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# Hourly Valley Concentration of Air Pollutants Associated with Increased Acute Myocardial Infarction Hospital Admissions in Beijing, China

**Jia Fu, Yanbo Liu, Yakun Zhao, Siqi Tang, Yuxiong Chen, Yijie Liu, Yitao Han and Zhongjie Fan ***

Peking Union Medical College Hospital, Peking Union Medical College & Chinese Academy of Medical Sciences, Beijing 100730, China
* Correspondence: fanzhongjie@pumch.cn

**Abstract:** (1) Background: Acute myocardial infarction (AMI) imposes a great burden on global health. Few studies have demonstrated the effects of valley concentration of air pollutants on AMI hospital admissions. (2) Methods: Hospitalizations for AMI from 1 May 2014 to 31 December 2019 were analyzed. Generalized additive models (GAM) were used to quantify the exposure–response association between the hourly peak, mean, and valley concentration of six air pollutants and AMI hospital admissions. Stratification analyses were conducted to identify the susceptible population. (3) Results: Hourly peak, mean, and valley concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO were significantly associated with AMI hospital admissions. Each 10-unit increase in the hourly valley concentration of them led to 0.50% (0.35–0.66%), 0.44 % (0.32–0.56%), 0.84% (0.47–1.22%), 1.86% (0.73–3.01%), and 44.6% (28.99–62.10%) excess risk in AMI hospital admissions, respectively. In addition, the effects of hourly valley concentration were larger than mean and peak concentrations. The effects in the female or older than 65 groups were larger than that in the male or younger than 65 groups. (4) Conclusions: $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO exposure contributed to increased AMI hospital admissions. Hourly valley concentration might be a more potent indicator of adverse cardiovascular events. Females and individuals older than 65 were more susceptible to ambient air pollutant exposure.

**Keywords:** acute myocardial infarction; air pollutants; China; hospital admission; generalized additive models

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**Citation:** Fu, J.; Liu, Y.; Zhao, Y.; Tang, S.; Chen, Y.; Liu, Y.; Han, Y.; Fan, Z. Hourly Valley Concentration of Air Pollutants Associated with Increased Acute Myocardial Infarction Hospital Admissions in Beijing, China. *Atmosphere* **2023**, *14*, 27. https://doi.org/10.3390/atmos14010027

Academic Editors: Kai-Jen Chuang and Daniele Contini

Received: 14 November 2022
Revised: 17 December 2022
Accepted: 21 December 2022
Published: 23 December 2022

## 1. Introduction

Cardiovascular disease is one of the significant causes of mortality all over the world [1]. It included the ischemic heart disease, stroke, and so on. Ischemic heart disease and stroke were the leading causes of disability-adjusted life years in the over-50 group in 2019 [2]. The estimated age-standardized death rate of ischemic heart disease remains increasing in many areas such as South, East, and Southeastern Asia [3]. Acute myocardial infarction (AMI) is one of the cardiovascular diseases with high disability and death rates. It imposes a huge burden on the global economy. For example, the total estimated annual cost of AMI was over 84 billion dollars in 2016 in the United States according to a study with a sample of over 320,000 AMI patients [4]. The AMI total estimated expense was over 1.178 billion dollars in 2012 in the South Korea [5]. Studies in the United Kingdom, China, and Brazil showed similar results [6–8]. In a word, the disease and economic burden of AMI are substantial.

Air pollution is one of the most important global topics and health problems [9]. It can affect nearly all the people on the planet and every organ in the body [10,11]. Air pollution is the most significant environmental risk factor for morbidity and mortality and causes considerable harm to human health [12]. For example, particulate matter exposure mediated increased risk of a wide spectrum of chronic diseases [13–15]. The World

