

1 **The Association between City-level Air Pollution and Frailty among the** 2 **Elderly Population in China**

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8 **1. Introduction**

9 Gross domestic product (GDP) has increased ten-fold in China during the last two decades, quality of
10 life for most of the Chinese population has greatly improved, and their life expectancy has substantially
11 increased as well (Ebenstein et al., 2015). However, the environmental effects of economic
12 development have been a concern to the government and the public (Zhang et al., 2010). Industrial
13 manufacturing is a major source of pollutants, contributing to harmful materials in air, water, soil and
14 food. Among these, air pollution (AP) has attracted a great deal of attention, as most Chinese cities
15 experience air pollution levels above national air quality standards (Wang et al., 2014). The association
16 between AP and poor health is well established. Specifically, studies have found a strong association
17 between exposure to air pollution and reduced life expectancy (Ebenstein et al., 2015), higher levels of
18 respiratory mortality (Richardson et al., 2011), chronic diseases such as chronic obstructive pulmonary
19 disease (COPD) (Liu et al., 2018; Wang et al., 2018), mental health (Signoretta et al., 2019; Zhong et
20 al., 2017), cognitive health (Zhang et al., 2018), functional health (Sun and Gu, 2008), and self-rated
21 health (Charafeddine and Boden, 2008).

22 Alongside rising pollution levels, the population of China is ageing rapidly. Projections from the United
23 Nations predict that the proportion of Chinese elderly people aged 65 years and over will more than
24 double in the next 30 years, increasing from 12% in 2020 to 27% of the total population in 2050 (Fang
25 et al., 2015; United Nations, 2019). The proportion of the oldest old (those over 80 years) in the Chinese

26 population is projected to quadruple by 2050 (United Nations, 2019). Along with extended lifespan
27 typically comes an expansion of physical and cognitive disability (Zeng et al., 2017). As elsewhere,
28 among the elderly population in China there is a high prevalence of co-morbid chronic diseases and
29 multimorbidity (Gu et al., 2017; Lei et al., 2014). Therefore, an adequate assessment of elderly health
30 must go beyond the single-disease model and take account of multiple co-morbid conditions.

31 Studies focussing on the Chinese elderly population largely confirm the links found between AP and
32 health, demonstrating a link between AP and individual chronic diseases, such as COPD (Wang et al.,
33 2018), heart diseases (Bai et al., 2019), diabetes (C. Liu et al., 2016) and cardiovascular diseases (CVD)
34 factors like hypertension (Liu et al., 2017; Yang et al., 2018). Therefore, it seems likely that air pollution
35 influences elderly health through multiple disease pathways. In this study, we focus on frailty as a multi-
36 dimensional measure of increased health vulnerability in the elderly population (Fried et al., 2001;
37 Walston et al., 2006). A recent meta-analysis across 13 cohorts suggested that increased frailty is
38 strongly associated with increased mortality (Kojima et al., 2018). Compared with younger adults, the
39 elderly are expected to be more vulnerable to air pollution due to their increased levels of frailty
40 (Fougère et al., 2015), in part because exposure to air pollution will exacerbate existing frailty through
41 many disease mechanisms. There have, however, been only a limited number of studies on air pollution
42 and frailty in elderly populations (García-Esquinas and Rodríguez-Artalejo, 2017). One study has
43 demonstrated that increased air pollution was associated with increased frailty incidence after
44 myocardial infarction (MI) (Myers et al., 2013), and others suggest that frailty moderates associations
45 between air pollution and lung function (Eckel et al., 2012) and adverse events after MI (Gerber et al.,
46 2014).

47 The overall aim of this study is to investigate the contribution of long- and short-term exposure to AP
48 on frailty incidence among the elderly in China. We advance previous studies in a number of ways.
49 First, to our knowledge this is the first study of the relationship between AP and frailty (a multi-
50 dimensional health indicator) in the elderly population, whose need for social and medical care leads to
51 important policy implications. Second, we use longitudinal data on frailty, linked to longitudinal
52 information on air pollution, to understand the association between air pollution and changes in frailty

53 over time. Third, we make use of this longitudinal data to distinguish the impact of long-term exposure
54 to AP from short-term fluctuations. This may be important as short-term fluctuations can impact
55 different disease pathways (Xiao et al., 2016). Finally, this study contributes to the literature by
56 exploring potential heterogeneities by age, sex, socioeconomic status, interview time, and regional
57 factors such as GDP per capita.

58 **2. Methods**

59 *2.1 Study population*

60 The data used in this study are from the 6th and 7th waves (2011 and 2014) of the Chinese Longitudinal
61 Healthy Longevity Survey (CLHLS 2011 & 2014). CLHLS started in 1998 and although initially
62 sampled older adults aged 85+, this was expanded to those aged 65+ from 2002. The survey collects
63 personal and family information, self-reports of functional health, lifestyle, diet, psychological health
64 and home care, as well as measures of cognitive health (according to a set of tests about memory,
65 calculation, recall and language). To allow purposive over-sampling of the older population, the
66 strategy of CLHLS is to randomly select some residential areas and then to interview some centenarians
67 (aged over 100) who are living in those areas. The second step is to interview randomly a nonagenarian
68 (aged over 90), an octogenarian (aged over 80) and a respondent aged 65-79, whose residential
69 addresses are close to the centenarians' home. This strategy can ensure that the proportion of
70 centenarians is similar to respondents who are aged over 80 or 90.

