



How effective is the regional joint environmental policy in China? Evidence from inverse difference-in-differences

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SETTING



- **Work bank in 2007**

350,000 and 500,000 people **die prematurely** each year in China as a result of air pollution

- **China's environment bulletin in 2016**

- (1) Roughly **75%** of Chinese cities still have **substandard air quality**
- (2) Nine cities in Beijing-Tianjin-Hebei (**BTH**) and the surrounding region were ranked in the **last ten nationally** in terms of air quality

- **Beijing-Tianjin-Hebei (BTH) Poor air quality**

Heavy industrialization, atmospheric stability, a large population and so on

World Bank (2007). Cost of pollution in China: economic estimates of physical damages. Washington, DC: The World Bank, 2007.

China Environmental Bulletin (2016). China Environmental Bulletin at 2016 (in Chinese). Ministry of Ecology and Environment of the People's Republic of China.

SETTING

To what extent has “2+26” policy alleviated air pollution in the region?



- “2+26” policy in February 2017

Venue: Two megacities (Beijing and Tianjin) and 26 nearby cities

Aim: To improve air quality in BTH and the surrounding region

Measures:

- (1) Adjust Industrial structure
- (2) Reduce by-product emission
- (3) limit the steel output by 50%
- (4) Change coal to clean energy
- (5) Meet the sixth national standard
- (6) Strengthen urban management

The official “2+26” policy name is “Air Pollution Prevention and Control Action Plan for the Beijing-Tianjin-Hebei and Surrounding Region”.



Figure 1: The BTH and its surrounding region (with 28 cities together)

SOLUTION: Policy Evaluation



- **Difference-in-differences (DID) framework**

To estimate the **average causal effect** of a treatment by comparing the differences in the outcome variable between the **treatment** and **control** groups over the **pre-treatment** and **post-treatment** periods

- **For the “2+26” policy**

Outcome: the Air Quality Index (AQI)

Treatment: “2+26” policy

Treatment group: “2+26” cities; **control** group: non-“2+26” cities

Post-treatment period: time periods exposed to the treatment

pre-treatment period: time periods in the absence of treatment.

DATASET



• AQI Data

- Air Quality Index (AQI) could quantitatively describe air quality, involving SO_2 , CO_2 , CO , O_3 , $PM_{2.5}$, PM_{10}
- An AQI value larger than 100 can be viewed as the benchmark for polluted air.
- AQI was measured hourly at the ground monitoring stations
- The names and locations (including province, city, longitude, and latitude) of the ground monitoring stations and the times of recording
- A **four-year** period (February 2015 to February 2019) that spans two years before the policy (February 2015 to February 2017) and two years after the policy (March 2017 to February 2019)

• Meteorological Data

- Air quality is not only affected by pollutant emissions from stationary, mobile, and area sources, it is also impacted by meteorological covariates

Table 1: Meteorological data: covariates incorporated to estimate the average quasi effects

	Type
Air temperature	numerical
Wind Power	numerical
Wind direction	categorical (8)
Weather	categorical (41)
Meteorological covariates	Yes

Notes: meteorological data are reported alternatively between daytime (7:00 a.m. to 7:00 p.m.) and nighttime (7:00 p.m. to 7:00 a.m.)

Chen, L., Guo, B., Huang, J., He, J., Wang, H., Zhang, S. and Chen, S. X. (2018). Assessing air-quality in Beijing-Tianjin-Hebei region: The method and mixed tales of PM_{2.5} and O₃. *Atmospheric Environment* 193, 290–301.

Huang, Y., Guo, B., Sun, H., Liu, H. and Chen, S. X. (2021). Relative importance of meteorological variables on air quality and role of boundary layer height. *Atmospheric Environment* 267, 118737

DATASET

• Spatial Data

- The **minimum** distance to the boundary of the treatment area (denoted by the variable “Distance”) for each ground monitoring station
- Only 21, rather than the entire 95, untreated ground monitoring stations was selected to form the control group, where these 21 selected untreated ground monitoring stations are geographically furthest away from the treatment group

The values of “Distance” (in meters) were taken from the website “<https://map.baidu.com/>.”

