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RESEARCH ARTICLE

Effect of air pollution on the prevalence of breast and cervical cancer in China: a panel data regression analysis

Meiyu Hu[1] · Chen Jiang[1] · Runtang Meng[1] · Yingxian Luo[1] · Yaxin Wang[1] · Mengyi Huang[1] · Fudong Li[2] · Haiyan Ma[1]

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Abstract
The association between the prevalence of breast and cervical cancer in Chinese women and air pollution is obscure. The study aims to analyze the correlation between air pollution and the prevalence of breast and cervical cancer, and whether the gross domestic product (GDP) has a modifying effect on the impact of air pollution on the prevalence of breast and cervical cancer. Extracting panel data from 31 provinces and cities between 2006 and 2020, we evaluated the association between breast and cervical cancer prevalence and pollutant emissions from 2006 to 2015 with two-way fixed-effect models. We also analyzed the interaction between GDP and pollutant emissions and further check the robustness of the moderating effect results using group regression from 2016 to 2020. Cluster robust standard errors were used to correct for the heteroskedasticity and autocorrelation. The coefficients of models show that the coefficients of logarithmic soot and dust emissions are estimated to be significantly positive, and the coefficients of their square terms are significantly negative. The robust results suggest that the relationship between soot and dust emissions and breast or cervical cancer prevalence is non-linear, from 2006 to 2015. In the analysis of particulate matter (PM) data in 2016–2020, the PM-GDP interaction term was also significantly negative, indicating that GDP growth weakened the effect of PM on the prevalence of breast cancer and cervical cancer. In provinces with higher GDP, the indirect effect of PM emissions concerning breast cancer is −0.396 while in provinces with lower GDP, it is about −0.215. The corresponding coefficient concerning cervical cancer is about −0.209 in provinces with higher GDP but not significant in provinces with lower GDP. Our results suggest that there is an inverted U-shaped relationship between the prevalence of breast cancer and cervical cancer and air pollutants from 2006 to 2015. GDP growth has a significant negative moderating effect on the impact of air pollutants on the prevalence of breast cancer and cervical cancer. PM emissions have a higher effect on the prevalence of breast and cervical cancer in provinces with higher GDP and a lower impact in provinces with lower GDP.

Keywords Breast cancer · Cervical cancer · Prevalence · Air pollution · Fixed-effect model

Abbreviations
GDP gross domestic product
PM particulate matter
soot soot and dust emissions

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✉ Haiyan Ma
mahaiyan@hznu.edu.cn

1 Department of Public Health, Hangzhou Normal University, Yuhangtang Road, Yuhang District, 311121 Hangzhou, Zhejiang Province, China

2 Department of Public Health Surveillance & Advisory, Zhejiang Provincial Center for Disease Control and Prevention, Xincheng Road, Binjiang District, 310051, Hangzhou, Zhejiang, China

Background

Breast and cervical cancers are the most common cancers, which have a high mortality rate for women. According to the latest global cancer burden data released by the World Health Organization's International Agency for Research on Cancer (IARC) in 2020, there are 19.29 million new cancer cases worldwide. One of the most obvious changes is the rapid increase in the number of new cases of breast cancer to 2.26 million, officially replacing lung cancer (2.2 million) as the world's largest cancer for the first time. There are 4.57 million new cancer cases in China, accounting for 23.7% of the world. Breast cancer makes up around 19.9% of all new cancer cases in Chinese women, making it the most prevailing cancer (Wild et al. 2020; Zheng et al. 2022). Cervical cancer is also one of the most common malignant tumors in women. Especially in developing countries, the incidence of cervical cancer ranked first, seriously endangering the health and even life of the majority of women. Meanwhile, the prevalence of breast and cervical cancer in women varied among provinces and cities in China, suggesting a possible association with environmental risk factors.

Moreover, with the rapid development of China's economy, the massive consumption of various energy fuels has made particulate matter and dust pollution in the atmosphere an important environmental pollution problem. Particle matter, dust, and soot are the principal particulate pollutants that contribute to air pollution. PM consists of organic matter such as polycyclic aromatic hydrocarbons (PAHs), formaldehyde, heavy metals, and dust particles. The category of PM includes dust and soot, which can be suspended in the air and enter the respiratory system. Particles between approximately 5 and 10 μm are more likely to be deposited in the tracheobronchial tree (Löndahl et al. 2007; Kim et al. 2013), due to their excessive penetration. Particles with diameters ranging from 1 to 5 μm are deposited in the respiratory bronchioles and alveoli where gas exchange occurs (Löndahl et al. 2006; Valavanidis et al. 2008; Kim et al. 2015). These particles can disrupt the exchange of gases in the lungs, and even escape into the bloodstream, posing serious health risks (Kim et al. 2015). Consequently, the air pollution is known as a significant risk factor for human health status.

With the growing increase of air pollution in developing countries, more and more scholars have started to study the effects of air pollution on the health of the population. Numerous epidemiological studies at home and abroad have demonstrated that air pollution is associated with the incidence and mortality of various cancers, especially respiratory diseases, such as increased risk of lung cancer, ovarian cancer, and thyroid cancer (Raaschou-Nielsen et al. 2013; Dehghani et al. 2021; 2022). At the same time, in recent years, many epidemiological studies on breast cancer and cervical cancer and air pollution have been published abroad, and the conclusions on the impact of air pollutants on the incidence rate or mortality of breast cancer and cervical cancer are inconsistent among the studies (Hung et al. 2012; Ancona et al. 2015; Reding et al. 2015; Hart et al. 2016; Parikh and Wei 2016). The literature in Asia has a relatively high concentration of $PM_{2.5}$, with an average concentration range of 20.8 to 76.98 μg/m^3, showing that $PM_{2.5}$ is related to breast cancer mortality, while the literature in North America suggests that $PM_{2.5}$ is not associated with incidence rate or mortality of breast cancer. For example, a Japanese cross-sectional study using air pollution data found an association between increased breast cancer mortality and airborne particulate matter levels (Iwai et al. 2005). Based on the data of prospective nationwide Nurses' Health Study II (NHSII) cohort in North America, Jaime E Hart et al. (2016) found no statistically significant associations between particulate matter exposures and incidence of breast cancer. Ole Raaschou-Nielsen et al. (2011) demonstrated that traffic-related air pollution might increase the risks for cervical and brain cancer by a Danish cohort study.

