Air Pollution's Grip: Drug Cost and Its Heterogeneity in China

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Abstract

We quantify the economic costs of air pollution associated with drug expenditures. First, following a 1% increase in the annual average of PM2.5, the combined expenditures on respiratory, cardiovascular, and antitumor drugs are predicted to rise by an amount equivalent to 1.81% of the annual per capita drug expenditure. Second, we compare expenditures on Western Medicine (WM) and Chinese Herbal Medicine (CHM), noting that research on the latter is significantly limited. After a rise in PM2.5 levels, the responsiveness and increase in expenditures for CHM drugs are similar to those for WM drugs, highlighting CHM's significance in understanding the economic impacts of air pollution. Third, cities with higher socioeconomic status—indicated by greater per capita fiscal revenue, higher disposable income, and a larger proportion of college graduates—exhibit a greater response in drug expenditures to air pollution.

JEL classification: I15, Q53
Keywords: outdoor air pollution, drug expenditure, Chinese herbal medicine, disparities in drug expenditure

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1 Introduction

Outdoor air pollution has significant health implications, particularly causing respiratory diseases, cardiovascular diseases, and tumors.[1] The economic costs of air pollution can be can be categorized, though not exclusively, into defensive expenditures (Deschenes, Greenstone, and Shapiro, 2017; Zhang and Mu, 2018; Ito and Zhang, 2020), drug expenditures (Williams et al., 2019), and hospitalization costs(Schlenker and Walker, 2016; Deryugina et al., 2019). While the health outcomes and economic costs of air pollution have been extensively studied in the context of developed countries (Currie and Neidell, 2005; Schlenker and Walker, 2016; Jans, Johansson, and Nilsson, 2018; Deryugina et al., 2019; Giaccherini, Kopinska, and Palma, 2021; Margaryan, 2021; Alexander and Schwandt, 2022; von Hinke and Sørensen, 2023; Bishop, Ketcham, and Kuminoff, 2023) and certain literature examines the impact of air pollution on mortality rates in China (Ebenstein et al., 2015; He, Fan, and Zhou, 2016; He, Liu, and Zhou, 2020) and India (Greenstone and Hanna, 2014), research on the economic costs of air pollution in middle- and low-income countries, including China, remains insufficient despite that the impact of air pollution is more pronounced in these countries.[2] In China, Chinese herbal medicine (CHM) is commonly used for the treatment of diseases related to air pollution, among other conditions, yet its usage patterns are unexplored.[3] Both the economic costs of air pollution in China and the usage patterns of CHM are under-studied in the fields of environmental economics and health economics.

[1]According to the World Health Organization, outdoor air pollution was estimated to cause 4.2 million premature deaths worldwide in 2019 (see https://www.who.int/zh/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health). Coarse particles with a diameter greater than 2.5 microns can penetrate into the lungs, while fine particles can cross the lung barrier and enter the bloodstream (Chang et al., 2019). Exposure to fine particulate matter of 2.5 microns or less in diameter (PM2.5) can lead to respiratory diseases, cardiovascular diseases, and tumors (Seaton et al., 1995).

[2]Middle- and low-income countries account for 89% of the 4.2 million premature deaths worldwide in 2019. Particularly affected are countries in South-East Asia and the Western Pacific region (see https://www.who.int/news-room/fact-sheets/detail/ambient-(outdoor)-air-quality-and-health).

[3]There exists a nontrivial preference for CHM drugs, as on average 13.5% of visits to hospital occur at Traditional Chinese Medicine hospitals in the provinces to which these cities belong.

The current study estimates the economic costs of air pollution in terms of drug expenditures in China, utilizing novel data that record drug-level expenditures from public hospitals in twenty major Chinese cities from 2014 to 2019. We examine how expenditures on Western Medicine (WM) and Chinese Herbal Medicine respond to air pollution, and how socioeconomic factors influence responses to air quality hazards across these cities.

Employing Two-Stage Least Squares (2SLS) regressions with maximum wind speed and temperature inversions as instrumental variables for air pollution, we obtain three key findings. First, air pollution exerts a substantial economic cost in terms of drug expenditures. A 1% increase in the annual average of PM2.5 results in a 2.96% rise in per capita expenditure on modern respiratory drugs, a 3.59% increase in expenditure on modern cardiovascular drugs, and a 4.91% rise in per capita expenditure on modern antitumor drugs. The corresponding combined increase in drug expenditures on WM drugs amounts to 9.10 yuan, equivalent to 1.00% of the annual per capita drug expenditure in our sample.

Second, CHM drugs are quantitatively important in accounting for the response of expenditures to air pollution.[4] Following a 1% increase in PM2.5, per capita expenditures on CHM drugs for treating the three groups of diseases increase by 5.57%, 4.35%, and 4.76%, respectively. In terms of expenditure increments, the corresponding rise in expenditures on CHM drugs (for respiratory diseases, cardiovascular diseases, and tumors combined) is 7.44 yuan, which is equivalent to 0.81% of the annual per capita drug expenditure.

Third, the socioeconomic status of cities affects the expenditure response to air pollution, contributing to regional disparities in drug expenditures. Cities with greater per capita fiscal revenue, higher per capita disposable income, and a larger proportion of college graduates among residents experience larger pollution-related increases in drug

[4] The WM drugs in our sample are classified into 14 groups, while the CHM drugs are classified into 13 groups. The classifications are detailed in Table 1.

expenditures. Additionally, the impact of air pollution on drug expenditures is larger in northern Chinese cities compared to southern cities, highlighting the higher costs associated with elevated air pollution levels in the north.

Our study contributes to the related literature in three ways. First, while most papers estimate the effects of air pollution on drug expenditures by disease groups, such as respiratory diseases, cardiovascular diseases (Schlenker and Walker, 2016; Xia et al., 2022), psychological disorders (Chen, Oliva, and Zhang, 2018), and flu (Graff Zivin et al., 2023), our study offers a more comprehensive assessment of the impact of air pollution on drug expenditures across three disease groups considered most susceptible to air pollution (Seaton et al., 1995). In the context of China, our study is related to research by Barwick et al. (2018) and Liao, Du, and Chen (2021), who estimate annual per capita medical spending using data on credit and debit card transactions and the China Family Panel Studies dataset, respectively. Drawing on a new data source, our study provides a specific focus on drug expenditures. By exploiting variation in air pollution and drug expenditures across major Chinese cities, we also improve upon Zhang et al. (2023) and Xia et al. (2022), who base their estimates of drug expenditure responses to air pollution on data from a single city.

Second, we highlight the importance of CHM drugs in the medical expenditures and practices of China. These drugs account for 60% of the combined expenditures on respiratory, cardiovascular, and antitumor drugs. Despite the widespread use of CHM, there is a significant lack of scientific evidence regarding the efficacy and pharmacoeconomic evaluation of CHM drugs (Zhou et al., 2019; Xiong et al., 2022). By exploiting the exogenous change in demand for medical attention prompted by the occurrence of air pollution, we demonstrate that the increase in expenditure on CHM drugs is comparable in magnitude to that on WM drugs. To the best of our knowledge, this study is the first to examine the usage pattern of CHM drugs. This finding has important implications for expanding research on CHM drugs.

Third, we contribute to the research on regional disparities in the impact of air pollution. Existing literature has demonstrated that locations with better socioeconomic status are less affected by air pollution. In the context of the U.S., a key finding by Currie, Voorheis, and Walker (2023) is that exposure to air pollution tends to be lower in communities with higher rates of home ownership, greater average educational attainment, and higher mean public assistance income. Exploiting variation in early childhood exposure to the London Smog of 1952, von Hinke and Sørensen (2023) find that individuals born in areas with higher socioeconomic status suffer fewer long-term effects from air pollution, presumably because they are better at avoiding pollution or possess superior health conditions. Our findings contribute to understanding how socioeconomic factors moderate the impact of pollution by revealing that Chinese cities with higher socioeconomic status spend more on drugs in response to air pollution. Additionally, the literature on air pollution in China (Chen et al., 2013; Ebenstein et al., 2017; Fan, He, and Zhou, 2020) has established that residents in northern China suffer from lower life expectancy because the free or subsidized coal-fired heating provided in northern cities during the winter causes severe air pollution. We complement this strand of literature by showing that there is also a higher economic cost in northern cities, as residents there spend more to treat pollution-related diseases.

The remainder of the paper is structured as follows. Section 2 provides an overview of the empirical strategy and data employed in this study. Section 3 presents the benchmark results. The disparities in expenditures associated with socioeconomic factors are presented in Section 4, and robustness and extension results are presented in Section 5. Finally, Section 6 concludes the paper.

2 Empirical Design

2.1 Regression setup

Building on recent studies such as Deryugina et al. (2019) and Xia et al. (2022), we estimate the log-linear effects of air pollution on drug expenditure. Our model is specified as follows:

$$lnY_{ijt} = \alpha + \beta \cdot lnPM2.5_{it} + \phi \cdot lnX_{it} + \gamma_i + \eta_t + \epsilon_{ijt} \quad (1)$$

where Y_{ijt} is per capita expenditure on drug j in city i during year t. In our study, we focus on three groups of diseases, the respiratory diseases, cardiovascular diseases and tumors. By the origin of medicine practice, there are two types of drugs. One type is the modern chemical drugs used in WM, such as penicillin, which are sold in countries around the world.

