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Order! the border: Multitasking, air pollution regulation and local government responses[☆]

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ABSTRACT

This paper presents new evidence on how multitasking local governments' strategic responses to top-down environmental regulations can induce pollution in border areas. Using the implementation of the Air Pollution Prevention and Control Action Plan in China as a quasi-experiment, we exploit a difference-in-differences model and find that this policy induces the border effect of air pollution. We further reveal a salient window dressing behavior of local governments, which air pollution in border counties reduces significantly as the high-stakes inspection time neared, followed by a dramatic increase soon after the inspection. These results are driven by local government responses to incomprehensive air quality monitor stations installed in non-border counties, and local officials with strong promotion incentives, who exert strict regulations in non-border counties while varied regulations in border counties over time to cater for the multitasking of economic growth and air quality targets.

1. Introduction

Economists have long been interested in evaluating how agents respond to multitasking problems, especially when tasks are opposing each other (Holmstrom and Milgrom, 1991; Baker, 1992; Dixit, 1997, 2002; Alesina and Tabellini, 2007, 2008). This is particularly important when considering the tradeoff between environmental protection and economic growth in developing countries (Chen et al., 2018). Local governments, as the multitasking agent, may adjust their behaviors both spatially (e.g., in areas where the central government pays more attention) and temporarily (e.g., in periods when the central government prioritizes environmental protection over economic growth). Despite the abundant studies that focus on revealing how local governments exploit externalities of pollution to accomplish multiple tasks (Cai et al., 2016; Lipscomb and Mobarak, 2017; He et al., 2020b; Xie and Yuan, 2023; Cui et al., 2024), evidence on how they adjust their behaviors in spatial and temporal dimension is still scant.

In this paper, we take the Air Pollution Prevention and Control Action Plan policy in China (hereafter, APPC policy) as a quasi-experiment, and exploit a standard difference-in-differences model that compares the air pollution level between border and non-border areas, before and after the APPC policy to investigate the strategic behaviors of local governments. For the spatial dimension, air quality regulation may be laxer in border areas than in non-border areas for several reasons. First, APPC policy implements

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less comprehensive automatic air pollution monitoring stations in major metropolitans where population is densely distributed (Axbard and Deng, 2024; Yang et al. 2024), which happens to be non-border areas. Local officials are inclined to regulate pollution in non-border areas where the efforts are more easily observed by the central government, thereby inducing the unintended border effect of air pollution. Second, the negative externality of air pollution abatement in border areas also impedes local governments from enforcing strict regulations. Border areas may exert environmental free-riding through the transfer of air pollution to neighbors, and the number of pollution-oriented firms and associated pollution border effects tend to increase substantially.

For the temporal dimension, the APPC policy is by far the most stringent air regulation policy ever implemented in China. The policy set strong and clear requirements for local government to reduce air pollution by pre-specified deadlines (2016 and 2017), and incorporate environmental protection into official's performance and promotion evaluation, as failure to meet these goals carries significant political penalties. However, such campaign-style institutional design can only promise to motivate local officials to abate pollution before the deadlines, local government would re-compromise environmental protection once the enforcement is finished, as the drive for promoting economic growth is still the key task of local governments.

Combining these features of the policy, we first study whether the APPC policy has caused heterogeneous impacts on air pollution levels between border and non-border areas. Based on a county-year panel, we find that after the implementation of the APPC policy, the pollution level in border counties has decreased much slower than in non-border counties. To exclude potential confounders of unobserved characteristics of borders, we conduct a triple difference design that compares the changes in pollution levels between border and non-border counties in regulated regions with unregulated regions that are geographically adjacent, before and after the APPC policy. We find almost identical results that the border effect on pollution only relatively exacerbates in post-policy periods and regulated regions. Results from event study and dynamic difference-in-differences also support our assertations. The results remain robust after addressing a series of confounding factors.

We also provide corresponding firm-level evidence on both extensive and intensive margins and find consistent evidence that compared with non-border counties, border counties have more startup polluting firms and fewer shutdown polluting firms after the APPC policy (extensive margin). Further, compared with non-border counties, polluting firms in border counties tend to expand their output and scale, with a significant value-added increase (intensive margin). In addition, we find polluting firms in border counties may consume more energy (e.g., oil and natural gas), which indicates that polluting firms in border counties may expand their production relative to non-border counties.

Secondly, we explore the dynamic response of local governments. There may be window-dressing behavior of local governments who allocate varied regulation stringency in border areas over time to cater to the principal ex-ante: Once the air quality is mandatory and tight constraint (in years 2016 and 2017 when APPC policy requires the fulfillment of pre-specified environmental goals), local government may strengthen regulation in border areas; while, if the air-quality is more of a laxer constraint (after 2017), local government would re-compromise air quality protection in border areas. Consistent with such hypothesis, we find a typical pattern of window dressing that pollution in border counties reduces significantly in window periods (2016 and 2017), while retaining its upward trend immediately afterward. The same pattern is found when we net out the pollution changes in unregulated regions using a triple difference design.

Accordingly, though we do not find the number of startups or shutdowns of air-polluting firms change significantly during the window period, we find the number of startups (shutdowns) increases (decreases) significantly in the post-window period. We also find nearly identical evidence that all air-polluting firm's economic indicators (output, scale, and value-added), as well as pollution-related energy consumption, drop moderately in window periods. These results suggest that local governments are more likely to adopt an intensive margin approach to environmental regulation (Xie and Yuan, 2023). As an indirect validation, we find environmental penalties in border counties increase significantly during the window period, while reducing to its conventional level after the window period ends. Taken together, the above evidence aligns with a narrative of the window-dressing behavior of local governments.

To understand the driving forces behind the above results, we provide three mechanisms which are local governments' responses to automated air monitoring stations, lenient regulations of border counties and their political incentives. Firstly, to increase the information capacity of the central government and reduce data manipulation of local officials (Greenstone et al. 2022; Xie and Yuan, 2023), APPC implemented real-time air quality monitoring stations. However, the roll-out of automated monitoring was not comprehensively assigned. Jurisdiction with larger populations was prioritized (Axbard and Deng, 2024; Yang et al., 2024), which happens to non-border counties. Local governments have incentives to enforce stringent regulations in non-border counties where their efforts are easily observed by the central government, while exerting leniency regulations in border counties to free-ride through the transfer of air pollution to neighbors. Consistently, we find that no border effects were observed in border counties that installed monitoring stations, or located in proximity to the monitoring stations. The border effect and window dressing effect of air pollution are driven by border counties without automated air monitoring stations installed or located far away from those stations.

Secondly, we investigate whether environmental regulations were exerted much laxer in border counties relative to non-border counties. Border counties provide more informal tax breaks for polluting firms and enforce less stringent environmental regulations (measured by the number of environmental administrative penalties). Furthermore, the border effects are more prominent in those border counties with lower GDP, lower population, larger fiscal pressure, or higher initial pollution levels. These results further indicate that local officials were willing to trade air quality in border counties with lenient regulations to achieve economic growth.

Lastly, we investigate the role of political incentives of local officials, especially prefectural leaders who face the direct evaluation of the enforcement of the APPC policy. China's political incentives are explained by the performance appraisal system established by the central government (Li and Zhou, 2005; Liu and Fan, 2023). For a long period, Chinese officials' performance appraisal system was solely based on economic growth (Lee, 2023); however, APPC policy highlights air quality targets for local officials. In practice, some prefectural officials are punished on probation due to their ineffective abatement of air pollution, indicating lower promotion possibilities in their political careers. Thus, officials with higher promotion incentives are more devoted to enforcing heterogeneous regulations both spatially and temporarily. To investigate how local officials' political incentives mediate our results, we collect data on the biography for each prefectural leader (i.e., prefectural party secretary and mayors) in our sample.[1] We find the higher the promotion incentives, the more salient the border effect occurs. Similarly, the higher the promotion incentives, the stronger the window dressing effect. Taken together, we verify local governments would regulate varied regulations spatially and temporarily. Local officials would sacrifice the environment for economic growth in border counties, while strictly regulating non-border counties to fulfill air pollution inspection.

A final qualifying remark is in order. The presence of the border effect in China is ubiquitous, and border areas are labeled as highly polluted and less developed, yet the top-down environment regulation policy may not necessarily exacerbate the border effect. It is the combination of the political selection system, an organization highlighting long-term target of economic growth, and top-down environmental regulation, a short-term attempt to reduce the overall level of pollution in the targeted jurisdictions, that border areas are selected to enforce varied regulations over space and time to cater to the dual-goal of regional economic growth and (perceived) environmental protection.

Our research speaks to four strands of literature. First, we enrich the studies on pollution border effects. A larger number of empirical studies have identified the border effect and analyzed its potential political and economic factors (Bernauer and Kuhn, 2010; Cai et al., 2016; Duvivier and Xiong, 2013; Lipscomb and Mobarak, 2017; Cui et al., 2024), but most of them focus on national borders rather than subnational administrative borders within a country. Besides, existing studies that explore the border effect have solely focused on water pollution due to its salient negative externality (Kahn et al., 2015; Cai et al., 2016; Lipscomb and Mobarak, 2017). To the best of our knowledge, this paper is one of the first empirical studies to evaluate the border effect of air pollution within a country. Our study indicates that the border effect on pollution could occur with less externality (i.e., air pollution) due to the geographic specialty of border regions.[2] One study related to our paper is Cui et al. (2024), which demonstrates that local governments would strategically exert air pollution reduction efforts in areas where regulation policies are implemented while shrinking in others. In our view, the phenomena studied in our paper have an important difference from them: The border effect in our paper is driven by varied efforts in border counties and non-border counties within regulated provinces; in contrast, Cui et al. (2024)'s findings are resulting from the varied efforts between regulated areas and non-regulated areas.

Second, we shed new light on the literature that examines the window-dressing behavior of local governments (Fang et al., 2023; Bischoff and Blaeschke, 2016). To the best of our knowledge, this paper is among the first to examine the window dressing of air pollution from the temporal dimension. Our paper provides evidence that local governments would enforce a unified regulation intensity when pollution control efforts in border and non-border regions are equally weighted upon the short periods of inspection, but reduce efforts soon after the inspection. Two studies related to window dressing of air pollution are Zhang and Zhao (2023) and Cui et al. (2024), which focus on the spatial leakage of environmental regulation, but rarely examine the temporal pollution changes in border counties caused by the policy.

Lastly, we contribute to the growing literature on the political economy of environment monitoring, regulation, and enforcement (Kahn et al., 2015; Cai et al., 2016; Lipscomb and Mobarak, 2017; He et al., 2020b; Zou, 2021; Xie and Yuan, 2023; Axbard and Deng, 2024; Yang et al., 2024). Our paper extends the work of three previous studies (Zou, 2021; Xie & Yuan, 2023; Yang et al., 2024) by providing evidence that the strategic delayed pollution reduction in border counties without motoring stations installed in China. We provide new evidence that monitoring designs that were efficient ex-ante do not necessarily remain efficient as the responses of local governments evolve. Besides, this paper provides evidence of incomprehensive environmental regulation, contributing to the economic literature on environmental justice (Bento et al., 2015; Banzhaf et al., 2019; Currie et al., 2023; Yang et al., 2024). Targeting improvement efforts in metropolitan with larger populations, which happens to be non-border areas, worsen geographic, and environmental inequality, with significant distributional consequences.

The rest of the paper is organized as follows. Section I provides a brief background on APPC policy implementation in China. Section II introduces the dataset used in our analysis. Section III presents the main identification strategy along with our empirical results. Section IV explores the underlying mechanism, and Section V concludes.

2. Institutional background

China is characterized by a regional decentralized authoritarian regime (Xu, 2011). Within this vast bureaucracy, orders are issued, implemented, and assessed in a top-down way, with a strict performance-based reward-and-punishment system, where high-level principals set performance goals for lower-level agents. Motivated by strong career concerns, local officials exert more effort to criteria that are valued by the upper-level government. In the past, local officials engaged in fierce competition for promotions by driving economic growth in their jurisdiction (Li and Zhou, 2005).

Over the past few decades, air pollution has become a severe social problem that has aroused heated discussions. At the beginning of 2013, the country's major metropolitans were plunged into severe haze, and the number of visits to respiratory medicine and allergen testing departments in major hospitals in Beijing, Shijiazhuang, and Nanning (all provincial capitals) soared seven to eight

[1] Prefectural leaders are the major appraisal subjects of APPC policy. See https://www.gov.cn/zwgk/2013-09/12/content_2486773.htm.

[2] The negative externality of air pollution is less than water pollution since meteorological factors would affect the direction of pollution flow, while the direction of water pollution is more deterministic.

times.[3] The central government responded immediately and issued the Air Pollution Prevention and Control Action Plan in September 2013, vowing to tackle the problem of significant air pollution within five years. This policy effectively incorporated environmental targets into the evaluation of local officials along with traditional criteria such as GDP growth.

To better implement APPC at the local level, the Chinese Ministry of Environmental Protection (MEP), signed the Air Pollution Control Target and Responsibility Contract with provincial governments in January 2014, and set up a three-year air quality plan to decrease the concentration of particulate matter, marking the formal implementation of APPC policy (Mao et al., 2023; Axbard and Deng, 2024). Since then, the policy has been labeled as "the most stringent environmental regulatory policy in history".[4] The most important performance metric is the air quality targets, which should be achieved by the end of 2017 compared to 2012, the reduction rates of $PM_{2.5}$ or PM_{10} concentrations (Axbard and Deng, 2024). These targets are calculated by averaging the pollution readings across monitoring stations, and they vary by province. It mainly focuses on three regions, namely Beijing-Tianjin-Hebei (BTH), the Yangtze River Delta (YRD), and the Pearl River Delta (PRD). Clear reduction targets were set for each region, in which the concentration of $PM_{2.5}$ shall decrease by 25%, 20%, and 15% by 2017, respectively.[5] Other regions and provinces have set the reduction targets on PM_{10}. In addition, the policy strictly controls the coal usage that three regions need to achieve negative growth in total coal consumption, and the share of coal consumption in total energy consumption should be less than 65% by 2017.

To ensure that the APPC policy is faithfully enforced by local bureaucrats, the central government introduced the new monitoring system as a part of the APPC policy. The new monitoring system is staggered rollout at the national level and eventually covers all prefecture-level cities in China by the end of 2014, and began to transmit real-time pollution readings directly to the central government on January 1st, 2015 (Axbard and Deng, 2024). Monitoring stations are constructed in three waves from 2012 to 2014 (Xie and Yuan, 2023). As the BTH, YRD, and PRD are highly regarded in terms of abating air pollution, all prefecture-level cities installed air pollution monitoring stations on January 1st, 2013 (Yang et al. 2024). The placement of monitoring stations is largely decided by the population and geographical size (Axbard and Deng, 2024), which happens to the non-border area of the province. In Appendix Figure A1, we plot the geographic distribution of the monitoring stations in the BTH, YRD, and PRD, and 154 monitoring stations, 98.1% of all stations installed, are placed in non-border regions.

In the subsequent implementation process, the central government further introduced a series of supporting policies, including the newly amended Act on Air Pollution Prevention and Control in 2015. The Act further regulates the total amount of air pollutant emissions and the consequences of exceeding the standard and violating the law. Under the Act, local governments have been entitled to the right to impose administrative penalties on individuals or legal representatives suspected of environmental pollution, which lends local governments additional discretion to flexibly adjust their regulation intensity.

To ensure accountability and successful implementation, the provincial targets are further broken down and allocated to city governments through the target responsibility system. Regions that fail the annual assessment for reducing air pollution will face penalties. For example, Hebei Province held the city of Handan, together with the other five municipalities accountable for worsened local air pollution and penalized the officials with probation. During the inspection period of 2016 and 2017, the central government sent out inspection teams nationwide to check on the completion of pollution reduction and to evaluate local officials' performance (Agarwal et al. 2023), which is the criteria for their career promotion.

The policy is proven to be effective (Greenstone and Schwarz, 2018; Zhang et al. 2019; Mao et al., 2023) from an overall perspective. Greenstone and Schwarz (2018) find that the APPC policy significantly improved air quality in densely populated areas and increased the life expectancy of residents. Meanwhile, monitoring data show that the average $PM_{2.5}$ concentrations in the key regions of BTH, YRD, and PRD in 2017 decreased by 39.6%, 34.3%, and 27.7%, respectively, compared with 2012.

Appendix Figure A2 displays the change rates of PM2.5 in three key regions at the county level in 2012–2013 (pre-policy), 2013–2017, and 2017–2020 (post-inspection). Several patterns can be drawn from Fig. 1: First, the pollution pattern has dramatically changed in 2013–2017. Border regions generally had lower rates of air pollution decline in 2013–2017, while border regions had larger reduction rates than that of non-border regions in 2012–2013, indicating the air quality improved greatly in non-border regions relative to border regions. Second, the pollution levels in the border regions were slightly lower in 2017 than in 2020, suggesting that the pollution may increase again after 2017(especially in BTH), the inspection year of APPC policy. Lastly, the change rate of PM2.5 presents latitude-zonal characteristics, and we need to exclude the potential confounder of atmospheric environment or geographical characteristics.

3. Data

To systematically assess the impact of APPC policy on border counties, we collect data from various sources. Our empirics are mainly based on county-level data, and we also leverage firm-level data to complement the analysis. We introduce these data in turn.

[3] More details in https://www.chinanews.com/tp/hd2011/2013/01-13/165199.shtml.

[4] See report in http://finance.people.com.cn/n/2014/0529/c1004-25078075.html.

[5] In order to fulfill the target, the policy specifies the need to strengthen standards for industrial emissions and promote the retrofitting of enterprises with emission reduction equipment such as desulfurization and nitrogen removal; and the replacement and upgrading of outdated industrial equipment (e.g., industrial boilers). See, for example, more discussion in Zhang et al. (2019).