Furthermore, there are only a very few provincial and municipal studies that link breast or cervical cancer with air pollution in China. An ecological study, conducted in Taiwan, is the first to show that exposure to high levels of $PM_{2.5}$ may be associated with an increased risk of death from breast cancer (Hung et al. 2012). The Hong Kong study of cohorts conducted among 66,820 persons reported a hazard rate (HR) of 1.8 (95% CI: 1.26, 2.55) per 10 μg/m^3 increase of $PM_{2.5}$ (Wong et al. 2016). For cervical cancer, (G. C. Liu et al. 2022b) retrospectively assessed the association between $PM_{2.5}$ exposure and the overall survival (OS) of cervical cancer patients residing in 14 urban areas of Liaoning Province, northeastern China, from January, 2014 to October, 2021. Cox regression (HR=1.06, 95% CI: 1.04, 1.08) indicated that $PM_{2.5}$ was significantly associated with shorter OS. Besides, there are significant differences between China and developed countries or other Asian countries in terms of the composition of air pollution, pollution levels, lifestyles, population composition, and economic levels. For example, the concentration of particulate matter in the atmosphere in China is higher in various regions than in developed countries. At the same time, elderly people account for a relatively high proportion of the population in Europe and the USA, and the proportion of susceptible population is also higher than that in China. This leads to the fact that research results from developed countries cannot reach uniform conclusions and cannot be directly used to extrapolate to China. Therefore, we urgently need to conduct local epidemiological studies to assess the effects of air pollution on breast and cervical cancers based on environmental pollution and cancer prevalence in China. To our knowledge, no quantitative analysis of the correlation between breast and cervical cancers and common air pollutants (soot and dust and PM) using a national annals database of 31 Chinese provinces and cities has been seen in the literature. In addition, few studies have assessed the association using prevalence data as the dependent variable.

In this study, we thus aim to explore the association between air pollutants and residents' prevalence of breast and cervical cancer and whether the association is influenced by economic development in China. The findings of this study might provide scientific clues for improving women's quality of life, significantly reducing the prevalence of cancer in women, and developing effective intervention strategies and offer a basis for clarifying the health risks of air pollution in China, which is of great importance in the field of public health and environmental protection.

Data

Data source

The data used in this paper are mainly from the official website of the National Bureau of Statistics, China Statistical Yearbooks Database, China Health and Family Planning Statistical Yearbook, and China Health Statistical Yearbook. This study used panel data of 31 provinces and cities on health and environment in China from 2006 to 2020, as well as some variables that reflect basic economic and social conditions, including dust and soot emissions, PM, GDP, the proportion of tertiary education, number of medical and health institutions, and number of health staff.

Variable definition

Dependent variable

As the purpose of this study is to study the effect of air pollution on breast and cervical cancers in women, taking into account the availability of data and the comprehensiveness of data collection, the prevalence of breast cancer and cervical cancer was selected as dependent variables, in units of per 100,000.

Independent variable

Air pollution is an important environmental and public health issue in China today, and the health risks it has posed have received close attention from the relevant authorities and numerous scholars. The impacts of air pollution on residents' health have been extensively researched (Yin et al. 2020; Baptista et al. 2021). The purpose of this study was to investigate the effect of air pollution on breast and cervical cancers. Therefore, the core explanatory variables are soot and dust emissions and PM emissions which are widely utilized in domestic research (Hao et al. 2018). In addition, PM contains a wide range of pollutants, the most dangerous of which for human health is fine particulate matter ($PM_{2.5}$). Previous literature shows that soot and dust are two important components of $PM_{2.5}$ (Lu et al. 2017). According to existing studies in the field of environmental epidemiology, $PM_{2.5}$ may induce the risk of various cancers, and long-term or short-term exposure to fine particulate matter may lead to increased morbidity and mortality of lung cancer, and reproductive system cancers (DuPré et al. 2019; Cheng et al. 2020; Prada et al. 2021; White et al. 2021). Furthermore, there is also a correlation between $PM_{2.5}$ and the survival rate of patients with the above diseases (Fang et al. 2016; Liu et al. 2018). Huo et al. (2013) found that $PM_{2.5}$ exposure was positively correlated with the survival of breast cancer patients. Liu et al. (2022a) found that $PM_{2.5}$ exposure may be associated with shorter overall survival in cervical cancer patients. However, official data on $PM_{2.5}$ concentration cannot be directly available. So we replaced $PM_{2.5}$ with the emissions of soot and dust and PM in research, which can reflect the effect of $PM_{2.5}$ pollution on female cancer during the sample period to some extent (Yao et al. 2016). In addition, the National Bureau of Statistics has no longer aggregated and published soot and dust emissions in recent years, and replaced them with PM. In consequence, we selected soot and dust emissions and PM as explanatory variables to study the impact of air pollution on the prevalence of breast and cervical cancer in women.

In addition to air pollution, economic and social variables may also influence the prevalence of breast and cervical cancer. GDP, as a core indicator of national economic accounting, is an important indicator of a country or region's economic status and level of development, as well as a comprehensive indicator of various factors that cause health problems. So, it is often widely used and discussed in studies of prevalence or health status (Preston 1975; Mackenbach et al. 2005; Subramanian and Kawachi 2006; Gu et al. 2013; Maruthappu et al. 2016). The proportion of tertiary education is defined as the number of people with tertiary education and above as a proportion of the population aged 6 years and above. Some literature shows an association between educational level and cancer mortality or prevalence. Well-educated people tend to be healthier, at less risk of disease, and have lower mortality rates (Hemminki and Li 2003; Gu et al. 2013; Isaevska et al. 2019; Alicandro et al. 2020; Dong and Qin 2020; Larsen et al. 2020; Lortet-Tieulent et al. 2020). Therefore, we chose the proportion of tertiary education and health resources as control variables. Health resources include the number of medical and health institutions (the sum of hospitals, primary medical and health institutions, professional public health institutions, the number of other medical and health institutions) and the number of health personnel (referring to the employees working in hospitals, primary medical and health institutions, professional public health institutions, and other medical and health institutions, including health technicians, rural doctors, and health workers, other technical personnel, managers, and staff). Furthermore, considering the joint effects of air pollution and economic development on breast and cervical cancer prevalence, we introduced the interaction term between air pollution and economic level as additional independent variables. Specifically, lnPM*lngdp refers to the interaction term between the logarithm of PM emissions and of the logarithm of GDP.

