The Impact of Haze on People's Averting Behavior: Evidence From Online Shopping in China

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Abstract

The poor air quality accompanying rapid economic growth in China attracted public attention worldwide when severe haze episodes caused by PM2.5 broke out in several major Chinese cities in 2011 and again in 2013 and early 2014. Previous studies have focused on the source of haze and its health impacts. Our study is the first to provide an analysis of pollution avoidance behavior by the Chinese in response to the recent haze episodes. We track the spatial-temporal variation of daily sales of anti-PM2.5 facemasks. In a standard utility maximization framework, the demand for anti-PM2.5 facemasks is a function of their price, the price of substitutes and other demand shifters affecting risk perceptions (visibility, level of PM2.5, haze alerts). We investigate whether an averting behavior exists, and how the purchases of masks depend on PM2.5 levels, and other factors directly observable: visibility and alert information. By providing insights on how citizens respond to air pollution, our research can help inform government agencies on how to better formulate policies to reduce exposure to air pollution and to more effectively communicate pollution alerts to those affected.

1. Introduction

With its gross domestic product (GDP) expanding 140 times, the Chinese economy has soared over the last three decades (National Bureau of Statistics, 2013). Since the implementation of free market reforms in 1979 and the opening up to foreign trade and investment, China has been among the world's fastest-growing economies, with annual growth of real GDP averaging about 10 percent per year (Morrison, 2014). China's rapid economic growth coupled with a model of economic development that emphasizes the growth of energy- and pollution-intensive heavy industry has resulted on very high levels or air pollution. The negative effects of air pollution on health are well documented (Dockery et al. 1993; Pope et al. 2002). Results of a recent study indicate that larger ambient concentrations of total suspended particulates (TSPs) in the north of China reduced life expectancies by about 5.5 years owing to an increased incidence of cardiorespiratory mortality (Chen et al., 2013).

Air pollution in China attracted public attention worldwide when severe haze episodes caused by PM2.5 broke out in 2011 and again in the winter of 2013. During the latter period (covering the end of 2013 to early 2014), the number of days of haze was the highest for the past 52 years, and affected over 600 million people in more than 17 provinces (Zhang, Yang and Zhong, 2013). Even though the U.S. Embassy started to monitor ambient PM2.5 in Beijing prior to the 2008 Olympic Games, it was not until the breaking out of these severe "airpocalypse" events that air pollution became a salient issue associated with increasing social unrest.

Among particular matters (PM), PM2.5 refers to fine particles with an aerodynamic diameter less than 2.5 micrometers that pose the greatest health risk to human health. They are small enough to penetrate into the deepest part of lungs and cause various diseases. They have been associated with an increase in emergency room admissions for cerebrovascular disease, cardiovascular and respiratory problems, decreasing of lung capability and rise in premature death (Leiva et al., 2013; Davidson , Phalen & Solomon, 2005; Fann et al., 2012; Tuo, Li & Wang, 2013). While previous studies have focused on the source of haze and on its health impacts, virtually no attention has been paid to the averting behavior that Chinese citizens undertake to avoid air pollution.

When a haze occurs, facemasks are the most effective and simple way to prevent an individual from being exposed to dangerous PM2.5 levels outdoors. If used correctly, anti-PM2.5 breathable facemasks remove PM from the air before it enters into the respiratory system with an effectiveness of 95-99 percent (3M web, 2014). Wearing particle-filtering facemasks has become a popular response to air pollution among urban residents in China. Chinese shoppers spent 870 million yuan ($141 million) in year 2013 buying them on Taobao, the country's largest e-commerce site. In early 2014, officials in Shanghai considered distributing 23 million protective masks to residents (Kuo, 2014).

Anti-PM2.5 masks are an interesting good to help reveal people's averting behavior towards air pollution. They should be changed frequently (they should not be worn for longer than 2 days or 30hrs of continued use) to ensure their efficiency. Otherwise, PM might block the airway in the masks and cause breathing problems. In addition, they are not too expensive, but expensive enough to prevent a hoarding behavior and to ensure that they are used for protection against PM2.5 concentrations and not for other ends for which cheaper alternatives exist.