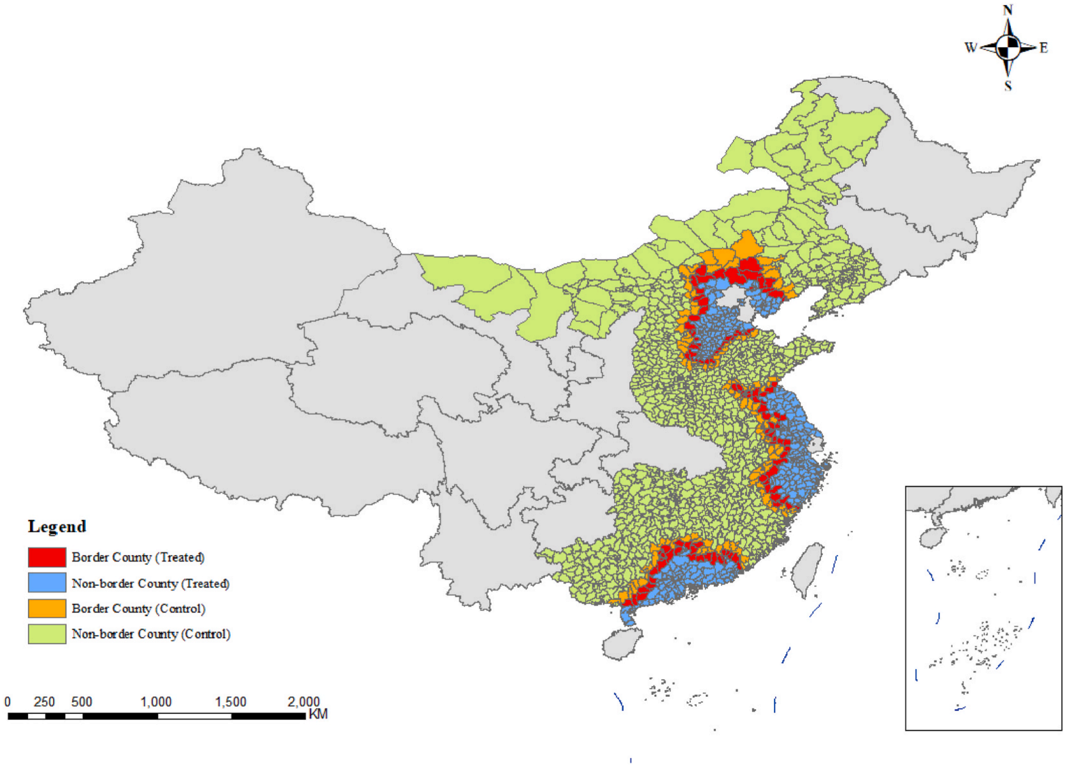


Fig. 1. Geographical distribution of baseline sample.
Notes: This figure presents the geographical location of our baseline and extended sample. For our baseline sample, we only consider treated provinces, within which we distinguish border counties and non-border counties, colored by red and blue, respectively. For extended sample, we further include neighboring provinces of treated provinces, labeled as non-treated provinces. We define counties in these provinces that share the same border with the treated provinces as border counties, with the rest counties are defined as non-border counties.

3.1. Research sample

APPC is to improve air quality in BTH, YRD, and PRD and set stricter reduction targets of $PM_{2.5}$ in three regions, while the requirements for other regions are PM_{10}. BTH, YRD, and PRD consist of four provinces (Hebei, Jiangsu, Zhejiang, and Guangdong), and three municipalities directly administrated by the central government (Beijing, Shanghai, Tianjin). There is limited comparability between the counties of provinces and municipalities directly administrated by the central government. Since the political hierarchy of counties in municipalities directly administrated by the central government is equal to prefecture-level cities and higher than counties of other provinces, we exclude the samples of municipalities directly administrated by the central government. Thus, our baseline sample consists of the counties of four provinces in BTH, YRD, and PRD that the APPC policy targeted, namely, Hebei, Jiangsu, Zhejiang, and Guangdong.

We define Hebei, Jiangsu, Zhejiang, and Guangdong as the treated provinces, and counties located on the border between treated and non-treated (or control) provinces are defined as border counties, and the others remained as non-border counties.[6] The geographical distribution of our sample is plotted in Fig. 1.

3.2. Air pollution data

The key pollutant we focus on is $PM_{2.5}$, which the central government mandates to reduce in BTH, YRD, and PRD. The pollution data are derived from NASA satellite observations, which combine NASA MODIS, MISR, and SeaWiFS aerosol optical depth (AOD) inversions with the GEOS-Chem chemical transport model and calibrating ground-based observations using geographically weighted regression (GWR) (Van Donkelaar et al. 2021). In addition to the wide temporal coverage, satellite observations of $PM_{2.5}$ have the advantage of covering the whole territory of China with a geographic resolution of 1×1 square kilometers per grid. The raw raster data are defined at the monthly level, based on which we calculated the year-by-year average $PM_{2.5}$ concentrations in each county. The

[6] There are counties located in the border area between treated provinces, notably in Jiangsu and Zhejiang province, and they are regarded as non-border since they do not share the boundary with control provinces. However, our results are nearly identical whether we define these counties as border counties or not.

data span from 2010 to 2020.

The Chinese government mainly use ground stations data to detect the air quality instead of NASA satellite. Thus, it is important to examine whether the satellite-derived air pollution data align with data derived from ground monitoring stations. Since not all counties have installed monitoring stations, we only use satellite data from counties that installed monitoring stations to make the comparison. In Appendix Figure A3, we plot the monthly pollution data from both sources, and it verifies the PM2.5 data from ground stations align with NASA satellite data.

In the subsequent analysis, we also examine the impact of the APPC policy on other pollutant emissions, such as sulfur dioxide emissions (SO_2), nitrogen oxide emissions (NO_x), and dust emissions. We collect these data from industrial production in each county from the County Statistical Yearbook.

3.3. Business Enterprise Registration Data

The enterprise registration data is from the Ministry of Industry and Information Technology's National Enterprise Credit Information Publication System. The data, which is the most comprehensive dataset regarding business registration, reflects the business status of enterprises, especially small businesses, and it records the business enterprise registration information of (almost) all individual business households on the Chinese mainland since 1949. It covers the date of business registration, business name, registered address, industry classification, and the date of business closure (if the business no longer continues to operate). We calculated the number of startup or shutdown firms by industry from 2010 to 2020 at the county level, as well as the number of startup or shutdown polluting versus non-polluting firms in each county based on industrial classification codes of the air pollution industry. The list of air-polluting industries derives from the "heavily polluting industries" list outlined by the Ministry of Environmental Protection (MEP) which consists of sixteen heavily polluting industries that involve both air and water pollution. Eleven industries related to air pollution are defined as air-polluting industries (Appendix Table B1).

3.4. National tax survey dataset

The National Tax Survey Dataset (NTSD) is jointly collected by the State Administration of Taxation and the Ministry of Finance, spanning from 2007 to 2016.[7] To match with the baseline time period, we mainly use data from 2010 to 2016. The data are based on a random stratified sample of nearly 700,000 firms across the country, which constitute nearly 20% of the country's output and 38% of its tax revenues (Mao et al., 2023). The NTSD contains a large range of information (such as firms' inputs, outputs, and indicators of energy consumption) that can help identify the impact of the APPC policy on firms' responses.

We obtain a range of firm-level variables from NTSD. To measure firms' inputs and outputs, we obtain firms' gross output, value-added, profits, and employment. To measure firms' energy consumption, we obtain firms' coal consumption, natural gas consumption and oil consumption. The first three indicators of energy consumption are strongly related to $PM_{2.5}$ concentrations. NTSD also includes variables such as the firm's address, industry, opening years, and ownership status, and we locate them into the specific county, and categorize them into air-polluting or non-air-polluting enterprises, and state-owned or privately owned enterprises.[8] We follow the convention and exclude firms with fewer than 8 employees (Brandt et al., 2012) and negative output or value-added (Chen et al. 2023).

3.5. Meteorological data

We obtain meteorological data from weather stations maintained by the National Oceanic and Atmospheric Administration (NOAA).[9] There are more than 400 stations in China that record surface meteorological data, including wind direction, wind speed, temperature, and barometric pressure, every 3 h. We first summarize the hourly observations at the annual level and match the stations to their nearest counties based on their latitude and longitude.

Specifically, our meteorological data include wind direction (angular degrees), wind speed (meters per second), atmospheric temperature (degrees Celsius), dew point temperature (degrees Celsius), and sea level pressure (Hectopascals). For the wind direction data, we use the vector decomposition method to calculate the wind angle on a daily basis, and then calculate the annual average wind direction thereby.

3.6. Other socio-economic data

We draw some control variables from the County Statistical Yearbook. Following Cai et al. (2016), we use the county's population (in logarithmic form) to control for the labor supply, GDP (in logarithmic form) to control for the economic development level, and the share of agricultural output in total output to control for industrial structure. We also control for some time-invariant variables such as the county's area and distance to the provincial capital. Both variables are interacted with a full set of year dummies to allow the effect to trend arbitrarily with time. To shed light on the political economics of environmental regulation, we manually collect the

[7] NTSD is no longer publicly available after 2016, thus our firm-level data ends at 2016.

[8] There are fewer than 0.5% of firms do not report the industry classification, and we drop these firm samples. Given the sample sizes, it would have a minimal impact on our analysis.

[9] Data are available at: https://www.ncei.noaa.gov/maps-and-geospatial-products.

bibliography of the prefectural party secretary and mayor, thus we obtain local officials' age, gender, the highest degree in education (i.e., college, bachelor, master, or doctor) and the province of the birthplace. For brevity, we only report the summary statistics of key variables in Table 1 that will be utilized in baseline specification, and relegate the rest summaries to Appendix Table A1.

The Panel A of Table 1 reports the mean and standard deviation for border and non-border counties, before and after the APPC policy. In Panel B, we report the significance test of mean differences for the set of baseline variables. It can be seen that $PM_{2.5}$ in border and non-border counties decreases; border counties are characterized by more severe air pollution, less population, and lower GDP than non-border counties. Besides, border counties are farther from the provincial capital and larger in county size. We also find some differences regarding the weather conditions. There may be concerns that the high differences between border and non-border counties may introduce potential bias to our estimation. It is worth noting that our identification assumption requires that the changes in outcome variables would evolve in a parallel fashion in the absence of the policy intervention, but does not require that the border and non-border counties should have similar characteristics.

4. Empirical design and results

4.1. Research design

We adopt a difference-in-differences (DID) model to evaluate the impact of APPC policy on border counties. Specifically, we compare the $PM_{2.5}$ concentrations in border counties with non-border counties, before and after the APPC policy with the following two-way fixed effect model:

$$Y_{it} = \beta\, Post_t \times Border_i + \boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{1}$$

Where Y_{it} is the logarithm value of $PM_{2.5}$ concentrations in county i at year t. In the subsequent analysis, the outcome variable may also represent the number of firm startups (or shutdowns), the firm's inputs, outputs values, and energy consumption. $Post_t$ is a dummy, indicating the starting year of the APPC policy. Since the APPC policy was firstly initiated in September 2013 and did not fully come into effect until 2014, we set 2014 as the beginning year of the policy (Mao et al., 2023). $Border_i$ denotes whether a county is located in border areas or not. We include a series of socio-economic variables $\boldsymbol{X}_{it}$ and meteorological variables $\boldsymbol{W}_{it}$ to control for the differentiated characteristics between border and non-border. The socio-economic variables include the county's population (logarithmic value), GDP (logarithmic value), the share of agricultural output in total output, the county's area, and the distance to the provincial capital. The last two time-invariant variables are interacted with the full set of year dummies to allow for time-varying effects. Meteorological variables include wind direction, wind speed, atmospheric temperature, dew point temperature, and sea level pressure. δ_i and γ_t represent county and year fixed effects respectively.

We should note that both border and non-border counties are affected by the APPC policy, and the coefficient of β can be perceived as the difference in the treatment effect of the APPC policy on border and non-border counties. We define such difference as the border effect induced by the APPC regulation. However, such a design also implies the existence of spillovers across border and non-border counties as they all get affected by the policy, thereby violating the Stable Unit Treatment Value Assumption (SUTVA). Although the violation does not affect the large sample properties of the DID estimator, the results still need to be interpreted with caution. We will discuss such spatial dependency in subsequent robustness checks.

Apart from the potential violation of SUTVA, there are two major concerns with the above design. First, the identification may fail to satisfy the parallel trend assumption. Our delineation of treatment and control groups is independent of (or predetermined to) policy interventions, yet the border and non-border counties may have diverged in the trajectory of air pollution before the policy interventions, which violates the parallel trend assumption. We test for the presence of pre-trend using an event-study approach:

$$Y_{it} = \sum_{\tau=2010,\tau\neq 2013}^{2020} \beta_\tau\, Year_\tau \times Border_i + \boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{2}$$

In equation (2) we replace the $Post_t$ dummy with a full set of time indicators, i.e., $Year_{2010}, \cdots, Year_{2020}$. 2013 is set to be the reference year and thus excluded. If the parallel trend assumption holds, we should observe that the estimated coefficients of the ex-ante variables β_τ ($\tau \leq 2012$) are not statistically significantly different from 0. Another advantage of flexible estimation using equation (2) is that we are able to observe the dynamic policy effects. Since the APPC policy proposes explicit assessment targets by 2017, we are equally interested in the change path of pollution levels in border and non-border counties around and after 2017, which will help us to further analyze the strategic responses of local governments.

The second concern is whether all of the post-policy divergence in pollution levels between border and non-border counties results from the APPC policy or not. There may be other unobserved time-varying factors that simultaneously affect pollution levels in border and/or non-border counties around the same time of policy implementation. To alleviate such concern, we construct a triple differences (DDD) as follows:

$$\begin{aligned} Y_{it} = {} & \beta_1\, Post_t \times Border_i \times Treat_p + \beta_2\, Post_t \times Border_i + \beta_3\, Post_t \times Treat_p \\ & + \boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{3}$$

In model (3), $Treat_p$ equals one if the province p is one of the four provinces subject to the APPC policy, otherwise it equals zero if it is

Table 1
Summary statistics of baseline variables.

Panel A:	Border counties				Non-border counties			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
log(PM$_{2.5}$)	1.520	0.400	1.330	0.420	1.440	0.370	1.220	0.390
log(Population)	3.900	0.610	3.880	0.650	4.020	0.660	4.050	0.650
log(GDP)	13.87	0.830	14.24	0.860	14.64	1.050	15.06	1.060
Agri. % to GDP	0.200	0.0900	0.180	0.090	0.210	3.110	0.100	0.090
Land area (km^2)	2093	1394	2093	1393	1028	876.2	1028	876.0
Dist. to Prov. Capital (km)	150.5	76.05	150.5	75.95	116.3	74.16	116.3	74.19
Wind speed (m/s)	21.68	6.590	23.21	6.060	25.26	8.810	25.42	7.460
Wind direction (°)	163.3	40.24	172.3	38.42	149.5	36.25	151.6	35.28
Atmospheric Temperature (°C)	15.10	5.478	16.35	4.990	16.68	4.300	17.53	4.090
Dew Point Temp (°C).	7.950	7.068	9.410	7.330	9.860	6.000	11.16	6.220
Sea Level Pressure (pa)	10158	18.75	10159	19.13	10156	17.79	10157	17.72
Sample Size	320		560		1588		2779	

Panel B:	Border county	Non-border county	Differences
log(PM$_{2.5}$)	1.400	1.296	0.104***
log(Population)	3.889	4.039	−0.150***
log(GDP)	14.10	14.91	−0.806***
Agri. % to GDP	0.187	0.139	0.0480
Land area (km^2)	2093	1028	1064.913***
Dist. to Prov. Capital (km)	150.5	116.3	34.165***
Wind speed (m/s)	22.66	25.36	−2.710***
Wind direction (°)	169.0	150.8	18.187***
Atmospheric Temperature (°C)	15.89	17.22	−1.324***
Dew Point Temp (°C).	8.876	10.69	−1.811***
Sea Level Pressure (pa)	10158	10156	2.115***

Notes: This table presents the summary statistics of baseline county-level variables, as well as the significance test between border and non-border counties on the covariates. For each variable in Panel A, we separately report the mean and standard deviation by treatment assignment (i.e., whether a county is a border county), and by treatment period (before and after the APPC policy). For each variable in Panel B, we report the mean by whether the county is a border county in the first two columns and report their differences in the last column. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

the neighboring province of the four treatment provinces. The estimated coefficients of $Post_t \times Border_i \times Treat_p$ is of interest, which measure the difference in pollution levels between border and non-border counties, before and after the policy between treated and non-treated provinces.

Unlike the parallel trend assumption of DID, DDD only requires that the difference in pollution levels between border and non-border counties in the treated and non-treated provinces remain parallel prior to the policy. DDD estimator first calculates the difference in pollution levels in border and non-border counties for both treated and non-treated provinces, and then compares these two differences before and after the policy. The validity of the DDD estimator lies in the assumption that the unobservables acting on treated provinces are equally likely to act on the non-treated provinces with similar effects (Olden and Møen, 2022). In other words, we're actually using the border-vis-non-border differences in non-treated provinces to serve as the counterfactual for the border-vis-non-border differences in treated provinces, therefore excluding unobservables resulting in our estimation.

Similarly, we can test for the parallel trend assumption of the DDD model, which assumes that differences in pollution levels between border and non-border counties in the treated and non-treated provinces will remain parallel in the absence of policy intervention (Olden and Møen, 2022). Formally, we estimate the following regression:

$$Y_{it} = \sum_{\tau=2010,\tau\neq 2013}^{2020} \beta_{1_\tau} Year_\tau \times Border_i \times Treat_p + \beta_2\, Post_t \times Border_i + \beta_3\, Post_t \times Treat_p$$
$$+\boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{4}$$

In equation (4), we are concerned with the estimated coefficients of $\beta_{1_\tau}s$. If the triple differences design satisfies the parallel trend assumption, we should observe that the estimated coefficients of β_{1_τ} $(\tau \leq 2012)$ are not statistically significantly different from 0. Similarly, with the help of the event-study model (also referred to as the dynamic DID model), we can focus on how the difference in pollution levels between border and non-border counties in the treatment province changes over time relative to that of non-treated provinces. If our baseline DID model captures policy-induced border effects, the DID results should be insignificantly different from the DDD results, and the patterns of pollution trajectory for both border county and the border-vis-non-border differences should be similar under the dynamic estimation.

