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Abstract: Wintertime ambient air quality in northern China has improved markedly over the past decade, yet the role of the household sector in this improvement remains unclear. This study evaluates the impact of an energy transition policy targeting the household sector—namely, the coal-to-gas policy—on wintertime air quality in northern China. Using balanced panel data covering the period from 2015 to 2023, we adopt a staggered difference-in-differences approach as our baseline empirical strategy to examine the policy's effects across five implementation phases, and report results using heterogeneity-robust estimators to address the "forbidden comparison" issue. The results show that the policy significantly improved the Air Quality Index (8.3–12.5 %) and reduced concentrations of PM2.5 (9.8–15.6 %,), PM_{10} (8.2–12.7 %), SO_2 (26.4–33.6 %), and NO_2 (7.4–10.5 %), though this was accompanied by an increase in ozone concentrations (8.3–12.9 %). To explore channels, we analyze household-level data from both urban and rural areas. We find that the policy has significantly increased urban clean energy infrastructure, promoted the expansion of centralized heating systems, and raised the likelihood of households adopting clean energy in rural areas.

Keywords: Air pollution; Coal-to-gas Policy; Energy transition; China

JEL Classifications: Q53, Q48, Q42, C23

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1. Introduction

Winter heating has been recognized as a critical contributor to air pollution in northern China (Dao et al., 2014). According to Chen et al. (2013), winter heating in the region increases total suspended particulates in the ambient air by 55%, lowering life expectancy by 5.5 years. Loose coal is a key culprit. Compared to policy-regulated coal, loose coal contains more sulfur and ash, and is usually combusted without washing (Zhi et al., 2015). In addition, due to limitations of household heating devices, loose coal combusts inefficiently and the emissions are not filtered before being discharged into the open air. Therefore, loose coal emits five to ten times more airborne pollutants than industrial coal per ton.[1]

In response to an air pollution crisis during the winter season, the Chinese government launched in 2017 the *Northern Region Winter Clean Heating Plan (2017–2021)* - commonly known as the coal-to-gas policy - which features a dual approach of administrative enforcement and financial subsidies. Under this top-down initiative, the central government set overarching targets on reducing ambient air pollution, while local governments developed implementation plans tailored to regional conditions. Financially, the policy is co-funded by both central and local governments. Since its inception, the policy has undergone five phases of pilot implementation, expanding from 43 cities during 2017–2019 to 88 cities by 2022, ultimately covering all provinces in northern China. Unlike traditional regulatory policies mainly aimed at enterprises engaged in production activities, the coal-to-gas policy is an energy transition initiative, targeting the household sector and widely regarded as the most significant and stringent household-oriented environmental policy of the past decade (Wang et al., 2024).

This study aims to evaluate the air quality improvement effects of China's five-phase coal-to-gas policy and to explore its underlying channels from the perspective of the household sector. Specifically, we focus on northern regions of China with winter seasons, using a balanced panel dataset at city-level from 2015 to 2023. The analysis centers on wintertime air quality, employing a staggered difference-in-differences model as the baseline strategy and reporting results based on heterogeneity-robust estimators. The results show that the policy significantly improved the Air Quality Index (8.3–12.5 %) and reduced concentrations of $PM_{2.5}$ (9.8–15.6 %,), PM_{10} (8.2–12.7 %), SO_2 (26.4–33.6 %), and NO_2 (7.4–10.5 %), though this was accompanied by an increase in ozone concentrations (8.3–12.9 %). These effects are sizeable. Using AQI

[1] http://news.163.com/17/0831/22/CT6TV2MC00018AOR.html (accessed in July 2025)

as an example, the estimated effect accounts for 27%–40% of the overall improvement in wintertime air quality during the study period (from 119 in 2015 to 82 in 2023), highlighting the policy's substantial contribution to the long-term decline in pollution levels. Beyond estimating policy effects, we examine the channels at the household sector from both urban and rural areas. We find that the policy has significantly increased urban clean energy infrastructure, promoted the expansion of centralized heating systems, and raised the likelihood of households adopting clean energy in rural areas, thereby alleviating air pollution.

This study makes three main contributions to the literature. First, we focus our analysis on northern China and provide an empirical assessment of the effects of all five phases of the coal-to-gas policy on air quality. In contrast, previous literature has either concentrated only on the Beijing-Tianjin-Hebei region (Wu et al., 2020; Wang et al., 2021) or extended the analysis to the national level (Yu et al., 2021; Zeng et al., 2022; Wang et al., 2023). However, most cities in the Beijing-Tianjin-Hebei region only participated in the first two phases of the policy pilot, making the region unrepresentative of the broader implementation of the coal-to-gas policy. On the other hand, since there is no winter heating season in southern China, including southern cities in the control group may lead to biased estimates of the policy's effects. To our knowledge, we are the first to extend analysis to all five phases of the coal-to-gas policy. Previous studies have primarily examined the air quality impacts of either the first phase (Leng et al., 2023; Tan et al., 2023; Wu et al., 2023; Wang et al., 2024) or the first three phases (Zhang et al., 2020; He et al., 2025). While official documents initially designated 43 pilot cities for implementation between 2017 and 2019 (phases one to three), the policy was subsequently expanded to include an additional 20 cities in 2021 (phase four) and 25 cities in 2022 (phase five). This expansion necessitates a more comprehensive evaluation of the policy over an extended time frame.

Second, existing studies often lack rigorous validation of the applicability of staggered DID models, and they rarely address the potential endogeneity in the selection of pilot cities. These limitations significantly constrain our understanding of the accuracy of estimated air quality improvement effects. Specifically, since the coal-to-gas policy was implemented across different cities and at different points in time, staggered difference-in-differences designs may suffer from heterogeneous treatment effects over time or across units, potentially generating biased estimates. Recent studies have highlighted this issue—often referred to as the "forbidden comparison" problem

(Borusyak et al., 2024)—which arises when earlier treated groups act as controls for later treated groups in two-way fixed effects models. To enhance the robustness of our identification strategy, we first employ the Goodman-Bacon (2021) decomposition and the method proposed by De Chaisemartin and D'Haultfoeuille (2020) to examine potential treatment effect heterogeneity and the presence of negative weights in the baseline specification. Then, we re-estimate the models using four heterogeneity-robust estimators and report these results in an effort to address the "forbidden comparison" problem. In addition, the selection of pilot cities for the coal-to-gas policy was not random; it was shaped by factors such as geographic location and economic development, (Li et al., 2025). This non-random selection raises concerns about endogeneity. To address this issue, we construct an instrumental variable based on the geographic distance between each sample city and the capital of its respective province. Following Nunn and Qian (2014), we interact the instrument with year fixed effects to account for time-varying treatment intensity and improve identification. Finally, to further mitigate potential selection bias, we adopt a propensity score matching approach combined with the DID framework.

Third, while prior studies have primarily focused on the average treatment effects of the coal-to-gas policy on air quality, the underlying channels - particularly those involving household-level behavioral changes - remain underexplored. Some studies (e.g., Yu et al., 2021; Wang et al., 2023) suggest that the policy improves air quality by promoting industrial upgrades and technological investments. Others, such as Tan et al. (2023), examine the energy transition channel at the city level. In contrast, our study employs multiple sets of urban and rural data to comprehensively investigate the effects of the coal-to-gas policy on the household sector. These findings enrich our understanding of the coal-to-gas policy's effectiveness and offer micro-level evidence for designing more targeted clean energy policies in the future.

The remainder of the paper is organized as follows. Section 2 reviews the policy background and the relevant literature. Section 3 describes the data, variables, and estimation strategy. Section 4 presents the main findings, while Section 5 analyzes the channels. The study is concluded in Section 6.

2. Background and literature review

Background

Between 1950 and 1980, during China's planned economy era, budget constraints led the government to prioritize winter heating in the northern regions. Using the Qinling–Huaihe line as a climatic and policy boundary, cities located north of this demarcation received heating services during the winter months. Traditionally, coal was the primary energy source for heating in northern China, particularly loose coal, which contributed significantly to severe air pollution.

To address the conflict between residential heating demand and severe air pollution, the Chinese government introduced a series of environmentally-oriented heating policies in northern China. In 2017, the central government officially launched the *Northern Region Winter Clean Heating Plan (2017–2021)*, marking the formal implementation of the coal-to-gas policy. The first phase involved 12 cities across five northern provinces. Subsequently, four additional rounds of pilot programs were carried out in 2018, 2019, 2021, and 2022, eventually covering 88 cities across 15 provinces. A detailed list of these pilot cities is presented in Figure 1.