Our study is the first to provide an analysis of pollution avoidance behavior by the Chinese in response to the increased pollution, and the resulting haze episodes. We investigate the relationship between daily purchases of anti-PM2.5 masks (and other types of facemasks), PM2.5 concentrations, haze alerts and visibility levels during the period of January 2013 to April 2014. This period covers the latest, most severe haze events. We match daily facemasks sales data from Taobao with daily PM2.5 concentrations collected by U.S. Embassies in the five large cities (Beijing, Shanghai, Guangzhou, Shenyang and Chengdu). Our results show that Chinese urban citizens engage in averting behavior: the purchase of anti-PM2.5 facemasks increases by 42.6 percent when current PM2.5 levels increase by 100 μg/m3 and by 88.1% when the average PM2.5 level during the previous three days increases by 100 $\mu g/m^3$. We also find that shoppers respond to haze alerts which are announced whenever the probability of the occurrence of a haze is high. Anti-PM2.5 facemasks sales increase by 32.7% when a yellow haze alert was announced. In contrast they do not seem to react to decreased visibility, which suggests that shoppers are quite sophisticated in the sense that they respond more strongly to the actual levels of pollution (disclosed by news or online) rather than to visibility indicators that, although more easily perceived, are worse proxies for the actual levels of pollution.

2. Averting behavior

Dating back to Michelson and Tourin (1966) and Ridker (1967) the study of people's averting behaviors towards pollutants is one of the earliest approaches for measuring pollution damages. The averting behavior method starts with the premise that people try to protect themselves when faced with environmental risks, incurring expenditures that would not otherwise be made. For example, the purchase of air filtering facemasks may only be made when faced with air pollution. These increased expenditures provide a lower bound for the economic benefits of environmental policy that reduces air pollution.

Applied to water pollution, Zivin et al. (2011) used sales data of bottled water to investigate the averting behavior towards drinking water violations. Beatty et al. (2014)

used sales of bottled water to analyze people's averting behavior before, during and after hurricane landings.

Regarding air pollution, most previous studies have focused on time spent outdoors. For one thing, reducing time spent outdoors is the easiest and most direct way to reduce exposure to outdoor air pollution. Another possible averting behavior, the use of facemasks for protection against air pollution, has only recently become widespread among urban residents in developing countries, most notably in China. In developed countries, the use of such masks is primarily a result of workplace safety and health regulations. Outdoor air quality in developed countries is much higher. When more infrequent air quality alerts do occur, for pollutants such as ozone or nitrogen oxide, cheap facemasks are less effective since those are gases and cannot be filtered. Zivin and Neidell (2009) find that, in response to smog alerts, people intertemporally substitute activities to reduce time spent outdoors, and that responses to consecutive alerts are decreasing. Sexton (2011) shows that air-quality alerts across the US reduce vigorous outdoor activities by 18 percent or 21 minutes on average during alert days. Welch et al. (2005) examine the influence of the smog alert program using train ridership data in Chicago, but do not find a significant overall effect. Tribby et al. (2013), however, find support for the effectiveness of air quality alert systems through an analysis of traffic data in Salt Lake City.

In contrast to previous studies, our paper analyzes averting behavior in a developing country by investigating the response of purchases of anti-PM2.5 facemasks to ambient PM2.5 levels. We recognize that the averting behavior towards PM 2.5 may be different from that towards other pollutants. Among all airborne pollutants, only PMs can affect atmospheric visibility; and among PMs the impact of PM2.5 is the strongest. Because its diameter approximates the wavelength of visible light, PM2.5 more effectively reflects and scatters visible light. Haze occurs whenever PM2.5 levels are high and largely influence people's visibility (Yadav et al., 2003; Watson, 2002; Schichtel, 2001). In this context, people's response to air-quality alerts arising from PM2.5 concentrations posing a health risk may be more limited than for other less visible pollutants. On the other hand, to mitigate the negative impacts of exposure to PM2.5, and in response to the widespread belief that it systematically underreports pollution levels, the Chinese Government has begun to disclose real-time air pollution concentrations (including PM2.5 levels) and issues air quality alerts precisely to promote averting behaviors. In this paper we test the effectiveness of these alerts.