4.2. Baseline results

Difference-in-Differences Estimates. We report the results from the baseline regressions in Table 2. Throughout the estimations, we control for two-way fixed effects of county and year to account for county-specific time-invariant unobservables and time-varying common confounders. Column (1) reports the most parsimonious result that does not incorporate any control variables. We test the stability of the coefficient estimates with respect to the different control variables by sequentially including socio-economic controls and meteorological controls in columns (2) and (3). The estimated coefficients remain stable after the inclusion of the aforementioned controls, mitigating the concerns of omitted variable bias. To account for the potential serial correlation and the endogeneity caused by lagged explanatory variables (e.g., the pollution level in the previous period influences both the implementation of the policy as well as the pollution level in the current period), we incorporate the lagged explanatory variables in Column (4), and the estimated coefficient remain qualitatively the same.[10] Across all specifications, the estimates are all positive and significant at the 1% level, suggesting a non-neglectable effect of the APPC policy on inducing the relatively more severe pollution level in border counties.[11]

Event-Study Estimates. To examine the validity of the parallel trend assumption, we estimate the dynamic difference in $PM_{2.5}$ over time between border and non-border counties using the event study method. Fig. 2 plots the regression coefficients and the corresponding 95% confidence intervals.

The figure delivers some interesting features. Firstly, before the implementation of the APPC policy, pollution levels in border counties and non-border counties remained the same trend, with all coefficients ex-ante being insignificant and close to 0. Secondly, after the policy shock, pollution levels in border counties rose drastically relative to non-border counties, with all ex-post estimates significantly different from 0 except for 2017. The difference in pollution levels between border and non-border counties widened as time went on, and reached 6% at the end of our sample period. It is noticed that the estimated coefficients for 2017, the year of APPC policy evaluation, are not significant from 0, indicating local governments may have enforced stricter regulations in border counties in 2017.

Triple Differences Estimates. As discussed above, the DID specification may fail to rule out time-varying unobservables that are concurrent with the APPC policy, thereby confounding our estimates of policy-induced border effects. To mitigate such concerns, we further adopt a triple differences approach that only compares the border effects between treated and non-treated provinces, before and after the APPC policy.

Table 3 reports the results. In all specifications, the estimated coefficients of the triple-D term $Post_t \times Border_i \times Treat_p$ are all positive and significant at 1% level. Similar to the baseline specifications, the estimated coefficients remain stable with the inclusion of socio-economic and meteorological covariates. To convert the DDD coefficients back to the border effects within the treated province, we add the triple interaction coefficient (0.056) to the coefficient of $Post_t \times Border_i$ (-0.029), resulting in a combined effect of 0.027, which is nearly identical to the DID coefficient. This close similarity further validates our baseline results.[12]

Dynamic DID estimates. The identification of the effect of the APPC policy by the triple-D model relies on the assumption that the trends of border effect across treated and non-treated provinces should be similar before the APPC policy. We use the so-called dynamic DID estimation similar to the event study approach to test the validity of the assumption. In the estimation of dynamic DID, we first estimate and construct a quadratic interaction $Border_i \times Treat_p$ to identify the difference in pollution levels between border and non-border counties, between treated and non-treated provinces, and to interact with a full set of time dummies to estimate how these double difference terms evolve with time.

Fig. 3 displays the coefficients of dynamic DID estimation and their corresponding 95% confidence intervals. Not surprisingly, the results of dynamic DID estimation are consistent with those from event study estimation. Before the policy, the trajectories of the border effect between treated and non-treated provinces remain parallel. Similarly, we found that the differences in border effects decreased to their lowest level around 2017, and significantly increased thereafter. This pattern coincides with the findings from event study estimates, and is further consistent with the narrative of the window dressing effect.

4.3. Robustness

In this section, we perform a battery of robustness checks as follows.

Comparability between Treatment and Control Provinces. Despite the stringency of the APPC policy on the three key regions studied in this paper, the policy itself is rolled out at the national level. Therefore, the control provinces are also subjected to the APPC policy, leading to potential contamination bias in our DDD estimation. For instance, it exits a compelling alternative explanation that all counties (both border and non-border) in the treated provinces have implemented pollution control measures with equal intensity. Subsequently, following the implementation of the APPC policy, polluting industries have relocated to the borders of control provinces, leading to the observed increase in pollution in the border counties of the treated provinces.

[10] The estimates in column (4) of Table 2 are nearly identical without the inclusion of a lagged dependent variable, which alleviate the concern of Nickell bias.

[11] Given the presence of potential window dressing behavior we will discuss in subsequent sections, our estimate for the border effect based on the full sample may be underestimated. In Appendix Table A2, we re-estimate our baseline specifications with the time window from 2010 to 2016. In addition, we also exclude year 2016 and 2017 to rule out the effect of window dressing. The results remain qualitative the same, and we therefore still apply the baseline model in the subsequent analyses.

[12] Since the results from DID and DDD are similar, in our following analyses, we will still use DID as our workhorse model.

Table 2
Baseline estimation results.

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.032***	0.034***	0.030***	0.029***
	(0.006)	(0.006)	(0.005)	(0.006)
L1. $ln(PM_{2.5})$				−0.010
				(0.013)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Observations	5,014	5,014	5,014	4,523
With-in R^2	0.050	0.056	0.103	0.108

Notes: This table presents the baseline estimation results. Regression specification is presented in Equation (1). County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

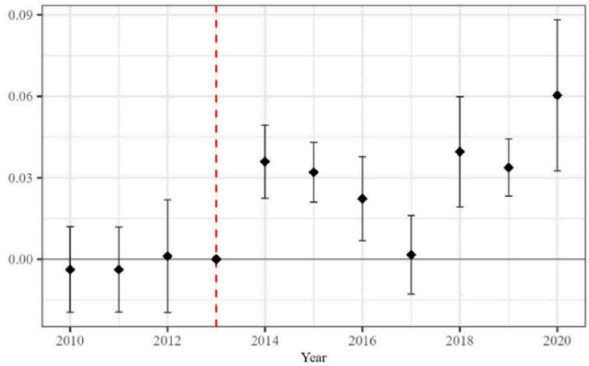


Fig. 2. Event study estimation.
Notes: This figure presents the event study coefficients. Regression specification is presented in Equation (2). The year 2013 is omitted as the reference year. The specification includes county fixed effects and year fixed effects; county controls and weather controls. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. The standard errors are clustered at the county level. Coefficient estimates and 95% confidence intervals are plotted in the figure.

Table 3
DDD estimation results.

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i \times Treat_p$	0.057***	0.054***	0.053***	0.056***
	(0.008)	(0.007)	(0.007)	(0.009)
$Post_t \times Border_i$	−0.025***	−0.026***	−0.025***	−0.029***
	(0.005)	(0.005)	(0.005)	(0.007)
$Post_t \times Treat_p$	−0.062***	−0.060***	−0.057***	−0.065***
	(0.003)	(0.003)	(0.003)	(0.004)
L1. $ln(PM_{2.5})$				−0.117***
				(0.009)
County FE & Year FE	Y	Y	Y	Y
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Observations	13,539	13,539	13,539	11,937
With-in R^2	0.042	0.076	0.139	0.179

Notes: This table presents the DDD estimation results. Regression specification is presented in Equation (3). County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

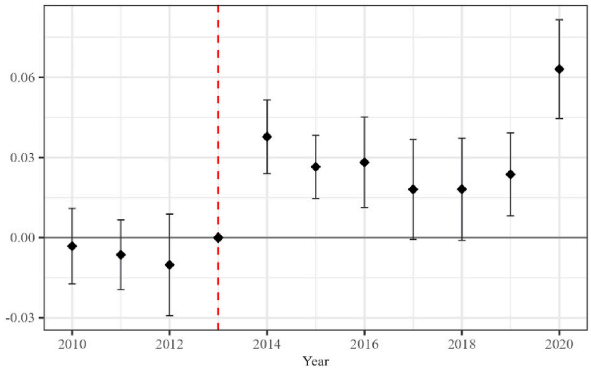


Fig. 3. Dynamic DID estimation.
Notes: This figure presents the dynamic DID coefficients. Regression specification is presented in Equation (4). The year 2013 is omitted as the reference year. The coefficients plotted in the figure correspond to $\beta_{1\tau}s$ in Equation (4). We also include the interaction of the full set of year dummies with $Border_i$ and $Treat_p$ to flexibly control for the heterogeneity between border and non-border, treated provinces with control provinces, respectively. The specification includes county fixed effects and year fixed effects; county controls and weather controls. County controls include the logged value of population and GDP, the agricultural share to the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. The standard errors are clustered at the county level. Coefficient estimates and 95% confidence intervals are plotted in the figure.

To alleviate this concern, we re-estimate equation (1) for the control provinces and report the corresponding results in Appendix Table A3. We find that the estimated coefficients, despite positive, are small in magnitude and are sensitive to the inclusion of controls. When we include a full set of control variables and the lagged term of the dependent variable, we cannot find any statistical significance of the estimated coefficient. These results indicate that although control provinces are subject to the APPC policy as well, the enforcement does not lead to significant border effects in control provinces. This alleviates our concerns that our DDD results may be confounded by the pollution dynamics in control provinces and provides further support to the validity of our DDD design.

The leakage effect of Beijing/Shanghai. From Fig. 1, we can see the air pollution pattern has changed dramatically from 2013 to 2017 the air pollution in counties near Beijing and Shanghai has reduced much larger than in others. It raises the concern that our estimations are potentially driven by the "Beijing effect" or "Shanghai effect", as border counties under our definition are farther away from either Beijing or Shanghai. Since air pollution is mostly strictly regulated in two metropolises, it is possible that the pollution is shifted further away to avoid the strong regulation.

To address this concern, we perform two tests. The first strategy is to estimate whether the pollution effects changed as the distance to Beijing/Shanghai increased. We calculate the distance of each county to either Beijing or Shanghai,[13] and interact the distance variable with our key explanatory variable, $Post_t \times Border_i$, to examine whether the border effects are mediated by the distance to Beijing/Shanghai. The second is to use only a sample from Guangdong Province to avoid confounding by other metropolises. The corresponding results are reported in Appendix Table A4. We do not find any suggestive evidence that the distance to Beijing/Shanghai can explain our main findings.

Sample Selection of border counties. We also exclude the confoundedness of potential sample selections. Although in our baseline analysis we do not include provincial municipalities (e.g., Beijing and Shanghai) to ensure the appropriate comparison between border and non-border counties, concerns may still arise as counties bordering Beijing or Shanghai may receive stricter regulation intensities, leading to overestimating to our baselines results. We therefore rerun our baseline regression while excluding counties bordering either Beijing or Shanghai and report the estimated results in Appendix Table A5. Reassuringly, we find no significant change in the coefficients when these counties are excluded from our regressions (the estimated coefficients slightly drop by around 0.001 to 0.003).

Coarsened Exact Matching. Another related concern to the sample selection issue is the unbalanced characteristics between border and non-border counties. To make the border and non-border counties more comparable in observed characteristics, we adopt the Coarsened Exact Matching (CEM) approach to refine our control group (i.e., non-border counties). The basic idea of CEM is to stratify the covariates and conduct matching based on the coarsened joint distribution of observables (Iacus et al., 2012). To implement CEM, we cut the matching variable into 5 bins with equal length, and category treatment and control groups with similar characteristics into the same bin (strata). We report the results based on CEM in Appendix Table A6. Throughout different specifications, the baseline results remain robust.

Refine Control Group and Re-Weighting. To better balance the potential unobserved characteristics between border and non-border counties, we restrict our non-border samples to only those geographically adjacent to border counties. The estimated results are reported in Appendix Table A7, columns (1) to (3). In columns (4) to (6), we use the inverse distance to the provincial border as

[13] We calculate the distance to Beijing for Hebei counties, and the distance to Shanghai for Jiangsu and Zhejiang counties.

weights and perform a weighted regression, which gives more weights to counties closer to the border. Our estimates remain robust under these tests.

Flexible Estimation. Our baseline specification only exploits the variation of whether a county is located at the provincial border. To assess its credibility, we conduct several robustness checks using the distance from each county's centroid to the provincial border. First, we adopt a continuous treatment assignment by interacting with the post-APPC dummy with the distance of each county to the provincial border. The results are reported in Appendix Table A8. We find consistent evidence that the border effects of pollution are significantly decreasing as the distance to the border increases, suggesting that the pollution is mostly concentrated in counties that are closest to the provincial border.

To show the results visually, we further partition the distance variable into 9 bins, with each bin spinning across 30 km (i.e., 0–30 km, 30–60 km, …, 240–270 km). The maximum of the distance variable is about 260 km, and we therefore set the last bin (i.e., 240–270 km) as the reference bin, and interact each bin with the post-APPC dummy to flexibly estimate how the pollution effects vary as the distance to the border increases. Appendix Figure A5 presents the results of the by-distance-bin estimation. We find that the treatment effects are mostly concentrated in counties with a distance to the border of less than 60 km, which coincides with the distance of border counties to the provincial border (the maximum distance to the border among border counties is roughly 50 km). The above exercises lend further credence that the pollution level relatively increased in border counties after the implementation of the APPC policy.

Provincial Heterogeneity. To make sure the estimated results are not driven by a single province, in Appendix Figure A6, we re-estimate the baseline regression by excluding one of the four treated provinces in turn. The results are relieving, none of the four provinces is exerting a disproportional rule in deciding the baseline results, suggesting that our results are less likely to be driven by only one of the four provinces.

Additional Controls and Fixed Effects. Our results remain robust to the inclusion of additional controls and fixed effects. In Appendix Table A9, we include three sets of additional controls that may have an impact on our estimates. These include the interaction of initial pollution levels (measured by the $PM_{2.5}$, SO_2, NOx, and Dust emitted in 2010) with linear year trends, industrial structure, and fiscal revenue. We do not find any discernible change in the estimated coefficients as the inclusion of these additional controls. In Appendix Table A10, we include additional fixed effects (as well as flexible linear time trends) to absorb time-varying confounders. Specifically, we include province-specific year trends and province-year fixed effects in columns (1) and (2). The inclusion of the province-year fixed effects can capture the effects of other province-specific environmental policies, thereby alleviating concerns that our results are driven by other concurring policies. In columns (3) and (4), we include city-specific year trends and city-year fixed effects, which are more demanding specifications that only exploit within-city variations for estimation. The estimated results decreased somewhat but remained significant at the 1% level. Finally, in column (5), we include county-specific year trends to absorb the differential trajectories in air pollution specific to each county. The results remain robust.

Flexibly Controlling for Weather Conditions. The pollutant level in border and non-border counties may be affected by various weather conditions, and their effects on pollutants are likely to be nonlinear. To exclude potential confounds as much as possible, we follow Deschênes and Greenstone (2011) and divide all weather variables into five equal-length intervals to flexibly control for the nonlinear effects of the weather variables. The regression results are reported in Appendix Table A11, and the estimated coefficients are only slightly different from the baseline estimates. We also adopt a two-stage estimation strategy to flexibly control weather conditions at the monthly level. Specifically, in the first stage, we exploit the monthly data and regress the outcome variable (i.e., logged $PM_{2.5}$) on a set of weather conditions described above. To allow nonlinear effects of the weather conditions, we incorporate their quadratic terms as well as pairwise interaction terms. We then obtain the residual from the first stage regression and aggregate it to the annual level. The residual can then be regarded as the pollution level after netting out the weather conditions.[14] In the second stage, we rerun our baseline specification with the dependent variable replaced by the residual derived from the first stage. The results are also robust, reported in Appendix Table A12.

Addressing Spatial Dependency. A critical challenge when assessing the effect of a regional policy is the potential existence of spatial dependency that violates the SUTVA assumption in DID design (as well as DDD design). To complement such drawbacks in traditional DID design, we adopt an interactive fixed effects model (or linear factor model), which is typically designed to address the unobserved common shocks that affect each unit differently (Bai, 2009).

We follow Bai's (2009) suggestion to estimate the key coefficients using an iterative approach. We first ignore the factor structure in the model and use OLS to directly estimate Equation (1) and use factor analysis to obtain the corresponding common factors and factor loadings based on the structure of the error term. We assume that the possible number of factors r takes the values of 1–5 and select the optimal number of factors based on the RMSE criterion, obtaining the optimal $r = 2$. We report the estimated coefficients and their corresponding 95% confidence intervals in Appendix Figure A4.[15] Overall, the estimated coefficients obtained after accounting for potential common factors are slightly lower than the estimates obtained from the two-way fixed effects model but remain significant at the 5% level, which suggests that our estimates are not sensitive to the presence of spatial dependency.

Controlling for Additional Lagged Dependent Variable. Given the possibility of long-term serial correlation in pollution levels, we flexibly control for up to 3 periods of lagged explanatory variables in Appendix Table A13. The estimates are still significant at the 1% level and are not significantly different from the baseline estimates. This suggests that our results are not largely driven by serial correlation in the explanatory variables *per se*.

[14] We do not incorporate a constant in the first stage regression so the residual is not centered at zero.

[15] Standard errors are computed follow the suggestion of Bai (2009).

Adjusting the Clustering Level. Our estimates are also robust to different clustering levels. In Appendix Table A14, we re-estimate the baseline regression and flexibly adjust the standard error to different clustering levels. In column (1) to column (2), we adopt the two-way clustering suggested by Cameron et al. (2008) and cluster the standard error to county and province-year level, as well as county and prefecture-year level. In column (3), we cluster the standard error to the city level. In columns (4) to column (6), we consider the spatial correlation in the error term and adjust the standard error from both spatial and temporal dimensions. In the spatial dimension, we allow the error terms to be correlated arbitrarily within a radius of 100 km, 200 km, and 300 km (corresponding to columns (4) to (6), respectively), while in the temporal dimension, we assume that the maximum number of lagged periods is infinite (i.e., 1000 periods). In all specifications, the standard error merely changes and the estimates remain significant at the 1% level.