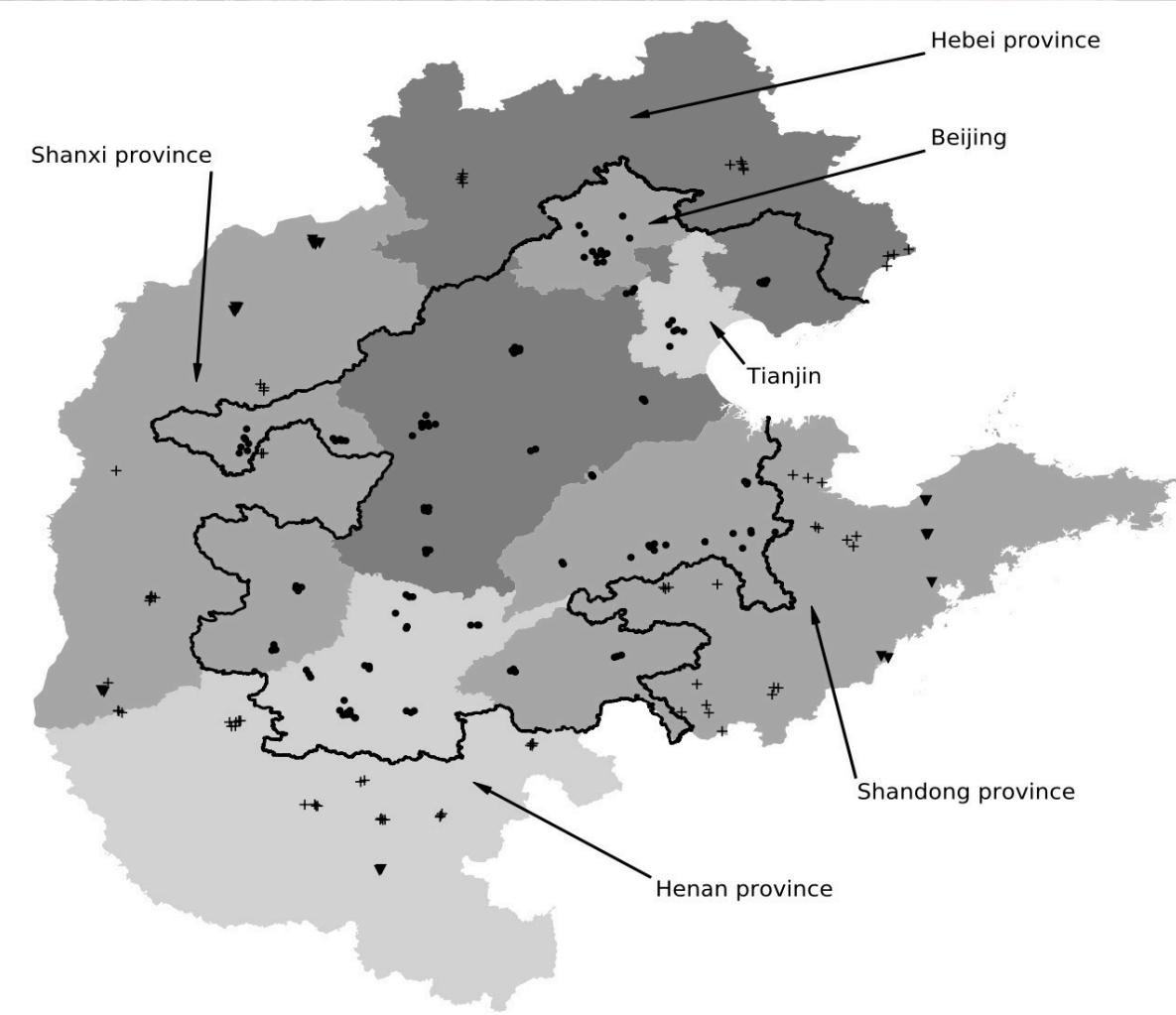


Figure 2: The geographical distribution of all studied ground monitoring stations. The dots symbols represent treated ground monitoring stations in the treatment area (bounded by the solid curve).



THE DID FRAMEWORK



- Let Y_{it} be the outcome of interest for individual i at time t .
- Let G_i and T_t be the group and time-period indicators, respectively, where

$$G_i = \begin{cases} 1, & \text{if the individual } i \text{ is from the treatment group,} \\ 0, & \text{if the individual } i \text{ is from the control group.} \end{cases}$$

$$T_t = \begin{cases} 1, & \text{if the time } t \text{ is in the post-treatment period,} \\ 0, & \text{if the time } t \text{ is in the pre-treatment period} \end{cases}$$

$$D_{it} = \begin{cases} 1, & \text{if } G_i = 1 \text{ and } T_t = 1, \\ 0, & \text{otherwise.} \end{cases}$$

- $Y_{it}(0) / Y_{it}(1)$: The potential outcome that individual i would attain at time t in the absence of the treatment / exposed to the treatment.

THE DID FRAMEWORK



- The observed outcome is $Y_{it} = Y_{it}(0)(1 - D_{it}) + Y_{it}(1)D_{it}$.
- The effect of the treatment on the outcome for individual i at time t is defined as $Y_{it}(1) - Y_{it}(0)$. (see Rubin ,1974 and Heckman,1990)
- The **average treatment effect** on the treated (ATT)

$$\mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = 1, T_t = 1],$$

or its more general conditional version

$$\tau_{DID} = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid X_{it}, G_i = 1, T_t = 1],$$

where X_{it} are observed covariates.

- The common trend condition is a crucial restriction to identify DID models.
(see Abadie, 2005)

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, 66, 688–701.

Heckman, J. J. (1990). Varieties of Selection Bias. *American Economic Review*, 80, 313–318.

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *Review of Economic Studies* 72, 1–19.

