Pharmacy Richness and Anti-smog-mask Wearing: Evidence from a Severely Polluted City in China

Highlights

- We investigate the causal effect of offline pharmacy richness on residents' adaption 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 mask wearing. The effect only appears in elders over 65 and is not significant for the younger.
- We develop a theoretical model to clarify the mechanisms behind the effect. Both *search cost effect* and *information effect* are supported by the data.
- Reasonably adjusting the distribution of offline medical resources can help to improve residents' defensive response to air pollution and mitigate the age-stratified pollution exposure inequality.

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Abstract
Exposure to fine particulate matter is associated with various health damages, and the negative effects are stronger in the elder compared to the younger, but limited literature has focused on measures that help to mitigate the air pollution exposure inequality. In this study, we investigate the causal effect of pharmacy richness around communities on the anti-smog-mask wearing of age-stratified residents in Shenyang City, a severely polluted city in China, in 2018. By constructing instrumental variables using administrative approval data for new pharmacy openings during 2014-16, 2SLS estimations indicate that higher pharmacy density promotes residents to take defensive behavior on heavily polluted days, but the effect only appears in the elder over 65. The theoretical model suggests that mechanisms can be decomposed as search cost effect and information effect, both supported by empirical findings.

Keywords: pharmacy richness, anti-smog-mask wearing, age heterogeneity, 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. Substantial evidence finds that air pollution exposure is associated with various diseases, such as cardiovascular and respiratory diseases (Dockery and Pope, 1994; Dominici et al., 2006; Dockery and Stone, 2007), and older people always suffer more serious health damage compared to younger people (Filleul et al., 2004; Deryugina et al., 2019). Ongoing research focuses on understanding the impacts of air pollution on socioeconomic behaviors and avoidance behaviors triggered by severe pollution (Bayer et al., 2009; Keiser et al., 2018; Zhang and Mu, 2018; Ito and Zhang, 2020; Greenstone et al., 2021). However, there is still little discussion on which measures help to promote residents' defensive response and narrow the air pollution exposure inequality across age groups, which are central to policy designs. Among preventive measures, wearing the anti-smog mask is considered one of the most convenient and cost-effective options.[1] However, the adoption rate is relatively low in China. According to the survey conducted by China Youth Daily in 2017, only 55.5% of respondents indicated that they would wear a mask when going out on a smoggy day.[2] In this paper, we investigate the causal effect of pharmacy density, the richness of a primary offline medical resource, on residents' anti-smog-mask wearing and age heterogeneity.

We develop a theoretical model to clarify underlying mechanisms- search cost effect and information effect. First, as the primary healthcare resource, the community pharmacy is the main channel for residents to obtain medicines (Rogers et al., 1998). Similar to 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 equipment at a lower cost and further increase the probability that residents take defense actions. Second, community pharmacies provide professional healthcare advice, changing residents' health risk awareness and improving their health through preventative interventions, benefiting both the youth (Horsfield et al., 2014) and the elderly (Sabater-Hernández et al., 2016). By disseminating information to residents, community pharmacies lead information about air pollution to more transparency, which triggers defensive behaviors (Barwick et al., 2019). More importantly, the effect of community pharmacies is heterogeneity across age groups. Young people can purchase defensive equipment through the Internet and receive related information through online media. However, due to the digital divide, elders have less access to online channels but are more dependent on offline resources. Therefore, the popularity of community pharmacies is expected to have a greater impact on elders, which helps to mitigate the growing air pollution exposure inequality across age groups.

We conducted a stratified random sample survey in Shenyang City in 2018, a heavily air-polluted city in northeastern China, to ensure the data is representative at the city level. The major empirical challenge in identifying the impact of pharmacy density on mask-wearing is that the distribution of pharmacies may be endogenous. That is, residents endogenously gathered in one community, who are health-conscious and tend to wear masks on polluted days, may reversely lead to higher pharmacy density around the community. We overcome the challenge by obtaining the

[1] 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 adaption rate of wearing the anti-smog mask is 40%.

pre-determined location data of newly opened pharmacies during 2014-16 from the official department and using that to construe instrument variables and perform the two-stage least squares (2SLS) estimation. The results show that a one-standard-deviation increase in pharmacy density within 1-2km around a community is associated with a 6.5% increase in the probability of residents wearing masks. Moreover, the effect is systematically found significant for elders over 65, but not among younger adults. This study suggests that governments can promote residents' defensive response to air pollution in an economically-effective way by optimizing the allocation of offline medical resources, which also contributes to mitigating the age-stratified exposure inequality.

