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Investing in a transition fuel: The remarkable decline in mortality from China's rollout of natural gas infrastructure

Wangyang Lai[a,*], Liguo Lin[b,e], Xiaochi Shen[c], Maigeng Zhou[d]

[a] School of Advanced Agricultural Sciences, Peking University, China
[b] School of Economics, Shanghai University of Finance and Economics, China
[c] Antai College of Economics & Management, Shanghai Jiao Tong University, China
[d] National Center for Chronic and Non-communicable Disease Control and Prevention, Chinese Center for Disease Control and Prevention, China
[e] Key Laboratory of Mathematical Economics (SUFE), Ministry of Education, Shanghai 200433, China

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ABSTRACT

The world is undergoing a monumental energy transition. Leveraging China's rollout of natural gas infrastructure, this study estimates the effects of energy access on mortality from 2004 to 2015. The data link the detailed locations and timings of pipeline setup with quarterly administrative death records. The results indicate a 53% increase in household gas usage and a 12% decline in death rate. Mortality reduction is largely driven by decreases in cardiorespiratory diseases and lung cancers, and particularly in the female population. This health benefit is primarily attributed to reduced air pollution due to the shift from dirty fuels to natural gas. The findings underscore the significant potential of transition fuel investments for public health.

1. Introduction

Substantial investments have been made to expand energy access around the world for many decades. Recognizing its importance, the United Nation included "ensuring access to clean and affordable energy" in its 17 Sustainable Development Goals. A natural question, and one that is central for policy, is the extent to which energy access can increase the welfare. This question has recently attracted renewed attention in light of global climate change concerns and widespread awareness of carbon neutrality. The energy sector, based primarily on fossil fuels, is undergoing a monumental transformation. Particularly, on the pathway towards green

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* Corresponding author.
E-mail addresses: laiwangyang@pku.edu.cn (W. Lai), lin.liguo@mail.shufe.edu.cn (L. Lin), romanann@foxmail.com (X. Shen), maigengzhou@126.com (M. Zhou).

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technologies and clean sources, whether it is worthwhile to invest in a transition fuel sparks considerable debates.[1]

This study estimates the health effects from investing in natural gas infrastructure. The research design explores a large scale of pipeline expansion in the context of China from 2004 to 2015. These projects connect the gas resources in western China to the eastern markets as well as users along the lines. The dramatic growth in pipeline expansion provides us a unique chance to examine the benefits and trade-offs of an energy transition. Among the most prominent projects is the West-East Gas Pipeline Project, the nation's largest and longest energy initiative, with an investment of 0.42 trillion yuan by 2016. Spanning over 20,000 km, it connects the Tarim Basin in Xinjiang with the Yangtze and Pearl Delta regions, extending through 30 provinces.

The data link detailed locations and timings of pipeline setup with administrative death records at the quarterly level, sourced from the China Disease Surveillance Point (DSP). The key empirical concern is attributing to pipeline projects the effect of other unobserved economic conditions that may be correlated with mortality. These large pipelines are designed and regulated by the central government owing to long-distance transfer over complicated geological conditions and thus plausibly exogenous to local economic conditions. Our identification strategy follows the event study framework. We validate the common trend assumption using the conventional approach and the interaction-weighted estimator (Sun and Abraham, 2021), which accounts for the heterogeneous treatment effects in recent difference-in-differences literature. The results are robust to a wide range of model specifications and placebo tests.

The results indicate that pipeline expansion increases household natural gas usage by 53% and decreases death rate by 12%. The mortality reduction is largely driven by cardiorespiratory diseases and lung cancers. The effects are notably stronger for women than men. Several potential mechanisms are examined, including air pollution, industrial labor employment, economic prosperity, and energy prices. We find that air pollution serves as a primary factor in mortality reduction. This aligns with the observation that natural gas is mainly used for cooking in households, promoting a shift from dirtier fuels and reducing indoor air pollution. Given that cooking fall disproportionately on women's shoulder in China, the energy transition also results in pronounced gender-specific health benefits.

This study contributes to the literature in three ways. First, it improves our understanding on the developmental effects of energy access. While many studies have explored this topic, their findings are mixed. Some studies document significant positive effects, whereas others find only modest effects for various reasons, including low adoption rate, intermittent usage, poor maintenance (Barron and Torero, 2017; Burlig and Preonas, 2024; Dinkelman, 2011; Hanna et al., 2016; Jack, 2017; Lee et al., 2020a; Lee et al., 2020b; Clay et al., 2024; Lipscomb et al., 2013; Rud, 2012). Therefore, we have a limited understanding on the full potential that energy upgrade can improve the welfare in the developing countries. We also speak to gender inequality by highlighting that energy transition can have differential gender effects, shaped by existing social, economic and cultural factors (Duflo, 2012; Jayachandran, 2015; Verma and Imelda, 2022).

Second, this study contributes to the policy debates on transition fuels. Natural gas, as a typical transition fuel, offers advantages such as ease of storage and delivery, helping to mitigate energy uncertainty caused by the variability of renewable energy sources. It also helps smooth seasonal and short-term demand fluctuations, supporting the stability of power systems and avoiding the devastating effects from power shortages (He and Tanaka, 2023; Fried and Lagakos, 2023). However, as a fossil fuel, natural gas still contributes to global warming. Investments in natural gas may also bring the "lock-in" situation, potentially delaying the transition to a zero-carbon future. Our findings highlight that the transition fuel accelerates the phasing out of coal and petroleum, which brings sizable health benefits. Our cost-benefit estimates have broader implications for countries striving to reach the goals of carbon net zero and a clean environment.

Third, this work speaks to the literature on air pollution and health outcomes. Many studies have examined the negative effects of air pollution from various sources, including winter heating (Ebenstein et al., 2017; Salvo et al., 2024), agricultural fire (Graff Zivin et al., 2020; He et al., 2020), traffic congestion (Currie and Walker, 2011; He et al., 2018) and environmental regulations (Greenstone and Hanna, 2014), but indoor air pollution remain understudied (Hanna et al., 2016; Imelda, 2020; Verma and Imelda, 2022). According to the World Health Organization, 2018, 43% of the global population, largely in developing countries, still relies on biomass fuels for their domestic needs, constituting a major source of household air pollution. Our research design exploits the exogenous variations from the largest pipeline projects in China, allowing us to provide one of the few causal estimates.

The remainder of this paper is organized as follows. Sections 2 and 3 cover the institutional background and data. Section 4 describes the empirical strategies. Section 5 examines the effects of pipeline expansion on natural gas usage and death rate, including regression results and heterogeneous effects. Section 6 provides the robustness tests. Sections 7 explores potential mechanisms. Section 8 conducts a cost-benefit analysis. Finally, Section 9 concludes the study.

2. Background

Since the late 1990s, China has made numerous breakthroughs in domestic gas exploration and development, achieving steady increases in both proven reserves and production (Xu and Allen, 2019). Accordingly, a network of gas pipelines began to develop rapidly; gas production and consumption also increased quickly. From 2004 to 2015, domestic natural gas production rose from 40.8 billion cubic meters to 118.3 billion cubic meters, with an average annual growth of 13.3%. Natural gas consumption rose from 41.5 billion cubic meters to 167.6 billion cubic meters, with an average annual growth of over 15%.

[1] See the debates from United Nation environment program (https://www.unep.org/news-and-stories/story/natural-gas-really-bridge-fuel-world-needs.) or European Commission endorsing fossil gas as a transition fuel for private investment (https://www.reuters.com/business/sustainable-business/eu-parliament-vote-green-gas-nuclear-rules-2022-07-06/.).

Pipeline construction. The West-East Gas Pipeline Project is one of the most famous natural gas transmission projects. The project involves the construction of four gas pipelines connecting the eastern markets of China with the western resources. The construction of the first west-east gas pipeline began in 2002 and the pipeline became commercially operational in 2004. It originates from the Tarim Basin in Xinjiang province, passes through 10 provinces, and ends in Shanghai, with a total length of 4380 km. The construction of the second pipeline began in 2008, and it was completed in December 2012. It connects Horgos in Xinjiang to Shanghai in the east and Guangzhou in the south, passing through 14 provinces with a total length of 8819 km (see Fig. 2).

The third pipeline runs from Horgos in Xinjiang to Fuzhou in Fujian, crossing ten provinces. It stretches over a total length of 6840 km. The construction of the third pipeline began in 2012, and the pipeline was put into operation in 2016. The fourth west-east gas pipeline is currently in the planning stage. Overall, the West-East Gas Pipeline project is the longest, with a total mileage of more than 20,000 km, delivering 77 billion cubic meters of natural gas annually to 30 provinces. This project is also the largest energy project with the highest number of beneficiaries. The total investment as of 2016 was 0.42 trillion yuan, and the number of beneficiaries was potentially 400 million.