Methodology

We used the soot and dust emissions and PM emissions in various regions of China as air pollution indicators to establish the association between the prevalence of breast and cervical cancer and air pollutants, and the model used is derived from the method of econometrics. All regression equations are estimated using the form of a log-linear function, and the standard formula of the model is as follows (1):

$$lny_{it} = \beta_1 \ln pollution_{it} + \beta_2 \left(\ln pollution_{it}\right)^2 + \beta_3 Hedu + \beta_4 x'_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{1}$$

variance of the data or eliminates heteroscedasticity data, not changing the original nature of the data simultaneously.

In addition to mathematical transformations, we provide the rationale for model selection below. Based on the properties of $\delta_)$, we tested three panel data models: mixed, fixed, and random effects models (Greene 2003). We first tested the suitability of the mixed regression and fixed effects models, based on the F test and the likelihood-ratio test, both of which showed the existence of fixed effects and time effects. Then, we performed the Breusch–Pagan multiplier test (Breusch and Pagan 1980), which indicated that differences between provinces explain a larger proportion of the total variance (Breusch and Pagan 1980; Tahir et al. 2021). This shows that the random effects model is more suitable than the pooled model. In addition, the exogeneity of the control variables plays an important role in parameter estimation consistency and unbiasedness. Therefore, in Eq. (1), the area-fixed effects are eliminated by using fixed effects estimator. Then, the Hausman test (Greene 2003) will be applied to the selection of fixed and random effects models. However, considering the heteroscedasticity and autocorrelation of the model, the traditional Hausman test is not applicable, so we used the over-identification test, which shows that the correlation between individual heterogeneity and explanatory variables is significant. Two-way fixed-effects models were best suited for estimating the relationship between breast and cervical cancer prevalence and independent variables. Furthermore, the panel model should meet the conditions of homoscedasticity and no autocorrelation. If the model comes from heteroskedasticity, the estimated results may be consistent but invalid. The serial correlation could also lead to inconsistencies in coefficient estimates. Therefore, we adopt a cluster robust standard error to deal with heteroskedasticity and autocorrelation. Detailed definition of the variable classification could be found in Table 1.

To account for the modifying effect of the value of GDP on the impact of air pollutant emissions on the prevalence of breast and cervical cancer, we introduced an interaction term between GDP and PM (Makuta and O'Hare 2015). The following regression equation is estimated:

$$\ln y_{it} = \gamma_1 \ln\left(PM_{it}\right) + \gamma_2 \mathrm{lngdp}_{\mathrm{it}} + \gamma_3 Hedu_{it} + \gamma_4 x'_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$\ln y_{it} = \eta_1 \ln\left(PM_{it}\right) + \eta_2 lngdp_{it} + \eta_3 \ln\left(PM_{it}\right) * lngdp_{it} + \eta_3 Hedu_{it} + \eta_4 x'_{it} + \delta_i + \lambda_t + \varepsilon_{it} \tag{3}$$

To further illustrate the modifying effect of GDP, we adopted the variable GDP to reflect the total, direct, and indirect effects of air pollutants on the prevalence of breast and cervical cancer. It should be observed from Eq. (3).

$$\frac{\partial y_{it}}{\partial \ln\left(PM_{it}\right)} = \eta_1 + \eta_3 * lngdp_{it} \tag{4}$$

That is, the overall effect of air pollution on breast and cervical cancer prevalence is the sum of the direct effect and the indirect effect $\eta_3 * lngdp_{it}$ through GDP; this is evident from Eq. (4). The impact of air pollution on breast and cervical cancer prevalence depends on the value of $lngdp_{it}$. We calculate this effect at two levels: below the median of GDP (lower), and above the median of GDP (upper).

Where t denoted the year ranged from 2006 to 2020 and i indexed the provinces. The y_{it} was the prevalence of breast or cervical cancer for province i in year t; $pollution_{it}$ represents soot and dust emissions; PM_{it} is PM emissions; $Hedu_{it}$ is the proportion of tertiary education, x'_{it} is the control variable; $\delta_)$ denotes area characteristics that do not change over time, λ_t denotes time effects that change over time, and ε_{it} denotes independent, identically distributed error terms. The prevalence of breast and cervical cancer and emissions of air pollutants are included in the model as natural logarithms because variables do not vary to the same extent and a natural logarithm transformation of the data reduces the absolute

Results

General description of the variables

The results of the descriptive statistics are shown in Table 2. The mean values for the dependent variables breast cancer and cervical cancer prevalence were 26.381

and 28.791 per 100,000 people respectively. Statistics for the independent variables show that the mean values for soot and dust emissions were 49.924 ten thousand tons and the average PM emissions were 36.936 ten thousand tons respectively.

The prevalence of breast and cervical cancer

Figure 1 shows the temporal distribution of breast and cervical cancer prevalence in China from 2006 to 2020. The nationwide prevalence of breast cancer and cervical cancer

Table 1 Definition of the variable classification

	Variable	Variable definition
Dependent variables	lnbreastcancer	Prevalence of breast cancer in each region (1/100,000) in the form of the natural logarithm
	lncervicalcancer	Prevalence of cervical cancer in each region (1/100,000) in the form of the natural logarithm
Environment variables	lnPM	Particulate matter in each region (10,000 tons) in the form of logarithm from 2016 to 2020
	lnsoot	Soot and dust emissions in each region (10,000 tons) in the form of logarithm from 2006 to 2015
	$(\text{lnsoot})^2$	The quadratic soot and dust emissions of each region in the form of the natural logarithm
Education level	hedu	Number of people with a junior college education and above as a percentage of the population aged 6 and over (%)
Economic variables	lngdp	GDP (hundred million yuan) in the form of the natural logarithm
Health resources	hef	Number of medical and health institutions in each region (10,000)
	hestaff	Number of health staff in each region (10,000 persons)
Interactions	lnPM*lngdp	The intersection of lnPM and lngdp