CONDITION FOR DID



- The **common trend condition** in the DID framework

$$\begin{aligned} & \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 1, T_t = 1] - \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 1, T_t = 0] \\ &= \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 0, T_t = 1] - \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 0, T_t = 0] \end{aligned}$$

- Conditional on the covariates, the average outcomes for the treated and controls would have followed **parallel paths** in the absence of the treatment.
- Y_{it} in the treatment and control groups needs two parallel paths in the absence of treatment

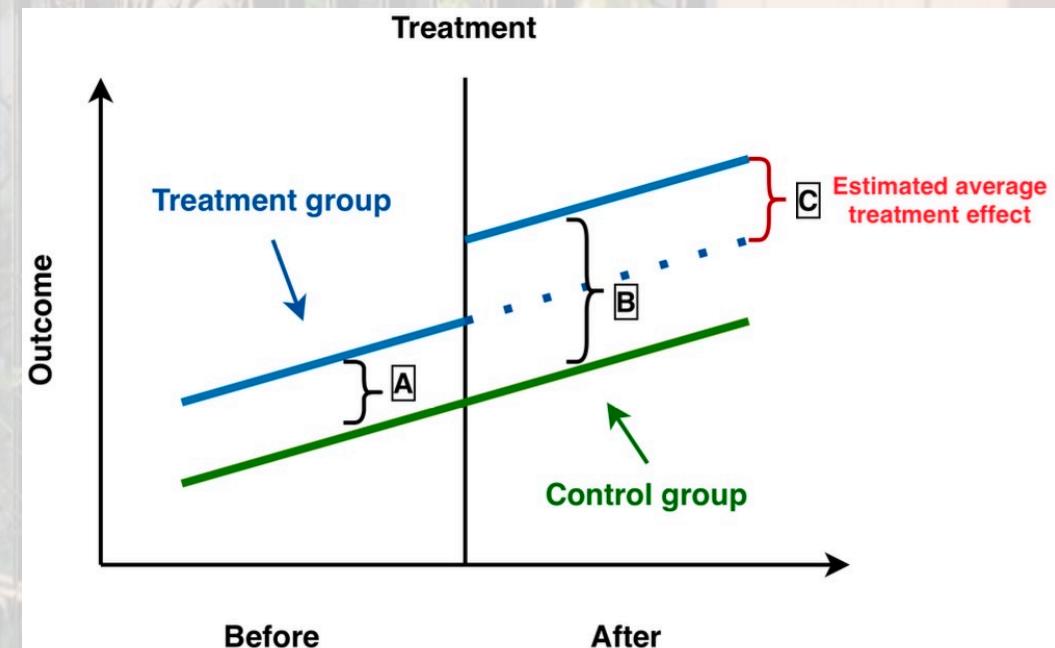


Figure 3: The common trend condition for identifying DID models

ATT FOR DID



- Under **common trend condition**, the ATT can be identified as

$$\begin{aligned}\tau_{DID} &= \mathbb{E}[Y_{it}(1) - Y_{it}(0) | X_{it}, G_i = 1, T_t = 1] \\ &= \{\mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 1] - \mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 1]\} \\ &\quad - \{\mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 0] - \mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 0]\} \\ &= B - A\end{aligned}$$