3. Data and Methods

3.1 Baseline model

Facemasks are an effective and simple way to prevent an individual from being exposed to dangerous PM2.5 levels outdoors. In a standard utility maximization framework, the demand for anti-PM2.5 masks is a function of their price, the price of substitutes and other demand shifters that affect risk perceptions (visibility, level of PM2.5, alert information):

$$ln(sales_{it}) = \alpha_0 + \alpha_1 pm2.5_{it} + \alpha_2 visibility_{it} + \alpha_3 yhaze_{it} + \alpha_4 ohaze_{it} + \delta_t + f_i + \varepsilon_{it} \quad (1)$$

$ln(sales_{it})$ is the log of daily sales of anti-PM2.5 masks in city i at date t. We consider five major cities for which pollution data are available: Beijing, Shanghai, Guangzhou, Shenyang, and Chengdu. The sample period, from January18, 2013 to April 2, 2014, includes three severe haze episodes in early 2013, late 2013 and early 2014. Daily sales data were collected from the Taobao website using the market analyzing tool released by Taobao called Data Cubic Professional (DCP). DCP collects original transaction information in Taobao to serve sellers and guide their businesses. It costs 600 dollars per year for a seller to get access to this tool and thus not every seller owns this software. We get our sales data from a seller who has access to DCP with the commitment not to release the original data of Taobao. Taobao is the largest online retailer in China with over 97% of the online market share in the consumer-to consumer (C2C) e-commerce space, and 75 percent of Chinese Internet users visit Taobao.com on a daily basis according to the China Internet Network Information Center (CINIC). It sells cheaply and is becoming the most popular shopping channel in China. Similar and as well-known as Taobao.com, Tmall.com is also a source to explore since it is the largest player in the business-to-consumer (B2C) e-commerce in China and both of them are under Alibaba Group. Consumers could also buy products from Tmall.com through Taobao.com. DCP collects information for both.

Since individuals purchase anti-PM2.5 facemasks to protect themselves against ambient PM2.5 pollution, we collected daily data on PM 2.5 levels disclosed by the U.S. Embassies located on the five major cities of Beijing, Shanghai, Guangzhou, Shenyang and Chengdu. Data for PM2.5 concentrations is a daily average, measured in $\mu g/m^3$. In addition to the U.S. Embassies, the Ministry of Environmental Protection of China (MEP) also discloses real-time air pollution concentrations. The MEP uses a daily Air Quality Index (AQI) which is a normalized index of six criteria pollutants: NO_2, SO_2, PM10, PM2.5, CO and O_3, to represent the overall air quality in a city. However, although the Chinese government discloses air quality information in a variety of media (including its official website) to encourage pollution avoidance, the MEP strictly restricts access to historical air pollution data, and even information made available online is retracted after a brief period. In addition to the issue of accessibility, recent evidence shows that air pollution readings in Chinese cities are manipulated by policymakers, with a tendency for officials to underreport pollution (Andrews 2008; Ghanem and Zhang, 2014).

In addition to pollution levels equation (1) includes a term measuring horizontal visibility. The concentration of PM2.5 greatly influences visibility, although bad visibility may be caused by other factors (e.g. by purely meteorological phenomena as in the case of fog). In this sense, visibility is a noisy proxy for PM2.5 levels, but its inclusion in the model can shed light on whether individuals base their averting behavior on actual pollution information or on what they see when they look through their windows. The visibility data come from the National Climatic Data Center (NCDC) under the U.S. National Oceanic and Atmospheric Administration (NOAA). Visibility (in statute miles) is computed as a daily average at the city level to match the temporal and spatial resolution of facemask sales.

We also included haze alert information for all five cities. We web scraped Google News for all the alert information and news stories during the research period. A haze is largely caused by human activities and is quite harmful. High PM2.5 level makes it much easier that a haze is formed, and the issuing of a haze alert is based on the probability of the occurrence of reduced visibility and high PM2.5 concentrations. There are three haze alerts levels that in order of severity are yellow, orange and red. A yellow alert is issued if in 24 hours one of the following three conditions will develop: (1) a haze with visibility < 3km and relative humidity < 80%; (2) a haze with visibility < 3km and relative humidity ≥ 80%, and the concentration of PM2.5 is between 115 $\mu g/m^3$ and 150 $\mu g/m^3$; (3) a haze with visibility > 5km, and the concentration of PM2.5 is between 150 $\mu g/m^3$ and 250 $\mu g/m^3$. An orange alert is issued if within 6 hours a haze with visibility < 2km will occur and persist. A red alert will be issued if in 24 hours one of the following three conditions satisfied: (1) a haze with visibility < 1km and relative humidity < 80%; (2) a haze with visibility < 1km and relative humidity ≥ 80%, and the concentration of PM2.5 is between 250 $\mu g/m^3$ and 500 $\mu g/m^3$; (3) a haze with visibility < 5km, and the concentration of PM2.5 is greater than 500 $\mu g/m^3$. Only yellow and orange haze alerts were announced during our research period, so we didn't include red alerts in our analysis.