In addition to the West-East Gas Project, three major gas pipeline projects connect the gas resources in western areas to eastern China. The most northern one is the Shaan-Jing Gas Pipeline Project, which starts from the gas processing plants in the Changqing gas field in Shaanxi province and ends in terminals in Beijing. The middle one is the Sichuan-Shanghai Gas Pipeline Project. It runs from the Pugang gas field in Sichuan province to Shanghai. The construction started in 2007 and was completed in 2010. The southernmost one is the Myanmar-China Gas Pipeline Project. It connects Ramree Island on the western coast of Myanmar to Ruili city in Yunnan province. The project became operational in 2013.

Major use. In order to shed light on the channels of pipeline effects on death rate, it is helpful to discuss the major uses of natural gas: the residential sector, the industrial sector and the transport, storage and post service sector (the transport sector hereafter). Figure A1 shows the composition of natural gas consumption according to the 2015 China Energy Statistics Yearbook. The residential, industrial and transport sectors account for 30%, 46% and 16% of total natural gas consumption, respectively.

Natural gas in the residential sector is mainly used in kitchens for cooking in urban areas.[2] The structure of residential energy consumption has changed over year owing to the introduction of natural gas. Fig. 1 shows the per capita usages of natural gas, coal and liquefied petroleum gas (in calorific value) for urban households. Natural gas (green diamonds) increases each year stably, ranging from 0.018 in 2005 to 0.061 tons in 2015. Coal (grey triangles) decreases stably over year, ranging from 0.042 in 2005 to 0.012 tons in 2015. Liquefied petroleum gas (LPG, purple circle) remains similar at both ends of the study period (0.033 in 2005 to 0.042 tons in 2015). Additionally, there is a downward trend in using biomass fuels, particularly in the suburban areas (Zhao et al., 2018). The shift in energy composition reflects the gradual phasing out of dirty energy sources, helping to reduce concentrated peaks of pollution exposure, while cooking at home is not continuous throughout the day.

The industrial sector uses the largest share of natural gas. Existing studies show that pipelines increase industrial gas intensity, decrease coal intensity and increase ambient air quality (Xu and Allen, 2019). While the industrial sector consumes a large portion of natural gas, natural gas only contributes to a small part of the energy consumption in the industrial sector. Figure A2 shows the consumption of different energies (in calorific value) in the industrial sector over the years. The usage of natural gas (green color) increases from 33.6 (4%) in 2004 to 108.6 (7%) million tons in 2015. The introduction of natural gas gradually changes the existing structure of industrial energy consumption. In the transport sector, the use of petroleum mostly dominates over year, as shown in Figure A2. Natural gas usage slightly increases but remains a small portion, from 2.6 (1.6%) in 2004 to 29.2 (8.1%) million tons in 2015.

3. Data

Pipeline data. The natural gas pipeline data come from the Allied Resources Allocator Research & Publication (ARARP). The ARARP provides research products for the energy sector including maps and industry reports. The pipeline dataset provides detailed locations and specific quarters for which the pipelines begin functioning. The blue lines in Fig. 2 show the existing major pipelines by 2015, which include the West-East Gas Project I and II, the Shaan-Jing Gas Pipeline Project, the Sichuan-Shanghai Gas Pipeline Project and the Myanmar-China Gas Pipeline Project. Figure A4 shows the share of cities each year when the pipelines become operational. These pipelines are the largest energy projects in China and they go through complicated geological conditions. Therefore, they are designed and regulated by the central government and thus largely exogenous to local economic conditions.

Mortality data. Mortality data are obtained from the Disease Surveillance Points (DSP) system in the Chinese Center for Disease

[2] Natural gas in the residential sector is mainly used for cooking rather than heating during the period of our study. Zheng et al. (2014) and Guo et al. (2015) report fuel usage patterns from a nationwide survey. For space heating, households use either central heating or distributed heating. Among those relying on distributed heating, 67% use electricity, 29% use wood and coal, and 4% other fuels including natural gas. For water heating, 43% of households use electricity, 31% use gas fuels, and 25% use solar power. Regarding kitchen stoves, 37% use natural gas, 26% use electricity and 21% use LPG. For other kitchen devices, 83% use electricity, 8% use natural gas and 6% use L PG. Figure A1 reports the number of home appliances over time based on the Urban Household Survey. It shows a gradual increase in appliance ownership, with air conditioner adoption accelerating at a faster rate.

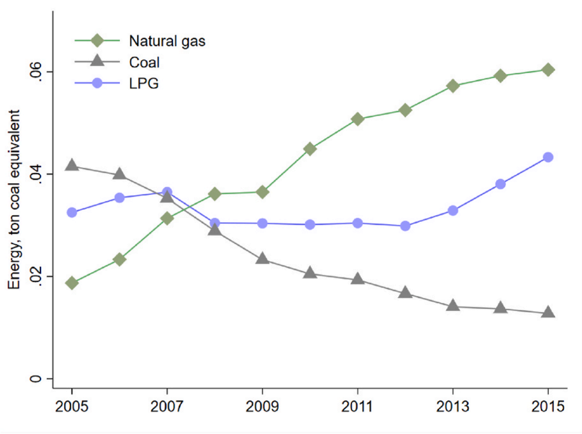


Fig. 1. Residential energy usage in urban China.
Notes: This figure shows the per capita usages of natural gas, coal and liquefied petroleum gas (LPG) over year for urban households. The data are from the China Energy Statistics Yearbook. Natural gas (green diamonds) increases each year stably, ranging from 0.018 in 2005 to 0.061 tons in 2015. Coal (grey triangles) decrease stably over the years, ranging from 0.042 in 2005 to 0.012 tons in 2015. LPG (purple circle) remains similar at both ends of the study period (0.033 in 2005 to 0.042 tons in 2015).

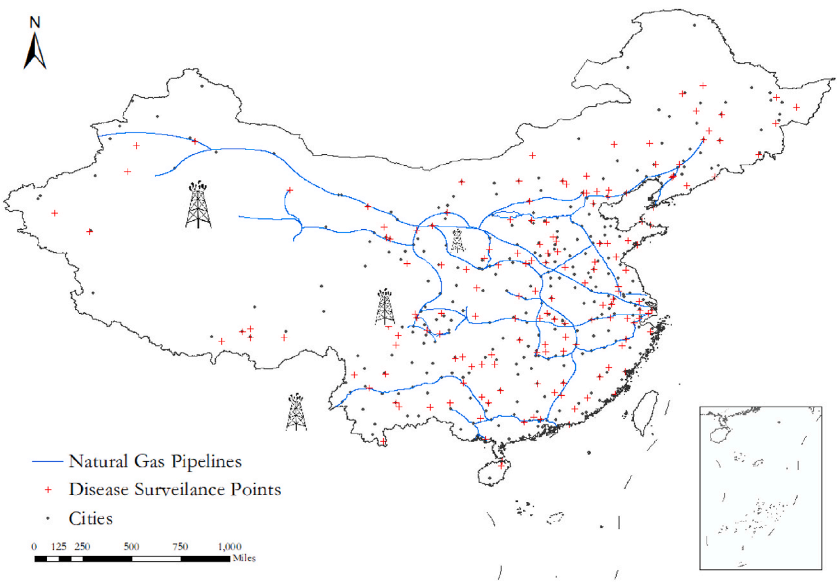


Fig. 2. Sample distributions.
Notes: This figure reports the geographic distribution of the samples. The blue lines show the existing major pipelines by 2015, which include the West-East Gas Project I and II, the Shaan-Jing Gas Pipeline Project, the Sichuan-Shanghai Gas Pipeline Project and the Myanmar-China Gas Pipeline Project. The red plus symbol indicates the location of the disease surveillance points. The black point indicates the location of cities.

Control and Prevention (CDC). The DSP dataset is a high-quality nationally representative survey, which is widely used to study mortality in China (Barwick et al., 2024; Chen et al., 2013; Ebenstein et al., 2017; Fan et al., 2020). It provides weekly death data with detailed causes for population coverage of over 73 million people in 161 counties between 2004 and 2015.[3] The data are aggregated at the county by year-quarter level. The cause of death information recorded in the autopsies is used to assign all deaths to either cardiovascular diseases, respiratory diseases and lung cancers that are plausibly related to air pollution exposure, or other causes. The division of death causes are mutually exclusive and we list the causes according to the Global Burden of Disease cause list (GBD) and

[3] *County* is the third level of administrative hierarchy in China. The first level is *Province* and the second level is *City*. Recent studies, such as Salvo et al. (2024), have utilized mortality data from 605 counties. The DSP system expanded in 2013, marking the end period of our analysis; therefore, we did not apply for the version covering the 605 counties.