The other type is CHM drugs, mainly sold and used in China and Japan. CHM drugs primarily originate from natural substances and their processed products, including herbs, animal-based drugs, mineral drugs, as well as certain chemical and biological products. The use of CHM drugs is widespread in China. Among the 685 drugs listed in China's National Essential Medicines List (2018 edition), 268 are CHM drugs, while 417 are WM drugs. For instance, "Huangqi Granules", produced by "Sichuan Biokin Pharmaceutical", are derived from the roots of Astragalus membranaceus (Fisch.) and Bunge. This CHM drug is commonly used to enhance immune function. National and provincial-level health authorities regularly issue guidelines regarding the inclusion of CHM drugs in public health insurance programs in China. The classifications of WM drugs and CHM drugs in our sample, reported in Table 1, largely overlap.

CHM drugs play a crucial role in our analysis, as the per capita expenditure on them is approximately 75% of the expenditure on WM drugs for treating respiratory diseases, cardiovascular diseases, and tumors. Since our sample includes both WM and CHM drugs

Table 1: Grouping of WM drugs and CHW drugs

WM drugs	CHW drugs
Identical grouping:	
Antitumor drugs	Antitumor drugs
Cardiovascular drugs	Cardiovascular drugs
Respiratory drugs	Respiratory drugs
Dermatological drugs	Dermatological drugs
Neurological drugs	Neurological drugs
Musculoskeletal drugs	Musculoskeletal drugs
Hematological drugs	Hematological drugs
Gastrointestinal drugs	Gastrointestinal drugs
Miscellaneous drugs	Miscellaneous drugs
Differentiated grouping:	
Anti-infective drugs	Otorhinolaryngology drugs
Systemic Hormonal Preparations	Pediatric drugs
Sensory System drugs	Gynecological drugs
Antiparasitic, Insecticide, and Repellent drugs	Urological Disorder drugs
Genitourinary and Sex Hormones	

Notes : [1] The classification of Western medicine drugs follows the Anatomical Therapeutic Chemical (ATC) classification developed by the World Health Organization. The classification of CHM drugs is developed by the MENET Database, with reference to the ATC classification. [2] Systemic Hormonal Preparations in WM drugs excluding Sex Hormones and Insulins.

for treating respiratory diseases, cardiovascular diseases and tumors, we conduct separate regressions for each of the six combinations of origin of medicine and disease group.

The variable $PM2.5_{it}$ represents the mean of PM2.5 in city i during year t. Considering the potential lag effects of air pollution on health and its typical peak in the winter in China, we define a year in the regression as the period from the fourth quarter of one calendar year to the third quarter of the following calendar year to better capture the dynamic effects of pollution.

X_{it} is a vector of control variables. Within X_{it}, the first set of controls comprises climate-related indicators, including the within-period average precipitation, average humidity, and average temperature. The second set of controls consists of socioeconomic characteristics of the cities: within-period per capita GDP in city i, fiscal revenue in city i, the fraction of urban residents covered by employment-based health insurance in city i, and the number of public hospitals at the provincial level. All regressions include city fixed effects and year fixed effects.

2.2 Data

2.2.1 Drug Expenditures

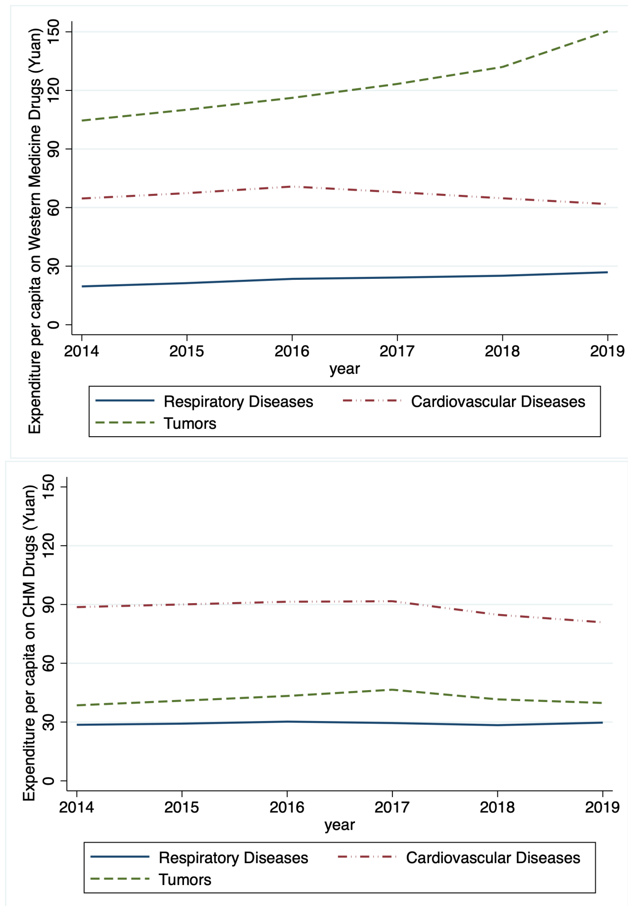
As discussed above, our main dependent variable is the total expenditure on a drug that occurs in public hospitals in a city in a year. Each drug is identified by its commercial product name, dosage, package, and producer. We obtain quarterly expenditure and quantity consumed data for WM drugs in public hospitals across 20 major Chinese cities from the MENET database[5]. For example, an observation in the original data represents the total expenditure in the city of Beijing in the fourth quarter of 2019 on "Felodipine Tablets" (dosage: 5mg; package: 28 tablets) produced by "Beijing Union Pharmaceutical Factory". We then aggregate the amounts to an annual frequency. The 20 cities include Beijing, Changchun, Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Hangzhou, Harbin, Jinan, Nanjing, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Tianjin, Wuhan, Xi'an, and Zhengzhou. The combined population of the 20 cities was 253.82 million by the end of 2019. Quarterly data on expenditure and quantity consumed for CHM drugs are available for nine cities (Beijing, Chengdu, Chongqing, Guangzhou, Harbin, Nanjing, Shenyang, Xi'an, and Zhengzhou) over the same period. The combined population of the nine cities was 130.79 million by the end of 2019. The WM drugs data and CHM drugs data are collected from 1,805 public hospitals, accounting for 60.17% of total public hospitals in all cities in China. Our sample period cover the years from 2014 to 2019.

To mitigate the impact of outliers, observations with annual per capita expenditure and annual average prices falling below the 1st percentile or exceeding the 99th percentile are excluded. Consequently, we retain 28,636, 49,110, and 47,205 observations for Western Medicine (WM) drugs associated with respiratory diseases, cardiovascular diseases, and tumors, respectively. Similarly, for CHM drugs in the same categories, we retain 8,748, 13,249, and 4,033 observations.

[5]Source: https://www.menet.com.cn/menetDatabase/dbCountyHispital.html

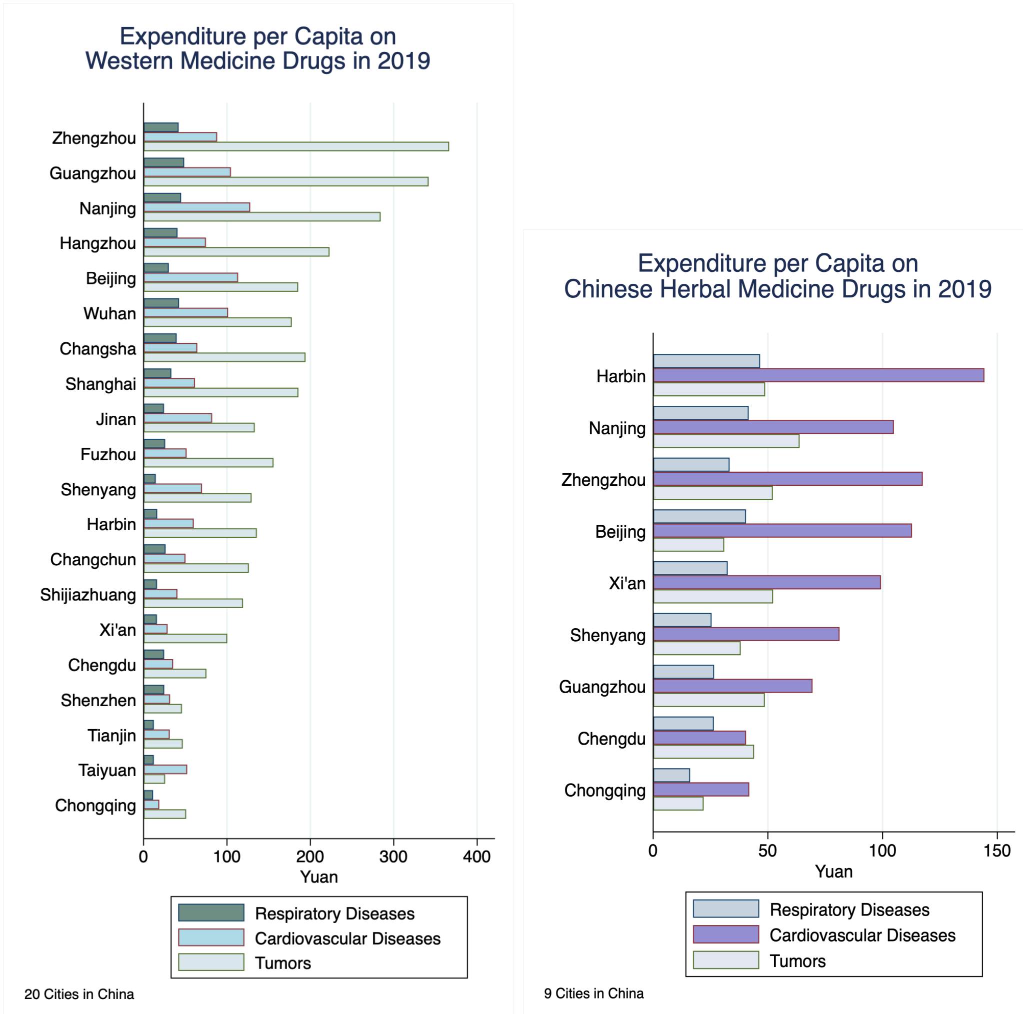
In Figure 1, the time series of nominal expenditures on WM drugs for the treatment of respiratory diseases and cardiovascular diseases exhibit no discernible trends, while expenditure on antitumor drugs demonstrates an upward trajectory. In contrast to WM drugs, the per capita expenditure on cardiovascular diseases is higher than that on tumors for CHM drugs. The expenditures remain stable over the sample period, signifying the enduring significance of CHM drugs in medical practice in China. Figure 2 illustrates the per capita drug expenditure for each type of drug in all cities in 2019. There is a pronounced regional disparity in per capita expenditure for both WM drugs and CHM drugs. Notably, in 2019, the city with the highest GDP per capita (Nanjing, 165,294 yuan) exceeded the expenditure of the city with the lowest GDP per capita (Shenyang, 40,324 yuan) by 310%. Locations of the cities, together with drug expenditures, are shown in Figure 3.