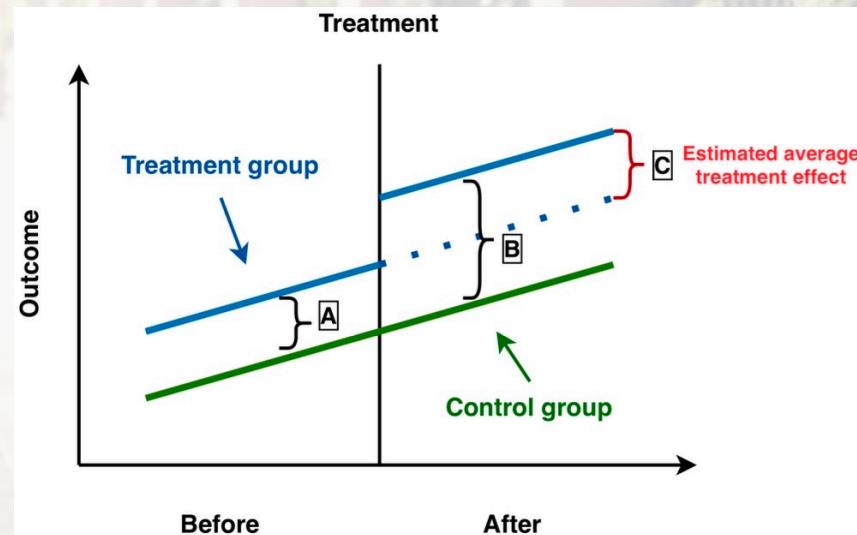


Figure 3: The Common trend condition for identifying DID models

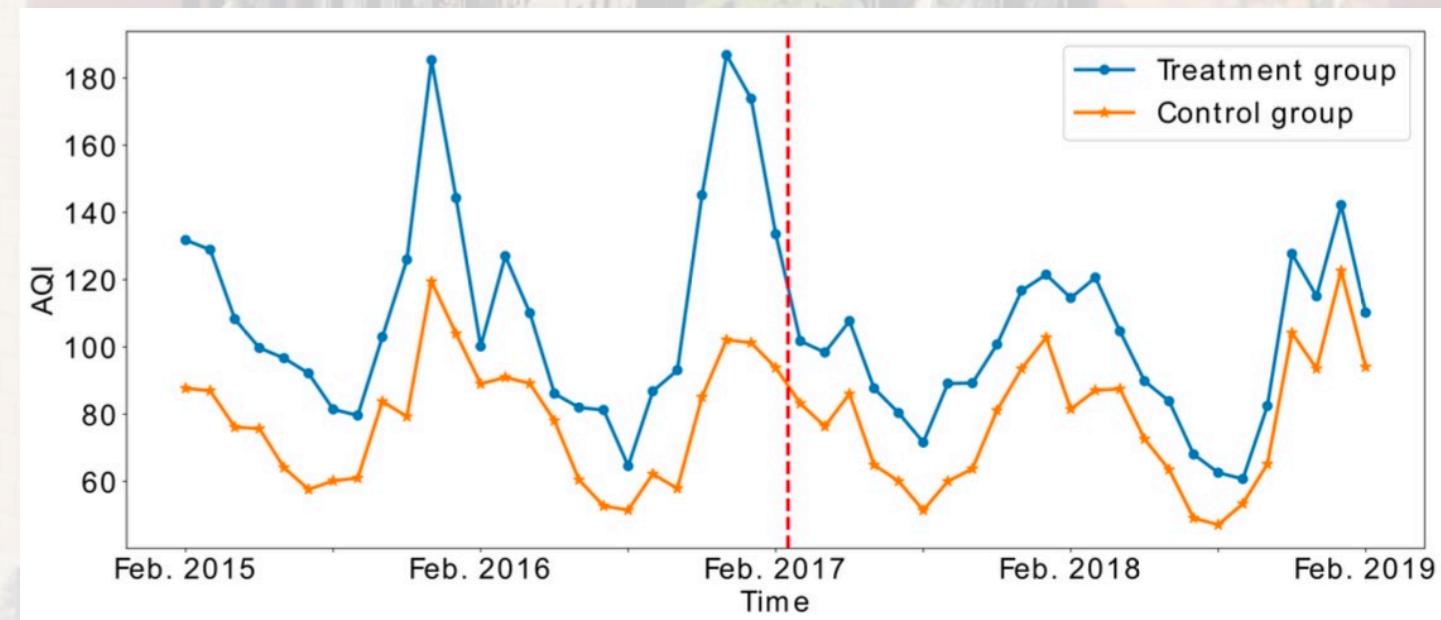


Figure 4: Paths of the AQI over time in the treatment and control groups before and after policy

THE IDID FRAMEWORK



- A new DID (**IDID**) framework is proposed to estimate the **quasi** average treatment effect on the treated (QATT)

$$\mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid G_i = 1, T_t = 0],$$

or its more general conditional version

$$\tau_{IDID} = \mathbb{E}[Y_{it}(1) - Y_{it}(0) \mid X_{it}, G_i = 1, T_t = 0],$$

where X_{it} are observed covariates.

- Since the treatment in **reality** is only implemented in the post-treatment period, the treatment effect captured by τ_{IDID} is for the treatment taking place in a **counterfactual** world, so it is called the quasi treatment effect on the treated.

CONDITION FOR IDID



- The inverse common trend condition in the IDID framework

$$\begin{aligned} & \mathbb{E}[Y_{it}(1) | X_{it}, G_i = 1, T_t = 1] - \mathbb{E}[Y_{it}(1) | X_{it}, G_i = 1, T_t = 0] \\ &= \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 0, T_t = 1] - \mathbb{E}[Y_{it}(0) | X_{it}, G_i = 0, T_t = 0] \end{aligned}$$

- What if this treatment had been implemented in the treatment group during the pre-treatment period
- To investigate this condition 4.2, a simple way is to see whether the paths of the outcome variable for treated and controls are parallel in the post-treatment period