71 In 2011, the full CLHLS sample size was 9,765. Between 2011 and 2014, 3,699 respondents (37.9%)
72 attrited due to death (29.5%) or non-specified reasons (8.4%). In 2014, the CLHLS added a refreshment
73 sample of 1,126 new respondents (making the 2014 sample N=7,192). In the longitudinal data 2011-
74 2014, restricting the sample to individuals living in cities with AP monitoring stations results in a
75 sample of 7,986 respondents (11,620 observations), living in 123 cities. Missingness on the frailty
76 indicators reduces the number of respondents to 6,943 (9,749 observations). We use listwise deletion
77 for missingness on other predictors (career is missing 4% and all other predictors are less than 1%
78 missing). This leaves 6,570 individuals (9,132 observations) from 123 cities in our longitudinal analysis

79 and sample of 4,284 from 117 cities in our cross-sectional analysis (only 2014). In the sensitivity
80 analysis where we use geographically weighted regression (GWR) to predict air pollution data, the
81 analytical sample is 8,644 respondents (12,743 observations), living in 174 cities.

82 Note that we made corrections to approximately 5% of sample by amending inconsistent reports of
83 gender, education and pre-retirement careers by drawing on data from earlier waves of the survey. All
84 results in the main body of this study are based on the complete case analysis, and GWR data is used to
85 conduct sensitivity analysis in the Supplementary material Table S8/12/13.

86 *2.2 Frailty index*

87 To capture an individual's cumulative health deficits most studies calculate the frailty index by a
88 standard comprehensive geriatric assessment (Cesari et al., 2014; Jones et al., 2004). Following the
89 established studies, Gu et al (2009) defined a frailty index using 39 indicators of various dimensions of
90 self-reported health status, cognitive functioning, disability, hearing and visual ability, depression, heart
91 rhythm, and numerous chronic diseases that were collected in the 2002 CLHLS. They validated the
92 measure, demonstrating strong associations with subsequent 3-year mortality (Gu et al., 2009). Based
93 on this research, we constructed the frailty index as an unweighted count of the number of deficits. We
94 excluded 2 of the 39 original indicators (bedsores and duodenal ulcer) because they are missing over
95 10% in CLHLS 2011 and 2014, had low prevalence of "yes", and high prevalence of reports of
96 "unknown". We also exclude interviewer-rated health, as its answers may be biased by the researcher
97 effect. Nevertheless, Gu et al (2009) suggested that so long as a reasonable number of indicators from
98 each dimension are included, the index will be robust. There are 36 components of the frailty index
99 including limitations in activities daily living (ADL), limitations in instrumental activities daily living
100 (IADL), functional limitations, cognitive health, self-rated health, hearing, vision, heart rhythm,
101 psychological disorders, number of serious illnesses in the past two years and multiple chronic diseases
102 (hypertension, diabetes, tuberculosis, heart diseases, stroke, bronchitis/asthma, cancer, arthritis and
103 Parkinson's disease). In the CLHLS, cognitive functioning was measured by a Chinese version of the
104 Mini-Mental State Examination (MMSE) with a total score of 30, and respondents with a score of 23

105 or lower were considered as cognitively impaired in this paper (Yang and Gu, 2016). All of the
106 components are listed in Supplementary Table S2. Each indicator is recorded as binary except the
107 number of serious illnesses in the past two years (which contains 0 for no illness, 1 for one illness and
108 2 for two or more illnesses), self-reported whether the respondent ever had a diagnosis. The frailty index
109 then sums the 36 indicators listed above and consequently ranges from 0 to 37.

110 **2.3 Air Quality Index (AQI)**

111 This study uses air quality data from the Ministry of Ecology and Environment of China provided for
112 each city for each day for the period from 1st January 2000 to 31st December 2014. The measure of air
113 pollution is the air quality index (AQI), which is calculated based on hourly readings of a set of air
114 pollutants (PM_{2.5}, PM₁₀, SO₂, NO₂, O₃, CO). Higher values of AQI mean more polluted air. AQI is
115 a standardised indicator for air pollution, which has been reported as the local air quality evaluation in
116 21 nations (Cochran et al., 1992). The association of AQI with the public health burden is used to
117 quantify the negative impacts attributable to air pollution (Stieb et al., 2005), and the validity of using
118 the AQI to assess health impacts of air pollution has been established (Li et al., 2015). We chose AQI
119 as the indicator for air pollution as ambient air consists of an amalgamation of numerous gaseous or
120 solid substances, which prevents isolation of the health effects of individual pollutants (Fougère et al.,
121 2015). The Ministry of Ecology and Environment of China provides more AQI values than other air
122 pollutants records before 2013, although there are still missing values for AQI. In this study, if AQI is
123 missing, but the records of air pollutants (which are the components of AQI) are available (accounting
124 for 5% of daily records), we computed it using a method provided by Ministry of Ecology and
125 Environment of China (2012). This computation of AQI is a piecewise linear function of the pollutant
126 concentration, using single air pollutants to calculate the individual air quality index (IAQI).

$$IAQI_p = \frac{IAQI_{Hi} - IAQI_{Lo}}{BP_{Hi} - BP_{Lo}} (C_p - BP_{Lo}) + IAQI_{Lo}, \quad (1)$$

127 where $IAQI_P$ is the individual air quality index of the pollutant of P ; C_p is the pollutant concentration;
128 BP_{Hi} is the concentration cut-point over C_p ; BP_{Lo} is the concentration cut-point below C_p ; $IAQI_{Hi}$ is the
129 index cut-point corresponding to BP_{Hi} ; $IAQI_{Lo}$ is the index cut-point corresponding to BP_{Lo} .

$$AQI = \max \{IAQI_1, IAQI_2, IAQI_3, \dots, IAQI_n\} \quad (2)$$

130 We take the value of AQI as the highest value in the list of calculated $IAQIs$ from different pollutants.
131 AQI data is available hourly. For each city, we use the daily average AQI.

132 This study follows the bulk of the research in defining long-term exposure as more than one-year of
133 exposure (R. Liu et al., 2016; Ma et al., 2016). However, this operationalisation is not unique, and we
134 also analysed longer periods of exposure (2-year and 3-year) in the Supplementary material (cross-
135 sectional analysis in Table S4 and S5, longitudinal analysis in Table S9 and S10) to test the robustness
136 of the estimates.