Effects on Other Pollutants. A remaining question is whether the policy effects we estimate are likely to capture the effect of other environmental regulations within treatment provinces after 2014. For example, there might be other unobservable factors that led to differentiated environmental regulatory policies in the treatment provinces after 2014 (i.e., less stringent environmental regulations in border counties and more stringent environmental regulations in non-border counties) that are independent of the APPC policy, causing a potential overestimating on the impacts of the policy.

We address the challenge by utilizing a specific feature of the APPC policy. The formally released document of the APPC policy only mandates to reduce $PM_{2.5}$ concentrations, while not explicitly requiring reduction for other common pollutants (e.g., sulfur dioxide, nitrogen oxides, etc.). If our estimates confound with the impact of other environmental regulations, then other pollutants should also show significant differences between border and non-border counties after 2014. Specifically, we obtain sulfur dioxide emissions (SO_2), nitrogen oxide emissions (NO_x), and industrial dust emissions (Dust) from the County Statistical Yearbook and compare the differences in these pollutants before and after 2014, between border and non-border counties. In Appendix Table A15, we report estimates of SO_2 (Panel A), NO_x (Panel B), and Dust (Panel C), respectively. In almost all of the specifications, we do not find any significant differences in these pollutants between border and non-border counties.

Confounding Effects of Other Policies. The APPC policy is not the only effort the central government made to reduce air pollution during the sample period. A directly related policy is the establishment of the Measures for Supervisory Monitoring of Pollution Sources and Disclosure of Information of Key State-monitored Enterprises (hereafter, the Measure for short), implemented from 1 January 2014, almost at the same time as the APPC policy. The Measures require all key state-monitored enterprises to report and disclose their pollution emission. Although the timing of the Measures implementation is very similar to the APPC policy, the Measure should not confound our results for several reasons.

First, as the Measures is a national policy, its effects should be (partially) captured by the year fixed effects if we assume that the Measure's impacts are the same across border and non-border counties. Second, even if the Measures' effects are heterogeneous across counties, the adoption of the Interactive Fixed Effect (Bai, 2009) Model, together with the inclusion of other province-year or city-year fixed effects in our previous robustness checks would alleviate such concerns (Appendix Table A10). Third, as the Measures aim at deterring polluting enterprises and thereby reducing their pollution emission, we should expect that the Measures could potentially reduce the firm's output. However, as we will illustrate in the next section, we find that polluting firms in border counties increased their output afterward (relative to firms in non-border counties). Lastly, as the Measures require that key state-monitored enterprises disclose all sources of pollutants, we should find similar effects on $PM_{2.5}$, SO_2, NO_x, and other pollutants. However, as we've shown in previous robustness checks, we find that the border effects are only salient for the concentration of $PM_{2.5}$, which is the key target of the APPC policy (Appendix Figure A7). Taking together, we believe that our estimated effects are unlikely to be driven by the establishment of the Measures.

Another two related policies are the "2 + 26″ cities policy (Zhang and Zhao, 2023) and the accompanying "coal-to-gas" policy (Wang et al. 2020). These two policies were launched in 2017 and aimed to reduce pollution in the BTH region by regulating firm pollution emissions and energy transitions from coal to natural gas. However, as we show in previous robustness checks (see Appendix Figure A6), our results are robust to the exclusion of Hebei province, the primary target of the "2 + 26″ cities policy and the coal-to-gas policy, thereby alleviating concerns that our results may be driven by these confounding policies.

Placebo Test. To examine whether the pollution diffusion only exists in border counties, we randomly selected a subsample of counties as "placebo border counties"[16] and calculated the trajectories in the difference in pollution levels between these "placebo border counties" and other counties. Repeating the random sampling 500 times resulted in 500 ″placebo paths". We then compared these placebo paths to the true path and plot the results in Fig. 4,[17] where the grey line represents the 500 "placebo paths" while the red line represents the true path. It can be seen that in all 500 sampling procedures, most of the paths are concentrated around 0 with large fluctuations. Meanwhile, the real path under each period is almost distributed at the top or bottom of the simulated paths, indicating that it is difficult for any path to fully simulate the real differences in pollution levels between border and non-border counties.

4.4. Economic Activities

The discussions above argue that the APPC policy leads to a significant relative pollution increase in the border counties; however, we are still unaware of the micro foundation behind the phenomenon. In this section, we delve into the impact of the APPC policy on

[16] The number of pseudo-border counties is equal to the number of genuine border counties, and the former may comprise both border and non-border counties.

[17] To plot the figure, we use the residual of $ln(PM_{2.5})$ that partialling out the county and year fixed effects.

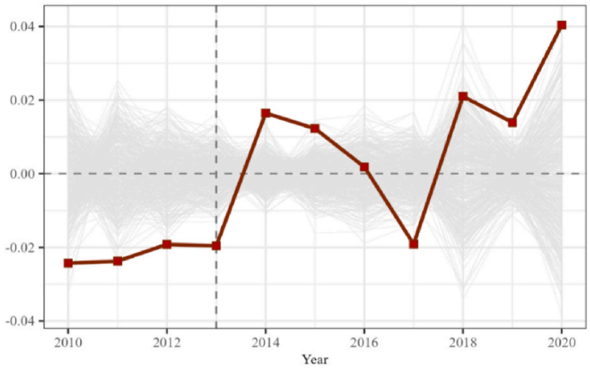


Fig. 4. Results of the placebo test.

Notes: This figure presents the results from the placebo test. We perform the placebo test in the following procedure. First, we calculate the difference in the outcome variable, partialling out county and year fixed effects, between border counties and non-border counties in a year-by-year manner to obtain the actual trajectory of the $PM_{2.5}$ difference. Next, we restrict the sample to all non-border counties and randomly draw certain counties that are equal to the number of border counties, labeled as "placebo border counties". We then calculate the year-by-year difference in the outcome variable, again partialling out county and year fixed effects, between these "placebo border counties" and other non-border counties to obtain the "placebo paths". The random draws are repeated 500 times. Finally, we plot the actual trajectory versus 500 placebo trajectories in the figure.

the behaviors of air-polluting firms. We first discuss whether the delayed reduction of air pollution in border counties is caused by the increasing startup air-polluting firms (or less shutdown air-polluting firms). We then apply firm-level data (NTSD) to examine how the production and energy consumption of air-polluting firms are affected by the APPC policy.

4.4.1. Startup or shutdown firms (extensive margin)

We firstly explore how the pattern of startup or shutdown of air-polluting firms in border and non-border counties is affected by the APPC policy. Based on the Business Enterprise Registration Data (BERD), we first distinguish whether a firm belongs to air pollution-related industries or not, and calculate the number of new startup or shutdown air-polluting firms in each county-year cell.[18] We then follow the standard DID model to estimate the effect of the APPC policy on firms' startups or shutdowns.

Table 4 reports the regression for air-polluting firms, where the dependent variable in columns (1) and (2) is the logged number of startup firms while the dependent variable in columns (3) and (4) is the logged number of shutdown firms.[19] The estimated results echo with our findings in baseline specifications. We find that, after the APPC policy, there are about 16.7% more startup air-polluting firms in border counties, compared with non-border counties. Meanwhile, there are fewer shutdown air-polluting firms in border counties. The above results are qualitatively the same when we apply a Poisson Pseudo Maximum Likelihood estimator (reported in Table A16). The results are also robust when we adopt an alternative DDD specification (reported in Table A17) that compares changes in firm startups or shutdowns between border and non-border counties, across treatment and control provinces. Overall, the pattern of more startup and less shutdown air-polluting firms in border counties may result in relative air quality worsening in border counties.

To further corroborate our results, we conduct two robustness checks. Similar to the strategy we used in baseline specifications, we first test for the parallel trend assumption to detect whether the pattern of start or shutdown of air-polluting firms in border and non-border counties is divergent before the APPC policy. Results are reported in Appendix Figure A9, where Panel A displays the dynamic pattern of startup air-polluting firms and Panel B displays the pattern of shutdown air-polluting firms. Reassuringly, we find no evidence of pre-trends in both Panels. However, the patterns exhibited in both panels are not consistent with the pattern of window dressing that we documented in Fig. 2. As most firms recorded in BERD are smaller firms, it is reasonable that we do not find drastic changes in firm startups and shutdowns. This is generally consistent with the enforcement strategy of environmental regulations, that local officials tend to "Grasp the Large and Let Go of the Small" (He et al., 2020a) to minimize the implementation cost by focusing on large enterprises and exerting less control over smaller firms. However, we indeed find that there are more startups and fewer shutdowns of polluting firms after 2017, when the inspection of the APPC policy finished.

We also consider the pattern of startups or shutdowns for non-air-polluting firms. There should be less or no effect on non-air-polluting firms since the change of non-polluting firms should be irrelevant to the APPC regulation. We verify such hypothesis in Appendix Table A18, and find no significant differences in the number of startups or shutdown of non-air-polluting firms. Taken together, the above evidence corroborates our confidence in attributing the change of startup or shutdown patterns of air-polluting

[18] We can hardly say it is the migration of firms, or the exit and entry of firms, for we have no clues on who invested on this firm or where the firm moved. To be rigorous, we call it the firm startups or shutdowns.

[19] To avoid sample loss that arises due to potential zero value, both variables is in the form of log (x+1). However, such transformation could induce additional bias (Chen and Roth, 2023). To address this concern, we perform the estimation using the Poisson regression in Appendix Table A16.

Table 4
Results for startup or shutdown air-polluting firms.

Dep. Var.:	(1)	(2)	(3)	(4)
	ln (# of firm startup + 1)		ln (# of firm shutdown + 1)	
$Post_t \times Border_i$	0.167***	0.224***	−0.099***	−0.092**
	(0.055)	(0.058)	(0.036)	(0.039)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Observations	5,014	5,014	5,014	5,014
With-in R^2	0.005	0.032	0.001	0.014

Notes: This table presents the estimation results of firm entry or exit. Regression specification is presented in Equation (1), with the dependent variable replaced by ln (# of startup firms + 1) and ln (# of shutdown firms + 1). Columns (1)–(2) report the effect of the APPC policy on startup firms while column (3)–(4) reports the effects on shutdown firms. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

firms in border counties to the implementation of the APPC policy.

4.4.2. *Firm production and energy consumptions (intensive margin)*

Next, we leverage the NTSD database to examine how firms' production and energy consumption respond to the APPC policy. In the production level, we focus on three indicators which are firms' output level (total outputs), productivity (value-added), and scale (number of employees). Table 5 investigates the effect of the APPC policy on firms' production. Apart from the county fixed effects, we also include the industry-year fixed effects to partial out the unobserved time-varying heterogeneity within each industry that may confound with our estimations (for example, different environmental regulatory policies faced by different industries). Firm-level controls include a dummy variable indicating whether the firm is of SOE ownership, the firm's age, and age squared. Consistently, we find that after the APPC policy, air-polluting firms in border counties have experienced a relative increase in outputs, value-added, and employment, indicating that air-polluting firms in border counties have relatively enlarged their production scales.

In the energy consumption level, we consider a set of energy inputs that are strongly correlated with $PM_{2.5}$ concentrations, including coal, oil, and natural gas consumption. Coal combustion is a major source of industrial $PM_{2.5}$, and was strictly limited by the APPC policy. Thus, firms may turn to alternative energies, such as oil or natural gas. In Table 6, we find that, even though the APPC policy has led to a mild increment in coal consumption, the coefficient is noisily estimated and does not pass the 10% significance test. Polluting firms in border counties use more natural gas and oil as alternative energies after the APPC policy. Similarly, we test for the existence of pre-trends and the dynamic patterns in firms' production and energy consumption (Appendix Figure A10),[20] and we also examine whether the above results only exist in the context of air-polluting firms (Appendix Table A19).

In general, we do not find that these variables were trending differently prior to the policy. However, all panels of Appendix Figure A10 follow an analogous pattern, where both production and energy consumption rise immediately after the policy and are soon coupled with a significant fall in 2016 (the estimated coefficients either change from positive significant to non-significant, or even change to negative). Such a pattern is particularly evident in the estimates of energy consumption. Taking coal consumption (Panel D) as an example, it has significantly increased in the first year of policy implementation, while decreasing significantly in the subsequent two years. The APPC policy requires negative growth in total coal consumption for the three regions by 2017, and it is reasonable that we only witness a short-term increase in coal consumption. In response to the stringent regulation over coal consumption, firms may substitute for other energy, such as oil (Panel E). Combining this pattern with the findings in baseline event studies (Figs. 2 and 3), we think it is not a coincidence, rather, a more appealing explanation that air-polluting firms in border counties are most likely to strategically reduce their productions in 2016 to cater for the reduction mandates set by the APPC policy.

Appendix Table A19 replicates the results of Tables 5 and 6, with the only difference being that we replace the sample of air-polluting firms with non-air-polluting firms. We do not find any significant changes in production and energy consumption of non-air-polluting firms in border counties after the policy, compared to non-air-polluting firms in non-border counties.

4.5. *Window dressing Effect*

This subsection formally discusses the presence of window dressing behavior in border counties. To motivate the econometric specification of the window dressing effect, we first provide some graphical evidence. Fig. 5 plots the evolution trajectories for both border and non-border counties (Panel A), and the border-vis-non-border differences between treated and non-treated provinces (Panel B). Where the y-axis of Panel A denotes the residualized dependent variable (partialling out controls as well as fixed effects). As for Panel B, we calculate the border-vis-non-border differences based on the residualized value. We define the years 2016 and 2017 as

[20] Since data for natural gas consumption is only available after year 2013, there is only one pre-treatment period, we therefore cannot test for the existence of pre-trends. Also, NTSD does not ask for firm's value added in year 2015, the estimated coefficient for year 2015 in Panel B of Fig. 6 is missing.

Table 5
Results for air-polluting firm production.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	ln (Output)		ln (Value-added)		ln (# of employees)	
$Post_t \times Border_i$	0.428**	0.383*	0.500**	0.465**	0.268**	0.231*
	(0.195)	(0.201)	(0.235)	(0.236)	(0.124)	(0.122)
County FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm Controls		Y		Y		Y
County Controls	–	Y	–	Y	–	Y
Observations	50,599	50,599	44,073	44,073	52,441	52,441
R^2	0.209	0.210	0.310	0.311	0.203	0.208

Notes: This table presents the estimation results of firm production. We use output, value-added, and # of employees to measure firms' production decisions in response to the APPC policy. Columns (1)–(2) report the effect of APPC policy on logged firm output, columns (3) and (4) report the effects on logged value-added, and columns (5)–(6) report the effects on logged # of employees. Data for value-added is unavailable in the year 2015. We include county and industry-by-year fixed effects in all regressions. Firm controls include a dummy variable indicating whether the firm is of SOE ownership, the firm's age, and age squared. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table 6
Results for firm energy consumption.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	ln (Coal)		ln (Natural gas)		ln (Oil)	
Panel A: $PM_{2.5}$ related energy consumption						
$Post_t \times Border_i$	0.049	0.049	0.163**	0.164**	0.492**	0.477**
	(0.211)	(0.213)	(0.065)	(0.068)	(0.194)	(0.192)
County FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm Controls		Y		Y		Y
County Controls	–	Y	–	Y	–	Y
Observations	45,044	45,044	22,072	22,072	45,441	45,441
R^2	0.247	0.248	0.144	0.144	0.168	0.169

Notes: This table presents the estimation results of firm energy consumption. Columns (1)–(2) of Panel A report the effect of the APPC policy on logged coal consumption, columns (3)–(4) report the effects on logged natural gas consumption, and columns (5)–(6) report the effects on logged oil consumption. Data for natural gas consumption is only available after the year 2013. We include county and industry-by-year fixed effects in all regressions. Firm controls include a dummy variable indicating whether the firm is a SOE ownership, the firm's age, and age squared. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

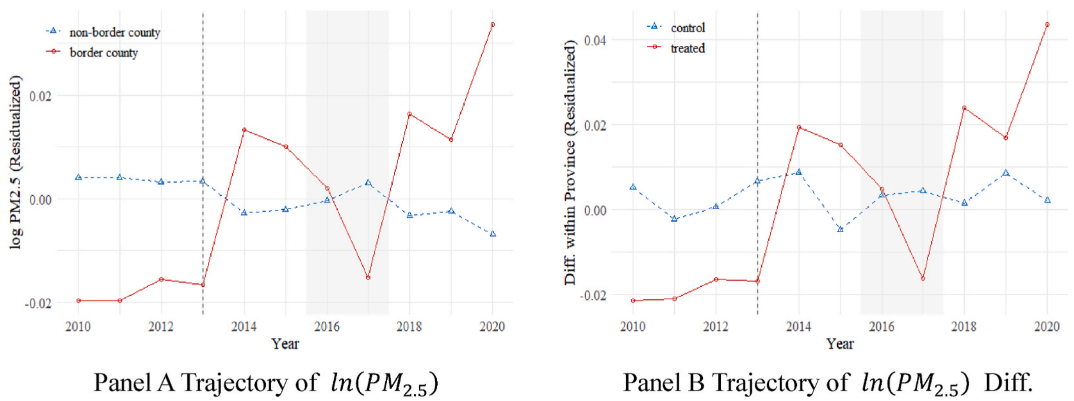


Fig. 5. Evolution trajectories of $PM_{2.5}$ and $PM_{2.5}$ differences.
Notes: This figure presents the evolutionary trajectories of $PM_{2.5}$, between border and non-border counties (Panel A), and the trajectories of $PM_{2.5}$ differences across border and non-border counties, between treated provinces and non-treated provinces (Panel B). The outcome variables are partialling out controls as well as fixed effects. The window periods (i.e., year 2016 and 2017) are shaded.

window periods. Although the formal inspection of the completion of the APPC policy was conducted in 2017, local governments, with such information in mind, may adjust their behaviors prior to the inspection. Such a setting also corresponds to other related studies investigating window dressing behaviors (Fang et al., 2023). To highlight the presence of the window dressing behavior, we shed the window periods in grey.