Health Organization estimates that the harmful effects of outdoor air pollution result in over 4 million deaths each year [16]. Previous literature suggested that both particulate (diameter < 2.5 mm ($PM_{2.5}$), diameter < 10 mm ($PM_{10}$)) and gaseous (sulfur dioxide ($SO_2$), nitrogen dioxide ($NO_2$), carbon monoxide (CO), ozone ($O_3$)) air pollutants had adverse impacts on cardiovascular diseases [17]. However, most of the studies established the effects of mean or peak concentration of air pollutants. Valley concentration represents an important metric of air pollution and a potential indicator for pollution control, but little has been investigated. In this study, we aimed to test the impact of six air pollutants on AMI hospitalization, with the larger perspective to identify efficient indicators for susceptible populations to provide data support for the formulation of prevention policies. To achieve the study objectives described above, we set the study population to AMI hospital admissions in Beijing between 1 May 2014 and 31 December 2019. At the same time, the exposure indicators were designated as the hourly peak, mean, and valley concentration of six air pollutants ($PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, $O_3$, CO). The generalized additive model (GAM) was used as the main statistical method, and the confounding factors such as meteorological factors were adjusted in the statistical model in the meantime. The stratification analysis and sensitivity analysis were also conducted to find out the susceptible population and test the robustness of our findings. We found that $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO exposure contributed to increased AMI hospital admissions. Hourly valley concentration might be a more potent indicator of adverse cardiovascular events.

## 2. Materials and Methods

### 2.1. Data Gathering

We analyzed AMI hospital admissions before the COVID-19 pandemic in Beijing, China, given its established impact on cardiovascular disease [18–20]. Data from 1 May 2014 to 31 December 2019 were obtained from the Beijing Municipal Health Commission Information Center. Anonymous clinical and residential information was collected. The 10th revision of the International Classification of Diseases provided the definition of AMI (ICD-10: I21-22). The data included the hourly concentration of both the particulate ($PM_{2.5}$, $PM_{10}$) and gaseous air pollutants ($SO_2$, $NO_2$, $O_3$, CO) from 35 air pollutant monitoring stations in Beijing. The hourly peak, mean, and valley concentration were defined as maximum, mean, and minimum of the hourly average concentration of the air pollutants in one day, respectively.

Data on potential confounding factors were also extracted. Influenza was independently linked to a higher risk of AMI according to prior research [21], and meteorological factors had an adverse effect on cardiovascular diseases [21–24], so the influenza endemic, daily mean temperature, and relative humidity were regarded as the confounding factors and were adjusted in our statistical model. When the positive rate of influenza virus isolation in any given week exceeded 20% of the highest weekly positive rate in the observation season in the north of China, it was defined as the influenza endemic (IF) [25,26], based on the data provided by the Chinese National Influenza Center [27]. The China Meteorological Administration provided the daily mean temperature and relative humidity. In addition, public holidays (PH) and day of the week (DOW) were linked to different behavioral patterns, so they were also included in the model. They were determined by the website of Central People's Government of the People's Republic of China [28].

### 2.2. Statistical Analysis

This study used the method of Lin et al., so the relevant description partly reproduces their wording [29]. We used the generalized additive model (GAM) to quantify the exposure–response association between the hourly peak, mean, and valley concentration of six air pollutants and AMI hospital admissions. The quasi-Poisson distribution was used to control the overdispersion in daily AMI hospital admissions [29,30]. The nonliner smooth functions were used to exclude the effects of temperature and relative humidity as well as the long-term trend and seasonality in daily AMI hospital admissions. The degrees of freedom (df) were set to 3 for the mean temperature and relative humidity and 6 per year for the time to control the long-term trend and seasonality. As mentioned above, the IF, PH, and DOW were also regarded as confounding factors and adjusted in the statistical model in the meantime. We used the abbreviations (e.g., $PM_{2.5\ peak}$, $PM_{2.5\ mean}$, and $PM_{2.5\ valley}$) to represent the hourly peak, mean, and valley concentrations of $PM_{2.5}$. The detailed main model is shown below:

$$\log[E(Y_t)] = \alpha + s(Time,\ df = 6\ per\ year) + s(Temperature,\ df = 3) + s(Humidity, df = 3) + \\ \beta_0 * Pollutant + \beta_1 * DOW + \beta_2 * IF + \beta_3 * PH$$

$E(Y_t)$ is the expected daily number of AMI hospital admissions on day $t$, and $s$ indicates the smooth function. $df$ is the degree of freedom. $\alpha$ is the model intercept, and $\beta$ is the regression coefficient. $Humidity$ and $Temperature$ refer to the relative humidity and mean temperature on day $t$, respectively. $Time$ refers to the time to adjust for long-term trends and seasonality. $Pollutant$ refers to the hourly peak, mean, or valley concentration of six kinds of air pollutants. $DOW$, $IF$, and $PH$ are the indicators for day of the week, influenza epidemic status and public holiday. R (ver. 4.1.1) software was used for all statistical analyses, and the two-sided $p$-value < 0.05 was used to determine statistical significance.