Figure 1: Expenditures on Western Medicine and Chinese Herbal Medicine Drugs



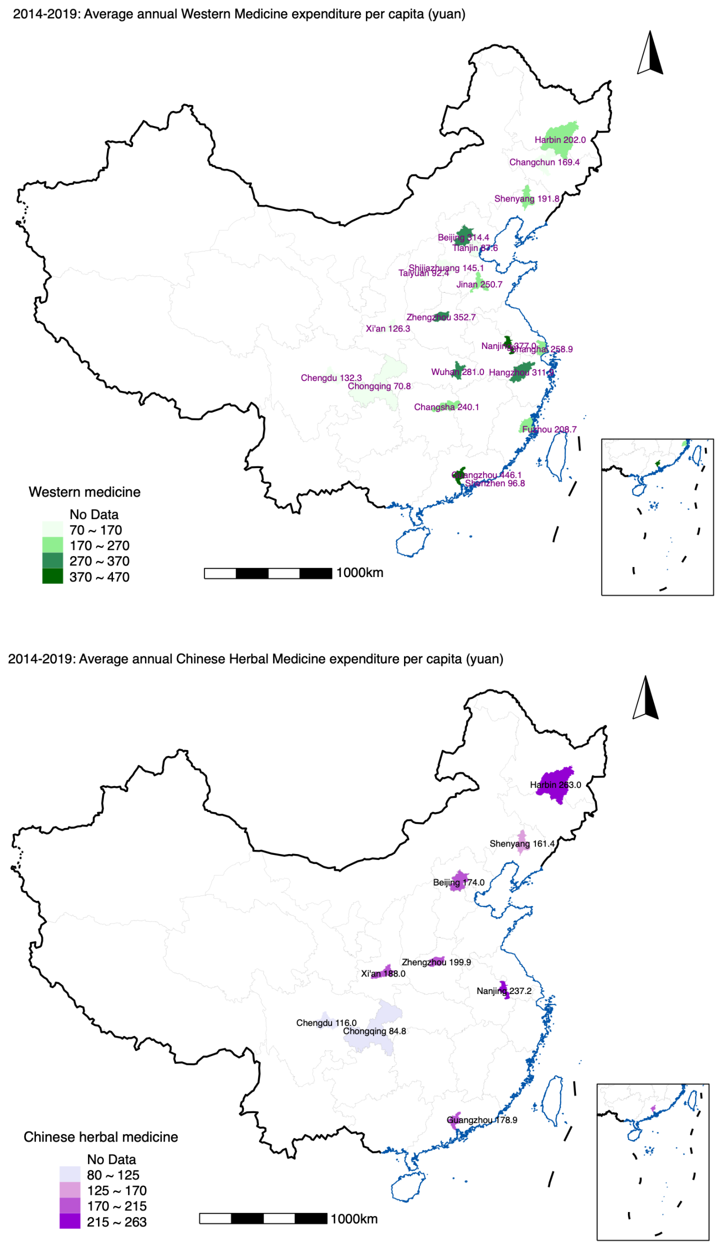
Notes : The top panel and bottom panel plot the current price expenditures per capita on WM drugs and CHM drugs, respectively. Source: authors' calculation.

Figure 2: City-level Expenditures on WM drugs and CHM drugs



Notes : The left panel shows the current price expenditures per capita on Western medicine drugs for treating respiratory diseases, cardiovascular diseases and tumors in 20 cities in 2019. The right panel shows the current price expenditures per capita on Chinese herbal medicine drugs for treating respiratory diseases, cardiovascular diseases and tumors in nine cities in 2019. Source: authors' calculation.

Figure 3: Maps of City-level Expenditures on WM drugs and CHM drugs



Notes : The top (bottom, respectively) panel shows locations of cities and combined current price expenditures per capita on Western medicine drugs (Chinese herbal medicine) for treating respiratory diseases, cardiovascular diseases and tumors, averaged between 2014 to 2019. Source: authors' calculation.

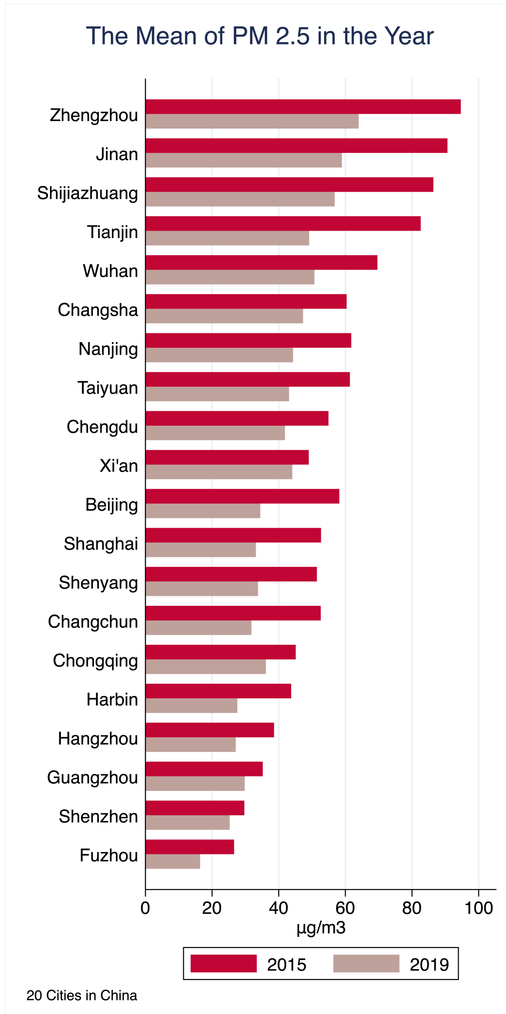
2.2.2 Air Pollution

Our measure for air pollution is PM2.5. The primary data source is PM2.5 pollution metric provided by the Tracking Air Pollution program. This program integrates data from satellite-based observations by the National Aeronautics and Space Administration (NASA) and ground-based facilities in China. [6] In the robustness checks, we also use the PM2.5 data from the Air Quality Index (AQI) published by the Chinese government, derived from readings obtained through a network of ground-based detection facilities.

To account for weather conditions, we have retrieved the daily values of temperature, precipitation, humidity, wind speed, and temperature inversion from representative meteorological stations in each city through the National Weather Bureau. We include their annual averages in the regressions. Following the common practice in the literature (Bondy, Roth, and Sager, 2020; Peet, 2021), we employ maximum wind speed and temperature inversion as instrumental variables for the weather data metrics. Figure 4 illustrates the substantial variation in air pollution levels across cities. Simultaneously, air quality has demonstrated improvement in all cities over time. From the map in Figure 5, we can see that the pollution level is higher in northern China on average.

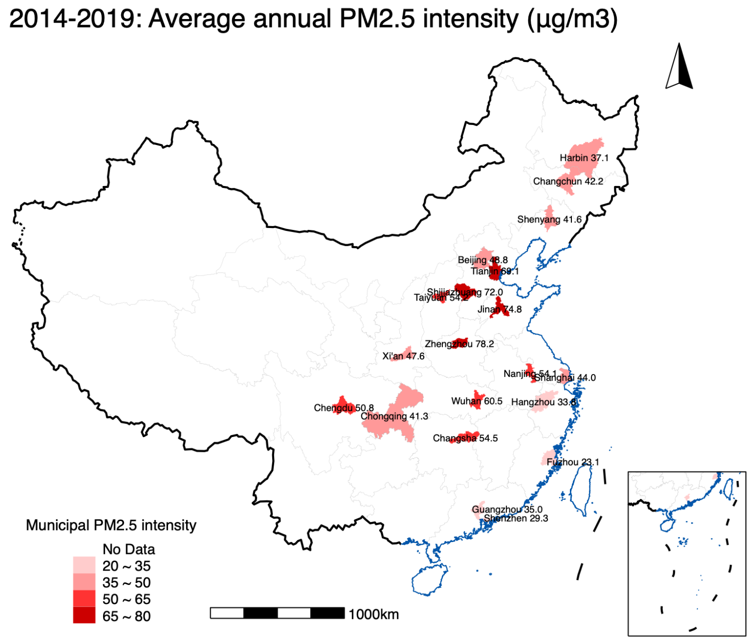
[6] The Tracking Air Pollution in China initiative is managed by a group of researchers at Tsinghua University, and the data is accessible at http://tapdata.org.cn.

