade war triggered an easing of environmental regulation in China and a worsening of air pollution.

We rationalize our findings by proposing a political-economy explanation given the existence of a trade off between income growth and local ambient air pollution. Politicians could use environmental policy to decrease the costs of regulated firms and boost their production. In support of this hypothesis, we find that prefectures that eased environmental regulation have suffered less from the negative impact of the rise in US tariffs, and their local mayor has a higher probability of promotion.

These results are essential for two reasons. First, the recent COVID-19 pandemic and the Russo-Ukrainian war have triggered adverse global environmental policy shocks that reversed decades of green policies. Our estimates shed light on the political mechanisms behind those policy changes and the induced danger to the environment, given the high health costs of increased local air pollution and carbon emission. Second, our results cast doubts on using trade policies to address environmental problems (e.g., the EU Carbon Border Tax). In a very influential paper, Shapiro (2020) shows that the import tariffs subsidize polluted industries, advocating for a trade reform that increases tariffs for polluting industries. However, in the same paper, the author highlights the importance of the political feasibility of such a reform. Our study complements this paper by showing that a unilateral increase in import tariffs could generate spillover effects on local environmental conditions in the partner country because of the policy reaction.

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Appendix

Appendix A Data Collection

As described before, the pollution targets are sourced from the official data of ecological and environmental bureaus of various prefecture-level cities using the "Government information disclosed upon request" system. In what follows, we will provide further details about the data collection of this paper.

At the national level, two major air quality documents were issued: the 2013–2017 "Air Pollution Control Action Plan" (focusing on PM_{10}) and the 2018–2020 "Three Year Action Plan to Wing the Blue Sky Defense War" (focusing on $PM_{2.5}$). The new focus of the Chinese government on $PM_{2.5}$ suggested concentrating on this pollutant in this paper. Every year, local governments also introduced corresponding policy documents like "Zhengzhou's 2017 Air Pollution Control Action Plan", "Tianjin's 2017 Air Pollution Control Work Plan", and "Jilin City's Implementation Plan for the Three Year Action Plan to Wing the Blue Sky Defense War." These policy documents contain annual air management goals. Some cities might still need to release such documents but still have yearly targets aligned with national objectives. Compared to the "Air Pollution Control Action Plan," the "Three-year Action Plan to Win the Blue Sky Defense War" does not set particularly ambitious goals. Local governments had the flexibility to adjust their targets around 2018.

In our paper, we apply the "government information disclosed upon request" platform to apply for the annual air management target data from various prefecture-level cities' ecological and environmental bureaus/provincial ecological and environmental departments. Typically, they respond within 20 working days after accepting the request. Cities with excellent air quality had no air management pressures or targets. In such cases, we supplemented this by collecting data online by checking if cities had ever issued relevant air management documents. For the air management target data we collected, most were pollution threshold values. In some years, we had percentage decline targets, which we converted based on actual air quality concentrations to get unified pollution threshold values. However, there were instances where we could not access the data that was classified and not disclosed (e.g., in the regions of Xinjiang and Tibet). Given that our data request spanned 2015–2020, some cities claimed older documents were lost or needed a dedicated air quality department. This can explain the presence of several missing prefectures in our data.

Figure A1

Examples of government reply to our request for $PM_{2.5}$ targets

辽环依复〔2022〕7 号

政府信息公开申请答复书

李泰鹏：

本机关于 2022 年 7 月 25 日收到您通过在线提交的《政府信息公开申请书》。

经审查，您申请公开的政府信息本机关予以公开，根据《政府信息公开条例》第三十六条第（二）项的规定，本机关将该政府信息提供如下：辽源市 2015-2020 年环境空气质量工作目标 $PM_{2.5}$年均浓度分别为 58、55、53、51、49、46 微克/立方米以下。

如对本答复不服，可以在收到本答复之日起 60 日内向辽源市人民政府申请行政复议，或者在 6 个月内向龙山区人民法院提起行政诉讼。

您申请公开的吉林市 2015-2020 下达的年度空气治理目标数据（即要求年度 PM2.5 或是 PM10 应下降的百分比或控制在什么浓度范围）本机关予以公开，根据《政府信息公开条例》第三十六条第（二）项的规定，本机关将该政府信息提供给您。2015-2020 年细颗粒物（PM2.5）年均浓度分别控制在 59 微克/立方米、56 微克/立方米、54 微克/立方米、52 微克/立方米、50 微克/立方米、47 微克/立方米以下。PM10 不列入国家省考核指标，在环境质量总体改善中评价。

如对本答复不服，可以在收到本答复之日起 60 日内向吉林市人民政府申请行政复议，或者在 6 个月内向吉林铁路运输法院提起行政诉讼。

吉林市生态环境局

2022 年 8 月 1 日

Notes. The figure shows us the responses from the government for the pollution limit data in the Liaoyuan prefecture.

