Pharmacy density and inequalities in defense against air pollution: Evidence from a severely polluted city in China

Highlights

- We investigate the causal effect of offline pharmacy richness on residents' adoption of wearing the anti-smog mask by using the administrative approval data to construct instrument variables and perform the 2SLS estimation.
- A one-standard-deviation increase in pharmacy density leads to a 6.5% increase in the probability of anti-smog mask wearing. The effect only appears in elders over 65 and is insignificant for the younger.
- We develop a theoretical model to clarify the underlying mechanisms. Both the *search cost effect* and *information effect* are supported by the data.
- Adjusting the distribution of offline medical resources can help improve the elderly's defensive response to air pollution and narrow pollution avoidance inequality.

Pharmacy density and inequalities in defense against air pollution: Evidence from a severely polluted city in China

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Abstract
This study uses survey data from 2,111 households in Shenyang City, a severely polluted city in China, to examine the role of community pharmacy density in narrowing the inequality of older-younger people's defenses against air pollution. To address endogeneity, we exploit the administrative approval data for new pharmacy openings during 2014-2016 as the instrumental variable for the stock of pharmacies in 2018. The 2SLS estimates indicate that richer pharmacy density increases the probability that residents wear the anti-smog mask on heavily polluted days, but the effect only appears in the elder over 65. The theoretical model reveals that the result can be led by the search cost effect and information effect, and both channels are supported by empirical findings.

Keywords: pharmacy richness, anti-smog-mask wearing, avoidance inequality, search cost effect, information effect

JEL Codes: Q53, I31, I18

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1. Introduction

Air pollution has been one of the most serious public health challenges in developing countries. Extensive research has established a strong link between air pollution exposure and various diseases, such as cardiovascular and respiratory ailments (Dockery and Pope, 1994; Dominici et al., 2006; Dockery and Stone, 2007). Among preventive measures, wearing the anti-smog mask is considered one of the most convenient and cost-effective options.[1] However, in a country heavily plagued by pollution like China, the adoption rate of masks remains relatively low. A survey conducted by China Youth Daily in 2017 revealed that only 55.5% of respondents expressed a willingness to wear masks on smoggy days.[2] Furthermore, numerous studies suggest that children and the elderly, in particular, are more vulnerable to air pollution than the general population (Deryugina et al., 2019; Filleul et al., 2004; Zhang et al., 2016). Worse still, due to limited knowledge about air pollution and access to protective facilities, vulnerable older adults may be less engaged in effective preventive behaviors, which further exacerbates inequalities in pollution exposure. Nevertheless, limited studies examine what interventions help reduce inequalities in air pollution avoidance across populations and provide detailed empirical evidence on underlying channels.

In this study, we focus on the effect of the abundance of an offline healthcare resource, community pharmacy density, on residents' mask-wearing willingness and age group heterogeneity. Firstly, the community pharmacy is the main channel for residents to obtain medicines (Rogers et al., 1998). Similarly, like the expansion of marijuana dispensaries exacerbates local marijuana abuse and dependence through increasing availability of marijuana (Mair et al., 2015), abundant pharmacies help residents obtain defensive facilities at a lower cost and further increase the likelihood of them taking defensive actions. Secondly, community pharmacies provide professional healthcare advice, changing residents' health risk awareness and improving their health through preventative interventions (Sabater-Hernández et al., 2016), and the information further triggers residents' defensive responses (Barwick et al., 2019). Moreover, the effect of community pharmacies can exhibit age heterogeneity. Young people can purchase defensive facilities and access information online, while the elderly, who have limited online access, rely more on offline resources. Therefore, community pharmacies are expected to have a greater impact on elders, which helps to narrow the air pollution defensive inequality.

We propose a theoretical model to clarify the role of the search cost effect and information effect above, and then use representative survey data collected in Shenyang City in 2018 to empirically examine the impact of pharmacy density on the mask-wearing decision. To address the endogeneity of pharmacy density, we obtain the location data of newly opened pharmacies in Shenyang from the official department for 2014-2016 to construct instrumental variables and employ the two-stage least squares (2SLS) estimation. The results indicate that a one-standard-deviation increase in pharmacy density within 1km-2km around a community is associated with a 6.5% increase in residents' willingness to wear anti-smog masks. The effect is systematically

[1] Defensive behaviors against air pollution include reducing outgoing (Wang and Zheng, 2020), wearing anti-smog masks (Zhang and Mu, 2018), using air purifiers (Ito and Zhang, 2020), and migrating to other areas (Chen et al., 2022). In this paper, anti-smog masks refer to the high-performance protective masks that can filter fine particles, distinguishing them from ordinary medical masks.

