AIR POLLUTION, HEALTH IMPACT AND WILLINGNESS TO PAY FOR CLEAN AIR IN CHINA

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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May 2017

ABSTRACT

Understanding the health impact of air pollution is critical for understanding the benefit of environmental regulations. While there is a rich literature from epidemiology and economics that quantify the mortality risk of air pollution, the morbidity impact of air pollution especially in developing countries is not well understood. This paper examines both the short- and long-term impacts of $PM_{2.5}$ on morbidity based on daily card spending in hospitals and drugstores in nearly 300 cities. To address the potential endogeneity in air pollution, we construct an IV by leveraging the spatial spillovers of air pollution due to long-range transport. Our analysis shows that $PM_{2.5}$ has significant impacts on health spending in both short term (within a week) and longer term (within three months). A reduction of 10 μg/m^3 in daily $PM_{2.5}$ could lead to a total annual savings of at least 75 billion *yuan* ($11 billion) in health spending in China.

BIOGRAPHICAL SKETCH

Deyu Rao was born in Jining, an inland industrial city in China. Living next door to a coal-fired power plant throughout his childhood, Deyu's experience has nurtured his interest in environmental and energy issues. Before coming to Cornell, he completed his undergraduate degree in Renmin University in 2015, majoring in energy economics.

ACKNOWLEDGEMENTS

I would like to thank my family for their enormous support through my master's study. I wish to express my sincere gratitude to my advisors, Prof. Shanjun Li and Prof. Panle Jia Barwick, for their guidance and wisdom throughout the project.

I would also like to thank my colleagues Nahim, Jianwei, and Yuanning for tolerating and helping me explore my random ideas. I would like to thank Justin, Jason, Jade, Bingyi, Whisky, and other members of the cohort, for the energy they brought to my life.

I would like to thank Chinese Scholarship Council for their financial support.

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CHAPTER 1

INTRODUCTION

Air quality regulation is a prominent example where continued scientific research informs and improves government policies. A rich literature from epidemiology and more recently economics has consistently shown a positive association between exposure to air pollution such as particulate matter and carbon monoxide and mortality. These findings have provided guidance on air quality regulations such as setting up or tightening ambient air quality standards. For example, research on the health impacts of particulate matter has led the U.S. Environmental Protection Agency (EPA) to establish a standard for PM_{10} in 1987 and for $PM_{2.5}$ in 1997 [Dockery, 2009].

There is a growing literature in economics that tries to better establish the causality by using the quasi-experimental methods to mimic random assignment of pollution exposure. The literature have shown significant impacts of air pollution on mortality [Chay and Greenstone, 2003, Currie and Neidell, 2005, Currie and Walker, 2011, Knittel et al., 2015] and contemporaneous health [Neidell, 2004, Moretti and Neidell, 2011, Schlenker and Walker, 2015], with the impact being much larger than the results from the analysis without addressing the issue of endogeneity. The literature has mainly focused on mortality risk in particular infant mortality in the U.S. and Europe. This begs the question of external validity of the estimated dose-response relations which are routinely used as inputs for developing and evaluating environmental regulations in developing countries [Arceo et al., 2015].

This paper examines the impact of $PM_{2.5}$ on health spending in China by combining hourly air pollution readings from all monitoring stations from 2013 to 2015 and the universe of credit/debit card transactions in China during the same period. In doing so, we provide the first comprehensive analysis of air pollution on medical expenditures from all medical conditions for the entire population in a developing country context. The key empirical challenge is the potential endogeneity in the key regressor $PM_{2.5}$ used to capture pollution exposure. The endogeneity can be due to multiple sources including measurement error, avoidance behavior, and unobservables. We construct an instrument by leveraging spatial spillovers of $PM_{2.5}$ due to the long-range transport while taking into account wind direction and speed. The level of $PM_{2.5}$ in a given city is predicted based on $PM_{2.5}$ concentration in cities of upwind directions in the same spirit of the source-receptor matrix in the atmospheric science literature to predict air quality. To address the concern of spatial correlation in unobservables such as economic activities, we create a buffer zone of 200 km and our results are robust to the size of the buffer zone.

Based on daily health spending by city, the OLS analysis with a rich set of temporal and location fixed effects suggest that an increase of 10 μg/m3 in $PM_{2.5}$ concentration is associated with a 0.19% increase in the total number of hospital and pharmacy transactions in the immediate short term (within a week) and 0.83% in the longer term (within 3 months). The spending increases in pharmacies and children's hospitals are around 0.32% and 0.24% in the short term, larger than spendings at other types of medical facilities. The results from IV analysis show much stronger impacts: an increase of 10 μg/m3 in $PM_{2.5}$ concentration would lead to a 0.31% increase in the total number of hospital and pharmacy transactions in the short term and a 2.74% increase in the longer term. The long-term impact implies that a reduction of 10 $\mu g/m^3$ in daily $PM_{2.5}$ could lead to a total annual savings of at least 75 billion *yuan* ($11 billion) in health spending in China. Falsification tests show that while an increase in $PM_{2.5}$ would lead to a modest reduction in spending on necessities and in supermarkets during the same day, likely due to avoidance behavior, there is no long-term impact on either type of transactions.