Figure 4: City-level PM2.5



Notes : This figure illustrates the annual average PM2.5 of 20 cities in 2015 and 2019. The PM2.5 data are based on readings from a system of ground-based facilities and the information from NASA satellites. Source: authors' calculation.

Figure 5: Map of City-level PM2.5



Notes : The map shows locations of cities and the level of PM2.5 averaged between 2014 to 2019. Source: authors' calculation.

As for socioeconomic characteristics, we incorporate the following indicators: per capita GDP from the National Bureau of Statistics, fiscal revenue from WIND datasets, the fraction of urban residents covered by employment-based health insurance from the China City Statistical Yearbook, and the number of public hospitals at the provincial level from the China Health Statistical Yearbook. A summary of the key variables is provided in Table 2. In addition to the previously noted disparities in drug expenditure, there exists substantial variation in key socioeconomic indicators such as GDP per capita, fiscal revenue per capita, household income, and educational attainment.

Table 2: Summary Statistics

Variable	N	Mean	SD	Min	Max
Dependent Variables :					
Annual expenditure per capita					
WM drugs: respiratory diseases (yuan)	28,636	0.067	0.157	0	1.338
CHM drugs: respiratory diseases (yuan)	8,748	0.131	0.372	0	3.911
WM drugs: cardiovascular diseases (yuan)	49,110	0.113	0.308	0	2.681
CHM drugs: cardiovascular diseases (yuan)	13,249	0.317	0.695	0	5.482
WM drugs: tumors (yuan)	47,205	0.246	0.522	0	3.794
CHM drugs: tumors (yuan)	4,033	0.526	1.026	0	7.008
Measures of Air Pollution					
Annual PM2.5 in TAP data, mean ($\mu g/m^3$)	140	52.290	19.104	16.410	106.205
Annual PM2.5 in TAP data, maximum ($\mu g/m^3$)	140	182.843	63.584	47.967	334.362
Annual PM2.5 in AQI data, mean ($\mu g/m^3$)	120	54.238	17.138	23.964	100.215
Annual PM2.5 in AQI data, maximum ($\mu g/m^3$)	120	263.486	141.669	72.375	903.792
Weather Controls					
Annual precipitation (mm)	140	3.188	1.043	1.366	5.970
Annual average relative humidity (%)	140	66.385	9.905	47.265	83.158
Annual average temperature (Celsius)	140	15.661	4.621	4.302	24.046
Socioeconomic Factors					
Annual GDP per capita (yuan)	140	88335.570	33034.430	13744	165294
Number of public hospitals in the province	133	1151.797	547.062	328	2615
Percentage of employee subscribed to basic health insurance over residents(%)	140	0.465	0.538	0.004	4.525
Annual fiscal revenue per capita (yuan)	140	11436	6438	3001	29509
Household income (yuan)	133	40823	11310	23058	73849
Fraction of residents with college education (%)	140	16.001	8.473	7.730	50.490

Notes : [1] Each drug is identified by commercial product name, dosage, package, and producer. For example, an observation is the total expenditure on 'Felodipine Tablets' (size:5mg; packaging: 28 tablets) produced by 'Beijing Union Pharmaceutical Factory' in the city of Beijing in 2019. [2] The source of Air Quality Index (AQI) data is prefecture-level governments in China. The source of TAP data is the Tracking Air Pollution in China program run by a group of researchers at Tsinghua University.

3 Benchmark Results

3.1 OLS estimates of effects of air pollution on drug expenditure

We report the OLS estimation results based on the specification in equation (1) in column (1) of Table 3. A 1% increase in the average level of PM2.5 during a year is associated with an average increase of 0.95% in per capita expenditure on western respiratory drugs. As for CHM drugs for treating respiratory diseases, the corresponding elasticity estimate in column (3) is 1.62%, exceeding that of WM drugs. The estimated coefficients of the socioeconomic control variables align with common intuition, as drug expenditures per capita are higher in cities with higher GDP per capita, higher medical insurance coverage, and better access to hospitals. Per capita fiscal revenue demonstrates a positive relationship with drug expenditure, although this association lacks statistical significance. Collectively, these regression results establish a statistically and practically significant relationship between the level of air pollution and expenditure on respiratory drugs.

Relative to respiratory diseases, cardiovascular diseases and tumors are typically more chronic and hence can be practically more important for understanding long-term consequences of air pollution. We report regression results for cardiovascular diseases in Table 4. In the OLS regressions reported in Columns (1) and (3), a 1% increase in the average level of PM2.5 during a year is associated with an average increase of 0.83% in per capita expenditure on WM drugs for treating cardiovascular diseases, and an average increase of 2.00% in per capita expenditure on CHM drugs. Antitumor drugs are also crucial for our analysis of drug expenditures, as the group of drugs ranks first in expenditures on WM drugs among all 14 groups of drugs and second in CHM drugs among all 13 groups of drugs reported in Table 1. In the OLS regression analysis presented in Columns (1) and (3) in Table 5, we observe that a 1% increase in the annual average level of PM2.5 is associated with a 1.27% increase in per capita spending on western tumor drugs and a 1.93% increase in per capita spending on CHM drugs.

Table 3: Per capita Drug Expenditure: Respiratory Diseases

	Western medicine		Chinese herbal medicine	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
ln(PM2.5)	0.952***	2.963***	1.623***	5.571***
	(0.067)	(0.295)	(0.242)	(0.560)
ln(Precipitation)	0.196***	0.522***	0.415***	1.319***
	(0.026)	(0.040)	(0.036)	(0.186)
ln(Humidity)	-0.181**	0.288**	-0.274	-0.700
	(0.083)	(0.075)	(0.284)	(0.492)
ln(Temperature)	0.516***	2.536***	0.894***	4.176***
	(0.047)	(0.176)	(0.264)	(0.491)
ln(GDP per capita)	2.638***	5.035***	2.713***	4.972***
	(0.176)	(0.368)	(0.053)	(0.053)
ln(Fiscal revenue)	0.282	1.252	0.830	2.081
	(0.489)	(0.669)	(1.297)	(1.155)
ln(Health insurance)	0.216***	0.611***	0.320***	0.946***
	(0.038)	(0.055)	(0.032)	(0.033)
ln(Hospital)	1.161***	1.518***	0.121	-0.921
	(0.107)	(0.241)	(0.505)	(0.476)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.423	2.423	2.957	2.957
CD F statistic		1270.697		558.707
KP F statistic		1662.084		322.563
Within R^2	0.224		0.268	
N	28,636	28,636	8,748	8,748

Notes : [1] Table reports OLS and 2SLS estimates of equation (1) from the main text. [2] Dependent variable is the log of per capita expenditure on drug j for treating respiratory diseases in city i in year t. The variables $PM2.5$, *Precipitation*, *Humidity*, *Temperature*, *GDP per capita*, *Fiscal revenue*, *Health insurance*, and *Hospital* are the annual average PM2.5, annual precipitation, annual average humidity, annual average temperature, GDP per capita, fiscal revenue per capita, and fraction of residents covered by basic public health insurance in city i in year t. The variable *Hospital* is the number of public hospitals in the province to which a city belongs in year t. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. [4] Standard errors reported in parenthesis are clustered by disease category. There are 6 categories of drugs within western medicine drugs for treating respiratory diseases.

Table 4: Per capita Drug Expenditure: Cardiovascular Diseases

	Western medicine		Chinese herbal medicine	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
ln(PM2.5)	0.829***	3.592***	1.998***	4.347***
	(0.060)	(0.198)	(0.167)	(0.313)
ln(Precipitation)	0.204***	0.587***	0.416***	1.098***
	(0.039)	(0.029)	(0.031)	(0.060)
ln(Humidity)	-0.145*	-0.066	-0.798***	-0.586***
	(0.083)	(0.075)	(0.023)	(0.040)
ln(Temperature)	0.573***	2.905***	1.284***	3.256***
	(0.027)	(0.187)	(0.077)	(0.188)
ln(GDP per capita)	2.696***	5.329***	3.260***	6.414***
	(0.167)	(0.124)	(0.198)	(0.267)
ln(Fiscal revenue)	-0.316	1.493**	-1.886***	-1.355**
	(0.406)	(0.563)	(0.461)	(0.400)
ln(Health insurance)	0.248***	0.668***	0.490***	1.010***
	(0.048)	(0.041)	(0.086)	(0.068)
ln(Hospital)	1.138***	1.501***	0.331***	0.455*
	(0.090)	(0.111)	(0.119)	(0.154)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.617	2.617	3.952	3.952
CD F statistic		1995.189		941.627
KP F statistic		1794.176		23781.385
Within R^2	0.198		0.267	
N	49,110	49,110	13,249	13,249

Notes : [1] Table reports OLS and 2SLS estimates of equation (1) from the main text. [2] Dependent variable is the log of per capita expenditure on drug j for treating cardiovascular diseases in city i in year t. The variables $PM2.5$, $Precipitation$, $Humidity$, $Temperature$, $GDP\ per\ capita$, $Fiscal\ revenue$, $Health\ insurance$, and $Hospital$ are the annual average PM2.5, annual precipitation, annual average humidity, annual average temperature, GDP per capita, fiscal revenue per capita, and fraction of residents covered by basic public health insurance in city i in year t. The variable $Hospital$ is the number of public hospitals in the province to which a city belongs in year t. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. [4] Standard errors reported in parenthesis are clustered by disease sub-category. [5] For OLS regression, we report within adjusted R^2.