The alert criteria for air pollution in China are different from those in the United States reflecting laxer standards. In China, the air quality standards for daily average PM2.5 concentration are set at 75μg/m3 and there are only three alert levels (China National Environmental Monitoring Center). In the US, the limit to PM2.5 concentration is 35μg/m3 and there are five alert levels including yellow, orange, red, purple and maroon (US EPA). A less restricted alert system in China reflects less attention paid by the government in dealing with environmental issues. However, the extent to which people react to these alerts in China is unknown, and this is what we are interested in looking at. Including both visibility and haze alert helps us distinguish whether people are reacting to what they see or to official alert information.

Finally, δ_t and f_i in regression (1) represent, respectively, date and city dummies to account for seasonality and city fixed effects.

3.2 Extensions to the model

It is reasonable to argue that people might not react immediately to an alert, since an alert is only a warning of the happening of a haze. Also, people might react only after they see what others do (e.g. are others wearing facemasks?), or after several consecutive alerts. Another factor to consider is that there is lag between when the order is placed and when it is fulfilled, time at which the transaction is regarded as completed. This lag is typically of 3 to 4 days. Because we focus on five large cities, this lag should be even shorter, and it is not unusual that orders are delivered on the same day that they are ordered. In any case, we address the issue of a delayed reaction by including lags of the explanatory variables:

$$ln\ sales_{it} = \alpha_0+\alpha_1 pm2.5_{it}+ \alpha_2 visibility_{it}+ \alpha_3 yhaze_{it}+ \alpha_4 ohaze_{it}+\alpha_5 lag\_pm2.5_{it}+ \alpha_6 lag\_visibility_{it} + \alpha_7 lag\_yhaze_{it}+ \alpha_8 lag\_ohaze_{it}+ \delta_t +f_i+\varepsilon \quad (2)$$

Lagged pollution and lagged visibility are constructed as the average of daily pollution levels and visibility, respectively, during the previous 3 days. Lagged alert is the number of alerts during the previous 3 days. We analyzed the robustness of the results to lags from 1 to 7 previous days.

Another factor to consider is that people may use other types of masks not specifically designed to filter PM2.5. In principle, if people are protecting themselves against PM2.5 pollution, they should buy anti-PM2.5 facemasks that can effectively block ambient PM2.5. But during severe haze episodes, there was some reporting of PM2.5 masks being so largely in demand that not all people could get access to them (Gao, 2013). Anti-PM2.5 masks are also more expensive than other types of masks. This means that it is not rational to purchase anti-PM2.5 masks for other purposes for which a cheaper alternative mask is available, but the reverse might happen. People might purchase imperfect substitutes assuming that they will be partially protected. Thus, we re-estimated equation 2 for three other major types of masks: H7N9 masks (preventing bird flu), one-time use masks, and anti-ultraviolet masks.

The dependent variable in equations (1) and (2) is the log of the value of sales. An observed increase in sales in response to larger PM2.5 levels could come not just from a response of the quantity of masks demanded but from a price increase. As noted above, PM2.5 masks were largely in demand during severe haze days, which might drive their price up. We checked if this is the case in our data by estimating an alternative version of equation (2) in which the dependent variable is the log *price* of anti-PM2.5 facemasks. To obtain the price of masks, we divide the daily sales value by the amount of masks sold. The average price of anti-PM2.5 masks is reasonable (roughly 10 yuan, as much as a normal meal), not low enough for people to horde masks and store them for a long time nor very expensive so that people will not buy them at all.

Another limitation of using aggregate sales data is that they cannot show the difference between single buyers and multiple buyers. To tackle this problem, we estimated an additional regression in which the dependent variable is the number of daily deals involving mask purchases, rather than the daily sales value.

Finally, there is the issue of storage. People could buy masks beforehand and store them, thus mitigating their averting behavior when alert days come. To address this issue we aggregate sales data weekly.

4. Empirical Results

Table 1 presents summary statistics of the key variables variables. Most of the sales are concentrated in Beijing, the largest of the 5 cities and also the most polluted in terms of PM2.5 concentrations and haze alerts (this not reported in the Table). Panel B of Table 1 displays the correlation between the variables. As one would expect, the correlation between PM2.5 levels and mask sales is positive (0.31), the correlations between PM2.5 levels and haze alerts (both yellow and orange) are also positive (0.32 and 0.25, respectively). Visibility is negatively correlated with PM2.5 levels (-0.13) as expected. Overall, the correlation coefficients are small, which suggests that multicolinearity should not be a problem for the estimates.