This study makes the following contributions to the literature. First, the paper adds to the nascent literature on estimating the health impact of air pollution in a developing country context [Arceo et al., 2015, Chen et al., 2013, Greenstone and Hanna, 2014, He et al., 2016]. Due to increased pressure from economic development and lax environmental regulations, developing countries and especially emerging economies such as China and India are experiencing the worst air pollution in the world. This is especially concerning given the size of population and the lack of access to adequate health care in these countries. While policy makers are increasingly aware of the negative impacts of air pollution on human health and the quality of life, and are adopting environmental regulations to address the issue, there is a lack of systematic evidence of the benefit of environmental regulations in these countries. A common practice for quantifying the benefit of environmental regulations in developing countries is to take the dose-response function estimated in developed countries, mostly the U.S., to interpolate the mortality or morbidity impact from (reduced) air pollution, for example, in Lelieveld et al. [2015] and World Bank [2007]. This benefit transfer approach is subject to criticism given the differences in the levels of air pollution, baseline health conditions and susceptibility between these two groups of countries.

Second, this study contributes to the growing literature on estimating consumer willingness to pay (WTP) for improved air quality based on medical expenditures [Deschenes et al., 2016, Williams and Phaneuf, 2016]. Consumer WTP estimates for improved air quality, expressed in monetary terms, can be used directly to calculate the benefit of environmental regulations. This is in contrast with the aforementioned literature based on health outcomes which would need to translate the reduced mortality or morbidity into monetary terms using concepts such as the Value of a Statistical Life (VSL).[1] The traditional approach to estimate consumer WTP for improved air quality is based on the

[1] Although there is a rich literature on estimating VSL in the US, there are very limited studies on VSL in developing countries [Viscusi and Aldy, 2003].

revealed preference method that infers consumer WTP based on real-world consumer choice data such as housing and consumer products [Chay and Greenstone, 2005, Bayer et al., 2009, Ito and Zhang, 2016]. Based on the utility maximization framework, this approach typically needs to invoke behavioral assumptions such as rationality and perfect information to infer consumer WTP. Different from the revealed preference literature, the studies using health spending data including this paper can provide a lower bound for consumer WTP without relying on these behavioral and modeling assumptions.

Third, the rich spatial and temporal variations in our data allow us to examine both the short- and longer-term impacts of air pollution on health spending. To deal with high serial correlations in daily air pollution measures which would render a model with many lags of air pollution unstable, we apply polynomial distributed lag model known as the Almon technique that uses finite order polynomials to capture the effects of long lags [Almon, 1965]. We adapt this technique to the instrumental variable framework to address the potential endogeneity in contemporaneous and lagged air pollution measures. To our knowledge, this is the first analysis in this literature to apply this type of technique to capture the long-term impacts using more frequent data than quarterly or annual data typically used in the literature.

The rest of the paper is organized as follows. Section 2 describes the data and the air pollution challenge in China. Section 3 discusses our empirical framework to examine both the short- and longer-term impacts and the identification strategy. Section 4 presents empirical results while Section 5 discusses our findings in relation to the literature. Section 6 concludes.

CHAPTER 2

DATA

We gather three comprehensive datasets at the national level on air pollution, health spending and meteorology conditions. Collectively, they form a daily city-level panel for more than 300 major Chinese cities during 2013 to 2015. This enables us to evaluate the health impacts of air pollution in both the short- and longer term, as well as possible heterogeneity across subgroups. Details on the datasets are provided below.

2.1 Air Pollution

For nearly four decades, China has maintained its GDP growth at an annual rate of nearly 10%. The economy has transformed from an agricultural economy to a manufacturing-dominated economy. China became the world's largest exporter of goods in 2009 and the largest trading nation in 2013. The unprecedented economic growth is largely propelled by fossil fuel, with coal accounting for about two-thirds of energy consumption and oil nearly 20%. China is by far the largest energy consumer, accounting for nearly a quarter of world's total energy consumption and half of world's coal consumption. As the vehicle ownership increases from 2.4 million in new vehicle sales in 2001 to over 28 million in 2016, oil consumption has risen dramatically, now accounting for nearly 20% of total energy consumption in China. The economic growth has put an enormous pressure on the environment and air, water and soil pollution has become serious challenges that adversely affect human health, ecosystems, and the quality of life.[1]

[1] Lelieveld et al. [2015] estimate that air pollution led to 1.3 million premature deaths in China in 2010, accounting for 40% of the world total premature deaths in that year. World Bank (2007) puts the health cost of air pollution at 1.2-3.8% of GDP in 2003.