Table 1
Summary statistics.

Variable	Obs.	Mean	S.D.	Min.	Max.
Death Rate (*quarterly,* per *100,000 population*)					
All diseases	2661	123.85	39.83	0	294.19
All diseases: age≥60	2661	467.05	178.62	0	1218.76
All diseases: 5≤age <60	2661	11.61	6.10	0	43.66
All diseases: age <5	2661	5.03	11.92	0	258.51
All diseases: female	2661	128.46	45.94	0	338.69
All diseases: male	2661	129.71	42.64	0	319.22
Cardiorespiratory diseases and lung cancers	2661	74.62	31.49	0	221.43
Non cardiorespiratory diseases and lung cancers (referred as “other diseases”)	2661	49.23	16.37	0	163.10
Other Data					
Temperature, *Fahrenheit*	2661	58.13	9.79	32.64	77.35
Precipitation, *Milimeter*	2661	23.44	24.20	0	154.60
Household natural gas usage per capita, m^3	734	24.68	44.63	0	445.93
Remote sensing SO_2, $\mu g/m^3$	734	19.66	13.16	0.27	53.70
Remote sensing $PM_{2.5}$, $\mu g/m^3$	734	41.30	13.28	11.00	95.89
Log night light intensity	734	7.82	10.44	0.05	57.00
Log employment in the industry sector	289,866	4.55	1.41	0.69	9.31

Notes: This table reports the summary statistics of the key variables for the whole sample. The death rate and weather data range from 2004 to 2015 and the unit of analysis is at the county-by-year-quarter level. The household gas usage, remote sensing SO_2, $PM_{2.5}$ and night light intensity range from 2005 to 2015 and the unit of analysis is at the city-by-year level. The employment ranges from 2008 to 2015 and the unit of analysis is at the firm-by-year level.

the International Classification of Diseases, Tenth Revision (ICD-10) in Table A1. As indicated in Table 1, the deaths from cardiorespiratory diseases and lung cancers are about 50% more than the deaths from other diseases.

The DSP data are linked with the pipeline data by merging the centroid of the city where the DSP counties are located, with pipelines with the shortest distances. The centroid of the city is chosen to merge the DSP data and pipelines for the reason that the city is the administrative unit to govern the county, including the management of DSP sites and pipeline connections. The timings when the cities are exposed to natural gas follow the year-quarter when the closest pipeline becomes operational. Cities that have pipelines functioning before 2004 are removed. Cities within 50 km to the pipelines and DSP counties in these cities are the main areas of interest. Cities between 50 km and 200 km to the pipelines serve as placebo tests. As a result, there are 96 cities and 70 counties within 50 km to the pipelines, and 71 cities and 43 counties between 50 km and 200 km. The number of cross-sectional units in our study is comparable to Ebenstein et al.'s (2017) seminal study.

Household natural gas data. Household natural gas usage per capita is calculated by dividing the amount of total residential natural gas consumption by the counts of population at the city level. This measure captures the changes at both extensive and intensive margins because the amount of gas consumption results from both a larger population using gas (extensive margin) and more gas usage among existing users (intensive margin). At the extensive margin, we also examine the population using natural gas as an additional dependent variable. The measures for residential natural gas consumption, the population using natural gas, and total population counts are sourced from the China City Construction Yearbook.

Weather data. The weather variables are from the China Meteorological Data Service Centre, hosted by the China Meteorological Administration. Weather information includes temperature and precipitation data from 2004 to 2015. The dataset has 699 monitoring stations in China that are in operation during the time period of our study. We calculate each DSP's weather conditions using weighted information from weather stations within 50 miles. The weights are the inverse of the distance between the centroid of the DSP counties and the surrounding weather stations. The original weather data are at the daily level and we average temperature and precipitation at the quarterly level in order to merge with the DSP data.

Other data. Data on outdoor $PM_{2.5}$ density come from the Global Annual $PM_{2.5}$ Grids derived from satellite data by Van Donkelaar et al. (2016). The original raster has a resolution of 0.01°, and we aggregate the grids at the city level using the inverse distances as weights. The $PM_{2.5}$ data are aggregated at the city-by-year level to be consistent with other measures in the analyses of mechanisms. The satellite $PM_{2.5}$, from 2004 to 2015, is used in our analysis because China only started to systematically roll-out $PM_{2.5}$ monitoring stations from 2013 and the process was only completed by the end of 2014. Data on outdoor SO_2 are from Chen et al. (2022). The sources of night light are from the Defense Meteorological Satellite Program Operational Linescan System (DMSP/OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS). The data are the harmonized version from Chen et al. (2021).[4] Table 1 presents the summary statistics.

[4] While the night light measures from both the DMSP/OLS and the VIIRS are acknowledged as good proxies for economic dynamics, their applications are limited by their available time span. The data from the DMSP/OLS can only be collected before 2013 and those from the VIIRS begin from 2012. Appendix Figure A5 shows the night light intensity over year. There is no break in time trend because these two datasets are harmonized by Chen et al. (2021).

4. Empirical strategy

The key challenge is attributing to pipeline expansion the effect of other unobserved economic conditions that may be correlated with mortality. While these largest pipeline projects are designed and regulated by the central government, it is still possible that the pipelines are placed in cities with different economic conditions. To obtain the causal effects of pipeline expansion, we employ the event study model specified as follows,

$$y_{it} = \sum_{r=-\underline{T}}^{-2} \mu_r I_r + \sum_{r=0}^{\overline{T}} \mu_r I_r + X_{it}\alpha + \lambda_i + \eta_t + \varepsilon_{it} \tag{1}$$

where y measures the household usage of natural gas per capita or the age-adjusted death rate. For household gas usage, the subscripts i and t represent city and year, respectively. For death rate, the subscripts i and t represent county and year-quarter, respectively. λ and η are the corresponding unit fixed effects (i) and time fixed effects (t), respectively. The unit fixed effects absorb any time invariant confounders and the time fixed effects control any common temporal shocks.

The key coefficients of interest, μ_r, estimate the outcomes in a given period r relative to the period before the pipeline setup (μ_{-1}). I_r equals one if the sample is in the relative period r and zero otherwise. T represents the periods before and after the pipeline setup, with $\underline{T} = 4$ and $\overline{T} = 3$ for natural gas regressions and $\underline{T} = 21$ and $\overline{T} = 24$ for death rate regressions.[5] For the causal interpretation, these coefficients are required to satisfy the identifying assumption that, conditional on the included controls and fixed effects, the timing of pipeline setup is not contemporaneously confounded by other economic conditions.

To further mitigate the concern of omitted variables, the model includes a vector of control variables (X), including 5 °F temperature bins and decile precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, the number of teachers per capita, the number of hospitals per capita and road length per capita. Additionally, in Table A2, we limit the samples to the years before the pipeline setup and report the mean differences of economic and environmental conditions between the early- and late-treated cities. The early (late) group is defined as the cities where the pipelines become operational before (after) 2010, the middle year of our sample period. While some unconditional means are different between early and late cities, the differences disappear after controlling the year trend.

We estimate Equation (1) following the conventional approach as well as the interaction-weighted estimator (Sun and Abraham, 2021). First, the relative time is constructed by deducting the setup time from the calendar time. The timing of the pipeline setup can be absorbed by the unit fixed effects and the calendar time can be absorbed by the time fixed effects. Therefore, unit fixed effects and time fixed effects cannot be jointly applied in Equation (1) due to perfect collinearity (Borusyak et al., 2024). Our first approach avoids the issue of collinearity by replacing city fixed effects with province fixed effects.

Second, Sun and Abraham (2021) show that in settings of event studies, if treatment timing varies across units,[6] the coefficient on a given lead or lag can be contaminated by effects from other periods. They propose the interaction-weighted (IW) estimator that is free of contamination. The issue of collinearity also exists for the IW estimator such that it requires the existence of the never-treated group. Our second approach keeps the city fixed effects and follows their practice by assigning the last period (2015 in our study) as the never-treated group to avoid collinearity.