[2] Source: http://zqb.cyol.com/html/2017-01/17/nw.D110000zgqnb_20170117_1-07.htm.
The survey did not emphasize wearing the anti-smog mask, and the sampling was not random. In our random sampling survey in Shenyang city, the adoption rate of wearing the anti-smog mask is 40%.

significant for the elderly over 65 and almost insignificant for younger adults. Furthermore, both the search cost and information effect are essential in driving the finding. The abundance of community pharmacies encourages the elderly to purchase masks through these establishments and enhances their awareness of the effectiveness of masks in combating air pollution.

This study adds to the literature from at least two aspects. First, we extend the study of inequalities in air pollution defenses by focusing on age group inequalities (Sun et al., 2017). To the best of our knowledge, we are the first to confirm that the abundance of offline healthcare resources contributes to narrowing the air pollution defensive inequality between the elderly and younger adults in the context of a heavily air-polluted city in a developing country. Moreover, we address the endogeneity in estimates by exploiting reliable administrative data. Second, we untangle the mechanisms of the pharmacy effect theoretically and empirically, showing that lower-cost access to protective facilities and raised awareness of defensive effectiveness contribute to the elderly taking protective actions. These findings provide policymakers with implementable interventions to improve the health outcomes of vulnerable residents.

2. Theoretical framework

We propose a concise framework to clarify channels behind the effect of pharmacy richness on residents' mask wearing. The utility of a representative resident in Shenyang depends on two parts: consumption of the composite good x (price is normalized to 1) and the health level in the heavily polluted ambient h. The utility function is in quasi-linear form following Barwick et al. (2019):

$$U(x,h) = x + u(h) \quad (1),$$

where $\partial u/\partial h > 0$, and $\partial^2 u/\partial h^2 < 0$.

The resident's health level on heavily polluted days is affected by two factors: whether to wear the anti-smog mask m (a dummy variable) and the pharmacy density around the community, PD (a continuous variable). Pharmacies provide information on air pollution and the effectiveness of masks in reducing health damage. Thus, when given $m = 1$, a higher PD implies a higher health level. Therefore, $h(1, PD_1) > h(1, PD_0)$ indicates the synergistic effect of pharmacy richness on health improvement. However, if the resident does not wear the mask while polluting, richer defensive information induced by richer pharmacies has a limited effect on health improvement. That is, $h(0, PD_1) = h(0, PD_0)$.[3]

The representative resident holds a wealth of W, and uses that for good consumption and the anti-smog mask purchase. Under a binding budget constraint, the problem comes to:

$$\max\ U(x,h) = x + u\big(h(m, PD)\big)$$
$$\text{s.t.}\, W = x + p_m \cdot m \quad (2),$$

where p_m is the relative price for obtaining the anti-smog mask. p_m consists of the original price of the mask and the search cost in the purchase. Richer pharmacies help to lower the search for obtaining the mask, which implies $\partial p_m/\partial PD < 0$.

The resident chooses whether or not to wear the mask in the heavily polluted ambient to maximize utility. When the utility in the wearing state $U_{m=1}$ is higher than that in the non-wearing

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[3] We assume that the mask-wearing status is critical to the health level, which implies $h(1, PD_1) > h(1, PD_0) > h(0, PD_1) = h(0, PD_0)$. This relationship guarantees that the rational resident always wears the anti-smog mask once he purchases one.

state $U_{m=0}$, wearing the mask denotes an improvement, which gives:

$$U_{m=1} - U_{m=0} > 0 \Rightarrow -p_m + u\big(h(1, PD)\big) - u\big(h(0, PD)\big) > 0 \tag{3}$$

The comparative static exercise indicates that:

$$\frac{\partial(U_{m=1} - U_{m=0})}{\partial PD} = \underbrace{-\frac{\partial p_m}{\partial PD}}_{>0,\text{search cost effect}} + \underbrace{\frac{\partial u}{\partial h} \cdot \frac{\partial h}{\partial PD}}_{>0,\text{information effect}} \tag{4}$$

and leads to the following propositions to be empirically examined:

Proposition 1. The increase in the pharmacy density raises the probability of residents wearing masks in severe air pollution;

Proposition 2. Mechanisms behind the effect of pharmacy richness can be decomposed into ***search cost effect-*** obtaining masks at a lower cost, and ***information effect-*** transmitting more information on defense against air pollution.