Table 2 shows the results of the estimation of the baseline regression, equation (1). As indicated above, all the regressions include city and month fixed effects (FE). Standard errors are clustered at the city level. The first three columns report the results when the three key independent variables are included in the regressions in isolation. All three variables are statistically significant and have the expected signs. For PM2.5 the results indicate that increasing PM2.5 daily average levels by 100 $\mu g/m^3$ would increase the sales of masks by 103%.[1] Results in column 4, when additional controls are included, still show a strong impact of PM2.5 levels. An increase of PM2.5 daily average concentrations by 100 $\mu g/m^3$ still results in a large increase in sales of 76.6%. Visibility, although significant in column 2, is no longer significant when actual pollution levels and alert announcements are considered. Yellow haze alerts continue being statistically

[1] To put the numbers into perspective an increase of 100 $\mu g/m^3$ would be roughly equivalent to doubling average daily PM2.5 concentrations in Beijing.

significant in column 4 after controlling for actual pollution concentrations although its magnitude is reduced by almost sixty percent, and orange alerts are no longer significant. These results suggest that Chinese urban citizens, or at least those who buy facemasks online, are quite sophisticated in their purchasing decisions. They react to actual information (in the form of concentration readings and yellow haze alerts) rather than to what they see (visibility).

In table 3, we added lagged variables to the baseline model to capture a potential sluggish reaction to pollution on the part of consumers as well as a possible delay between the order and receipt of facemasks. We considered a variety of lags, up to the previous 7 days, to see how past information influences purchasing behavior. In each specification in Table 3 the lagged independent variables represent the sum of alerts, the average of the daily PM2.5 levels and the average visibility during the previous x days (where x varies from 1 to 7). To illustrate: when considering a 3-day lag, in addition to the contemporaneous independent variables the regression includes the average values of independent variables during the previous 3 days. Contemporaneous impacts of PM2.5 and yellow haze alerts are robust across specifications. Previous levels of PM2.5 and sum of previous yellow haze alerts are also significant, and for PM2.5 lagged levels (up to the previous 7 days) have a larger impact on the purchase of masks than contemporaneous levels of pollution. For example, in column 3, an increase of $100\,\mu g/m^3$ in the average PM2.5 levels over the previous 3 days is associated with an 88.1% increase in the sales of masks, while the same increase in same-day pollution is associated with a 43% increase in sales.

Table 4 shows regression results for other three types of masks. The increase in purchases of H7N9 masks to increased levels of PM2.5 (either in the same day or in the previous 3 days) is similar to that of anti-PM2.5 masks. On the other hand, one-time-use masks and ultraviolet masks do not seem to be used as substitutes for anti-PM2.5 masks in response to PM2.5 concentrations, visibility or alerts, although, as indicated before they are cheaper.

Table 5 shows the regression results for the price of anti-PM2.5 masks and the number of deals to check whether price for pm2.5 masks varies during the research period, and whether we have a single buyer problem. In column (1) of table 5, only the average lagged information of the past 3 days is statistically significant at a 10% significance level. This indicates that price of PM2.5 masks is relative stable. Column (2) shows the regression results for deals. The amount of deals increases by around 44% given a yellow alert and by 54% given an increase of one more day of yellow alert during the past 3 days. These results increase our confidence in the previous results.

To account for problems such as masks storage, we ran the model with weekly data. From Table 6, we can see that the results are consistent with those presented in Tables 2 and 3.

5. Conclusion

Using sales data of pm2.5 masks from Taobao, we show that Chinese citizens in the five major cities of Beijing, Shanghai, Guangzhou, Shenyang and Chengdu buy anti-PM2.5 facemasks to protect themselves against air pollution, and that they seem to be sophisticated in their reactions to air pollution. In other words, they seem to buy masks in response to actual information (current and past levels of PM2.5 and haze alerts) rather than to what they see (level of visibility). Also, past levels of pollution matter up to 7 days, with the average of lagged PM2.5 levels having a larger impact on the purchase of masks than contemporaneous levels of pollution. Our results also reflect a substitution with H7N9 masks but not with other types of masks even though they are relatively cheaper. Our results are driven by an increase in the quantity of masks demanded rather than by an increase in their price. The regression results with data aggregated at the weekly level are also consistent with our previous results.