It is clear that compared with the beginning of the treatment period (i.e., year 2014 and 2015), pollution levels decrease in border counties during the window period, and increase after the window period. For non-border counties, there was no significant change in pollution levels between the window and non-window periods. The figure also extends the fact that the relative increase in border counties' pollution is due to its genuine increase, rather than the decrease in pollution levels in non-border counties. To verify the pollution reduction pattern only occurs in border counties of treated provinces, Panel B compares the difference in pollution levels between border and non-border counties, for both treated and non-treated provinces, which yields almost identical features.

Overall, the graphical evidence suggests that the pollution reduction is specific to the border counties in treated provinces. For any other unobservable factor to mimic such a pattern, it would have to affect only the border counties of the treated provinces during the window periods, while having no significant effect on the non-border counties of the treated province, as well as counties in non-treated province. The probability of such an unobservable factor is negligible, suggesting that the pattern we observe is indeed caused by the window-dressing effects of local governments.

To statistically estimate the significance of the window dressing effects, we divide the post-treatment periods into three stages: the pre-window period (corresponds to years 2014 and 2015), the window period (corresponds to years 2016 and 2017), and the post-window period (correspond to the year 2018 and beyond). According to the three periods, we set the pre-period as the reference period and estimate the following equation:

$$Y_{it} = \beta_1 Window_t \times Border_i + \beta_2 PostWindow_t \times Border_i + \boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \tag{5}$$

Where $Window_t$ is a dummy indicator for years 2016 and 2017, and $PostWindow_t$ indicates for years 2018 and beyond. The pre-window period is set as the reference. Note that, the above specification does not include observations prior to the APPC policy into the regression. All other notations share the same definitions with previous specifications. The coefficients of interest are β_1 and β_2, which portray the changes in the differences in air pollution between border and non-border counties during the window or post-window periods relative to the pre-window period.

For the extended sample that includes non-treated provinces, we adopt a similar specification and regress the following model:

$$\begin{aligned} Y_{it} = {} & \beta_1 Window_t \times Border_i \times Treat_p + \beta_2 PostWindow_t \times Border_i \times Treat_p \\ & + \beta_3 Window_t \times Border_i + + \beta_4 PostWindow_t \times Border_i + \\ & + \beta_5 Window_t \times Treat_p + + \beta_6 \, PostWindow_t \times Treat_p + \boldsymbol{X}_{it} + \boldsymbol{W}_{it} + \delta_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{6}$$

The regression results for Equations (5) and (6) are reported in Table 7. We estimate a strong negative effect for $Window_t \times Border_i$ and $Window_t \times Border_i \times Treat_p$, with both significant at 1% level. The results are consistent with the graphical evidence in Fig. 5, where the pollution level in border counties declined in the window period. As for the post-periods, the estimated coefficients are either positive or close to zero, suggesting the pollution regained its pre-window level after the assessment of APPC. Taken together, our results in Table 7 consistently support the presence of window dressing effects.

Readers may doubt that such a pattern could be the result of technological advances, such as the adoption of clean energies and technologies by polluting firms in border counties. However, the pollution level should not rise after the window period if the technological advances work. Otherwise, firms in border counties may shut down equipment of clean energies and technologies to lower their production costs when laxer environmental regulations are enforced after the assessment of APPC. We also examine whether the total factor productivity (TFP) of polluting firms is affected by the APPC policy. We follow the convention and proxy the TFP using the OP and LP methods proposed by Olley and Pakes (1996), and Levinsohn and Petrin (2003). We also use the Ackerber-Caves-Frazer (ACF) correction of the two methods to serve as robustness checks. The results are reported in Appendix Table A20, where we estimate the exact null effect of the APPC policy on different TFP measures. The estimated coefficients are all close to zero and the standard errors are large to prevent any meaningful interpretation.

As an additional supplementary, we further examine whether the intensity of environmental supervision is affected by the assessment in the window period. Specifically, we use the number of environmental administrative penalties to reflect the intensity of environmental supervision. Appendix Figure A8 presents the graphical results. Consistently, we find a similar pattern in environmental regulatory intensity. The number of environmental penalties in border counties rises significantly during the window period, while reducing to its conventional level after the window period ends, suggesting that local officials enforce varied regulatory intensities over time.

Another possible confounding factor is the effect of other policies implemented during the same period on pollution dynamics in the border counties. We note that in order to further improve air quality around Beijing, the central government implemented the "2 + 26″ city policy in 2017 (Zhang and Zhao, 2023). The policy aimed to strengthen environmental controls in and around Beijing, Tianjin, and their surrounding areas to improve air quality. Zhang and Zhao (2023) find that this policy leads to air pollution leakage, i.e., emissions from polluting firms in the regulated areas fall while emissions from polluting firms in the unregulated neighboring areas rise.

Table 7
Effects of APPC policy assessment on pollution dynamics.

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Window_t \times Border_i$	−0.022***	−0.021***		
	(0.007)	(0.007)		
$PostWindow_t \times Border_i$	0.011**	0.005		
	(0.005)	(0.005)		
$Window_t \times Border_i \times Treat_p$			−0.047***	−0.049***
			(0.009)	(0.010)
$PostWindow_t \times Border_i \times Treat_p$			−0.000	−0.004
			(0.007)	(0.007)
County FE & Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Weather Controls	–	Y	–	Y
Observations	3,346	3,174	8,767	8,597
With-in R^2	0.016	0.020	0.014	0.025

Notes: This table presents the estimation results of the APPC Policy assessment on pollution dynamics. Columns (1) to (2) report the regression results from specification (5) while columns (3) to (4) report the results from specification (6). For specification (6), we also include all other double interaction terms. All regressions control for county and year fixed effects, county and weather controls. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

However, this policy effect runs the opposite of what we found in 2017: emissions in neighboring areas (border counties in our setting) fall instead of rising. Thus, this policy should not confound with our identification of window dressing effects. Nonetheless, to ensure the robustness of our estimation results, we exclude the Hebei Province from our sample in Appendix Table A21 and rerun the regressions. The results remain largely unchanged.

In Appendix Table A22, we examine how policy assessment affects the startup or shutdown of air-polluting firms. We find that though the number of startups or shutdowns of air-polluting firms does not change significantly during the window period compared to the pre-period, the number of startups (shutdowns) increases (decreases) significantly in the post-window period, indicating an agglomeration of polluting firms in border counties in the post-window period. The results are also confirmed by using the specification listed in equation (6) that extends the comparison further to the treatment and control provinces (in Appendix Table A23).[21]

In Appendix Table A24, we examine how the assessment affects the production and energy consumption of polluting firms. Since the NTSD only updated to 2016, we can only examine changes in the indicators between the window period and pre-window period, while the changes in the post-window period remain unexplored. We find that the output and oil consumption of polluting firms decreased significantly in 2016, suggesting polluting firms reduced production and energy consumption during the window period to fulfill the assessment targets. We estimate negative results for other variables, such as employment and coal consumption, but the estimated coefficients are relatively small and insignificant at conventional levels.

Finally, in Appendix Figure A7, we examine the evolution trajectory of other pollutants (i.e., SO_2, NO_x, and Dust) as a placebo test. Since these pollutants are not the targets of policy assessment, their pollution level should not change significantly during the window period. Figure A7 confirms our hypothesis that no significant change in any of the three pollutants during the window period.

5. Potential explanations

This section delves into the potential explanations and mechanisms for the above findings. Typically, we highlight three complementary mechanisms that give rise to the salient border effects and the window dressing effects, that is, the responses of local governments to automated air monitoring stations, lenient regulation of border counties, and the promotion incentives of local officials.

5.1. Responses to air quality monitoring stations

An important feature of the APPC policy is the establishment of pollution monitoring stations that automatically supervise whether the local agents are faithfully enforcing the environmental regulations. There is a rich set of literature discussing the role of monitoring stations (Greenstone et al. 2022; Xie and Yuan, 2023; Axbard and Deng, 2024; Yang et al. 2024). As revealed by Axbard and Deng (2024), the selection of monitoring stations is largely determined by the population or geographical size. As a result, monitoring stations are more likely to be installed in non-border areas which have higher population sizes. Such differences may unintendedly lead to the strategic behavior of local officials.

[21] We also find that there is no significant change in either startup or shutdown of non-polluting firms in the window periods.

To verify this mechanism, we proceed in several steps. Firstly, in Appendix Figure A1, we plot the geographic distribution of air pollution monitoring stations to verify that fewer stations are installed in border counties. The same results are also documented in Appendix Table A25, where we find that border counties have a significantly lower probability of installing monitoring stations. Even conditional on the observable county characteristics (e.g., population, GDP) and weather conditions, the difference is still statistically significant. Secondly, we investigate whether the border effects we estimate are affected by the presence of monitoring stations. We should expect no occurrence of border effects in border counties with monitoring stations installed (compared to non-border counties that also have monitoring stations installed), as the effort is easy to observe by central governments. To verify such an argument, we geocode the location of monitoring stations whether a county has installed monitoring stations or not. We also calculate the distance of each county to its nearest monitoring stations. Besides, using the wind direction data, we determine whether a county is located in the upwind region to its nearest monitoring stations, following the definition in the literature (He et al., 2020b; Xie and Yuan, 2023). Fig. 6 presents our results, where we partition our sample into different groups and compare the magnitude of the estimates.

The patterns presented in Fig. 6 are generally in line with our hypothesis. Specifically, we find that the border effects are no longer prominent if we compare border and non-border counties with monitoring stations installed or located closer to the monitoring stations. The effects are weaker if we compare border and non-border counties that are both located in the upwind region of the monitoring stations (an implicit measure of the regulation stringency as in Xie and Yuan (2023)), though the magnitude is still comparable to non-upwind counties due to large standard errors, indicating the limited credibility of wind direction in larger-granularity studies in the seasonal wind region.

However, a more interesting pattern we documented in Fig. 6 is that, the border effects are still prevalent as we compare border and non-border counties that are located farther away from monitoring stations or without monitoring stations installed. In Appendix Table A26, we examine the window dressing effect of those border counties, and it is robust and prevalent for border counties that are located farther away from monitoring stations or without monitoring stations installed.

5.2. Lenient regulations of Border counties

Local officials (mostly the prefectural leaders) who face the direct evaluation of the APPC policy, may not be incentivized to exert regulation efforts in border counties, as the efforts are less observed by the central government. Besides, the negative externality of air pollution abatement in border areas also impedes local governments from enforcing strict regulations. Border areas may exert environmental free-riding through the transfer of air pollution to neighbors. Further, we will investigate the heterogeneity of border counties to verify the strategic behavior.

First, we examine whether border counties have provided informal tax breaks for polluting firms. As the majority of taxes paid by manufactory enterprises, such as VAT and income tax, are directly collected by the central government, local governments have less power to provide formal tax breaks for firms. Instead, local governments have discretions over the charges (e.g., sewerage charges), namely the informal tax breaks, for polluting firms. In this regard, we use the administrative fees (which are charged by local governments) as a proxy for the informal tax breaks.[22] The results are reported in Appendix Table A27, where we find consistent evidence that polluting firms located in border counties paid less administrative charges relative to their non-border counterparts, after the APPC policy. Taken together, the above evidence is in line with our interpretation that border counties may offer more lenient environmental regulations and informal tax breaks on polluting firms.

Second, as shown in Appendix Figure A8, border counties impose fewer environmental penalties against polluting firms. And polluting firms in border counties expand their production and energy consumption after the APPC policy, relative to their non-border counterparts (Tables 5 and 6). Taken together, these results indicate that border counties were willing to exert lenient regulations to tradeoff air quality to economic growth, relative to non-border counties.

Lastly, we conduct several heterogeneous analyses to examine the strategic behavior of border counties. Border counties may enforce lenient regulations where the economic growth is lower, to trade environmental qualities to economic growth (He et al., 2020b). Besides, we considered the following characteristics that may have impacts on the salience of border effects, such as fiscal pressure, initial pollution levels, and population levels. We examine the above hypotheses in Appendix Table A28, where we run an augmented version of the baseline regression with the ex-ante county characteristics included as interaction terms.[23] The estimated results again confirm our hypothesis that we find more salient increases in pollution for border counties with higher fiscal pressure, higher initial pollution levels, and less population.

5.3. Promotion incentives of local officials

In this subsection, we further investigate the role of promotion incentives of local officials and explore how these misaligned

[22] The sewage charge was a part of administrative fees levied by local governments before the Environmental Protection Tax Law of the People's Republic of China came into effect in 2018 (https://www.gov.cn/xinwen/2018-01/16/content_5257052.htm). The NTSD ranges from 2007 to 2016 does not record the sewerage charges but categorized it into the administrative fees, thus we use the administrative fee as a proxy for the informal tax breaks.

[23] These ex-ante characteristics are measured in year 2013, just prior to the implementation of the APPC policy We dichotomize the continuous moderating variables into dummy variables based on their median for the ease of interpretation. The dummy variable equals to 1 if the value is above median.

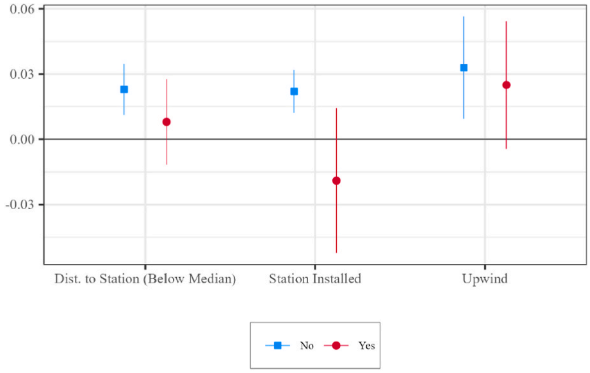


Fig. 6. The heterogeneity analysis of monitoring station.
Notes: This figure explores the potential mechanism of monitoring stations. We partition the sample into different groups and compare the magnitudes of estimated coefficients. In the first column, we partition the sample based on whether their distance to the nearest stations is below the sample median or not. In the second column, we partition the sample based on whether it has installed monitoring stations or not. In the third column, we partition the sample based on whether the county is located in the upwind region of the monitoring station or not. We run the baseline regression on each subsample and plot the coefficients and corresponding 95% confidence intervals. All regressions have included county and weather controls. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure.

political incentives lead to both the border effects of pollution and the window dressing effects. The focal of our analysis is prefectural leaders, who are the main subjects of the APPC policy assessment. Since the evaluation is of high stakes, prefectural leaders may have strong incentives to enforce varied regulations in border counties over time to cater to their multi-tasking missions of balancing economic growth as well as environmental protection.

China's political selection system sets strict age thresholds for bureaucrats' promotion, roughly between 55 and 57 years old (Yao and Zhang, 2015), resulting in officials' stronger willingness to strive for promotion when they are around the threshold (Li and Zhou, 2005). We infer that officials aged within this range have stronger incentives to be promoted than their counterparts, and generate a dummy variable *Incentive* to indicate whether officials' age falls between 55 and 57 years old. We then construct a triple difference

Table 8
Results for political promotion.

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
	Party Secretary Incentive		Mayor Incentive	
$Post_t \times Border_i \times Incentive$	0.045***	0.045***	−0.006	−0.014
	(0.011)	(0.012)	(0.013)	(0.012)
$Post_t \times Border_i$	0.017***	0.015***	0.031***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)
$Post_t \times Incentive$	0.009*	0.007	0.018***	0.021***
	(0.005)	(0.005)	(0.006)	(0.006)
$Border_i \times Incentive$	−0.016*	−0.016*	−0.021**	−0.021**
	(0.009)	(0.009)	(0.009)	(0.009)
Incentive	−0.020***	−0.023***	0.009**	0.007
	(0.004)	(0.004)	(0.004)	(0.005)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Leader's Characteristics	Y	Y	Y	Y
County Controls		Y		Y
Weather Controls	–	Y	–	Y
Observations	4,088	4,027	4,258	4,037
With-in R^2	0.062	0.112	0.071	0.120

Notes: This table reports the heterogeneity analysis by interacting the DID term with a dummy indicating the promotion incentives for prefecture leaders (i.e., party secretary and mayor). All pairwise interactions and main terms are included in the regressions as well. Leader's characteristics include gender, birthplace province, and the highest education level which includes a college degree, bachelor's degree, master's degree, and doctor's degree. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

model by interacting the variable with our key explanatory variable and include all possible quadratic and main terms in the regression. In addition to the baseline controls, we additionally control for officials' characteristics such as gender, the highest education level, and birthplace to further ensure the robustness of the regression results.

The estimated coefficients are reported in Table 8. Columns (1) and (2) report how promotion incentives for prefectural party secretaries mitigate the border effects, and columns (3) and (4) report the results of promotion incentives for mayors. We find clear evidence that party secretaries with stronger promotion incentives will cause more severe air pollution in border counties, indicating more significantly varied regulation compared to non-border counties. In contrast, we find such an effect is not significant for mayors. The power of the party secretary is more comprehensive than the mayor, and the promotion criteria for the party secretary and mayor differ (Zuo, 2015; Agarwal et al. 2023). These results provide further support that local officials' promotion incentives play an important role in worsening air quality in border counties after the APPC policy.

We further examine how the promotion incentives of local officials affect their window-dressing behaviors. We interact the *Incentive* variable with the two DID interaction terms $Window_t \times Border_i$ as well as $PostWindow_t \times Border_i$, and similarly controlling for all other pairwise and main terms. The regression results are reported in Appendix Table A29, our results suggest that the stronger the incentives to promotion, the stronger the incentives to window dressing. Again, we find that this effect is largely centered on party secretaries, with no significant results for mayors.