The coal-to-gas policy features a top-down enforcement mechanism and strong fiscal support (Xie et al., 2022; Wang and Xie, 2023). First, since the launch of the *Northern Region Winter Clean Heating Plan (2017–2021)* in 2017, the central government has issued directives while local governments have overseen implementation, forming a multi-level accountability system. For example, in urban areas, the policy objectives were achieved through measures such as phasing out high-emission and low-efficiency regional coal-fired boilers, expanding the retrofitting of coal-fired boilers to clean energy sources, extending centralized heating systems, and providing subsidies for households to install clean energy equipment[2]. In contrast, in rural areas, the main measures included dismantling coal-fired boilers, banning the distribution and use of loose coal, setting up checkpoint stations at village entrances, and imposing heavy penalties for non-compliance (Wang and Xie, 2023). These stringent regulatory measures are believed to have promoted the use of clean energy in northern China.

Second, the policy's generous subsidy approach has played a crucial role in facilitating energy transition to cleaner heating sources, thereby serving as a key pillar of its successful implementation (Zhang et al., 2023). Funded by both central and local governments, subsidies covered infrastructure, equipment, installation, and fuel costs. Typically, subsidies were structured across municipal, district, and village levels, with variations reflecting local fiscal capacity (Wang and Xie, 2023). The scope of subsidies

[2] http://www.sohu.com/a/214986980_100066267 (accessed in July 2025)

includes natural gas pipeline construction, equipment procurement, one-time installation grants, and annual fuel price subsidies, thereby spanning the full spectrum from infrastructure investment to household energy consumption. For example, Beijing upgraded heating boilers to cleaner energy sources through fiscal subsidies. Specifically, for coal-fired boilers with a capacity below 20 steam tons, the subsidy was CNY 55,000 per ton (approximately USD 7,971), while for those above 20 tons, the subsidy reached CNY 100,000 per ton (approximately USD 14,492)[3]. Other cities also encouraged residents to adopt clean energy by subsidizing gas and electricity prices. In rural areas, Hebei Province stipulated that residents are eligible for total seasonal subsidies of up to CNY 7,900 (approximately USD 1,145), which are intended to facilitate the transition from coal to cleaner heating energy sources (Xu and Ge, 2020). According to the *China Coal Management Research Report 2021*, between 2017 and 2019, the central government allocated a cumulative total of CNY 35.12 billion (approximately USD 5.10 billion), while local governments contributed CNY 77.7 billion (approximately USD 11.28 billion), establishing a stable and coordinated fiscal support system.

Literature review

The urgency of a global transition to clean energy has become increasingly evident, as growing reliance on fossil fuels has significantly accelerated the process of air pollution. Although the share of clean energy in the global energy mix is rising, high-polluting energy sources - particularly coal - continue to dominate (Rafindadi et al., 2014). Coal remains the second largest contributor to $PM_{2.5}$ emissions globally[4]. Consequently, energy transition policies aimed at reducing coal consumption have emerged as a key policy priority for mitigating particulate matter and other pollutants. Examples from developed countries have provided empirical support that reducing coal use effectively improves air quality (Scott and Scarrott, 2011; Lueken et al., 2016). Natural gas is widely regarded as a viable alternative (McGlade et al., 2018), as it generates significantly fewer pollutant emissions compared to other fossil fuels (Yoon et al., 2018), particularly in terms of reducing particulate matter and sulfur dioxide emissions (Mao et al., 2005).

Existing studies from China have found that the coal-to-gas policy significantly improved air quality (Leng et al., 2023; Wu et al., 2023; Tan et al., 2023), particularly by reducing concentrations of particulate matter (Wang et al., 2021; Zeng et al., 2022;

[3] http://www.sohu.com/a/214986980_100066267 (accessed in July 2025)
[4] https://www.iea.org/publications/freepublications/publication/weo-2016-special-report-energy-and-air-pollution.html (accessed in July 2025)

Wang et al., 2023; Shi et al., 2024), sulfur dioxide (Yu et al., 2021; Zeng et al., 2022) and nitrogen dioxide (Zhang et al., 2020; Wu et al., 2023; Wang et al., 2024). However, due to substantial differences in sample coverage and time spans across these studies, the estimated effects of the coal-to-gas policy vary considerably (see Table 1). Furthermore, heterogeneity analysis indicates that the implementation of the policy accelerates the penetration rate of natural gas, thereby enhancing its environmental benefits, especially in more polluted cities (Wang et al., 2021). While the above studies have found beneficial effects of the coal-to-gas policy, critics argued that the use of clean energy can also lead to unintended environmental consequences. Specifically, natural gas is not a completely clean energy source, as its combustion produces nitrates - key compounds contributing to smog formation (Zornitza, 2017). Nitrates is a major precursor of atmospheric aerosols (Lin and McElroy, 2011), and it can lead to secondary pollution through photochemical reactions with volatile organic compounds (VOCs), thereby promoting the formation of tropospheric ozone and contributing to urban photochemical smog (Mauzerall et al., 2005). Additionally, Wu et al. (2023) found that the policy unexpectedly increased ozone concentrations by 11.9%. Our expectation based on the previous literature is hence that the implementation of the coal-to-gas policy has significantly improved air quality, especially reduced the emissions of particulate matter, and sulfur dioxide. However, the policy may have also increased ozone concentrations.

While previous literature provides valuable insights into the implementation and outcomes of the coal-to-gas policy, there remains room for improvement in terms of sample coverage and methodological rigor in identifying its causal impact. Building on prior studies, our paper contributes by employing a staggered DID framework to evaluate the air quality improvement effects of five phases of the coal-to-gas policy in northern China.

3. Data and methods

Data

The first phase of the coal-to-gas policy was officially implemented in 2017, followed by subsequent phases in 2018, 2019, 2021, and 2022. Accordingly, we assemble a city-year level dataset covering 129 northern cities in the main estimation sample, for a period ranging from 2015 to 2023[5]. This gives us 1,161 city-year observations. We follow Zeng et al. (2022) and exclude Beijing and Tianjin, despite being pilot cities, as they are administered centrally and hence are not directly comparable to other prefecture-level cities.

Our data are derived from the following primary sources: First, for air pollution indicators, data are obtained from the real-time air quality monitoring platform of the China National Environmental Monitoring Centre[6]. These platforms provide data at a monthly frequency, which allows us to calculate seasonal air quality indicators for winter (November, December, and January). We focus on Air Quality Index (AQI) and five major pollutants: $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3. To later interpret our estimated results in percentage terms, we convert all measures to their natural logarithm.

Second, the coal-to-gas policy variable ($CTG\_policy_{c,t}$) is the key explanatory variable. In our analysis, we include a dummy variable indicating whether a city adopted the policy. To be precise, we set $CTG\_policy_{c,t} = 1$ for all years following the policy's initial adoption in a city, and 0 otherwise. Information about coal-to-gas policy adoptions since 2017 was collected via official documents and related news reports[7].

Third, to address potential confounding from overlapping policies, we control for three major environmental initiatives related to the coal-to-gas policy. The first is *The Air Pollution Prevention and Control Action Plan* (*APPCAP*, 2013–2017), a stringent policy tied to local officials' performance (Hong and Huang, 2025). Excluding it could bias the estimated effects of the coal-to-gas policy. Additionally, we control for the *New Energy Demonstration City (NEDC)* policy and the *Low-Carbon City Pilot (LCCP)* policy, both of which overlap with the coal-to-gas policy in timing and coverage. We include dummy variables for all three to mitigate policy interference.

Fourth, meteorological data are sourced from the National Centers for Environmental Information under the National Oceanic and Atmospheric Administration[8], and include average temperature, average visibility, average wind speed, and average precipitation during winter.

Fifth, given that our study period spans the COVID-19 pandemic, we control for

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5 Due to missing data, our sample does not include Shizuishan City in Ningxia Hui Autonomous Region and Baicheng City in Jilin Province. For the same reason, our data does not include administrative units such as autonomous prefectures, leagues and Xinjiang Production and Construction Corps.

6 https://air.cnemc.cn:18007 (accessed on July 2025)

7 http://www.shangyexinzhi.com/article/4818232.html (accessed in July 2025)

8 https://www.ncei.noaa.gov/data/global-summary-of-the-day/archive (accessed in July 2025)

pandemic intensity by incorporating city-level data on the daily cumulative number of confirmed COVID-19 cases, obtained from the Health Commissions of prefecture-level cities. Following Li et al. (2022), we use the logarithm of cumulative confirmed cases per capita as a proxy for pandemic intensity. Specifically, this variable is defined as the logarithm of cumulative confirmed COVID-19 cases per capita during the winter season in each prefecture-level city from 2020 to 2022, and is set to zero for all other years.

Finally, we construct control variables based on data from the *Statistical Yearbook of Chinese Prefecture-level Cities*. Drawing on prior literature, which highlights the importance of socioeconomic factors in shaping air quality (Jiang et al., 2018; Zeng et al., 2019; Liu et al., 2019; Li et al., 2019; Xie et al., 2021; Wang et al., 2024), we include the following variables: economic development (GDP_pc), population density (Pop_density), level of industrialization (IndusFirms), industrial structure (SecGDP_ratio), per capita foreign direct investment (FDI_pc), and Vehicle transport capacity (Vehicle_cap)[9]. Detailed definitions and data sources for all variables are presented in Table 2.