3. Data

Our data consists of three parts. Residents' perceptions of air pollution and defensive behaviors on polluted days, also their individual and household characteristics, are from a face-to-face survey conducted in Shenyang City in 2018. Shenyang City is located in Northeast China, known for its developed heavy industry and long-standing severe air pollution. The survey follows a stratified random sampling design with 3-5 communities randomly selected in each of the ten districts in Shenyang City as the sample. Then in each community, 40 households are randomly selected for interviews, half of whom are elders over 65, to ensure data representation for people of each age group. Finally, our data include 2,111 households, and 48.18% of respondents are older adults. Fig.1 illustrates the spatial distribution of sample communities.

The distribution of stock pharmacies around sample communities in 2018 is from the points of interest (POI) provided by four maps- Baidu Map, Gaode Map, Tencent Map, and 360 Map. POIs from separate map sources are aggregated and deduplicated.[4] Finally, 2,712 pharmacies are located within 2km of forty sample communities, and the pharmacy density varies sharply across communities, as shown in Fig.1(a).

We also obtain the list of pharmacies newly opened during 2014-16 from the Shenyang Administration for Market Regulation (SAMR).[5] We match the newly opened pharmacies with sample communities according to the list of approved pharmacies and business registration address information. During 2014-16, 1,347 pharmacies were approved to open in Shenyang City, of which 666 were located within 2km of the sample communities, as illustrated in Fig.1(b).

4. Empirical evidence

4.1 Empirical specification

We use the following probability model to analyze the association between pharmacy richness

[4] We convert each map to the same coordinate system- BD09, to make POIs cross-map comparability. The coordinate system of Gaode, Tencent, and 360 Map is GCJ-02, which is converted to BD-09 to be comparable with Baidu Map.

[5] Based on the Drug Administration Law of the People's Republic of China, a newly opened pharmacy must have corresponding qualifications (including qualified pharmacists, premises, rules, and regulations) and obtain the drug distribution certificate approved by SAMR.
Article 51 and Article 52. Source: http://en.npc.gov.cn.cdurl.cn/2019-08/26/c_674712_2.htm.

and residents' mask-wearing decisions:[6]

$$m_{ic} = \alpha_0 + \alpha_1 PD\_R_c + \boldsymbol{X}_{ic}\beta + \varepsilon_{ic} \quad (5),$$

where m_{ic} indicates whether resident i in community c wears the anti-smog mask when going out on a polluted day.[7] If the respondent answers that he wears a disposable or reusable anti-smog mask on an air pollution day, then m_{ic} takes a value of 1 and 0 otherwise. PD_R_c denotes the pharmacy richness around the community c, defined as the pharmacy density in a circle centered on community c with a radius of R.[8] We choose 1km, 1.5km, and 2km as the radius, respectively, to test the sensitivity of the results to radius selection. Therefore, the coefficient α_1 is of first interest, interpreted as the association between pharmacy richness and residents' defensive willingness.

$\boldsymbol{X}_{ic}$ is a vector of control variables, including other defensive behaviors -using air purifiers and reducing outdoor activities, demographic variables- gender, age, education years, whether married, whether a city *hukou*, whether the household head, and logarithmic annual household income (descriptive statistics are in Table A1). We also include the survey day dummies to mitigate the interference of recall bias varies across survey days and improve the estimate's efficiency.[9] Standard errors are clustered at the community level to allow for intra-group correlation of residents within the same community.

We first estimate Eq.(5) using a linear probability model (LPM). Nevertheless, since the explanatory variables PD_R_c could be endogenous, LPM estimations may yield an inconsistent estimate of α_1. We then recalculate pharmacy density variables based on the distribution of newly opened pharmacies during 2014-2016 and use that as instrumental variables of PD_R_c. Pre-determined pharmacies formed part of stock pharmacies in 2018, though some close later.[10] Moreover, pharmacies seeking profit-maximizing decide their locations according to residents' contemporaneous demand, while unpredictable future air quality is not a major consideration, which helps us to identify the causal effects of pharmacy density. For the model with the instrumental variable, we perform the 2SLS estimation to estimate the α_1.

