Mitigating the Air Pollution Effect?

The Remarkable Decline in the Pollution-Mortality Relationship in Hong Kong

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Abstract

Using transboundary pollution from mainland China as an instrument, we show that air pollution leads to higher cardio-respiratory mortality in Hong Kong. However, the air pollution effect has dramatically decreased over the past two decades: before 2003, a 10-unit increase in the Air Pollution Index (API) could lead to a 3.1% increase in monthly cardio-respiratory mortality, but this effect has reduced to 0.5% using recent data and become statistically insignificant. Exploratory analyses suggest that a well-functioning medical system and immediate access to emergency services can help mitigate the contemporaneous effects of pollution on health.

Keywords: air pollution, health, transboundary pollution, healthcare, emergency service

JEL: Q53, Q52, I18

I. Introduction

Hong Kong (HK) is an autonomous territory, and former British colony, in southeastern China. The city has about 7.5 million people and among the highest per capita incomes in the world.[1] Notably, HK people have the highest life expectancy in the world, with male life expectancy being 81.32 years and female life expectancy being 87.34 years in 2017. Unlike other rich economies in the rest of the world, however, air quality in HK is poor and transboundary air pollution is a serious concern. The annual average concentration of particulate matter (PM_{10}) in HK was 45 $\mu g/m^3$ during 2000 to 2015, which was more than twice WHO's recommended level of 20 $\mu g/m^3$.

This study estimates the causal impact of air pollution on mortality using 16 years' micro-level death data from HK. Our identification strategy builds on the fact that, while a large portion of HK's pollution comes from local sources, transboundary pollution (i.e., pollution transmitted from mainland China) plays an important role in determining HK's air quality. HK is located near mainland China's Pearl River Delta Economic Zone (PRDEZ), a major manufacturing center. Emissions from heavy industrial activities in the PRDEZ are brought to HK by wind, creating exogenous variations in local air quality.

Using instruments based on combinations of wind direction, air pollution in the PRDEZ, and distance between the PRDEZ and different districts of HK, we estimate that a 10-unit increase in the Air Pollution Index (API) can cause a 1.77% increase in monthly cardio-respiratory mortality. The elderly are particularly vulnerable to air pollution, with a 10-unit change in the API leading to a 8.41% change in mortality. To understand how the air pollution effects change over the years, we split the sample by different sub-periods and find that the effect has been diminishing over time. Further analyses reveal that the diminishing effect is likely to be driven medical improvement initiatives and the advancement of community-based healthcare services after the SARS (Severe

[1] The GDP per capita of the HK is 46,000 USD as of 2017.
Source: https://www.ceicdata.com/en/indicator/hong-kong/gdp-per-capita.

Acute Respiratory Syndrome) epidemic, not by changes in avoidance behaviors or public awareness of air pollution.

This study makes two primary contributions to the existing literature. First, this study is among the first efforts to estimate the causal health effects of air pollution in a high-income and high-pollution context. Existing literature mostly focuses on developed countries with a low level of pollution, such as the U.S. and the E.U., or developing countries with a high level of pollution, such as China and India. The high-income and high-pollution setting is important because the air pollution effect can be non-linear and the pollution-mortality relationship may be altered by better institutional, and socio-economic background (Arceo et al., 2016; Burnett et al., 2014). Within the small set of studies that focus on HK, most of them are associational studies that may suffer from endogeneity concerns (e.g., Ko et al., 2007; Qiu et al., 2012; Wong et al., 2001; Wong et al., 2002). The only exception is Colmer et al. (2019), a concurrent study that also emphasizes the importance of investigating Hong Kong. We differ from Colmer et al. (2019) in that we focus on different health outcomes, adopt a new identification strategy, and explore a rich set of heterogeneities that are unique in the HK's context.

The second contribution is that we document the remarkable decline in the air pollution-mortality relationship and explore the role of medical institutions in mitigating the health effects of air pollution. Our analyses suggest that the significant improvements in healthcare systems after the SARS epidemic may help explain why the effect of air pollution on mortality becomes attenuated in recent years. We also find that the air pollution effect is larger for districts that do not have immediate access to emergency services, suggesting the availability of quality healthcare plays a critical role. Several alternative explanations, including non-linear dose-response between pollution and mortality, smoking, and avoidance behavior, can be ruled out after further analyzing relevant data. These findings show that a well-established medical system and good institution can help mitigate the contemporaneous health effect of air pollution. This also partly explains why HK people can live the longest around the world despite breathing relatively dirty air.

The rest of this paper is constructed as follows. Section II discusses air pollution in HK, existing evidence, and our empirical strategy. Section III describes our data and presents some stylized facts about HK and the PRDEZ's air quality. Section IV reports the main findings and Section V discusses the diminishing air pollution effect. Section VI concludes.

II. Existing Evidence and Empirical Setup

Air Pollution in Hong Kong

Hong Kong (HK), officially the Hong Kong Special Administrative Region of the People's Republic of China, is an autonomous territory on the eastern side of the Pearl River Delta Economic Zone (PRDEZ) in South China (Figure 1). The PRDEZ is China's major manufacturing center, consisting of several highly industrialized cities, including Guangzhou, Dongguan, Foshan, Jiangmen, Shenzhen, Zhuhai, Zhongshan, and parts of Huizhou and Zhaoqing.

Air quality is a major concern in HK and transboundary pollution is an important source of HK's air pollution. In the science literature, studies have examined how air pollutants from the PRDEZ affect HK's air quality. For example, because of the heavy manufacturing and economic activities in the PRDEZ, particulate matter from the PRDEZ can account for approximately 50% to 60% of the pollution level in HK on average and this number can be as high as 70% during certain periods (e.g., Wu et al., 2013; Yuan et al., 2006).

Several factors influence the severity of transboundary pollution in HK, including the baseline air pollution levels in the PRDEZ, wind patterns, and distances between the PRDEZ and different districts of HK. Depending on the wind's direction, HK's air pollution can be escalated or alleviated: when HK is downwind of the PRDEZ, wind will carry the PRDEZ's pollutants to HK

and the air quality in HK will be negatively affected. In contrast, when HK is upwind of the PRDEZ, HK's air quality will be improved as regional air pollutants are repelled by the wind.

The PRDEZ's air pollution affects different districts in HK differentially and the effect depends on whether a district is close to or far away from the PRDEZ. In general, western HK, which is closer to the PRDEZ, is more strongly affected by transboundary air pollution. On some extreme occasions, the air pollution level along the western edge of HK could be several times higher than the rest of HK, although there is much less economic and production activity taking place in these areas (Lau et al., 2007).

Because of the "one-country two-systems," although mainland China's air pollution can significantly affect HK's air quality, HK has no direct administrative power to regulate the polluting activities in mainland China.[2] Although in recent years, there are multiple rounds of discussions between HK and the Guangdong governments on air pollution control coordination, the agreements between the two parties often focus on the long-term targets and lack concrete enforcement plans. As a result, transboundary pollution remains a controversial issue between mainland and HK.

Figure 1 presents the annual average of $PM_{2.5}$ concentrations derived from satellite data for the region.[3] We observe that air quality in the PRDEZ is significantly worse than in HK. This is reasonable because the PRDEZ has massive manufacturing, while HK has almost no industrial pollution.[4] Besides, the northwestern part of HK has higher levels of air pollution than the southeastern part, because it is closer to the PRDEZ. These variations provide the basis for the instrumental variable approach used in this study.

[2] "One Country, Two Systems" is a constitutional principle formulated by Deng Xiaoping to accomplish the peaceful reunification of China by resolving the sovereignty questions of Hong Kong, Macao and perhaps Taiwan arising from a complicated historical background. Under the principle, the mainland China adopts the socialism with Chinese characteristics system, while Hong Kong and Macao have their own governmental systems, legal, economic and financial affairs.

[3] The $PM_{2.5}$ concentrations are derived from Aerosol Optical Depth (AOD) satellite data using the GEOS-Chem chemical transport model (van Donkelaar et al., 2014). The AOD data are extracted from the National Aeronautics and Space Administration (NASA) of the United States. For illustrative purposes, we use data from 2006 in Figure 1.

[4] According to the HK government, local emission sources mainly include motor vehicles, marine vessels, and power plants. Details can be found at https://www.gov.hk/en/residents/environment/air/airquality.htm

The Air Pollution Effect and Existing Evidence in HK

Understanding the impact of air pollution on health is an important research topic in science, public health, and economics. Thus, the literature consists of a large number of studies using different empirical methodologies, reflecting the norms and evolution of different fields. This section is not intended to provide a comprehensive review of the literature; instead, it aims at providing a basic framework summarizing previous findings in HK.

Existing evidence often adopts one of the following four methodologies to estimate the effect of air pollution on health: 1) time-series studies, 2) cross-sectional and cohort-based studies, 3) panel or fixed effects studies, and 4) quasi-experimental studies.

Time-series studies analyze the relationship between the temporal fluctuations in air pollution and health outcomes and try to estimate the contemporaneous effect of air pollution on health. The identification typically relies on the assumption that, after controlling for a set of observed weather confounders and different trends, day-to-day variation in air pollution can be treated as exogenous. A large number of public health studies rely on time-series models and they generally find that poorer air quality is associated with worse health outcomes. Early time-series studies mostly focused on the developed countries (e.g., Bell et al., 2004; Dockery et al., 1993; Levy et al., 2012; Pope III et al., 2002; Stieb et al., 2002), while in recent years, there was also an emerging literature focusing on developing countries (e.g., Aunan & Pan, 2004; Lai et al., 2013; Lu et al., 2015; Shang et al., 2013).

However, time-series studies often suffer from omitted variable bias because not all the confounders can be properly controlled. To address this issue, researchers often control for a large set of fixed effects and include flexible functions of time trends and weather conditions in the model. This introduces several potential problems. First, the estimates from time-series analyses tend to be sensitive to different controls and inclusion of trends, making it difficult to assess which estimates are the most reliable. Second, if air pollution is measured with error, overfitting the time-

series model can attenuate the estimates and understate the air pollution effect. As a result, it is difficult to determine whether the poorer health outcomes were actually caused by elevated air pollution levels or by other confounding factors (Chay & Greenstone, 2003a, b; Pope III & Burnett, 2007; He et al., 2016). For HK, we find that most previous studies rely on time-series models (Ko et al., 2007; Qiu et al., 2012; Wong et al., 2001; Wong et al., 2002), and similar critiques also apply to those studies.

Cross-sectional studies analyze the associations between air pollution levels and health outcomes across different locations at a specific point in time. Many of the cross-sectional studies were conducted in the early years and recent literature has shifted attention to other research designs. The drawbacks of cross-sectional studies are obvious: people's health and exposure to air pollution across different locations are simultaneously affected by many socio-economic factors and it is often impractical to account for all these confounders. For HK, Gao et al. (2014) show that children living in high-pollution districts are at higher risk for respiratory morbidities than those living in low-pollution districts.

Cohort-based studies analyze the long-term health effect of air pollution by following people over many years. Existing evidence shows that long-term exposure to air pollution is associated with worse health outcomes in both developed countries (Abbey et al., 1999; Dockery et al., 1993; Pope III et al., 1995) and developing countries (Cao et al., 2011; Zhang et al., 2011; Zhou et al., 2014). For HK, Qiu et al. (2017) and Qiu et al. (2018) use similar approaches and find that long-term exposure to air pollution is associated with the development of Type II diabetes and incident ischemic stroke among the elderly. Yet, aside from potential omitted variable bias mentioned above, cohort-based studies are further complicated by potential sorting (Chay & Greenstone, 2003b; Evans et al., 1984). In the end, people choose where to live and these choices may depend on pollution and other factors. For example, the wealthier population tend to migrate to areas with lower pollution, while the poorer population may remain in the polluted areas. The observed

association between air quality and mortality could be driven by factors related to sorting, instead of pollution itself.

As large-scale administrative data become more available to researchers, fixed effects models become increasingly popular. These models are powerful in addressing the endogeneity issue when potential confounders are time-invariant (Currie & Neidell, 2005; Currie, Neidell, and Schmieder, 2009). However, the identifying assumption of the fixed effects models can still be too strong because many time-varying variables, such as weather and traffic, can affect both air quality and health outcomes. In addition, estimates from fixed effects models may suffer from exaggerated attenuation bias if the regressor is measured with error (Wansbeek & Meijer, 2008).