Methods

The coal-to-gas policy has been divided into five phases by the year of implementation (2017, 2018, 2019, 2021 and 2022). Given this heterogeneity in the multi-period pilot policy, the basic DID model may not accurately capture its effects. Accordingly, this study employs a staggered DID model (Callaway and Sant'Anna, 2021). Meanwhile, considering that city as well as time differences may have an impact on the estimation results, this paper adopts city and year two-way fixed effect models (TWFE) for baseline regression analysis.

$$\ln(Y_{c,t}) = \beta_0 + \beta_1 CTG\_policy_{c,t} + \beta_2 X_{c,t} + \delta_c + \tau_t + \varepsilon_{c,t} \tag{1}$$

Where c is the city, t is the year, and the outcome variable $\ln(Y_{c,t})$ represents concentrations of winter air pollutants measured in city *c* in year *t*. $CTG\_policy_{c,t}$ is a dummy variable. In addition, $X_{c,t}$ is a set of city-level control variables, δ_c represents city fixed effects, τ_t represents year fixed effects, and $\varepsilon_{c,t}$ is an error term.

[9] This study uses the standardized Z-scores of local passenger and freight volumes to measure vehicle transport capacity.

4. Results

Validity tests of the staggered DID model

Before conducting our main empirical analysis, we first carry out validity tests of the staggered DID model in our setting. According to Goodman-Bacon (2021), when the treatment effects for each timing group change over time, the two-way fixed effects staggered DID estimator may be biased due to treatment effects heterogeneity. Therefore, we use the Goodman-Bacon (2021) decomposition method with control variables to test the treatment effects heterogeneity of the coal-to-gas policy. Table A1 in the Appendix shows the results and indicates that the *never* component remains the primary determinant of the overall policy impact (60%), the *timing* component contributes about 36%, and the *within* component accounts for about 4%.

Next, we diagnose the negative weights issue that may arise in staggered DID models. As highlighted by De Chaisemartin and D'Haultfoeuille (2020), staggered DID estimators can be interpreted as weighted averages of all possible two-period DID comparisons. When treatment effects are heterogeneous across groups and time, some comparisons may receive negative weights, potentially leading to biased estimates and difficult-to-interpret standard errors. To assess this concern, we implement the diagnostic decomposition method proposed by De Chaisemartin and D'Haultfoeuille (2020). Table A2 in the Appendix reports the decomposition results, which show a total of 333 average treatment effects on the treated (ATTs), with 93.4% of the total weight attributed to comparisons with positive weights.

Taken together, the above results suggest that while potential heterogeneity bias and the negative weights issue are not severe, they may still have an impact on our study's results. Therefore, we retain the staggered DID specification as our baseline model and re-estimate the baseline regression using four commonly used heterogeneity-robust estimators to address the "forbidden comparison" problem (De Chaisemartin & D'Haultfoeuille, 2020; Callaway & Sant'Anna, 2021; Gardner, 2022; Borusyak et al., 2024). These heterogeneity-robust models represent our preferred specifications.

Baseline regression

Table 3 reports the impact of the coal-to-gas policy on air pollution. Our empirical results indicate that the policy has significantly improved the AQI, reduced concentrations of particulate matter, SO_2, and NO_2, while leading to an increase in O_3 levels. Specifically, the policy has improved AQI by 4.4% ($\exp(-0.045) - 1 \approx -0.0440$), and reduced $PM_{2.5}$, PM_{10}, SO_2 and NO_2 by 5.7%, 3.4%, 18.6% and 2.9%, respectively;

while it increased O_3 level by 3.4%. Compared with the results of existing studies (see Table 1), our estimates fall within the wide range of findings reported in the literature, but are closer to the lower bound.

The results obtained from the four heterogeneity-robust estimators are broadly consistent with those of the baseline model. As reported in Table 4, the policy improved the AQI (8.3–12.5 %) and reduced concentrations of $PM_{2.5}$ (9.8–15.6 %,), PM_{10} (8.2–12.7 %), SO_2 (26.4–33.6 %), and NO_2 (7.4–10.5 %). This was, however, accompanied by an increase in ozone concentrations (8.3–12.9 %). In terms of magnitude, the coefficients in Table 4 are, on average, about twice as large as those from the baseline regression; nevertheless, they remain within the range of estimates documented in the existing literature (see Table 1).

Instrumental variable estimation

The implementation of the coal-to-gas policy may be endogenous, as policy adoption could be systematically related to certain city characteristics, such as the extent of pre-existing local air pollution. To mitigate concerns regarding endogeneity, we construct an instrumental variable (IV) based on the natural geographical distance of each sample city from the capital city of its respective province. The rationale for doing this is that it has been logistically easier to expand the policy to cities closer to the capital city. We follow the approach of Nunn and Qian (2014) and interact this time-invariant city-level variable with year dummies in our estimation to allow for temporal variation. The empirical strategy is implemented using a two-stage least squares framework embedded within the staggered DID design (Hanley, Li, and Wu, 2022).

The rollout pattern of the coal-to-gas policy supports the validity of this instrument. At the provincial level, the policy was generally initiated in the capital city and then gradually expanded to surrounding areas. This sequencing implies that cities located farther from the provincial capital were less likely to be treated in the early phases of the policy, thus satisfying the relevance condition of the instrument.

Moreover, the exclusion restriction is likely to hold because the distance to the provincial capital is plausibly exogenous to unobserved determinants of air quality. In particular, not all provincial capitals were more polluted than other cities in the same province, and distance from the capital is less likely—compared to more direct economic or environmental variables such as industrial structure or income levels—to be correlated with unobserved factors driving changes in air quality. This makes the instrument a relatively clean source of quasi-exogenous variation in policy exposure.

As shown in Table A3 in the Appendix, Column (1), the instrument is significantly negatively correlated with the endogenous treatment variable, supporting its relevance. Specially, the results suggest that an increase of 100 kilometers in the distance between a city and its provincial capital is associated with a 1.3 percentage point decrease in the probability of being selected as a pilot city for the coal-to-gas policy. The Kleibergen-Paap rk Wald F-statistics exceed the 10% critical value thresholds for weak instrument tests, confirming the instrument's strength. In addition, the Kleibergen-Paap rk LM statistics indicate that the model is sufficiently identified, ruling out under-identification. To further verify the exogeneity assumption, Column (2) of Table A3 presents results from a placebo regression using summer AQI as the dependent variable. Since the coal-to-gas policy targets winter heating, any significant correlation between the instrument and summer AQI would suggest the presence of alternative channels. However, the coefficient is small and statistically insignificant, suggesting that the instrument influences winter air pollution primarily through the coal-to-gas policy itself, rather than through other unobserved channels.

Table 5 displays the second-stage IV estimates, which reinforce the baseline findings. Notably, the IV estimates are considerably larger - about seven times higher than those obtained from the baseline model (e.g., –0.045 in the baseline regression vs. –0.299 in the IV model). This difference in magnitudes is consistent with prior research that combines DID and IV methodologies (Hua et al., 2025; Shao et al., 2025). We posit two main reasons for this discrepancy. First, the policy was non-randomly assigned based on pollution severity, with more polluted cities more likely to be selected as pilot sites. Consequently, DID estimates may understate the policy's effect by failing to account for this selection bias, as the most polluted cities would likely have continued to perform poorly in the absence of intervention, making the DID estimates a lower bound of the policy's actual effect. Second, the IV approach identifies the Local Average Treatment Effect (LATE) for compliers - those cities whose treatment status was influenced by the instrument. These cities may experience larger treatment effects than the average treated city due to factors such as higher baseline pollution levels or greater policy enforcement, thus leading to higher IV estimates. Overall, while the IV estimates are substantially larger, they remain within the range of estimates reported in the existing literature, suggesting that the results are plausible and robust (see Table 1).

PSM-DID estimation

To mitigate potential selection biases, this study employs the PSM method combined with the DID framework. Initially, we treat the sample as a pooled cross-section and perform 1:4 nearest-neighbor matching. Then, we implement year-by-year matching following Böckerman and Ilmakunnas (2009). The results are presented in Table 6 and provide evidence that the policy improved the AQI by 4.3% (pooled matching) and 4.5% (year-by-year matching).

It is important to note that the assumption of common support is one of the prerequisites for employing the PSM method (Caliendo and Kopeinig, 2008). The results of common support tests are presented in Figure A1 in the Appendix. Analysis reveals that the majority of observational values fall within the common support range, with only a negligible portion outside this range. Another crucial assumption of the PSM method is the balance assumption. The results of covariate matching quality tests are presented in Figure A2 in the Appendix. Analysis reveals that prior to matching, significant differences exist in the means of most covariates between the treatment and control groups. However, post propensity score matching, the distribution of all covariates between the treatment and control groups becomes balanced. Hence, PSM is an appropriate method in this case.