6. Concluding remarks

In summary, by comparing the changes in pollution levels between border and non-border counties before and after the APPC policy, the strictest air pollution regulation policy that China ever issued in the millennium, we find that even though the pollution levels in non-border counties have been effectively curbed after the policy implementation, the pollution levels in border counties decreased much slowly. We find consistent patterns when investigating firms' responses: there are more startups and fewer shutdowns of polluting firms in border counties, and polluting firms tend to increase their production and energy consumption, relative to their counterparts in non-border counties, where the intensity of policy enforcement is stronger.

We discuss the formation of such a strengthened border effect in the framework of the principal-agent model, where central and local governments are misaligned in objectives, and are asymmetry in information. The primary policy focus lies in controlling $PM_{2.5}$ concentrations in major metropolitans where monitoring stations are installed, while border counties have fewer monitoring stations installed. Local officials have an incentive to exert varied regulation in border counties over time to cater to multitasking economic growth and air quality targets. To shed further light on the political economics behind the scenes, we reveal that promotion incentives of local officials play an essential role in explaining the emergence of border effects after the APPC policy, and we also discover the presence of window dressing effect of local officials in facing the policy assessment.

At this point, we can finally answer the question of whether China has won the War on Pollution (Greenstone and Schwarz, 2018). Considering the tremendous efforts China has made in environmental protection over the past decade, the air quality in all three key regions (BTH, Yangtze River Delta, and Peral River Delta) regulated by APPC policy has significantly improved, and the life expectancy of residents has also increased. However, it brings severe environmental injustice within the regulated region.

China has become aware of the severity of pollution in border areas in recent years and set mandates to control it. Unlike pollution abatement in key areas, pollution controls in border areas not only need to take the negative externalities of pollution into consideration, the strategic behavior of local governments and enterprises should also be accounted for. This calls for the establishment of a cross-regional collaborative pollution control mechanism. Our research shows that when regional environmental policies are combined with promotion incentives, local governments will strategically enforce varied regulations across different areas within their jurisdictions to accomplish the multi-tasking. At the same time, when the policy has the attribute of campaign-style enforcement (i.e. specifies certain assessment objectives and deadlines), local governments will resort to window dressing to partly invalidate the policy. Based on our research findings and specific policy practices, we believe that future policy formulation should focus more on border areas and weaken the mobilization attributes of policies to overcome the opportunism of local government. Due to space constraints, this paper cannot go on to discuss what kind of policy formulation can achieve optimal environmental governance. Subsequent studies can build on our paper to discuss further.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Additional Figures and Table

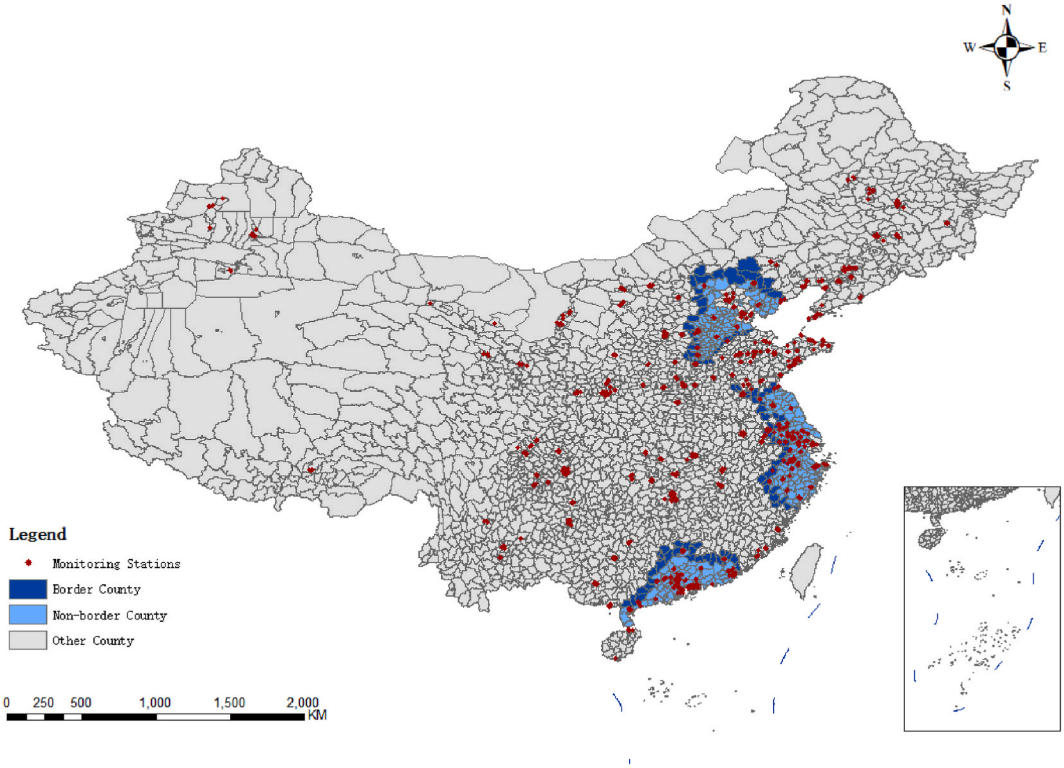
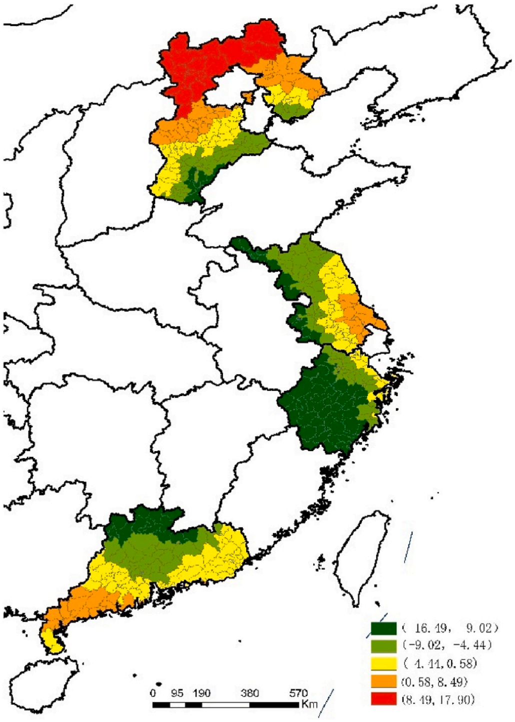
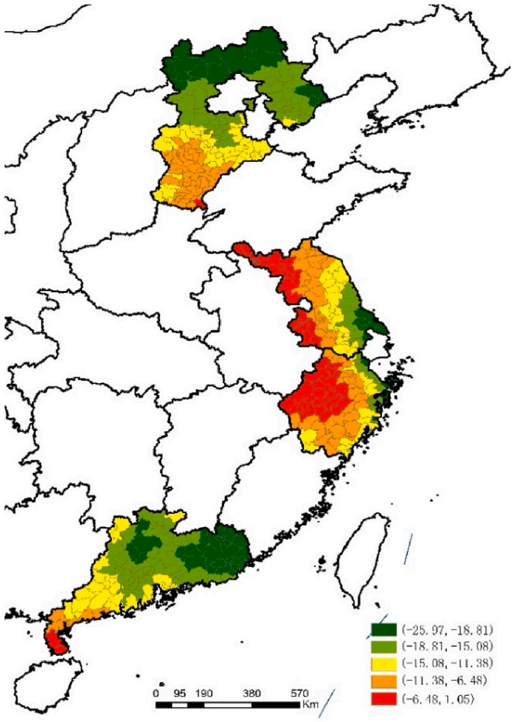


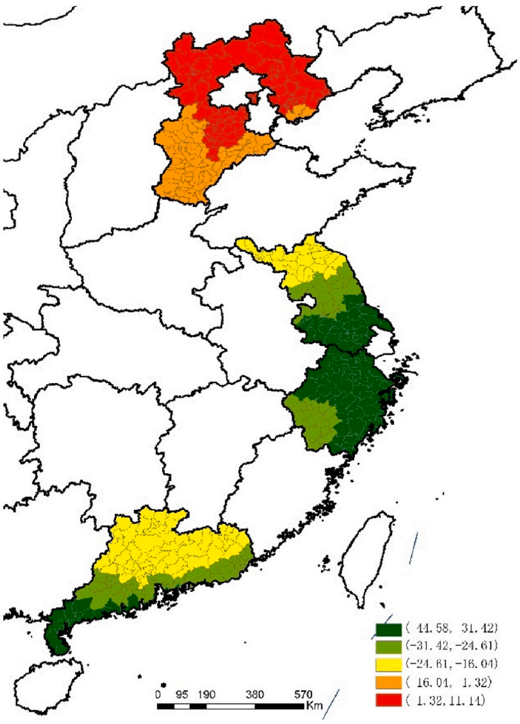
Fig. A1. Geographic Distribution of Monitoring Stations
Notes: This figure presents the geographical distribution of the monitoring stations. The three regions studied in this paper are colored blue with border counties colored dark blue and non-border counties colored light blue



(a) 2012-2013



(b) 2013-2017



(c) 2017-2020

Fig. A2. Changes Rates of PM2.5 in 2012–2013, 2013–2017, and 2017–2020 of Three Key Regions

Notes: This figure presents the change rates of $PM_{2.5}$ in 2012–2013, 2013–2013 and 2017–2020 of BTH, YRD and PRD. Green color represents the counties with the largest reduction rates, and red represents the counties with the lowest reduction rates (some increase in PM2.5 value, such as the red ones in 2017–2020); Light green, yellow, and orange lie in between, with declining reduction rates.

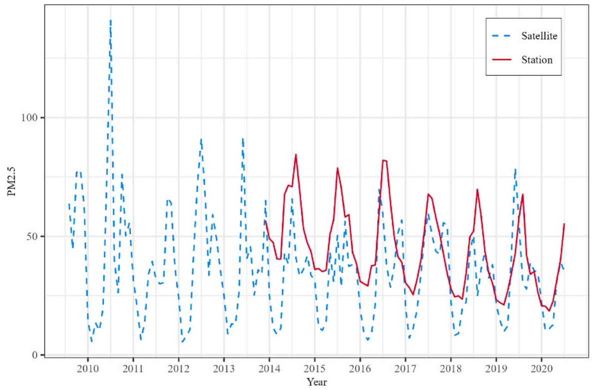


Fig. A3. Comparison of Satellite-derived $PM_{2.5}$ and Ground Monitoring $PM_{2.5}$
Notes: This figure presents the monthly $PM_{2.5}$ from different sources. The red solid line plots $PM_{2.5}$ derived from ground monitoring station while the blue dashed line plots $PM_{2.5}$ derived from satellite observations.

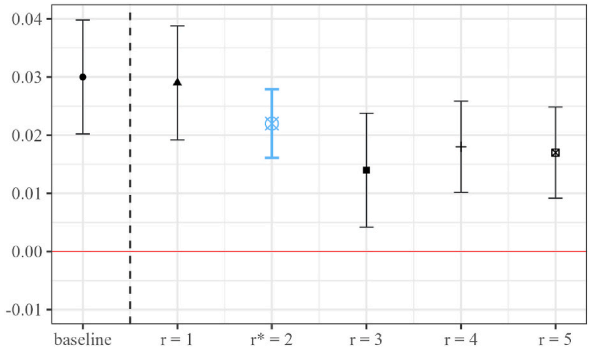


Fig. A4. Interactive Fixed Effects Estimation
Notes: This figure presents the results of interactive fixed effects estimation under various choices of r. We plot the estimated coefficients (points of different shapes) and the 95% confidence intervals. Standard errors are computed follow the suggestion in section 6 of Bai (2009). We consider r ranging from 1 to 5 and use the RMSE criterion to select the optimal choice of r, which returns the optimal value of 2. To highlight this optimal choice, we bold and color the confidence interval and coefficient with a different color. For the ease of comparison, we also plot the baseline results in the left. The covariates are county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure.

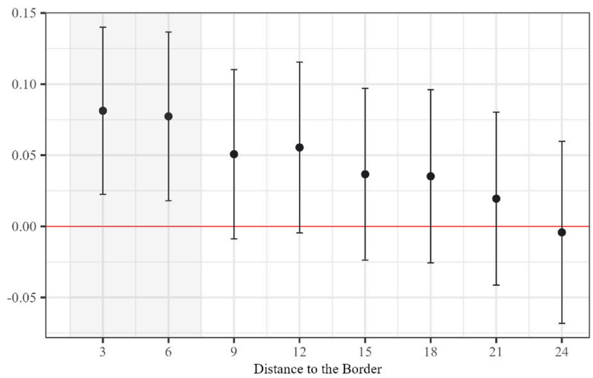


Fig. A5. By-distance-bin Estimation
Notes: This figure presents the results of by-distance-bin estimation. We plot the estimated coefficients for each distance bin and their 95% confidence intervals in the figure. The regression includes county and year fixed effects, as well as county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure.

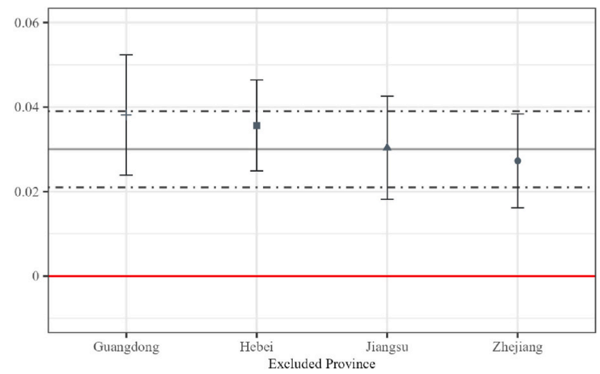


Fig. A6. Testing for Provincial Heterogeneity
Notes: This figure presents the results of baseline estimation with one province (total of 4) excluded at one time. We plot the estimated coefficients (points of different shapes) and the 95% confidence intervals. For the ease of comparison, we also plot the baseline results (horizontal solid line) and the 95% confidence intervals (two horizontal dashed lines). All regressions include county and year fixed effects, as well as county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure.

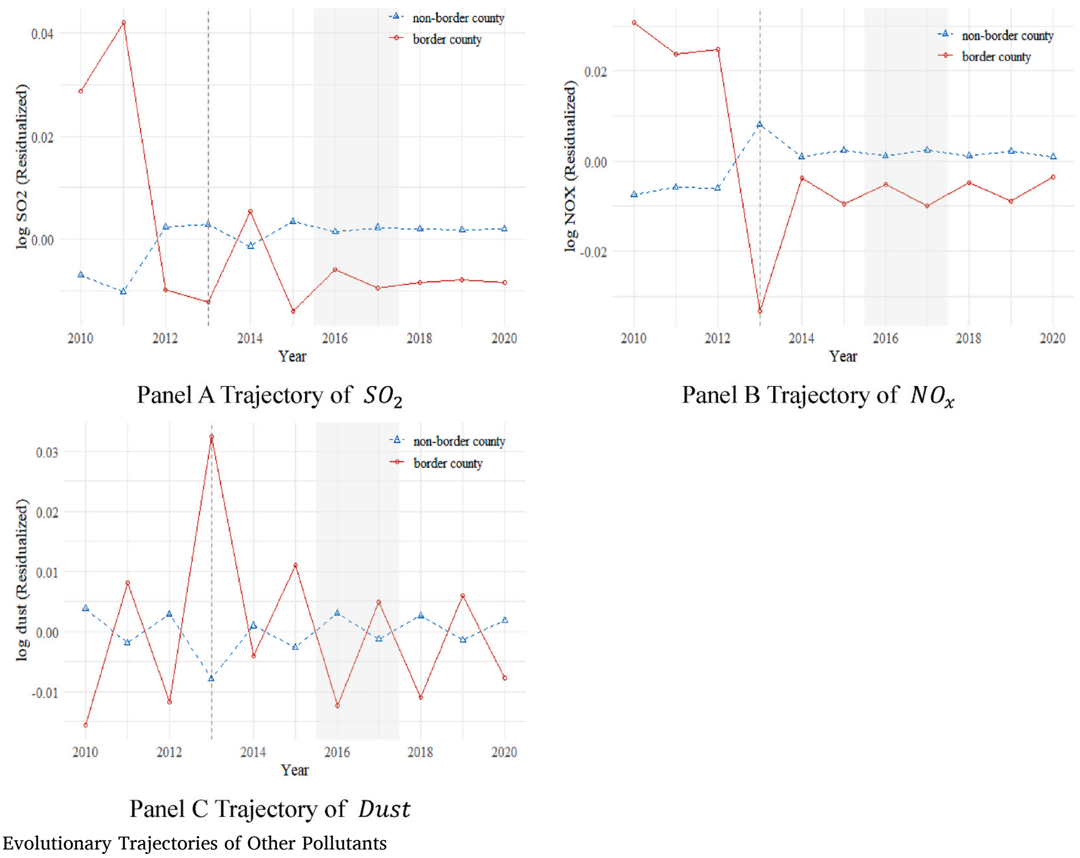


Fig. A7. Evolutionary Trajectories of Other Pollutants
Notes: This figure presents the evolutionary trajectories of SO_2 emission (Panel A), NO_x emission (Panel B) and *Dust* emission (Panel C) between border and non-border counties. The outcome variables are partialling out of county and year fixed effects. The window periods (i.e., year 2016 and 2017) are shaded.