Table 2 Descriptive statistics of the variables

Variable	Mean	Std. Dev.	Minimum	Maximum	Observations
Breast cancer (1/100,000)	26.381	30.167	1.3	314.1	465
Cervical cancer (1/100,000)	28.791	27.298	2.00	276.7	465
PM (10,000 tons)	36.936	26.282	0.94	124.42	155
Soot (10,000 tons)	49.924	34.872	0.20	179.77	310
Lngdp (hundred million yuan)	9.400	1.095	5.656	11.619	465
Hef (10,000)	2.705	2.171	0.132	8.694	465
Hestaff (10,000 persons)	30.893	21.28	1.015	102.792	465
Hedu (%)	0.12	0.073	0.011	0.505	465

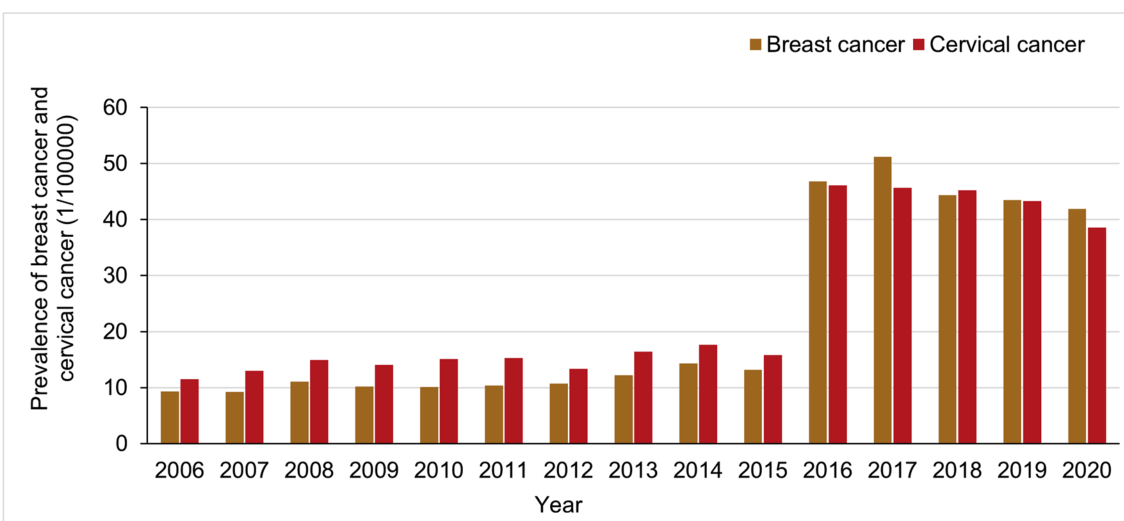

Fig. 1 Prevalence of breast and cervical cancer (1/100,000) in China from 2006 to 2020

was relatively stable before 2015, yet the prevalence of breast and cervical cancer in China surged significantly, from less than 20 per 100,000 people to nearly 50 per 100,000 people, in 2015–2016, and there is a slow downward since 2016.

Figure 2 shows the geographical distribution and regional differences in breast and cervical cancer prevalence, with data from 31 provinces and cities in China from 2006 to 2020. The darker the color, the higher the average value of each variable is.

It can be seen from sub-graph (a) in Fig. 2 that the prevalence of breast cancer is higher in Yunnan, Fujian, Xinjiang, and Liaoning, compared to other provinces. Sub-graph (b) in Fig. 2 shows that the prevalence of cervical cancer in Qinghai, Hubei, Fujian, and Xinjiang is higher than in other provinces, which may be caused by the population distribution, health, and economic status of the provinces and the extent of promotion of rural screening programs for both cancers in each province.

Emissions of air pollutants

Figure 3 shows a slow decline in soot and dust emissions year by year, but soot and dust emissions have risen from an annual average of about 12 million tons in 2012 to 17 million tons in 2014, which may be influenced by the national environmental protection policy. Particulate matter emissions have been gradually reduced from 2016 to 2020 under the control of the state.

Figure 4 shows the geographical distribution and regional differences in the emissions of air pollutants. Sub-figure (a) of Fig. 4 shows that soot and dust emissions are relatively high in northern and central China including Shanxi, Hebei, Liaoning, Henan, Inner Mongolia, and so on. The distribution of soot and dust emissions pollutants is generally consistent with the distribution of heavy industry in China, which may be the fact that many energy and pollution-intensive enterprises and their processing plants are located in northern China (Hao and Liu 2016; Hao et al. 2018).

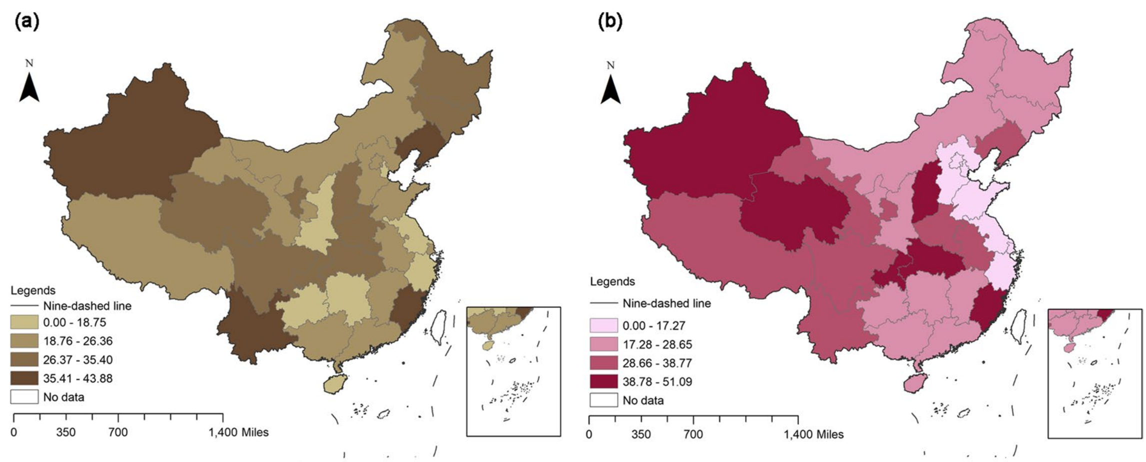

Fig. 2 The average provincial distribution of the prevalence of breast and cervical cancer from 2006 to 2020. **a** The distribution of the prevalence of breast cancer (1/100,000). **b** The distribution of the prevalence of cervical cancer (1/100,000)