As the economics profession becomes more demanding about identification, quasi-experimental approaches are favored in estimating the air pollution effect because they provide more compelling identification strategies. Quasi-experimental studies often explore exogenous variation in air pollution caused by policy or nature that can mimic random assignment of treatment and control groups. Zivin and Neidell (2013) provide a thorough survey on this line of research. Notable examples in this line of literature include, but are not limited to, Chay and Greenstone (2003), Currie and Neidell (2005), Jayachandran (2009), Lleras-Muney (2010), Currie and Walker (2011), Greenstone and Hanna (2014), Luechinger (2014), Anderson (2015), Cesur et al. (2015), and Schlenker and Walker (2015). For the Chinese context, Chen et al. (2013) and Ebenstein et al. (2017) exploit China's Huai River policy and estimate the impact of air pollution on life expectancy. He et al. (2016) estimate the short-term effects of air pollution on mortality using the Beijing 2008 Olympic Games as a quasi-experiment.

Despite the growing number of quasi-experimental studies, existing evidence either focuses on high-pollution/low-income (such as India and mainland China) or low-pollution and high-income settings (mostly the U.S.). Since the relationship between exposure of air pollution and health response can be non-linear and depend on local socio-economic background (Arceo et al., 2016;

Burnett et al., 2014), the results from previous studies may have limited validity for a high-pollution and high-income setting.

This study tries to fill in this gap by providing causal estimates for HK. As pollution from mainland China creates quasi-random shocks to HK's local air quality, we utilize this transboundary pollution to identify the air pollution effect. The identification strategy is similar in spirit to Anderson (2015) and Jia and Ku (2018). Anderson (2015) compares population groups living downwind and upwind of the Los Angeles highways and estimates the long-term effects of air pollution exposure on the population mortality of the elderly. Jia and Ku (2018) assess the impact of cross-border air pollution from China to South Korea and find that "yellow dust" (sand) blowing in from China leads to extra deaths in South Korea.

Empirical Strategy

Our analysis exploits the variations in HK's air quality caused by the PRDEZ's air pollution. In the first stage, we estimate the following equation:

$$(1) \qquad P_{it} = \lambda_1 S_{it} + \sum_{n=0^\circ}^{270^\circ} \varphi_n W_{int} + \lambda_2 R_t D_i + \sum_{n=0^\circ}^{270^\circ} \rho_n R_t W_{int} + \sum_{n=0^\circ}^{270^\circ} \sigma_n D_i W_{int} + \sum_{n=0^\circ}^{270^\circ} \omega_n R_t D_i W_{int} + X_{it}'\theta + \tau_i + \pi_t + \xi_{it}$$

where P_{it} is the monthly air pollution level in district i at time t, R_t is the average monthly air pollution level in the PRDEZ at time t, S_{it} is the wind speed in district i at time t, W_{int} is the percentage of days with wind direction n as the prevailing wind direction in district i at time t,[5] and D_i is the distance between the PRDEZ and district i. The interactions among R_t, S_{it}, W_{int}, and D_i are also included in the first-stage regression. X_{it} are control variables including temperature, temperature squared, and precipitation in district i at time t, τ_i are district fixed effects, π_t are year by month fixed effects, and ξ_{it} indicates the error term.

[5] Wind data are categorized into eight wind directions: 0° (north wind), 45° (northeast wind), 90° (east wind), 135° (southeast wind), 180° (south wind), 225° (southwest wind), 270° (west wind), and 315° (northwest wind). In practice, wind direction of 315° is dropped to avoid collinearity. The classification of wind directions is shown in Appendix Figure S1.

The first-stage regression helps us understand how air pollution in the PRDEZ affects HK's air quality under different meteorological conditions. φ_n captures the effect of different wind directions on HK's air quality. λ_1 captures the effect of wind speed on air pollution. For the interaction terms, λ_2 describes how the distance between different areas in HK and the PRDEZ changes the effect of regional air pollution on HK's air quality, ρ_n captures how the local wind direction changes the effect of regional air pollution on HK's air quality, σ_n estimates how the distance between HK and the PRDEZ changes the effect of the local wind direction on HK's air quality, and ω_n captures how the distance between Hong and the PRDEZ and the local wind direction simultaneously change the effect of regional air pollution on HK's air quality.

The interaction terms are included to improve the predictive power in the first stage. We interact the PRDEZ's air pollution level, R_t, with different wind directions in HK, W_{int}, because the pollution will be more severe when wind blows air pollutants from PRDEZ to HK. Additionally, because the transboundary pollution also depends on the distance between PRDEZ and HK's different districts, we further include interactions between distances, regional air pollution level, and wind directions as instruments.

In the second stage, we estimate the following equation:

$$Y_{it} = \beta \hat{P}_{it} + X'_{it}\theta + u_i + \upsilon_t + \varepsilon_{it} \quad (2)$$

where Y_{it} is the logarithm of the monthly mortality rate per 10,000 in district i at time t, and $\hat{P}_{it}$ is the predicted air pollution levels from the first stage. u_i and υ_t are district and time fixed effects. ε_{it} are unobservable disturbances. β is the coefficient of interest, which captures the causal impact of air pollution on mortality rate.

We use monthly data to avoid estimating the very short-term health effect (i.e., the effect of daily air pollution on mortality rate), because the effect can be confounded by mortality displacement or "harvesting", a phenomenon that is a temporary increase in the mortality rate (or number of

deaths) in a given population caused by sudden air pollution shocks. To address the potential cumulative effect, we also check how lagged air pollution affects current mortality rate.

For comparison, we also estimate the associations between air pollution and mortality rate using pooled Ordinary Least Squares (OLS) and fixed effects models. The pooled OLS is estimated by the following equation:

$$Y_{it} = \delta P_{it} + X'_{it}\eta + u_{it} \quad (3)$$

where all the variables are defined as above. δ captures the effect of air pollution on mortality rate if air pollution is uncorrelated with unobserved health determinants (i.e., $\mathrm{E}[\mathrm{P_{it}}, \mathrm{u_{it}}] = 0$). However, because local air quality and people's health are often simultaneously determined by many socio-economic and meteorological factors, the assumption that $\mathrm{E}[\mathrm{P_{it}}, \mathrm{u_{it}}] = 0$ can be violated results in a biased estimate of δ.

To account for time-invariant confounders, one can further include district fixed effects in Equation (3). Year-month fixed effects can also be included in the regression to account for shocks that are common to all the districts in a particular year and month. In practice, we can estimate the following equation:

$$Y_{it} = \delta P_{it} + X'_{it}\eta + u_i + \upsilon_t + \varepsilon_{it} \quad (4)$$

The fixed effects model can alleviate the endogeneity concern to some extent, as many confounding factors are controlled. However, the fixed effects model may also suffer from omitted variable bias if the unobserved confounders change across locations and over time (such as local weather and traffic conditions).

III. Data

Air Quality and Weather Data

HK's air quality data are collected from the Air Quality Monitoring Network administrated by the Environmental Protection Department of the HK Government. The PRDEZ's air quality data are reported by the local environmental bureaus and collected by the Environmental Central Facility of the Hong Kong University of Science and Technology.

Figure 1 shows the geographical locations of the air quality monitoring stations in HK and the PRDEZ. There are ten fixed monitoring stations measuring the concentration levels of air pollution in the urban districts of HK.[6]

We use the Air Pollution Index (API) as the primary explanatory outcome. The API is a comprehensive air pollution measure and is used by both the HK and mainland governments. The calculation of API is based on the concentrations of several air pollutants, including ambient respiratory particulate matter (PM_{10}), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and nitrogen dioxide (NO_2). To construct the API, an API sub-index for each pollutant is first calculated and the highest API sub-index calculated will become the API. The API is set with reference to the HK Air Quality Objectives (AQO). Appendix Table S1 shows the sub-index levels for the API and their corresponding concentrations. To make the API values comparable across years and locations, the same calculation method is used to convert concentration levels of each air pollutant to API for both HK and the PRDEZ for the whole study period.[7] To construct the instrumental variable, we average the air pollution readings from all the stations in PRDEZ and calculate the regional API.

[6] There are six other air pollution monitoring stations in Hong Kong. One of them is located far away from the city and measures the background air quality, two were built after the study period, and the rest measure roadside air pollution.

[7] More details about API can be found in He et al. (2016).

Weather data, including wind direction, wind speed, temperature, and precipitation, are extracted from the HK Observatory (HKO). Each air quality monitoring station in HK is matched with the weather station nearest to it.

Mortality Data

Mortality data are obtained from the Census and Statistics Department (C&SD) of the HK Government. We use the "known death microdata" for the period 2000-2015 in this study. The dataset recorded detailed attributes for each death, including the date of death, age, sex, cause of death, occupation, place of residence, and length of stay in HK.

The classification of cause of death is based on the Ninth and Tenth Revisions of the International Statistical Classification of Diseases and Related Health Problems (ICD-9 and ICD-10). Following previous literature, the mortality data were classified using ICD-9 and ICD-10 into deaths from cardiovascular and respiratory diseases (CVR) and deaths from non-cardiovascular and respiratory diseases (non-CVR).

The place of residence is categorized by 3-digit tertiary planning units (TPUs) code. The whole territory of HK is divided into 289 TPUs by the Planning Department of the HK Government for town planning purposes. These TPUs are then grouped into 151 Large Tertiary Planning Unit Groups (LTPUGs) by the C&SD, where each LTPUG would have a population of at least 10,000 by 2001. The areas of LTPUG ranges from 0.09 to 85.12 km^2 with a mean of 7.35 km^2. We thus focus on death and air pollution at the LTPUG level, which is referred to as a "district" in this paper.

Mortality data are then matched with air pollution data and LTPUG-level population data. The population data is extracted from HK's Population By-census in 2006, 2011, and 2016. We conduct a linear interpolation approach to fill the population data in other years. Each LTPUG is assigned to the nearest air quality monitoring station. A map of the LTPUGs is provided in Appendix Figure S2.

Data for the year of the SARS outbreak, 2003, are dropped in the analysis because it can confound the air pollution effect estimates. Nearly three hundred people died from SARS, but these deaths were not related to air pollution. In addition, during the SARS epidemic, economic activities and daily life of people in HK were significantly changed (Hung, 2003; Siu & Wong, 2004). For example, most people used face masks and avoided going out during the outbreak, which could affect pollution exposure and reduce their chances of contracting other types of respiratory diseases.

Summary Statistics

We first present some stylized facts from our data and summarize the descriptive statistics in this section. First, as shown in Figure 2, there exists a strong correlation between HK and the PRDEZ's air quality. The trend of air pollution in HK has closely followed the trend in the PRDEZ. The air quality deteriorated from 2000 to 2004, and then started to improve in both the PRDEZ and HK.

Table 1 provides summary statistics of the key variables. The mean API in HK is about 45 during our sample period, 13 units lower than that in the PRDEZ. The distance between the LTPUGs and the PRDEZ's air quality stations ranges from 103.1 to 131.9 km. About 40% of the time, the wind blows from the PRDEZ to HK (the north and northwest wind). The average monthly standardized mortality rates for CVR and non-CVR diseases are 2.20 and 2.60 per 10,000, respectively.

IV. Main Results

The Effects of Air Pollution on Mortality

Table 2 summarizes the IV estimates on the impacts of air pollution on different mortality rates. Existing evidence suggests that exposure to short-term and long-term ambient air pollution primarily affects CVR diseases (Pope III et al., 1995; Chen et al., 2013; He et al. 2016; Ebenstein et al. 2017). We follow the literature and estimate the effect of air pollution separately for CVR (Columns 1-3) and non-CVR causes (Columns 4-6). The dependent variable is the logarithm of the monthly standardized mortality rate per 10,000; the interpretation of the estimated coefficient is therefore percentage change in monthly mortality rate. In all the regressions, district (LTPUG) fixed effects and year-month fixed effects are included. We gradually include precipitation and temperature (and the square of temperature), which are typical confounders in the regressions, to check the robustness of the estimates. We also report the standard errors clustered at different levels to examine the sensitivity of the significance: the LTPUG level, the LTPUG and year level, and the LTPUG and year-quarter level (Cameron, Gelbach, and Miller, 2011).

Results in Columns 1 to 3 show that air pollution has a statistically significant impact on CVR deaths. A 10-unit increase in API will result in a 1.77% to 1.82% increase in monthly CVR mortality in HK. In contrast, the estimates for non-CVR deaths in Columns 4 to 6 are smaller in magnitude and statistically insignificant at the 5% level. In Column 7, we compare the difference between the estimates in Columns 3 and 6 and find that the difference is statistically significant at 10% level.

The first-stage regression results, which have a long list of variables, are reported in Appendix Table S2. We see that many instruments are statistically significant, suggesting that the PRDEZ's air pollution, wind direction, and distances between the PRDEZ and different HK districts can strongly predict HK's air pollution.