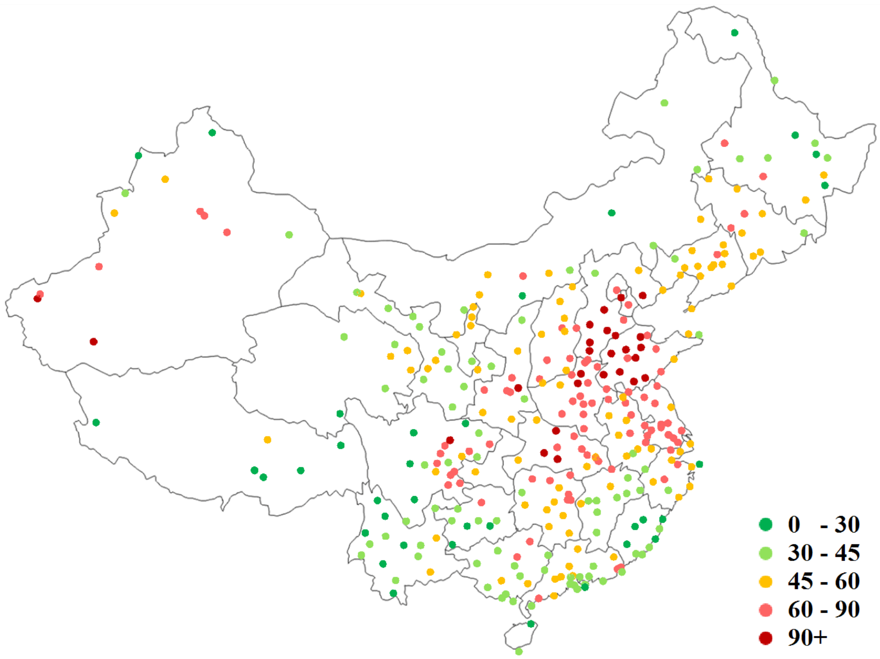


Figure 2.1: Three-Year Average $PM_{2.5}$ Concentration
2013 - 2015, $\mu g/m^3$

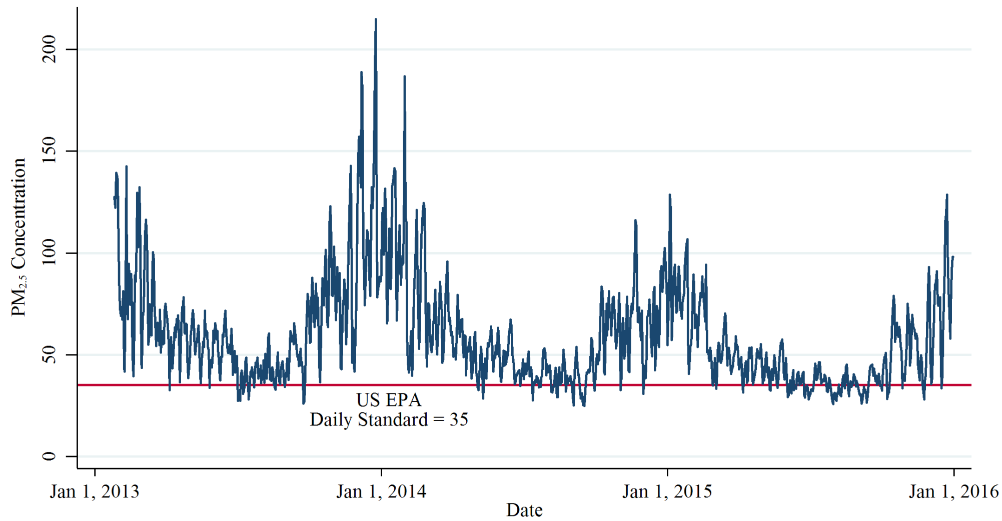
We construct daily measures of air quality from hourly observations published by the Ministry of Environmental Protection (MEP) in China. The dataset covers 1003 stations in 159 cities in 2013, 1055 stations in 190 cities in 2014, and 1582 stations in 367 cities in 2015. Daily $PM_{2.5}$ concentration is calculated for each city by averaging data across monitoring stations within the city. Figure 2.1 maps the three-year average level of $PM_{2.5}$ for each city from 2013 to 2015. Nationwide average during the period is around 56 $\mu g/m^3$, with a standard error of 46. Air quality for most cities are substantially worse than the annual standard by the US EPA (12 $\mu g/m^3$) or by China MEP (35 $\mu g/m^3$). The annual concentration in many large population centers in northern and central China exceeds 90 $\mu g/m^3$. There is considerable regional disparity in air quality with cities in the north and central china where heavy-polluting industries are clustered suffering the most severe pollution. The less-developed region in the west and the most developed region in the south have better air quality. In the recent years, the southern region along the coast has relocated the heavy polluting industries to the north and west and instead focused on the development of high tech industries.

