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

Highlights

- We examine 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 channels. Both the *search cost effect* and *information effect* are verified by empirical analysis.
- 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

Acknowledgments: We thank participants at the Chinese Economists Society Annual Conference for their helpful comments. We are highly grateful to the Shenyang Administration for Market Regulation for the help in providing the administrative approval data. This work is supported by the National Natural Science Foundation of China (#71773135).

1. Introduction

The impacts of air pollution on health outcomes (morbidity and mortality) and non-health consequences (including cognition, productivity, and subjective well-being), also its distributional effects across age, gender, and wealth levels, have been extensively explored in the existing literature (Aguilar-Gomez et al., 2022; Graff Zivin and Neidell, 2013; Greenstone et al., 2021). However, limited studies focus on interventions to mitigate the detrimental impacts of air pollution, which is crucial for policy design. Notably, children and the elderly are more vulnerable to the adverse impacts of air pollution than the general population (Deryugina et al., 2019; Filleul et al., 2004; Zhang et al., 2016), which reflects air pollution exposure inequality.[1] Unfortunately, these vulnerable populations may face barriers to engaging in effective preventive behaviors due to insufficient knowledge about pollution and limited access to protective facilities, thus exacerbating the inequality of pollution impacts.

Wearing an anti-smog mask can effectively reduce health damage from air pollution when going out on severely polluted days (Laumbach et al., 2022; Zhang and Mu, 2018).[2] However, in a country heavily plagued by pollution like China, the adoption rate of this cost-effective defensive measure remains relatively low. A survey conducted by China Youth Daily in 2017 revealed that only 55.5% of respondents expressed a willingness to wear a mask on smoggy days.[3] In our survey in Shenyang City in 2017, only 40.0% of respondents reported wearing masks on severely polluted days. The adoption rate presents significant age disparities: 45.0% of young adults aged 21 to 64, compared to 34.2% of the elderly above 65.[4] This fact raises policymaking-related problems: what interventions can increase residents' defensive response and narrow avoidance inequality across age groups?

In this study, we focus on the effect of the density of community pharmacy, an offline healthcare resource, on residents' mask-wearing willingness and the heterogeneity of age groups. Firstly, the community pharmacy serves as a vital channel for residents to obtain medicines (Rogers et al., 1998). Just as the expansion of marijuana dispensaries exacerbates local marijuana abuse and dependence through the increasing availability of marijuana (Mair et al., 2015), abundant pharmacies help residents obtain defensive facilities at a lower cost. Secondly, community pharmacies provide professional healthcare advice, fostering a transformation in residents' awareness of health risks and enhancing their health status (Sabater-Hernández et al., 2016). Residents receive information about air pollution through prominently displayed posters within pharmacies and interactions with physicians, which further triggers their defensive responses (Barwick et al., 2019). Moreover, the effect of community pharmacies can be age-specified. Since younger residents mainly depend on online platforms to purchase defensive facilities and access information, while the elderly rely more on offline resources due to limited online accessibility, the

[1] In the *Guidelines for Health Protection of Populations in Air Pollution* issued by the National Health Commission of China, children and the elderly are recognized as key populations that are sensitive to air pollution. Source: https://www.gov.cn/fuwu/2019-12/10/content_5459931.htm.

[2] In this paper, anti-smog masks refer to the high-performance protective masks that can filter fine particles, distinguishing them from ordinary medical masks.

[3] 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..

[4] According to the National Statistical Bureau of China, people aged 65 years and above are categorized as the elderly. Source: http://www.stats.gov.cn/hd/lyzx/zxgk/202207/t20220704_1858761.html.

expansion of pharmacies is expected to benefit the elderly more and reduce the air pollution defensive disparities.