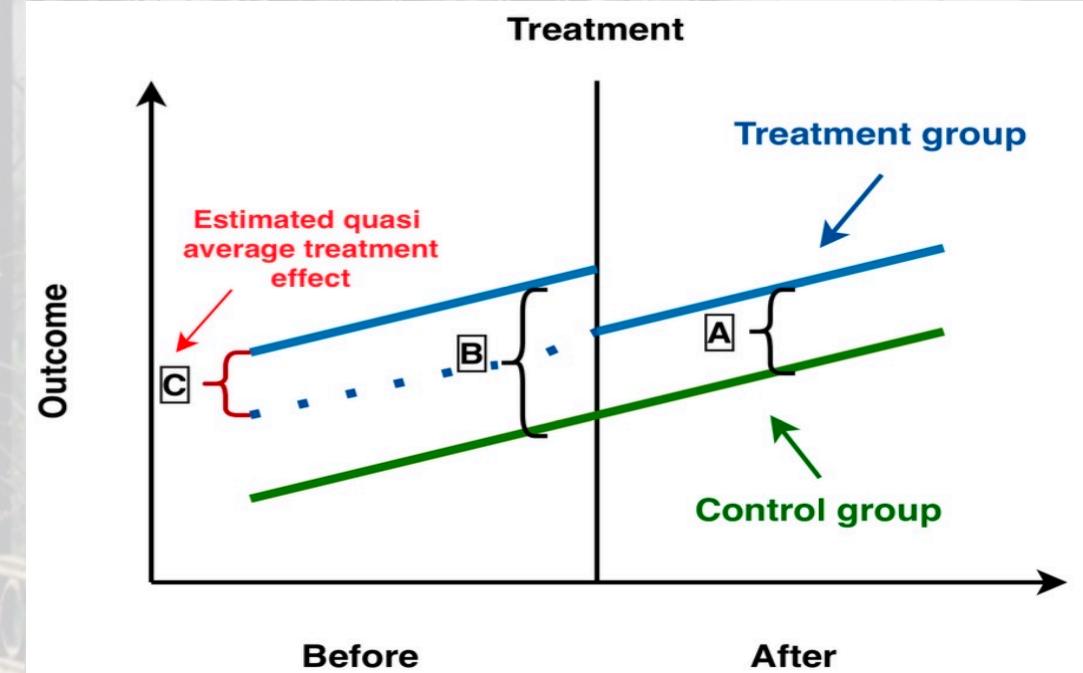


Figure 5: The inverse common trend condition to identify IDID models

QATT FOR IDID



- Under **inverse common trend condition**, the QATT can be identified as
- $\tau_{IDID} = \mathbb{E}[Y_{it}(1) - Y_{it}(0) | X_{it}, G_i = 1, T_t = 0]$
 $= \{\mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 1] - \mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 1]\}$
 $- \{\mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 0] - \mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 0]\}$
 $= A - B$

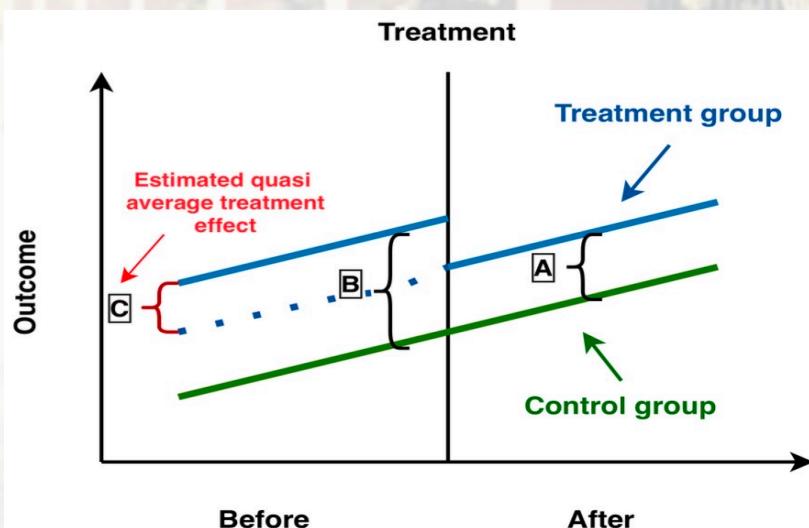


Figure 5: The inverse common trend condition to identify IDID models

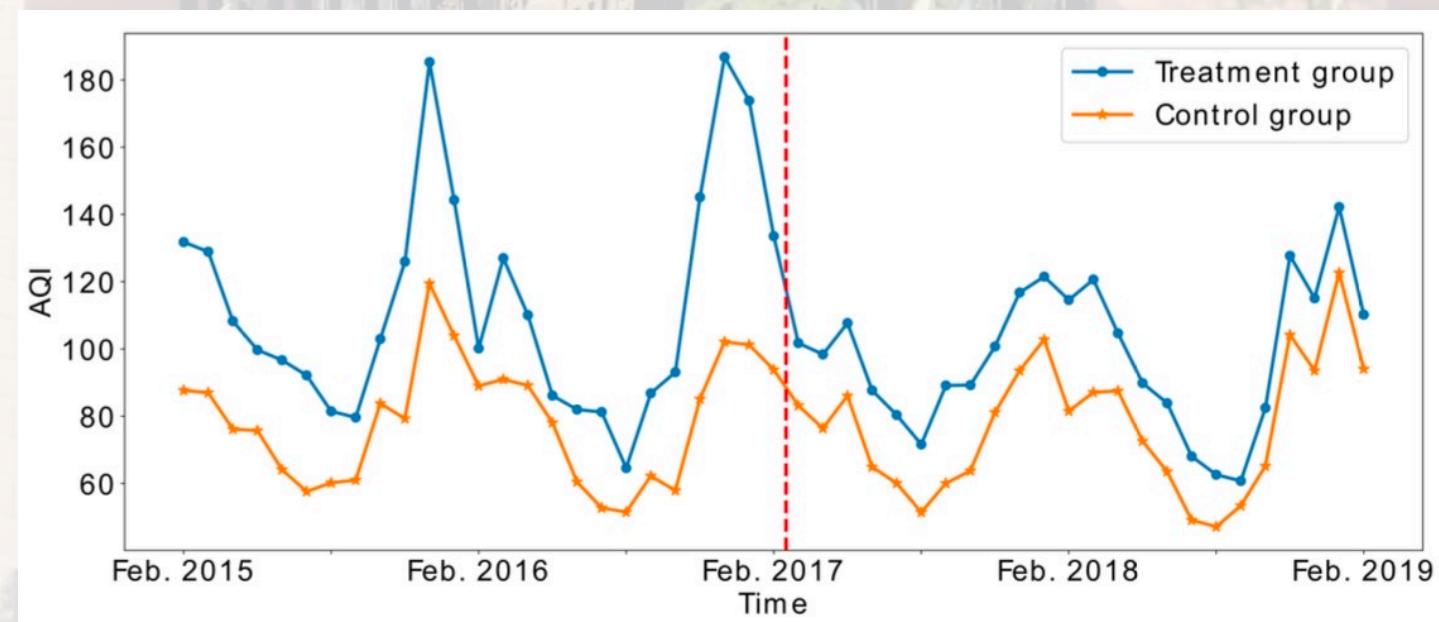


Figure 4: Paths of the AQI over time in the treatment and control groups before and after policy