137 Note that the CLHLS does not provide the exact names of cities but it provides some community
138 information, like population size, administrative area, and GDP. The community information provided
139 in the CLHLS can be used to identify the city of residence in the CLHLS dataset via cross-referencing
140 to Tabulation in the 2010 Population Census of China by County (National Bureau of Statistics of China,
141 2010). Specifically, we used the population size of a county/district in 2010 to match it to county/district
142 names, as population size is unique for each county/district; these match perfectly. It is then a simple
143 step to locate the city of residence when county/district names are clear, because the county/district is
144 the secondary administrative area within the city in China. After matching, we inserted the cities names
145 into our dataset and then use these names to link the CHLHS dataset to the AQI data.

146 Due to the limited number of air quality monitoring stations before 2013 in China, over 30% of CLHLS
147 cities was missing air pollution data (details in the Supplementary material Table S3). Therefore, spatial
148 interpolation for AQI is necessary for this study as a sensitivity analysis. This study used the GWR to
149 interpolate the missing AQI data, which can include more information compared with the traditional
150 interpolation method. GWR characterized the distribution of daily AQI well with the cross-validation
151 (R^2) of 1235.13 (0.379), compared with R^2 (0.249) in global regression (details in Supplementary

152 material Table S1). We also examined the residuals from the GWR (comparing actual and predicted
153 values), by plotting these on a histogram and Q-Q plot, which are normally distributed shown in the
154 Supplementary material Figure S1.

155 **2.4 Z-score of AQI**

156 There is some research suggesting that some the components of our frailty index are related to long-
157 term air pollution exposure (Ranft et al., 2009), while other components are related to both long-term
158 and short-term exposure (Brunekreef and Holgate, 2002; Dauchet et al., 2018). For example, the
159 associations between exposure to air pollution and ADLs, IADLs, and cognitive impairment, which
160 stem from the degeneration of biological functions, have been examined (Kampa and Castanas, 2008).
161 Results suggest cumulative exposure has a more significant effect (Brunekreef and Holgate, 2002).
162 However, short-term exposure to air pollution can lead to some chronic diseases (e.g., bronchitis, stroke)
163 because air pollutants can lead to acute inflammatory responses induced in the respiratory,
164 cardiovascular and blood circulation system (Brunekreef and Holgate, 2002; Scheers et al., 2018).
165 Therefore, this is another reason for adjusting the short-term exposure in our models.

166 However, the literature is inconsistent in terms of defining short-term exposure. Daily exposure is
167 mostly measured as the short-term exposure but there is little evidence showing that daily exposure
168 effectively captures short-term exposure effects. Thus, this study calculated averages of AQI over a day,
169 week, month and quarter to account for shorter-term exposure and weekly z-score is the main short-
170 term fluctuation in our analysis as it has been found that there is an association between weekly
171 exposure to air pollution and human health (Karakatsani et al., 2017). We use the z-score to capture
172 short-term exposure calculated as:

$$z_score = \frac{Mean_{short} - Mean_{long}}{SD_{long}} \quad (3)$$

173 Note that the z-score is a relative indicator capturing the relative deviation of the short-term average
174 from the long-term background level. Compared with a similar study that used absolute values of short-
175 and long-term exposure to air pollution simultaneously (Zhang et al., 2018), using the z-score for this
176 study is to decrease the collinearity between them and is beneficial to take into consideration the

177 interactive effects. For example, we hypothesize that a spike in air pollution from a higher level of long-
 178 term exposure may have different health effects than the same spike (in absolute terms) from a lower
 179 level of exposure. Also, the z-score including the variation of long-term AQI can capture the exposure
 180 to air pollution better.

181 In measuring short- and long-term exposure to air pollution, we used the interview date as the end of
 182 duration of exposure and then calculate the mean of AQI for the respective period prior to the interview
 183 date: one week (7 days), one month (30 days), one quarter (90 days), previous one year (365 days),
 184 previous two year (730 days), previous three year (1,095 days) for this study. The advantage of this
 185 measure is that it can capture the comparable value for exposure to air pollution. As the interview dates
 186 for respondents are different, the exposure window is respondent-specific and dynamic. Figure 1 uses
 187 the 1-year exposure to show how the measure works for three exemplary respondents A, B and C.



Note: A, B, and C mean three respondents interviewed at different dates.

Fig. 1. Hypothetical example of how 1-year exposure to air pollution is calculated

2.5 AQI category

195 In order to distinguish the long-term effects and short-term effects of exposure clearly, in some models
 196 the long-term AQI measurements are adjusted for short-term exposures. As for long-term exposure,
 197 there are four categories of AQI according to national air quality standards. Considering the cumulative
 198 effects of air pollution on health, the concentration cut-point or threshold, of China's AQI is set at the
 199 National Ambient Air Quality Standards (NAAQS) (Ruggieri and Plaia, 2012). The standardising
 200 transformation separates the AQI into five categories: good (0 - 50), moderate (51 - 100), unhealthy
 201 (101 - 150), very unhealthy (151 - 200) and hazardous (200+). Different from the NAAQS's standard,
 202 the AQI category in this study is adjusted into four groups because its distribution is skewed, and there

203 are few respondents living in the most polluted area. The detailed index value of categories is shown in
204 Table 1 below.

205 **Table 1** Sub-index of the Air Quality Index (AQI) in China

AQI categories	AQI 1 Good	AQI 2 Moderate	AQI 3 Unhealthy	AQI 4 Very unhealthy
Index value	0-50	51-75	76-100	101-

206

207 **2.6 Change in AQI variable**

208 We also generated a new variable at the city level for change or stability of AQI category between
209 waves. For example, based on the AQI categories above, if one respondent resided in a city with AQI
210 1 in 2011 but that city had AQI 2 level in 2014, the change of AQI is categorized as ‘AQI 1-2’; however,
211 if a respondent was recorded as living in a city with AQI 1 in both waves, the change of AQI is
212 categorized as ‘AQI 1-1’. In the data we analysed, we find that all of cities with AQI 1 in 2011 remain
213 the AQI 1 in 2014; for the cities with AQI 2 in 2011, 21.55% cities remain AQI 2, but 66.17% cities
214 experience AQI 3 and 12.28% cities are with AQI 4 in 2014. However, most cities with AQI 3 in 2011
215 record AQI 4 (84.37%) in 2014, while 10.66% cities remain, and 4.97% cities move down to AQI 2.