Results by Gender and Age Group

Air pollution may affect males and females in different ways. Existing evidence on gender difference in air pollution epidemiology is far from conclusive and the mechanisms are not yet clear (Clougherty, 2010). This is because males and females are different in fundamental ways that can affect the pollution-mortality relationship, including time use, smoking, inner dermal absorption and lung function, and the availability of target organs (McCracken et al., 2007; Becklake and Kauffmann, 1999). We explore the gender heterogeneity in HK and report the results separately for males and females in Table 3. We find that the impacts of air pollution on males are generally larger and more statistically significant than females. A 10-point change in the API increases male mortality rate by 2.22%, which is two times larger than its impact on females. In the literature, several other studies also find stronger air pollution effects on males (e.g.,-Pope III et al., 1995; Galizia and Kinney, 1999; Tanaka, 2015; Ebenstein et al., 2015; Cohen et al., 2017).

Next, we examine the air pollution effects by age group. Because the exact number of people in each age group is not available at the district level, we directly estimate the impacts of air pollution on the number of deaths with respect to different age groups. Figure 3 summarizes the results. In line with the previous studies, we find that the air pollution effect is statistically significant for the elderly group (age>60) (Chen et al., 2013). Specifically, for people who are older than 60, a 10-point increase in API leads to an 8.41% increase in the total number of CVR deaths. The corresponding regression results are reported in Table 4.

Infants, children, and young adults do not die from air pollution in HK. Note that our finding that air pollution does not lead to more deaths in the infant and young children group differs from most previous studies (e.g., Chay and Greenstone, 2003a; Currie and Neidell, 2005; Currie, Neidell, and Schmieder, 2009; Currie and Walker, 2011; Greenstone and Hanna, 2014), but is consistent with Colmer et al. (2019). Colmer et al. (2019) focuses on infant health in HK and find that

although bad air decreases the birth weights, it does not cause more infants deaths. Their argument is similar to ours: better institutions effectively prevent infants from dying from air pollution.

Lagged Effect

Many time-series studies show that the effects of air pollution on health can be cumulative; the lagged effect can range from a few days to a few weeks. In Table 5, we examine this issue by including the lagged pollution measure in the regressions. Current and lagged IVs are used in the first stage to predict current and lagged API and we include two lags in the regressions.

Column 1 shows that the effect of air pollution on CVR deaths is only statistically significant for current API. One- and two-month lagged API are both statistically insignificant with a smaller magnitude. Column 2 shows that there is no statistically significant relationship between air pollution and non-CVR deaths. These results suggest that there is no significant lag effect at the monthly level.

Comparison with Associational Estimates

Table 6 reports the OLS and fixed effects estimates of the air pollution effect on mortality. In Column 1, we do not include any control or fixed effects; we estimate a pooled OLS regression model. In Column 2, we add temperature and its square term as controls. In Column 3, precipitation is also included as a control variable. Columns 4 to 6 include different combinations of district and year-month fixed effects and explore the sensitivity of estimates with respect to weather controls. The results for all deaths, CVR mortality, and non-CVR mortality are summarized in Panels A to C, respectively.

We draw two conclusions from these results. First, the estimated effects vary greatly across different specifications. For example, if nothing is controlled, a 10-unit increase in API is associated with a 0.92% change in the CVR mortality rate and the estimate is statistically significant at the 1% level. Adding controls and fixed effects significantly changes the point estimates and the

significance. These findings suggest that associational estimates can suffer from severe omitted variable bias. Second, in the most restrictive model (i.e., Column 6), a 10-unit increase in API is associated with a 0.67% change in CVR mortality rate. This estimate is substantially smaller than the IV estimate (1.77%) in Table 2, suggesting the potential attenuation bias in the fixed effects models. The findings are consistent with several quasi-experimental studies (e.g., Schlenker and Walker, 2015; He et al. 2016), which also find that estimates of the air pollution effects obtained using a quasi-experimental design were much larger than estimates obtained from associational approaches.

Robustness Checks

We check the robustness of our main findings in several different ways and report the results in the appendix. First, some LTPUGs are located relatively far away from air quality monitoring stations and the air pollution levels measured in these districts may be measured with error. To address this concern, we exclude LTPUGs that are far away from their nearest stations and check the sensitivity of the results. Appendix Table S3 reports the results. We use samples within 12km, 10km, and 8km radius from monitoring stations and repeat the IV estimations for each subsample. We find that all the estimates are quantitatively similar.

Second, our empirical strategy relies on the fact that HK's local air pollution can be exogenously varied by air pollution in PRDEZ conditionally on different meteorological conditions. We check the robustness of the results in the Appendix Table S3 by only using the meteorological conditions (i.e., local wind patterns) as the instruments. Excluding the API in PRDEZ from the IV regressions can help address the potential concern that air pollution in PRDEZ may be affected by policies in HK. As shown in the Appendix Table S3, doing so generates similar results to our baseline estimates.

Third, we check whether the results still hold using alternative air pollution measures. In our data, PM_{10} is the primary pollutant in constructing the API 40.8% of the time during our sample

period.[8] Presumably, the health impact is driven mostly by the primary pollutant, so we can estimate the same set of regressions using PM_{10} as the air pollution measure. The results are reported in Appendix Table S5. The PRDEZ's PM_{10} concentration are used as instruments in the first stage. We find that a 10 $\mu g/m^3$ increase in PM_{10} concentration leads to a 0.94% to 0.99% increase in CVR mortality rate and this effect is statistically significant at the 1% level. The relationship between PM_{10} and the non-CVR mortality rate, however, is statistically insignificant in all regressions. These findings are again consistent with our baseline results.

Using a similar approach, we can further examine the health impacts of other pollutants. The results are summarized in Appendix Table S6. Here, we estimate the pollutant-mortality relationship separately for SO_2, O_3, and NO_2, using the PRDEZ's respective pollutant concentrations as instruments. Among them, SO_2 is statistically significant at the 1% level, and O_3 and NO_2 are statistically insignificant. These results suggest that the air pollution effect in HK is likely to be driven by PM_{10} and SO_2.

Finally, some of the previous studies use non-accidental deaths as the outcome measure. For comparison purpose, we report the results for the non-accidental mortality rate in Appendix Table S7. The results show that a 10-unit change in API is associated with a 1.44% to 1.54% change in the monthly non-accidental mortality rate, and that a 10 $\mu g/m^3$ increase in PM_{10} concentration can lead to a 0.67% to 0.73% increase in the outcome. A 1 ppb increase in SO_2 concentration can cause 0.06% in the monthly non-accidental mortality rate. Again, all these results are statistically significant at the 1% level and robust to the inclusion of different weather controls.

[8] PM_{10} contributes most of the primary pollution in API construction during our sample period. The contributions of other pollutants are: $PM_{2.5}$ (22.6%), CO (0.4%), NO_2 (36.0%), O_3 (0.1%), and SO_2 (0.0%).

V. Diminishing Air Pollution Effect

Air Pollution Effects over Time

We examine the air pollution effect over time by splitting our sample into different periods: 2000 to 2002, 2004 to 2008, and 2009 to 2015.[9] The results are reported in Table 7. In Column 1, we see that the effect is the largest using 2000-2002 data: a 10-unit increase in API will lead to a 3.13% increase in the CVR mortality rate and the effect is statistically significant at the 5% level. In Columns 2 to 4, we find that the air pollution effect becomes smaller and statistically insignificant in recent periods. In other words, the air pollution effect on mortality in HK is diminishing over the years.

We choose Year 2003 as the point to split the sample because many factors that affect population health in HK, especially the healthcare infrastructure, were drastically changed during the 2003 SARS epidemic. The SARS epidemic started in the Guangdong province of China and spread to HK in February 2003. It differed from previous epidemic infectious diseases in its explosive spread, which caught the health and hospital authorities by surprise. Before it was contained in late June 2003, there were over 1,700 cases of SARS infections in HK, resulting in 299 deaths.[10]

The SARS epidemic in HK caused broad social, economic, and humanitarian repercussions (Hung, 2003; Siu & Wong, 2004). Particularly, it unveiled some basic failings of HK's healthcare system, including overcrowded wards, poor ventilation in some hospitals, lack of isolation facilities, inadequate intensive care facilities, and difficulty in isolating and cohorting patients with suspected or possible SARS (Hung, 2003). Following SARS, numerous healthcare improvements were carried out. For example, after reviewing the medical practices at the time, the Hospital Authority (HA) of HK built additional isolation beds, revamped the Intensive Care Units (ICU), rationalized existing beds, adopted a series of infection control practices, and launched massive staff training

[9] Year 2003 data are dropped from this analysis because several hundred people died from SARS, but these deaths are unrelated to air pollution.

[10] Source: World Health Organization: http://www.who.int/csr/sars/country/2003_07_04/en/

programs. The HA also worked closely with the HK Government to construct longer-term isolation facilities and set over 200 improvement targets at the beginning of 2004. In addition, the Centre for Health Protection was established to deal with public health issues and to help prevent communicable and non-communicable diseases. Since pneumonia is one of the leading causes of death in HK, various improvement measures were also adopted to reduce the transmission of respiratory diseases.

In addition, the HA enhanced community-based services and paid particular attention to the vulnerable groups, including the elderly. Several community-based teams, including Community Nursing Service, Community Geriatric Assessment, and Community Psychiatric Teams, were established. The provision of community-based healthcare among the elderly population has increased rapidly since 2003 (see Appendix Figure S3). After 2003, HA also launched a Visiting Medical Officer Scheme, which provided outreach, medical consultation, and after-care services to residential care homes for the elderly, introduced Family Medicine practice in clinics, and enlarged the proportion of doctors undergoing training in community care.

These changes have significantly improved the availability of quality medical services in HK and are considered an important contributor to longevity in HK. While it is difficult to demonstrate empirically that the improvement in healthcare availability and quality (which are difficult to measure) causally mitigated the effect of air pollution on mortality, we believe this channel is highly likely. Below, we offer additional supporting evidence for this argument and try to rule out several alternative explanations.

Access to Emergency Services and the Air Pollution Effect

A large number of medical studies have shown that air pollution often triggers acute cardiovascular diseases, such as strokes and heart attacks (see Mustafić et al., 2012; Shah et al., 2013; Cohen et al., 2017 for recent reviews). Air pollution also damages the immune system and increases the risk of various respiratory diseases, such as acute upper respiratory tract infections.

When one's life is threatened by such acute diseases, immediate access to emergency care is critical. For example, if a patient is struck by acute ischemic stroke, the treatment modality is highly time dependent and better outcomes can only be achieved when treatment is administered soon enough. Treatment within 60 minutes of symptom onset, known as the Golden Hour, produces excellent outcomes with significantly lower rates of morbidity and mortality (Ebinger et al., 2015). As a result, we conjecture that access to immediate emergency care and the quality of healthcare service may have important implications for the air pollution effect.

Hong Kong has a stunningly efficient emergency services, in which the ambulance service is almost free and pledged to arrive at the patient's address within 12 minutes upon request. In 2014, for example, the total number of ambulance transportations was more than 20,000, with 95% of them arriving in less than 12 minutes.[11] Whether a patient can receive immediate healthcare thus largely depends on the distance between the patient's address and the nearby hospital. In light of this, we explore the heterogeneity of the air pollution effect based on whether a LTPUG has immediate access to a hospital with accident and emergency (A&E) services. In HK, 20 hospitals provide A&E services and the locations of these hospitals have not been changed during our sample period. We generate 2-km buffer zones surrounding all the hospitals with A&E services and compare the air pollution effects for LTPUGs that are located within and outside those buffer zones. We use the 2-km buffer zone because it roughly divide all the LTPUGs into two groups with equal sample sizes (Appendix Figure S4).[12]

Table 8 summarizes our findings separately for these two groups. Columns 1 and 2 report the results for districts located within the 2km radius of A&E services and Columns 3 and 4 report the results for districts located outside the radius. The estimates are statistically insignificant for both CVR and non-CVR mortality rate in Columns 1 and 2, suggesting that air pollution is less likely to kill people in districts with A&E services. In contrast, air pollution has a statistically

[11] http://news.ifeng.com/a/20140523/40427482_0.shtml

[12] In Appendix Figure S4, we observe that both groups of LTPUGs are dispersed equally in different areas of HK and are equally close to subway (the Massive Transport Railway) stations.

significant impact on CVR mortality for people living far away from hospitals with A&E services. These results suggest that easy access to emergency medical services can reduce pollution-related deaths, which are consistent with our argument that availability of high-quality medical service is important for mitigating the air pollution effect. In addition, we check the robustness by varying the buffer zones of A&E services to 1.5km and 3km and report the results in Appendix Table S8. The estimates are quantitatively similar and indicate the same pattern that closer to A&E services are associated with less mortality from air pollution.

In Appendix Table S9, we also separately examine the impacts of A&E services and air pollution over time. The results show that the impacts of air pollution on populations with easier access to A&E services remain statistically insignificant during the entire period of time. For regions with A&E services outside 2km, however, the impact has reduced from 7.00% to 1.47%, and becomes statistically insignificant at the end of the period.