To find out the susceptible population to the health effects of air pollutants, we conducted the stratification analysis with different gender subgroups (male, female) and different age subgroups (age < 65, age $\geq$ 65). Previous studies showed that the influences of air pollutants had lag effects, so we adjusted our model with different lag structures from lag 0 day (LAG0, the current day of the AMI hospital admissions) to lag 3 days (LAG3, three days before the AMI hospital admissions) [31]. We also adjusted our model with different multiday average lag structures from LAG01 (moving averages from the current day to 1 day ago) to LAG03 (moving averages from the current day to 3 days ago) to control the potential misalignment of the single lag day exposure [32].

In addition, sensitivity analyses were performed using various degrees of freedom in the model to test the robustness of our findings. The degree of freedom of the $Temp$ and $Humidity$ were changed to 5, and the $Time$ was changed to 8 per year.

## 3. Results

### 3.1. Descriptive Analysis

A total of 124,765 AMI hospitalizations were analyzed. Among them, 86,581 (69.40%) were male, and 57,760 (46.30%) were younger than 65 years old. On average, there were 60.24 admissions per day, comprising 27.89 individuals younger than 65 years old. The hourly mean concentration of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, $O_3$, and CO were 64.60 $\mu g/m^3$, 96.21 $\mu g/m^3$, 45.26 $\mu g/m^3$, 9.51 $\mu g/m^3$, 1.01 $mg/m^3$, and 59.38 $\mu g/m^3$, respectively. The mean daily temperature was 14.34 °C, and relative humidity was 51.14% during the study. Table 1 details the AMI hospital admissions, air pollutants, and meteorological data.

### 3.2. Overall and Stratified Effects

Hourly peak, mean, and valley concentrations of the pollutants were all significantly associated with AMI hospitalization, except for $O_3$. Each 10-unit increase in the hourly valley concentration of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO led to 0.50% (95% CI: 0.35–0.66%), 0.44% (95% CI: 0.32–0.56%), 0.84% (95% CI: 0.47–1.22%), 1.86% (95% CI: 0.73–3.01%), and 44.6% (95% CI: 28.99–62.10%) excess risk in AMI hospital admissions among the total population in the current day (LAG0). Hourly valley concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, and CO had stronger effects compared to the hourly mean concentrations. Each 10 $\mu g/m^3$ increase in hourly peak, mean, and valley concentration of $PM_{2.5}$ led to 0.25% (95% CI: 0.17–0.34%), 0.43% (95% CI: 0.3–0.55%), and 0.5% (95% CI: 0.35–0.66%) excess risk in AMI hospitalization, respectively.