We propose a theoretical model to reveal the channels mentioned above, and then leverage representative survey data collected in Shenyang City in 2018 to empirically examine the impact of pharmacy density on residents' mask-wearing behavior. 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. The two-stage least squares (2SLS) results indicate that a one-standard-deviation increase in pharmacy density within 1km-2km around a neighborhood is associated with a 6.5% increase in residents' likelihood to wear masks.[5] Interestingly, the effect is mostly significant for the elderly and almost negligible for younger adults. Furthermore, our findings indicate that both the search cost effect and information effect play crucial roles in driving the impact.

This study adds to the literature in two key aspects. Firstly, we extend the investigation on air pollution defensive inequality by specifically focusing on age group disparities (Sun et al., 2017). Notably, we are among the first to demonstrate that offline healthcare resources play a significant role in triggering avoidance response to air pollution among the elderly, while previous studies mainly focus on the effect of pollution-related information (Barwick et al., 2019; Graff Zivin and Neidell, 2009; Neidell, 2009). Secondly, we reveal the underlying channels of the pharmacy effect both theoretically and empirically. Our results not only echo the importance of information for adopting defensive behaviors identified in previous studies, but also highlight the role of affordable protective facilities. These findings offer policymakers tangible and actionable interventions to enhance the health outcomes of vulnerable residents.

2. Theoretical framework

We propose a concise framework to elucidate channels through which pharmacy richness influences residents' decisions regarding mask wearing. The utility of a representative resident in Shenyang consists of two components: consumption of the composite good x (with its price normalized to 1) and the health stock in the heavily polluted ambient h. We adopt a quasi-linear utility function 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 stock on heavily polluted days depends on both whether to wear the anti-smog mask m and the pharmacy density around the neighborhood PD, and thereby, $h = h(m, PD)$. Pharmacy density affects the health stock in two ways. Firstly, pharmacies provide residents with information about air pollution damages and the effectiveness of masks in defending against pollution. Therefore, richer pharmacies trigger residents' risk awareness, which motivates their mask-wearing and improves the health stock. The relationships yield that, $\partial m/\partial PD > 0$ and $h(m=1) > h(m=0)|_{PD=\overline{PD}}$. Secondly, given the state that the resident wears a mask, pharmacies provide information on the appropriate way to wear the mask, which improves the protection efficiency of the mask. However, this effect disappears if the resident does not wear a mask.

[5] A community is a larger geographical unit consisting of many neighborhoods. In this paper, we use the term neighborhood to refer to the sampling unit of our survey.

Therefore, we have $\partial h/\partial PD > 0|_{m=1}$ and $\partial h/\partial PD > 0|_{m=0}$.[6] To sum up, the impact of pharmacy density on health stock is expressed as:

$$\frac{dh}{dPD} = \underbrace{\frac{\partial h}{\partial m} \cdot \frac{\partial m}{\partial PD}}_{>0} + \underbrace{\frac{\partial h}{\partial PD}}_{\geq 0} \quad (2).$$

The representative resident, with a wealth of W, allocates it between goods for consumption and the anti-smog mask for defense against pollution. This allocation is subject to a binding budget constraint, leading to the following optimization problem:

$$\max U(x,h) = x + u\big(h(m,PD)\big)$$
$$\text{s.t.} W = x + p_m \cdot m \quad (3),$$

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 to either wear or not wear the mask in the heavily polluted environment to maximize the utility. When the utility of the wearing state, denoted as $U_{m=1}$, is higher than that of the non-wearing state, denoted as $U_{m=0}$, wearing the mask indicates a utility improvement, which can be expressed as follows:

$$U_{m=1} - U_{m=0} > 0 \Rightarrow -p_m + u\big(h(1,PD)\big) - u\big(h(0,PD)\big) > 0 \quad (4).$$

The comparative static exercise indicates that:

$$\frac{\partial(U_{m=1}-U_{m=0})}{\partial PD} = \underbrace{-\frac{\partial p_m}{\partial PD}}_{>0,\text{search cost effect}} + \underbrace{\frac{\partial u}{\partial h} \cdot \frac{\partial h}{\partial PD}}_{>0,\text{information effect}} \quad (5),$$

and leads to the following propositions to be empirically examined:

Proposition 1. An increase in the pharmacy density raises the probability of residents wearing masks during severe air pollution episodes.