216 **2.7 Additional covariates**

217 We also include a set of control variables that may confound or explain the association between air
218 pollution and later-life health. First, the demographic variables include sex, age and age squared (as
219 continuous measures). Marital status comprises three categories: married and living with their spouse,
220 widowed and single (including separate, never married and divorced respondents). The second set of
221 covariates capture socioeconomic status: education, self-rated economic status and pre-retirement
222 career. The education variable in CLHLS is recorded by years of education; however, as more than 50%
223 of respondents are without schooling experience, the education variable is divided into two categories:
224 no schooling or some education. Self-rated economic status was collected using the question “How do
225 you rate your economic status compared with others in your local area?” as a 5-point scale (very rich,
226 rich, so so, poor, very poor). Due to small variation of this variable, we combine rich and very rich to

227 “rich” and poor and very poor into “poor,” thus self-rated economic status has three categories: rich,
228 median and poor. Pre-retirement career is based on self-reports of primary job and includes two
229 categories: white collar (including industrial, governmental, commercial and military personnel) and
230 blue collar (including self-rated employed and agricultural personnel, houseworkers and people who
231 never had paid employment). Some area-level confounding factors are also included: natural logarithm
232 of population density, natural logarithm of GDP per capita, both of which are based on the annual city-
233 level information.

234 *2.8 Statistical Models*

235 To estimate the effects of air pollution on health, we test the association between AQI values and
236 incidence rate of frailty. We start with the cross-sectional analysis using the CLHLS 2014, as this one
237 wave provides more observations linked with AQI data. This allows us to explore the associations of
238 exposure to air pollution with frailty with less missing data. As frailty is a count variable, we use
239 multilevel random-intercept Poisson regression models. Individuals are nested within cities, and the air
240 pollution data, population density, and GDP per capita are city-level predictors. We next conduct a
241 three-level longitudinal analysis based on both CLHLS 2011 and 2014, where person-waves are nested
242 in persons, which are nested in cities. The benefit of the longitudinal analysis is that it reduces
243 confounding from unobserved heterogeneity at both the city and individual level.

244 Additionally, to assess whether change in AP between 2011 and 2014 was associated with frailty change
245 between 2011 and 2014, we also fitted another set of random-effects models with Poisson distribution,
246 which we fitted on a balanced dataset where everyone took part in both waves. No one in our data had
247 moved cities between 2011 and 2014. We generated a new variable at the city level for change or
248 stability of AQI category between waves. We fitted the random-effects model using this ‘change in
249 AQI’ variable instead of the main AQI variable, including all of the same covariates, and including a
250 time fixed effect (see Table 5).

251 **3. Results**

252 Descriptive statistics for the 4,746 CLHLS sample respondents in 2011 and 4,284 in 2014 are presented
 253 in Table 2. This shows that there are some differences in the sample characteristics between the two
 254 waves of CLHLS. As could be expected with an ageing sample, the frailty score goes up between 2011
 255 and 2014, while the proportions male, educated and blue-collar respondents are relatively stable. The
 256 proportion of cities recording ‘unhealthy’ and ‘very unhealthy’ AQI scores increased over time.

257 **Table 2** Sample characteristics for analysis sample created from CLHLS, Ministry of Ecology and
 258 Environment of China, and Yearbooks 2011 & 2014

	2011		2014	
	Mean ± SD	N (%)	Mean ± SD	N (%)
Individual Level				
Variables from CLHLS				
<i>Frailty Score</i>	7.43 ± 5.54		7.22 ± 5.60	
<i>Sex (%)</i>				
Male		2,214 (45.65)		2,024 (47.25)
Female		2,532 (54.35)		2,260 (52.75)
<i>Age</i>				
65-74		1,040 (21.91)		737 (17.20)
75-84		1,321 (27.83)		1,469 (34.29)
85-94		1,372 (28.91)		1,256 (29.32)
95-104		1,013 (21.34)		822 (19.19)
<i>Education (%)</i>				
Educated		2,541 (53.54)		2,335 (54.51)
No schooling		2,205 (46.46)		1,949 (45.49)
<i>Pre-retirement career (%)</i>				
White-collar		1,223 (25.77)		877 (20.47)
Blue-collar		3,523 (74.23)		3,407 (79.53)
<i>Marital status (%)</i>				
Married		1,889 (39.80)		1,712 (39.96)
Single		131 (2.76)		116 (2.71)
Widowed		3,153 (57.44)		2,456 (57.33)
<i>Self-rated economic position (%)</i>				
Rich/Very-rich		869 (18.31)		725 (16.92)
Median		3,271 (68.92)		3,113 (72.67)
Poor/Very poor		606 (12.77)		446 (10.41)
Total N		4,746		4,284
City Level				
Variables from MEE				
<i>AQI (1-year mean) (%)</i>				
Good (AQI = 1)		204 (4.30)		479 (11.18)
Moderate (AQI = 2)		3,743 (78.87)		1,011 (23.60)
Unhealthy (AQI = 3)		799 (16.84)		1,999 (46.66)
Very unhealthy (AQI = 4)		-		795 (18.56)
<i>AQI Z-score (1-year)</i>				

Daily Z-score	-0.40 ± 0.66	-0.06 ± 0.65
Weekly Z-score	-0.41 ± 0.44	-0.08 ± 0.47
Monthly Z-score	-0.41 ± 0.33	-0.04 ± 0.29
Quarterly Z-score	-0.25 ± 0.32	0.09 ± 0.25

Variables from Yearbooks

<i>Logarithm of GDP</i>	10.87 ± 0.41	10.97 ± 0.52
<i>Logarithm of population density</i>	6.39 ± 0.51	6.32 ± 0.54

<i>Number of cities</i>	77	117
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Note: Variables in CLHLS are individual level; variables from Ministry of Ecology and Environment of China, and variables from yearbooks are city-level.