Figure A2

The $PM_{2.5}$ air density from the Quanzhou prefecture

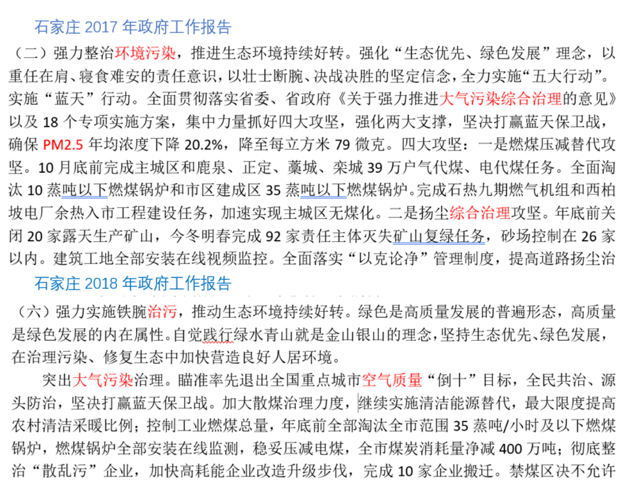
2015-2020 年泉州市年度空气治理目标数据

年度	优良天数比例目标	$PM_{2.5}$ 年度目标	PM_{10} 年度目标
2015 年	未下达	未下达	不 高 于 58ug/m³
2016 年	98.9%	不高于 34ug/m³	不 高 于 56ug/m³
2017 年	98.1%	达到或优于国家二级标准	不 高 于 56ug/m³
2018 年	97.9%	达到或优于国家二级标准，浓度持续下降。	未下达
2019 年	97.2%	不高于 26ug/m³	进一步下降
2020 年	97.5%	不高于 26ug/m³	未下达

Notes. The figure shows us the pollution target of Quanzhou prefecture city from 2015 to 2020.

Figure A3

Examples of government word report



石家庄 2017 年政府工作报告

（二）强力整治环境污染，推进生态环境持续好转。强化“生态优先、绿色发展”理念，以重任在肩、寝食难安的责任意识，以壮士断腕、决战决胜的坚定信念，全力实施“五大行动”。实施“蓝天”行动。全面贯彻落实省委、省政府《关于强力推进大气污染综合治理的意见》以及 18 个专项实施方案，集中力量抓好四大攻坚，强化两大支撑，坚决打赢蓝天保卫战，确保 PM2.5 年均浓度下降 20.2%，降至每立方米 79 微克。四大攻坚：一是燃煤压减替代攻坚。10 月底前完成主城区和鹿泉、正定、藁城、栾城 39 万户气代煤、电代煤任务。全面淘汰 10 蒸吨以下燃煤锅炉和市区建成区 35 蒸吨以下燃煤锅炉。完成石热九期燃气机组和西柏坡电厂余热入市工程建设任务，加速实现主城区无煤化。二是扬尘综合治理攻坚。年底前关闭 20 家露天生产矿山，今冬明春完成 92 家责任主体灭失矿山复绿任务，砂场控制在 26 家以内。建筑工地全部安装在线视频监控。全面落实“以克论净”管理制度，提高道路扬尘治

石家庄 2018 年政府工作报告

（六）强力实施铁腕治污，推动生态环境持续好转。绿色是高质量发展的普遍形态，高质量是绿色发展的内在属性。自觉践行绿水青山就是金山银山的理念，坚持生态优先、绿色发展，在治理污染、修复生态中加快营造良好人居环境。