The primary advantage of Equation (1) is that it allows us to examine the patterns of outcomes in the periods leading up to the beginning of pipeline setup as well as assess whether outcomes start to change at the event period. After confirming the causal effects of pipeline setup, as we will see in the section of results, we summarize the magnitude of the estimated effects and their statistical significance in the following model,

$$y_{it} = \sum\nolimits_{r=0}^{\overline{T}} \mu_r I_r + X_{it}\alpha + \lambda_i + \eta_t + \varepsilon_{it} \tag{2}$$

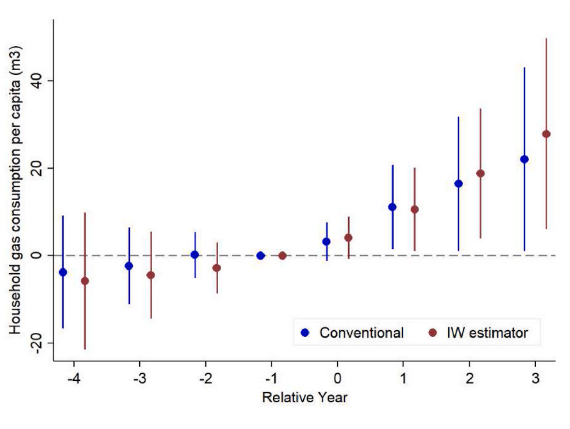
where the key coefficients of interest, μ_r, show the change in outcomes in a dynamic way following the pipeline setup. Other variables are defined as in Equation (1). All standard errors are clustered at the city level. The regressions are weighted by population size.

5. Results

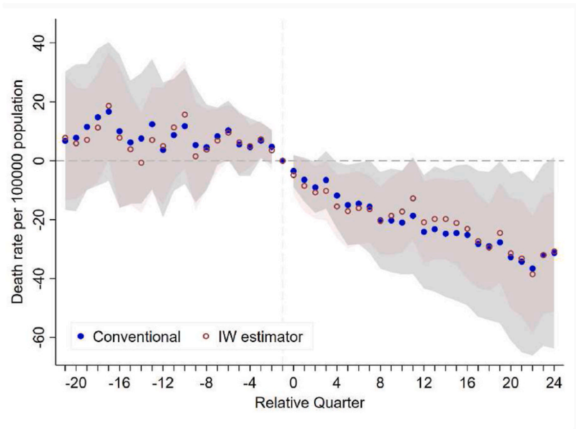
Fig. 3A shows the effects of pipeline setup on household gas usage. We plot the coefficients of the event time (μ_r) from estimating

[5] The difference in time windows for the natural gas usage and mortality regressions arises from differences in the temporal coverage and the unit of analysis for each dataset. For the natural gas regression, expanding the relative time window increases noises at both ends, particularly for city-level dependent variables in the mechanism analysis. To maintain consistency, we limit the temporal coverage of all city-level analyses to be 4 periods before and after the pipeline setup (periods -4 -3 -2 -1 and 0 1 2 3). For the mortality regression, the high quality of DSP data and the granular temporal coverage allow us to extend the relative time window.

[6] In the setting of staggered difference-in-differences, recent literature concerns the potential bias due to the heterogeneous treatment effects across both unit and time. However, the heterogeneous treatment effects across time is not a concern in the event study specification (Roth et al., 2023; Sun and Abraham, 2021). Therefore, we follow the interaction-weighted estimator proposed by Sun and Abraham (2021) to address the concern from heterogeneous treatment effects across unit. Additionally, we adopt the estimator proposed by Callaway and Sant'Anna (2021) in Table 8 to confirm our results.



A: Household Gas Usage



B: Death Rate

Fig. 3. Effects of pipeline setup on gas usage and death rate.
Notes: This figure shows the effects of pipeline setup on gas usage and death rate by estimating Equation (1). Panels A and B show the results for the annual household gas usage per capita and the quarterly death rate, respectively. The blue and red dots are the estimated coefficients from the conventional approach and the IW estimator, respectively. The grey areas are 95% confidence intervals.

Equation (1). Blue dots are from the conventional approach and red dots are from the IW estimator. We have two findings. First, consistent with the identifying assumption, the coefficients remain flat before the pipeline setup but gradually increase after the introduction of the pipelines. Second, the estimates are robust to both the conventional approach and the IW estimator, suggesting that the heterogeneous treatment effects are not a major concern in our study.

Table 2 reports the regression results from estimating Equation (2). Panel A reports the effects each year and panel B summarizes the results in Panel A by reporting the average annual effects. The results are consistent with Fig. 3 that the effect size gradually increases. On average, the pipeline expansion increases the household gas usage per capita by 10.64 m^3. This is equivalent to 53%, given the average gas usage per capita before pipeline setup is 19.98 m^3. To assess the stability of our estimates, Column 1 deletes the control variables, and Column 2 adds the control variables. The results are little changed, suggesting that our estimates are unlikely to be affected by omitted variables.

Increases in gas usage per capita captures the changes at both extensive and intensive margins. In Table A3, we also examine the extensive margin effects by estimating the effects of pipeline setup on population using natural gas. On average, the pipeline expansion increases the population using natural gas by 18.37 thousands (41%). Assuming that gas increases were solely driven by the extensive margin, the gas usage per capita in Table 2 would also increase by 41%. The difference between above two numbers (53% v.s. 41%) suggests that increases in gas usage are realized through both extensive and intensive margins.

Fig. 3B shows the effects of pipeline setup on the quarterly death rate from estimating Equation (1). We have three findings. First, consistent with the identification assumption, the coefficients remain flat before the pipeline setup but gradually decrease after the introduction of the pipelines. Second, the coefficients are little affected by the heterogeneous treatment effects, validating the estimates in the conventional regression. Third, after the pipeline setup, the death rate decreases gradually as the household gas usage increases, as shown in Fig. 3A and B.

Table 3 reports the regression results from estimating Equation (2). Panel A reports the effects in each of the four quarters and panel

Table 2
Effects of pipeline setup on household gas usage.

Variable	(1)	(2)
	Household gas usage per capita (m^3)	
Panel A: Annual effects after pipeline setup		
0 year after setup	1.60	1.87
	(1.96)	(1.98)
1 year after setup	8.38*	9.51**
	(4.59)	(4.41)
2 years after setup	12.99*	13.41*
	(7.17)	(6.79)
3 years after setup	17.86*	17.78*
	(9.89)	(9.36)
Panel B: Average effects		
0–3 years after setup	10.21*	10.64*
	(5.77)	(5.47)
Mean gas usage per capita before setup	19.98	19.98
Observations in both panels	734	734
Controls in both panels	No	Yes
City fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Notes: This table reports the effects of pipeline setup on residential gas usage per capita by estimating Equation (2). Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 3
Effects of pipeline setup on death rate.

	(1)	(2)
Variable	Quarterly deaths per 100,000 population	
Panel A: Quarterly effects after pipeline setup		
0 - 3 quarters after setup	−5.88	−5.52
	(4.03)	(4.02)
4 - 7 quarters after setup	−12.08*	−11.81*
	(7.14)	(6.89)
8 - 11 quarters after setup	−16.21*	−16.18*
	(9.10)	(8.96)
12 - 15 quarters after setup	−18.41*	−18.63*
	(10.41)	(10.39)
16 - 19 quarters after setup	−19.20	−19.31
	(11.97)	(11.90)
20 - 24 quarters after setup	−21.19	−21.36
	(14.13)	(14.38)
Panel B: Average effects		
0 - 24 quarters after setup	−15.50*	−15.47*
	(9.28)	(9.21)
Mean quarterly death rate before setup	128.80	128.80
Observations in both panels	2661	2661
Controls in both panels	No	Yes
County fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes

Notes: This table reports the effects of pipeline setup on death rate by estimating Equation (2). Panel A reports the effects in each four quarters after the pipeline setup and panel B reports the average quarterly effects. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

B reports the average quarterly effects. The results are consistent with Fig. 3 that the effect size in the absolute value gradually increases. On average, the pipeline expansion decreases 15.47 deaths per 100,000 population. This is equivalent to 12%, given the average quarterly death rate before pipeline setup is 128.8. The results are also robust to adding or deleting control variables.

Our findings differ from Hanna et al. (2016), which show that the introduction of modern cooking stoves in India has only modest health effects, and the effects tend to vanish in the longer period. This is mainly due to the fact that the use of such new technologies is not always continued in time, and maintenance is often neglected. However, the pipelines in urban China are well maintained. Residents receive multiple facility checks and usage guidance each year (Wu et al., 2023). The well-functioning and timely repair in China allow us to examine the full benefits of energy transition.