DID V.S. IDID (Differences)



- IDID relies on the inverse common trend condition, while DID leans upon the common trend condition.
- IDID identifies the average **quasi** causal effect of the treatment taking place in a **counterfactual** world, while DID identifies the average causal effect of the treatment taking place in the **real** world.
- IDID measures how much the difference in differences of the outcome variable between the two groups would be **removed by the treatment** over the two periods, while DID measures how much the difference in differences of the outcome variable between the two groups would be **created by the treatment** over the two periods.

IDID Regression Model



- The baseline IDID regression model to estimate the quasi effects of the “2+26” policy

$$Y_{it} = A_i + \sum_{\theta=-25}^{24} \alpha_\theta I_t^\theta + \tau \tilde{D}_{it} + X_{it}^T \beta + \varepsilon_{it}$$

where

A_i represents individual fixed effects; θ is the year-month time period index

I_t^θ is a dummy that takes a value of 1 if it is in the time period θ

α_θ captures fixed effects of months; τ captures the opposite of quasi effect

\tilde{D}_{it} takes a value of 1 if the i th ground monitoring station is in the treatment group and the time t is in the pre-treatment period.

X_{it} includes all observed meteorological covariates;

β is the coefficient vector of X_{it}

ε_{it} is the error term with mean zero

IDID Regression Model



- Under the baseline regression model

$$\begin{aligned} & \{\mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 1] - \mathbb{E}[Y_{it} | X_{it}, G_i = 1, T_t = 0]\} \\ & - \{\mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 1] - \mathbb{E}[Y_{it} | X_{it}, G_i = 0, T_t = 0]\} \\ & = \{\sum_{\theta=-25}^{24} \alpha_\theta \mathbb{E}[I_t^\theta | T_t = 1] - \sum_{\theta=-25}^{24} \alpha_\theta \mathbb{E}[I_t^\theta | T_t = 0] - \tau\} \\ & - \{\sum_{\theta=-25}^{24} \alpha_\theta \mathbb{E}[I_t^\theta | T_t = 1] - \sum_{\theta=-25}^{24} \alpha_\theta \mathbb{E}[I_t^\theta | T_t = 0]\} \\ & = -\tau \end{aligned}$$

- The quasi effect of the “2+26” policy could be identified, if the inverse trend condition holds



Checking Inverse Common Trend Condition

- A more rigorous method is to statistically examine the condition based on the following model

$$Y_{it} = A_i + \sum_{\theta=-25}^{24} \alpha_\theta I_t^\theta + \sum_{\theta=-25}^{24} \gamma_\theta (G_i \times I_t^\theta) + X_{it}^T \beta + \varepsilon_{it}$$

where γ_θ captures the difference in the time trends of the AQI between the treatment and control groups in period θ

- We could detect the null hypothesis $\gamma_\theta = 0$ after a fixed θ after the policy and an acceptance of this null hypothesis supports the validity of inverse common trend condition in the IDID framework

Investigating Inverse Common Trend Condition



- The coefficients γ_θ after the policy most likely fluctuate around 0 over time
- The 95% confidence intervals of γ_θ before the policy mostly lie above 0