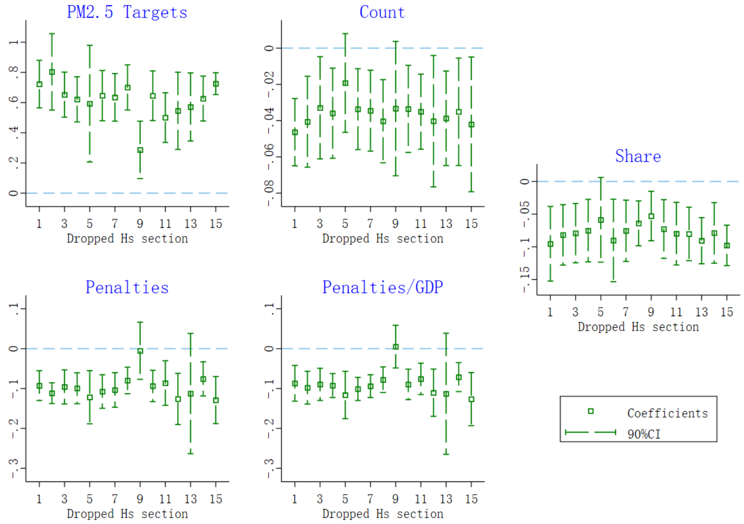
突出大气污染治理。瞄准率先退出全国重点城市空气质量“倒十”目标，全民共治、源头防治，坚决打赢蓝天保卫战。加大散煤治理力度，继续实施清洁能源替代，最大限度提高农村清洁采暖比例；控制工业燃煤总量，年底前全部淘汰全市范围 35 蒸吨/小时及以下燃煤锅炉，燃煤锅炉全部安装在线监测，稳妥压减电煤，全市煤炭消耗量净减 400 万吨；彻底整治“散乱污”企业，加快高耗能企业改造升级步伐，完成 10 家企业搬迁。禁煤区决不允许

Notes. The figure shows examples of two government word reports in Chinese for Shijiazhuang prefecture in 2017 and 2018. The words in red refer to the key word we collect from this report.

Appendix B Additional Figures

Figure B4

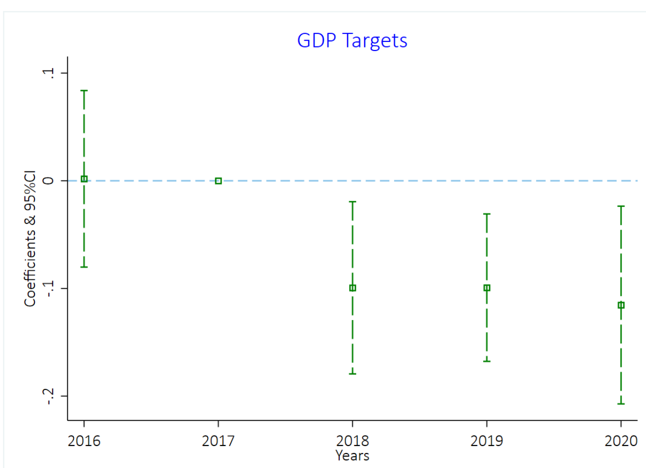
Robustness check: dropping industries of the product-level DID estimates for environmental regulation



Notes. The figure plots the point estimates and the 90% confidence intervals of the baseline regression with the five environmental regulation measures defined in Section 4.1 if we omit one HS section at a time. In the figure, the following 15 HS sections are represented: 1 - Animal & Animal Products; 2- Vegetable Products; 3 - Food; 4 - Mineral Products; 5 - Chemicals & Allied Industries; 6 - Plastics & Rubbers; 7 - Raw Hides, Skins, Leather, & Furs; 8 - Wood & Wood Products; 9 - Textiles; 10 - Footwear & Headgear; 11 - Stone & Glass; 12 - Metals; 13 - Machinery / Electrical, 14 - Transportation; 15 - Miscellaneous.

Figure B5

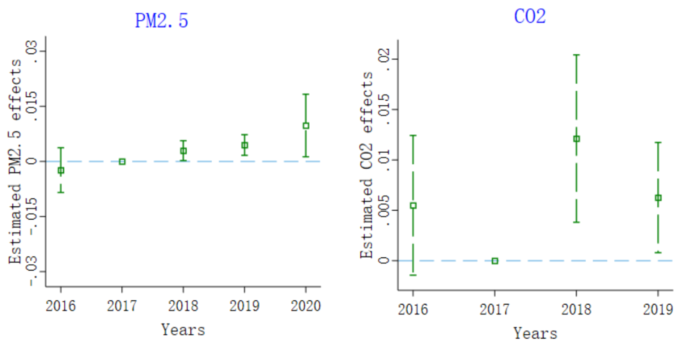
The Impact of Trade Protection on GDP growth Target



Notes. The figure plots the point estimates and the 90% confidence intervals of the baseline regression with the GDP targets in Section 6.3.1.

Figure B6

Impacts of Trade Protection on $PM_{2.5}$ and CO_2



The figure plots the impact of the change in US tariffs on the $PM_{2.5}$ and CO_2 emissions. Each figure shows the point estimates with a 95% confidence interval. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level.