2. Theoretical framework

We propose a concise framework to clarify the association between pharmacy richness, residents' anti-smog mask wearing, and underlying mechanisms. The utility of a representative resident in Shenyang City depends on two parts: consumption of the composite good x (price is normalized to 1) and his health level in the heavily polluted ambient. To simplify the analysis, we assume the utility function is in quasi-linear form following Barwick et al. (2019):

$$U(x,h) = x + u(h), \tag{1}$$

where health-related utility is positively associated with health level, $\frac{\partial u}{\partial h} > 0$, and with a decreasing rate, $\frac{\partial^2 u}{\partial h^2} < 0$. 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 he is located in, PD (a continuous variable). Pharmacies provide information on air pollution and the effect of anti-smog masks on reducing health damages. Thus, when $m = 1$ is given, a higher PD implies a higher health level. Suppose $PD_1 > PD_0$, $h(1, PD_1) > h(1, PD_0)$ 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, $h(0, PD_1) = h(0, PD_0)$.[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:

[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.

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

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 $\frac{\partial p_m}{\partial PD}<0$.

The resident chooses whether to wear the mask in the heavily polluted ambient to maximize his utility. When the utility in the wearing state $U_{m=1}$ is higher than that in the non-wearing state $U_{m=0}$, wearing the mask denotes an improvement, which gives:

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

The comparative static exercise indicates that:

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

and leads to the following propositions to be empirically tested:

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

Proposition 2. Mechanisms behind the positive effect of richer pharmacies 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, 3-5 communities are 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. The survey was completed in seven days, on November 3, 4, 9, 10, 11, 17, and 18. 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] 2,712 pharmacies are located within

[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.

2km of 40 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 propose the following linear probability model (LPM) to examine the association between pharmacy richness and residents' mask-wearing decisions on severely polluted days:[6]

$$m_{ic} = \alpha_0 + \alpha_1 PD\_R_c + \boldsymbol{X}_{ic}\beta + \gamma_d + \varepsilon_{ic}\,, \tag{5}$$

m_{ic} indicates whether the resident i in the 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} is equal to one. PD_R_c represents the pharmacy richness around the community c, defined as the pharmacy density within a circle with the community as the center and R as the radius.[8] To guarantee the representativeness and sufficient variation of the pharmacy density, we choose 1km, 1.5km, and 2km as the radius. Coefficients α_1 are our first interest. $\boldsymbol{X}_{ic}$ 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 Shenyang *hukou*, whether the household-head, and logarithmic annual household income (descriptive statistics are in Table A1). We also include the survey day fixed effects, γ_d, to mitigate the interference of recall bias varies across survey days and to improve the estimation's precision. Standard errors are clustered at the community level to allow behavior among residents within the same community to be related.

Since the explanatory variables PD_R_c could be endogenous and lead LPM estimations are biased, we recalculate a pharmacy density variable based on the distribution of pharmacies newly opened during 2014-16 and use that to perform the 2SLS estimation. Pre-determined pharmacies formed part of stock pharmacies in 2018, though some close later.[9] Moreover, pharmacies seeking profit-maximizing decide their locations according to residents' contemporaneous demand for medicines, while unpredictable future air quality is not a major consideration, which helps to

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[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.

[6] Equation (5) can be estimated by a Probit model, considering 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] $PD\_R_C = \dfrac{\#\ pharmacies\ in\ a\ circle\ with\ raidus = R}{\pi R^2}$

[9] 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.

overcome the endogenous problem.