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

3. Data

Our data consist of three parts. The first part is residents' perceptions of air pollution and defensive behaviors on polluted days, as well as their individual and household characteristics. This data were collected through a face-to-face survey conducted in Shenyang in 2018. Shenyang is the capital of Liaoning Province, located in Northeast China, known for its developed heavy industry and long-standing severe air pollution. We used a stratified sampling method to randomly draw 40 neighborhoods from a population of 3,785 neighborhoods in nine urban districts in Shenyang. The number of neighborhoods assigned to each district is determined according to the proportion of their respective populations relative to the total urban population. In each neighborhood, 40 households are randomly selected for interviews, ensuring representation for each age group, half of whom are elders over 65 and half are between 18 and 64 years old. In total, our data include 2,111 households, with 48.18% of respondents being older people. Fig.1 illustrates the spatial distribution of sample neighborhoods.

The second part of our data consists of the distribution of stock pharmacies around sample neighborhoods in 2018. This information was obtained from the points of interest (POI) provided

[6] This assumption guarantees that a rational resident always wears the anti-smog mask once he purchases one.

by four maps- Baidu, AutoNavi, Tencent, and 360 Maps.[7] To ensure accuracy, POIs from these separate map sources are aggregated and deduplicated.[8] In total, we identify 2,712 pharmacies within 2 km of the 40 sample neighborhoods, and the pharmacy density varies sharply across neighborhoods, as shown in Fig.1(a).

The third part of our data was obtained from the list of pharmacies newly opened during 2014-16 from the Shenyang Administration for Market Regulation (SAMR).[9] These newly opened pharmacies are matched with the 40 sample neighborhoods using business registration address information. Out of the 1,347 pharmacies approved to open in Shenyang during that period, 666 of them were located within 2 km of the sample neighborhoods, as illustrated in Fig.1(b).

4. Empirical evidence

4.1 Empirical specification

We use the following specification to analyze the association between pharmacy richness and residents' mask-wearing decisions:[10]

$$m_{ic} = \alpha_0 + \alpha_1 PD\_R_c + \boldsymbol{X}_{ic}\beta + \varepsilon_{ic} \quad (6),$$

where m_{ic} indicates whether resident i in neighborhood c wears the anti-smog mask when going out on a polluted day.[11] The dummy variable m_{ic} takes a value of one if the respondent confirms that a disposable or reusable anti-smog mask is worn, and zero otherwise. PD_R_c represents the pharmacy richness around neighborhood c, defined as the pharmacy density in a circle centered on neighborhood c with a radius of R.[12] We test the sensitivity of the results to radius selection by choosing three different radii: 1 km, 1.5 km, and 2 km. The coefficient α_1 is of primary interest as it indicates the association between pharmacy richness and residents' defensive probability.

$\boldsymbol{X}_{ic}$ 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.[13]

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[7] Baidu, AutoNavi, Tencent, and 360 Maps are leading mobile mapping applications in China. Similar to Google Maps, they provide coordinates of POI, business survival status, and other information. According to a research report by iiMedia, Baidu Maps held a market share of 33.8% in China in 2017, with 32.9% of AutoNavi Maps and 14.7% of Tencent Maps (See: https://www.iimedia.cn/c400/60970.html). This pattern remained consistent even in 2019 (https://www.qianzhan.com/analyst/detail/220/190925-cff7088a.html). Although 360 Maps possesses a more specialized user base, we utilized it to cross-validate with other maps to ensure the precision of our pharmacy density measure.

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

[9] 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.

[10] Eq.(6) 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.

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

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

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

Standard errors are clustered at the community level to allow for intra-group correlation of residents within the same community.