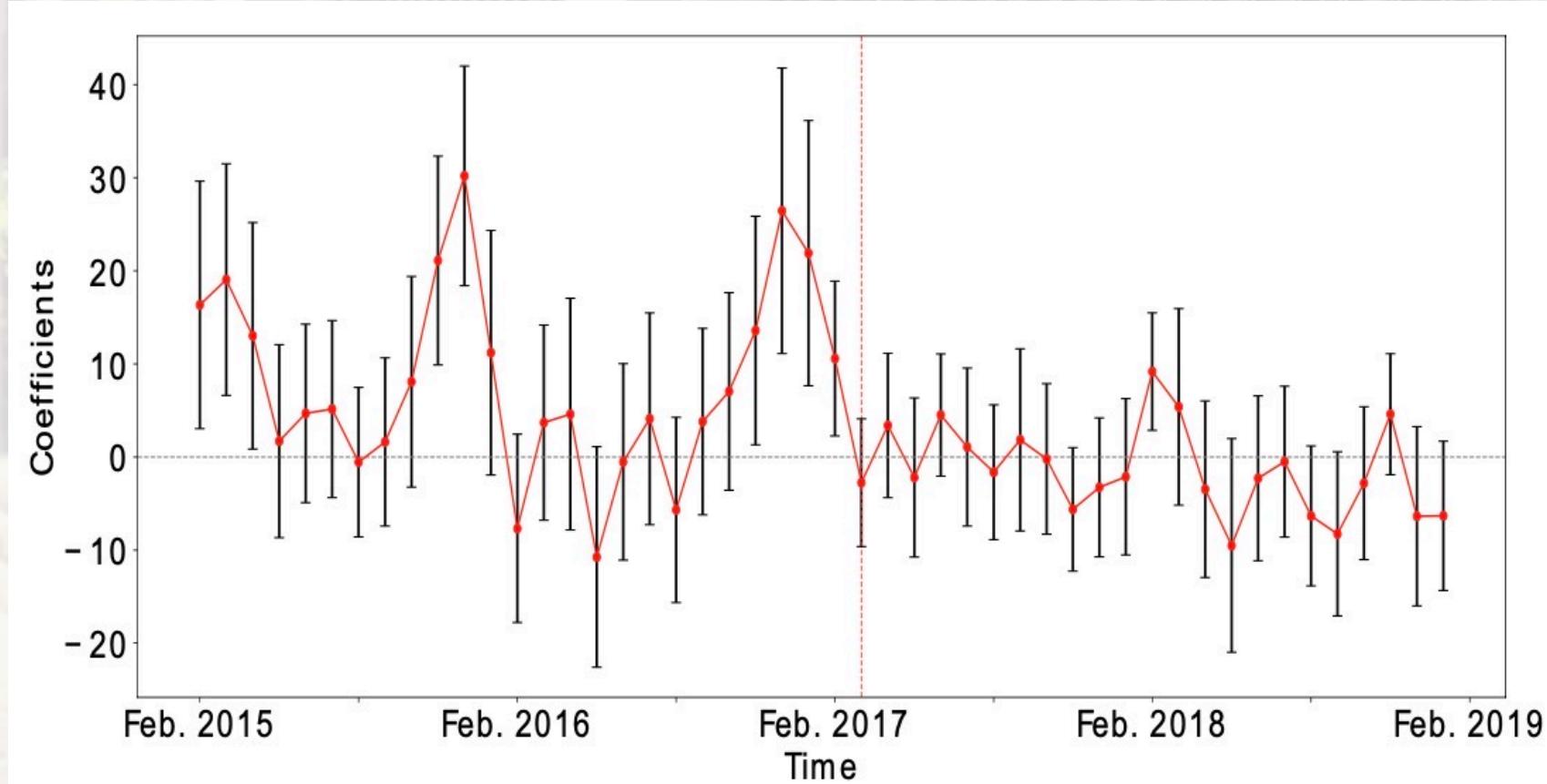


Figure 6: Estimates of coefficients γ_θ over time, with their 95% confidence intervals denoted by error bars.

IDID Estimation results



- During the pre-treatment period, if the “2+26” policy had been implemented in the treatment group, the average AQI value in this group would drop by 9.338, indicating that the “2+26” policy is significantly effective.

Table 2: Baseline IDID regression model: IDID estimate for the average quasi effect of the “2+26” policy

IDID coefficient (τ)	9.338*** (2.527)
Individual fixed effects	Yes
Year-month joint fixed effects	Yes
Meteorological covariates	Yes
Observations	422,072
R^2	0.309

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

$$CI = (9.338 - 1.96 \times 2.527, 9.338 + 1.96 \times 2.527) = (4.385, 14.291)$$



Robustness checks - Control Groups

Table 3: Alternative control groups: IDID estimates for the average quasi effects of the “2+26” policy

	Alternative control groups				
	(1)	(2)	(3)	(4)	(5)
IDID coefficient (τ)	9.615*** (2.444)	8.251*** (2.184)	7.607*** (2.154)	7.549*** (2.105)	7.146*** (2.034)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year-month joint fixed effects	Yes	Yes	Yes	Yes	Yes
Meteorological covariates	Yes	Yes	Yes	Yes	Yes
Number of untreated ground monitoring stations	22	29	31	32	34
Observations	424,980	445,270	451,084	453,992	459,779
R^2	0.309	0.306	0.305	0.304	0.303

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

$$CI = (9.338 - 1.96 \times 2.527, 9.338 + 1.96 \times 2.527) = (4.385, 14.291)$$



Robustness checks - Explanatory Variables

Table 4: Alternative meteorological covariates: IDID estimates for the average quasi effects of the “2+26” policy

	Alternative meteorological covariates				
	(1)	(2)	(3)	(4)	(5)
IDID coefficient (τ)	9.202*** (2.526)	9.832*** (2.492)	9.506*** (2.542)	13.060*** (2.561)	14.200*** (2.510)
Individual fixed effects	Yes	Yes	Yes	Yes	Yes
Year-month joint fixed effects	Yes	Yes	Yes	Yes	Yes
Meteorological covariates					
Air temperature	No	Yes	Yes	Yes	No
Wind power	Yes	No	Yes	Yes	No
Wind direction	Yes	Yes	No	Yes	No
Weather	Yes	Yes	Yes	No	No
Observations	422,072	422,072	422,072	422,072	422,072
R^2	0.294	0.308	0.305	0.239	0.208

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

$$CI = (9.338 - 1.96 \times 2.527, 9.338 + 1.96 \times 2.527) = (4.385, 14.291)$$



Robustness checks - Outcome Variables

Table 5: Alternative outcome variables: IDID estimates for the average quasi effects of the “2+26” policy