Other Explanations

In this section, we discuss several alternative explanations for the diminishing air pollution effect, including a potential non-linear dose-response relationship between air pollution and health, smoking, and people's avoidance behavior in response to pollution.

First, it is unlikely that the non-linearity of the air pollution effect drives our main findings. As shown in Appendix Figure S5, the API in HK was between 40 and 50 during most of the time and there was no dramatic improvements or deteriorations in air quality in Hong Kong during the sample period. Particularly, the API between 2000 and 2002, during which we find the largest air pollution effect, was not very different from the later periods (e.g. 2004 to 2007). This finding suggests that the diminishing air pollution effect cannot be driven by changes in air pollution levels.

Second, existing literature also suggests that smokers can be more sensitive to air pollution, in that they have higher relative risk of all-cause mortality, cardiopulmonary mortality, and lung cancer (Hoek et al., 2002; Pope III et al., 2011; Hamra et al., 2014). This argument is often used to

explain the finding that males are more likely to die from air pollution than females. If this argument were true and if there were fewer and fewer smokers over the years, the air pollution effect could decrease. To examine this hypothesis, we collect data from the HK Government and compare the smoking population over time. We find that, somewhat to our surprise, the percentage of smokers and daily smokers has remained unchanged during the entire period (see data in Appendix Table S8 and Appendix Figure S10). In other words, it is also unlikely that smoking is contributing to the diminishing air pollution effect.

The last hypothesis is that people's awareness of air pollution might have increased over the years, so more people adopt avoidance behaviors against air pollution. In the literature, studies find that people take actions to avoid exposure to air pollution (e.g., Neidell, 2004; Neidell, 2009). To test this hypothesis, we collect data from Google Trends and examine how air pollution is correlated with online searches for keywords related to "air pollution."

The results are reported in Table 9. In Panel A, we see that API is not statistically significantly associated with the search volumes for "$PM_{2.5}$", "PM_{10}", or "API", but is positively associated with search volume for "air pollution." These results suggest people's knowledge about air pollution is relatively limited and do not dig into the technical terms describing specific air pollutant. In Panels B and C, we show that the associations between API and people's searches for "air pollution" are stable in all the years during which the Google Trends data are available, suggesting that people's responses to air pollution do not change much over time.

In Table 10, we further examine the relationship between API and searches for air pollution-related avoidance measures. The regression results show that, while people are to some extent aware of air pollution, this awareness does not lead to meaningful avoidance behaviors. In particular, there is no correlation between API and searches for masks and air purifiers, the two most commonly used defensive measures against air pollution. We also use HK's search volume for "watching films" as a way to measure indoor activities and again see no correlation. Therefore, we conclude that people in HK adopt minimal avoidance behaviors against air pollution, so the

diminishing air pollution effect cannot be driven by awareness or avoidance of air pollution.[13] These patterns are different from what we observe in mainland Chinese cities, in which people search for and buy more masks and air filters when air quality is bad (Ito & Zhang, 2016; Zhang & Mu, 2017; Liu et al., 2018).

VI. Conclusion

In many metropolitan cities in the developing world, income levels are rising quickly, while air pollution levels remain high. HK offers an imminent scenario for these cities as it has a high level of income, yet faces severe air pollution. In this study, we estimate the causal effect of air pollution on mortality using 16 years of data from in HK. To address the endogeneity problem, we use an instrumental variable approach based on the transboundary air pollution from mainland China. Our analyses show that a 10-unit increase in the API will cause a 1.77% increase in the monthly cardio-respiratory mortality rate and the elderly are particular vulnerable to air pollution.

The key finding in this study is that the effect of air pollution on mortality has dramatically declined and becomes statistically significant after the SARS epidemic in 2003. We argue that medical improvement initiatives and development of community-based services implemented after SARS are likely to drive the diminishing air pollution effect. Empirically, we show people with immediate access to emergency healthcare are less susceptible to air pollution in comparison to those without, and the diminishing impacts are not driven by several alternative explanations. As pre-mature deaths are considered as the largest social cost of air pollution (other costs include morbidity, reduced productivity, etc.), our findings show that better socio-economic conditions and a well-functioning medical system can help reduce the damage of air pollution, at least in the

[13] These findings are consistent with some earlier studies. For example, DeGolyer (2008) conducted two surveys in 2000 and 2008 to understand HK residents' awareness of air pollution. In the survey, people were explicitly asked whether they were concerned with air pollution; the share of people worrying about air pollution remained very similar in both surveys.

short run. Governments and policymakers should thus consider the role of healthcare when formulating air pollution policies.

There are three caveats in this study. First, while a diminishing effect of air pollution on mortality is observed, it does not mean that air pollution becomes less important in HK. To what extent air pollution affects morbidity and the long-term effect remains underexplored. Second, while the heterogeneity results between districts with and without immediate A&E services suggest quality medical service can be important, this finding does not have a causal interpretation. To what extent the A&E services causally affect the air pollution-mortality relationship requires exogenous changes in the A&E service availability, which is missing in this study. Finally, the API is a comprehensive air quality measure and is determined by the pollutant with the highest concentration level in the standard. Our analyses do not distinguish between which pollutants are more health-damaging and tell little about how the interactions of different air pollutants can affect human health. Further studies are needed to investigate these issues.

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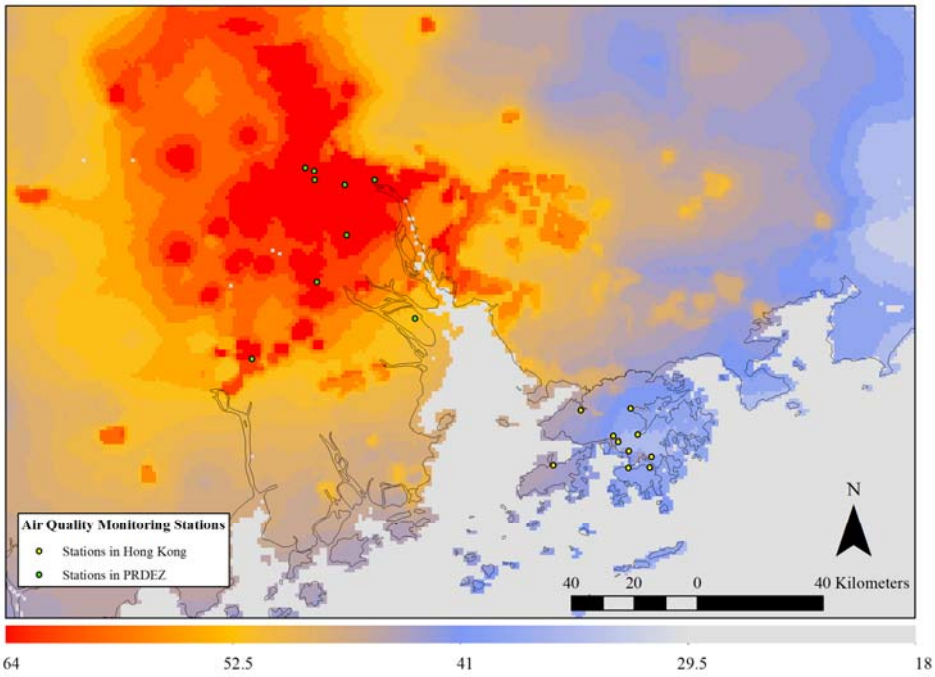
FIGURE 1. THE ANNUAL AVERAGE OF $PM_{2.5}$ CONCENTRATIONS (MG/M^3) FOR THE PEARL RIVER DELTA REGION



Source: $PM_{2.5}$ concentrations in 2006 are derived from Aerosol Optical Depth (AOD) satellite data. AOD data are extracted from the National Aeronautics and Space Administration (NASA) of the United States.

FIGURE 2. COMPARISON OF ANNUAL AVERAGE AIR POLLUTION INDEX IN THE PRDEZ AND HK

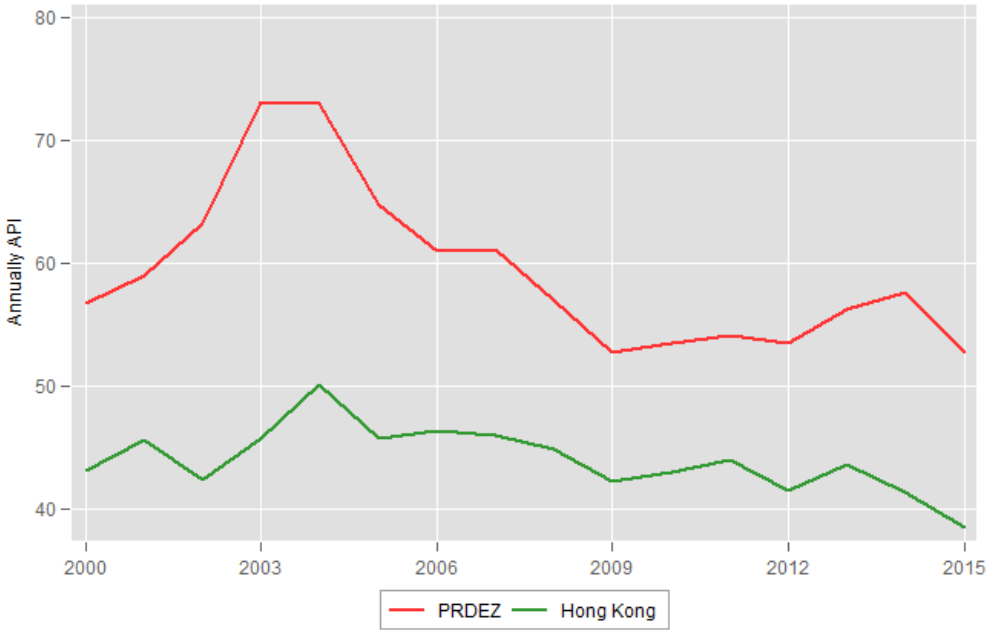
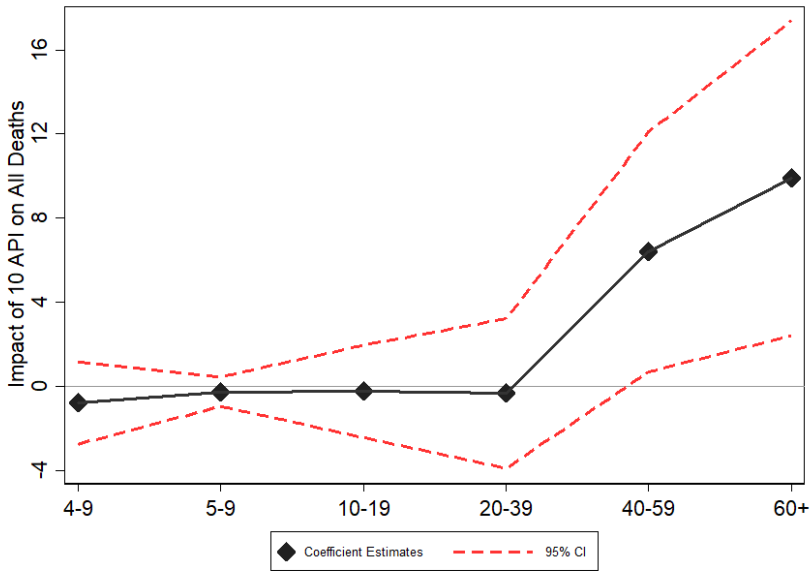
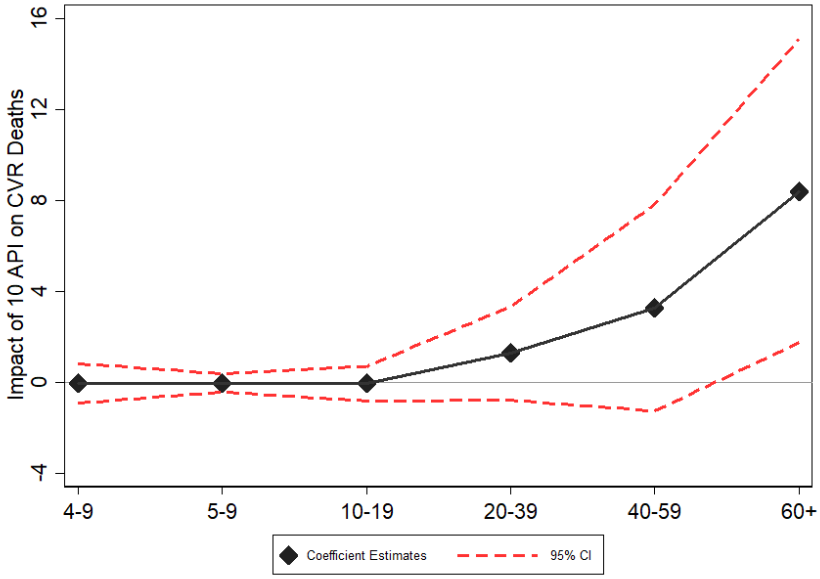