**Table 1.** The baseline information of the AMI hospital admissions, air pollutants, and meteorological data.

| Variable | Observation Days | Mean ± SD | Percentiles | | | | |
|---|---|---|---|---|---|---|---|
| | | | Min | P25 | P50 | P75 | Max |
| Daily AMI count | | | | | | | |
| Total | 2071 | 60.24 ± 14.32 | 24 | 49 | 60 | 70 | 110 |
| Age < 65 | 2071 | 27.89 ± 7.04 | 7 | 23 | 28 | 32 | 58 |
| Age ≥ 65 | 2071 | 32.35 ± 9.54 | 8 | 25 | 32 | 39 | 68 |
| Male | 2071 | 41.81 ± 10.60 | 13 | 34 | 41 | 49 | 85 |
| Female | 2071 | 18.44 ± 5.72 | 4 | 14 | 18 | 22 | 41 |
| Meteorological factors | | | | | | | |
| Temperature (°C) | 2070 | 14.34 ± 11.21 | −14.3 | 3.3 | 16.1 | 24.7 | 32.6 |
| Relative humidity (%) | 2070 | 51.14 ± 19.92 | 8 | 35 | 51 | 67 | 99 |
| Air pollutants | | | | | | | |
| $PM_{2.5\ valley}$ ($\mu g/m^3$) | 2049 | 38.01 ± 43.79 | 2.45 | 10.25 | 23.56 | 48.06 | 400.43 |
| $PM_{2.5\ mean}$ ($\mu g/m^3$) | 2049 | 64.60 ± 57.58 | 4.31 | 25.80 | 48.25 | 83.34 | 439.81 |
| $PM_{2.5\ peak}$ ($\mu g/m^3$) | 2049 | 100.83 ± 81.16 | 6.03 | 45.19 | 78.91 | 131.20 | 640.57 |
| $PM_{10\ valley}$ ($\mu g/m^3$) | 2044 | 54.72 ± 49.61 | 2.00 | 20.19 | 38.85 | 74.32 | 471.43 |
| $PM_{10\ mean}$ ($\mu g/m^3$) | 2044 | 96.21 ± 68.42 | 5.63 | 50.06 | 79.17 | 122.17 | 830.72 |
| $PM_{10\ peak}$ ($\mu g/m^3$) | 2044 | 153.90 ± 116.42 | 8.80 | 86.28 | 125.62 | 185.20 | 1680.26 |
| $NO_{2\ valley}$ ($\mu g/m^3$) | 2050 | 27.26 ± 18.33 | 3.91 | 14.60 | 22.00 | 33.79 | 130.69 |
| $NO_{2\ mean}$ ($\mu g/m^3$) | 2050 | 45.26 ± 20.50 | 9.12 | 31.27 | 41.22 | 54.63 | 146.46 |
| $NO_{2\ peak}$ ($\mu g/m^3$) | 2050 | 66.95 ± 26.02 | 11.53 | 49.44 | 64.03 | 79.88 | 179.65 |
| $SO_{2\ valley}$ ($\mu g/m^3$) | 2050 | 5.24 ± 6.00 | 1.59 | 2.32 | 3.03 | 5.47 | 57.67 |
| $SO_{2\ mean}$ ($\mu g/m^3$) | 2050 | 9.51 ± 10.16 | 2.03 | 3.27 | 5.85 | 11.10 | 82.10 |
| $SO_{2\ peak}$ ($\mu g/m^3$) | 2050 | 16.24 ± 16.88 | 2.09 | 5.48 | 10.77 | 19.98 | 213.77 |
| $CO_{valley}$ ($mg/m^3$) | 2026 | 0.65 ± 0.60 | 0.16 | 0.31 | 0.50 | 0.75 | 7.13 |
| $CO_{mean}$ ($mg/m^3$) | 2026 | 1.01 ± 0.81 | 0.21 | 0.55 | 0.81 | 1.15 | 7.72 |
| $CO_{peak}$ ($mg/m^3$) | 2026 | 1.48 ± 1.16 | 0.29 | 0.80 | 1.16 | 1.74 | 13.29 |
| $O_{3\ valley}$ ($\mu g/m^3$) | 2050 | 19.50 ± 16.79 | 1.71 | 6.57 | 14.09 | 27.57 | 156.70 |
| $O_{3\ mean}$ ($\mu g/m^3$) | 2050 | 59.38 ± 36.60 | 3.30 | 30.21 | 53.87 | 81.85 | 173.98 |
| $O_{3\ peak}$ ($\mu g/m^3$) | 2050 | 107.83 ± 65.78 | 4.21 | 59.59 | 91.00 | 153.38 | 334.32 |

Similar effects were found in the subgroups. All the pollutants had greater impacts on females and individuals older than 65 years old. For example, each 10 $\mu g/m^3$ increase in hourly valley concentration of $PM_{2.5}$ led to 0.41% (95% CI: 0.23–0.59%) excess risk in females, as compared to 0.71% (95% CI: 0.44–0.98%) in their male counterparts; a 10 $\mu g/m^3$ increase in hourly valley concentration of $PM_{2.5}$ led to 0.69% (95% CI: 0.48–0.89%) excess risk in individuals older than 65, as compared to 0.29% (95% CI: 0.07–0.52%) in their younger counterparts. Table 2 shows the excess risk of AMI hospitalization related to hourly peak, mean, and valley concentration of the six air pollutants in the current day (LAG0) in the total population and different subgroups.