259 The results from the cross-sectional analysis are shown in Table 3 (in the Supplementary material Table
260 S6 shows more results from different combinations between long-term exposure and z-score). Model 1
261 includes all the covariates and the 1-year AQI exposure mean as the long-term measure. Model 2 adds
262 the weekly z-score to adjust for short-term AQI exposure. Model 3 includes an interaction term between
263 long- and short-term exposure. Overall, the results suggest that long-term AQI exposure is more
264 significantly associated with frailty than short-term weekly exposures. The results from Model 1 show
265 that, compared with those exposed to the AQI 1 (good air quality), the estimated effect of exposure to
266 AQI 4 (very unhealthy air quality) is to increase the incidence rate, and therefore the expected score of
267 frailty index in a year period, by about 12.6% higher, a result significant at the 10% level. In addition,
268 Model 1 also shows that each extra year of age is associated with an estimated 3.9% increase in the
269 incidence rate and the incidence-rate ratio for a 10-year increase in age is estimated as $1.039^{10} = 1.466$,
270 corresponding to a 46.6% increase in the score of frailty index, holding other covariates constant. The
271 estimates also suggest that having some education vs. none is associated with reduced incidence rate
272 (over 5%) and that the frailty incidence rate increases by 23.7% for females relative to males, controlling
273 for the other variables. Similarly, the estimates of self-rated reported economic status show the higher
274 incidence rate of frailty among those with lower economic status. For example, frailty incidence rate
275 increases by 41.4% for respondents with poor self-rated economic status, compared with rich
276 respondents. However, compared with respondents who held blue-collar jobs before retirement, those
277 who had white-collar jobs have higher incident rate, 1.235 (95% CI: 1.196, 1.276), of being frail. We
278 tested whether the impact of air pollution varied by socio-economic status by including interaction
279 terms between sociodemographic factors and exposure to air pollution (results show in the
280 Supplementary material Table S7) but there are no significant effects.

281 **Table 3** Incidence rate ratio (95% Confidence Intervals) and random-effect parameters of cross-sectional
 282 impact of 1-year and weekly exposure to air pollution on frailty among Chinese elderly, CLHLS 2014

VARIABLES	Model 1 Long-term	Model 2 Model 1 + short-term	Model 3 Model 2 + Long- # short-term
<i>Long-term (1-year) (ref: AQI 1(good))</i>			
AQI 2 (Moderate)	1.109* (1.012 - 1.215)	1.113* (1.015 - 1.219)	1.130** (1.032 - 1.237)
AQI 3 (Unhealthy)	1.052 (0.943 - 1.175)	1.071 (0.960 - 1.196)	1.104# (0.991 - 1.231)
AQI 4 (Very unhealthy)	1.126# (0.991 - 1.279)	1.140* (1.004 - 1.295)	1.144* (1.011 - 1.295)
<i>Short-term</i>			
z-score (Weekly)		1.040* (1.006 - 1.076)	0.947 (0.882 - 1.018)
<i>Interaction terms (ref: weekly z-score # AQI 1)</i>			
Weekly z-score # AQI 2			1.283*** (1.160 - 1.418)
Weekly z-score # AQI 3			1.114* (1.020 - 1.216)
Weekly z-score # AQI 4			0.962 (0.859 - 1.077)
Female (ref: Male)	1.146*** (1.114 - 1.178)	1.147*** (1.115 - 1.179)	1.146*** (1.115 - 1.179)
Age	1.039*** (1.020 - 1.058)	1.038*** (1.020 - 1.057)	1.036*** (1.017 - 1.055)
Age # Age	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)
Educated (ref: no schooling)	0.935*** (0.907 - 0.963)	0.935*** (0.908 - 0.963)	0.933*** (0.906 - 0.961)
Career (ref: Blue-collar)	1.235*** (1.196 - 1.276)	1.234*** (1.194 - 1.274)	1.234*** (1.195 - 1.275)
<i>Self-rated economic (ref: Rich)</i>			
Median	1.076*** (1.042 - 1.111)	1.077*** (1.043 - 1.112)	1.078*** (1.044 - 1.113)
Poor	1.411*** (1.351 - 1.474)	1.412*** (1.352 - 1.475)	1.414*** (1.354 - 1.477)
<i>Marriage (ref: Married)</i>			
Single	1.071# (0.991 - 1.156)	1.069# (0.990 - 1.154)	1.068# (0.989 - 1.153)
Widowed	1.024 (0.994 - 1.055)	1.022 (0.992 - 1.053)	1.020 (0.990 - 1.051)
Logarithm of GDP	1.037 (0.954 - 1.128)	1.033 (0.951 - 1.123)	1.017 (0.939 - 1.102)
Logarithm of Population density	0.997 (0.922 - 1.077)	1.004 (0.930 - 1.085)	0.994 (0.923 - 1.071)
Constant	0.208** (0.0648 - 0.668)	0.206** (0.0647 - 0.657)	0.280* (0.0896 - 0.877)
<i>Random-effect parameters</i>			
Between-city Variance	0.035*** (0.021 - 0.049)	0.034*** (0.020 - 0.048)	0.030*** (0.018 - 0.043)
Observations (Individual)	4,194	4,194	4,194
Number of cities	112	112	112

Note:

1. City-level variables include AQI, z-score, logarithm of GDP per capita, logarithm of population density;
2. *** p<0.001, ** p<0.01, * p<0.05, # p<0.1

283 In Model 2, when the short-term exposure term (weekly z-score) is included, the effect of long-term
284 exposure is strengthened in effect size and significance, that is those living in cities with a longer-term
285 AQI levels of 4 had higher frailty scores compared to those with AQI level 1, accounting for short-term
286 fluctuations and other covariates. Specifically, compared with exposure to AQI 1, the estimated effect
287 of exposure to AQI 4 is to increase the incidence rate ratio of frailty index score in a given year period,
288 by about 14.0% (p=0.02). Despite a positive coefficient for z-score, this is not significant when adding
289 interaction terms, suggesting that as expected, short-term exposure fluctuations are not associated with
290 the frailty score. The coefficients for marital status, GDP and population density are not significant.