FIGURE 3. THE EFFECT OF API (PER 10 UNITS) ON DEATHS BY DIFFERENT AGE GROUPS



(A) ALL DEATHS



(B) CVR DEATHS

Table 1. Summary Statistics of the Main Variables

	Mean	SD	Min	Max	Obs
Monthly Average API in Hong Kong	44.55	10.83	15.52	76.24	24,029
Monthly Average API in the PRDEZ	58.53	11.09	32.83	94.15	23,625
Distance with the PRDEZ (10km)	12.18	0.88	10.31	13.19	24,300
Standardized Monthly CVR Mortality Rate (per 10,000)	2.20	1.59	0.00	14.36	24,132
Standardized Monthly Non-CVR Mortality Rate (per 10,000)	2.60	1.59	0.00	14.35	24,132
Days with wind direction 0°	26.11%	0.22	0.00%	100.00%	24,201
Days with wind direction 45°	0.05%	0.00	0.00%	3.33%	24,201
Days with wind direction 90°	39.21%	0.23	0.00%	96.77%	24,201
Days with wind direction 135°	13.75%	0.18	0.00%	100.00%	24,201
Days with wind direction 180°	6.60%	0.12	0.00%	80.00%	24,201
Days with wind direction 225°	5.17%	0.10	0.00%	100.00%	24,201
Days with wind direction 270°	7.19%	0.12	0.00%	70.97%	24,201
Days with wind direction 315°	1.93%	0.05	0.00%	67.74%	24,201
Wind Speed (m/s)	3.52	1.84	1.16	46.56	24,201
Precipitation (100mm)	5.95	6.92	0.00	49.28	24,250
Temperature (°C)	22.03	5.07	6.99	29.82	24,300

Notes: All variables are measured at the monthly level. CVR stands for cardiovascular and respiratory diseases. The classification and definition of wind directions are illustrated in Appendix Figure S1.

Table 2. The Effect of Air Pollution on CVR and Non-CVR Mortality Rate

	CVR Mortality			Non-CVR Mortality			*Diff.*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	%	%	%	%	%	%	%
Hong Kong's API	1.82***	1.83***	1.77***	0.97*	0.97*	0.86	0.90*
(per 10 units)	(0.57)	(0.58)	(0.59)	(0.53)	(0.54)	(0.54)	(0.54)
	(0.69)	(0.69)	(0.69)	(0.56)	(0.57)	(0.57)	(0.48)
	(0.63)	(0.63)	(0.64)	(0.56)	(0.58)	(0.58)	(0.48)
Temp and Sq.	N	Y	Y	N	Y	Y	Y
Precipitation	N	N	Y	N	N	Y	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y	Y	Y
Observations	23,094	23,094	23,044	23,094	23,094	23,044	23,044
Number of LTPUG	135	135	135	135	135	135	135
First stage F-statistics	277.2	171.0	183.2	196.0	194.3	229.0	
RMSE	0.66	0.66	0.66	0.60	0.60	0.60	
First stage Shea Partial R^2	0.22	0.22	0.21	0.23	0.22	0.23	
R^2	0.08	0.08	0.08	0.03	0.03	0.03	

Notes: This table reports the two-stage least squares regression results. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths and non-CVR deaths. Column (7) presents the akin-to Wald estimator to compare the difference between the coefficients estimated from Column (3) and (6). We probe the robustness of estimates accuracy by clustering the standard errors at three different levels: the Large Tertiary Planning Unit Group (LTPUG) level, LTPUG and year, and LTPUG and year-quarter level (multi-way clustering suggested by Cameron Gelbach, and Miller (2011)). The standard errors are respectively reported in the parentheses below the estimated coefficients. Our preferred specification clusters standard errors at the LTPUG level. *** p<0.01, **p<0.05, *p<0.1

Table 3. The Effect of Air Pollution on CVR Mortality Rate by Gender

	Male			Female		
	(1)	(2)	(3)	(4)	(5)	(6)
	%	%	%	%	%	%
Hong Kong's API	2.36***	2.40***	2.22***	1.07*	1.07*	1.09*
(per 10 units)	(0.83)	(0.84)	(0.85)	(0.57)	(0.60)	(0.58)
Temp and Sq.	N	Y	Y	N	Y	Y
Precipitation	N	N	Y	N	N	Y
Year-month FE	Y	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y	Y
Observations	23,094	23,094	23,044	23,094	23,094	23,044
Number of LTPUG	135	135	135	135	135	135
First stage F-statistics	430.3	359.0	375.9	121.8	63.78	149.6
RMSE	0.61	0.61	0.61	0.79	0.79	0.79
R^2	0.07	0.07	0.07	0.05	0.05	0.05

Notes: This table reports the two-stage least squares regression results. The PRDEZ's API, local wind conditions, distances to the PRDEZ, and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are logarithm of the monthly mortality rate for cardiovascular and respiratory (CVR) deaths. Columns 1–3 and 4–6 show estimates for males and females respectively. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 4. The Effect of Air Pollution by Age Group

	CVR Mortality	Non-CVR Mortality
	(1)	(2)
	%	%
Ages 0 to 4	-0.06	-0.81
	(0.44)	(0.90)
Ages 5 to 9	-0.04	0.23
	(0.21)	(0.31)
Ages 10 to 19	-0.06	0.21
	(0.39)	(0.94)
Ages 20 to 39	1.27	-1.18
	(1.05)	(1.91)
Ages 40 to 59	3.27	4.59
	(2.32)	(2.78)
Age 60+	8.41**	4.40
	(3.55)	(3.67)

Notes: This table reports the two-stage least squares regression results. Each cell reports a separate regression of logarithm of monthly cardiovascular and respiratory (CVR) deaths and non-CVR deaths on Hong Kong's API. The PRDEZ's API, local wind conditions, distances to the PRDEZ, and their interaction terms are used as the instrumental variables for Hong Kong's API. Weather, LTPUG fixed effects, and year-month fixed effects are controlled for each regression, following the model specification of Table 6. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 5. The Effect of Air Pollution on Mortality Rate with Lags

	CVR Mortality	Non-CVR Mortality
	(1)	(2)
	%	%
(per 10 units)		
Hong Kong's API	1.20**	0.01
	(0.56)	(0.48)
Hong Kong's API, Lag = 1	0.02	0.54
	(0.52)	(0.53)
Hong Kong's API, Lag = 2	0.65	0.32
	(0.46)	(0.47)
Temp and Sq.	Y	Y
Precipitation	Y	Y
Year-month FE	Y	Y
LTPUG FE	Y	Y
Observations	22,184	22,184
Number of LTPUG	135	135
First stage F-statistics	236.4	61.25
RMSE	0.66	0.60
R^2	0.08	0.03

Notes: This table reports the two-stage least squares regression results. Current and lagged PRDEZ's API, local wind conditions distances to the PRDEZ, and their interaction terms are used as the instrumental variables for current and lagged Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths and non-CVR deaths for the period 2000 to 2015. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 6. Estimates from Associational Approaches

	Non-Fixed Effect Models			Fixed Effect Models		
	(1) %	(2) %	(3) %	(4) %	(5) %	(6) %
Panel A. All Deaths Mortality Rate						
Hong Kong's API	0.57***	0.52**	0.62**	0.37	0.35	0.33
(per 10 units)	(0.11)	(0.26)	(0.27)	(0.25)	(0.25)	(0.25)
Observations	23,863	23,863	23,813	23,863	23,863	23,813
Adjust-R^2	0.01	0.01	0.01	0.58	0.58	0.58
Panel B. CVR Mortality Rate						
Hong Kong's API	0.92***	0.66**	0.81***	0.70**	0.68**	0.67**
(per 10 units)	(0.11)	(0.27)	(0.28)	(0.27)	(0.27)	(0.27)
Observations	23,863	23,863	23,813	23,863	23,863	23,813
Adjust-R^2	0.01	0.01	0.02	0.49	0.49	0.49
Panel C. Non-CVR Mortality Rate						
Hong Kong's API	0.31***	0.38	0.51**	0.02	-0.00	-0.02
(per 10 units)	(0.10)	(0.24)	(0.25)	(0.26)	(0.25)	(0.25)
Observations	23,863	23,863	23,813	23,863	23,863	23,813
Adjust-R^2	0.00	0.00	0.01	0.46	0.46	0.46
Temp and Sq.	N	Y	Y	N	Y	Y
Precipitation	N	N	Y	N	N	Y
Year-month FE	N	N	N	Y	Y	Y
LTPUG FE	N	N	N	Y	Y	Y
Number of LTPUG	135	135	135	135	135	135

Notes: This table reports estimates from OLS and fixed effects models. The independent variable is Hong Kong's API and the dependent variables are the logarithm of monthly mortality rate for all deaths, cardiovascular and respiratory (CVR) deaths, and non-CVR deaths. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 7. Diminishing Air Pollution Effect

	CVR Mortality Rate			
	Before SARS	After SARS		
	(1)	(2)	(3)	(4)
	2000 - 2002	2004-2007	2008-2011	2012-2015
	%	%	%	%
Hong Kong's API	3.13**	1.44*	0.67	0.46
(per 10 units)	(1.30)	(0.79)	(0.60)	(0.31)
Temp and Sq.	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y
Observations	3,960	6,310	6,375	6,399
Number of LTPUG	134	135	134	134
RMSE	0.62	0.62	0.58	0.70
R^2	0.03	0.07	0.10	0.07

Notes: This table reports the two-stage least squares regression results. The PRDEZ's API, local wind conditions, distances to the PRDEZ, and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths for the 4 periods: 2000 to 2002, 2004 to 2007, 2008 to 2011, and 2012 to 2015. The year of SARS outbreak, 2003, is excluded because the daily life of citizens, and hence exposure to air pollution, could be affected tremendously. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 8. Availability of Accident and Emergency (A&E) Services in Hospitals and the Air Pollution Effect

	A&E Hospitals within 2km		No A&E Hospitals within 2km	
	(1)	(2)	(3)	(4)
	CVR	Non-CVR	CVR	Non-CVR
	%	%	%	%
Hong Kong's API	0.70	0.38	2.51***	1.34
(per 10 units)	(0.60)	(0.63)	(0.90)	(0.83)
Temp and Sq.	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y
Observations	12,057	12,057	10,987	10,987
Number of LTPUG	71	74	64	64
RMSE	0.60	0.55	0.71	0.65
R^2	0.10	0.05	0.07	0.03

Notes: This table reports the two-stage least squares regression results. The PRDEZ's API, local wind conditions, distances to the PRDEZ, and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for all cardiovascular and respiratory (CVR) deaths and non-CVR deaths. Columns 1–2 and 3–4 show estimates for the population who lives within and outside the 2km zone to hospitals with A&E services, respectively. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table 9. Air Pollution and Avoidance Behaviors

	(1)	(2)	(3)	(4)	(5)
Panel A. The Associations between API and Avoidance Measures					
	Search for "PM2.5" (Log)	*Search for "PM10" (Log)*	*Search for "API" (Log)*	*Search for "Air Pollution" (Log)*	*Search for "Air Pollution (in Chinese)" (Log)*
Hong Kong's API	0.38	6.63	2.35	25.2***	28.1***
(per 10 units)	(6.10)	(4.16)	(1.63)	(5.62)	(6.59)
Sample	2004-2015	2004-2015	2004-2015	2004-2015	2004-2015
Observations	144	144	144	144	144
R^2	0.00	0.03	0.01	0.30	0.16
Panel B. The Associations between API and Search Index for "Air Pollution" (Log)					
Hong Kong's API	29.3***	21.0***	26.7***	23.7***	25.2***
(per 10 units)	(1.16)	(3.43)	(7.66)	(5.60)	(5.62)
Sample	2004-2006	2007-2009	2010-2012	2013-2015	2004-2015
Observations	36	36	36	36	144
R^2	0.28	0.38	0.38	0.46	0.30
Panel C. The Associations between API and Search Index for "Air Pollution (in Chinese)" (Log)					
Hong Kong's API	51.3***	24.5***	24.3**	20.4***	28.1***
(per 10 units)	(12.1)	(7.28)	(10.5)	(3.88)	(6.59)
Sample	2004-2006	2007-2009	2010-2012	2013-2015	2004-2015
Observations	36	36	36	36	144
R^2	0.21	0.19	0.24	0.45	0.16

Notes: This table reports the OLS regression results. The independent variable is the average API in Hong Kong and the dependent variables are the Google Trends for different keywords. Google Trends points range from 0 to 100, with a higher score indicating more online searches. We use data from 2004 to 2015, as Google Trends data only became available since 2004. Standard errors are reported in the parentheses. *** p<0.01, **p<0.05, *p<0.1

Table 10. Air Pollution and Other Measures of Avoidance Behaviors

	Search for "Mask"	*Search for "Mask (in Chinese)"*	*Search for "Air Purifier"*	*Search for "Air Purifier (in Chinese)"*	*Search for "Film"*	*Search for "Film (in Chinese)"*
	(1)	(2)	(3)	(4)	(5)	(6)
	%	*%*	*%*	*%*	*%*	*%*
Hong Kong's API	-0.75	-3.63	1.91	0.20	1.65	-2.25
(per 10 units)	(1.82)	(9.32)	(3.70)	(10.00)	(1.14)	(2.30)
Observations	144	144	144	144	144	144
R^2	0.00	0.00	0.00	0.00	0.01	0.00

Notes: This table reports the OLS regression results. The independent variable is average API in Hong Kong and the dependent variables are the Google Trends points for different keywords. Google Trends points range from 0 to 100, with a higher score indicating more online searches. We use data from 2004 to 2015, as Google Trends data only became available since 2004. Standard errors are reported in the parentheses. *** p<0.01, **p<0.05, *p<0.1

Appendix to "Mitigating the Air Pollution Effect? The Remarkable Decline in the Pollution-Mortality Relationship in Hong Kong"

Appendix A. Sub-index Levels for the API and Their Corresponding Concentrations

The calculation of Air Pollution Index (API), a proxy measure of the ambient air quality, is based on the concentration of several air pollutants as shown in Table S1. The API is determined by the maximum concentration of different air pollutants. More details about API can be found in He et al. (2016).