### 3.3. Lag Effect

Figure 1 shows the relationship between the excess risk of AMI hospital admissions and the concentration of pollutants on different lag days. Maximum effects of $PM_{2.5}$, $PM_{10}$, and CO occurred on LAG0 and diminished in the following days. Each 10-unit increase in hourly valley concentration of $PM_{2.5}$, $PM_{10}$, and CO generated 0.5% (95% CI: 0.35–0.66%), 0.44% (95% CI: 0.32–0.56%), and 44.6% (95% CI: 28.99–62.1%) excess risk in AMI hospitalization in LAG0, respectively. Maximum effects of $NO_2$ and $SO_2$ occurred in LAG1. Each 10 $\mu g/m^3$ increase in hourly valley concentration of $NO_2$ and $SO_2$ generated 0.89% (95% CI: 0.53–1.24%) and 2.51% (95% CI: 1.39–3.63%) excess risk in AMI hospital admissions in LAG1, respectively. Concentrations of $O_3$ were not associated with excess risks in the lag days examined. The findings were consistent using the moving average lag days. Figures S1 and S2 and Table S1 present the excess risk of AMI hospitalization related to concentrations of pollutants in different lag days.

### 3.4. Sensitivity Analyses

Alternative df was used to adjust for temporal trends (df = 7 per year) and meteorological factors (df = 4 for relative humidity and daily mean temperature). As shown in Supplementary Table S2, the results remained consistent. It meant that hourly peak, mean, and valley concentration of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO were significantly associated with the AMI hospital admissions, and the main models produced reliable results.

