Growth preference and air pollution in China

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ONLINE APPENDIX

A1. Descriptive statistics for main and mechanism variables

Table A1 presents the summary statistics for variables included in the main analysis, while Panel E of Table A1 offers summary statistics for the variables involved in mechanism analysis. Panel F of Table A1 presents summary statistics for a dummy variable indicating whether the minimum air quality improvement targets have been achieved, aiming to further examine the rationales of local officials.

Table A1. Summary statistics

Variables	Definition	Obs	Mean	Std Dev
Panel A: The growth rate of GDP				
GDPGR	The growth of GDP in each city (%).	291	3.408	2.179
Panel B: Instrumental variable				
log(AIC)	Accumulated infected cases (log).	291	5.157	1.742
Panel C: Ambient pollution concentrations				
ΔAQI	The AQI index changes from year 2023 to 2022 in each city.	291	3.727	3.409
ΔPM2.5	PM2.5 concentration changes from 2023 to 2022 in each city (μg/m^3).	291	1.656	2.277
ΔPM10	PM10 concentration changes from 2023 to 2022 in each city (μg/m^3).	291	7.068	5.561
ΔNO2	NO2 concentration changes from 2023 to 2022 in each city (μg/m^3).	291	0.620	1.724
Panel D: Weather conditions				
WIND	Average wind speed (m/s).	291	2.502	0.548
RAIN	Average rainfall (mm)	291	2.803	1.393
TEMP	Average temperature (°C)	291	15.012	5.207
Panel E: Mechanism analysis and alternative explanations				
VASIGR	The growth rate of city's value added of the secondary industry.	291	0.010	0.121
FIAGR	The growth rate of city's fixed assets investment.	291	0.035	0.104
IERGR	The growth rate of city's industrial enterprise registrations.	291	-0.387	0.267
Non_IERGR	The growth rate of city's non-industrial enterprise registrations.	291	-0.297	0.283
OWGR	The growth rate of city's overtime work hours.	291	0.154	0.325
Population	Registered population in each city (10 thousand persons).	291	455.069	390.570
Panel F: Whether officials are rational or not				
Dummy	Have the air quality improvement targets been achieved? (YES=1, NO=0)	291	0.722	0.449

Notes: The sample comprises 291 major Chinese cities. Certain minority autonomous cities are excluded due to the data availability.

Appendix A2. Change in air pollution by GDP growth ranking groups

Figure A1 displays a bar chart illustrating the mean change in AQI and pollutant concentrations from 2022 to 2023, categorized by regions with differing GDP growth rankings. For PM2.5 and NO2, cities where GDP growth rankings improved (red bars, indicating ΔRank(GDPGR)<0) generally experienced smaller increases in pollutant concentrations, while cities with declining GDP growth rankings (blue bars, indicating ΔRank(GDPGR)>0) saw greater increases in pollutant levels. This suggests that regions with a drop in GDP rankings may have prioritized economic development in 2023 at the expense of air quality, whereas regions with improved GDP rankings achieved better air quality outcomes. But we cannot observe similar findings for AQI and PM10. Figure A1 only provides an ambiguous trade-off between economic development and environmental quality. Nonetheless, the simple comparison provides prima facie evidence and further analysis is required to robustly establish the relationship between growth preference and air pollution.