Table S1. The Relationship between the API and Air Pollutant Concentrations (mg/m^3)

API	SO_2	NO_2	PM_{10}	CO	O_3	Air Quality Levels
0-50	0-0.050	0-0.080	0-0.050	0-5	0-0.120	Excellent
50-100	0.050-0.150	0.080-0.120	0.050-0.150	5-10	0.120-0.200	Good
100-200	0.150-0.800	0.120-0.280	0.150-0.350	10-60	0.200-0.400	Slightly Polluted
200-300	0.800-1.600	0.280-0.565	0.350-0.420	60-90	0.400-0.800	Moderately Polluted
300-400	1.600-2.100	0.565-0.750	0.420-0.50	90-120	0.800-1.000	Severely Polluted
400-500	2.100-2.620	0.750-0.940	0.500-0.600	120-150	1.000-1.200	Severely Polluted

Notes. This table reports the API sub-index levels for each air pollutant. The sub-index with the highest value will then be used as the API.

Table S2. First Stage Regression Results

	Hong Kong's API		
	(1)	(2)	(3)
Wind direction0°	-120.416*	-120.825	-145.232**
	(72.215)	(73.154)	(73.447)
Wind direction45°	605.942**	500.593**	502.619**
	(267.646)	(244.419)	(244.126)
Wind direction90°	-94.462	-99.082	-122.187*
	(67.363)	(68.845)	(69.489)
Wind direction135°	-78.839	-76.583	-104.567
	(69.570)	(69.930)	(69.140)
Winddirection180°	-105.420*	-106.809*	-130.863**
	(61.290)	(62.455)	(63.424)
Winddirection225°	-136.590**	-133.208*	-154.388**
	(68.872)	(71.345)	(70.688)
Winddirection270°	33.711	38.494	22.786
	(75.583)	(75.496)	(76.211)
PRDEZ's API * Winddirection0°	2.794**	3.010**	3.390**
	(1.273)	(1.307)	(1.308)
PRDEZ's API * Winddirection45°	-2.449	-0.861	-0.818
	(3.576)	(3.279)	(3.293)
PRDEZ's API * Winddirection90°	1.874	2.169*	2.497**
	(1.211)	(1.251)	(1.261)
PRDEZ's API * Winddirection135°	0.824	1.015	1.425
	(1.240)	(1.264)	(1.248)
PRDEZ's API * Winddirection180°	2.423**	2.706**	2.977**
	(1.145)	(1.176)	(1.202)
PRDEZ's API * Winddirection225°	2.355*	2.475*	2.765**
	(1.277)	(1.333)	(1.328)
PRDEZ's API * Winddirection270°	0.713	0.861	1.105
	(1.401)	(1.413)	(1.424)
PRDEZ's API * Distance to the PRDEZ	0.106	0.129	0.155
	(0.093)	(0.096)	(0.097)
Wind direction 0° * Distance to the PRDEZ	11.404**	11.501**	13.443**
	(5.728)	(5.796)	(5.814)
Wind direction 45° * Distance to the PRDEZ	-44.116*	-35.343*	-35.943*
	(22.687)	(20.757)	(20.878)
Wind direction 90° * Distance to the PRDEZ	9.793*	10.230*	12.079**
	(5.310)	(5.416)	(5.459)
Wind direction 135° * Distance to the PRDEZ	9.729*	9.574*	11.856**
	(5.542)	(5.567)	(5.500)

Wind direction 180° * Distance to the PRDEZ	10.106**	10.043**	11.960**
	(4.841)	(4.904)	(4.960)
Wind direction 225° * Distance to the PRDEZ	14.569***	14.236**	15.939***
	(5.393)	(5.563)	(5.492)
Wind direction 270° * Distance to the PRDEZ	-0.546	-0.828	0.479
	(5.958)	(5.931)	(5.983)
PRDEZ's API * Wind direction 0° * Distance to the PRDEZ	-0.249**	-0.268**	-0.298***
	(0.100)	(0.103)	(0.103)
PRDEZ's API * Wind direction 45° * Distance to the PRDEZ	0.139	0.005	0.006
	(0.301)	(0.276)	(0.279)
PRDEZ's API * Wind direction 90° * Distance to the PRDEZ	-0.181*	-0.206**	-0.232**
	(0.095)	(0.098)	(0.098)
PRDEZ's API * Wind direction 135° * Distance to the PRDEZ	-0.115	-0.131	-0.164*
	(0.098)	(0.100)	(0.098)
PRDEZ's API * Wind direction 180° * Distance to the PRDEZ	-0.221**	-0.241***	-0.262***
	(0.090)	(0.092)	(0.093)
PRDEZ's API * Wind direction 225° * Distance to the PRDEZ	-0.252**	-0.260**	-0.283***
	(0.100)	(0.104)	(0.103)
PRDEZ's API * Wind direction 270° * Distance to the PRDEZ	-0.089	-0.102	-0.122
	(0.110)	(0.110)	(0.111)
Windspeed	-0.078***	-0.084***	-0.083***
	(0.008)	(0.008)	(0.009)
Temp and Sq.	N	Y	Y
Precipitation	N	N	Y
LTPUGFE	Y	Y	Y
Year-month FE	Y	Y	Y
Observations	24,438	24,438	24,375
R^2	0.95	0.95	0.95

Notes: This table reports the first stage regression results. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1.

Table S3. The Effect of Air Pollution on CVR Mortality Rate using Different Distance Tolerances

	CVR Mortality					
	Within 12 km		Within 10 km		Within 8 km	
	(1)	(2)	(3)	(4)	(5)	(6)
	%	%	%	%	%	%
Hong Kong's API	1.95***	1.90***	1.85***	1.79***	1.73***	1.67***
(per 10 units)	(0.58)	(0.58)	(0.60)	(0.60)	(0.65)	(0.64)
Temp and Sq.	Y	Y	Y	Y	Y	Y
Precipitation	N	Y	N	Y	N	Y
Year-month FE	Y	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y	Y
Observations	22,582	22,532	22,228	22,179	21,192	21,145
Number of LTPUG	132	132	130	130	124	124
RMSE	0.66	0.66	0.65	0.65	0.65	0.65
R^2	0.08	0.08	0.08	0.08	0.08	0.08

Notes: This table reports the two-stage least squares regression results. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. Large Tertiary Planning Unit Groups (LTPUGs) that are far away from the general air quality stations are excluded and more stations are dropped across Columns 1 to 6. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths for the period 2000 to 2015. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S4. The Effect of API on CVR and Non-CVR Mortality Rate Using Local Wind Speed as IV

	First Stage			Second Stage					
	Hong Kong's API			CVR Mortality			Non-CVR Mortality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Unit	Unit	Unit	%	%	%	%	%	%
Hong Kong's API				2.30*	2.04**	2.00**	1.49	1.33	1.39*
(per 10 units)				(1.18)	(1.02)	(0.98)	(1.06)	(0.84)	(0.82)
Local Windspeed	-0.12***	-0.13***	-0.13***						
	(0.01)	(0.02)	(0.01)						
Wind direction 0°	7.72***	6.54***	6.28***						
	(0.94)	(1.12)	(1.05)						
Wind direction 45°	53.97***	57.21***	56.44***						
	(8.49)	(7.39)	(7.35)						
Wind direction 90°	8.70***	8.04***	7.84***						
	(1.09)	(1.25)	(1.21)						
Wind direction 135°	7.78***	7.33***	7.18***						
	(1.07)	(1.31)	(1.31)						
Wind direction 180°	4.80***	3.29**	2.92**						
	(1.34)	(1.29)	(1.18)						
Wind direction 225°	8.33***	7.36***	7.06***						
	(1.28)	(0.94)	(0.81)						
Wind direction 270°	9.85***	10.04***	9.60***						
	(1.53)	(1.40)	(1.23)						
Temp and Sq.	N	Y	Y	N	Y	Y	N	Y	Y
Precipitation	N	N	Y	N	N	Y	N	N	Y
Year-month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	23,930	23,930	23,880	23764	23764	23714	23764	23764	23714
Number of LTPUG	135	135	135	135	135	135	135	135	135
RMSE				0.66	0.66	0.66	0.61	0.61	0.61
First stage F-statistics				180.6	491.6	456.9	162.5	227.0	227.0
R^2	0.94	0.94	0.94	0.05	0.05	0.05	0.02	0.02	0.02

Notes: This table reports the instrumental regression results. Local wind condition are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for all cardiovascular and respiratory (CVR) deaths and non-CVR deaths. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S5. The Effect of PM10 on CVR and Non-CVR Mortality Rate

	CVR Mortality			Non-CVR Mortality		
	(1)	(2)	(3)	(4)	(5)	(6)
	%	%	%	%	%	%
Hong Kong's PM10	0.99***	0.97***	0.94***	0.34	0.32	0.29
(per 10 μg/m³)	(0.32)	(0.32)	(0.32)	(0.28)	(0.28)	(0.28)
Temp and Sq.	N	Y	Y	N	Y	Y
Precipitation	N	N	Y	N	N	Y
Year-month FE	Y	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y	Y
Observations	23,090	23,090	23,040	23,090	23,090	23,040
Number of LTPUG	135	135	135	135	135	135
RMSE	0.66	0.66	0.66	0.60	0.60	0.60
R^2	0.08	0.08	0.08	0.03	0.03	0.03

Notes: This table reports the two-stage least squares regression results. PRDEZ's PM10, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's PM10. The dependent variables are the logarithm of monthly mortality rate for all cardiovascular and respiratory (CVR) deaths and non-CVR deaths. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S6. The Effect of Different Air Pollution Measures on CVR Deaths

	CVR Mortality Rate				
	(1)	(2)	(3)	(4)	(5)
	%	%	%	%	%
Hong Kong's API	1.77***				
(per 10 units)	(0.59)				
PM_{10}		0.94***			
(per 10 $\mu g/m^3$)		(0.32)			
SO_2			0.64***		
(per ppb)			(0.02)		
O_3				0.01	
(per ppb)				(0.05)	
NO_2					0.14*
(per ppb)					(0.08)
Temp and Sq.	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y	Y
Observations	23,044	23,040	23,027	14,405	23,037
Number of LTPUG	135	135	135	135	135
RMSE	0.66	0.66	0.66	0.64	0.66
R^2	0.08	0.08	0.07	0.07	0.08

Notes: This table reports the two-stage least squares regression results. PRDEZ's API and concentration levels for 4 types of air pollutants (PM_{10}, O_3, NO_2, SO_2), local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's respective air pollution measures. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths for the period 2000 to 2015. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S7. The Effect of Air Pollutants on the Non-Accidental Mortality Rate