Parallel trends test

Although the aforementioned findings offer supportive evidence regarding the impact of the coal-to-gas policy on air quality, it is important to acknowledge that the validity of these results relies heavily on the satisfaction of the identification assumption, namely the parallel trends assumption between pilot and non-pilot cities. In accordance with the methodology proposed by Beck et al. (2010), this study employs an event analysis approach to assess the parallel trends assumption. The methodology is outlined below:

$$\ln\left(Y_{c,t}\right) = \beta_0 + \sum_{t=-7}^{6} \beta_t\, CTG\_policy_{c,t} + \beta_2 X_{c,t} + \delta_c + \tau_t + \varepsilon_{c,t} \tag{2}$$

Where β_t represents the difference in air quality between the pilot city and non-pilot cities in different years of the implementation of the coal-to-gas policy. The meaning of other variables is the same as in Equation (1).

Figure 2 reports the results of the parallel trends test for AQI and $PM_{2.5}$ (further evidence from additional parallel trends tests is provided in Appendix Figures A3.) As hypothesized, there is no significant difference in the trend of air pollutant indicators between the treatment group and the control group before policy implementation. This lack of significant pre-impact differences suggests that there is no notable pre-trend before the shock, thereby satisfying the parallel trends assumption.

Although the event study results presented above (Figure 2) reveal no significant pre-treatment differences across the treatment groups, they do not fully address the staggered timing of policy implementation. In particular, the event study tests for average pre-trend differences relative to the treatment year, but may not detect subtler, phase-specific temporal patterns in the data. Therefore, as a conservative robustness check—and to mitigate potential bias arising from treatment effect heterogeneity—we follow Braghieri et al. (2022) by incorporating phase-specific linear time trends into the baseline model. This approach allows for flexible pre-treatment dynamics across implementation phases, enabling more accurate identification of the policy's causal impact on air quality. The results, reported in Table A4 in the Appendix, remain consistent with the baseline findings, reinforcing the robustness of our conclusions.

Placebo test

It is possible that the significant air quality improvements observed above may not be causal effects of the coal-to-gas policy but rather the result of capturing some coincidental occurrence. To rule out this possibility, we conduct a placebo test. First, we perform an in-time placebo test, in which the policy implementation years are randomly reassigned. Second, we conduct an in-space placebo test, where the pilot cities are randomly reassigned. For both tests, we generate 1,000 random samples and re-estimate the baseline model accordingly to obtain the distribution of placebo estimates. If the significant air quality improvement effects found in this study are not driven by coincidence, then the vast majority of placebo regression coefficients should be centered around zero.

Figure 3 visualizes the results of the placebo tests. As seen, the regression coefficients from the 1,000 random assignments are approximately normally distributed around zero. Moreover, all placebo regression coefficients are very small, falling within the range of (-0.02, 0.02), and do not overlap with the baseline regression coefficient (the estimate in Column (1) of Table 3, which is −0.045). This suggests that the significant air quality improvement effects found in this study are indeed causal and not driven by coincidence.

Other robustness checks

To further ensure the robustness of our regression results, we conduct a series of additional checks using AQI as an example. First, following Zhang et al. (2024), we include interaction terms between major concurrent environmental policies (*APPCAP*, *NEDC*, and *LCCP*) and a linear time trend to account for potential time-varying policy effects. Second, following Zhang et al. (2025), we exclude observations from the year immediately preceding the policy rollout to eliminate possible anticipatory effects. Third, following Chen et al. (2024), we test whether wind speed—which accelerates pollutant dispersion—affects our estimates by interacting the policy variable with maximum winter wind speed. Finally, we assess the robustness of our results to excluding regions with strict enforcement of the coal-to-gas policy (e.g., the first phase of pilot programs, provincial capitals, and cities in Hebei Province) as well as regions with relatively lax enforcement (e.g., provinces experiencing extremely cold winters[10]). All robustness checks, reported in Appendix Tables A5 and A6, consistently confirm the stability of our main findings.

5. Channel analysis

In this section, we turn to household-level channels, recognizing the urban–rural heterogeneity inherent in the implementation of the coal-to-gas policy. Accordingly, we analyze urban and rural areas separately.

We begin with urban areas, using data from the *China City Construction Statistical Yearbook*, an official publication by the Ministry of Housing and Urban-Rural Development. This source offers comprehensive data on urban infrastructure and urbanization progress, providing a valuable foundation for assessing energy transition dynamics in cities.

We use *natural gas storage capacity* and *the length of natural gas pipelines* as proxies for municipal gas infrastructure, and employ indicators related to centralized heating in the urban residential sector to measure policy-driven changes in heating systems. Columns (1) and (2) of Table 7 report the relationship between the coal-to-gas policy and municipal gas infrastructure. We find that the policy significantly increased natural gas storage capacity in pilot cities by approximately 37.7% (Column 1), suggesting infrastructure improvements that support residential energy switching. Concurrently, it was associated with only a small and statistically insignificant increase in the length of natural gas pipelines (Column 2). Columns (3) and (4) present the relationship between the policy and centralized heating in the urban residential sector. Here, we find that the policy significantly expanded the floor area covered by

[10] These provinces—Heilongjiang, Jilin, Inner Mongolia, and Xinjiang—are characterized by average winter temperatures below −10 °C, in contrast to most other northern provinces, where average winter temperatures are around 0 °C.

centralized heating by approximately 14% (Column 3), as well as the hot water heating capacity of heating companies by about 14.6% (Column 4). These findings provide supporting evidence that household-level energy transitions—particularly in urban areas—played an important role in improving air quality.

Next, we use micro-level data to further examine the role of households in the policy's air quality effects aiming at rural areas. Specifically, to align with the period covered in the main regressions as closely as possible, we employ three waves of the China Health and Retirement Longitudinal Study (CHARLS) - a nationally representative biennial survey targeting individuals aged 45 and above - conducted in 2015, 2018, and 2020. While a limitation of CHARLS is that it focuses on older adults only, it is arguably still well suited for our analysis as the age restriction allows us to focus on those who are especially sensitive to winter temperatures and are more likely to comply with mandatory energy transition policies (Li et al., 2025). Given the temporal coverage of CHARLS, it is also important to note that our micro-level analysis focuses on the first three phases of the coal-to-gas policy only. Since early pilot implementation tended to be more stringent (Wang et al., 2024), we can expect compliance with the policy to be higher during the initial stages. For both reasons, our micro-level results should be treated as an upper bound of the overall impact of the coal-to-gas policy on households.

Table 8 presents results using CHARLS data. The dependent variables are: (1) whether the household is connected to a natural gas pipeline; (2) whether it uses clean energy for heating; and (3) whether it uses clean energy for cooking. We control for a range of individual and household characteristics—including the household head's age, gender, marital status, education, smoking and drinking habits—as well as annual household income, household size, COVID-19 intensity, and climatic conditions. The results show that the coal-to-gas policy significantly accelerated rural energy transitions. Specifically, it increased the likelihood of rural households being connected to natural gas pipelines by 4.4%, and raised the probability of using clean heating and cooking energy sources by 11.9% and 7.3%, respectively. These findings suggest that household adoption of cleaner energy sources served as a critical pathway through which the policy contributed to air quality improvements. The particularly strong effect on heating likely reflects the policy's emphasis on winter heating in northern China.

6. Conclusions

As China's clean heating initiative advances, the expansion of pilot programs and the consolidation of achieved progress call for a comprehensive evaluation of existing clean heating projects. This study evaluates five phases of the coal-to-gas policy, focusing on northern regions of China with winter seasons. Using balanced city-level panel data from 2015 to 2023, we employ a staggered difference-in-differences framework as the baseline empirical strategy and report results based on heterogeneity-robust estimators.

Our results suggest that the policy improved the Air Quality Index (8.3–12.5 %) and reduced concentrations of $PM_{2.5}$ (9.8–15.6 %,), PM_{10} (8.2–12.7 %), SO_2 (26.4–33.6 %), and NO_2 (7.4–10.5 %). This was, however, accompanied by an increase in ozone concentrations (8.3–12.9 %). Compared with previous studies, these estimated effects fall within the broad ranges reported in the literature but are closer to their lower bound.

Channel analysis suggests that the improvement in air quality is at least partly driven by the promotion of clean energy adoption at the household level. Specifically, the policy has significantly increased urban clean energy infrastructure, promoted the expansion of centralized heating systems, and raised the likelihood of households adopting clean energy in rural areas.

Although our findings indicate that the coal-to-gas policy significantly improved wintertime air quality in northern China, its broader implementation should be considered with caution—particularly given the policy's heavy reliance on government subsidies—raising the question of whether households would continue to adopt clean energy in the absence of substantial financial support. This touches on the broader issue of cost–benefit analysis from the perspective of energy users, which, however, falls beyond the scope of the present study.

Given that the observed air quality improvements are apparently at least partly driven by changes at the household level, policymakers could continue to support the development of clean energy infrastructure - such as natural gas pipelines and centralized heating systems - and enhance accessibility and affordability of clean energy for residents. Strengthening incentives for household-level energy switching will be key to consolidating the environmental gains achieved thus far.