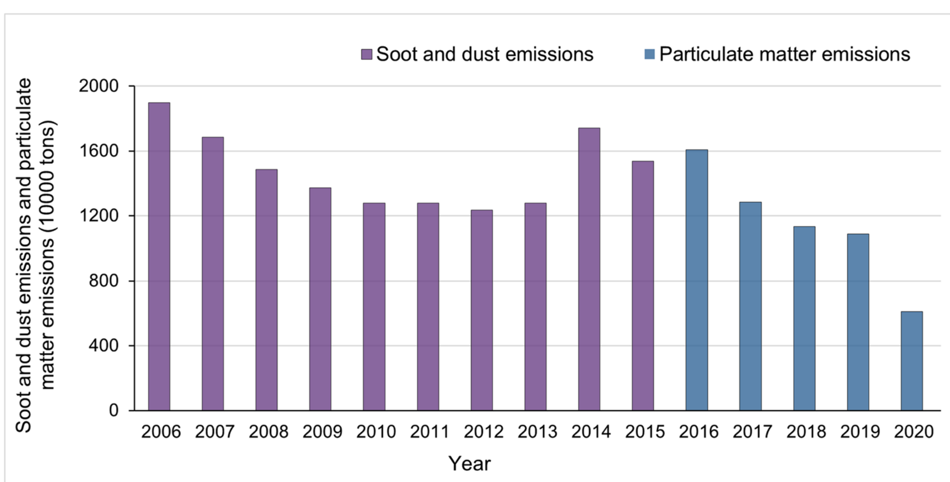

Fig. 3 Emissions of soot and dust (10,000 tons) in China from 2006 to 2015 and PM (10,000 tons) from 2016 to 2020

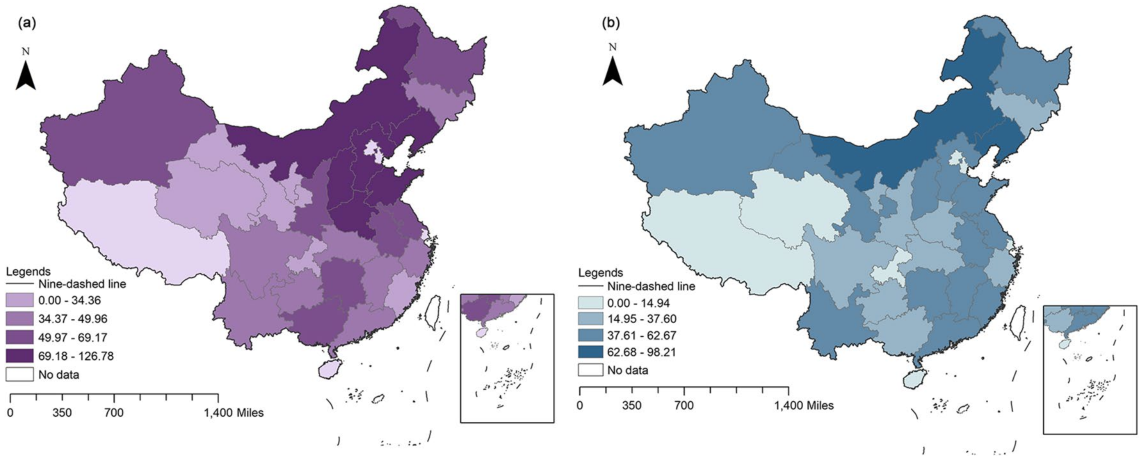

Fig. 4 The average provincial distribution of soot and dust emissions or PM emissions. **a** Emissions of soot and dust (10,000 tons) from 2006 to 2015. **b** Emissions of PM (10,000 tons) from 2016 to 2020

Sub-figure (b) of Fig. 4 presents the average PM emissions in all regions from 2016 to 2020, and the basic distribution of PM emissions is the same as that of soot and dust emissions shown in sub-figure (a); Northern China is generally more seriously polluted than southern China.

Figure 5 shows the nonlinear relationship between the prevalence of breast cancer and cervical cancer and soot and dust emissions. In sub figure (a), it can be seen that the prevalence of breast cancer and soot and dust emissions shows an obvious inverted U-shaped relationship. In subgraph (b), although no obvious inverted U-shaped relationship is shown, there is still a downward trend at the top of the curve. In addition, we conducted a utest test and found that there is a significant presence of inverted U-shape, as shown in supplementary material.

Analysis of the regression results

Relationship between the prevalence of breast and cervical cancer and soot and dust emissions

Tables 3 and 4 compared the results and goodness of fit obtained from pooled, fixed effect and random effect models. Based on the Akaike information criterion (AIC) values and over-identification test, we selected the fixed-effect model. We use the clustering method which renders robust standard errors. The results of the two-way fixed-effect model in model (4) show the coefficients of logarithmic soot and dust emissions are estimated to be positive and significant, while the coefficients of their square term are significantly negative. The robust results suggest that the relationship between soot and dust emissions and breast or cervical cancer prevalence is non-linear: at the early stage of pollutant emissions, the prevalence of breast and cervical cancer increases with the increase of pollutant emissions; when pollutant emissions reach a certain threshold, higher pollutant emissions may lead to a decrease in prevalence, showing an inverted U-shape. One possible reason for this finding is that the risk factors affecting the prevalence of breast and cervical cancer are complex and diverse. There are still other relevant factors that affect the prevalence of breast and cervical cancer, after controlling for environmental pollution.