We first estimate Eq.(6) using a linear probability model (LPM). Nevertheless, the explanatory variables PD_R_c could be endogenous. For example, neighborhoods with residents more concerned about air pollution may call for more offline healthcare resources, reversely leading to the expansion of pharmacies. If that, LPM estimations may yield an inconsistent estimate of α_1. We then construct instrument variables (IVs) for PD_R_c by calculating pharmacy density based on the distribution of newly opened pharmacies during 2014-2016, the phase before our survey time. [14] These pre-determined pharmacies decide their locations according to residents' prevailing demand, and pharmacy distribution is negligibly related to air quality in the early stage since air pollution problems were not widely recognized then. We provide more evidence to support the validity of our IVs in Section 4.2. For models incorporating IVs, we employ the 2SLS approach to estimate α_1.

4.2 Baseline results

Columns (1)-(3) of Table 1 report the LPM results for Eq.(6), 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)). We also estimate Eq.(6) employing a Probit model, and the marginal effects of pharmacy density reported in Table A2 are very close to the results in Table 1.

The largest concern about the baseline results is that the pharmacy density calculated by stock pharmacies in 2018 may be endogenous, thereby biasing the estimates. We use the pre-determined newly opened pharmacies to construct IVs for identification, and check the validity of IVs through the following methods. Firstly, as shown in Fig.1, the distribution of pharmacies opened during 2014-2016 is highly spatially correlated with that of stock pharmacies in 2018, which reflects the relevance of our IVs. Table A3 presents the first stage results of 2SLS, where IVs are statistically significantly correlated with explanatory variables. Moreover, all types of statistics are large enough to reject that our IVs are weak. Secondly, we examine whether the deployment of pre-determined pharmacies is induced by deteriorating air quality, which violates the exogeneity requirement of IVs. In Fig.S1, we do not observe a positive correlation between AQI and the frequency of pharmacy openings. As described in Supplementary Analysis, we further rule out that air quality was statistically significantly associated with pharmacy deployment during 2014-2016. Therefore, the opening of pre-determined pharmacies is, associated with pharmacies in later years through their business status, and is not induced by deteriorating air and residents' demand for anti-smog masks. One fact also deepens our understanding of the validity of our IVs. China implemented a national standard for masks that are protective against fine particulate matter in November 2016, a point near the end of our period to construct IVs.[15] While before that, residents knew less about which kind

[14] 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.

[15] This standard file is Technical Specification of Daily Protective Mask.
See: https://openstd.samr.gov.cn/bzgk/gb/newGbInfo?hcno=96C74EE21B892F77AA3918F92BB6558F.

of masks are effective in defending against particulates, and the expansion of pharmacies could hardly be attributed to residents' demand for protective equipment. Lastly, we perform the reduced-form analysis by using IVs as explanatory variables. As shown in Table A4, the effects of pre-determined pharmacies on defensive adoption are slightly larger than the results in Table 1.

We report the results of the second stage of 2SLS estimates in Table 1, and the results of IV-Probit estimates are reported in Table A5. 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 Table 1,[16] which indicate that positive effects of pharmacy richness systematically appear in the elderly over 65, while for younger residents, the 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 Channels

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[17]. 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.

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.

Therefore, we confirm that both the search cost and information effect play a channeling 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 the distribution of offline healthcare resources, policymakers can improve the health outcomes of the elderly and narrow pollution avoidance inequality.

[16] The results of the Probit and IV-Probit estimates of age heterogeneity are reported in Tables A2 and A5.
[17] The LPM results are reported in Table A6.

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 adopting other defensive behaviors.