Appendix C Additional Results and Robustness Checks

Table C1

Descriptive statistics

Variable	(1) Observations	(2) Mean	(3) SD	(4) p10	(5) p50	(6) p90
PANEL A: Tariff Exposure						
$\Delta\tau_p$	291	20.10	21.21	0.745	13.01	47.96
PANEL B: Air Pollution Measures						
$\text{PM}_{2.5,p,t}$	1,748	43.00	24.34	18.96	36.61	75.03
$\text{CO}_{2,p,t}$	1,124	1,457	2,276	147.1	570.8	3,561
PANEL C: Environmental Regulation						
$\overline{\text{PM}}_{2.5,p,t}$	995	45.08	12.76	30	43	63
$\text{Penalties}_{p,t}$	1,503	3.774	1.726	1.386	3.850	5.900
$\text{Penalties Share}_{p,t}$	1,485	-2.995	1.518	-4.958	-2.882	-1.199
$\text{Count}_{p,t}$	1,712	1.246	0.964	0.0953	1.411	2.092
$\text{Share}_{p,t}$	1,693	-2.859	1.386	-3.819	-2.632	-1.927
PANEL D: Political Variables						
$\text{Promote}_{p,t}$	1,470	0.13	0.34	0	0	1
$\text{GDP}_{p,t}$	1,418	7.51	0.99	6.29	7.42	8.82
$\text{Nightlight}_{p,t}$	1,680	5.90	1.35	4.33	6.03	7.28
$\overline{\text{GDP}}_{p,t}$	1,628	7.63	1.49	6	7.5	9.4
PANEL E: Control Variables						
τ_p^{SOE}	332	3.516	10.55	0	0.029	9.827
Highspeed Rail_p	330	0.533	0.500	0	1	1
Heating_p	332	0.479	0.500	0	0	1
Port Distance_p	331	638	663.4	52.91	462.7	1,320
$\text{Export}_p^{skilled}$	322	0.426	0.236	0.138	0.398	0.778
Capital_p^{SOE}	331	0.213	0.175	0.046	0.156	0.442
Export_p^{SOE}	332	0.086	0.157	0	0.019	0.292

Notes: The table reports descriptive statistics of the main variables of our analysis as described in Section 4.

Table C2

The impact of the trade war on environmental protection - Unweighted regression

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	0.910^{***}	-0.032	-0.073^{*}	-0.135^{**}	-0.127^{**}
	(0.171)	(0.017)	(0.032)	(0.034)	(0.037)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	887	1416	1416	1229	1229
R^2	0.971	0.431	0.363	0.775	0.688

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C3

The impact of the trade war on environmental protection - Removing control variables

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	0.623^{**}	-0.032	-0.071	-0.085^{**}	-0.079^{*}
	(0.238)	(0.017)	(0.036)	(0.031)	(0.031)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Observations	887	1416	1416	1229	1229
R^2	0.962	0.426	0.358	0.761	0.669

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C4

The impact of trade protection on environmental regulation (2020 excluded)

	(1) $\overline{\text{PM}}_{2.5,p,t}$	(2) $\text{Count}_{p,t}$	(3) $\text{Share}_{p,t}$	(4) $\text{Penalties}_{p,t}$	(5) $\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	1.060***	-0.136***	-0.129**	-0.008*	-0.014**
	(0.182)	(0.048)	(0.049)	(0.005)	(0.007)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	No	No	No	No	No
Controls	Yes	Yes	Yes	Yes	Yes
Obs.	692	917	917	1125	1125
R^2	0.976	0.814	0.730	0.471	0.455

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C5

Robustness check: exposure shares constructed using industry-prefecture employment

	(1) $\overline{\text{PM}}_{2.5,p,t}$	(2) $\text{Count}_{p,t}$	(3) $\text{Share}_{p,t}$	(4) $\text{Penalties}_{p,t}$	(5) $\text{Penalties Share}_{p,t}$
$\Delta\tau_p^L \times I_{(t\geq 2018)}$	2.328***	-0.192	-0.119	-0.121**	-0.130**
	(0.518)	(0.142)	(0.144)	(0.037)	(0.041)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	887	1229	1229	1411	1411
R^2	0.971	0.789	0.698	0.438	0.373

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C6

Placebo test

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2017)}$	-0.659	-0.000	-0.002	0.043	0.040
	(0.112)	(0.918)	(0.791)	(0.519)	(0.566)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	886	1411	1411	1156	1149
R^2	0.970	0.444	0.453	0.804	0.715