The estimation results for interaction models

To take into account the modifying effect of GDP on air pollution, we run the regression with the interaction between the two factors (Eq. 3). Tables 5 and 6 describe the results of

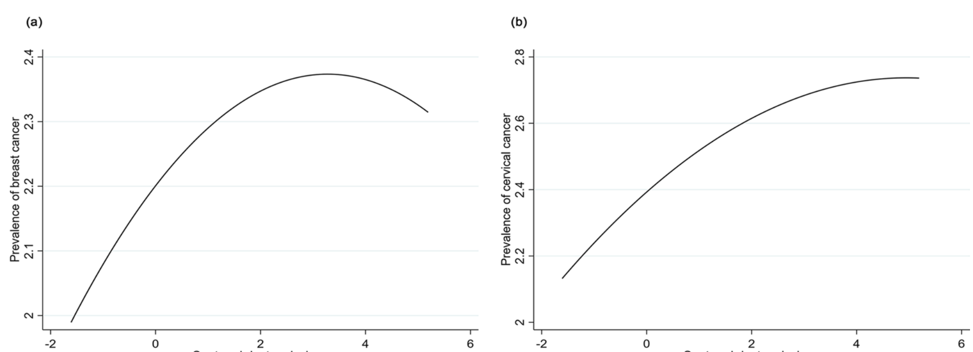

Fig. 5 Fitting curve of the relationship between breast cancer and cervical cancer prevalence and soot and dust emissions from 2006 to 2015. **a** The relationship between breast cancer and soot and dust emissions. **b** The relationship between cervical cancer and soot and dust emissions

Table 3 Estimates corrected for heteroscedasticity and autocorrelation with breast cancer as dependent variable and soot and dust emissions as an air pollution variable from 2006 to 2015

lnbreastcancer	(1) Pooled OLS	(2) Fixed effect	(3) Random effect	(4) Two-way fixed effect
lnsoot	−0.020	0.533***	0.235***	0.550***
	(0.126)	(0.096)	(0.091)	(0.123)
$(\text{lnsoot})^2$	0.023	−0.085***	−0.045	−0.091***
	(0.028)	(0.024)	(0.028)	(0.033)
hedu	3.625***	−1.818	1.667	−0.481
	(0.881)	(1.763)	(1.152)	(1.998)
hestaff	−0.006	0.042***	0.012**	0.045***
	(0.005)	(0.009)	(0.006)	(0.012)
hef	0.024	−0.151***	−0.057*	−0.168**
	(0.036)	(0.037)	(0.029)	(0.066)
Constant	1.826***	1.085**	1.774***	1.010
	(0.147)	(0.460)	(0.200)	(0.610)
R^2	0.112	0.132	0.093	0.145
N	310	310	310	310
AIC	559.009	349.4346	–	362.912

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$, standard errors in parentheses

Table 4 Estimates corrected for heteroscedasticity and autocorrelation with cervical cancer as dependent variable and soot and dust as air pollution variable from 2006 to 2015

lncervicalcancer	(1) Pooled OLS	(2) Fixed effect	(3) Random effect	(4) Two-way fixed effect
lnsoot	0.275*	0.243***	0.217**	0.219*
	(0.152)	(0.088)	(0.091)	(0.113)
$(\text{lnsoot})^2$	−0.040	−0.062***	−0.053**	−0.062**
	(0.035)	(0.022)	(0.023)	(0.026)
hedu	−2.349*	−2.362*	−1.573	−2.095
	(1.330)	(1.284)	(1.249)	(1.769)
hestaff	−0.015**	0.030***	0.012**	0.032***
	(0.006)	(0.007)	(0.005)	(0.010)
hef	0.093**	−0.088**	−0.016	−0.114*
	(0.040)	(0.034)	(0.027)	(0.057)
Constant	2.681***	2.322***	2.529***	2.271***
	(0.278)	(0.391)	(0.276)	(0.658)
R^2	0.155	0.112	0.092	0.157
N	310	310	310	310
AIC	546.7849	230.6011	-	232.4645

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$, standard errors in parentheses

the model incorporating the interaction term using clustering robust standard errors to correct for heteroskedasticity and autocorrelation.

Table 5 shows results from regression (Eq. 3) for the prevalence of breast and cervical cancer. Our focus in these regressions is on the interaction terms. In models (1) and (3), the estimated coefficients of PM emissions are significant and negative. The interaction term, the product of log PM emissions and the logarithm of GDP, is significantly negative. Its coefficients are −0.189 for breast cancer and −0.123 for cervical cancer, which means that a 1% improvement in the indicator of GDP leads to 0.189% or 0.123% decrease in the impact of PM in increasing the prevalence of breast and cervical cancer. This suggests that improving GDP could weaken the influence of PM on the prevalence of breast and cervical cancer. That is, with the continuous growth of the economy, the impact of GDP has a negative modifying effect on the impact of PM emissions on the prevalence of breast cancer and cervical cancer.

Table 6 shows where the effect on the same PM emissions is assessed at different levels of GDP, using Eq. (4). We call these levels lower (below the median of GDP) and

Table 5 Two-way fixed-effects model results corrected for heteroscedasticity and autocorrelation-with interactions from 2016 to 2020

	lnbreastcancer		lncervicalcancer	
	(1)	(2)	(3)	(4)
lnPM	−0.347**	1.466***	−0.082	1.099***
	(0.162)	(0.338)	(0.125)	(0.358)
lngdp	−3.592***	−2.249*	−1.956**	−1.081
	(1.251)	(1.188)	(0.918)	(0.742)
hedu	−1.656	−1.195	1.815	2.115
	(3.008)	(2.850)	(2.690)	(2.779)
hestaff	0.028	0.001	−0.004	−0.021
	(0.023)	(0.023)	(0.023)	(0.022)
hef	−0.470*	−0.424	−0.193	−0.163
	(0.250)	(0.267)	(0.188)	(0.172)
lnPM*lngdp		−0.189***		−0.123***
		(0.038)		(0.039)
Constant	40.804***	28.637**	23.511**	15.583**
	(12.762)	(11.990)	(9.062)	(7.498)
R^2	0.222	0.267	0.136	0.164
N	155	155	155	155

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$, standard errors in parentheses

Table 6 Effect of PM on breast cancer and cervical cancer at different levels of GDP — with interactions

	lnbreastcancer		lncervicalcancer	
	Lower	Upper	Lower	Upper
lnPM	1.654**	3.975***	−0.169	1.819
	(0.616)	(1.199)	(0.642)	(1.233)
lngdp	−1.463	−3.176	−1.428	−2.563
	(1.481)	(1.954)	(0.826)	(1.491)
lnPM*lngdp	−0.215**	−0.396***	0.042	−0.209*
	(0.083)	(0.110)	(0.072)	(0.112)
Constant	19.625	40.566*	15.380*	34.249*
	(13.594)	(21.636)	(7.588)	(16.268)
R^2	0.231	0.409	0.184	0.334
N	78	77	78	77

***$P < 0.01$, **$P < 0.05$, *$P < 0.1$, standard errors in parentheses; lower denotes a group below the median GDP, and upper denotes a group above the median of GDP

upper (above the median of GDP). In this section, we perform grouped regression method to check the robustness of our main findings in Table 5. The indirect effect of PM emissions on breast cancer prevalence is dependent on GDP in provinces and cities; in provinces with higher GDP, the indirect effect of PM emissions concerning breast cancer is −0.396 while in provinces with lower GDP, it is about −0.215; that is, it will have more impact in a province with a better economic level and minimal impact in a province with poor economics in China. The corresponding coefficient with respect to cervical cancer is about −0.209 in provinces with higher GDP but not significant in provinces with lower GDP. These results suggest that improved GDP could improve another relevant factor in explaining PM emissions can be converted to the higher prevalence of breast and cervical cancer. In addition, the basic conclusion from estimation results shown in Table 5 is basically consistent with in Table 6.