Heterogeneities. Since burning natural gas produces far less air pollution, we expect to see that the mortality reduction is mainly driven by the decreases in cardiovascular diseases, respiratory diseases and lung cancers, which are plausibly related to air pollution exposure. Table 4 reports the separate results for cardiorespiratory diseases and lung cancers, and all other diseases from estimating Equation (2). Column 1 shows that the effect size for cardiorespiratory diseases and lung cancers is an average reduction of 11.14 deaths per 100,000 population (15%), while the effect size for other diseases in Column 2 is −4.33 (8%). The effect sizes for cardiorespiratory diseases and lung cancers are twice more than those for other diseases, supporting the channel of air pollution.

Table 5 explores the gender-specific effects for cardiorespiratory diseases and lung cancers. We find that the mortality reduction is driven mainly by the female population, with the effect size of −12.27 (15%) for females, compared to −6.97 (9%) for males.[7] The gender disparities may allude to indoor air pollution caused by cooking.[8] Verma and Imelda (2022) show that a nationwide fuel-switching program in Indonesia leads to a 4% increase in lung capacity among women but the program's effects on other outcomes, such as cough and self-report health, are small and not significant. The effect sizes in our study differ because 1) our outcome variable is mortality and theirs are lung capacity, and 2) their other outcomes are self-reported, introducing potential measurement errors. Given differences in context and measurement, readers should interpret the size differences cautiously.

Table 6 further explores the effects by age group for cardiorespiratory diseases and lung cancers. We find that the mortality reduction is mainly driven by the population above age 60 and below 5. This aligns with the fact that older and younger populations are more vulnerable to hazardous environments. Particularly, the results indicate that pipeline expansion decreases death rate by 39% for the age group below 5. This is consistent with Imelda (2020) that the reduction in infant mortality, due to a nationwide fuel-switching program in Indonesia, ranges from 25% to 43%. Additionally, the findings for the below-5 group reinforce the causal relationship between pipeline expansion and mortality because younger children generally have less cumulative exposure to other pollution over their lifetime.

6. Robustness

This section evaluates the robustness of our baseline results with a battery of checks. First, we conduct a placebo test by estimating the event study regression for cities with distances between 50 km and 200 km to the pipelines. Examining outcomes in both near and far areas test the identification assumption that, if not for the pipeline expansion, the outcomes in the close areas would have changed similarly to those in distant areas. The timings when the placebo cities are exposed to natural gas follow the periods when the closest pipeline become operational.

Table 7 reports the findings. Panel A shows that the effects of pipeline setup on household gas usage are not significant, and the average effect size (1.38 m^3, 11.5%) is smaller than the results for cities within 50 km to the pipelines (10.64 m^3, 53%).[9] Accordingly, Panel B shows that the effects of pipeline setup on the death rate are small and not significant as well. The effect size for distant counties is −0.25 deaths per 100,000 population (0.18%), which is smaller than the one for near counties (−15.47, 12%) in the absolute value. These results reassure that the findings are unlikely to be affected by omitted variables.

Second, we re-estimate Equation (2) with additional control variables including GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. These control variables are contemporary measures, instead of the interactions between initial values and time trends. While these contemporary variables are potentially endogenous, they serve as a way to test whether our results capture the effects from other economic confounders. Column 1 in Table 8 reports the pipeline effects on household gas usage and death rate in Panel A and Panel B, respectively. The findings remain stable, suggesting our findings are immune to omitted variables.

Third, our baseline model includes the city fixed effects in Equation (2). In Table 8, Column 2 re-estimates the baseline model by replacing the city fixed effects with the province fixed effects. Column 2 is less conservative in the sense that province fixed effects are coarser than city fixed effects. The results show that coarser controls produce largely similar results. Additionally, motivated by the pattern of coefficients before pipeline setup in Fig. 3, we follow Dobkin et al. (2018) by including a common linear trend based on Column 2. Column 3 shows that the results on gas usage and death rate remain stable, suggesting that a common linear trend captures any secular trend quite well. These findings reassure that our baseline results are unlikely to be affected by omitted variable bias.

[7] The gender-specific differences in mortality reduction are statistically significant at the 5% level when stack the female and male samples, and re-estimate the main equation by adding the interactions between the *Female* dummy and relative year dummies.The average death rate before pipeline setup in Table 5 is higher for females than for males. However, the overall mean death rate in Table 1 is higher for males. This discrepancy is primarily due to the larger share of elderly women compared to elderly men, as well as the higher death rate among women in the oldest age groups. As a result, when calculating the gender-specific age-adjusted death rate, the female death rate receives a larger population weight. For further details, refer to Figure A7.

[8] We also explore the gender heterogeneous effects on other diseasesin Table A5. First, the marginal effects on other diseases are smaller than the estimates of cardiorespiratory diseases and lung cancers. Second, we don't find heterogeneous results by gender on other diseases.

[9] The mean gas usage per capita before pipeline setup in Table 7 is 11.97, which is lower than 19.98 in Table 2. The differences likely stem from that the placebo regions are less developed than those closer to pipelines. However, this difference does not undermine the conclusions as our identification utilizes time variation before and after pipeline setup.

Table 4
Effects of pipeline setup on death rate by disease.

Variable	(1)	(2)
	Quarterly deaths per 100,000 population	
Sample	Cardiorespiratory diseases and lung cancers	Other diseases
Panel A: Quarterly effects after pipeline setup		
0 - 3 quarters after setup	−3.27	−2.25
	(2.18)	(2.30)
4 - 7 quarters after setup	−8.31**	−3.50
	(4.02)	(3.76)
8 - 11 quarters after setup	−11.70**	−4.49
	(5.60)	(4.31)
12 - 15 quarters after setup	−12.86*	−5.78
	(6.630)	(4.92)
16 - 19 quarters after setup	−14.39*	−4.92
	(7.61)	(5.83)
20 - 24 quarters after setup	−16.30*	−5.07
	(9.27)	(6.95)
Panel B: Average effects		
0 - 24 quarters after setup	−11.14**	−4.33
	(5.67)	(4.54)
Mean quarterly death rate before setup	76.40	52.41
Observations in both panels	2661	2661
Controls in both panels	Yes	Yes
County fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes

Notes: This table reports the effects of pipeline setup on death rate across disease by estimating Equation (2). Column 1 reports results for cardiorespiratory diseases and lung cancers, and column 2 reports results for other diseases. Panel A reports the effects in each four quarters after the pipeline setup and panel B reports the average quarterly effects. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Fourth, to further assess the robustness to heterogeneous treatment effects, we estimate Equation (2) following Callaway and Sant'Anna (2021). The control groups are the not-yet-treated units. We adopt the doubly robust DID estimator and estimate the simple average treatment effects for all groups across all periods. The findings are reported in Column 4. The results are little changed for both household gas usage and death rate. This test confirms our findings in the baseline model.

Fifth, the central government may prioritize providing natural gas to large cities. Particularly, the West-East Gas Pipeline Project was proposed to connect the gas resources in western China to the eastern coastal areas. As an additional test, we remove the samples from four municipalities and cities in three most developed coastal regions (Beijing-Tianjin-Hebei region, Yangtze River delta and Pearl River delta).[10] This strategy actually speaks to the inconsequential unit approach, pioneered in Chandra and Thompson (2000). By excluding the developed eastern coastal cities, the remaining areas receive the gas "by chance", strengthening the causal interpretation of our estimates.

Table A6 reports the findings. Panels A and B show that the effects of pipeline setup on household gas usage and death rate, respectively. First, consistent with the baseline results, the pipeline setup increases household gas usage and decreases death rate, suggesting that our findings are not driven by confounding factors in the developed coastal regions. Second, the marginal effect in household gas usage is larger than the baseline results and thus the pipeline setup brings larger health benefits. These findings suggest larger potentials in health improvement in less developed areas from investing in transition fuels.

7. Mechanisms

There are a number of potential pathways by which pipeline expansion may have induced the reduction in mortality. First, we explore whether mortality responds to changes in indoor air pollution resulting from household gas usage. Second, we consider the impact of outdoor air pollution on mortality. Third, we examine how pipeline setup may impact labor employment, as natural gas could either substitute or complement labor inputs. Fourth, we evaluate whether pipeline construction contributes to economic prosperity, which may further reduce mortality. Lastly, we assess the role of energy prices to determine if they play a significant part in

[10] These three developed coastal regions are defined as the areas within a 150 km radius to Beijing, Shanghai and Guangzhou, respectively.

Table 5
Gender effects of pipeline setup from cardiorespiratory diseases and lung cancers.