291 We might also expect that the effect of short-term fluctuations might vary by the overall background
292 level of air pollution exposure, and that short-term fluctuations might affect the long-term mean and
293 then result in biased estimates for long-term exposure. Thus, we added interaction terms between long-
294 term exposure and short-term fluctuations. In Model 3, the interaction effects between weekly z-score
295 and yearly mean AQI are not always significant, providing no evidence that short-term exposure has a
296 differential impact on health at different longer-term air pollution levels.

297 In addition, all three models show the city-level specific random effects also appear significant,
298 suggesting that a significant amount of variance in frailty can be explained by city-level factors. For
299 example, in Model 3, the city-level random effects present a residual variance between cities $\widehat{\sigma}_u^2 =$
300 0.030 with the confidence interval (0.018 - 0.043). The other coefficients (marital status, logarithm of
301 GDP per capita and logarithm of population density) are not significant at the 5%-level.

302 In addition, Tables S4 and S5 in the Supplementary material show effects of 2-year and 3-year exposure.
303 The results are mostly consistent with Table 3 (1-year exposure as the long-term exposure). Results
304 estimated using data obtained by means of GWR interpolation for the cross-sectional analysis also
305 supports the above findings (details shown in Supplementary material Table S8), which provide
306 reassurance that our complete case analysis is not substantially biased.

307 Moving to the longitudinal analysis, we present a similar set of models based on the two-wave panel
308 dataset in Table 4 which model the change in frailty between waves. Results clearly show that long-
309 term (1-year) exposure to air pollution has a positive association with frailty, and poorer air quality is
310 associated with higher frailty over a 3-year period from 2011 to 2014. Compared with the cross-
311 sectional analysis, the estimates of the frailty score associated with long-term exposure are much bigger
312 and more significant. Specifically, in Model 3, compared with those exposed to the AQI 1 (good air
313 quality), the estimated effect of exposure to AQI 4 (very unhealthy air quality) is to increase the
314 incidence rate, and therefore the expected score of frailty index in a year period, by about 23.3%
315 ($p=0.003$). In terms of the weekly z-score, Model 2 shows that the estimated effect of increasing weekly
316 z-score on frailty is not significant. Similar to the results from the cross-sectional analysis, the
317 interaction terms in Table 4 do not show consistently significant effects on frailty. In the Supplementary
318 material, we used 2-year and 3-year periods as the long-term exposure measure and found that long-
319 term effects are significantly associated with frailty but short-term exposure (weekly z-score) and
320 interaction terms have no significant effects on frailty (details shown in Tables S9-10). The analysis
321 from GWR data shows there is an association of long-term exposure with frailty score in Table S12. In
322 addition, in Table 4, gender, age, education, marital status and career are significantly associated with
323 frailty; but the coefficients of GDP and population density are not significant.

324 **Table 4** Incidence rate ratio (95% Confidence Intervals) and random-effect parameters of longitudinal
325 impact of 1-year and weekly exposure to air pollution on frailty among Chinese elderly, CLHLS 2011 &
326 2014

VARIABLES	Model 1 Long-term	Model 2 Model 1+ short-term	Model 3 Model 2 + Long- # short-term
<i>Long-term (1-year) (ref: AQI 1(good))</i>			
AQI 2 (Moderate)	1.212** (1.071 - 1.370)	1.218** (1.077 - 1.377)	1.217** (1.076 - 1.375)
AQI 3 (Unhealthy)	1.246*** (1.099 - 1.413)	1.254*** (1.106 - 1.422)	1.246*** (1.099 - 1.413)
AQI 4 (Very unhealthy)	1.255*** (1.098 - 1.434)	1.269*** (1.110 - 1.452)	1.233** (1.076 - 1.413)
<i>Short-term</i>			
z-score (Weekly)		1.023 (0.994 - 1.054)	0.911* (0.835 - 0.995)
<i>Interaction terms</i>			
Weekly z-score # AQI 2			1.148** (1.044 - 1.264)
Weekly z-score # AQI 3			1.146**

Weekly z-score # AQI 4			(1.038 - 1.266) 1.054 (0.928 - 1.197)
Female (ref: Male)	1.119*** (1.080 - 1.160)	1.120*** (1.080 - 1.161)	1.124*** (1.084 - 1.165)
Age	1.025* (1.002 - 1.047)	1.024* (1.002 - 1.047)	1.026* (1.004 - 1.049)
Age # Age	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)
Educated (ref: no schooling)	0.929*** (0.894 - 0.966)	0.930*** (0.894 - 0.966)	0.933*** (0.897 - 0.969)
Career (ref: Blue-collar)	1.159*** (1.112 - 1.208)	1.159*** (1.112 - 1.208)	1.161*** (1.114 - 1.210)
<i>Self-rated economic (ref: Rich)</i>			
Median	1.120*** (1.084 - 1.157)	1.120*** (1.084 - 1.158)	1.121*** (1.085 - 1.158)
Poor	1.398*** (1.335 - 1.464)	1.398*** (1.336 - 1.464)	1.400*** (1.337 - 1.465)
Marriage (ref: Married)			
Single	1.120** (1.029 - 1.219)	1.119** (1.028 - 1.218)	1.119** (1.028 - 1.218)
Widowed	1.048** (1.011 - 1.085)	1.048** (1.011 - 1.085)	1.047* (1.010 - 1.084)
Logarithm of GDP	1.028 (0.956 - 1.106)	1.028 (0.955 - 1.106)	1.029 (0.955 - 1.107)
Logarithm of Population density	1.018 (0.949 - 1.092)	1.020 (0.951 - 1.093)	1.018 (0.949 - 1.091)
Constant	0.199** (0.0605 - 0.652)	0.199** (0.0607 - 0.651)	0.203** (0.0622 - 0.665)
Year of 2014 (ref: 2011)	1.081*** (1.042 - 1.121)	1.071*** (1.031 - 1.112)	1.069*** (1.029 - 1.110)
<i>Random-effect parameters</i>			
Between-city Variance	0.017*** (0.008 - 0.025)	0.016*** (0.008 - 0.025)	0.016*** (0.008 - 0.024)
Between-individual Variance	0.281*** (0.264 - 0.298)	0.281*** (0.2614 - 0.297)	0.280*** (0.263 - 0.296)
Observations (Individual)	8,753	8,753	8,753
Number of cities	108	108	108