Table 5: Per capita Drug Expenditure: Tumors

	Western medicine		Chinese herbal medicine	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
ln(PM2.5)	1.268^{***}	4.910^{***}	1.928^{***}	4.763^{*}
	(0.065)	(0.348)	(0.032)	(0.430)
ln(Precipitation)	0.274^{***}	0.701^{***}	0.567^{***}	1.082
	(0.013)	(0.031)	(0.061)	(0.195)
ln(Humidity)	-0.217^{**}	0.033	-0.712	-1.262^{*}
	(0.096)	(0.104)	(0.503)	(0.101)
ln(Temperature)	0.863^{***}	4.050^{***}	1.072^{***}	3.516^{*}
	(0.048)	(0.311)	(0.199)	(0.377)
ln(GDP per capita)	3.506^{***}	6.047^{***}	3.707^{***}	6.929^{**}
	(0.025)	(0.113)	(0.173)	(0.152)
ln(Fiscal revenue)	1.473^{**}	3.542^{***}	2.274	1.269
	(0.681)	(0.348)	(1.791)	(2.421)
ln(Health insurance)	0.379^{***}	0.826^{***}	0.669^{***}	1.210^{**}
	(0.011)	(0.117)	(0.067)	(0.030)
ln(Hospital)	1.572^{***}	2.051^{***}	1.392^{**}	1.076
	(0.102)	(0.150)	(0.688)	(0.717)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.623	3.623	4.667	4.667
CD F statistic		1842.036		277.304
KP F statistic		5925.387		.
Within R^2	0.247		0.265	
N	47,205	47,205	4,033	4,033

Notes : [1] Table reports OLS and 2SLS estimates of equation (1) from the main text. [2] Dependent variable is the log of per capita expenditure on drug j for treating tumors in city i in year t. The variables $PM2.5$, $Precipitation$, $Humidity$, $Temperature$, $GDP\ per\ capita$, $Fiscal\ revenue$, $Health\ insurance$, and $Hospital$ are the annual average PM2.5, annual precipitation, annual average humidity, annual average temperature, GDP per capita, fiscal revenue per capita, and fraction of residents covered by basic public health insurance in city i in year t. The variable $Hospital$ is the number of public hospitals in the province to which a city belongs in year t. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. [4] Standard errors reported in parenthesis are clustered by disease sub-category. [5] For OLS regression, we report within adjusted R^2.

3.2 Two-Stage Least Squares estimates

Before suggesting that the estimated relation is causal, we must consider and address potential endogeneity bias in estimation. The leading cause of endogeneity bias is missing variable. For instance, it is well known in China that individuals sensitive to air pollution may travel, especially in the winter, to cities with better air quality to avoid the adverse effect of air pollution. Such seasonal migration pattern will reduce expenditure on drugs in cities subject to heavy air pollution and bias our estimates toward zero. Another source of endogeneity bias is measurement error in PM2.5 that is correlated with control variables. For instance, because a city with fewer fiscal resources faces more challenge in maintaining the quality in data collection, the measured level of PM2.5 may not adequately reflect the average degree of air pollution experienced by residents in the city. Meanwhile, because it is unlikely that expenditures on drugs affect air quality, endogeneity bias caused by reverse causality is a lesser concern.

To address the potential endogeneity bias associated with missing variables or measurement errors, we follow the literature to use maximum wind speed and temperature inversion in a year as instrumental variables for PM2.5 in regression analysis. When wind is strong at a location, pollution tends to linger in the local air for a shorter period of time. Temperature inversion refers to the situation in which air temperature near the ground level is lower than in the layer of atmosphere above. When temperature inversion occurs, it is more difficult for pollutants to diffuse in the air, leading to a higher concentration of air pollutants. The 2SLS regression results in columns (2) and (4) of Table 3 reveal that the coefficients on PM2.5 remain positive and significant, indicating a likely causal effect of PM2.5 on expenditure on respiratory drugs. The magnitude of the coefficients (2.96 and 5.57) is substantially larger than the OLS estimates (0.95 and 1.62).[7]

Regarding cardiovascular diseases and tumors, the 2SLS regressions in columns (2)

[7] In unreported regressions, we use indicators for four directions of wind as instrumental variables and obtain similar results.

and (4) of Table 4 and Table 5 reveal that a 1% increase in the average level of PM2.5 during a year is associated with an average increase of 3.59% and 4.91%, respectively, in per capita expenditure on WM drugs for treating cardiovascular diseases and tumors. The coefficients of PM2.5 for CHM drugs are 4.35 and 4.76, respectively. Similar to the regressions for expenditure on respiratory drugs, the coefficients in 2SLS are significantly larger compared to the OLS coefficients in columns (1) and (3) of the same table.

The large difference between OLS and 2SLS coefficients is common in studies that use wind speed and temperature inversion as IVs (e.g., Fu, Viard, and Zhang 2021). In the remainder of the paper, we mainly report and discuss results based on 2SLS regressions with the understanding that OLS estimates provide conservative yet still practically large estimate of the impact of air pollution. Overall, the benchmark results in Table 3, Table 4, and Table 5 provide city-level evidence of the adverse health effects of air pollution on drug expenditures. In addition, the responsiveness of drug expenditure on CHM drugs is much larger in the sample of respiratory and cardiovascular diseases, as the coefficients on PM2.5 for CHM drugs(5.57 and 4.35) are larger than their WM drug counterparts (2.96 and 3.59). For tumors, the coefficient for PM2.5 in the case of CHM drugs (4.76) is slightly smaller than WM drugs (4.91).

To assess the explanatory power of PM2.5, we follow Korovkin and Makarin (2023) to compute the following statistic

$$explanatory\ power = \frac{[ln(PM2.5_{p75}) - ln(PM2.5_{p25})] \cdot |\beta_{PM2.5}|}{ln(expenditure_{p75}) - ln(expenditure_{p25})} \cdot 100\% \tag{2}$$

where $PM2.5_{p25}$ and $PM2.5_{p75}$ are the 25th and 75th centiles of PM2.5 values net of year and city fixed effects,[8] $\beta_{PM2.5}$ the coefficient on PM2.5 in the 2SLS regressions, and $expenditure_{p25}$ and $expenditure_{p75}$ the 25th and 75th centiles of per capital expenditure net of year and fixed effects.

[8]To obtain these values, we regress $lnPM2.5_{i,t}$ on year and city fixed effects and obtain the residuals. The 25th and 75th centiles of the residuals are the 25th and 75th centiles of PM2.5 values net of year and city fixed effects.

As summarized by Table 6, the statistics for explanatory power are 9.7%, 10.9% and 14.0% for WM drugs for treating respiratory diseases, cardiovascular diseases and tumors, respectively. The corresponding percentages for CHM drugs for the same three groups of diseases are 17.1%, 12.8% and 14.8%. Therefore, air pollution appears to be an important factor in explaining the variation in drug expenditures, especially expenditures on CHM drugs.

Table 6: Explanatory Power of PM2.5

Variables	p25	p75	p75-p25	β	Power(%)
	Panel A. Respiratory Diseases: Western medicine				
$ln(PM2.5)$	-0.042	0.064	0.107	2.963	9.658
$ln(expenditure\ per\ capita)$	-1.742	1.550	3.292		
	Panel B. Respiratory Diseases: Chinese herbal medicine				
$ln(PM2.5)$	-0.032	0.064	0.097	5.571	17.108
$ln(expenditure\ per\ capita)$	-1.683	1.466	3.149		
	Panel C. Cardiovascular Diseases: Western medicine				
$ln(PM2.5)$	-0.040	0.063	0.103	3.592	10.939
$ln(expenditure\ per\ capita)$	-1.833	1.539	3.373		
	Panel D. Cardiovascular Diseases: Chinese herbal medicine				
$ln(PM2.5)$	-0.036	0.056	0.092	4.347	12.823
$ln(expenditure\ per\ capita)$	-1.581	1.544	3.125		
	Panel E. Tumors: Western medicine				
$ln(PM2.5)$	-0.036	0.063	0.099	4.910	14.048
$ln(expenditure\ per\ capita)$	-1.750	1.711	3.461		
	Panel F. Tumors: Chinese herbal medicine				
$ln(PM2.5)$	-0.036	0.058	0.094	4.763	14.772
$ln(expenditure\ per\ capita)$	-1.531	1.495	3.026		

Note: The table reports statistics for explanatory power of PM2.5, which is the fraction of interquartile range of log per capita expenditure on drugs explained by the interquartile range of log PM2.5. The formula for the statistic is $explanatory\ power = \frac{[ln(PM2.5_{p75}) - ln(PM2.5_{p25})] \cdot |\beta_{PM2.5}|}{ln(expenditure_{p75}) - ln(expenditure_{p25})} \cdot 100\%$.

Our estimates suggest that a 10 $\mu g/m^3$ increase in the annual average PM2.5 results in a per capita annual increase of 108.27 yuan in both WM and CHM drug expenditures related to the three disease groups. This figure is calculated as follows: In our sample, the mean annual satellite-measured PM2.5 is 52.3 $\mu g/m^3$ (denoted as $PM2.5_{base}$), and a 10 $\mu g/m^3$ increase corresponds to a new value of 62.3 $\mu g/m^3$ (denoted as $PM2.5_{new}$).