Discussion

In this study, we explored the association between the prevalence of breast and cervical cancer and soot and dust emissions, PM emissions, and the interaction between GDP and PM. Our results showed that the relationship between soot and dust emissions and breast or cervical cancers prevalence is non-linear, and that the impacts of air pollutants on the prevalence of breast and cervical cancers may depend on GDP.

More specifically, there is a significant inverted U-shaped relationship between soot and dust emissions and the prevalence of breast and cervical cancer, indicating that there is a positive relationship between pollutant emissions and the prevalence of breast and cervical cancer before reaching the threshold of the inverted U. However, soot and dust emissions are greater than a certain threshold; there is a negative correlation between pollutant emissions and the prevalence of breast and cervical cancer. This is not consistent with the findings of previous studies (Hwang et al. 2020; Guo et al. 2021; White et al. 2021). White et al. observed no association between air pollution and increased breast cancer risk in a large prospective population of Black women, except among women living in the Midwestern US (White et al. 2021). A review summarized seventeen studies evaluating the risk of breast cancer associated with air pollution, and suggested little evidence to support a relationship between PM and breast cancer risk (White et al. 2018). On the other hand, Hung et al. found that exposure to high levels of $PM_{2.5}$ may be associated with an increased risk of death from breast cancer using an ecological design in Taiwan (Hung et al. 2012). Furthermore, Li et al. showed that most participants who were exposed to the high concentration of air pollutants had a significantly higher risk of breast cancer by the retrospective cohort study in 74 municipalities in Taiwan (Li et al. 2021). Qing Guo et al. assessed the relationship between particulate matter exposure and female breast cancer incidence and mortality by meta-analysis. Corresponding results indicated that $PM_{2.5}$ exposure was related to breast cancer mortality (Guo et al. 2021). For cervical cancer, only two previous studies found significantly association between exposure to air pollution and cervical cancer in China. The study in Liaoning Province indicated that $PM_{2.5}$ was significantly associated with shorter overall survival of cervical cancer patients (G. C. Liu et al.). The other provided the first evidence that short-term exposure to ambient pollutants may be indirectly related to the increased risk of HPV infections in Chongqing (Liang et al. 2020). In contrast to the above studies, our results are the first to show a non-linear association between exposure to ambient air pollution and the prevalence of breast and cervical cancer using the nationwide population data from 31 provinces and cities in China. The potential reasons for the non-linear relationship between breast and cervical cancer and soot and dust emissions may be related to population distribution, age structure, different parameters of statistical models, different types of air pollutants, and different study methods in different country regions.

In addition, the development of breast cancer is a complex process involving multiple factors including environmental factors and genetic factors (Johnson-Thompson and Guthrie 2000; Brody et al. 2007a; Brody et al. 2007b). Thus, it is not enough to control the emission of air pollutants only. A large number of studies have shown that genetic factor is one of the most important risk factors affecting the incidence of breast cancer, and other risk factors can cause the occurrence of breast cancer through interaction with genetic factors. Previous studies found that dietary habits, obesity, smoking, drinking, and other factors may also be related to the incidence of breast cancer (Hamajima et al. 2002; Pieta et al. 2009). Meanwhile, studies have proved that maintaining an appropriate BMI and consumption of foods with a low dietary glycemic index (GI) and glycemic load (GL) play an important role in preventing cervical cancer (Brody et al. 2007b; Lee et al. 2013; Sreeja et al. 2020). Conversely, in our study, the interference of factors such as lifestyle, heredity, and reproduction could not be adjusted, which may cause instability in the estimated results of this study, and be one of the reasons for the inverted-U-shaped relationship.

Furthermore, since economic development brings about changes in the environment, health care, and people's lifestyle, indirectly affecting cancer prevalence, we attempted for the first time to analyze the impact of the interaction between GDP and particulate matter on the prevalence of breast and cervical cancer in China by region, which has no similar studies in the domestic and international literature. In our study, it was discovered that the impact of PM emissions on the prevalence of breast and cervical cancer is dependent on GDP, and that the positive effect of particulate matter on breast and cervical cancer prevalence weakened with economic growth, leading to a decrease in the prevalence of breast and cervical cancer. Therefore, continued economic growth will ultimately reduce breast and cervical cancer prevalence through its negative impact on the environment. Meanwhile, the results of subgroup regression showed that the effect of the interaction term lnPM*lngdp on the prevalence of breast and cervical cancer was twice as high in the provinces with better economic status as in those provinces with lower economic status. These results revealed that the positive impact of PM emissions on the prevalence of breast and cervical cancer is more effective in provinces with better economic conditions; it has virtually less or no impact in the lower economic areas. Specifically, economic development might reduce the level of environmental pollution through the environmental protection consciousness enhancement and the formulation of relevant regulations and policies (Hao et al. 2018). At the same time, rapid economic growth has enabled governments to invest more in the health department and ensure more medical facilities and more effective cancer treatment technologies (Rahman and Alam 2021). Raising the level of the economy will lead to the improvement of people's income. Higher incomes are often associated with better health (Lange and Vollmer 2017). Women in regions with higher income levels are more conscious of healthy lifestyles and the prevention of breast and cervical cancer, which leads to a decrease in the prevalence of cancer.