	AQI (Day) (1)	AQI (Night) (2)	$PM_{2.5}$ (3)	PM_{10} (contains $PM_{2.5}$) (4)
IDID coefficient (τ)	8.263*** (2.596)	11.610*** (2.594)	4.704*** (1.810)	14.860*** (4.660)
Individual fixed effects	Yes	Yes	Yes	Yes
Year-month joint fixed effects	Yes	Yes	Yes	Yes
Meteorological covariates	Yes	Yes	Yes	Yes
Observations	210,708	221,364	453,788	391,055
R^2	0.317	0.356	0.338	0.284

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

Heterogeneity analysis



- BTH and the surrounding region are located in the warm temperate subhumid continental monsoon climate (暖温带半湿润大陆性季风气候), is there any **seasonal heterogeneous** that do affect the quasi policy effect?
- The treatment area is disk-shaped (圆盘形), and before the policy, the ground monitoring stations in this area with larger values of “Distance” tend to have worse air quality. And the treatment area is generally chosen with **the worst polluted subarea at its center, surrounded by other less polluted subareas**, thereby avoiding the problem of air transmission. Is there any **spatial heterogeneity** that do affect the quasi policy effect?

The choice of spatial clusters



- The “Distance” values of all **treated** ground monitoring stations lie in the interval $(0, 137, 111]$.
- Split all treated ground monitoring stations into $k = 2^i$ equidistant clusters (for $i = 0, 1, \dots$), and find the **smallest i_0** such that the inverse common trend condition fails.
- Following the aforementioned strategy, $i_0 = 3$ in the examined data, and thus divide all treated ground monitoring stations into $2^{i_0-1} = 4$ equidistant clusters, in which the range of “Distance” lies in the intervals $(0, 34, 278]$, $(34, 278, 68, 555]$, $(68, 555, 102, 833]$, and $(102, 833, 137, 111]$, respectively.

Spatial Heterogeneity in Policy Effects



Table 6: Spatial IDID regression model: IDID estimate for the average quasi effect of the “2+26” policy

IDID coefficient ($\tau^{c=1}$)		3.297 (4.038)
IDID coefficient ($\tau^{c=2}$)		10.960*** (3.335)
IDID coefficient ($\tau^{c=3}$)		13.750*** (3.567)
IDID coefficient ($\tau^{c=4}$)		15.200*** (3.761)
Individual fixed effects		Yes
Year-month joint fixed effects		Yes
Meteorological covariates		Yes
Observations		381,564
R^2		0.308

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

- The quasi effect of the “2+26” policy in Cluster 1 is **not significant**, while the quasi effects in Clusters 2–4 are significant. (no room for improvement, or spillover effects from the untreated area due to air transmission.)
- The Wald test for checking the equivalence of $\tau^{c=1}$ and $\tau^{c=2}$ has a p-value 0.014, while other all three coefficients $\tau^{c=2}$, $\tau^{c=3}$, and $\tau^{c=4}$ seem to have no remarkable differences.

Seasonal Heterogeneity in Policy Effects



Table 7: Seasonal IDID regression model: IDID estimate for the average quasi effect of the “2+26” policy

IDID coefficient ($\tau^{s=1}$)	18.220*** (4.721)
IDID coefficient ($\tau^{s=2}$)	1.291 (2.133)
Individual fixed effects	Yes
Year-month joint fixed effects	Yes
Meteorological covariates	Yes
Observations	381,564
R^2	0.307

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

- The quasi effect of the “2+26” policy in the **cold** season is remarkably better than that in the warm season, while this policy is likely to have no effects in improving air quality in the warm season.
- The Wald test for checking the equivalence of $\tau^{s=1}$ and $\tau^{s=2}$ has a p-value 0.0001, indicating that the two coefficients are significantly different.

Spatial-seasonal Heterogeneity in Policy Effects



Table 8: Spatial-seasonal IDID regression model: IDID estimate for the average quasi effect of the “2+26” policy

	Cold season($s = 1$) (1)	Warm season($s = 2$) (2)
IDID coefficient ($\tau^{c=1,s}$)	6.086 (4.156)	-0.340 (3.700)
IDID coefficient ($\tau^{c=2,s}$)	16.450*** (3.480)	4.339 (2.796)
IDID coefficient ($\tau^{c=3,s}$)	24.570*** (3.886)	1.799 (3.041)
IDID coefficient ($\tau^{c=4,s}$)	20.340*** (4.205)	9.141*** (3.216)
Individual fixed effects		Yes
Year-month joint fixed effects		Yes
Meteorological covariates		Yes
Observations	422,072	
R^2	0.312	

Notes: *** denotes significance at 1% level. Robust standard error is in parenthesis.

- The cold season effects contribute significantly to the overall effects, and are much stronger than the insignificant warm season effects (industrial production and traditional coal-fired heating).
- The strong cold season effects in Clusters 3–4 are greatly underestimated by the overall cold season effect.

Inspiration for Zero Markup Drug Policy



- (Inverse) common trend condition check
PC-DID, PSM-DID, if the condition fails
- Alternative outcome variables (robustness checks)
- Potential heterogeneity (hospital district location, level, classification)
- Since ZMDP was fully implemented in 2017 in Shanghai, only the treatment group exists in this case (generalized DID)
- Since Shanghai gradually reduced the markup rate of drugs from 2015 to 2017 in public hospitals, a situation in which each individual's treatment period is not exactly the same ensues (heterogeneous timing DID)



Thank you!