Using the elasticity coefficients (β_g) from benchmark regressions, we calculate the predicted change in expenditure for each disease group g:

$$ln(expenditure_{g,new}) - ln(expenditure_{g,base}) = \beta_g \times [ln(PM2.5_{new}) - ln(PM2.5_{base})]. \quad (3)$$

For the baseline expenditure on WM drugs treating respiratory diseases, cardiovascular diseases, and tumors (23.44, 66.21, and 122.76 yuan per capita annually from 2014 to 2019) and the respective coefficients of 2.963, 3.592, and 4.910, we use the formula: $ln(expenditure_{g,new}) = [ln(62.3) - ln(52.3)] * \beta_g + ln(expenditure_{g,base})$. Consequently, the annual expenditures for the three groups are projected to increase to 27.69, 76.55, and 153.26 yuan per capita, respectively.

For CHM drugs used in the treatment of respiratory diseases, cardiovascular diseases, and tumors, the anticipated new expenditure levels are 38.90, 124.71, and 58.54 yuan per capita annually. The total increase in annual expenditure across these six groups, 108.27 yuan per capita, is obtained by adding the new expenditures and subtracting the baseline figures: (27.69 + 76.55 + 153.26 + 38.90 + 124.71 + 58.54) - (23.44 + 66.21 + 122.76 + 29.28 + 87.91 + 41.77).[9]

[9] In the context of China, several studies based on different datasets consistently report a significant economic cost of air pollution. Utilizing a dataset comprising the universe of credit and debit card transactions from 2013 to 2015, Barwick et al. (2018) estimate the impact of air pollution on healthcare spending. Their estimates imply that a decrease of PM2.5 by 10 micrograms per cubic meter ($\mu g/m^3$) would result in at least 43.47 yuan reduction in annual healthcare spending per capita. This amount is equivalent to 1.5% of the annual healthcare expenditure in their sample. Based on the China Family Panel Studies dataset, Liao, Du, and Chen (2021) suggest a larger estimate that an increase of PM2.5 by 10 $\mu g/m^3$ is associated with an increase in annual per capita medical cost of 60.84 yuan in 2016-2018. Focusing on the single city of Wuhan, Zhang et al. (2023) analyze the expenditure records of 1% randomly-selected patients at public health access points in 2013-2015. They found that a 10$\mu g/m^3$ reduction in monthly average PM2.5 is estimated to lower annual healthcare expenditure by 43.87 yuan. In comparison, Xia et al. (2022) take a short-term perspective. They found that following a 10$\mu g/m^3$ increase in daily PM2.5 concentrations in Beijing, per beneficiary expenditure recorded in public health care system in the subsequent three-day period increases by 0.38%.

In the current study, we estimate that a 10 $\mu g/m^3$ increase in annual average PM2.5 will result in a 108.27 yuan increase in drug expenditures associated with the three groups of diseases. While the difference in data sources, scope of expenditures, and time interval studied prevents a straightforward comparison of economic costs between the above four studies and ours, our estimated expenditure effect confirms the existence of a significant medical cost. In comparison to these studies, we emphasize the importance of CHM drugs in understanding the impact of air pollution, as the expenditure response associated with CHM drugs is also quantitatively large.

Lastly, exploiting the information on the quantity of drugs consumed in our dataset, we run regressions with quantity as the dependent variable. We report the results in Panel A of Table 7, while the benchmark results from the expenditure regressions are reproduced in Panel B for comparison. The relation between PM2.5 and the quantity of drugs consumed are all positive and significant. The sizes of coefficients in the quantity regressions are equal to 0.30 to 0.75 times their counterparts in the expenditure regressions. Loosely speaking, around half of the increase in expenditure can be explained by increase in quantities of drug consumed.

Table 7: Effects of Air Pollution on Quantity of Drugs Consumption: 2SLS

	Respiratory Diseases		Cardiovascular Diseases		Tumors	
Panel A: Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
ln(Quantity per capita)	WM	CHM	WM	CHM	WM	CHM
ln(PM2.5)	1.857***	2.513***	2.695***	2.273***	1.497**	1.749*
	(0.240)	(0.331)	(0.264)	(0.144)	(0.414)	(0.227)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.480	1.032	1.888	1.389	0.936	1.261
N	28638	8748	49110	13249	47205	4033
	Respiratory Diseases		Cardiovascular Diseases		Tumors	
Panel B: Dep. Var.	(1)	(2)	(3)	(4)	(5)	(6)
ln(Expenditure per capita)	WM	CHM	WM	CHM	WM	CHM
ln(PM2.5)	2.963***	5.571***	3.592***	4.347***	4.910***	4.763*
	(0.295)	(0.560)	(0.198)	(0.313)	(0.348)	(0.430)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.423	2.957	2.617	3.952	3.623	4.667
N	28636	8748	49110	13249	47205	4033

Notes : [1] Table reports 2SLS estimates of equation (1) from the main text. [2] Dependent variable in Panel A is the log of quantity of drug consumption per capita of the relevant city in a year. Dependent variable in Panel B is the log of expenditure of drug consumption per capita of the relevant city in a year. [3] ***, **, * denote significance at the 1%, 5% and 10% level, respectively. [4] Standard errors reported in parenthesis are clustered by disease sub-category. [5] All other controls include weather and socioeconomic controls.

3.3 Significance of expenditures on CHM drugs

In this subsection, we highlight the practical significance of estimated effects of air pollution on expenditure on drugs, especially CHM drugs. In our sample, per capita expenditure on WM and CHM drugs is 652.23 yuan and 262.22 yuan, respectively.[10] Within the per capita expenditure on WM drugs (CHM drugs, respectively), the share of WM drugs (CHM drugs) for treating respiratory diseases is 3.59% (11.17%) and the amount is 23.44 yuan (29.28 yuan).

Multiplying coefficient on PM2.5 in the 2SLS regression for WM drugs in Table 3 with the per capita drug expenditures on WM drugs, a 1% increase in PM2.5 value is expected to increase the expenditure on WM drugs for treating respiratory diseases by 0.69 yuan ($23.44 \times 2.963\% = 0.69$ yuan), which is equivalent to 0.1% of per capita expenditure on WM drugs. The corresponding numbers for CHM drugs for treating respiratory diseases are 1.63 yuan and 0.62%.

In terms of the share in drug expenditure, cardiovascular diseases are more prominent than respiratory diseases, as the share of WM drugs (CHM drugs, respectively) for treating cardiovascular diseases make up 10.15% (33.53%) of total expenditure on all WM drugs (CHM drugs). Multiplying coefficient on PM2.5 in the 2SLS regression for WM drugs in Table 4 with the per capita drug expenditures on WM drugs, we find that a 1% increase in PM2.5 value is associated with a 2.38 yuan rise in expenditure on WM drugs for treating cardiovascular diseases, resulting in 0.36% increase in per capital expenditure on WM drugs. The corresponding figures for CHM drugs used in the treatment of cardiovascular diseases are 3.82 yuan and 1.50%.

WM drugs (and CHM drugs, respectively) for treating tumors make up 18.82% (15.93%) of the total expenditure on all WM drugs (CHM drugs). And the expenditure

[10]The per capita expenditure on WM drugs (CHM drugs, respectively) is calculated by dividing total expenditure on all WM drugs (CHM drugs) in all cities in the sample by the total population of these cities.

on antitumor drugs is the highest among 14 groups of drugs. By multiplying the coefficient on PM2.5 in the 2SLS regression on WM drugs in Table 5 with per capita expenditures on WM drugs, we observe that a 1% increase in the PM2.5 value is associated with a 6.03 yuan increase in expenses on WM drugs for treating tumors, resulting in a 0.92% rise in per capita expenditure on WM drugs. The corresponding figures for CHM drugs used in the treatment of tumors are 1.99 yuan and 0.76%.

Taken together, a 1% increase in PM2.5 causes practically significant rise in drug expenditures. The combined increase in drug expenditures on WM drugs at 9.10 yuan (the sum of 0.69 yuan for respiratory diseases, 2.38 yuan for cardiovascular diseases, and 6.03 for tumors) which is equal to 1.00% of the per capital expenditure on all drugs in our sample. In comparison, following a 1% rise in PM2.5, the combined increase in drug expenditures on CHM drugs at 7.44 yuan (the sum of 1.63 yuan for respiratory diseases, 3.82 yuan for cardiovascular diseases, and 1.99 for tumors) which is equal to 0.81% of the per capital expenditure on all drugs in our sample. To the best of our knowledge, we are the first to examine separately expenditures on WM drugs and CHM drugs. Our results highlight the importance of CHM drugs in the understanding of drug expenditures in general.

4 Regional Disparities in Response of Drug Expenditures to Pollution

4.1 Socioeconomic factors

Existing research indicates that individual-level factors affect their exposure to pollution. Individuals at low socioeconomic status, measured by income, level of education, occupation, ethnicity, nationality, social security enrollment, neighborhood, and household registration status, are disproportionately exposed to environmental pollution (Tonne et al., 2008; Currie, Neidell, and Schmieder, 2009; Currie, 2011). Recognizing the importance of socioeconomic factors, we examine whether the regional disparities in three such factors contribute to the disparities in drug expenditures associated with air pollution.

The first factor is local fiscal resources. In the discussion of public health policy, differences in fiscal resources across countries are known to be a driver of disparities in health care spending (WHO et al., 2018). In the context of China, because as a significant portion of the funding of local public health programs comes from the budgets of cities, the fraction of expenditure covered by the public medical insurance programs vary considerably across cities.[11] We include in the regression fiscal revenue per resident to capture the effect of local fiscal resources on drug expenditure.