Variable	(1)	(2)
	Quarterly deaths per 100,000 population (Cardiorespiratory diseases and lung cancers)	
Sample	Female	Male
Panel A: Quarterly effects after pipeline setup		
0 - 3 quarters after setup	−4.27*	−0.61
	(2.36)	(2.29)
4 - 7 quarters after setup	−8.76**	−3.87
	(3.99)	(4.32)
8 - 11 quarters after setup	−13.81**	−6.89
	(5.67)	(5.72)
12 - 15 quarters after setup	−14.19**	−8.80
	(6.68)	(6.88)
16 - 19 quarters after setup	−15.99**	−9.94
	(7.48)	(7.91)
20 - 24 quarters after setup	−16.60*	−11.76
	(9.41)	(9.54)
Panel B: Average effects		
0 - 24 quarters after setup	−12.27**	−6.97
	(5.65)	(5.87)
Mean quarterly death rate before setup	83.61	76.25
Observations in both panels	2661	2661
Controls in both panels	Yes	Yes
County fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes

Notes: This table reports the effects of pipeline setup on death rate across gender from cardiorespiratory diseases and lung cancers by estimating Equation (2). The gender-specific death rate is calculated by dividing the gender-specific number of deaths by gender-specific population. Columns 1 and 2 report results for the female and the male, respectively. Panel A reports the effects in each four quarters after the pipeline setup and panel B reports the average quarterly effects. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

mortality reduction.

Indoor air pollution. Because burning natural gas produces fewer pollutants, household gas usage mitigates indoor air pollution.[11] Unfortunately, there is no comprehensive measurement of indoor air quality that covers the whole China to test the pipeline effects. Nonetheless, we compile supporting evidence from case studies that document indoor air quality, location and year.[12] We link the indoor air quality with household gas usage per capita at the city-year level. As shown in Panel A of Fig. 4, a clear negative correlation emerges between indoor air pollution and household natural gas usage. The findings align with Zhao et al. (2018) that changes in household fuels dominate the decrease in $PM_{2.5}$ exposure in urban China from 2005 to 2015.

Recall that, in the residential sector, natural gas is mainly used in kitchens for cooking in urban areas. The differential health impacts across gender in the previous section lend support to the findings that the pipeline expansion reduces indoor air pollution, particularly in kitchens, where women tend to spend more time. The findings echo Zhao et al. (2018) which separately estimate the exposure from household fuels used for cooking and space heating. They find that the exposure attributed to cooking is about 2.5 times as much as that of space heating. The findings also echo the literature that energy interventions can yield significant gender benefits when designed and targeted thoughtfully (Köhlin et al., 2013).

Additionally, the magnitude of mortality reduction we observe aligns closely with existing literature on indoor air pollution. Zhao et al. (2018) show that the average annual extra indoor $PM_{2.5}$ exposure from 2005 to 2015 for urban coal users is 38 $\mu g/m^3$. Fan et al. (2020) find that a 10 $\mu g/m^3$ increase in outdoor $PM_{2.5}$ due to coal burning increases death rate by 3.78%. Taken together, these two studies suggest that, if replacing dirty fuels with natural gas, the mortality reduction, for urban coal users is 14%, which are largely comparable with our findings. Our results are also consistent with the findings in other countries that gas usage reduces death rate through air pollution, particularly indoor air pollution (Cesur et al., 2017; Clay et al., 2024; Imelda, 2020).

Outdoor air pollution. As we discussed in the section of background, the major uses of natural gas are residential, industrial and transport sectors. Particularly, the industrial and transport sectors account for 62% natural gas usage in total. Natural gas application in these sectors may reduce outdoor air pollution.

Formally, we test whether the pipeline expansion reduces outdoor air pollution, measured by remote sensing $PM_{2.5}$ and SO_2, from

[11] There is broad consensus that burning natural gas produces far fewer pollutants. Figure A3 shows the proportion of pollutants that different types of energy contribute. The use of coal and petroleum dominates the emissions of particulate matter, sulfur dioxide, and nitrogen oxides; however, natural gas makes only a minor contribution.

[12] See Fig. 4 for more details how these studies are compiled.

Table 6
Age effects of pipeline setup from cardiorespiratory diseases and lung cancers.

Variable	(1)	(2)	(3)
	Quarterly deaths per 100,000 population (Cardiorespiratory diseases and lung cancers)		
Sample	Age ≥ 60	5 ≤ Age<60	Age<5
Panel A: Quarterly effects after pipeline setup			
0 - 3 quarters after setup	−16.61	−0.55	−1.08*
	(14.26)	(0.36)	(0.61)
4 - 7 quarters after setup	−48.12*	−1.09*	−2.16***
	(24.09)	(0.60)	(0.80)
8 - 11 quarters after setup	−65.27*	−1.45*	−2.79***
	(32.99)	(0.77)	(0.97)
12 - 15 quarters after setup	−70.12*	−2.11**	−2.28*
	(39.49)	(0.94)	(1.14)
16 - 19 quarters after setup	−78.28*	−2.23**	−1.72
	(45.55)	(1.10)	(1.18)
20 - 24 quarters after setup	−87.11	−2.36*	−2.55*
	(56.49)	(1.31)	(1.39)
Panel B: Average effects			
0 - 24 quarters after setup	−60.92*	−1.63**	−2.10***
	(33.97)	(0.80)	(0.96)
Mean quarterly death rate before setup	476.30	11.65	5.32
Observations in both panels	2661	2661	2661
Controls in both panels	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes

Notes: This table reports the effects of pipeline setup on death rate across age cohorts by estimating Equation (2). Columns 1, 2 and 3 report results for the age group above 60, 5 to 60 and below 5, respectively. Panel A reports the effects in each four quarters after the pipeline setup and panel B reports the average quarterly effects. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 7
Placebo effects of pipeline setup on gas usage and death rate.

Variable	(1)	(2)
	Placebo test: 50 km < distance≤200 km	
Panel A: Average effects	Household gas usage per capita (m^3)	
0–3 years after setup	0.96	1.38
	(3.36)	(3.49)
Mean gas usage per capita before setup	11.97	11.97
Observations	542	542
Control variables	No	Yes
City fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Panel B: Average effects	Quarterly deaths per 100,000 population	
0 - 24 quarters after setup	−0.92	−0.25
	(4.57)	(4.55)
Mean quarterly death rate before setup	135.50	135.50
Observations	1564	1564
Control variables	No	Yes
County fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes

Notes: This table reports the effects of pipeline setup on household gas usage (Panel A) and death rate (Panel B) by estimating Equation (2). Column 1 reports the results without control variables and column 2 reports the results with control variables. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

estimating Equation (1). Fig. 4B and C shows the effects of the pipeline setup on $PM_{2.5}$ and SO_2, respectively. We find the estimates gradually decrease after the pipeline setup. Panel A in Table 9 shows that the $PM_{2.5}$ significantly decreases after the pipeline setup, as indicated in Column 1. On average, the pipeline expansion reduces outdoor $PM_{2.5}$ by 3.44 μg/m^3, which is equivalent to 8% given the

Table 8
Robustness tests of pipeline effects on gas usage and death rate.

Variable	(1)	(2)	(3)	(4)
	Additional controls	Prov. FE	Prov. FE & linear trend	CS estimator
Panel A: Average effects	Household gas usage per capita (m^3)			
0–3 years after setup	10.71*	11.90*	12.11*	11.59**
	(5.63)	(6.16)	(6.19)	(4.74)
Mean gas usage per capita before setup	19.98	19.98	19.98	19.98
Observations	734	734	734	734
Control variables	Yes	Yes	Yes	Yes
City fixed effects	Yes	No	No	Yes
Province fixed effects	No	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	Yes
Panel B: Average effects	Quarterly deaths per 100,000 population			
0 - 24 quarters after setup	−15.48*	−21.15**	−15.80*	−10.65*
	(9.05)	(10.11)	(8.79)	(5.63)
Mean quarterly death rate before setup	128.80	128.80	128.80	128.80
Observations	2661	2661	2661	2661
Control variables	Yes	Yes	Yes	Yes
County fixed effects	Yes	No	No	Yes
Province fixed effects	No	Yes	Yes	No
Year-quarter fixed effects	Yes	Yes	Yes	Yes

Notes: This table assesses the robustness of the pipeline effects on household gas usage (Panel A) and death rate (Panel B) by estimating Equation (2). Column 1 includes additional contemporary control variables, including GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. Column 2 re-estimates Equation (2) by replacing city fixed effects with province fixed effects. Column 3 re-estimates Equation (2) by including a common linear trend and replacing city fixed effects with province fixed effects. Column 4 reports the results following Callaway and Sant'Anna (2021). Control variables in columns 2–4 include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

average $PM_{2.5}$ before the pipeline setup is 42.04 μg/m^3. The pipeline effect on outdoor SO_2 is −0.43 μg/m^3 (2%) but the estimate is not significant, as indicated in Column 2.