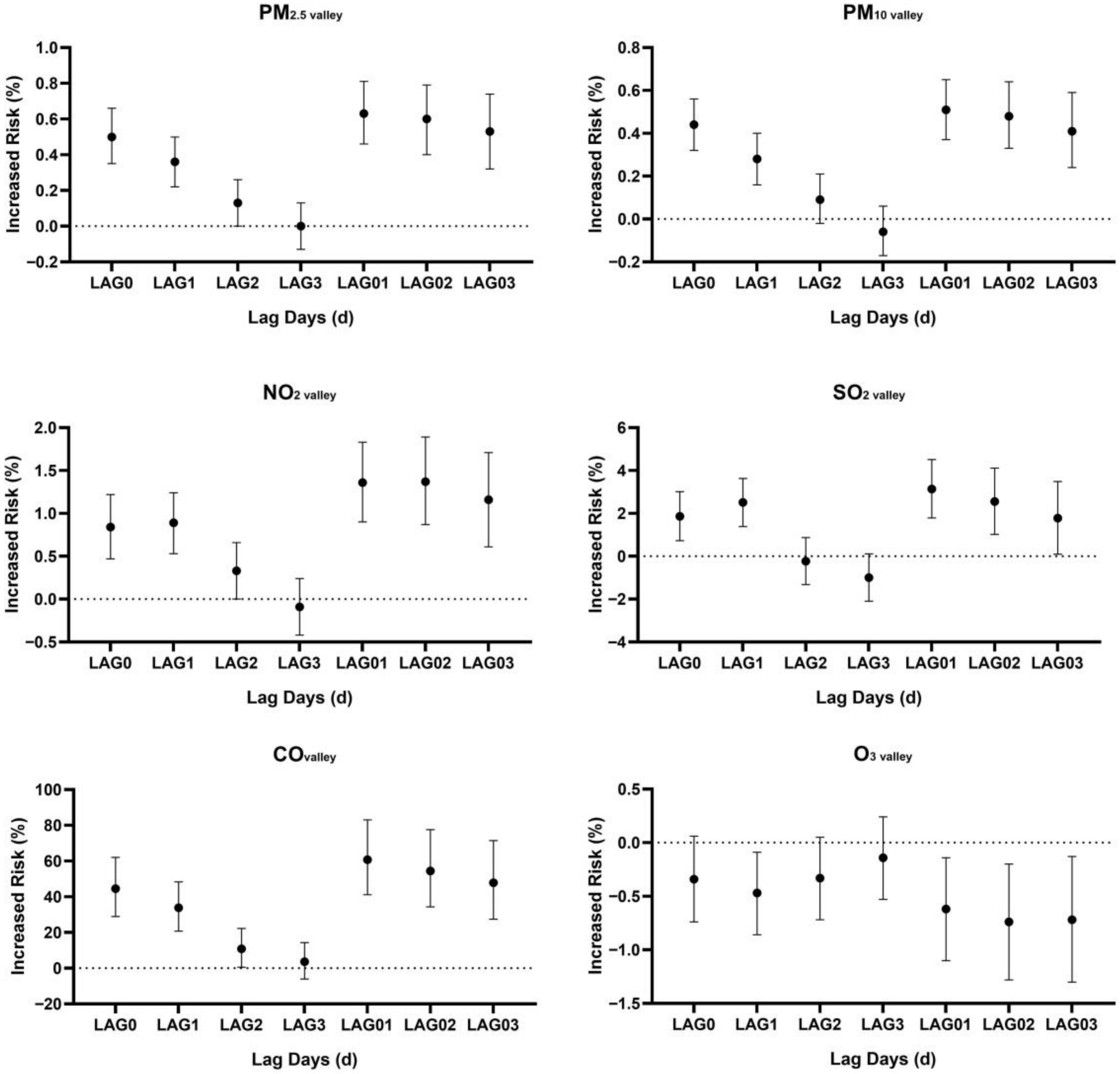

**Figure 1.** The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10-unit increase in hourly valley concentration of six kinds of air pollutants in different lag days among the total population in Beijing, China.

**Table 2.** The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10 units increase in hourly peak, mean, and valley concentration of six kinds of air pollutants in the current day (LAG0) among the total population and different subgroups in Beijing, China.

| Variable | Total | Age < 65 | Age ≥ 65 | Male | Female |
|---|---|---|---|---|---|
| $PM_{2.5\ valley}$ | 0.5 (0.35–0.66) | 0.29 (0.07–0.52) | 0.69 (0.48–0.89) | 0.41 (0.23–0.59) | 0.71 (0.44–0.98) |
| $PM_{2.5\ mean}$ | 0.43 (0.3–0.55) | 0.32 (0.14–0.5) | 0.53 (0.37–0.7) | 0.34 (0.2–0.49) | 0.62 (0.4–0.84) |
| $PM_{2.5\ peak}$ | 0.25 (0.17–0.34) | 0.23 (0.11–0.35) | 0.28 (0.17–0.39) | 0.2 (0.1–0.3) | 0.37 (0.23–0.52) |

**Table 2.** *Cont.*

| Variable | Total | Age < 65 | Age ≥ 65 | Male | Female |
|---|---|---|---|---|---|
| $PM_{10\ \text{valley}}$ | 0.44 (0.32–0.56) | 0.23 (0.05–0.41) | 0.64 (0.48–0.8) | 0.37 (0.23–0.52) | 0.61 (0.39–0.82) |
| $PM_{10\ \text{mean}}$ | 0.3 (0.21–0.39) | 0.24 (0.11–0.37) | 0.36 (0.24–0.48) | 0.26 (0.15–0.36) | 0.4 (0.24–0.55) |
| $PM_{10\ \text{peak}}$ | 0.11 (0.06–0.16) | 0.11 (0.04–0.19) | 0.12 (0.05–0.18) | 0.09 (0.03–0.15) | 0.16 (0.07–0.25) |
| $NO_{2\ \text{valley}}$ | 0.84 (0.47–1.22) | 0.39 (−0.16–0.95) | 1.25 (0.74–1.76) | 0.48 (0.03–0.93) | 1.66 (0.99–2.34) |
| $NO_{2\ \text{mean}}$ | 0.87 (0.54–1.2) | 0.49 (0–0.97) | 1.22 (0.77–1.67) | 0.55 (0.16–0.95) | 1.59 (0.99–2.18) |
| $NO_{2\ \text{peak}}$ | 0.7 (0.45–0.95) | 0.37 (0.01–0.73) | 1 (0.66–1.34) | 0.44 (0.14–0.74) | 1.27 (0.82–1.72) |
| $SO_{2\ \text{valley}}$ | 1.86 (0.73–3.01) | 0.33 (−1.33–2.02) | 3.09 (1.55–4.66) | 0.4 (−0.97–1.79) | 4.9 (2.88–6.95) |
| $SO_{2\ \text{mean}}$ | 1.05 (0.33–1.77) | 0.34 (−0.71–1.4) | 1.62 (0.65–2.6) | 0.16 (−0.71–1.03) | 2.92 (1.65–4.2) |
| $SO_{2\ \text{peak}}$ | 0.47 (0.05–0.9) | 0.14 (−0.49–0.78) | 0.74 (0.17–1.32) | 0.06 (−0.46–0.57) | 1.35 (0.6–2.11) |
| $CO_{\ \text{valley}}$ | 44.6 (28.99–62.1) | 20.89 (1.99–43.29) | 69.6 (45.52–97.67) | 26.53 (10.1–45.4) | 93.66 (58.69–136.34) |
| $CO_{\ \text{mean}}$ | 37.5 (25.37–50.8) | 21.34 (5.83–39.14) | 53.09 (35.21–73.33) | 22.31 (9.32–36.83) | 76.7 (50.35–107.67) |
| $CO_{\ \text{peak}}$ | 23.64 (16.28–31.46) | 18.2 (7.96–29.41) | 28.34 (18.09–39.48) | 15.69 (7.39–24.64) | 42.61 (28.08–58.79) |
| $O_{3\ \text{valley}}$ | −0.34 (−0.74–0.06) | 0.04 (−0.54–0.63) | −0.68 (−1.24–−0.13) | −0.06 (−0.55–0.42) | −1.02 (−1.75–−0.29) |
| $O_{3\ \text{mean}}$ | −0.01 (−0.29–0.27) | 0.06 (−0.34–0.46) | −0.12 (−0.5–0.26) | 0.2 (−0.13–0.54) | −0.55 (−1.05–−0.05) |
| $O_{3\ \text{peak}}$ | 0.08 (−0.07–0.22) | −0.04 (−0.24–0.17) | 0.15 (−0.05–0.35) | 0.12 (−0.05–0.3) | −0.07 (−0.34–0.19) |