4.2 Baseline results

Columns (1)-(3) of Table 1 report the LPM results for Eq.(5), which show that pharmacy density is positively associated with anti-smog mask wearing. Column (1) shows that a one-standard-deviation increase in pharmacy density is associated with a 5.02% increase in the probability of wearing the mask (St.D. of PD_1km is 6.60), a non-negligible effect considering the relatively low proportion of mask adoption in Shenyang. The promotion effect is still robust for different radius settings, with the one-standard-deviation effect varying from 5.13% (R=1.5km, column (2)) to 5.39% (R=2km, column (3)). However, since the pharmacy density may be endogenous, results from LPM should be interpreted cautiously. We construct instrumental variables using the abovementioned method and perform the 2SLS estimation. In the first stage, pharmacy densities calculated by stock pharmacies in 2018 and pharmacies newly opened during 2014-16 are

[6] Eq.(5) can be estimated by a Probit model since m_{ic} is a dummy variable. However, for the convenience of interpretation and performing 2SLS estimation, we use LPM throughout the paper. The results obtained by the LPM and Probit model are highly consistent and are available upon request.

[7] We especially emphasize the difference between wearing the anti-smog mask and the ordinary mask in the survey.

[8] $PD\_R_c = \frac{\text{number of pharmacies in a circle with radius} = R}{\pi R^2}$.

[9] The survey was completed in seven days, on November 3, 4, 9, 10, 11, 17, and 18.

[10] The distribution of pharmacies opened in 2014-16 is highly spatially correlated with the distribution of stock pharmacies in 2018, as shown in Fig.1.

positively correlated and statistically significant.[11] The Cragg-Donald Wald F statistics are large enough to reject the weak instruments hypothesis, further confirming the validation of the 2SLS strategy. The second stage results are reported in columns (4)-(6) of Table 1. The impacts of pharmacy density are slightly larger than LPM results but still statistically and economically significant, consistent with **Proposition 1**.

We then explore the distributional effect of pharmacy density across age groups by flexibly constructing seven age-group dummy variables and interacting that with the pharmacy density variable. We also interact instrument variables with age-group dummy variables to obtain consistent estimates (Nizalova and Murtazashvili, 2016). The 2SLS results are reported in columns (10)-(12) of Table 1, indicating that positive effects of pharmacy richness systematically appear in the elderly over 65, while for younger residents, effects are almost insignificant. These findings confirm the elderly-specific impacts of pharmacies on the likelihood of taking defensive actions. As main consumers of offline pharmacies, elders benefit more from the abundance of pharmacies, thereby increasing the possibility of defense against severe air pollution.

4.3 Mechanisms

We turn to analyzing underlying mechanisms, as proposed in **Proposition 2**. We first examine the ***search cost effect***. The 2SLS estimates in columns (1)-(3) of Table 2 represent that pharmacy density contributes to the probability that residents purchase masks through offline pharmacies but are still only practical for elders over 65[12]. Young people mainly purchase masks through online stores at a relatively low search cost, and the richness of offline pharmacies has a limited effect on them. However, for elders who lack online channels, the abundance of offline pharmacies increases their availability of defensive facilities and further promotes defensive behaviors. Sun et al. (2017) highlight wealth heterogeneity in investment in air pollution defense equipment. We enrich the literature from the perspective of age heterogeneity.

We then explore the ***information effect***. As the primary healthcare resource, offline pharmacies not only directly provide defensive facilities to residents but also transmit information about air pollution's health damage and how to use defensive facilities properly. Columns (4)-(6) of Table 2 show that higher pharmacy richness increases the awareness of the elders that wearing the anti-smog mask can effectively reduce health damage. Again, the information channel does not hold for residents under 65, who mainly receive information about real-time pollution and defensive choices online. We extend the ongoing literature that discusses the effect of providing air pollution-related information on the public's awareness of pollution and defensive behaviors (Barwick et al., 2019; Graff Zivin and Neidell, 2009; Neidell, 2009).

We confirm that both the search cost and information effect play a mechanistic role in the age-stratified impacts of pharmacy density, consistent with **Proposition 2**.

5. Conclusion

Using representative survey data combined with the community pharmacy POI and administrative approval data, this study reveals the elderly-specific positive impact of offline pharmacy richness on anti-smog mask wearing. Our findings imply that by appropriately adjusting

[11] Results of the first stage are not reported and are available upon request.
[12] Table 2 provides the 2SLS results. The LPM results are reported in Table A2.

the distribution of offline healthcare resources, policymakers can improve the health outcomes of the elderly and narrow pollution avoidance inequality.