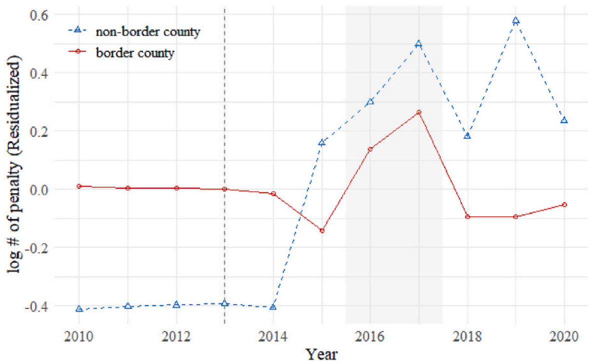
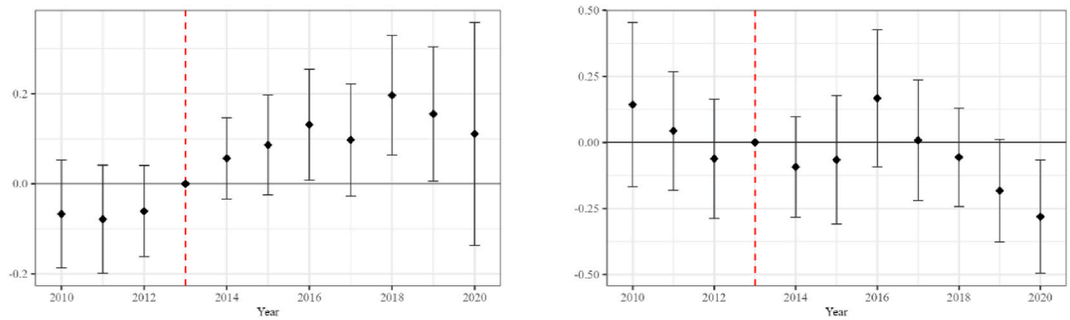


Fig. A8. Evolutionary Trajectories of Environmental Administrative Penalties
Notes: This figure presents the evolutionary trajectories of environmental administrative penalties between border and non-border counties. The outcome variables are partialling out of county and year fixed effects. The window periods (i.e., year 2016 and 2017) are shaded.



Panel A: Startup Firms

Panel B: Shutdown Firms

Fig. A9. Event Study for Startup or Shutdown Air-polluting Firms
Notes: This figure presents the event study coefficients. Regression specification is presented in Equation (2). The year 2013 is omitted as the reference year. The specification includes county fixed effects and year fixed effects; county controls and weather controls. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature, and sea level pressure. The standard errors are clustered at the county level. Coefficient estimates and 95% confidence intervals are plotted in the figure.

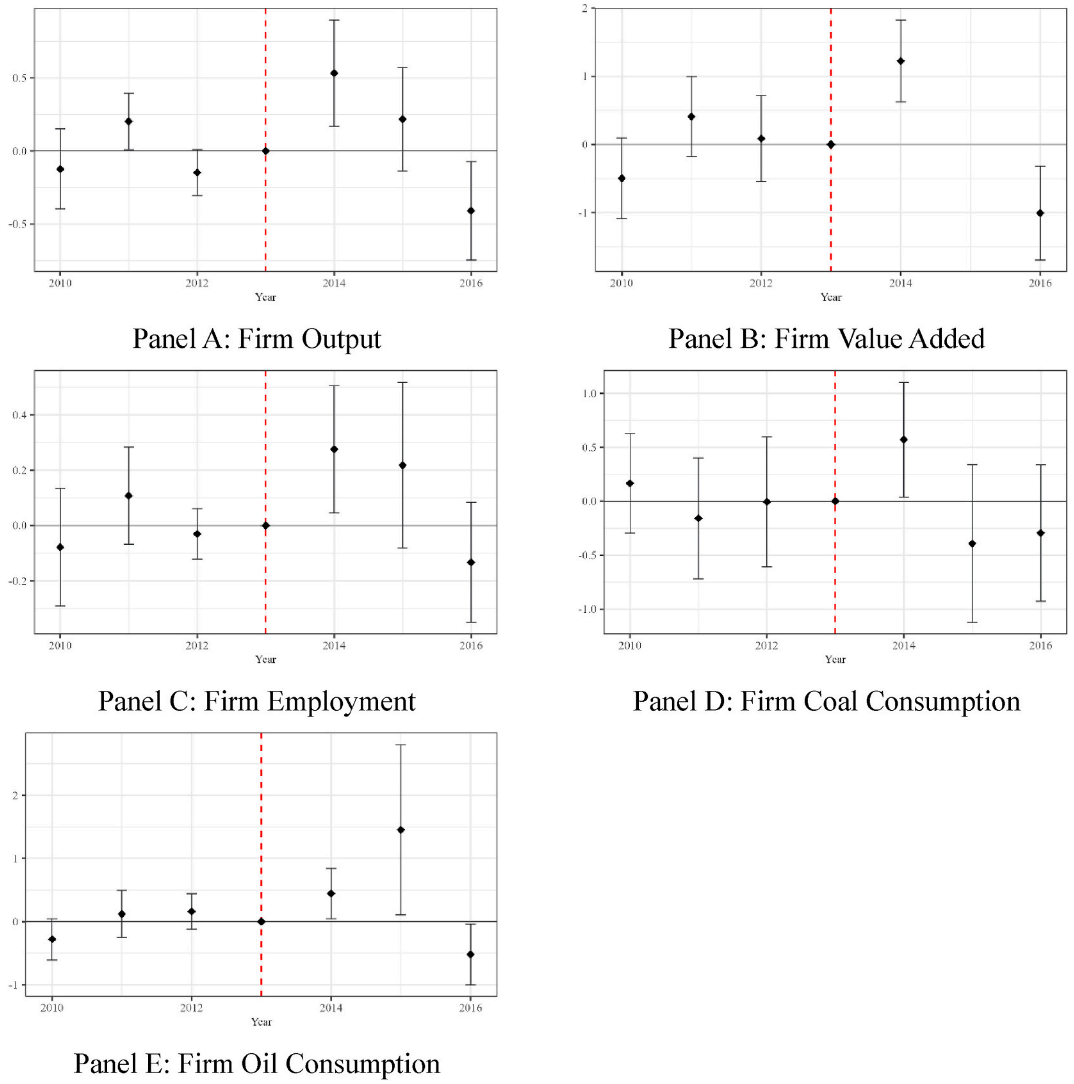


Fig. A10. Event Study for Firm Production and Energy Consumption
Notes: This figure presents the event study coefficients. We interact the border county indicator with the full set of time dummies to estimate the dynamic effect of the APPC policy. The year 2013 is omitted as the reference year. We include county, year, and industry fixed effects in all regressions. Firm controls include a dummy variable indicating whether the firm is a SOE ownership, the firm's age, and age squared. County controls include the logged value of population and GDP, the agricultural share of the total output, the counties' area, and the distance to the provincial capital. The last two variables are interacted with the full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. The standard errors are clustered at the county level. Coefficient estimates and 95% confidence intervals are plotted in the figure.

Table A1
Summary Statistics of Additional Variables

Variables	Border county				Non-border county			
	Pre-treatment		Post-treatment		Pre-treatment		Post-treatment	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: County Level								
log(SO_2)	8.070	0.650	7.960	0.710	8.150	0.600	8.070	0.610
log(NO_x)	7.500	0.930	7.560	0.870	7.490	0.900	7.580	0.800
log(Dust)	7.590	0.730	7.650	0.820	7.620	0.670	7.690	0.700
log(# Pollute firm entry)	5.060	1.060	5.460	1.000	5.870	1.270	6.090	1.180
log(# Pollute firm exit)	1.110	0.220	1.120	0.230	1.170	0.340	1.230	0.460
log(# non-Pollute firm entry)	7.510	0.730	8.260	0.850	8.110	0.950	8.880	0.920
log(# non-Pollute firm exit)	2.020	0.870	2.250	0.980	3.060	1.230	3.470	1.400
Fiscal Pressure	0.110	0.0700	0.190	0.130	0.060	0.080	0.0900	0.100
Industry Concentration	0.150	0.100	0.150	0.100	0.240	0.200	0.240	0.200
log(# of env. penalty)	0	0	0.800	1.340	0.001	0.060	1.100	1.770
log(industry output)	12.94	0.910	13.20	0.950	13.40	1.080	13.65	1.100
Sample Size	320		560		1588		2779	
Panel B: Firm Level								
log(output)	8.430	4.660	8.760	4.680	8.980	4.540	9.170	4.580
log(value added)	5.950	4.420	5.650	4.610	6.730	4.370	6.170	4.560
log(# of employee)	4.580	1.240	4.580	1.310	4.860	1.350	4.820	1.370
log(coal consumption)	1.710	3.160	2.400	3.260	1.020	2.560	1.940	2.860
log(nat. gas consumption)	0.100	0.730	0.570	1.660	0.160	0.970	0.560	1.590
log(oil consumption)	1.620	2.380	1.750	2.820	1.560	2.360	1.330	2.400

Notes: This table presents the summary statistics of additional data sources, include county level data, firm level data and household level data. For each variable, we separately report the mean and standard deviation by treatment assignment (i.e., whether a county is located in border region), and by treatment period (before and after the APPC policy).

Table A2
Restriction on Different Time Windows

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
Time Period	2010–2016		Exclude 2016; 2017	
$Post_t \times Border_i$	0.032***	0.028***	0.043***	0.031***
	(0.004)	(0.004)	(0.007)	(0.007)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Weather	–	Y	–	Y
Observations	3,339	3,289	4,293	4,074
With-in R^2	0.015	0.092	0.014	0.132

Notes: This table presents the estimation results of controlling for more granular fixed effects. Regression specification is presented in Equation (1). All regressions control for county fixed effects, county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Column (1) to (4) controls for provincial year trend, province by year fixed effects, prefectural year trend and prefecture by year fixed effects, respectively. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A3
Baseline Estimation using Control Provinces

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.008**	0.004	0.006*	0.006
	(0.003)	(0.003)	(0.003)	(0.004)
L1. $ln(PM_{2.5})$				−0.128***
				(0.014)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Observations	8,895	8,822	8,243	7,235
With-in R^2	0.0341	0.0447	0.106	0.108

Notes: This table presents the baseline estimation results for control provinces. Regression specification is presented in Equation (1). County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A4
Heterogeneous Effects of Distance to Beijing/Shanghai

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i \times Dist.\ BJ/SH$		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)
$Post_t \times Border_i$	0.034***	0.027***	0.033***	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
$Post_t \times Dist.\ BJ/SH$		−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	Y	–	Y	Y
Weather Controls	Y	–	–	Y
Observations	1,364	3,883	3,757	3,757
With-in R^2	0.0230	0.0185	0.0851	0.132

Notes: This table presents the two set of results. The first is the baseline estimation results for using the Guangdong sample. Regression specification is presented in Equation (1). The second is the triple interaction estimation results that considers the heterogeneous effects of distance to Beijing/Shanghai, denoted by the variable *Dist. BJ/SH*. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A5
Baseline Estimation Excluding Counties Bordering Beijing or Shanghai

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.034***	0.035***	0.027***	0.028***
	(0.006)	(0.006)	(0.005)	(0.005)
L1. $ln(PM_{2.5})$				−0.011
				(0.012)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Observations	4,862	4,862	4,862	4,406
With-in R^2	0.0553	0.0617	0.107	0.107

Notes: This table presents the baseline estimation results after excluding counties that bordering Beijing or Shanghai. Regression specification is presented in Equation (1). County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A6
Coarsened Exact Matching

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.034***	0.027***	0.033***	0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Matching Variables	Population, GDP	All County Controls	All Weather Controls	All Controls
Observations	5,244	5,222	5,244	5,244
With-in R^2	0.0245	0.0401	0.0484	0.0160

Notes: This table presents the baseline estimation results for using the Coarsened Exact Matching (CEM) approach. Regression specification is presented in Equation (1). County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A7
Refine control group and re-weighting

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(4)	(5)
$Post_t \times Border_i$	0.015**	0.011*	0.064***	0.030***
	(0.006)	(0.006)	(0.006)	(0.009)
County & Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Weather Controls	–	Y	–	Y
Weight	–		1/distance to the border	
Observations	2,398	2,367	5,014	5,014
With-in R^2	0.134	0.135	0.174	0.200

Notes: This table presents the estimation results of refine control group and re-weighting. Regression specification is presented in Equation (1). All regressions control for county and year fixed effects. In columns (1) and (2), we refine the control groups to non-border counties that share boundary with border counties (i.e., counties that are in close proximity to the border counties). In columns (3) and (4), we use the 1/distance to the border as the weight and estimate the WLS regressions. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The weather variables include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A8
Robustness to Continuous Treatment

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)
$Post_t \times Dist.\ Border_i$	−0.038***	−0.036***
	(0.003)	(0.003)
County FE	Y	Y
Year FE	Y	Y
County Controls	–	Y
Weather Controls	–	Y
Observations	5,203	5,005
Within R^2	0.0287	0.121

Notes: This table presents the estimation results by using the continuous treatment design. The treatment variable is now a continuous variable that measure the distance from each county's centroid to the provincial border. We include county and year fixed effects in both regressions. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The standard errors are clustered at the county level.

Table A9
Include Additional Controls

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.030***	0.031***	0.029***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)
County FE & Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Pollutant Trends	Y	–	–	Y
Industrial Structure	–	Y	–	Y
Fiscal Revenue	–	–	Y	Y
Observations	5,244	5,244	5,244	5,244
With-in R^2	0.0349	0.0544	0.0420	0.0581

Notes: This table presents the DID estimation results for including additional controls. Regression specification is presented in Equation (1). County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. In the first column, we include the interaction of initial pollutants (i.e., $PM_{2.5}$, SO_2, NO_x, and Dust emitted in 2010) with the linear time trends. In the second and third columns, we include the industrial structure (measured by the ratio of industrial output to the county GDP) and fiscal revenue. In the last column, we include all the additional controls. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A10
Include Additional Fixed Effects

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)	(5)
$Post_t \times Border_i$	0.038***	0.031***	0.020***	0.021***	0.018***
	(0.008)	(0.008)	(0.003)	(0.003)	(0.004)
County FE & Year FE	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Province-Year Trends	Y	–	–	–	–
Province-Year FE	–	Y	–	–	–
City-Year Trends	–	–	Y	–	–
City-Year FE	–	–	–	Y	–
County-Year Tend					Y
Observations	5,244	5,222	5,244	5,244	5,244
With-in R^2	0.0245	0.0401	0.0484	0.0160	0.00519

Notes: This table presents the baseline estimation results for including additional fixed effects. Regression specification is presented in Equation (1). County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A11
Control for Weather Bins

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)	(5)
$Post_t \times Border_i$	0.027***	0.024***	0.022***	0.023***	0.023***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
County & Year FE	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y
Temperature Bins	Y	Y	Y	Y	Y
Wind Speed Bins		Y	Y	Y	Y
Wind Direction Bins			Y	Y	Y
DP Temperature Bins				Y	Y
Sea Level Pressure Bins					Y
Observations	5,025	5,025	5,025	5,025	5,025
With-in R^2	0.095	0.106	0.115	0.153	0.161

Notes: This table presents the estimation results of controlling for weather bins. Regression specification is presented in Equation (1). All regressions control for county and year fixed effects, as well as county controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Each weather control variable is cut into five equal-length bins and is sequentially added to the regression to control for the nonlinearity effect. These weather variables include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A12
Flexible Controls for Weather Conditions

Dep. Var.: residualized $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i$	0.060*	0.086**	0.063*	0.086**
	(0.033)	(0.037)	(0.032)	(0.037)
County & Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
First Stage Regression	OLS	OLS	LASSO	LASSO
Observations	5,025	5,025	5,025	5,025
With-in R^2	0.190	0.205	0.250	0.262

Notes: This table presents the two-stage estimation results to flexibly control for weather conditions. Specifically, in the first stage, we exploit the monthly data and regress the outcome variable on a set of weather conditions (i.e., wind direction, wind speed, humidity, rainfall, air pressure, and temperature). To allow nonlinear effects of the weather conditions, we incorporate their quadratic terms as well as pairwise interaction terms. We then obtain the residual from the first stage regression and aggregate it to the annual level. In the second stage, we rerun our baseline specification with the dependent variable replaced with the residual derived from the first stage. All regressions control for county and year fixed effects, as well as county controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Standard errors in parentheses are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A13
Flexibly Controlling for Lagged Dependent Variable

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)	(5)
$Post_t \times Border_i$	0.027***	0.025***	0.031***	0.029***	0.037***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
L1. $ln(PM_{2.5})$		0.084***		0.070***	0.072***
		(0.014)		(0.015)	(0.017)
L2. $ln(PM_{2.5})$	−0.114***	−0.117***			−0.245***
	(0.018)	(0.018)			(0.024)
L3. $ln(PM_{2.5})$			−0.209***	−0.194***	−0.239***
			(0.017)	(0.017)	(0.019)
County & Year FE	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y
Observations	4,069	4,052	3,603	3,582	3,581
With-in R^2	0.091	0.096	0.131	0.133	0.173

Notes: This table presents the estimation results of flexibly controlling for lagged dependent variable. Regression specification is presented in Equation (1). All regressions control for county and year fixed effects, as well as county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A14
Adjusting for the Clustering Level

Dep. Var.: $ln(PM_{2.5})$ Clustering Methods:	(1) Two way Clustering	(2) Two way Clustering	(3) Prefectural Level	(4) Conley SE	(5) Conley SE	(6) Conley SE
$Post_t \times Border_i$	0.030***	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.008)	(0.007)	(0.008)	(0.006)	(0.007)	(0.008)
County & Year FE	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Clustering Level/Distance	Province by Year	Prefecture by Year	Prefecture	100 km	200 km	300 km
Observations	5,025	5,025	5,025	5,025	5,025	5,025
With-in R^2	0.103	0.103	0.103	0.103	0.103	0.103

Notes: This table presents the estimation results of adjusting for the clustering level. Regression specification is presented in Equation (1). All regressions control for county and year fixed effects, as well as county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors are in parentheses with varied clustering level. Column (1) cluster the standard error at county and province by year level while column (2) cluster the standard error at county and prefecture by year level (multi-way clustering suggested by Cameron et al., 2008). Column (3) cluster the standard error at prefecture level. In column (4) to (6), we consider possible spatial correlation by allowing arbitrary correlation across spatially adjacent observations (Conley, 1999). Column (4) allows for standard errors to arbitrarily correlate within a radius of 100 km, while column (5) and (6) allow for arbitrary correlation within a radius of 200 and 300 km, respectively. Serial correlations are also adjusted to allow for infinitely temporal correlations (Hsiang et al., 2011). ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A15
Estimated Results for Different Pollutants