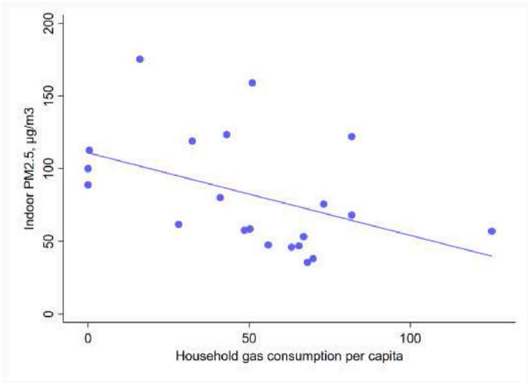
Next, we compare our findings with those in Fan et al. (2020). They use DSP data from the northern China in 2014 and 2015. Our work uses DSP data within 50 km of pipelines from 2004 to 2015. Despite differences in sample regions and time periods, the findings allow for a rough comparison. They find that activating the winter heating system causes a 14% increase in death rate. This 14% change in death rate is driven by a 37 μg/m^3 increase in outdoor $PM_{2.5}$ (40 units in air quality index) due to coal burning. We observe that pipelines decrease death rate by 12% and reduce outdoor air pollution by 3.4 μg/m^3, suggesting that ambient pollution reduction roughly explains 11% in mortality reduction (calculated as 3.4/((37/14)*12)). Readers should be cautious in this interpretation because the air quality data are not comprehensive before 2013.

Our study is closely linked to the influential Huai River literature (HR), as both emphasize air pollution as a critical factor affecting human health (Almond et al., 2009; Ebenstein et al., 2017; Salvo et al., 2024). However, our study differs in two aspects. First, while the gas pipelines intersect the Huai River (see Figure A6), our identification strategy differs substantially. The HR literature utilizes cross-sectional variations in the regression discontinuity setting but our study utilizes time variations in the event study setting. Second, the findings in the HR literature represent the long-term effects but our findings capture the mid to long term effects. The reduced form effects in our study (Pipeline effects, 12%) are generally smaller than those in the HR literature (Huai River effects, between 15% and 32% using data before 2015). Our study also adds to the literature using spatiotemporal variation in the removal of dirty fuels (e.g. Currie and Walker, 2011; He et al., 2018).

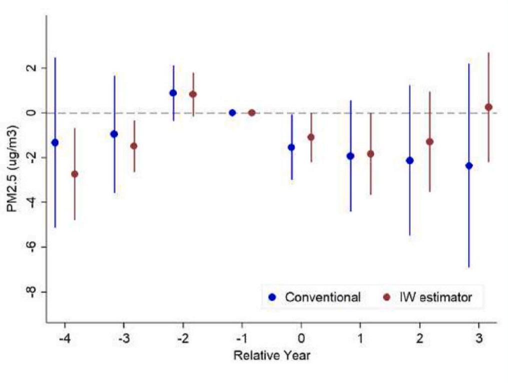
Labor employment. The usage of natural gas in the industrial sector may affect human health because natural gas may serve as a substitute or complement to labor inputs. This section examines the effects of pipeline expansion on labor employment. Employment data in the industry sector are from the National Tax Survey Database.[13] It is jointly collected by the Ministry of Finance and the State Administration of Tax using a stratified random sampling method. The data cover the years from 2008 to 2015 and include annual information on inputs, outputs, sales, etc. We remove invalid samples whose employment, real capital and output are less than zero. To avoid extreme values, we winsorize the employment data by 0.5 percent at both ends.

Fig. 4D shows the effect of the pipeline setup on employment in the industrial sector by estimating Equation (1). We find that employment exhibits similar downward trends before and after the pipeline setup. The findings hold for both the conventional approach and the IW estimator. The regression results from estimating Equation (2) are reported in Table 9. The effects of pipeline expansion on labor employment are small and not significant. This is consistent with our expectation that the model with city fixed

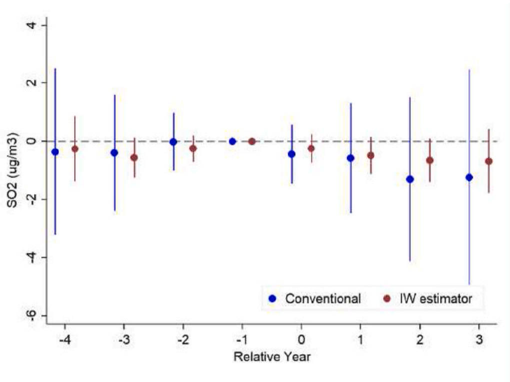
[13] There are several advantages of this unique dataset (See Liu and Jie, 2019 for more details). First, the dataset is characterized with high accuracy because it is collected to evaluate tax policies. Second, this dataset is representative, as it provides information in all sectors and consists of firms in both small and large scales.



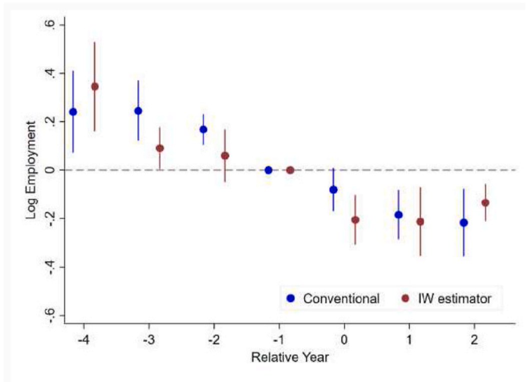
A: Gas Usage and Indoor $PM_{2.5}$



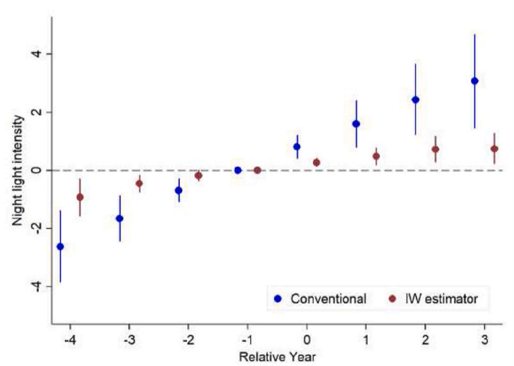
B: Remote Sensing $PM_{2.5}$



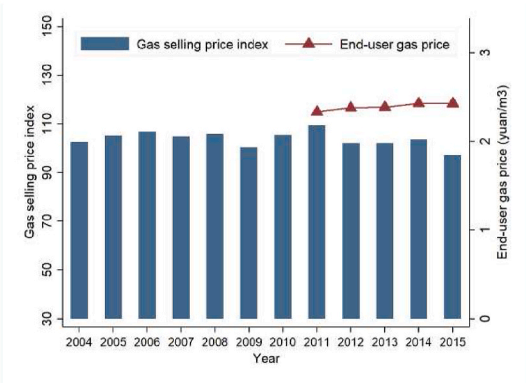
C: Remote Sensing SO_2



D: Employment in the Industrial Sector



E: Night Light Intensity



F: Natural Gas Prices over Year

Fig. 4. Potential mechanisms of pipeline effects.

Notes: This figure explores potential mechanisms of pipeline effects. Panel A shows the correlation between household gas usage and indoor $PM_{2.5}$. One dot represents one research article. The data are from compiling measures of indoor air pollution in existing case studies from the biggest Chinese research database (CNKI, https://www.cnki.net) by searching the key words *ShiNeiWuRan* (indoor air pollution in Chinese). We exclude samples in the rural areas, samples collected in restaurants, hospitals and schools, samples that are not in our study period as well as samples with sampling duration less than 24h. Finally, 21 articles are included in the analysis. Panels B, C, D and E show the results of remote sensing $PM_{2.5}$, remote sensing SO_2, log industrial employment and night light intensity, respectively. The blue and red dots are the estimated coefficients from the conventional approach and the IW estimator, respectively. The bars are 95% confidence intervals. Panel F shows the selling price index of natural gas and the end-user price over year. The price data are from the China Statistics Yearbook and the Wind Data Service.

Table 9
Potential mechanisms of pipeline effects.