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Table 1: Descriptive statistics

Panel A Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
PM2.5 (μg/m^3)	1705	79.72	61.42	3.57	449.75
Beijing	375	106.26	85.51	7.13	449.75
Shanghai	370	62.71	44.84	3.57	382.88
Guangzhou	369	55.69	30.96	8.71	162.67
Shenyang	255	74.16	50.85	12.82	307.17
Chengdu	336	99.41	60.34	14.54	380.00
Visibility (miles)	1864	38.4	173.9	0.4	999.9
Beijing	375	147.6	350.0	0.8	999.9
Shanghai	370	16.0	72.8	0.8	999.9
Guangzhou	374	4.7	2.5	0.4	13.7
Shenyang	371	17.1	88.9	2.9	999.9
Chengdu	374	6.0	3.0	0.4	14.7
Yellow haze alert (dummy)	1864	0.039163	0.194035	0	1
Beijing	375	0.056	0.230229	0	1
Shanghai	370	0.035135	0.184371	0	1
Guangzhou	374	0.053476	0.225282	0	1
Shenyang	371	0.013477	0.115462	0	1
Chengdu	374	0.037433	0.190075	0	1
Orange haze alert (dummy)	1864	0.006438	0.079999	0	1
Beijing	375	0.018667	0.135526	0	1
Shanghai	370	0.008108	0.089801	0	1
Guangzhou	374	0	0	0	0
Shenyang	371	0	0	0	0
Chengdu	374	0.005348	0.073029	0	1

Panel B Correlation between variables

	Anti-pm2.5 mask sales (CNY)	PM2.5 (μg/m^3)	Visibility (miles)	Yellow haze alert	Orange haze alert
PM2.5 (μg/m^3)	0.3143	1			
Visibility (miles)	0.0298	-0.1318	1		
Yellow haze alert	0.1385	0.3167	-0.0408	1	
Orange haze alert	0.1754	0.2518	-0.0171	-0.0163	1

Table 2: Baseline Regression

VARIABLES	PM2.5	Visibility	Haze	All
PM2.5_level	0.0103***			0.00766**
	(0.00214)			(0.00241)
Visibility		-0.171**		-0.0666
		(0.0411)		(0.0805)
Yhaze_alert			1.631***	0.696***
			(0.111)	(0.111)
Ohaze_alert			2.357**	0.714
			(0.612)	(0.687)
Observations	1,704	1,863	1,863	1,704
R-squared	0.151	0.074	0.056	0.167
City & Month FE	YES	YES	YES	YES

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regression with Lagged Independent Variables

	Number of lags considered						
VARIABLES	1 Lag	2 Lags	3 Lags	4 Lags	5 Lags	6 Lags	7 Lags
PM2.5_level	0.00385*	0.00401*	0.00426**	0.00434**	0.00440**	0.00464**	0.00496***
	(0.00158)	(0.00147)	(0.00149)	(0.00139)	(0.00119)	(0.00108)	(0.000936)
Lag_PM2.5_level	0.00588**						
	(0.00158)						
Visibility	-0.0624	-0.0531	-0.0466	-0.0443	-0.0413	-0.0403	-0.0378
	(0.0505)	(0.0426)	(0.0397)	(0.0355)	(0.0315)	(0.0286)	(0.0254)
Lag_visibility	-0.0139						
	(0.0446)						
Yhaze_Alert	0.443***	0.392***	0.327**	0.347**	0.348**	0.346**	0.361***
	(0.0510)	(0.0850)	(0.0832)	(0.0924)	(0.0848)	(0.0762)	(0.0771)
Ohaze_Alert	0.167	0.0832	0.116	0.149	0.224	0.200	0.132
	(0.376)	(0.592)	(0.588)	(0.593)	(0.600)	(0.573)	(0.529)
Lag_Yhaze	0.546**						
	(0.163)						
Lag_Ohaze	0.174						
	(0.593)						
Lag2_PM2.5_ AVE		0.00754**					
		(0.00236)					
Lag2_visibility_ AVE		-0.0240					
		(0.0645)					
Lag2_Yhaze_ SUM		0.397**					
		(0.129)					
Lag2_Ohaze_ SUM		0.0136					
		(0.0693)					
Lag3_PM2.5_ AVE			0.00881**				
			(0.00300)				
Lag3_visibility_ AVE			-0.0322				
			(0.0739)				
Lag3_Yhaze_ SUM			0.387**				
			(0.124)				
Lag3_Ohaze_ SUM			-0.0612				
			(0.0394)				
Lag4_PM2.5_ AVE				0.0101*			
				(0.00372)			
Lag4_visibility_ AVE				-0.0319			
				(0.0813)			
Lag4_Yhaze_ SUM				0.351**			
				(0.120)			
Lag4_Ohaze_				-0.0596			