Meanwhile, despite the significant reductions in particulate matter NO_2, and SO_2, the unintended rise in ozone concentrations underscores a growing challenge. Therefore, in addition to targeting primary pollutants, future environmental policies should place greater emphasis on the coordinated control of multiple pollutants, particularly volatile organic compounds and nitrogen oxides, to achieve comprehensive and sustainable air quality improvements.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Available from the corresponding author upon request.

References

Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. Journal of Econometrics. 2021. 225(2): 254-277. https://doi.org/10.1016/j.jeconom.2021.03.014.

Beck T, Levine R, Levkov A. Big bad banks? The winners and losers from bank deregulation in the United States. The journal of finance, 2010. 65(5): 1637-1667.

Braghieri L, Levy R, Makarin A. Social media and mental health. American Economic Review. 2022. 112(11): 3660-3693.

Böckerman P, Ilmakunnas P. Unemployment and self-assessed health: evidence from panel data. Health Econ. 2009.18(2):161-79. doi: 10.1002/hec.1361.

Caliendo, M. and Kopeinig, S. Some Practical Guidance For the Implementation of Propensity Score Matching. Journal of Economic Surveys. 2008. 22: 31-72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Callaway B, and Sant'Anna. Pedro H.C. Difference-in-Differences with multiple time periods. Journal of Econometrics. 2021. 225(2) 200-230. https://doi.org/10.1016/j.jeconom.2020.12.001.

Chen Y, Ebenstein A, Greenstone M, Li H. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc Natl Acad Sci U S A. 2013. 110(32):12936-41. doi: 10.1073/pnas.1300018110.

Chen Qifei, Huang Biyin, Wu Jinlong. Industrial Undertaking and Air Quality in Inland: Evidence from National Demonstration of Industrial Undertaking Transfer. The Journal of Quantitative and Technical Economics. 2024. 41(2):151-170. (in Chinese)

Dao X, Wang Z, Lv Y, Teng E, Zhang L, Wang C. Chemical characteristics of water-soluble ions in particulate matter in three metropolitan areas in the North China Plain. PLoS One. 2014. 9(12): e113831. doi: 10.1371/journal.pone.0113831.

Denise L. Mauzerall, Babar Sultan, Namsoug Kim, David F. Bradford. NOx emissions from large point sources: variability in ozone production, resulting health damages and economic costs. Atmospheric Environment. 2005. 39(16): 2851-2866. https://doi.org/10.1016/j.atmosenv.2004.12.041.

de Chaisemartin, Clément, and Xavier D'Haultfœuille. Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. American Economic Review. 2020. 110(9): 2964–96.DOI: 10.1257/aer.20181169

Gardner J. Two-stage differences in differences. arXiv preprint arXiv:2207.05943, 2022.

He Yichao, Wang Huili, Zheng Yixuan, Feng Yueyi, Chen Xiaojun, Jin Ling, Lei Yu. Revealing air quality impacts of the clean heating campaign in northern China. Energy Economics. 2025. 141:108078. https://doi.org/10.1016/j.eneco.2024.108078.

Hong Hai, Huang Yongbin. Order! the border: Multitasking, air pollution regulation and local government responses. Journal of Environmental Economics and Management. 2025. 131: 103135. https://doi.org/10.1016/j.jeem.2025.103135.

Hanley Douglas, Li Jiancheng, Wu Mingqin. High-speed railways and collaborative innovation. Regional Science and Urban Economics. 2022. 93: 103717. https://doi.org/10.1016/j.regsciurbeco.2021.103717.

Hua Zesu, Kong Shuning, Yu Yihua. Talent magnets in China: Can talent attraction policies catalyze digital transformation in enterprises? China Economic Review. 2025. 90: 102376. https://doi.org/10.1016/j.chieco.2025.102376.

Jiang Lei, Zhou Hai-feng, Bai Ling, Zhou Peng. Does foreign direct investment drive environmental degradation in China? An empirical study based on air quality index from a spatial perspective. Journal of Cleaner Production. 2018. 176: 864-872. https://doi.org/10.1016/j.jclepro.2017.12.048.

Kirill Borusyak, Xavier Jaravel, Jann Spiess, Revisiting Event-Study Designs: Robust and Efficient Estimation. The Review of Economic Studies. 2024. 91, Issue 6: 3253–3285. https://doi.org/10.1093/restud/rdae007

Leng, X., Zhao, X. and Li, H. Assessing the effect of the coal-to-gas program on air pollution: evidence from China. Environ Sci Pollut Res. 2023. 30, 24027–24042. https://doi.org/10.1007/s11356-022-23739-6

Li Tianxin, Li Yong, An Difei, Han Yangwen, Xu Shuiyang, Lu Zhongming, John Crittenden. Mining of the association rules between industrialization level and air quality to inform high-quality development in China. Journal of Environmental Management. 2019. 246: 564-574. https://doi.org/10.1016/j.jenvman.2019.06.022.

Li Haizheng, Ma Mingyu, Liu Qinyi. How the COVID-19 pandemic affects job sentiments of rural teachers. China Economic Review. 2022. 72: 101759. https://doi.org/10.1016/j.chieco.2022.101759.

Li Fanlue, He Ke, Zhu Run. The health effect of the clean energy transition on middle-aged and elderly farmers: Evidence from clean heating program in China. Journal of Asian Economics. 2025. 98, 101924. https://doi.org/10.1016/j.asieco.2025.101924.

Lin, J-T., and Michael Brendon McElroy. Detection from space of a reduction in anthropogenic emissions of nitrogen oxides during the Chinese economic downturn. Atmospheric Chemistry and Physics. 2011. 11.15: 8171-8188.

Liu Qianqian, Wang Shaojian, Zhang Wenzhong, Li Jiaming, Dong Guanpeng. The effect of natural and anthropogenic factors on PM2.5: Empirical evidence from Chinese cities with different income levels. Science of The Total Environment. 2019. 653: 157-167. https://doi.org/10.1016/j.scitotenv.2018.10.367.

Lueken Roger, Klima Kelly, W. Michael Griffin, Apt Jay. The climate and health effects of a USA switch from coal to gas electricity generation. Energy. 2016. 109: 1160-1166. https://doi.org/10.1016/j.energy.2016.03.078

Mao Xianqiang, Guo Xiurui, Chang Yongguan, Peng Yingdeng. Improving air quality in large cities by substituting natural gas for coal in China: changing idea and incentive policy implications. Energy Policy. 2005. 33(3): 307-318. https://doi.org/10.1016/j.enpol.2003.08.002.

McGlade Christophe, Pye Steve, Ekins Paul, Bradshaw Michael, Jim Watson. The future role of natural gas in the UK: A bridge to nowhere? Energy Policy. 2018. 113: 454-465. https://doi.org/10.1016/j.enpol.2017.11.022.

Nunn, Nathan, and Nancy Qian. US Food Aid and Civil Conflict. American Economic Review. 2014. 104 (6): 1630–66.DOI: 10.1257/aer.104.6.1630

Rafindadi AA, Yusof Z, Zaman K, Kyophilavong P, Akhmat G. The relationship between air pollution, fossil fuel energy consumption, and water resources in the panel of selected Asia-Pacific countries. Environ Sci Pollut Res Int. 2014. 21(19):11395-400. doi: 10.1007/s11356-014-3095-1.

Scott Angelique J., Scarrott Carl. Impacts of residential heating intervention measures on air quality and progress towards targets in Christchurch and Timaru, New Zealand. Atmospheric Environment. 2011. 45(17): 2972-2980. https://doi.org/10.1016/j.atmosenv.2010.09.008.

Shao Xu, Yang Qicheng, Liu Zhao. China's aid-giving modalities: Impacts on sustainable growth in China-Africa trade. China Economic Review. 2025. 90: 2025. https://doi.org/10.1016/j.chieco.2025.102370.

Shi Tianqi, Peng Yanran, Ma Xin, Han Ge et al. China's “coal-to-gas” policy had large impact on PM1.0 distribution during 2016–2019. Journal of Environmental Management. 2024. 359: 121071. https://doi.org/10.1016/j.jenvman.2024.121071.

Tan Xin, Chen Guanghui, Chen Kunxian. Clean heating and air pollution: Evidence from Northern China. Energy Reports. 2023. 9: 303-313. https://doi.org/10.1016/j.egyr.2022.11.166

Wang, J., Li, Z., Ye, H. *et al.* Do China's coal-to-gas policies improve regional environmental quality? A case of Beijing. Environ Sci Pollut Res. 2021. 28, 57667–57685. https://doi.org/10.1007/s11356-021-14727-3

Wang Xueyang, Sun Xiumei, Ahmad Mahmood, Zhang Haotian. Does low carbon energy transition impede air pollution? Evidence from China's coal-to-gas policy. Resources Policy. 2023. 83: 103723. https://doi.org/10.1016/j.resourpol.2023.103723

Wang Manyu, Xie Lunyu. Households' participation in energy transition and sustained use of clean energy: Evidence from China's clean heating program. China Economic Review. 2023. 80, 102005. https://doi.org/10.1016/j.chieco.2023.102005.