4.2 Baseline results

Columns (1)-(3) of Table 1 report the LPM estimation results for Equation (5), which show that pharmacy density is positively associated with anti-smog mask wearing. Results in column (1) show 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 City (mean of the mask-wearing variable is 0.40). The promotion effect is still robust for different radius settings, with the one-standard-deviation effect varies 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 method mentioned above 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 positively correlated and statistically significant.[10] The Cragg-Donald Wald F statistics are large enough to reject *PD_Rkm_approved* as weak instruments, 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 estimations (Nizalova and Murtazashvili, 2016). The 2SLS results are reported in columns (10)-(12) of Table 1, indicating that positive effects of pharmacy richness are systematically found for elders over 65, while for younger residents, effects are almost statistically insignificant. These results differ slightly from LPM results, as reported in columns (7)-(9) of Table 1. Our findings indicate the age-heterogeneity promotion effect of pharmacy richness on mask-wearing. As main consumers of offline pharmacies, elders benefit more from the abundance of pharmacies, thereby increasing the possibility of defense against severe air pollution by wearing anti-smog masks.

4.3 Mechanisms

We turn to the mechanisms behind baseline results, as proposed in Proposition 2. We first examine the *search cost effect*. Purchasing anti-smog masks through offline pharmacies is considered the proxy for search cost reduction in obtaining defensive equipment. The 2SLS results reported in columns (1)-(3) of Table 2 show that the increase in pharmacy density contributes to the probability that residents obtain masks through pharmacies, but still only practical for elders over 65[11]. Young people can 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 defense equipment and further promotes defensive behaviors. Sun et al. (2017) highlights wealth heterogeneity in investment in air pollution defense equipment. We enrich the literature from the perspective of age heterogeneity.

[10] Results of the first stage are not reported and are available upon request.

[11] Table 2 shows the 2SLS results. The LPM results are reported in Table A2.

We then explore the *information effect*. As the primary healthcare resource, offline pharmacies not only directly provide defense equipment to residents but also transmit information about air pollution's health damages and how to use defense equipment properly. In columns (4)-(6) of Table 2, we find 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 contribute to the ongoing literature that discusses the effect of providing air pollution-related information on the public's awareness of pollution and defensive behaviors (Cutter and Neidell, 2009; Neidell, 2009; Graff Zivin and Neidell, 2009; Liu et al., 2018; Barwick et al., 2019).

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

5. Conclusion

Using a random sample survey data representative at the city level, combined with the community pharmacy POI data and administrative approval data, this study finds an elders-specific positive link between offline pharmacy richness and anti-smog mask wearing. We contribute to the literature focusing on interventions that help to improve residents' defensive response to air pollution and mitigate the age-stratified pollution exposure inequality in developing countries like China that are troubled by severe air pollution.

Before closing, we state the caveats of the study. First, we chose Shenyang City as the study sample to investigate the pharmacy richness effect in heavily polluted cities in China. 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 the behavior of wearing the anti-smog mask, with both cost and protective efficiency, but omits the discussion of other defensive behaviors. That will be an interesting topic to analyze the impact of offline medical resources on the adaption of other defensive behaviors and the interaction of multiple behaviors.

References

Bayer, P., Keohane, N., & Timmins, C. (2009). Migration and hedonic valuation: The case of air quality. Journal of Environmental Economics and Management, 58(1), 1-14.

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).

Cutter, W. B., & Neidell, M. (2009). Voluntary information programs and environmental regulation: Evidence from 'Spare the Air'. Journal of Environmental Economics and Management, 58(3), 253-265.

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

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. JAMA, 295(10), 1127-1134.

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

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.

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.

Greenstone, M., He, G., Li, S., & Zou, E. Y. (2021). China's war on pollution: Evidence from the first 5 years. Review of Environmental Economics and Policy, 15(2), 281-299.

Horsfield, E., Kelly, F., Sheridan, J., Stewart, J., & Clark, T. (2014). Could community pharmacies help to improve youth health? Service availability and views of pharmacy personnel in New Zealand. International Journal of Public Health, 59(5), 789-798.

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.