SUM							
				(0.0306)			
Lag5_PM2.5_ AVE					0.0110*		
					(0.00439)		
Lag5_visibility_ AVE					-0.0338		
					(0.0869)		
Lag5_Yhaze_ SUM					0.373**		
					(0.116)		
Lag5_Ohaze_ SUM					-0.115**		
					(0.0327)		
Lag6_PM2.5_ AVE						0.0113*	
						(0.00494)	
Lag6_visibility_ AVE						-0.0319	
						(0.0931)	
Lag6_Yhaze_ SUM						0.379**	
						(0.116)	
Lag6_Ohaze_ SUM						-0.128***	
						(0.0239)	
Lag7_PM2.5_ AVE							0.0114
							(0.00540)
Lag7_visibility_ AVE							-0.0321
							(0.1000)
Lag7_Yhaze_ SUM							0.392**
							(0.119)
Lag7_Ohaze_ SUM							-0.143***
							(0.0257)
Observations	1,694	1,684	1,674	1,664	1,654	1,644	1,634
R-squared	0.211	0.237	0.257	0.273	0.282	0.283	0.282
City & Month FE	YES	YES	YES	YES	YES	YES	YES

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regressions for Other Types of Masks

VARIABLES	PM2.5 Masks	H7N9 Masks	OTU Masks	Ultraviolet Masks
PM2.5_level	0.00426**	0.00368**	0.00101	-0.00152**
	(0.00149)	(0.00118)	(0.00189)	(0.000463)
Lag3_PM2.5_AVE	0.00881**	0.00866**	0.00216	-0.00290
	(0.00300)	(0.00204)	(0.00300)	(0.00324)
Visibility	-0.0466	0.00788	-0.0260	0.0381*
	(0.0397)	(0.0223)	(0.0401)	(0.0157)
Lag3_visibility_AVE	-0.0322	0.0636**	-0.0440	0.0346
	(0.0739)	(0.0148)	(0.0636)	(0.0345)
Yhaze_Alert	0.327**	0.115	0.400**	0.115
	(0.0832)	(0.138)	(0.123)	(0.225)
Ohaze_Alert	0.116	0.702*	0.491	0.364
	(0.588)	(0.307)	(0.352)	(0.712)
Lag3_Yhaze_ SUM	0.387**	0.232	0.299*	0.0929
	(0.124)	(0.143)	(0.119)	(0.212)
Lag3_Ohaze_ SUM	-0.0612	-0.268**	0.0141	-0.114
	(0.0394)	(0.0934)	(0.0862)	(0.123)
Observations	1,674	1,330	1,656	1,590
R-squared	0.257	0.115	0.090	0.041
City & Month FE	YES	YES	YES	YES

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regressions for Price and Deals of Anti-PM2.5 Masks

VARIABLES	Price	Deals
PM2.5_level	0.00213	0.00341
	(0.00113)	(0.00206)
Lag3_PM2.5_AVE	0.00345*	0.00680
	(0.00151)	(0.00343)
Visibility	0.0335	-0.0766
	(0.0268)	(0.0499)
Lag3_visibility_AVE	0.0475	-0.0866
	(0.0503)	(0.0942)
Yhaze_Alert	-0.148	0.442**
	(0.133)	(0.151)
Ohaze_Alert	0.206	0.210
	(0.208)	(0.537)
Lag3_Yhaze_ SUM	-0.0697	0.538**
	(0.0634)	(0.142)
Lag3_Ohaze_ SUM	0.0708	-0.119
	(0.0435)	(0.0718)
Observations	1,671	1,672
R-squared	0.066	0.275
City & Month FE	YES	YES

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regressions for Weekly Aggregates.

VARIABLES	PM2.5 masks
PM2.5_level	0.0142*
	(0.00571)
Visibility	-0.0560
	(0.115)
Haze_Alert	0.217**
	(0.0497)
Observations	245
R-squared	0.295
City & Month FE	YES

Robust clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1