Before closing, we state the caveats of the study. First, Shenyang is represented as a heavily polluted city in China in this study. Future studies could examine the external validity of our findings with the help of richer observations in more cities and countries. Second, this study focuses on anti-smog mask wearing, leaving room to discuss other defensive behaviors. It will be informative to analyze the determinants of the adaption of other defensive behaviors.

References

Barwick, P. J., Li, S., Lin, L., & Zou, E. (2019). From fog to smog: The value of pollution information. National Bureau of Economic Research (No. w26541).

Chen, S., Oliva, P., & Zhang, P. (2022). The effect of air pollution on migration: Evidence from China. *Journal of Development Economics*, 156, 102833.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12), 4178-4219.

Dockery, D. W., & Pope, C. A. (1994). Acute respiratory effects of particulate air pollution. *Annual Review of Public Health*, 15(1), 107-132.

Dockery, D. W., & Stone, P. H. (2007). Cardiovascular risks from fine particulate air pollution. *New England Journal of Medicine*, 356(5), 511-513.

Dominici, F., Peng, R. D., Bell, M. L., Pham, L., McDermott, A., Zeger, S. L., & Samet, J. M. (2006). Fine particulate air pollution and hospital admission for cardiovascular and respiratory diseases. *Journal of the American Medical Association*, 295(10), 1127-1134.

Filleul, L., Le Tertre, A., Baldi, I., & Tessier, J. F. (2004). Difference in the relation between daily mortality and air pollution among elderly and all-ages populations in southwestern France. *Environmental Research*, 94(3), 249-253.

Graff Zivin, J., & Neidell, M. (2009). Days of haze: Environmental information disclosure and intertemporal avoidance behavior. *Journal of Environmental Economics and Management*, 58(2), 119-128.

Ito, K., & Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in China. *Journal of Political Economy*, 128(5), 1627-1672.

Mair, C., Freisthler, B., Ponicki, W. R., & Gaidus, A. (2015). The impacts of marijuana dispensary density and neighborhood ecology on marijuana abuse and dependence. *Drug and Alcohol Dependence*, 154, 111-116.

Neidell, M. (2009). Information, avoidance behavior, and health the effect of ozone on asthma hospitalizations. *Journal of Human Resources*, 44(2), 450-478.

Nizalova, O. Y., & Murtazashvili, I. (2016). Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, 5(1), 71-77.

Rogers, A., Hassell, K., Noyce, P., & Harris, J. (1998). Advice-giving in community pharmacy: variations between pharmacies in different locations. *Health and Place*, 4(4), 365-373.

Sabater-Hernández, D., Sabater-Galindo, M., Fernandez-Llimos, F., Rotta, I., Hossain, L. N., Durks, D., ... & Benrimoj, S. I. (2016). A systematic review of evidence-based community pharmacy services aimed at the prevention of cardiovascular disease. *Journal of Managed Care and Specialty Pharmacy*, 22(6), 699-713.

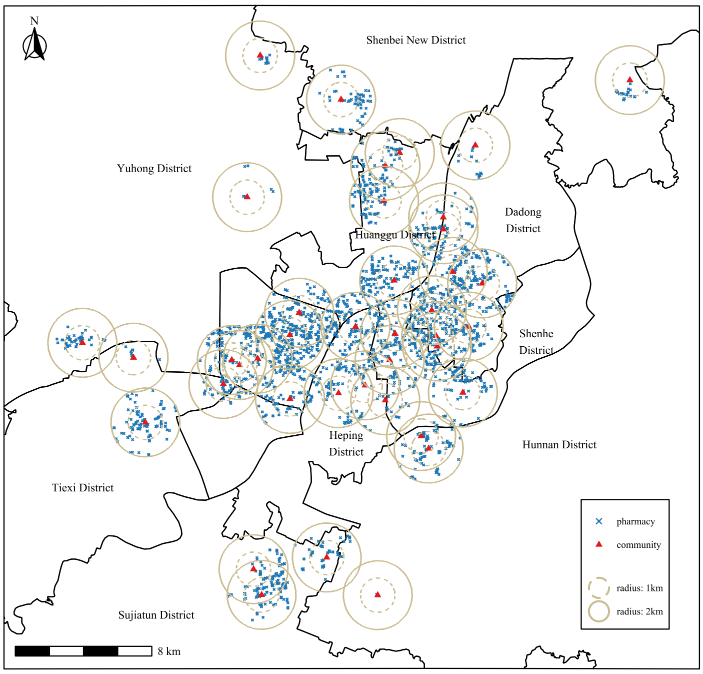
Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. *Ecological Economics*, 131, 468-474.