Keiser, D., Lade, G., & Rudik, I. (2018). Air pollution and visitation at US national parks. Science Advances, 4(7), eaat1613.

Liu, T., He, G., & Lau, A. (2018). Avoidance behavior against air pollution: evidence from online search indices for anti-PM2.5 masks and air filters in Chinese cities. Environmental Economics and Policy Studies, 20(2), 325-363.

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:

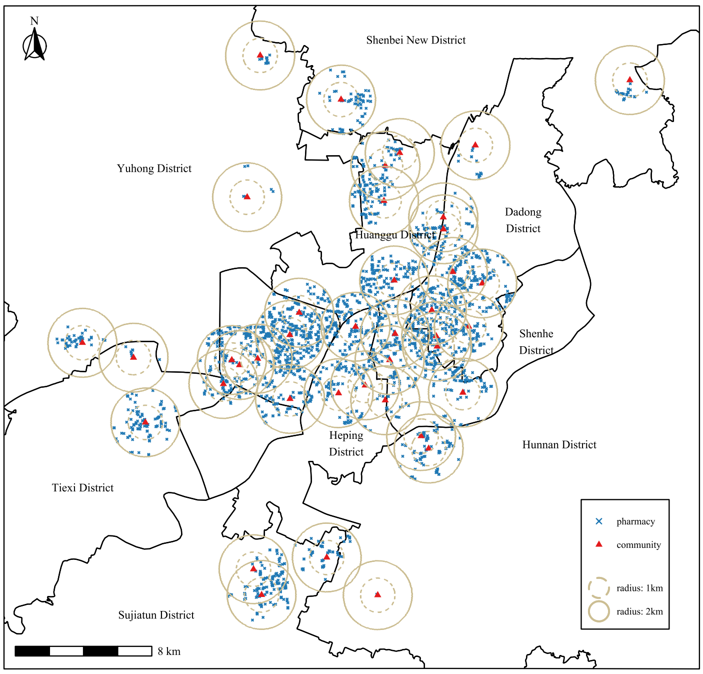
Vanishing of omitted variable bias on the interaction term. Journal of Econometric Methods, 5(1), 71-77.

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.

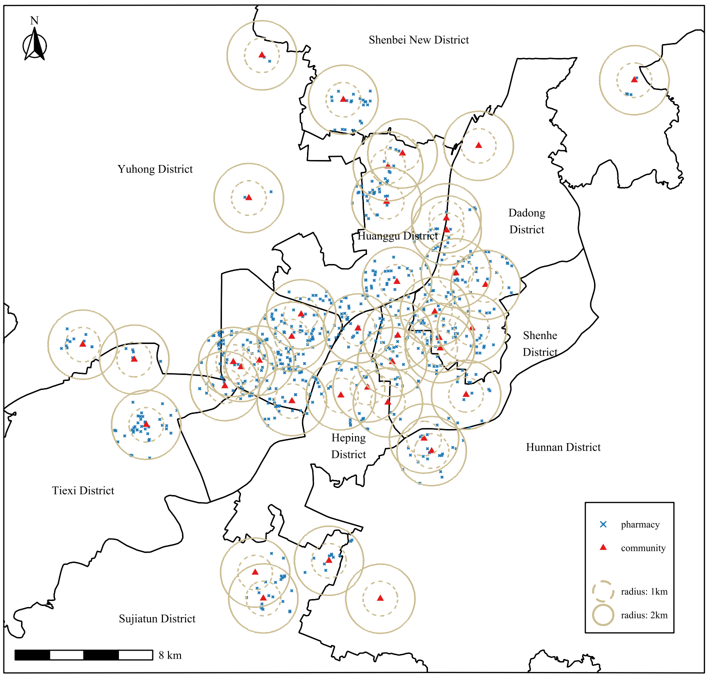
Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. Ecological Economics, 131, 468-474.

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 fixed effects 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 fixed effects 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_*R*km is calculated by $\frac{\#\ pharmacies\ in\ a\ circle\ with\ raidus = R}{\pi R^2}$.

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 fixed effects 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