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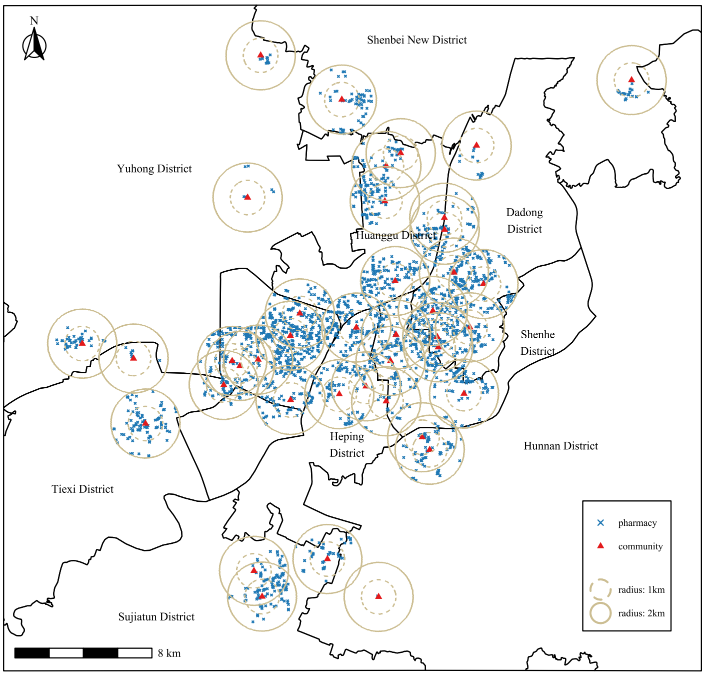
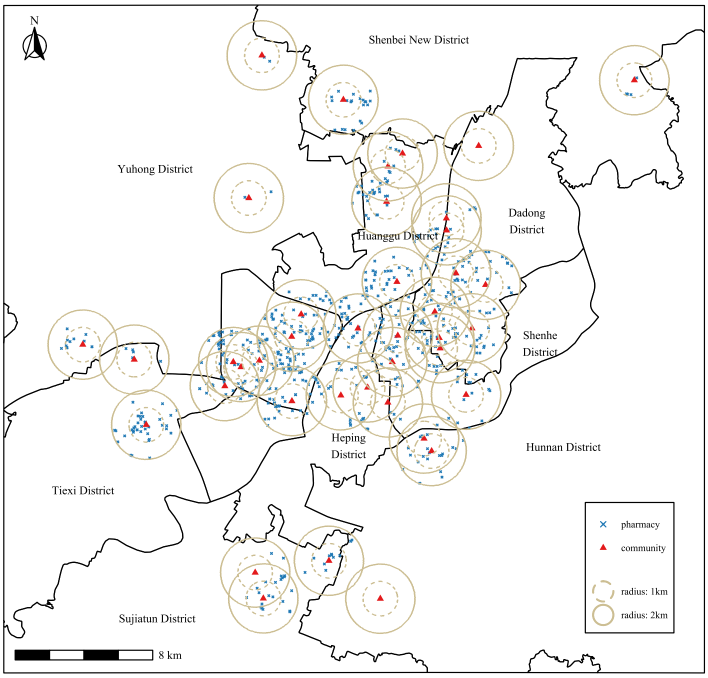
Figures and Tables



(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

Channels: 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

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

Online Appendix

Appendix Tables

Supplementary Analysis: The relationship between air quality and pharmacy deployments during 2014-2016

Appendix Tables

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
Channel 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: 1=Yes, 0=No	0.84	0.370	0	1	1
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. Effects of pharmacy density and age heterogeneity: Probit results.