The second factor is household disposable income. If the burden of drug costs is significant enough, we should observe that cities with lower per capita disposable income will spend less on drugs following a rise in air pollution. Moreover, individuals with more disposable income are more likely to seek information related to personal health, have better access to information, and achieve a higher level of health literacy (Tang et al., 2019). Therefore, we conjecture individuals with more disposable income are more likely to spend more on medical treatment following an increase in air pollution.

The third factor is education attainment. Individuals with better education are more likely to possess better knowledge of air pollution and seek medical help after observing symptoms related to pollution. In addition, these individuals may contribute to positive externalities by sharing their knowledge about air pollution. Therefore, we add the fraction of college graduates among residents to the regression to examine the effect of education on drug expenditure.[12]

We introduce each of the three variables along with its interaction with PM2.5 into the benchmark regressions. Due to our focus on these socioeconomic factors, in this

[11]In a policy document titled "Key Tasks For Further Reform of the Medical and Health Care System in 2022" (*Shenhua Yiyao Weisheng Tizhi Gaige 2021 Nian Zhongdian Gongzuo Renwu*), the State Council of China recognized the substantial difference in coverage of medical insurance programs that are run by and called for further integration of the programs in each province.

[12]The three variables are retrieved from the National Bureau of Statistics of China and China Health Statistical Yearbook.

section, we pool the observations from all three disease groups to estimate the interaction effects. In the regressions reported in Table 8, we remove the sample mean from all variables that are interacted, such that the main coefficient on each of these variables is the marginal effect of the variable evaluated at the sample mean.

The coefficient on the interaction term between fiscal revenue per resident and PM2.5 is 1.430 and statistically significant for expenditure on WM drugs. If ln(Fiscal revenue) increases by one standard deviation (0.527 in the sample), pollution elasticity of per capita expenditure on WM drugs rises by 0.75 ($0.527 \times 1.430 = 0.75$). As for expenditure on CHM drugs, the coefficient on the interaction term is 3.65 but not significant. Thus there is some evidence that the expenditure response is larger in cities with a higher level of fiscal revenue per resident.

As for household disposable income, the coefficient on the variable is negative and significant in two relevant regressions in Table 8. Thus, cities with a higher level of income report a lower baseline level of drug expenditures, i.e. the expenditure level at a very low level of air pollution. Meanwhile, coefficients on the two interaction terms involving household disposable income are 1.892 and 1.861. For cities with ln(HHD income) that is one standard deviation (0.275 in the sample) above the mean level, pollution elasticity of per capita expenditure on WM drugs rises by 0.52 ($0.275 \times 1.892 = 0.52$), and the corresponding elasticity of per capita expenditure on CHM drugs rises by 0.51 ($0.275 \times 1.861 = 0.51$). Therefore, average household disposable income has a strong influence of regional disparity in drug expenditures.

Lastly, cities with a higher percentage of college graduates among residents generally report a lower baseline level of drug expenditures. As the coefficient on the interaction term in column (3) of Table 8 is 0.112 and highly significant, the expenditures on WM drugs rise sharply with air pollution in cities with more college-educated residents. For cities in which the percentage of college graduates is one standard deviation (8.473 in the

Table 8: Socioeconomic Factors and Regional Disparities in Drug Expenditure

	Western medicine:2SLS			Chinese herbal medicine:2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(PM2.5)	4.038***	4.209***	6.197***	5.290***	5.762***	7.157***
	(0.195)	(0.228)	(0.280)	(0.311)	(0.332)	(0.378)
ln(Fiscal revenue)	-2.742	4.693***	6.760***	-12.547	-1.838	3.172***
	(2.833)	(0.638)	(0.577)	(11.462)	(1.290)	(0.806)
ln(PM2.5)*ln(Fiscal revenue)	1.430*			3.650		
	(0.804)			(3.010)		
ln(HHD income)		-6.277***			-5.450***	
		(0.613)			(1.170)	
ln(PM2.5)*ln(HHD income)		1.892***			1.861***	
		(0.153)			(0.372)	
Education			-0.376***			-0.074*
			(0.017)			(0.037)
ln(PM2.5)*Education			0.112***			0.008
			(0.005)			(0.009)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.952	2.952	2.952	3.728	3.728	3.728
CD F statistic	2810.254	2350.493	2472.813	913.213	950.186	1353.908
KP F statistic	2383.254	2678.538	3120.141	515.259	511.661	454.628
N	124,951	124,951	124,951	26,030	26,030	26,030

Notes : [1] Table reports disparities associated with socioeconomic factors. Dependent variable is the log of per capita expenditure on drugs of the relevant city in a year. [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [3] Standard errors, clustered by disease sub-category, are reported in parenthesis. [4] All other controls include socioeconomic and weather controls.

sample) above the mean level, pollution elasticity of per capita expenditure on WM drugs rises by 0.95 ($8.473 \times 1.112 = 0.95$). In comparison, the coefficient on the interaction term in column (6) is 0.008 and insignificant. Thus, there is no evidence that the responsiveness of expenditure on CHM drugs is higher in other cities with more college-educated residents.

Overall, the three socioeconomic factors contribute to regional disparities in response of drug expenditures to air pollution. Cities with a higher level of fiscal revenue, household disposable income, and a higher fraction of college graduates among residents report a higher degree of responsiveness in expenditures on WM drug to air pollution. Meanwhile, household disposable income is the only significant factor that contributes to a higher degree of responsiveness of expenditure on CHM drugs. To different extents, both public and private ability to pay contribute, as well as the education attainment of residents, all contribute to disparities in drug expenditure. [13]

4.2 Northern vs. Southern Chinese Cities

Disparities in health care utilization can be ascribed not only to socioeconomic factors detailed in the preceding subsection, but also to the geographical region of residence (Sözmen and Ünal, 2016). When it comes to China, air quality in northern China is poorer than southern China because of heavier use of coal in heating seasons, less precipitation, and other factors. The literature on air pollution in China has established that the poor air quality in northern China lowers life expectancy and raises mortality rate (Chen et al., 2013; Ebenstein et al., 2017; Gong et al., 2023). Therefore, residents in northern China might be forced to spend more to treat pollution-related diseases. On the other hand, because humans can adapt to the environment (Komolafe et al., 2014), expenditure effects of air pollution in the north may be mitigated by such adaptation.

To investigate whether the poor air quality in northern China leads to an expenditure

[13] It is perhaps surprising that higher values of the latter two variables are related to a lower level of baseline drug expenditure. Future work is required to understand the mechanism through which higher household income and better education reduce baseline drug expenditures.

pattern different from southern China, we introduce to 2SLS regressions an indicator variable for northern cities and interact it with air pollution.[14] Similar to Subsection 4.1, we pool all observations from all three diseases groups. As presented in Table 9, the coefficients on the interaction term between PM2.5 and indicator for northern cities are positive and significant, which indicates a larger response of drug expenditure to air pollution in northern cities than southern cities. As we alternate the dependent variable among expenditure on WM and CHM drugs, the coefficients on the interaction term are 1.02 and 2.03. Overall, the difference in pollution elasticicities between southern and northern China is significant in both economic and statistical sense.

Table 9: Difference between Northern and Southern Cities of China

	(1) Western medicine: 2SLS	(2) Chinese herbal medicine: 2SLS
ln(PM2.5)*North	1.022^{***}	2.029^{***}
	(0.107)	(0.153)
ln(PM2.5)	3.573^{***}	3.678^{***}
	(0.229)	(0.209)
All other controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Category FE	Yes	Yes
Dep. Var. Mean	2.952	3.728
CD F statistic	2764.136	1140.193
KP F statistic	2218.415	444.321
N	124,951	26030

Notes : [1] Table reports disparities between northern and southern Chinese cities. [2] Dependent variable is the log of expenditure on drug per capita of the relevant city in a year. [3] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [4] Standard errors, clustered by disease category, are reported in parenthesis. [5] All other controls include weather and socio-economic controls.

The findings in Table 9 suggest that northern residents' drug expenditure is significantly more responsive to rise in air pollution than their southern counterparts. In particular, the north-south difference in sensitivity of drug expenditure is larger for CHM

[14] In our samples, the northern cities include Beijing, Changchun, Harbin, Jinan, Shijiazhuang, Shenyang, Taiyuan, Tianjin, Xi'an, and Zhengzhou; the southern cities include Changsha, Chengdu, Chongqing, Fuzhou, Guangzhou, Hangzhou, Nanjing, Shanghai, Shenzhen, and Wuhan.

drugs than WM drugs. Based on these results, targeted interventions aimed at reducing air pollution in the northern cities may be particularly effective in mitigating the burden of drug expenditure.

5 Robustness and Extension

In this section, we present results on the robustness of results to alternative measures of air pollution and the long-term impact of air pollution. We adopt three alternative measures of air pollution. Firstly, to alleviate the concern that the PM2.5 based on TAP dataset, which incorporates information from the ground facilities and NASA satellites, may be subject to measurement errors, we use the PM2.5 pollution measure from Air Quality Index (AQI) published by the Chinese government based on readings from a system of ground-based detection facilities. The data includes information on PM2.5 which is one of the five components of the AQI. Second, because the exposure to extreme pollution might be more damaging to health than average exposure, we measure air pollution as the within-year maximum level of PM2.5 in AQI data and the maximum level of PM2.5 in TAP data. To facilitate comparison, we reproduce benchmark regressions results for respiratory diseases in column (1) of Panel A and B in Table 10, and report regressions with alternative pollution measures in other columns.