Wang Haijian, Zhou Shaojie, Zhang Penglong. Clean heating and clean air: Evidence from the coal-to-gas program in China. China Economic Review. 2024. 85, 102179. https://doi.org/10.1016/j.chieco.2024.102179.

Wu Shimei, Zheng Xinye, Nina Khanna, Feng Wei. Fighting coal — Effectiveness of coal-replacement programs for residential heating in China: Empirical findings from a household survey. Energy for Sustainable Development. 2020. 55: 170-180. https://doi.org/10.1016/j.esd.2020.02.002.

Wu Desheng, Xie Yu, Liu Dingjie. Rethinking the complex effects of the clean energy transition on air pollution abatement: Evidence from China's coal-to-gas policy. Energy. 2023. 283: 128413. https://doi.org/10.1016/j.energy.2023.128413

Xie Yu, Wu Desheng, Zhu Shujin. Can new energy vehicles subsidy curb the urban air pollution? Empirical evidence from pilot cities in China. Science of The Total Environment. 2021. 754: 142232. https://doi.org/10.1016/j.scitotenv.2020.142232

Xie Lunyu, Hu Xian, Zhang Xinyi, Zhang Xiao-Bing. Who suffers from energy poverty in household energy transition? Evidence from clean heating program in rural China. Energy Economics. 2022. 106, 105795.https://doi.org/10.1016/j.eneco.2021.105795

Xu Shuo, Ge Jianping. Sustainable shifting from coal to gas in North China: An analysis of resident satisfaction. Energy Policy. 2020. 138, 111296. https://doi.org/10.1016/j.enpol.2020.111296

Yoon Byungun, Shin Juneseuk, Lee Sungjoo. Technology assessment model for sustainable development of LNG terminals. Journal of Cleaner Production. 2018. 172: 927-937. https://doi.org/10.1016/j.jclepro.2017.10.187

Yu Chenyang, Kang Jijun, Teng Jing, Long Hongyu, Fu Yunying. Does coal-to-gas policy reduce air pollution? Evidence from a quasi-natural experiment in China. Science of The Total Environment. 2021. 773: 144645. https://doi.org/10.1016/j.scitotenv.2020.144645

Zeng Bohan, Wu Tian, Guo Xiaoxian. Interprovincial trade, economic development and the impact on air quality in China. Resources, Conservation and Recycling. 2019. 142: 204-214. https://doi.org/10.1016/j.resconrec.2018.12.002

Zeng Jingjing, Bao Rui, Michael McFarland. Clean energy substitution: The effect of transitioning from coal to gas on air pollution. Energy Economics. 2022. 107: 105816. https://doi.org/10.1016/j.eneco.2022.105816

Zhang Yali, Li Wenqi, Wu Feng. Does energy transition improve air quality? Evidence derived from China's Winter Clean Heating Pilot (WCHP) project. Energy. 2020. 206: 118130. https://doi.org/10.1016/j.energy.2020.118130

Zhang Ruining, Ai Xianneng, Li Hui. How to design subsidy policies for clean energy projects? A study on "coal-to-gas" project in China. Resources Policy. 2023. 85, Part B. 103928. https://doi.org/10.1016/j.resourpol.2023.103928

Zhang Zhijian, Zhang Lingyan, Wu Shu. Does ethanol-blended gasoline policy improve air quality in China? Energy Economics. 2024. 134: 107579. https://doi.org/10.1016/j.eneco.2024.107579

Zhang Jingxue, Yu Shiwei, Zhang Yue-Jun, Su Bin, Sun Ya-Fang. How do renewable energy policies affect energy green development? Evidence from Chinese listed energy firms. Energy Economics. 2025. 142: 108154. https://doi.org/10.1016/j.eneco.2024.108154

Zhi, Guorui, et al. Rural household coal use survey, emission estimation and policy implications. Research of environmental science. 2015. 28 (8): 1179-1185

Zornitza Kirova-Yordanova. Exergy-based estimation and comparison of urea and ammonium nitrate production efficiency and environmental impact. Energy. 2017. 140(1): 158-169. https://doi.org/10.1016/j.energy.2017.08.086

Figures and Tables

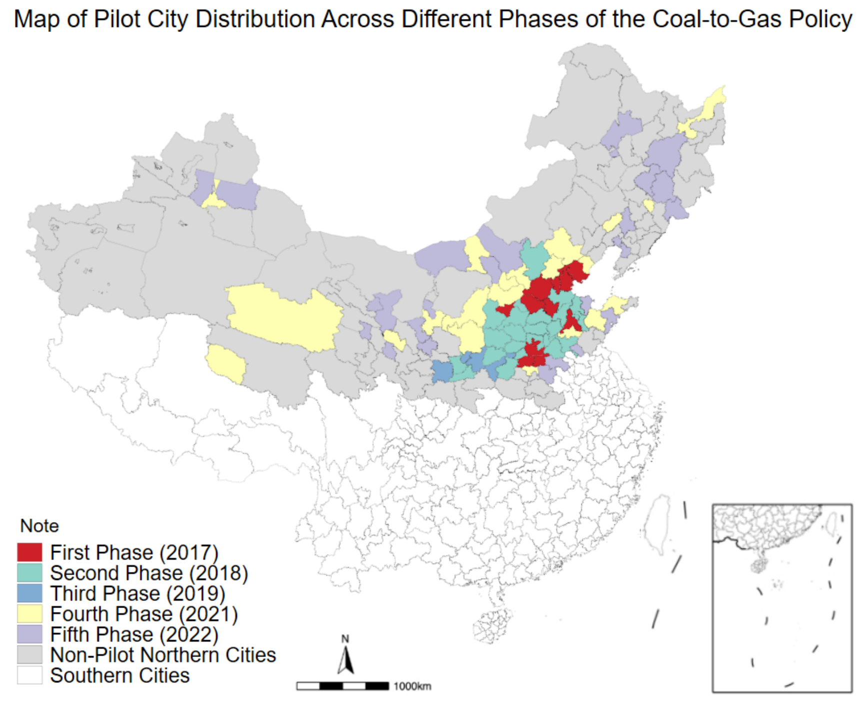

Figure 1. Distribution of pilot cities.

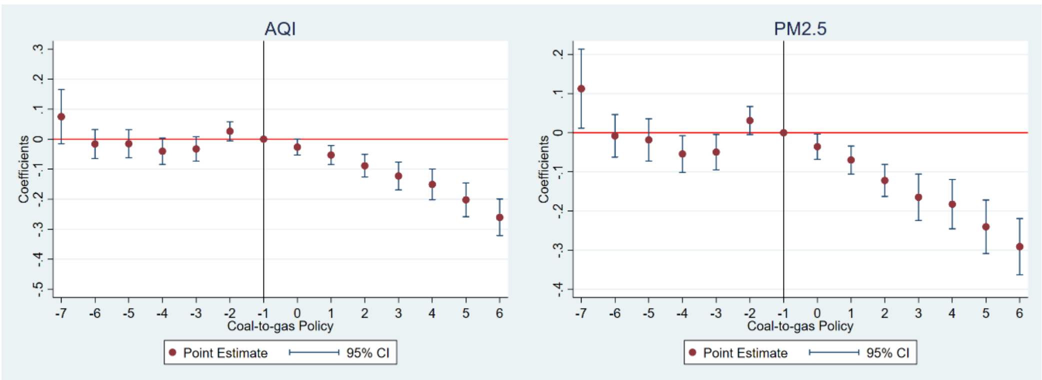

Figure 2. Parallel trends test of AQI and $PM_{2.5}$ in the treated and control groups.

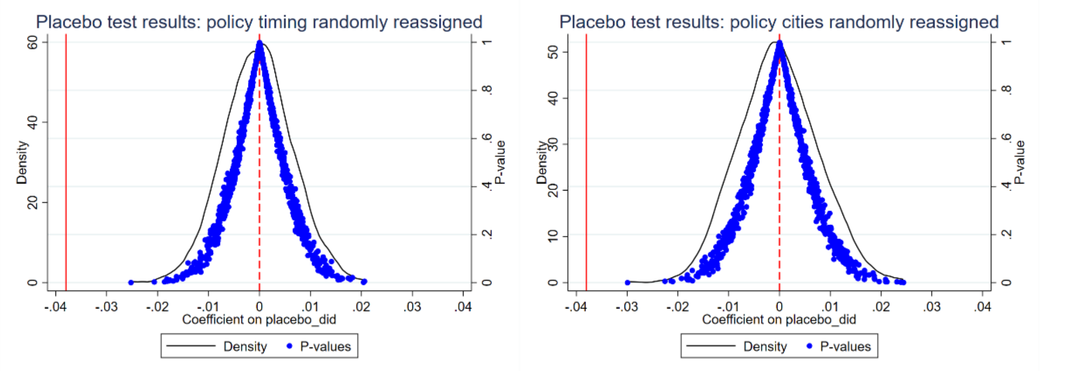

Figure 3. Placebo test.