	(1)	(2)
Panel A: Outdoor air pollution	$PM_{2.5}$	SO_2
0–3 years after setup	−3.44***	−0.43
	(0.77)	(0.30)
Mean pollution before setup	42.04	20.93
Observations	734	734
Control variables	Yes	Yes
Panel B: Employment in the industry sector (log)		
0–2 years after setup	0.04	0.04
	(0.04)	(0.04)
Mean log employment before setup	4.08	4.08
Observations	289,866	289,866
Control variables	No	Yes
Panel C: Night light intensity		
0–3 years after setup	−0.19	−0.16
	(0.19)	(0.19)
Mean night light intensity before setup	7.52	7.52
Observations	734	734
Control variables	No	Yes
Panel D: Deaths per 100,000 population	Functional form of gas price	
	Linear	Quadratic
0 - 24 quarters after setup	−15.11*	−15.24*
	(8.67)	(8.73)
Mean quarterly death rate before setup	128.80	128.80
Observations	2661	2661
Control variables	Yes	Yes

Notes: This table explores potential mechanisms of pipeline effects by estimating Equation (2). Panel A, B and C report the results of outdoor $PM_{2.5}$ and SO_2 intensities, log employment in the industry sector and night light intensity, respectively. Panel D reports the results of death rate with gas prices as additional control variables. Gas prices enter the equation in a linear or quadratic form. Panel A, B and C include city fixed effects and year fixed effects. Panel D includes county fixed effects and year-quarter fixed effects. In panels B and C, column 1 does not include control variables and column 2 includes control variables; in panels A and D, both columns 1 and 2 include control variables. Control variables include temperature and precipitation bins as well as the interactions between economic conditions in 2004 and the time trend. Economic conditions include GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The standard errors in parentheses are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

effects is sufficient to control for the linear pre-setup time trend. The findings suggest that the substitution between natural gas and labor employment is unlikely to be the driver of the observed mortality reduction during the period of our study.

Economic prosperity. Another possible explanation is that pipeline construction may contribute to economic prosperity, which in turn could lead to a reduction in death rate. First, the baseline model includes the interaction between GDP per capita in 2004 and the time trend. This interaction soaks up temporal variation that scales linearly with GDP per capita, e.g., the trend is double as strong for regions that are initially twice as rich. The robustness of our results alleviates the concern of economic prosperity. Second, we formally rule out this hypothesis by testing the effects of pipeline expansion on economic activities, measured by remote sensing night light intensity.

Fig. 4E shows the results from estimating Equation (1). We find that economic activities have similar upward trends before and after the pipeline setup. The findings hold for both the conventional approach and the IW estimator. The linear trend before the pipeline setup suggests that the model with city fixed effects is sufficient to control for the confounding effects. The regression results from estimating Equation (2) are reported in Table 9. Consistent with our expectation, the effects of pipeline expansion on economic activities are small and not significant. As additional proxies for economic activiti es, Table A4 reports the effects of pipeline expansion on GDP per capita, number of teachers per capita, number of hospitals per capita and road length per capita. The effects of pipeline expansion are small and not significant as well. The findings suggest that economic prosperity due to pipeline expansion is unlikely to drive the main findings in our study period. It's important to note that this discussion pertains only to the short run.

Energy prices. One additional explanation is that the pipeline setup may change energy prices, and the corresponding income effects may be associated with mortality reduction. We rule out this hypothesis by two reasons. On the one hand, Fig. 4F shows that both the selling price index of natural gas and the end-user price are largely stable over year. On the other hand, we test the stability of our results by adding the gas prices as control variables. While disaggregated gas prices at the city level are not available, we add into the regression the interaction between natural gas usage per capita in 2004 and the annual selling price index. The selling prices enter the equation in both linear and quadratic functional forms. The results, presented in Table 9, show minimal changes. Therefore, mortality reduction is unlikely to be driven by the change in energy prices and the associated income effects.

8. Benefits and costs

In this section, we provide a back-of-envelope calculation on the benefits and costs of pipeline expansion. The benefit per county per year can be obtained by multiplying the number of lives saved by the pipelines per county per year with the value of a statistical life (VSL).

For the number of lives saved by the pipelines, recall that the marginal effect of pipeline setup on death rate in Table 3 is 15.47 deaths per 100,000 population. With an average county population of 0.52 million, the number of lives saved by the pipeline expansion is 318 per year (or 79 per quarter) in each county. Given 1240 counties located within 50 km of the pipelines, the total lives saved annually amount to 0.39 million. This figure aligns broadly with the World Health Organization (WHO) estimates. The WHO attributes 1.03 million deaths in China in 2012 to ambient air pollution and 0.38 million deaths in 2006 to indoor air pollution.[14] Our estimates are smaller than the WHO's 1.41 million in total, likely due to differences in geographic coverage. Our analysis focuses on urban areas within 1240 counties, whereas the WHO estimates cover both urban and rural areas in roughly 3000 counties across China.

For the VSL, Qin et al. (2013) show that the number for the national sample in China is 1.81 million yuan. Note that the number from Qin et al. (2013) is derived from the 2005 data. Given our data span from 2004 to 2015, we follow Fan et al. (2020) to adjust the VSL from Qin et al. (2013) to 2010 by the difference of GDP per capita (2.14 times, obtained from the China Statistical Yearbook). That is, the VSL in our analysis is 3.87 million yuan. Therefore, the benefit per county per year is 1229 million yuan. Given that 1240 counties are within 50 km to the pipelines, the overall benefit from pipeline expansion is 1.5 trillion yuan annually. If the pipelines continue to function for ten years, the total benefits from the saved lives would be 15 trillion yuan.

The cost of pipeline expansion includes the costs of construction and maintenance. Construction costs come from two parts: transmission and distribution pipelines. Transmission pipelines are large lines that reallocate natural gas long distances across regions. Distribution pipelines are a system of lines that deliver natural gas to individual homes. The cost of transmission pipelines is approximately 385 billion, based on reports from the China Petroleum & Chemical Corp, and the distribution pipelines is about 276.58 billion, based on the City Construction Yearbook. Therefore, the full construction cost is 662 billion. As for the operating and maintenance costs, the value is 13.2 billion annually, which is obtained from 2% of the investment cost following Nwabueze et al. (2020). Therefore, given a functioning period of 10 years, the total cost of the pipeline setup is 0.79 trillion yuan. Overall, the benefit clearly far exceeds the cost.

More broadly, our analyses have implications for developing countries in Southeast Asia. Southeast Asia is a major engine of global economic growth and energy demand. Coal has accounted for the largest share of the growth in total energy supply since 2000.[15] Investing in natural gas will facilitate the transition away from coal and petroleum, which brings sizable health benefits. Our earlier result indicates that a 10% increase in gas usage leads to a 2.3% reduction in mortality. If the gas usage was to increase by 10%, the save lives were to be 15 million, given the population in Southeast Asia was 666 million in 2020. A similar logic applies for Africa. Africa has the world's fastest growing population. Rapid demographic change will undoubtedly drive up demand for energy in the coming decades. Notably, 40% of gas discovered worldwide between 2010 and 2020 was in Africa, which provides an opportunity for natural gas to complement solar and other technologies in expanding Africa's energy system.[16]

9. Conclusions

To meet the rising energy demand while avoiding serious consequences of climate change, a substantial transformation of the energy system is required. In particular, the value of investing in transition fuels has generated significant debates. This study estimates the effect of energy infrastructure on the death rate in the context of China from 2004 to 2015. The identification relies on a large scale expansion of natural gas pipelines. The data link detailed locations and timings of the pipeline setup with administrative death records at the quarterly level from the China Disease Surveillance Point.

We first document a 53% increase in household natural gas usage after the pipeline functioning. Next, we find that the pipeline expansion reduces death rate by 12%. Mortality reduction is mainly driven by cardiorespiratory diseases and lung cancers as well as by the female population. This reduction in mortality is largely attributed to improved air quality from replacing dirty fuels with natural gas. Our findings also highlight the differential gender effects of energy transition due to existing social, economic, and cultural factors. Further research on energy change, climate change and gender inequality in the developing countries is required.

CRediT authorship contribution statement

Wangyang Lai: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Liguo Lin:** Writing – review & editing, Writing – original draft, Data curation, Conceptualization. **Xiaochi Shen:** Writing – review & editing, Writing – original draft, Formal analysis. **Maigeng Zhou:** Data curation.

[14] WHO's report on ambient air pollution is from https://www.who.int/publications/i/item/9789241511353.WHO's report on indoor air pollution is from https://www.who.int/publications/i/item/WHO-SDE-PHE-07.01rev.

[15] Southeast Asia Energy Outlook. https://www.iea.org/reports/southeast-asia-energy-outlook-2022.

[16] Africa Energy Outlook. https://www.iea.org/reports/africa-energy-outlook-2022.

Data and code availability

Mortality data from the Disease Surveillance Points are confidential and can be applied from the Chinese Center for Disease Control and Prevention. The map of natural gas pipelines is proprietary and can be accessed from the Allied Resources Allocator Research & Publication. All other data and codes will be openly available on Dataverse.

Declaration of competing interest

The authors declare no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2025.103131.

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