Wang, B., & Zheng, S. (2020). Air pollution lowers travel demand in a consumer city. *Transportation Research Part D: Transport and Environment*, 89, 102616.

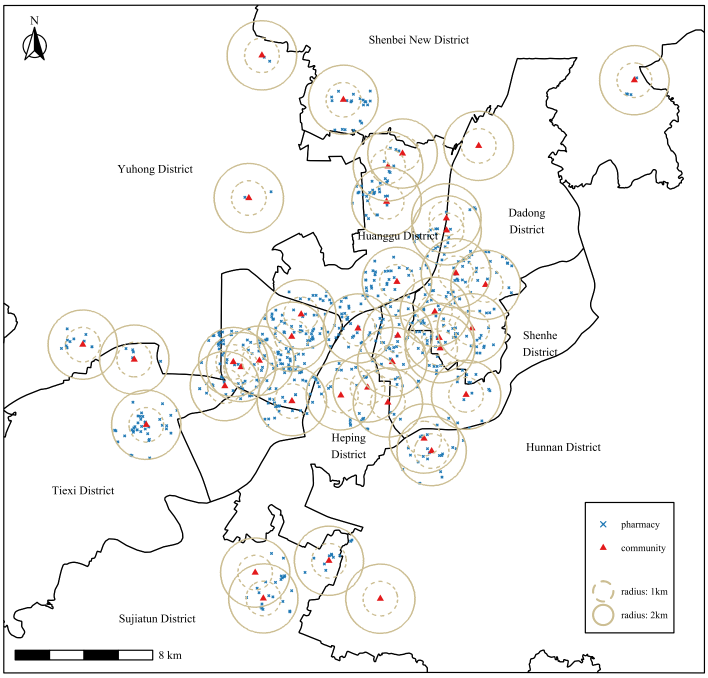
Zhang, S., Li, L., Gao, W., Wang, Y., & Yao, X. (2016). Interventions to reduce individual exposure of elderly individuals and children to haze: a review. *Journal of Thoracic Disease*, 8(1), E62.

Zhang, J., & Mu, Q. (2018). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management*, 92, 517-536.

Figures and Tables



(a) stock pharmacies in 2018



(b) newly opened pharmacies in 2014-16

Fig.1 Communities and pharmacies distribution.

Table 1

Impacts of pharmacy richness on residents' anti-smog mask wearing and age-group heterogeneity.

Outcome variable: wearing the anti-smog mask	LPM			2SLS			LPM			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm	0.0076***	0.0078***	0.0084***	0.0103**	0.0099***	0.0098***						
	(0.0025)	(0.0024)	(0.0023)	(0.0045)	(0.0029)	(0.0025)						
PD_Rkm***1**(age<40)							0.0065	0.0093*	0.0109**	0.0035	0.0089	0.0086
							(0.0053)	(0.0052)	(0.0048)	(0.0074)	(0.0058)	(0.0053)
PD_Rkm***1**(age∈[40,50))							0.0055	0.0050	0.0066	0.0113	0.0103	0.0078
							(0.0071)	(0.0067)	(0.0068)	(0.0083)	(0.0072)	(0.0066)
PD_Rkm***1**(age∈[50,55))							0.0050	0.0078	0.0130**	0.0111	0.0114	0.0170**
							(0.0051)	(0.0055)	(0.0063)	(0.0075)	(0.0078)	(0.0078)
PD_Rkm***1**(age∈[55,60))							0.0103*	0.0075	0.0053	0.0094	0.0076	0.0080
							(0.0052)	(0.0053)	(0.0058)	(0.0079)	(0.0063)	(0.0063)
PD_Rkm***1**(age∈[60,65))							0.0088**	0.0071*	0.0069*	0.0122	0.0084	0.0093
							(0.0043)	(0.0039)	(0.0041)	(0.0078)	(0.0050)	(0.0059)
PD_Rkm***1**(age∈[65,70))							0.0061**	0.0067**	0.0066**	0.0095*	0.0089**	0.0067*
							(0.0029)	(0.0030)	(0.0029)	(0.0052)	(0.0039)	(0.0036)
PD_Rkm***1**(age≥70))							0.0062**	0.0078***	0.0090***	0.0081*	0.0100***	0.0097***
							(0.0026)	(0.0026)	(0.0026)	(0.0044)	(0.0034)	(0.0029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0487	0.0491	0.0495	0.0430	0.0437	0.0444	0.0569	0.0568	0.0578	0.0503	0.0512	0.0524
Cragg-Donald Wald F				2136.323	5187.265	7243.604				298.347	714.937	988.059