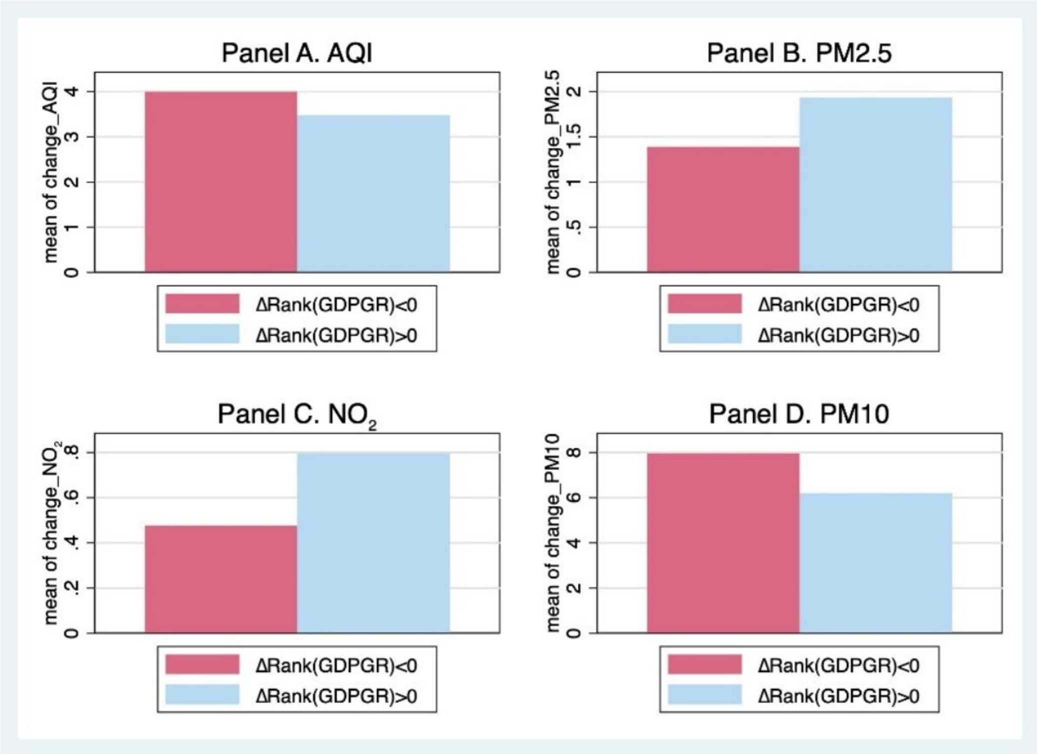

Figure A1. Changes in pollutant concentration by growth ranking changes.

A3. Additional robustness analyses

We present the results of various robustness checks in Table A2. Overall, the findings remain consistent and significant across multiple specifications, reinforcing the reliability of our analysis. In Panel A, we exclude samples from Hubei province, where Wuhan is located. Due to its proximity to Wuhan, cities in Hubei experienced significantly higher infection rates and a greater impact from the COVID-19 pandemic compared to other cities. In Panel B, we further control for city-specific covariates to account for potential confounding factors. Panel C shows the results after winsorizing the sample by excluding the bottom 5% and top 95% of growth ranking changes. This approach minimizes the influence of outliers. In Panel D, we replace the dependent variable with the change in air pollution from 2018 to 2019. This period should not be affected by the ranking changes during the 2020-2022 COVID-19 pandemic. As expected, the results in Panel D show no significant impacts. Across these robustness checks, the estimates generally remain significant at the 5% level for most specifications and are qualitatively similar in magnitude. This consistency strengthens our confidence in the validity of the reported findings.

Table A2. Robustness checks

	1st stage	2nd stage			
Dependent variable	$\Delta Rank(GDPGR)_{2019-2022}$	ΔAQI	ΔPM2.5	ΔPM10	ΔNO2
	(1)	(2)	(3)	(4)	(5)
Panel A: Excluding Hubei Province					
log(AIC)	10.756 (3.072)				
$\Delta Rank(\widehat{GDPGR})_{2019-2022}$		0.024 (0.012)	0.024 (0.011)	0.040 (0.017)	0.013 (0.008)
N	279	279	279	279	279
Panel B: Adding some city control variables					
log(AIC)	10.368 (2.792)				
$\Delta Rank(\widehat{GDPGR})_{2019-2022}$		0.023 (0.011)	0.025 (0.010)	0.039 (0.015)	0.013 (0.007)
	291	291	291	291	291
Panel C: Winsorizing below 5% and above 95%					
log(AIC)	10.632 (2.639)				
$\Delta Rank(\widehat{GDPGR})_{2019-2022}$		0.022 (0.012)	0.025 (0.009)	0.037 (0.016)	0.013 (0.007)
	263	263	263	263	263
Panel D: Impact of growth ranking change on air pollution from 2018 to 2019					
log(AIC)	10.169 (3.048)				
$\Delta Rank(\widehat{GDPGR})_{2019-2022}$		-0.001 (0.019)	-0.009 (0.016)	-0.009 (0.029)	-0.020 (0.014)
N	291	291	291	291	291
Weather control	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES

Notes: Clustered standard errors in parentheses.

A4. Nighttime light data and overtime activity

Nighttime light observations from remote sensing technology effectively reflect low-intensity lights from nighttime illumination, fires, and even vehicle traffic, making it a valuable resource for monitoring human activities. The data used in this study comes from the NPP/VIIRS nighttime light dataset, which is derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor onboard the Suomi National Polar-orbiting Partnership (Suomi-NPP), the new generation U.S. polar-orbiting satellite. This dataset addresses the issue of light oversaturation and offers the advantage of comparability across different time periods. However, due to cloud cover and other factors, some areas may exhibit negative or anomalous brightness values during certain periods. Additionally, in high-latitude regions, winter snow accumulation and intense summer sunlight can cause increased nighttime light reflection in winter and the exclusion of nighttime lights as stray light in summer.

To address these issues, we resampled and geolocated the data, removing noise factors such as cloud pollution, atmosphere, snow, and stray light, resulting in a corrected NPP/VIIRS data product with a 500-meter resolution. The high resolution and dynamic range of the corrected NPP VIIRS data allow it to accurately capture light changes in small areas, which is useful for monitoring nighttime lights in cities, industrial areas, office buildings, and other specific locations. Overtime work typically involves increased and prolonged nighttime lighting, and high-resolution data can help identify these changes. Therefore, this study uses this data to measure the annual average nighttime overtime in various regions. Specifically, we use the rate of change in nighttime light data from 2023 compared to 2022 as the measure of the change in average nighttime overtime work from 2023 to 2022 (ΔOWGR).