	(1)	(2)	(3)	(4)
Panel A: Dep. Var. $ln(SO_2)$				
$Post_t \times Border_i$	−0.037	−0.016	−0.014	−0.008
	(0.024)	(0.025)	(0.025)	(0.016)
L1. $ln(SO_2)$				0.120
				(0.147)
With-in R^2	0.003	0.011	0.011	0.027
Panel B: Dep. Var. $ln(NOx)$				
$Post_t \times Border_i$	−0.010	0.023	0.028	0.027**
	(0.054)	(0.061)	(0.059)	(0.013)
L1. $ln(NOx)$				0.697***
				(0.081)
With-in R^2	0.004	0.006	0.007	0.584
Panel C: Dep. Var. $ln(Dust)$				
$Post_t \times Border_i$	0.005	−0.007	0.004	−0.023
	(0.042)	(0.049)	(0.048)	(0.020)
L1. $ln(Dust)$				0.577***
				(0.101)

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Table A15 (*continued*)

	(1)	(2)	(3)	(4)
With-in R^2	0.003	0.011	0.011	0.027
County FE & Year FE	Y	Y	Y	Y
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Observations	0.001	0.005	0.011	0.401

Notes: This table presents the baseline estimation results with dependent variable replaced by other pollutants, including the logged value of SO_2 (Panel A), NO_x (Panel B) and *Dust* (Panel C). Regression specification is presented in Equation (1). All regressions have controlled for county and year fixed effects. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A16
Results for Firm Startup or Shutdown (PPML estimator)

Dep. Var.:	(1)	(2)	(3)	(4)
	# of firm startups		# of firm shutdowns	
$Post_t \times Border_i$	0.192*	0.281*	−0.284**	−0.255**
	(0.116)	(0.147)	(0.122)	(0.127)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Observations	5,014	5,014	4,720	4,720
Pseudo R^2	0.846	0.850	0.468	0.473

Notes: This table presents the estimation results of firm entry and exit. Regression specification is presented in Equation (1), with dependent variable replaced by # of firm entry and # of firm exit. The results are obtained from PPML estimator. Column (1)–(2) reports the effect of APPC policy on firm entry while column (3)–(4) reports the effects on firm exit. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A17
DDD Estimation Results for Firm Startup and Shutdown

Dep. Var.:	(1)	(2)	(3)	(4)
	Polluting firms		Non-polluting firms	
	log (# startup +1)	log (# shutdown +1)	log (# startup +1)	log (# shutdown +1)
$Post_t \times Border_i \times Treat_p$	0.105**	−0.090**	−0.027	−0.086
	(0.044)	(0.036)	(0.029)	(0.054)
$Post_t \times Border_i$	0.006	0.001	−0.016	−0.009
	(0.029)	(0.004)	(0.021)	(0.010)
$Post_t \times Treat_p$	−0.089***	0.109***	0.140***	0.389***
	(0.017)	(0.017)	(0.012)	(0.020)
County FE & Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	13,539	13,539	13,539	11,937
With-in R^2	0.042	0.076	0.139	0.179

Notes: This table presents the DDD estimation results for firm entry and exit (both polluting and non-polluting firms). Regression specification is presented in Equation (3). Controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A18
Results for Non-air Polluting Firm Startup or Shutdown

Dep. Var.:	(1)	(2)	(3)	(4)
	ln (# of firm startup + 1)		ln (# of firm shutdown + 1)	
$Post_t \times Border_i$	−0.028	0.065	−0.103**	−0.079
	(0.040)	(0.042)	(0.051)	(0.056)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y

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Table A18 (*continued*)

Dep. Var.:	(1)	(2)	(3)	(4)
	ln (# of firm startup + 1)		ln (# of firm shutdown + 1)	
Observations	5,014	5,014	5,014	5,014
With-in R^2	0.005	0.032	0.001	0.014

Notes: This table presents the estimation results of startup or shutdown for non-air polluting firms. Regression specification is presented in Equation (1), with dependent variable replaced by ln (# of firm entry + 1) and ln (# of firm exit + 1). Column (1)–(3) reports the effect of APPC policy on firm entry while column (4)–(6) reports the effects on firm exit. County Controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A19
Results for Non-air Polluting Firm Production and Energy Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	ln (Output)	ln (VA)	ln (Emp)	ln (Coal)	ln (NG)	ln (Oil)
$Post_t \times Border_i$	0.030	0.073	−0.008	−0.191*	−0.036	0.143
	(0.183)	(0.297)	(0.034)	(0.107)	(0.046)	(0.089)
County FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
Observations	502,308	432,030	568,676	420,786	249,056	430,423
R^2	0.348	0.381	0.242	0.310	0.209	0.195

Notes: This table presents the estimation results of non-air polluting firm production and energy consumption. The dependent variable in each column is firm's output, value added, # of employees, coal consumption, natural gas consumption and oil consumption. Data for value added is unavailable in year 2015. Data for natural gas is unavailable in year 2010–2012. All dependent variables are in logged form. We include county and industry-by-year fixed effects in all regressions. Firm controls include a dummy variable indicating that whether the firm is SOE ownership, firm's age and age squared. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A20
Results for Air Polluting Firm TFP

Dep. Var.: Firm TFP	(1)	(2)	(3)	(4)
Methods:	LP	OP	LP-ACF	OP-ACF
$Post_t \times Border_i$	0.004	0.004	−0.004	0.002
	(0.073)	(0.074)	(0.064)	(0.071)
County FE	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Observations	24,423	24,423	24,423	24,423
R^2	0.177	0.181	0.153	0.177

Notes: This table presents the estimation results of firm TFP. We use four different measures to proxy the TFP, namely, LP, OP, LP-ACF, and OP-ACF, to measure firms' total factor productivity in response to the APPC policy. We include county and industry-by-year fixed effects in all regressions. Firm controls include a dummy variable indicating whether the firm is of SOE ownership, firm's age and age squared. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level.

Table A21
Effects of APPC Assessment on Pollution Dynamics (Exclude Hebei)

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Window_t \times Border_i$	−0.034***	−0.033***		
	(0.010)	(0.011)		
$PostWindow_t \times Border_i$	0.004	0.003		
	(0.006)	(0.006)		
$Window_t \times Border_i \times Treat_p$			−0.059***	−0.061***
			(0.012)	(0.013)
$PostWindow_t \times Border_i \times Treat_p$			−0.006	−0.007
			(0.007)	(0.007)
County FE & Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y

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Table A21 (*continued*)

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
Weather Controls	–	Y	–	Y
Observations	2,177	2,030	7,601	7,453
With-in R^2	0.011	0.016	0.034	0.044

Notes: This table presents the estimation results of APPC Policy assessment on pollution dynamics, after excluding Hebei province. Column (1) to (2) report the regression results from specification (5) while column (3) to (4) report the results from specification (6). For specification (6), we also include other double interaction terms. All regressions control for county and year fixed effects, county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A22
Effects of APPC Assessment on Firm Startups or Shutdowns

Dep. Var.:	(1)	(2)	(3)	(4)
	log (# of firm startup + 1)		log (# of firm shutdown + 1)	
$Window_t \times Border_i$	0.047	0.033	0.009	−0.007
	(0.037)	(0.041)	(0.034)	(0.036)
$PostWindow_t \times Border_i$	0.185***	0.137**	−0.078***	−0.052*
	(0.057)	(0.063)	(0.029)	(0.031)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County Controls	–	Y	–	Y
Observations	3,318	3,141	3,346	3,141
With-in R^2	0.009	0.019	0.003	0.009

Notes: This table presents the estimation results of APPC Policy assessment on air polluting firm startups and shutdowns. Regression specification is presented in equation (5). All regressions control for county and year fixed effects. County controls are included as well. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A23
Effects of APPC Assessment on Firm Startup and Shutdown (DDD Estimation)

Dep. Var.:	(1)	(2)	(3)	(4)
	Polluting firms		Non-polluting firms	
	log (# startup +1)	log (# shutdown +1)	log (# startup +1)	log (# shutdown +1)
$Window_t \times Border_i \times Treat_p$	0.040	−0.057	0.016	−0.019
	(0.047)	(0.046)	(0.031)	(0.057)
$PostWindow_t \times Border_i \times Treat_p$	0.130**	−0.094*	−0.115***	−0.170
	(0.056)	(0.050)	(0.037)	(0.107)
$Window_t \times Border_i$	0.043	0.000	−0.043**	−0.005
	(0.032)	(0.003)	(0.022)	(0.009)
$PostWindow_t \times Border_i$	0.048	0.001	0.035	−0.006
	(0.035)	(0.004)	(0.027)	(0.013)
$Window_t \times Treat_p$	−0.086***	0.155***	0.112***	0.480***
	(0.019)	(0.023)	(0.014)	(0.025)
$PostWindow_t \times Treat_p$	−0.313***	0.128***	0.194***	0.307***
	(0.023)	(0.026)	(0.016)	(0.045)
County FE & Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	13,539	13,539	13,539	11,937
With-in R^2	0.042	0.076	0.139	0.179

Notes: This table presents the DDD estimation results for firm startup and shutdown (both polluting and non-air polluting firms). Regression specification is presented in Equation (6). Controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A24
Effects of APPC Assessment on Firm Production and Energy Consumption Dynamics

Dep. Var.:	(1)	(2)	(3)	(4)	(5)	(6)
	ln (Output)	ln (VA)	ln (Emp)	ln (Coal)	ln (NG)	ln (Oil)
$Window_t \times$ $Border_i$	−0.760**	−1.345***	−0.037	−0.368	−0.224	−0.905***
	(0.385)	(0.387)	(0.089)	(0.303)	(0.180)	(0.227)
County FE	Y	Y	Y	Y	Y	Y
Industry-Year FE	Y	Y	Y	Y	Y	Y
Firm Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
Observations	13,209	7,776	13,977	12,682	14,026	11,686
R^2	0.266	0.333	0.241	0.408	0.151	0.223

Notes: This table presents the estimation results of APPC policy assessment on firm production and energy consumption. The dependent variable in each column is firm's output, value added, # of employees, coal consumption, natural gas consumption and oil consumption. Data for value added is unavailable in year 2015. Data for natural gas is unavailable in year 2010–2012. All dependent variables are in logged form. We include county, and industry-year fixed effects in all regressions. Firm controls include a dummy variable indicating that whether the firm is SOE ownership, firm's age and age squared. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A25
The Probability of Establishing Monitoring Stations

Dep. Var.: I (Monitor Station)	(1)	(2)	(3)	(4)
$Border_i$	−0.350***	−0.095*	−0.116**	−0.098*
	(0.055)	(0.055)	(0.055)	(0.056)
County Controls	–	Y	Y	Y
Weather Controls	–	–	Y	Y
Initial Pollution Level	–	–	–	Y
Observations	470	470	470	470
Adjusted R^2	0.0757	0.271	0.284	0.287

Notes: This table reports the differences in the probability of establishing monitoring stations between border and non-border counties. I (Monitor Station) is a dummy variable indicating whether a county established the monitoring station. Border is also a dummy variable indicating whether the specific county is located at the regional border. We use county level cross-sectional data to perform the analysis, where all variables are defined at their 2010 value. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area, and the distance to the provincial capital. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The last column includes the initial $PM_{2.5}$ level. Robust standard errors in parentheses. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A26
Effects of APPC Assessment on Pollution Dynamics (subsample)

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)	(5)	(6)
	No monitoring station		Dist. above median		Non-upwind	
$Window_t \times$ $Border_i$	−0.020***	−0.017**	−0.024***	−0.021**	−0.032**	−0.034**
	(0.007)	(0.008)	(0.008)	(0.009)	(0.014)	(0.015)
$PostWindow_t \times$ $Border_i$	0.007	0.003	0.010	0.008	−0.019*	−0.017
	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)
County FE & Year FE	Y	Y	Y	Y	Y	Y
County Controls	–	Y	–	Y	–	Y
Weather Controls	–	Y	–	Y	–	Y
Observations	2,208	2,018	1,667	1,526	836	750
With-in R^2	0.025	0.194	0.027	0.209	0.015	0.123

Notes: This table presents the estimation results of the APPC Policy assessment on pollution dynamics of subsample. Column (1) to (2) report the regression results from border counties without monitoring stations installed vs non-border counties without monitoring stations installed, and Column (3) to (4) report the regression results from border counties locate far away from monitoring stations vs non-border counties far away from monitoring stations, and Column (5) to (6) report the regression results from border counties locate in non-upwind of monitoring stations vs non-border counties locate in non-upwind of monitoring stations. All estimations from specification (5). All regressions control for county and year fixed effects, county and weather controls. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A27
Results for Air-polluting Firm Administrative Charges

Dep. Var.: Administrative Charges	(1)	(2)
$Post_t \times Border_i$	−1,396.771**	−1,419.042**
	(557.585)	(563.798)
County FE	Y	Y
Industry-Year FE	Y	Y
Firm Controls	–	Y
County Controls	–	Y
Observations	42,456	42,456
R^2	0.097	0.097

Notes: This table presents the estimation results of the APPC policy on firms' administrative charges. The dependent variable is the administrative charges firms actually paid, measured in RMB. We include county and industry-by-year fixed effects in both regressions. Firm controls include a dummy variable indicating whether the firm is of SOE ownership, firm's age and age squared. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. The standard errors are clustered at the county level.

Table A28
Heterogeneity Analysis of Border Counties

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
$Post_t \times Border_i \times High\ GDP$	−0.021**			
	(0.009)			
$Post_t \times Border_i \times High\ Fiscal\ Pressure$		0.022***		
		(0.008)		
$Post_t \times Border_i \times High\ Pollution\ Level$			0.029***	
			(0.009)	
$Post_t \times Border_i \times Population$				−0.018**
				(0.009)
$Post_t \times Border_i$	0.032***	0.012*	0.010	0.033***
	(0.006)	(0.007)	(0.008)	(0.006)
County FE & Year FE	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	5,014	5,014	5,014	5,014
With-in R^2	0.104	0.104	0.105	0.104

Notes: This table presents the estimation results of the bottom-up incentive mechanism. We consider 4 factors that potentially reflect the bottom-up incentives faced by the local officials, 1 County's economic development (measured by the initial GDP); 2. County's fiscal pressure; 3. County's initial pollution level, and 4. County's population. All the moderating variables are measured before the APPC policy to avoid potential endogeneity (i.e., year 2013). We divide the four moderating variables by their median and interact the dummies with our explanatory variable $Post_t \times Border_i$ to examine the potential treatment heterogeneity. All regressions have controlled for county and year fixed effects. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table A29
Effects of APPC Assessment and Promotion Incentives on Pollution Dynamics

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
	Party Secretary Incentive		Mayor Incentive	
$Window_t \times Border_i \times Incentive$	−0.034**	−0.029**	−0.041*	−0.041
	(0.013)	(0.013)	(0.024)	(0.025)
$PostWindow_t \times Border_i \times Incentive$	0.055**	0.055**	−0.029	−0.034
	(0.024)	(0.024)	(0.023)	(0.024)
$Window_t \times Border_i$	−0.024***	−0.023***	−0.019**	−0.019**
	(0.008)	(0.008)	(0.008)	(0.008)
$PostWindow_t \times Border_i$	−0.014	−0.013	0.013	0.012
	(0.011)	(0.011)	(0.012)	(0.012)
$Window_t \times Incentive$	−0.011*	−0.012**	0.028***	0.024**
	(0.006)	(0.006)	(0.010)	(0.010)
$PostWindow_t \times Incentive$	−0.062***	−0.063***	0.047***	0.051***
	(0.012)	(0.012)	(0.012)	(0.012)
$Border_i \times Incentive$	0.016	0.014	−0.023***	−0.023***
	(0.012)	(0.012)	(0.007)	(0.007)

(*continued on next page*)

Table A29 (*continued*)

Dep. Var.: $ln(PM_{2.5})$	(1)	(2)	(3)	(4)
	Party Secretary Incentive		Mayor Incentive	
Incentive	−0.007	−0.005	−0.006	−0.005
	(0.005)	(0.005)	(0.004)	(0.004)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Leader's Characteristics	Y	Y	Y	Y
County Controls		Y		Y
Weather Controls	–	Y	–	Y
Observations	2,212	2,208	2,137	2,128
With-in R^2	0.094	0.109	0.126	0.127

Notes: This table reports the heterogeneity analysis of window dressing effect by interacting the two DID term $Window_t \times Border_i$ and $PostWindow_t \times Border_i$ with a dummy indicating the promotion incentives for prefecture leaders (i.e., party secretary and mayor). All pairwise interactions and main term are included in the regressions as well. Leader's characteristics include gender, a categorical variable indicating the birth province, and a categorical variable indicating the highest education level the leader has attained, including college degree, bachelor degree, master degree and doctor degree. County controls include logged value of population and GDP, the agricultural share to the total output, counties' area and the distance to the provincial capital. The last two variables are interacted with full set of year dummies due to their time-invariant nature. Weather controls include wind direction, wind speed, temperature, dew point temperature and sea level pressure. Standard errors in parentheses. The standard errors are clustered at the county level. ***, **, and * denote significant at 1%, 5% and 10%, respectively.

Table B1
Definition of Air Polluting Industries

Industry	Industry Code
Coal mining and washing	06
Ferrous Metal Mining and Processing	08
Non-metallic Mining and Processing	10
Petroleum, coal and other fuel processing industry	25
Chemical raw materials and chemical products manufacturing	26
Pharmaceutical Manufacturing	27
Chemical Fiber Manufacturing	28
Ferrous metal smelting and rolling processing industry	31
Non-ferrous metal smelting and rolling processing industry	32
Metal Products Industry	33
Electricity, heat production and supply industry	44

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