Notes: N=2,111 for all columns; Individual and household characteristics and survey day dummies are controlled for. **1**(age∈$group_i$) is a dummy variable that indicates whether the individual's age falls into the age group *i*; Standard errors in parentheses are clustered at the community level; *** p<0.01, ** p<0.05, * p<0.1

Table 2

Mechanisms: search cost effect and information effect

	Outcome variable: purchase anti-smog masks through pharmacies			Outcome variable: wearing anti-smog masks can reduce health damage from air pollution		
	(1)	(2)	(3)	(4)	(5)	(6)
	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm***1**(age<40)	-0.0074	-0.0083	-0.0062	-0.0013	-0.0018	-0.0032
	(0.0080)	(0.0066)	(0.0057)	(0.0037)	(0.0028)	(0.0026)
PD_Rkm***1**(age∈[40,50))	-0.0003	-0.0005	0.0008	0.0026	-0.0002	0.0026
	(0.0088)	(0.0075)	(0.0074)	(0.0054)	(0.0051)	(0.0048)
PD_Rkm***1**(age∈[50,55))	0.0013	0.0000	0.0035	-0.0042	-0.0056	-0.0060
	(0.0078)	(0.0076)	(0.0071)	(0.0057)	(0.0058)	(0.0057)
PD_Rkm***1**(age∈[55,60))	0.0008	0.0028	0.0013	0.0037	-0.0002	-0.0024
	(0.0067)	(0.0060)	(0.0057)	(0.0065)	(0.0052)	(0.0058)
PD_Rkm***1**(age∈[60,65))	0.0049	0.0089*	0.0095**	0.0046	0.0026	0.0012
	(0.0042)	(0.0045)	(0.0046)	(0.0034)	(0.0029)	(0.0030)
PD_Rkm***1**(age∈[65,70))	0.0071*	0.0092**	0.0108***	0.0078**	0.0064**	0.0032
	(0.0043)	(0.0040)	(0.0039)	(0.0030)	(0.0032)	(0.0030)
PD_Rkm***1**(age≥70))	0.0056	0.0103*	0.0116**	0.0105*	0.0104**	0.0092*
	(0.0058)	(0.0053)	(0.0053)	(0.0056)	(0.0043)	(0.0049)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0132	0.0152	0.0163	0.0669	0.0656	0.0638
Cragg-Donald Wald F	298.347	714.937	988.059	293.769	701.831	969.958

Notes: All columns are estimated by 2SLS, and *PD_Rkm_approved* is used as the instrumental variable for *PD_Rkm*; N=2,111 for columns (1)-(3), and N=2,093 for columns (4)-(6); Individual and household characteristics and survey day dummies are controlled for. **1**(age∈group$_i$) is a dummy variable that indicates whether the individual's age falls into the age group *i*; Standard errors in parentheses are clustered at the community level; *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1
Definitions and summary statistics of variables.

Variables	Definition	Mean	St. D.	Min	Median	Max
Explained variable						
anti-smog mask	wear an anti-smog mask when going out on severely polluted days: 1=Yes, 0=No	0.40	0.489	0	0	1
Explanatory variables						
PD_1km	pharmacy density with R=1km, calculated by stock pharmacies in 2018: #pharmacies/km^2	11.06	6.600	0.318	9.549	30.558
PD_1.5km	pharmacy density with R=1.5km, calculated by stock pharmacies in 2018: #pharmacies/km^2	10.43	6.571	0.141	9.762	28.577
PD_2km	pharmacy density with R=2km, calculated by stock pharmacies in 2018: #pharmacies/km^2	9.81	6.411	0.080	8.913	26.658
Instrumental variables						
PD_1km_approved	pharmacy density with R=1km, calculated by newly established pharmacies in 2014-16: #pharmacies/km^2	2.50	1.656	0	2.546	7.639
PD_1.5km_approved	pharmacy density with R=1.5km, calculated by newly established pharmacies in 2014-16: #pharmacies/km^2	5.51	3.778	0	4.456	14.642
PD_2km_approved	pharmacy density with R=2km, calculated by newly established pharmacies in 2014-16: #pharmacies/km^2	9.41	6.341	0	9.549	25.783
Mechanism variables						
mask_by_pharmacy	purchase anti-smog masks through pharmacies: 1=Yes, 0=No	0.46	0.499	0	0	1
mask_reduce_damage	wearing an anti-smog mask when going out on severely polluted days can reduce the damage from air pollution:	0.84	0.370	0	1	1