## 4. Discussion

Beijing represents the industrialized city in Northern China. Our data showed that higher hourly peak, mean, and valley concentrations of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO were associated with increased AMI hospitalization. Previous research from several geological fields supports the findings. A Belgian study showed that each 10 µg/m$^3$ increase in $PM_{2.5}$ and $NO_2$ during the 24 h preceding the event led to 5.1% and 2.8% increased risk of the hospital admissions of ST-elevation myocardial infarction (STEMI) [33]. Zeynab et al. found that increased $PM_{2.5}$ exposure (48 h before admission) was related to the increased risk of the hospital admissions of STEMI [34]. An American study estimated that each 10 µg/m$^3$ increase in the 2-day averaged $PM_{2.5}$ concentration contributed to the 1.22% (95% CI: 0.62, 1.82%) increase in myocardial infarction death [35]. A Chinese study including 151,608 myocardial infarction deaths in Hubei province from 2013 to 2018 found that each 10 mg/m$^3$ increase in $NO_2$ exposure delivered a 1.46% (95% CI: 0.76–2.17%) increase in myocardial infarction mortality [17]. Yusef et al. indicated that 2.7% (95% CI: 1.1–4.2%) of AMIs were attributable to daily mean $SO_2$ levels over 10 µg/m$^3$ [36]. Other studies reported results differently. For example, a study in Eastern Massachusetts described that each 10 ppb increase in ozone led to an 8.28% (95% CI: 0.66%, 16.48%) increase in deaths from cardiovascular diseases [37]. No significant association was found between the $PM_{2.5}$, $PM_{10}$, $SO_2$, CO and the increased risk of myocardial infarction according to the research in England and Wales [38]. Inflammation, imbalanced autophagy, and oxidative stress might contribute to the potential mechanism [39]. For instance, a panel study showed that short-term exposure to $PM_{10}$ and $PM_{2.5}$ resulted in a proinflammatory state and elevated von Willebrand factor (vWF) [40]. Particulate matter impaired autophagy by inducing lysosomal disequilibrium [41].

However, it is worth noting that most of previous studies tended to use the daily mean concentration of air pollutants as the exposure indicators, and a few studies used the hourly peak concentration of air pollutants. The related literature about the association between the hourly valley concentration of air pollutants and AMI hospital admissions was absent, to our knowledge. Our study showed that the effects of hourly valley concentration were larger than the hourly mean concentration and that the effects of hourly mean concentration were larger than the hourly peak concentration. The findings were consistent with the results of the previous literature, though few in number. For example, a 10 µg/m$^3$ increase in daily mean concentration of $PM_{2.5}$ at lag03 led to 1.56% (95% CI: 0.91%, 2.21%) excess risk, and a 10 µg/m$^3$ increase in the hourly peak concentration of $PM_{2.5}$ at lag03 led to 1.15% (95% CI: 0.67%, 1.63%) increase for total cardiovascular diseases [29]. However, some studies reported conflicting results. For example, the peak concentrations of $NO_2$

were significantly associated with the nonaccidental mortality in lag04 and lag05, while no significant association was found in daily mean concentrations of $NO_2$ [42]. Our results indicated that the hourly valley concentration of air pollutants might be a better exposure indicator than the mean or peak concentration. Therefore, we suggest that hourly valley concentration of pollutants might be a better exposure indicator and a more practical target for environmental intervention. Further studies about it are needed in the future.