Note:

1. City-level variables include AQI, z-score, logarithm of GDP per capita, logarithm of population density;

2. *** p<0.001, ** p<0.01, * p<0.05, # p<0.1

327

328 Additionally, to make the analysis above more robust, we run some similar models but use weekly,

329 monthly and quarterly z-score as the short-term exposure in Table S11. We can see the estimated effect

330 of exposure to long-term air pollution on frailty slightly rises when the measures of short-term exposure

331 refer to different periods, from weekly z-score to quarterly z-score; but short-term fluctuations at a week,

332 a month or a quarter are not significantly associated with frailty even at the 10% level.

333 To assess whether long-term exposure to air pollution is associated with a more unfavourable change
 334 in frailty between CLHLS 2011 and 2014, we set up two random-effects models using the type of AQI
 335 change. Table 5 compares the effects of the change in AQI on the frailty index. Model 1 shows that
 336 living in an area where AQI moved from 2 to 3, 2 to 4, or 3 to 4, compared with living in a constant
 337 ‘AQI 2’ area, is associated with increased frailty scores. Specifically, in Model 1, with AQI worsening
 338 from 2 to 4, the incidence rate of frailty increases by about 21.4% (p=0.000), compared with a constant
 339 ‘AQI 2’. More control variables are added, such as year and other covariates, in Model 2 and Model 3.
 340 When controlling all of covariates in Model 3, we can see respondents living in ‘AQI 1-1’, i.e. a constant
 341 low level of AP, decreases frailty risk by 21.6% (p<0.001), while those living in ‘AQI 3-3’, i.e. a
 342 constant high level, increases the risk by 19.0% (p=0.028), compared with the reference group ‘AQI 2-
 343 2’. The same analysis using the GWR-interpolated data shows that the change in AQI is associated with
 344 the change in frailty score (Table S13).

345 **Table 5** Incidence rate ratio (95% Confidence Intervals) of longitudinal impact of 1-year AQI change on
 346 frailty among Chinese elderly from random-effects models, CLHLS 2011 & 2014

VARIABLES	Model 1: Basic	Model 2: Model 1+year	Model 3: Model 2+covariates
<i>AQI change type (ref: AQI 2-2)</i>			
AQI 1-1	0.853* (0.753 - 0.966)	0.835** (0.737 - 0.947)	0.784*** (0.698 - 0.880)
AQI 3-3	1.161# (0.976 - 1.380)	1.145 (0.963 - 1.362)	1.190* (1.018 - 1.390)
AQI 2-3	1.055# (0.992 - 1.123)	1.056# (0.992 - 1.124)	1.117*** (1.057 - 1.181)
AQI 2-4	1.214*** (1.113 - 1.324)	1.203*** (1.102 - 1.313)	1.163*** (1.075 - 1.259)
AQI 3-2	0.895 (0.696 - 1.150)	0.872 (0.678 - 1.122)	0.958 (0.769 - 1.195)
AQI 3-4	1.091* (1.008 - 1.182)	1.081# (0.998 - 1.172)	1.090* (1.013 - 1.173)
z-score (Weekly)	1.164*** (1.129 - 1.200)	1.020 (0.986 - 1.055)	1.012 (0.980 - 1.046)
Observations (Individual)	5,926	5,926	5,926
Number of cities	73	73	73

Note:

1. Model 2 includes time variables;

2. Model 3 includes control variables at individual level include sex, age, age square, marital status, education, self-rated economic, career; City-level variables include AQI, z-score, logarithm of GDP per capita, logarithm of population density and year;

3. *** p<0.001, ** p<0.01, * p<0.05, # p<0.1

347

348 **4. Discussion**

349 We conducted cross-sectional and longitudinal analysis among Chinese elderly people based on
350 CLHLS, a national dataset, linked to air pollution monitoring station data, to investigate the association
351 between air pollution at the city level and frailty. We also calculated comprehensive measures to assess
352 and adjust models for long- and short-term AP exposure. We identified that the frailty score among
353 Chinese elderly 65+ was strongly associated with long-term exposure (1-year) to AP rather than short-
354 term fluctuations, after individual and neighbourhood characteristics are controlled. Moreover, we also
355 established that living in a city with worsening AP over a three-year period, compared with one where
356 air pollution was stable, was associated with a higher incident frailty score, suggesting that increasing
357 air pollution could exacerbate the ageing process.

358 It is already well established that air pollution has an impact on elderly health in terms of individual
359 diseases, (Zeng et al., 2010), and others have established that in sub-populations AP is linked to the
360 development of frailty (Lüscher, 2017; Myers et al., 2013). This is the first study to our knowledge to
361 establish a longitudinal link between air pollution and frailty in the general elderly population. Previous
362 research about AP and frailty has not explored the role of long- and short-term exposure. As expected,
363 due to the chronic nature of many of the indicators in the frailty index, long-term exposure was the
364 dominant influence. However, this lack of association could also be related to the way health data were
365 collected. Given a source of health data that captured health shocks more adequately, such as acute
366 hospital admissions, it is plausible that short-term exposures may influence some components of frailty.