	1=Yes, 0=No					
Control variables						
air_purifier	use an air purifier at home on severely polluted days: 1=Yes, 0=No	0.23	0.421	0	0	1
reduce_out	reduce going out on severely polluted days: 1=Yes, 0=No	0.89	0.316	0	1	1
age	years old	60.73	12.364	21	64	86
gender	1=male, 0=female	0.47	0.499	0	0	1
edu_year	education years	10.24	3.617	0	9	30
married	1=married, 0=others	0.86	0.351	0	1	1
hukou	own a Shenyang *Hukou*: 1=Yes, 0=No	0.89	0.319	0	1	1
household-head	1=house-head, 0=No	0.58	0.493	0	1	1
ln(yearly_inc)	logarithmic annual household income	10.92	0.690	9.798	11.051	12.437
survey_day1	surveyed on November 3, 2018	0.17	0.379	0	0	1
survey_day2	surveyed on November 4, 2018	0.10	0.299	0	0	1
survey_day3	surveyed on November 9, 2018	0.03	0.173	0	0	1
survey_day4	surveyed on November 10, 2018	0.21	0.405	0	0	1
survey_day5	surveyed on November 11, 2018	0.15	0.356	0	0	1
survey_day6	surveyed on November 17, 2018	0.19	0.395	0	0	1
survey_day7	surveyed on November 18, 2018	0.15	0.354	0	0	1

Notes: N=2,093 for variable *mask_reduce_damage*, and N=2,111 for other variables. PD_Rkm is calculated by $\frac{\text{number of pharmacies in a circle with radius} = R}{\pi R^2}$.

Table A2

Mechanisms: search cost effect and information effect, LPM estimations

	Outcome variable: purchase anti-smog masks through pharmacies			Outcome variable: wearing anti-smog masks can reduce health damage from air pollution		
	(1)	(2)	(3)	(4)	(5)	(6)
	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm***1**(age<40)	-0.0054	-0.0059	-0.0035	-0.0053**	-0.0046*	-0.0046*
	(0.0065)	(0.0063)	(0.0063)	(0.0026)	(0.0023)	(0.0023)
PD_Rkm***1**(age∈[40,50))	-0.0020	0.0001	0.0005	0.0004	0.0011	0.0034
	(0.0074)	(0.0071)	(0.0071)	(0.0045)	(0.0041)	(0.0044)
PD_Rkm***1**(age∈[50,55))	-0.0007	0.0010	0.0035	-0.0134***	-0.0114**	-0.0102**
	(0.0055)	(0.0058)	(0.0062)	(0.0042)	(0.0045)	(0.0047)
PD_Rkm***1**(age∈[55,60))	0.0006	0.0008	-0.0009	0.0045	0.0022	0.0001
	(0.0058)	(0.0057)	(0.0056)	(0.0045)	(0.0044)	(0.0046)
PD_Rkm***1**(age∈[60,65))	0.0063	0.0079*	0.0078*	0.0036	0.0033	0.0014
	(0.0040)	(0.0042)	(0.0042)	(0.0024)	(0.0024)	(0.0024)
PD_Rkm***1**(age∈[65,70))	0.0093***	0.0107***	0.0119***	0.0055**	0.0051*	0.0034
	(0.0032)	(0.0034)	(0.0034)	(0.0026)	(0.0026)	(0.0028)
PD_Rkm***1**(age≥70))	0.0056	0.0077*	0.0099**	0.0119**	0.0117***	0.0119**
	(0.0043)	(0.0044)	(0.0045)	(0.0045)	(0.0043)	(0.0045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0238	0.0259	0.0269	0.0760	0.0734	0.0713

Notes: All columns are estimated by LPM; N=2,111 for columns (1)-(3), and N=2,093 for columns (4)-(6); Individual and household characteristics and survey day dummies are controlled for. **1**(age∈$group_i$) is a dummy variable that indicates whether the individual's age falls into the age group *i*; Standard errors in parentheses are clustered at the community level; *** p<0.01, ** p<0.05, * p<0.1