Notes: Figure 3 presents placebo estimates of the impact of the coal-to-gas policy on AQI.

The left panel displays results from the placebo test in which the policy implementation timing is randomly reassigned, while the right panel shows results from the test with randomly reassigned pilot cities.

A solid, vertical red line in the figure marks the coefficient estimate from our baseline regression.

Table 1. Overview of existing research

	Estimated range of the air quality improvement effect of the coal-to-gas policy
AQI	1.8% (Wu et al., 2023) ~ 49.3% (Wang et al., 2024)
$PM_{2.5}$	1.2% (Zeng et al., 2022) ~ 67.4% (Wang et al., 2024)
SO_2	5.9 % (Zeng et al., 2022) ~ 144% (Wang et al., 2024)
NO_2	6.3% (Wu et al., 2023) ~ 34.1 % (Zhang et al., 2020)

Table 2. Descriptive statistics

Variable name	**Description**	**Mean (SD)**
Dependent Variables		
AQI	Air quality index (range 0-500)	97.281 (31.753)
$PM_{2.5}$	$PM_{2.5}$ concentration (μg/m^3)	65.727 (27.634)
PM_{10}	PM_{10} concentration (μg/m^3)	109.956 (39.980)
SO_2	Sulfur dioxide concentration (μg/m^3)	27.730 (23.428)
NO_2	Nitrogen dioxide concentration (μg/m^3)	40.360 (12.525)
O_3	Ozone concentration (μg/m^3)	36.188 (8.833)
Control Variables		
GDP_pc	GDP per capita (log)	10.848 (0.486)
Pop_density	Population per unit area (log)	5.441 (1.014)
IndusFirms	The number of industrial enterprises (log)	6.217 (1.027)
SecGDP_ratio	Share of secondary industry value added in GDP (%)	41.292 (11.786)
FDI_pc	Annual foreign capital investment per company (log)	10.235 (2.302)
Vehicle_cap	Vehicle transport capacity (z-score standardization)	0.009 (0.490)
COVID_intensity	Cumulative confirmed COVID-19 cases per capita (log)	0.674 (1.208)
APPCPA	Whether the city was an APPCPA pilot city in that year (0/1)	0.021 (0.142)
NEDC	Whether the city was an NEDC pilot city in that year (0/1)	0.172 (0.378)
LCCP	Whether the city was an LCCP pilot city in that year (0/1)	0.339 (0.473)
Avg_temp	Winter average temperature (Celsius)	-2.282 (6.179)

Avg_visibility	Winter average visibility (Miles)	11.608 (23.375)
Avg_wind_speed	Winter average wind speed (Knots)	8.570 (16.367)
Avg_precip	Winter average precipitation (Inches)	0.864 (2.921)

Note: Based on a sample of 1,161 city-year observations.

APPCPA stands for Air Pollution Prevention and Control Action Plan, NEDC for New Energy Demonstration City policy, and LCCP for Low-Carbon City Pilot policy.

Table 3. The impact of coal-to-gas policy on air pollution: baseline model

Panel A	ln (AQI)	ln ($PM_{2.5}$)	ln (PM_{10})
$CTG\_policy_{c,t}$	-0.045***	-0.059***	-0.035**
	(0.014)	(0.016)	(0.017)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	-1.618	-2.743	0.333
	(2.453)	(2.808)	(2.815)
N	1,161	1,161	1,161
R^2	0.902	0.924	0.882
Panel B	**ln (SO_2)**	**ln (NO_2)**	**ln (O_3)**
$CTG\_policy_{c,t}$	-0.205***	-0.029**	0.035**
	(0.034)	(0.015)	(0.014)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	5.018	3.047	-0.641
	(6.269)	(2.099)	(2.445)
N	1,161	1,161	1,161
R^2	0.907	0.912	0.866

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively. The values in parentheses represent robust standard errors clustered at the city level.

Table 4. The impact of coal-to-gas policy on air pollution: heterogeneity-robust estimators

Method	De Chaisemartin & D'Haultfoeuille (2020)	Callaway & Sant'Anna (2021)	Borusyak et al. (2024)	Gardner (2022)
Outcome variable	ln (AQI)	ln (AQI)	ln (AQI)	ln (AQI)
$CTG\_policy_{c,t}$	-0.093***	-0.133***	-0.087***	-0.100***
	(0.018)	（0.019）	（0.018）	(0.018)
Outcome variable	ln ($PM_{2.5}$)	ln ($PM_{2.5}$)	ln ($PM_{2.5}$)	ln ($PM_{2.5}$)
$CTG\_policy_{c,t}$	-0.119***	-0.169***	-0.103***	-0.118***
	(0.021)	(0.023)	(0.021)	(0.021)
Outcome variable	ln (PM_{10})	ln (PM_{10})	ln (PM_{10})	ln (PM_{10})
$CTG\_policy_{c,t}$	-0.086***	-0.136***	-0.095***	-0.102***
	(0.021)	(0.023)	(0.021)	(0.022)
Outcome variable	ln (SO_2)	ln (SO_2)	ln (SO_2)	ln (SO_2)
$CTG\_policy_{c,t}$	-0.307***	-0.409***	-0.381***	-0.343***
	(0.040)	(0.051)	(0.452)	(0.043)
Outcome variable	ln (NO_2)	ln (NO_2)	ln (NO_2)	ln (NO_2)
$CTG\_policy_{c,t}$	-0.082***	-0.111***	-0.077***	-0.078***
	(0.015)	(0.018)	(0.021)	(0.018)
Outcome variable	ln (O_3)	ln (O_3)	ln (O_3)	ln (O_3)
$CTG\_policy_{c,t}$	0.080***	0.121***	0.107***	0.092***
	(0.015)	(0.017)	(0.017)	(0.018)

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.
The above estimates include control variables and fixed effects.

Table 5. The impact of coal-to-gas policy on air pollution: IV model

Panel A	ln (AQI)	ln ($PM_{2.5}$)	ln (PM_{10})
$CTG\_policy_{c,t}$	-0.299***	-0.253***	-0.336***
	(0.085)	(0.084)	(0.109)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	-5.797*	-5.935*	-4.608
	(3.124)	(3.214)	(3.529)
N	1,161	1,161	1,161
R^2	0.904	0.924	0.884
Panel B	**ln (SO_2)**	**ln (NO_2)**	**ln (O_3)**
$CTG\_policy_{c,t}$	-1.050***	-0.234**	0.269***
	(0.196)	(0.115)	(0.095)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	-8.852	-0.316	3.202
	(5.897)	(2.595)	(2.741)
N	1,161	1,161	1,161
R^2	0.907	0.913	0.869

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively. The values in parentheses represent robust standard errors clustered at the city level.

Table 6. The impact of coal-to-gas policy on air pollution, measured by AQI: PSM-DID

Method	Pooled (cross-sectional) matching	Year-by-year matching
$CTG\_policy_{c,t}$	-0.044***	-0.046***
	(0.015)	(0.015)
Control variables	YES	YES
Fixed effects	YES	YES
Constant	-2.000	-2.324
	(2.601)	(2.496)
N	1,086	1,056
R^2	0.900	0.902

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively. The values in parentheses represent robust standard errors clustered at the city level.

Table 7. Energy transition channels in urban areas

	Natural gas storage capacity	Length of natural gas pipelines	Residential floor area covered by centralized heating	Hot water heating capacity for residential centralized heating
$CTG\_policy_{c,t}$	0.320^{**}	0.009	0.131^{*}	0.136^{**}
	(0.142)	(0.057)	(0.074)	(0.067)
Control variables	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
Constant	19.365	12.907	-10.035	-11.664
	(26.696)	(8.882)	(9.177)	(12.327)
N	1,038	1,021	1,161	1,104
R^2	0.789	0.945	0.957	0.860

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.

Table 8. Energy transition channels in rural areas

	Household connection to natural gas pipelines	Use of clean energy for heating	Use of clean energy for cooking
$CTG\_policy_{c,t}$	0.043^{**}	0.112^{***}	0.070^{***}
	(0.018)	(0.023)	(0.022)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	0.361	0.789^{***}	0.829^{***}
	(0.234)	(0.291)	(0.235)
N	6,182	6,178	6,166
R^2	0.537	0.624	0.728

Notes: Clean energy refers to natural gas or electricity.
The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.
Fixed effects include household fixed effects and year fixed effects.