	Non-accidental Mortality Rate		
	(1)	(2)	(3)
	%	%	%
Panel A. API, (per 10 units)			
Hong Kong's API	1.54***	1.54***	1.44***
	(0.52)	(0.54)	(0.54)
Observations	23,094	23,094	23,044
Number of LTPUG	135	135	135
RMSE	0.51	0.51	0.51
R^2	0.07	0.07	0.07
Panel B. PM10 (per 10 $\mu g/m^3$)			
Hong Kong's PM10	0.73***	0.70***	0.67***
	(0.25)	(0.26)	(0.26)
Observations	23,090	23,090	23,040
Number of LTPUG	135	135	135
RMSE	0.51	0.51	0.51
R^2	0.07	0.07	0.07
Panel C. SO_2 (per ppb)			
Hong Kong's SO2	0.06***	0.06***	0.06***
	(0.02)	(0.02)	(0.02)
Observations	23,077	23,077	23,027
Number of LTPUG	135	135	135
RMSE	0.51	0.51	0.51
R^2	0.05	0.05	0.05
Temp and Sq.	N	Y	Y
Precipitation	N	N	Y
Year-month FE	Y	Y	Y
LTPUG FE	Y	Y	Y

Notes: This table reports the two-stage least squares regression results. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for non-accidental deaths for the period 2000 to 2015. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S8. Availability of Accident and Emergency (A&E) Services in Hospitals and the Air Pollution Effect

	A&E Hospitals within Buffering Zone		No A&E Hospitals within Buffering Zone	
	(1)	(2)	(3)	(4)
	CVR	Non-CVR	CVR	Non-CVR
	%	%	%	%
Panel A. Buffering Zone = 1.5km				
Hong Kong's API	0.82	0.65	2.10**	0.98
(per 10 units)	(0.52)	(0.56)	(0.83)	(0.76)
Observations	8,785	8,785	14,259	14,259
Number of LTPUG	51	51	84	84
RMSE	0.59	0.53	0.70	0.64
R^2	0.07	0.03	0.04	0.02
Panel B. Buffering Zone = 3km				
Hong Kong's API	0.54	0.21	2.75**	1.83*
(per 10 units)	(0.51)	(0.52)	(1.01)	(1.04)
Observations	17,694	17,694	5,350	5,350
Number of LTPUG	104	104	31	31
RMSE	0.57	0.52	0.87	0.81
R^2	0.06	0.02	0.04	0.02
Temp and Sq.	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y

Notes: This table reports the two-stage least squares regression coefficients and standard errors. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for all cardiovascular and respiratory (CVR) deaths and non-CVR deaths. Columns 1–2 and 3–4 show estimates for the population who lives within and outside the buffering zone to hospitals with A&E services respectively. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S9. Accident and Emergency (A&E) Services and Air Pollution Impacts Over Time

	CVR Mortality Rate			
	Before SARS	After SARS		
	(1)	(2)	(3)	(4)
	2000 - 2002	2004-2007	2008-2011	2012-2015
	%	%	%	%
Panel A. A&E hospitals within 2km				
Hong Kong's API	1.74	-0.56	0.47	-0.32
(per 10 units)	(1.08)	(0.63)	(0.31)	(0.49)
Observations	2,096	3,287	3,331	3,344
Number of LTPUG	70	71	70	70
RMSE	0.54	0.56	0.59	0.55
R^2	0.05	0.07	0.11	0.10
Panel B. A&E hospitals outside 2km				
Hong Kong's API	7.00**	2.53**	1.90	1.47
(per 10 units)	(1.70)	(1.13)	(3.04)	(0.90)
Observations	1,865	3,023	3,044	2,291
Number of LTPUG	64	64	64	64
RMSE	0.57	0.68	0.39	0.53
R^2	0.04	0,07	0.12	0.09
Temp and Sq.	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
LTPUG FE	Y	Y	Y	Y

Notes: This table reports the two-stage least squares regression results. PRDEZ's API, local wind conditions, distances to the PRDEZ and their interaction terms are used as the instrumental variables for Hong Kong's API. The dependent variables are the logarithm of monthly mortality rate for cardiovascular and respiratory (CVR) deaths for the 3 periods: 2000 to 2002, 2004 to 2007, 2008 to 2011, and 2012 to 2015. Panel A and B show estimates for the population who lives within and outside the 2km zone to hospitals with A&E services respectively. The year of SARS outbreak, 2003, is excluded as the daily life of citizens, and hence exposure to air pollution could be affected tremendously. Standard errors in parentheses are clustered at the Large Tertiary Planning Unit Group (LTPUG) level. *** p<0.01, **p<0.05, *p<0.1

Table S10. Smoking Pattern in Hong Kong

	2000	2003	2005	2008	2010	2012	2015
% of current smokers	14.40%	15.30%	14.80%	13.20%	12.00%	11.80%	11.40%
% of current daily smokers	12.40%	14.40%	14.10%	11.80%	11.20%	10.80%	10.60%
% of current non-daily smokers	2.00%	0.80%	0.70%	1.30%	0.90%	1.00%	0.70%
% of Ex-smokers	3.80%	3.20%	4.50%	5.60%	5.10%	6.70%	6.20%
% of Ex-daily smokers	-	2.70%	4.50%	5.10%	4.90%	5.80%	5.60%
% of Ex-non-daily smokers	-	0.40%	0.00%	0.50%	0.30%	0.90%	0.60%
% Non-smokers	81.80%	81.60%	80.60%	81.20%	82.90%	81.60%	82.50%

Notes: Data extracted from Thematic Household Survey Report No. 5, 16, 26, 36, 48, 53 and 59 by Census and Statistics Department (C&SD). % of smokers and daily smokers represents their respective percentage of the whole sampled population. % of (current, current daily, current non-daily, ex-, ex-daily. ex-non-daily) smokers refers to percentage of current, current daily, current non-daily, ex-, ex-daily. ex-non-daily) cigarette smokers aged 15 and over at the time of enumeration among all persons aged 15 and over.

Figure S1. Classification of Wind Directions

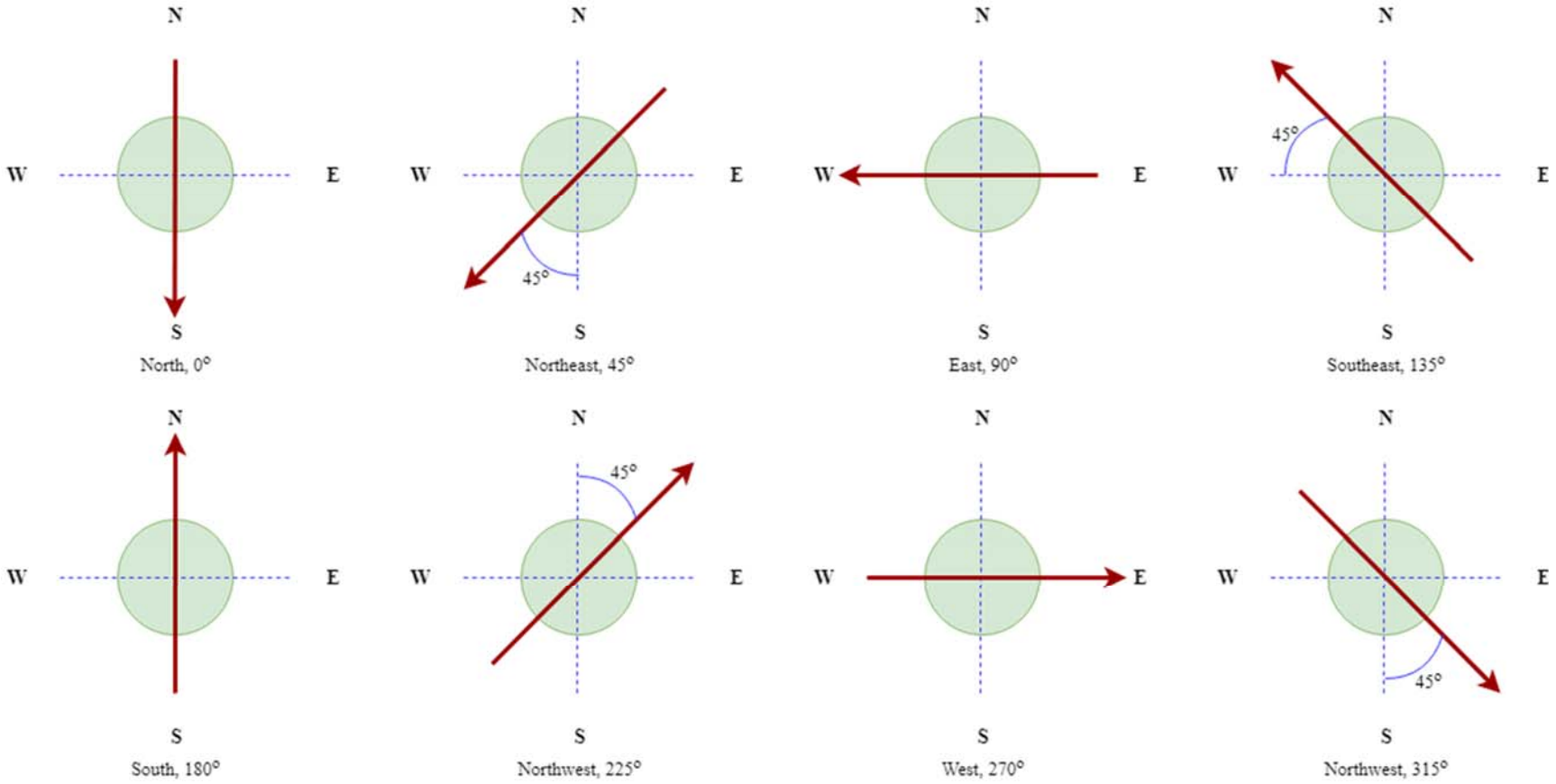
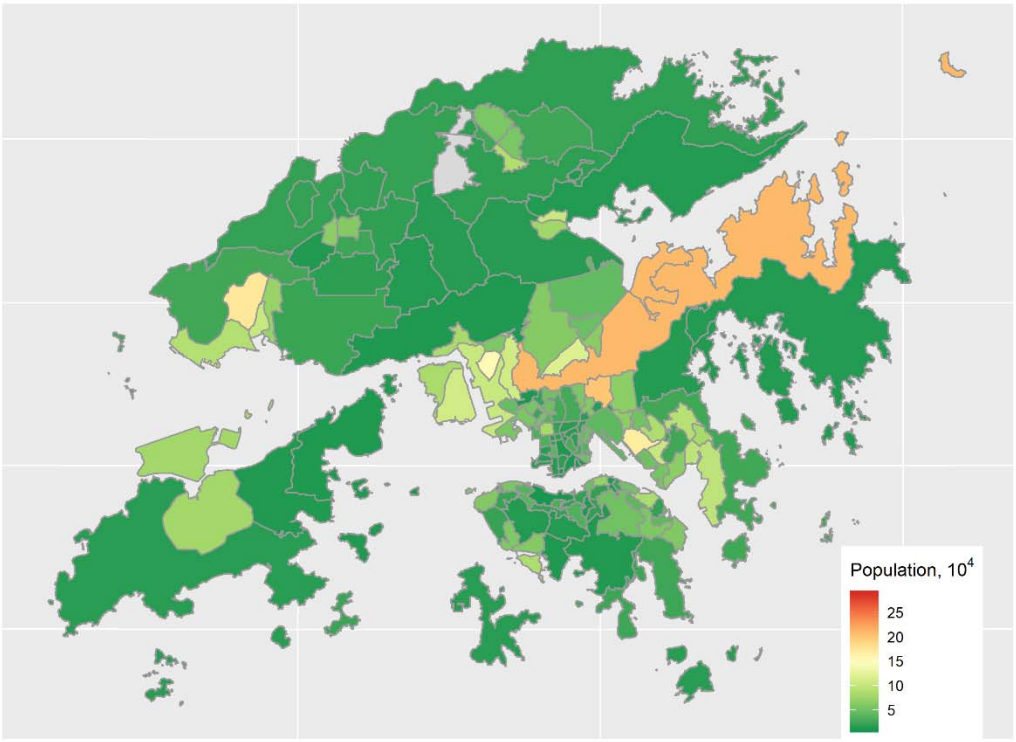
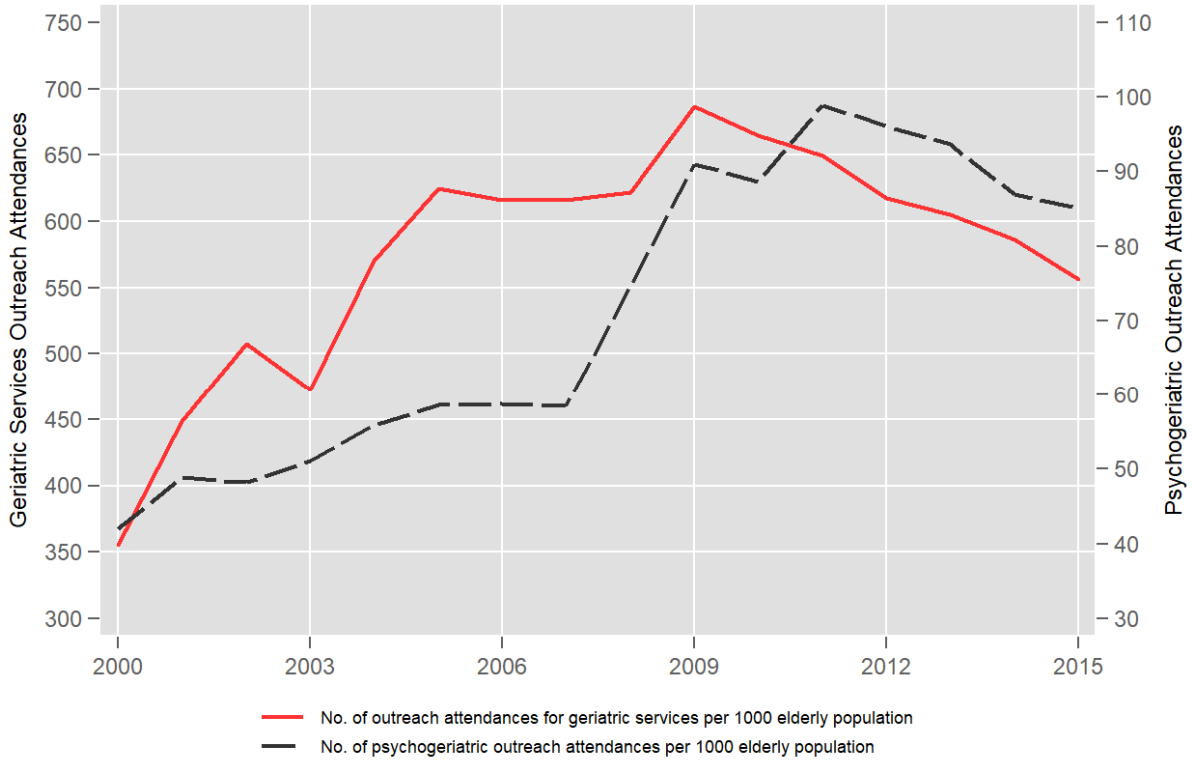