Based on column (2) of Table 10 Panel A, a 1% increase in maximum level of PM2.5 is associated with a 1.91% increase in per capita expenditure on WM drugs for respiratory diseases. Columns (3) and (4) of Table 10 are regression of expenditure on the mean and maximum level of PM2.5 from the AQI data. For both panel A and B, relative to columns (1) and (3), the coefficient on maximum level of PM2.5 is smaller than mean level of PM2.5. From the results, it is not conclusive which of mean pollution level and maximum pollution level is a better indicator for measuring the effect of air pollution on drug expenditure. Nevertheless, it remains robust that the negative effect of air pollution

Table 10: Alternative Measures of Air Pollution: Respiratory Diseases

	Panel A: Western medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	2.963***			
	(0.295)			
ln(PM2.5 max)		1.906***		
		(0.102)		
ln(AQI:PM2.5 mean)			2.296***	
			(0.365)	
ln(AQI:PM2.5 max)				1.552***
				(0.084)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.423	2.423	2.454	2.454
N	28,636	28,636	28,215	28,215
	Panel B: Chinese herbal medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	5.571***			
	(0.560)			
ln(PM2.5 max)		3.934***		
		(0.205)		
ln(AQI:PM2.5 mean)			12.003**	
			(2.306)	
ln(AQI:PM2.5 max)				2.919***
				(0.191)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.957	2.957	2.996	2.996
N	8,748	8,748	8,587	8,587

Notes : [1] Table reports 2SLS estimates of equation (1) from the main text. [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [3] Standard errors, clustered by disease category, are reported in parenthesis. [4] All other controls include socioeconomic and weather controls.

on health is significant. The results of cardiovascular diseases regressions reported in Table 11 and tumors regressions reported in Table 12, also confirm the robustness regarding different measures of PM2.5.

Table 11: Alternative Measures of Air Pollution: Cardiovascular Diseases

	Panel A: Western medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	3.592***			
	(0.198)			
ln(PM2.5 max)		2.065***		
		(0.071)		
ln(AQI:PM2.5 mean)			3.041***	
			(0.292)	
ln(AQI:PM2.5 max)				1.708***
				(0.070)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.617	2.617	2.645	2.645
N	49,110	49,110	48,457	48,457
	Panel B: Chinese herbal medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	4.347***			
	(0.313)			
ln(PM2.5 max)		2.788***		
		(0.109)		
ln(AQI:PM2.5 mean)			2.882**	
			(0.686)	
ln(AQI:PM2.5 max)				2.277***
				(0.010)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.952	3.952	3.982	3.982
N	13,249	13,249	13,103	13,103

Notes : [1] Table reports 2SLS estimates of equation (1) from the main text. [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [3] Standard errors, clustered by disease category, are reported in parenthesis. [4] All other controls include socioeconomic and weather controls.

To examine whether the impact of air pollution lasts beyond a year, we include the one-year lag of PM2.5 in regressions and report the results in Table 13.[15] The benchmark regressions results for respiratory diseases, cardiovascular diseases and tumors are repro-

[15] When further lags are introduced in unreported regressions, they are statistically insignificant.

Table 12: Alternative Measures of Air Pollution: Tumors

	Panel A: Western medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	4.910^{***}			
	(0.348)			
ln(PM2.5 max)		2.362^{***}		
		(0.172)		
ln(AQI:PM2.5 mean)			4.757^{***}	
			(0.591)	
ln(AQI:PM2.5 max)				1.980^{***}
				(0.194)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.623	3.623	3.651	3.651
N	47,205	47,205	46,675	46,675
	Panel B: Chinese herbal medicine			
	(1)	(2)	(3)	(4)
ln(PM2.5)	4.763^{*}			
	(0.430)			
ln(PM2.5 max)		3.239^{*}		
		(0.400)		
ln(AQI:PM2.5 mean)			2.907^{*}	
			(0.425)	
ln(AQI:PM2.5 max)				2.537^{*}
				(0.319)
All other controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	4.667	4.667	4.698	4.698
N	4,033	4,033	3,995	3,995

Notes : [1] Table reports 2SLS estimates of equation (1) from the main text. [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [3] Standard errors, clustered by disease category, are reported in parenthesis. [4] All other controls include socioeconomic and weather controls.

duced in Column (1), Column (3) and Column (5) respectively. In column (2) of Panel A, the coefficient on the current year PM2.5 is positive but becomes insignificant, while the one-year lag of PM2.5 is significant. In Panel B, the lag of PM2.5 has practically zero effect on CHM drugs, while the current year PM2.5 remains positive and significant.

Table 13: Longer-term Effects of Air Pollution

PanelA:	Respiratory Diseases		Cardiovascular Diseases		Tumors	
Western medicine	(1)	(2)	(3)	(4)	(5)	(6)
ln(PM2.5)	2.963***	0.370	3.592***	0.483**	4.910***	2.240***
	(0.295)	(0.243)	(0.198)	(0.185)	(0.348)	(0.196)
Lag.ln(PM2.5)		0.531**		0.947***		1.055**
		(0.194)		(0.220)		(0.195)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.423	2.678	2.617	2.871	3.623	3.873
N	28,636	20,605	49,110	35,657	47,205	34,539
PanelB:	Respiratory Diseases		Cardiovascular Diseases		Tumors	
Chinese herbal medicine	(1)	(2)	(3)	(4)	(5)	(6)
ln(PM2.5)	5.571***	4.076**	4.347***	1.956**	4.763*	1.814
	(0.560)	(0.918)	(0.313)	(0.371)	(0.430)	(0.552)
Lag.ln(PM2.5)		-0.058		0.737***		0.915
		(0.155)		(0.081)		(0.630)
All other controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	2.957	3.184	3.952	4.165	4.667	4.886
N	8,748	6,224	13,249	9,901	4,033	3,057

Notes : [1] Table reports TSLS estimates of equation (1) combined with the lag of PM2.5 from the main text. [2] *, ** and *** are significance levels at 1%, 5% and 10%, respectively. [3] Standard errors, clustered by disease category, are reported in parenthesis. [4] All other controls include socioeconomic and weather controls.

As for cardiovascular diseases, the results in Column (4) show that the one year lag of PM2.5 has a positive and statistically significant effect on expenditure on both WM and CHM drugs. The PM2.5 in the current year remains significant. In the case of tumors, the findings in Column (6) of Panel A reveal a positive and significant impact of a one-year lag in PM2.5 on WM drug expenditures while the PM2.5 levels in the current year remain significant. As for the impact on expenditures for CHM drugs, both the current-year PM2.5 and the one-year lag of PM2.5 are positive but insignificant. Thus, for all three groups of diseases, there is strong evidence that the effect of air pollution on expenditures on WM drugs are persistent. In comparison, the degree of persistence of effect of air pollution on CHM drugs varies across three groups of diseases.

Lastly, to address the potential impact of the COVID-19 Pandemic on our results, we also run regressions with data from 2020 to 2021. The findings, not reported here but available upon request, confirm the baseline results that air pollution continues to have a significant positive effect on per capita expenditure on WM and CHM drugs for all three groups of diseases.

6 Conclusion

By utilizing panel data on drug expenditures from major public hospitals in 20 large Chinese cities over the period from 2014 to 2019, we estimate the impact of air pollution on expenditures for Western Medicine (WM) and Chinese Herbal Medicine (CHM) drugs used in treating respiratory diseases, cardiovascular diseases, and tumors. To address the potential confounding effects of human migration activities and measurement errors on causal identification, we employ maximum wind speed and temperature inversions as instrumental variables to establish causality.

The results indicate that air pollution exerts a heavy economic burden by causing an increase in drug expenditures. After a 1% rise in the annual average of PM2.5, the total spending on respiratory, cardiovascular, and antitumor medications (including both Western Medicine and Chinese Herbal Medicine drugs) is expected to rise by 1.81% of the annual per capita drug expenditure. We examine how air pollution affects spending on WM and CHM drugs, with the latter having been understudied in the literature. Our findings indicate that following a PM2.5 increase, the rise in spending and the responsiveness of spending for CHM drugs are comparable to those for WM drugs, highlighting the significance of CHM in assessing the economic impacts of air pollution. Socioeconomic factors are found to be significant in explaining disparities in the impact of air pollution. Cities with higher socioeconomic status—proxied by greater per capita fiscal revenue, higher per capita disposable income, and a larger proportion of college graduates among residents—spend more on drugs in response to air pollution. Moreover, the response of drug expenditures to air pollution is more pronounced in cities in Northern China compared to those in the South.

This study sheds light on the multifaceted impacts of air pollution on drug expenditures, underscoring the importance of considering both WM and CHM drugs in future research and policy initiatives. Within the medical community and broader Chinese society, there is an ongoing discussion about the relative uses of WM versus CHM drugs. In the context of treating respiratory diseases, cardiovascular diseases, and tumors, our findings highlight the significant role of CHM drugs in China's overall drug expenditures. Clearly, further research is necessary to fully understand the factors that influence the prescription and consumption patterns of CHM drugs.

CRediT authorship contribution statement

Heng Ju: Conceptualization, Resources, Data Curation, Writing - Review & Editing, Supervision, Funding acquisition. **Yao Tang:** Conceptualization, Methodology, Validation, Formal analysis, Writing - Review & Editing, Project administration, Funding acquisition. **Meilan Zhang:** Conceptualization, Software, Formal analysis, Investigation, Writing - Original Draft, Writing - Review & Editing, Visualization.

Declaration of competing interest

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

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used GPT4.0 in order to improve readability and language. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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