The pathogenic mechanism of breast and cervical cancers in women exposed to air pollutants is unclear. Several previous studies have revealed some possible potential pathways. For example, Qiang et al. (Huo et al. 2013) found that PM correlated well with a high incidence of breast cancer because of its estrogen-like effect, and chronic exposure to high levels of inhalable particulate pollution promotes the development of estrogen-dependent breast cancer in the crowd (Parl et al. 2009; Rana et al. 2010). Secondly, air pollutants are complex in form and composition, including organic matter, PM, and heavy metals. Studies suggest that air pollution can impair the function of the cardiovascular system or respiratory system and increase the risk of cancer (Deng et al. 2013; Hu et al. 2013). Furthermore, it has been found in many studies that PM, especially fine particulate matter, is a strong oxidant that can generate reactive oxygen species (ROS). The organic components of $PM_{2.5}$ and heavy metals adsorbed can also induce the production of free radicals in cells. Oxygen free radicals (ROS) are an important factor in oxidative DNA damage (Vattanasit et al. 2014). Valko et al. (2006) pointed out that free radicals can cause oxidative stress, resulting in cellular redox imbalance, which further leads to different biological processes, such as inflammatory damage and cell cancer or death (Lodovici and Bigagli 2011). This may be another critical mechanism to explain the associations we observed.

To obtain the best estimate of the coefficients, we explored different models and further determined the rationale for building the model. We observed inconsistent estimates between different models, implying that model selection needs to be justified. Based on the nature of the panel data, we expect that the random error terms in the model may display autocorrelation and heteroscedasticity. This expectation is based on two reasons. Firstly, we selected panel data with multiple cross-sections and short periods. There is probably heteroskedasticity in the panel data consisting of 31 provinces during these 15 years. Secondly, there is probably correlation between outcome variables in each province and region in adjacent years. Similar serial autocorrelation has been observed in previous studies for mortality in a given region (Kanjala et al. 2010). Therefore, it is most appropriate to use clustering robust standard errors. In panel data, all observations in each region at different periods constitute a "cluster." Observations in the same cluster are correlated with each other, but observations between different clusters are not. For such clustered samples, OLS estimation can still be performed. Because the homoskedasticity assumption is not used in the derivation, the clustering-robust standard errors are also heteroskedasticity-robust.

In addition, in this study, we divide 15-year panel data into two parts, to describe and analyze the relationship between air pollution and the prevalence of breast cancer and cervical cancer. The specific reasons are as follows. Firstly, the surge in the prevalence of breast cancer and cervical cancer from 2015 to 2016 resulted in unstable dependent variable, which may lead to deviation in the correlation analysis between independent variables and dependent variables, due to the implementation and promotion of the national rural women's breast and cervical cancers inspection project, the amplification of the pilot area, the improvement of screening technology, and the increased women's awareness of the prevention and treatment of cervical and breast cancer since 2015. Secondly, soot, dust, inhalable particulate matter (PM_{10}), and fine particulate matter ($PM_{2.5}$) are often used as air pollution indicators. But soot and dust were replaced with PM in recent years in the statistical yearbook, which means soot and dust were no longer used as a statistical indicator of exhaust gas pollutants in the statistical yearbook. We have to use soot and dust as the core explanatory variable from 2006 to 2015 and PM as the main explanatory variable from 2016 to 2020. Therefore, to exclude the effect of these external factors on the association between air pollution and prevalence, we analyzed the data in segments. To be specific, in 2006–2015, we chose a two-way fixed effects model to analyze the non-linear relationship between air pollution and breast and cervical cancer owing to the presence of individual and time fixed effects. Considering the reasons for the existence of this nonlinear relationship, we analyzed the effect of GDP on the association between particulate matter and the prevalence of breast and cervical cancer using the interaction term, the product of logarithm of GDP and logarithm of PM, in 2016–2020.

Our analysis was also limited. Firstly, the data we selected came from public databases, and the process of data collection and collation is unknown. From a scientific point of view, public databases make it impossible for anyone to reproduce or verify the accuracy of the data. Secondly, this study analyzes ecological data rather than individual data; thus, confounders, such as demographic variables, smoking behavior, genetic background, and viral infections, cannot be controlled. Besides, the crude province-level data, potential confounding factors, and the limited cognition of biological mechanisms of breast cancer and cervical cancer may lead to the possibility of ecological fallacy. Finally, although we have tried to remove all biases, the most complex statistical models might have limitations.

Our study only provides preliminary evidence that the breast and cervical cancer prevalence was not only owning to emissions of air pollutants but also owning to other relevant risk factors. Therefore, it is essential to further study the relationship between environmental pollution or other factors in China and the prevalence of breast and cervical cancers in the population by conducting a massive crowd cohort study. Meanwhile, the relevant biological mechanisms involved are worthy of further exploration.

Finally, we believe that this study provides useful clues for policymakers to formulate effective public health planning and measures to lower the risk of breast and cervical cancers. For example, we can actively develop a green economy (resource-saving and environment-friendly economy), reduce resource consumption, and promote sustainable growth of the economy and environmental protection. At the same time, the prevalence of breast and cervical cancers can be cut by improving women's lifestyles and dietary habits when environmental pollution is gradually improving.

Conclusion

This paper explored the relationship between air pollutants and the prevalence of breast and cervical cancer in women in 31 provinces and municipalities. Robust results were obtained by using panel data from 2006 to 2020 and applying cluster robust standard errors. There is an inverted U-shaped relationship between air pollutant emissions and breast and cervical cancer prevalence from 2006 to 2015 and the growth of GDP has a significant negative moderating effect on the impact of pollutants on the prevalence of breast and cervical cancer from 2016 to 2020. The PM emissions have a higher impact on the prevalence of breast and cervical cancer in areas with better economic conditions and a lower impact in areas with poor economic conditions. These results are logical and can provide some policy recommendations for the health department to improve women's health.

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Author contribution All authors contributed to the study conception and design. Meiyu Hu: material preparation, data collection, visualization, methodology, formal analysis, writing—original draft. Chen Jiang: software, writing—original draft, visualization. Yingxian Luo: software, validation, formal analysis. Yaxin Wang: investigation, resources, data curation. Mengyi Huang: investigation, resources, data. Runtang Meng: conceptualization,writing—review and editing, supervision. Fudong Li: methodology, writing—review. Haiyan Ma: conceptualization, methodology, writing—review and editing. The first draft of the manuscript was written by Meiyu Hu and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability The sources of data generated and analyzed during the current study are publicly available and may also be obtained from the corresponding authors on reasonable request.

Declarations

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