Outcome variable:	Probit			Probit		
Wearing the anti-smog	(1)	(2)	(3)	(4)	(5)	(6)
mask	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm	0.0076***	0.0079***	0.0085***			
	(0.0025)	(0.0023)	(0.0022)			
PD_Rkm***1**(age<40)				0.0053	0.0065	0.0082**
				(0.0044)	(0.0041)	(0.0039)
PD_Rkm***1**(age∈[40,50))				0.0068	0.0069	0.0082
				(0.0049)	(0.0050)	(0.0051)
PD_Rkm***1**(age∈[50,55))				0.0093**	0.0102**	0.0123***
				(0.0039)	(0.0042)	(0.0042)
PD_Rkm***1**(age∈[55,60))				0.0063*	0.0057	0.0055
				(0.0037)	(0.0037)	(0.0038)
PD_Rkm***1**(age∈[60,65))				0.0127***	0.0128***	0.0136***
				(0.0030)	(0.0028)	(0.0028)
PD_Rkm***1**(age∈[65,70))				0.0066***	0.0072***	0.0075***
				(0.0024)	(0.0023)	(0.0023)
PD_Rkm***1**(age≥70))				0.0040	0.0047*	0.0052**
				(0.0025)	(0.0026)	(0.0026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.0487	0.0491	0.0495	0.0430	0.0437	0.0444

Notes: N=2,111 for all columns; The results are estimated by a Probit model, with marginal effects reported; Individual and household characteristics and survey day dummies are controlled for. 1(age∈groupi) 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 A3. First stage results of IV estimation.

Outcome variable: PD_Rkm	first-stage of 2SLS		
	(1)	(2)	(3)
	R=1km	R=1.5km	R=2km
PD_1km_IV	2.7146***		
	(0.5454)		
PD_1.5km_IV		1.3807***	
		(0.1534)	
PD_2km_IV			0.8294***
			(0.0725)
Controls	Yes	Yes	Yes
Kleibergen-Paap rk LM statistic	13.151***	17.227***	17.329***
Cragg-Donald Wald F	2136.323	5187.265	7243.604
Kleibergen-Paap rk Wald F	24.775	80.988	130.882

Notes: N=2,111 for all columns; *PD_Rkm_IV* represents the pharmacy density around neighborhoods in a circle with a radius of *R*, calculated by pre-determined newly opened pharmacies during 2014-2016; *PD_Rkm* represents the pharmacy density around neighborhoods in a circle with a radius of *R* calculated by stock pharmacies in 2018; The Stock-Yogo weak ID test critical value under 10% maximal IV size is 16.38 for all columns; Individual and household characteristics and survey day dummies are controlled for; Standard errors in parentheses are clustered at the community level; *** p<0.01, ** p<0.05, * p<0.1

Table A4. Reduced-form results of instrumental variables.

Outcome variable: Wearing the anti-smog mask	LPM			LPM		
	(1)	(2)	(3)	(4)	(5)	(6)
	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm_IV	0.0280***	0.0136***	0.0081***			
	(0.0094)	(0.0039)	(0.0021)			
PD_Rkm_IV***1**(age<40)				0.0066	0.0117	0.0070
				(0.0259)	(0.0087)	(0.0050)
PD_Rkm_IV***1**(age∈[40,50))				0.0316	0.0139	0.0065
				(0.0257)	(0.0104)	(0.0062)
PD_Rkm_IV***1**(age∈[50,55))				0.0323	0.0157	0.0145**
				(0.0247)	(0.0111)	(0.0066)
PD_Rkm_IV***1**(age∈[55,60))				0.0240	0.0102	0.0065
				(0.0199)	(0.0097)	(0.0056)
PD_Rkm_IV***1**(age∈[60,65))				0.0340*	0.0124	0.0078
				(0.0179)	(0.0079)	(0.0053)
PD_Rkm_IV***1**(age∈[65,70))				0.0245**	0.0124**	0.0055
				(0.0109)	(0.0055)	(0.0033)
PD_Rkm_IV***1**(age≥70))				0.0224*	0.0137***	0.0080***
				(0.0123)	(0.0041)	(0.0022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0483	0.0500	0.0498	0.0564	0.0576	0.0581

Notes: N=2,111 for all columns; *PD_Rkm_IV* represents the pharmacy density around neighborhoods in a circle with a radius of *R*, calculated by pre-determined newly opened pharmacies during 2014-2016; IV-Probit models are estimated by the maximum likelihood estimation method; Individual and household characteristics and survey day dummies are controlled for. 1(age∈groupi) 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 A5. Effects of pharmacy density and age heterogeneity: IV-Probit results.