Figure S2. Hong Kong's Population in Large Tertiary Planning Unit Groups (LTPUGs), 2011



Notes: This figure displays Hong Kong's LTPUGs with its population in 2011. The population data is from the census 2011.

Figure S3. Trend on the Provision of Community-based Healthcare Services in Hong Kong



Notes: This figure displays Hong Kong's annual trends on the provision of community-based health services per 1000 elderly population. Data Source: Various Annual Reports of Hospital Authority.

Figure S4. Geographical Locations of LTPUGs and Hospitals Providing A&E Services in HK

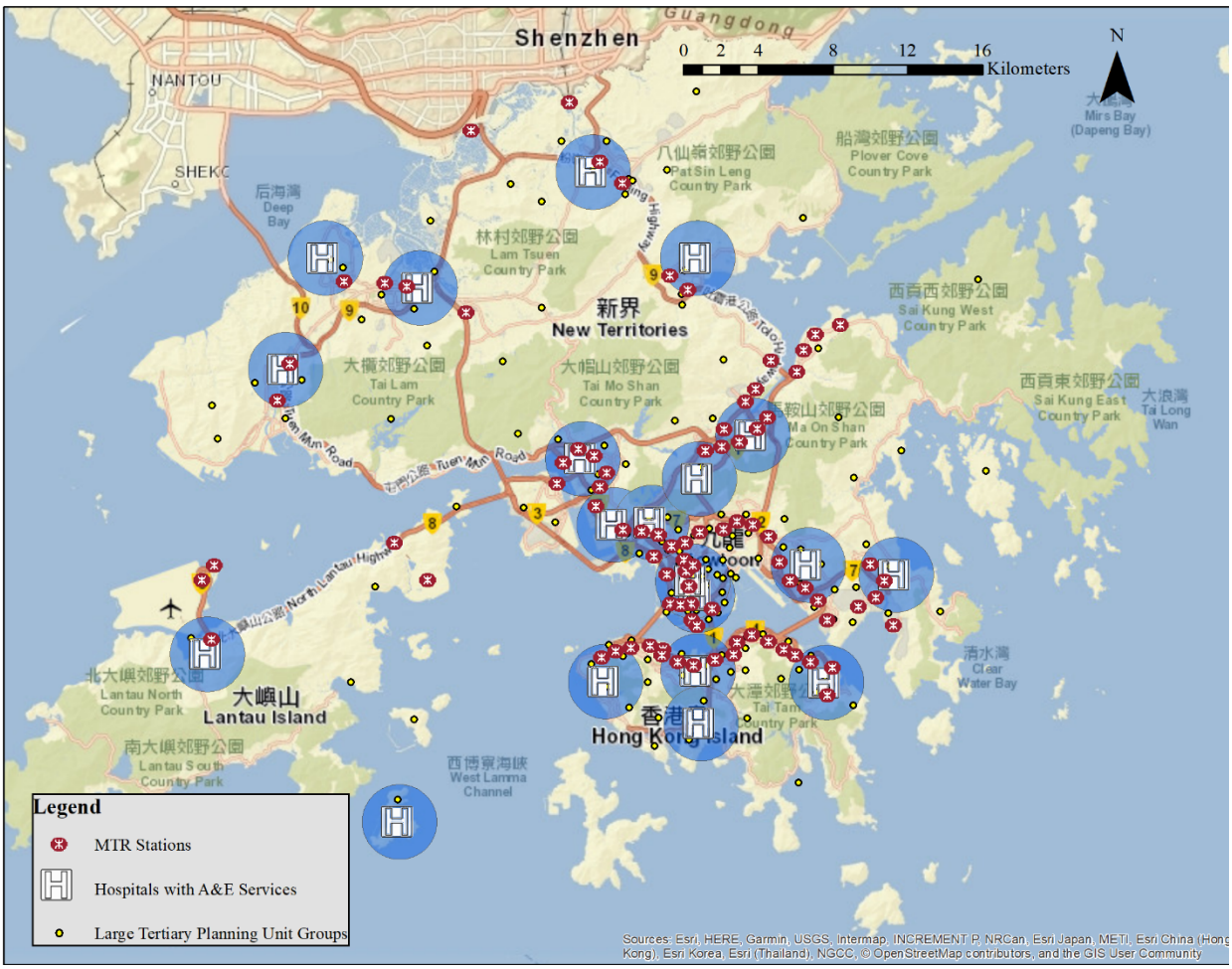


Figure S5. Comparison of Annual Average Air Pollution Index in the PRDEZ and HK

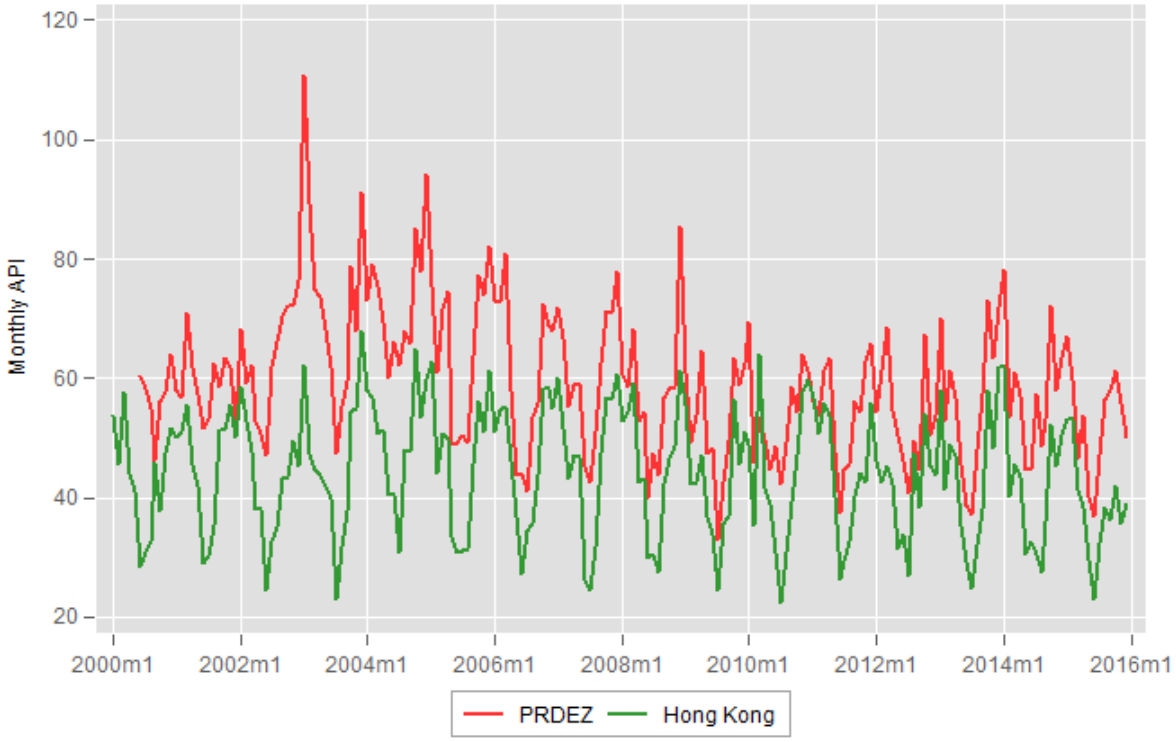
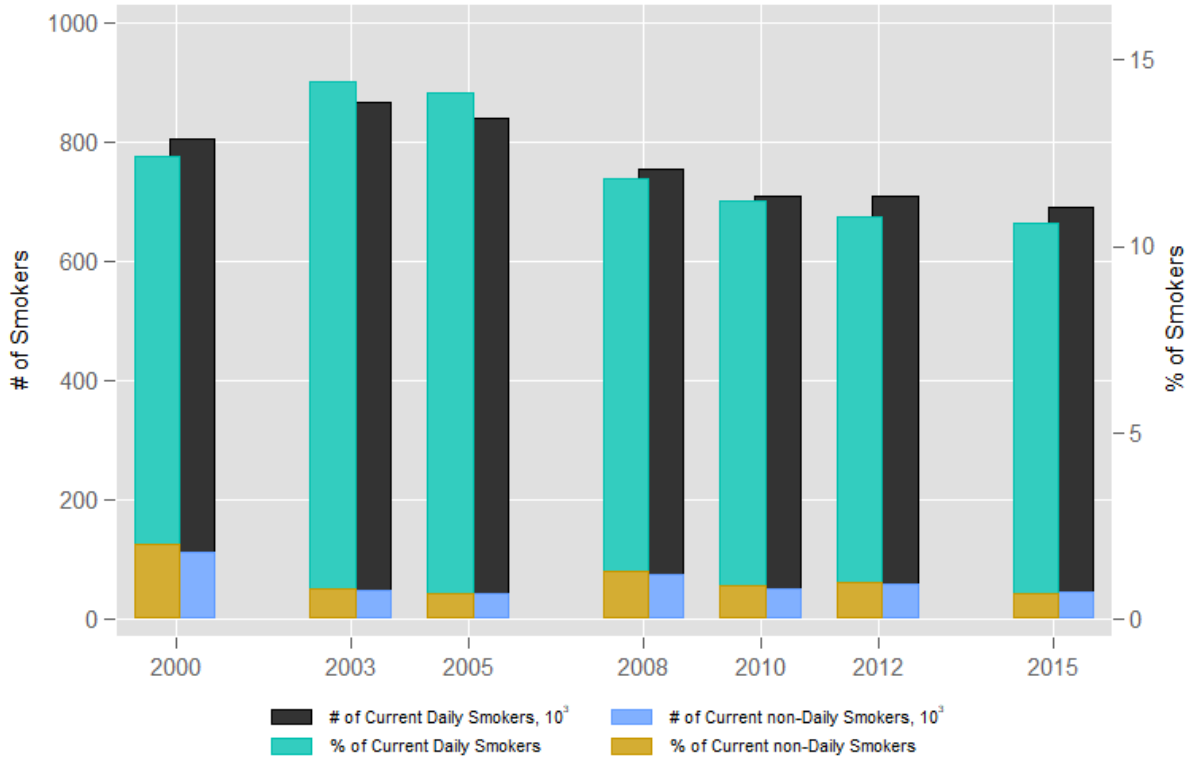


Figure S6. Smoking Pattern in Hong Kong



Notes: Data extracted from Thematic Household Survey Report No. 5, 16, 26, 36, 48, 53 and 59 by Census and Statistics Department (C&SD). % of smokers and daily smokers represents their respective percentage of the whole sampled population. % of (current, current daily, current non-daily) smokers refers to percentage of current, current daily, current non-daily) cigarette smokers aged 15 and over at the time of enumeration among all persons aged 15 and over.