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In this placebo test, we consider a counterfactual case in which 2017 is the starting year of the US-China trade war. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C7

Falsification test

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	0.473	0.055	0.055	-0.007	-0.004
	(0.317)	(0.007)	(0.004)	(0.062)	(0.066)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	692	1125	1125	917	917
R^2	0.976	0.455	0.471	0.814	0.730

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. For these regressions, we construct our measure of prefecture exposure to US tariffs described by equation 3 by substituting exports to the United States with exports to the European Union. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C8

The Impact of the Trade War on Environmental Protection - Retaliatory Tariffs

	(1)	(2)	(3)	(4)	(5)
	$\overline{\text{PM}}_{2.5,p,t}$	$\text{Penalties}_{p,t}$	$\text{Penalties Share}_{p,t}$	$\text{Count}_{p,t}$	$\text{Share}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	1.141***	-0.094*	-0.087	-0.049**	-0.114**
	(0.173)	(0.039)	(0.046)	(0.014)	(0.032)
$\Delta\tau_p^{Ret} \times I_{(t\geq 2018)}$	-0.002	0.001	0.002	0.006	0.009
	(0.042)	(0.020)	(0.021)	(0.004)	(0.005)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	887	1411	1411	1156	1156
R^2	0.972	0.451	0.441	0.785	0.695

Notes. This table reports the estimates for α in equation 1 for our five main environmental regulation measures. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. Observations are weighted by the 2015 population. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C9

The Impact of Trade Protection on GDP target

	(1)	(2)	(3)
	$\overline{\text{GDP}}_{p,t}$	$\overline{\text{GDP}}_{p,t}$	$\overline{\text{GDP}}_{p,t}$
$\Delta\tau_p \times I_{(t\geq 2018)}$	-0.087**	-0.089**	-0.098***
	(0.022)	(0.017)	(0.007)
Prefecture FE	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes
Control	No	Yes	Yes
2020 Included	No	Yes	No
Observations	1453	1453	1121
R^2	0.898	0.902	0.880

Notes. This table reports the estimates for α in equation 1 for the annual GDP target, $\overline{\text{GDP}}_{p,t}$ of the local government. Our estimates always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C10

Heterogeneous Impacts of Trade Protection on Local GDP - Grid-Level Panel Analysis

	(1)	(2)	(3)	(4)	(5)
	$\text{Nightlight}_{p,t}$	$\text{Nightlight}_{p,t}$	$\text{Nightlight}_{p,t}$	$\text{Nightlight}_{p,t}$	$\text{Nightlight}_{p,t}$
$\Delta_p \times I_{t \geq t_0}$	-0.004*	-0.005	-0.005*	-0.005*	-0.005*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$\Delta_p \times I_{t \geq t_0} \times I_{40\%,p}$		0.001			
		(0.000)			
$\Delta_p \times I_{t \geq t_0} \times I_{30\%,p}$			0.001*		
			(0.000)		
$\Delta_p \times I_{t \geq t_0} \times I_{20\%,p}$				0.002*	
				(0.001)	
$\Delta_p \times I_{t \geq t_0} \times I_{10\%,p}$					0.004***
					(0.000)
Prefecture FE	Yes	Yes	Yes	Yes	Yes
Region×Year FE	Yes	Yes	Yes	Yes	Yes
2020 Included	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	1148	1148	1148	1148	1148
R^2	0.972	0.972	0.972	0.972	0.972

Notes. This table reports the estimates for α in equation 1 for the log of local GDP. In our estimates, we always include the prefecture fixed effects, the region-year fixed effects, and pre-sample prefecture controls interacted with year dummies. The 2015 population weights observations. Standard errors are clustered at the region level. Significance levels: *: 10%; **: 5%; ***: 1%.

Table C11

Top 10 Polluting Sectors

CIC4	Sector	$PM_{2.5}$ Emission
3112	Lime and gypsum manufacturing	12.27
3131	Manufacturing of clay bricks, tiles and building blocks	5.45
3317	Magnesium smelting	4.23
1030	Chemical Mining and Dressing	3.85
1754	Silk Fabric Manufacturing	2.71
2612	Inorganic Alkali Manufacturing	2.71
1393	Egg processing	2.48
4111	Manufacturing of Industrial Automatic Control System Devices	2.29
2824	Vinylon Fiber Manufacturing	2.08
2625	Organic and Microbial Fertilizer Manufacturing	2.02

Note. The third column of this table shows that average emission intensity of each industry. We construct this variable using firm-level emission and sales information in 2005. The unit of this variable is ton per 10 thousands of RMB