Outcome variable:	IV-Probit			IV-Probit		
Wearing the anti-smog	(1)	(2)	(3)	(4)	(5)	(6)
mask	R=1km	R=1.5km	R=2km	R=1km	R=1.5km	R=2km
PD_Rkm	0.0281**	0.0269***	0.0269***			
	(0.0120)	(0.0080)	(0.0071)			
PD_Rkm***1**(age<40)				0.0097	0.0234	0.0226
				(0.0192)	(0.0153)	(0.0140)
PD_Rkm***1**(age∈[40,50))				0.0304	0.0282	0.0211
				(0.0218)	(0.0192)	(0.0173)
PD_Rkm***1**(age∈[50,55))				0.0295	0.0300	0.0453**
				(0.0194)	(0.0203)	(0.0211)
PD_Rkm***1**(age∈[55,60))				0.0260	0.0208	0.0220
				(0.0206)	(0.0170)	(0.0169)
PD_Rkm***1**(age∈[60,65))				0.0327	0.0229*	0.0253*
				(0.0205)	(0.0130)	(0.0152)
PD_Rkm***1**(age∈[65,70))				0.0263*	0.0246**	0.0185*
				(0.0140)	(0.0106)	(0.0099)
PD_Rkm***1**(age≥70))				0.0233*	0.0287***	0.0285***
				(0.0129)	(0.0100)	(0.0089)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: N=2,111 for all columns; The results are estimated by an IV-Probit model, with marginal effects reported; Pharmacy density in 2018 is instrumented by pre-determined newly opened pharmacies during 2014-2016; IV-Probit models are estimated by the maximum likelihood estimation method; Individual and household characteristics and survey day dummies are controlled for. 1(age∈groupi) 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 A6. Channel analysis: LPM results.

Outcome variable	Purchase anti-smog masks through pharmacies: 1=Yes, 0=No			Wearing anti-smog masks can reduce health damage from air pollution: 1=Yes, 0=No		
	(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: 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

Supplementary Analysis: The relationship between air quality and pharmacy deployments during 2014-2016

The validity of instrumental variable identification requires that IVs are only correlated with the explanatory variable and do not link to the explained variable through other channels. In this section, we examine whether newly opening pharmacies during 2014-2016 are related to air quality. If so, the deployment of pharmacies during the period we pick to construct IVs may be induced by deteriorating air quality and residents' appeals for offline healthcare resources, thereby is not only related to pharmacy density in 2018 through business survival status.

We obtain the opening date, location, and name of each newly opened pharmacy during 2014-2016 from the Shenyang Administration for Market Regulation (SAMR), and compile the data to the district-month level to obtain the variable named the number of newly opened pharmacies. We also obtain the district-month level air quality index (AQI) variable from the China National Environmental Monitoring Center[1], which is a comprehensive measure of air quality. Since the air quality monitoring data were not released before April 2014, our data include observations for nine districts in Shenyang City from May 2014 to December 2016.

We first merge these two parts of data and plot the association between AQI and the frequency of pharmacy openings in Figure S1. The fit line presents a downward trend, implying a worse air quality (a larger AQI) is associated with fewer establishment pharmacies. This relationship gives us an initial intuition that deteriorating air does not prompt more offline pharmacy establishments.