Appendices

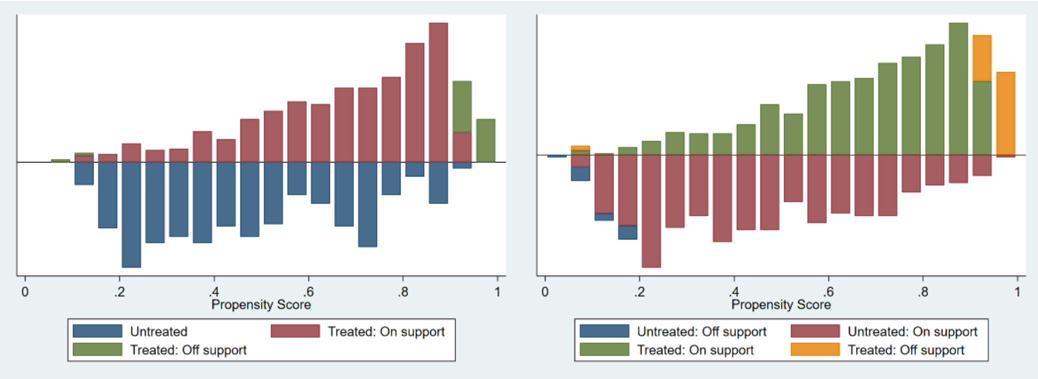

Figure A1. Common range of values for the propensity score

Note: The left panel reports results based on pooled (cross-sectional) matching; the right panel reports results based on year-by-year matching.

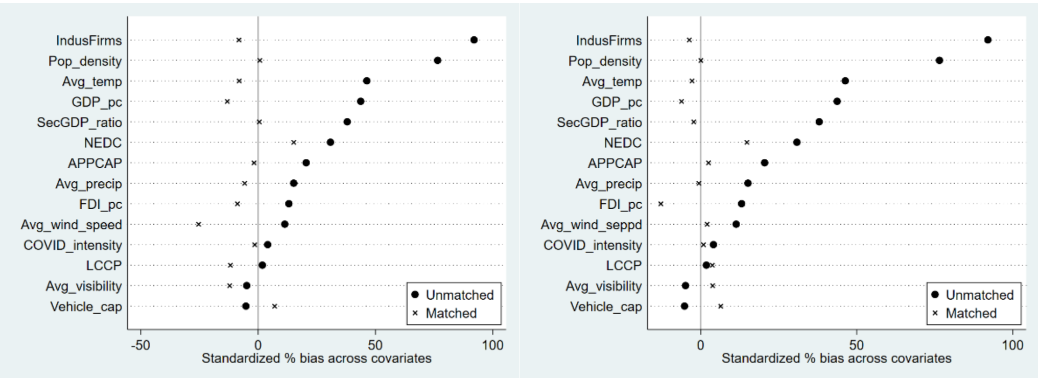

Figure A2. Standardized bias of covariates before and after matching

Note: The left panel reports results based on pooled (cross-sectional) matching; the right panel reports results based on year-by-year matching.

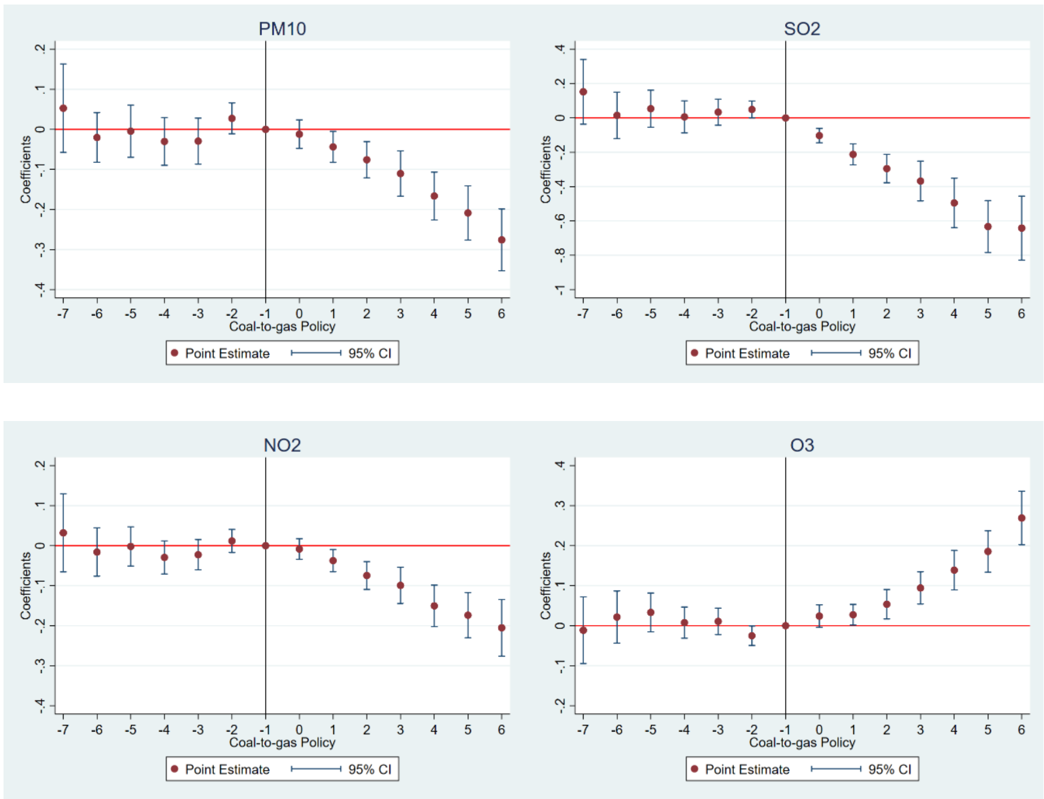

Figure A3. Parallel trends test of PM_{10}, SO_2, NO_2 and O_3 in the treatment and control groups

Table A1. Goodman-Bacon decomposition

	ln (AQI)	
Bacon Decomposition	Beta	Total Weight
Timing groups	0.016	0.355
Never treated vs. Timing groups	-0.063	0.601
Within	-0.291	0.044

Notes: The table above presents the estimates of the impact of the coal-to-gas policy on AQI.

Table A2. De Chaisemartin - D'Haultfoeuille decomposition

Variable	Total ATTs	Positive ATTs	Negative ATTs	Weight of Positive ATTs	Standard Deviation
ln (AQI)	333	311	22	93.393%	0.361

Notes: The table above presents the estimates of the impact of the coal-to-gas policy on AQI.

Table A3. The impact of coal-to-gas policy on air pollution: IV validity tests

	First stage	ln (AQI) (summer-season)
IV	-0.013***	0.001
	(0.003)	(0.001)
F-statistic	22.268	
Kleibergen-Paap rk LM	12.186***	
Control variables	YES	YES
Fixed effects	YES	YES
Constant	35.573***	0.152
	(11.615)	(4.714)
N	1,161	1,161
R^2	0.667	0.914

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.
The table above presents the estimates of the impact of the coal-to-gas policy on AQI.

Table A4. The impact of coal-to-gas policy on air pollution after controlling for phase-level linear time trends

Panel A	ln (AQI)	ln ($PM_{2.5}$)	ln (PM_{10})
$CTG\_policy_{c,t}$	-0.050***	-0.058***	-0.044**
	(0.014)	(0.016)	(0.017)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Phase-level linear time trends	YES	YES	YES
Constant	-1.569	-2.747	0.418
	(2.440)	(2.830)	(2.793)
N	1,161	1,161	1,161
R^2	0.902	0.924	0.882
Panel B	ln (SO_2)	ln (NO_2)	ln (O_3)
$CTG\_policy_{c,t}$	-0.209***	-0.033**	0.051***
	(0.031)	(0.016)	(0.015)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Phase-level linear time trends	YES	YES	YES
Constant	5.051	3.090	-0.793
	(6.263)	(2.093)	(2.479)
N	1,161	1,161	1,161
R^2	0.907	0.912	0.867

The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.

Table A5. Additional robustness tests

Model specification	Controls for other environmental policies and their time trends	Addressing policy anticipation	Controls for pollutant dispersion
Outcome variable	ln (AQI)	ln (AQI)	ln (AQI)
$CTG\_policy_{c,t}$	-0.058***	-0.034**	-0.045***
	(0.015)	(0.014)	(0.014)
Control variables	YES	YES	YES
Fixed effects	YES	YES	YES
Constant	-1.699	-1.509	-1.574
	(1.913)	(1.982)	(1.895)
N	1,161	1,083	1,161
R^2	0.903	0.898	0.902

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.
Column 3 controls for maximum wind speed and the interaction term between maximum wind speed and the policy.

Table A6. Robustness tests: subsample regressions

Alternative samples	Without pilot cities from the first phase	Without provincial capitals	Without Hebei Province	Without provinces with extremely cold winters
Outcome variable	ln (AQI)	ln (AQI)	ln (AQI)	ln (AQI)
$CTG\_policy_{c,t}$	-0.037***	-0.048***	-0.036***	-0.033***
	(0.012)	(0.012)	(0.012)	(0.012)
Control variables	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES
Constant	-2.667	-1.504	-3.283*	1.223
	(2.114)	(2.105)	(1.978)	(2.189)
N	1,062	1,044	1,062	873
R^2	0.899	0.905	0.900	0.900

Notes: The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.
The values in parentheses represent robust standard errors clustered at the city level.