367 The associations between frailty and other covariates showed expected links with sex (women have a
368 higher frailty score than men), education (people with no schooling have a higher frailty score) and SES
369 (people with lower SES have a higher frailty score). However, it is interesting that respondents with
370 white-collar jobs before their retirement are much frailer than those who had worked in blue-collar jobs,
371 which seems to be incompatible with previous findings, because the effects of career should be same to
372 the effects of education and economic status (Goodman et al., 2011; O'Neill et al., 2003). Explanations
373 for this contradictory result should consider the social structure in China. Respondents with white-collar

374 jobs as their main occupation before retirement typically live in cities because most of them are well-
375 educated or working for government, whereby work opportunities depend on education and political
376 loyalty before the 1980s in China (Walder, 1995). In addition, urban residents have access to more
377 ancillary services to acquire health diagnoses than their rural counterparts (Mueser et al., 2001), which
378 might explain an underestimation of the incidence rate of diseases among rural residents. Popkin et al.
379 (1995) proposed that urban residents or high-income populations are likely to have higher fat intake
380 and lower physical activity. There is evidence showing urban adults in China have a higher probability
381 of being obese (Chen et al., 2011) and having hypertension (Xiaohui Hou, 2008). All of those reasons
382 can explain the association of white-collar jobs with higher risks of being frail in this study. Note that
383 all interactions between AP and these socio-demographic factors were insignificant, meaning that the
384 impact of AP on health is uniform regardless of socio-economic status.

385 In this study, frailty is positively related to long-term exposure to air pollution rather than short-term
386 fluctuations. This is partly contrary to what has been found in previous studies, which identified short-
387 term exposure to air pollution are associated with hospitalisation due to cardiovascular and respiratory
388 diseases (Raza et al., 2018), which are components of our frailty index. For example, Bedada et al.
389 (2012) found a positive association between short-term exposure to sulphur dioxide and stroke. As
390 another example, an increase of weekly exposure to ozone was associated with a decrease of
391 cardiopulmonary function (Karakatsani et al., 2017). However, it is likely that chronic conditions based
392 on survey self-reports are less sensitive to these recent short-term effects, which could explain why
393 short-term AP fluctuations were not found to be significant.

394 This study has not found a consistent interaction effect of long- and short-term exposure on frailty
395 among Chinese elderly people. However, this finding provides a more solid evidence to examine the
396 effect of long-term exposure than previous researches. For example, Zhang et al. (2018) recognised that
397 exploring the impact of exposure to AP on cognitive ability should consider the cumulative and
398 transitory exposure AP together. However, they neglected the variance of cumulative exposure to AP
399 and the collinearity between the mean of cumulative exposure and the mean of transitory exposure to

400 AP. In this study, using a z-score to operationalize and control short-term exposure to AP more
401 accurately measures the association between long-term exposure and frailty.

402 Our study has several methodological advantages over previous studies. First, the linkages of survey
403 data with air quality data were established using exact interview date and locations, enabling us to
404 accurately identify temporal trends in air pollution, even if interview dates varied between respondents.
405 We also used a comprehensive validated frailty index. Moreover, we exploited the available AP data to
406 measure both the average AQI exposure and the level of AQI short-term fluctuation through the AQI
407 z-score. Third, the samples in this study were aged 65 and more, a population who are vulnerable to
408 exposure to air pollution, rarely migrating and moving their residences, hardly changing their
409 socioeconomic status. Thus, the analysis was more likely to identify associations of exposure to air
410 when they are unaffected by time varying confounding. Finally, this study used a GWR method to
411 interpolate missing air pollution data, which provides reassurance as to the robustness of the results,
412 and that the complete case analysis was not biased. GWR contains more parameters (spatial information
413 and socioeconomic factors) for interpolation, which improves previous imputation or interpolation
414 approaches.

415 Several limitations should be considered in this study. First, our analyses do not include all of the
416 CLHLS sample, only using 60% respondents due to missing of AQI data, which cannot be nationally
417 representative. However, robustness checks using GWR to interpolate missing data suggested our
418 sample did not lead to biased estimates. Second, our AQI data is city-level; however, there is likely to
419 be variation of AQI within a city. This measure cannot compare the difference between respondents
420 within the same city, despite using the multilevel modelling in this study. Third, the explanatory variable
421 is a composite index of AP rather than specific air pollutants (such as PM10, ozone, SO2 etc.), and we
422 cannot separate the effect of each component of AQI. Nevertheless, numerous studies have used AQI
423 and found that it is a robust estimate of health risks (Li et al., 2015; Stieb et al., 2005). Fourth, as only
424 two waves of data are used in this paper, we are unable to truly understand trajectories of frailty (for
425 that, we need 3 waves, and our linked data are not sufficient). Furthermore, some unmeasured time-
426 variant variables, such as health or social-environmental factors, cannot be ruled out in this study, which

427 might affect the relationship we estimated. In addition, we are unable to address survival bias, a
428 perennial question in epidemiology. Finally, participation bias should be noted as all indicators of frailty
429 are self-rated, and some people could be suffering from conditions but not diagnosed. Therefore, our
430 estimations possibly underestimate the level of frailty.

431 **5. Conclusions**

432 This study expands the evidence that long-term exposure to air pollution contribute to higher incidence
433 of frailty among Chinese elderly people, when controlled for sex, age, self-rated economic status,
434 education, career, marital status, regional factors (GDP per capita and population density) and interview
435 time. Moreover, it suggests that worsening air quality may influence poorer frailty trajectories. Further
436 research is needed using a longer time span of data to understand how the interaction between short-
437 and long-term exposure to air pollution accumulate to affect elderly health trajectories. Our results
438 highlight the importance of improving air pollution for successful healthy ageing.

439

440 **Declaration of Competing Interest**

441 All authors declared no conflicts of interests.

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