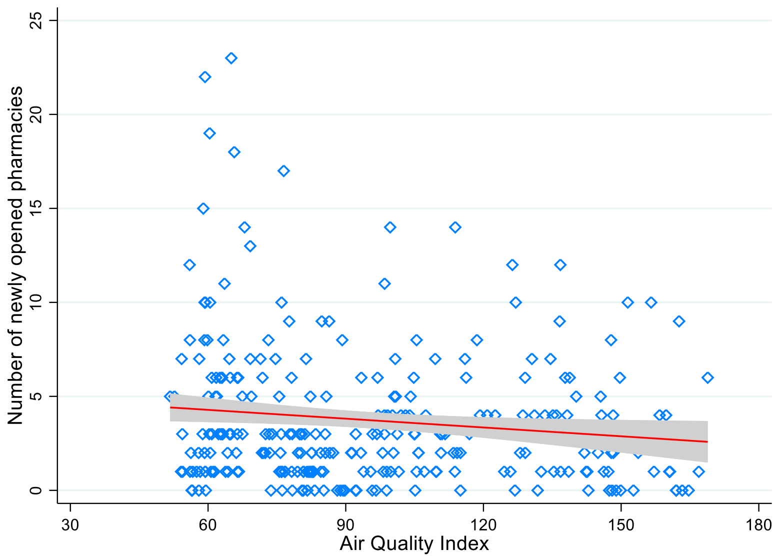


Figure S1. The correlation between AQI and frequency of newly opened pharmacies.

Notes: The observations are at the district-by-month-by-year level during 2014-2016; The blue diamonds constitute the scatterplot which describes the relationship between AQI and the number of newly opened pharmacies; The red line represents their linear fit, and the grey shaded area represents a 95% confidence interval.

We formally examine the relationship between air quality and the number of newly opened pharmacies by applying econometric analysis. To control for confounders that may simultaneously be related to AQI and pharmacy deployments, we collect district-year level control variables from

[1] The air quality data are available at: https://air.cnemc.cn:18007/.

Shenyang Statistical Yearbook 2015-2017. These variables include the ratio of value-added of the secondary industry to GDP (in percent), total population at the end of the year (in 10,000 people), and GDP per capita (in 10,000 Chinese Yuan per person).

We conduct the analysis by exploiting a district-by-month-by-year panel, and flexibly controlling for year and district fixed effects. The results are reported in Table S1. In column (1), we add no control variables, and find AQI is negatively correlated with the frequency of pharmacy openings, but only marginally statistically significant. The correlation does not change after we add district-year controls, as shown in column (3). However, once we control for monthly time trends common for all districts, as shown in columns (2) and (4), the coefficients of AQI are no longer significant. To address concerns that the results in columns (1)-(4) may be influenced by a large number of records with no newly-opened pharmacies, as illustrated in Figure S1, we exclude these observations from further analysis. Column (5) indicates that air quality is not statistically significantly correlated with pharmacy openings at the intensive margin, and the results still hold when we use the log of pharmacy openings as the explanatory variable, as presented in column (6).

In summary, these results suggest that air quality was not significantly, or at least not positively, associated with pharmacy deployments during the period of 2014-2016, which further reinforces the validity of our IVs.

Table S1. The association between AQI and the number of newly opened pharmacies.

Outcomes	number of newly opening pharmacies					log(# new pharmacies)
	(1)	(2)	(3)	(4)	(5)	(6)
AQI	-0.0127*	-0.0049	-0.0127*	-0.0047	-0.0120	-0.0011
	(0.0059)	(0.0072)	(0.0060)	(0.0072)	(0.0072)	(0.0014)
ratio of secondary industry			1.5115	1.6246	3.7389	1.0731
			(4.0435)	(4.2025)	(2.8546)	(0.7755)
population			0.0042	0.0009	0.0379	0.0186*
			(0.0692)	(0.0687)	(0.0604)	(0.0086)
GDP per capita			-0.2919	-0.2991	-0.3220*	-0.0396
			(0.2337)	(0.2458)	(0.1719)	(0.0380)
Year fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	NO	YES	NO	YES	NO	NO
District fixed effects	YES	YES	YES	YES	YES	YES
Observations	288	288	288	288	253	253
R^2	0.3752	0.5016	0.3785	0.5049	0.3535	0.3519

Notes: The observations are at the district-by-month-by-year level during 2014-2016; Standard errors in parentheses are clustered at the district level; *** p<0.01, ** p<0.05, * p<0.1