In the stratified analyses, we found that the effects in the female group were larger than those in the male group. This is probably because women have narrower airways, higher airway responsiveness [43], and higher lung deposition of fine particles in comparison to men [44]. Therefore, women might be more vulnerable to exposure to air pollution. Our results also showed that the effects in the people over the age of 65 were larger than the people under the age of 65. This is probably because the older people tend to suffer from multiple underlying medical conditions and seem to be more sensitive to air pollution as the antioxidant status is decreased in old age [45–47]. In addition, decreased heart rate variability is associated with cardiac autonomic dysfunction, and it is a predictor of cardiovascular risk [48]. Prior studies have shown that $PM_{2.5}$ exposure would decrease the heart rate variability in elderly people [49] and increase it in the young people [50].

There are several strong points in the study. First of all, this is the first study to explore the association between hourly valley concentration of six kinds of air pollutants and AMI hospital admissions to our knowledge. Secondly, our study covered all the secondary and tertiary hospitals in Beijing during the period from 1 May 2014 to 31 December 2019, and there were over 120,000 AMI hospital admissions recorded in the study. A long study time and large sample size could obtain more reliable and accurate research results. Last but not least, the effect of age, gender, and lag days were explored in our research, which could be conducive to identifying vulnerable populations and provide a theoretical foundation in policy making for AMI prevention in Beijing. However, there are also several limitations study in our study. Firstly, exposure data of meteorological factors and air pollutants were obtained from fixed sites provided by the government sectors, and we lacked the individualized exposure data. Therefore, many potential risk factors that could influence the AMI hospital admissions such as social-economic status, complication, and medication situation were not included. Moreover, we only studied the Beijing area, so our results might not be applicable to other areas.

## 5. Conclusions

The hourly peak, mean, and valley concentration of $PM_{2.5}$, $PM_{10}$, $SO_2$, $NO_2$, and CO were significantly positively associated with the AMI hospital admissions. The effects of hourly valley concentration were larger than the hourly mean or peak concentration. Furthermore, the effects in the female or older than 65 groups were larger than those in the male or younger than 65 groups.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/atmos14010027/s1, Table S1 The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10 units increase in hourly peak, mean and valley concentration of six kinds of air pollutants in different lag days among the total population in Beijing, China; Figure S1. The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10 units increase in hourly mean concentration of six kinds of air pollutants in different lag days among the total population in Beijing, China; Figure S2. The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10 units increase in hourly peak concentration of six kinds of air pollutants in different lag days among the total population in Beijing, China; Table S2 The excess risk (%) and 95% confidence interval in AMI hospital admissions for per 10 units increase in hourly peak, mean and valley concentration of six kinds of air pollutants among the total population in Beijing, China ( used alternative degrees of freedom).

**Author Contributions:** Conceptualization, J.F. and Z.F.; methodology, J.F. and Z.F.; software, J.F.; validation, S.T., Y.L. (Yijie Liu) and Y.Z.; formal analysis and data curation, Y.C., Y.H. and Y.L. (Yanbo Liu); writing—original draft preparation, S.T. and J.F.; writing—review and editing, J.F., Y.L. (Yijie Liu), Y.C., Y.H., Y.L. (Yanbo Liu) and Y.Z.; funding acquisition, Z.F. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by Chinese Academy of Medical Sciences Innovation Fund for Medical Sciences 2017-I2M-2-001, the National Key Research and Development Program of China 2017YFC0211703, and the National Natural Science Foundation of China 91643208.

**Institutional Review Board Statement:** Only anonymized patient data were used in our study; no patient or public privacy was compromised. Our research did not involve any human subjects. The Peking Union Medical College Hospital (PUMCH) Institutional Review Board gave its approval for this investigation.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author. The data are not publicly available due to this dataset is now confidential.

**Acknowledgments:** We sincerely acknowledge the data collection efforts of the Beijing Municipal Health Commission Information Center, the Chinese National Influenza Center, and the China Meteorological Administration.

**Conflicts of Interest:** The authors declare no conflict of interest.

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