Figure 2.2 depicts the daily concentration during our data period for the nation (the top panel) and each of four regions (the bottom panel). The daily standard of 35 μg/m^3 by the US EPA is violated on the most days in all four regions. The regional heterogeneity is also clearly displayed where the southern region (the bottom right) has considerable better air quality than the other three regions. Figure 2.2 also shows the temporal pattern in $PM_{2.5}$ concentration: pollution peaks in every winter due to winter heating. Coal-fired central heating systems in cities north of Huai River is a main source of pollution for winter days [Chen et al., 2013]. During the data period, the pollution level is trending downwards in all regions although the regional average of $PM_{2.5}$ concentration is still rarely below the standard even in 2015.

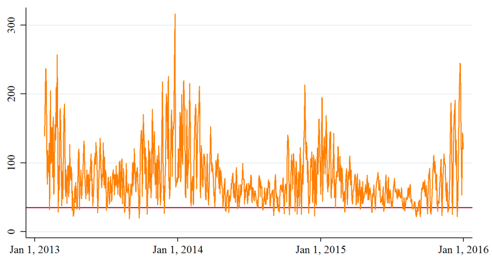
2.2 Health Spending Data

The health spending dataset contains the universe of credit and debit card transactions settled through the UnionPay network, the only interbank payment network in China. The universe of transactions are for 2.7 billion cards from 2011 to 2015 across over 300 merchant categories. For each transaction, we observe the location, time, and value of the transaction, and they are collapsed to a daily city-level panel. In our study, we focus on transactions in the healthcare industry, including hospitals, pharmacies, and other health service providers.

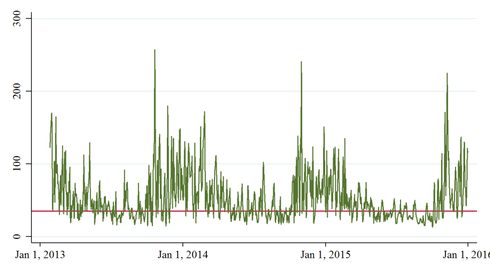
The credit/debit transactions accounted for about 31% of total out-of-pocket healthcare spending in 2013, and as the card penetration rises, the coverage rose to 51% in 2015. This is consistent with the official statistics from Central Bank of China [2015]



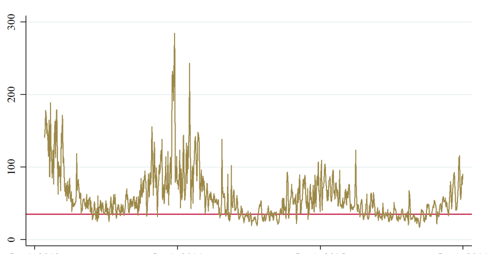
(a) Northern Region



(b) Northeastern Region



(c) Northwestern Region



(d) Southern Region

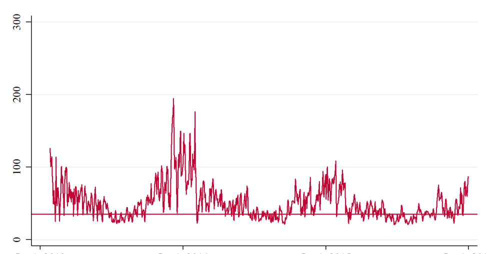


Figure 2.2: Daily $PM_{2.5}$ Concentration
Jan. 2013 - Dec. 2015
National & Regional Averages, $\mu g/m^3$

Notes: Red line in all subfigures indicates the daily standard set by US EPA: 35 $\mu g/m^3$.

that transactions from credit/debit cards accounted for more than 48% of overall expenditures in the third quarter of 2015. In the U.S., the share of spending from credit/debit cards was 57% [Bagnall et al., 2014]. One potential concern is the coverage provided by health insurances and government-provided medicare. For the Chinese *Medicare* program, medical expenses are directly billed on *Medicare* cards, most of which are settled through the UnionPay network, and enter the database as regular transactions. For commercial insurances, it is a common practice to have the patient billed first, and refunded by insurance companies later. In either cases, as long as the use of non-card payments are not systematically biased towards more polluting days (or less polluting days), consumption by Unionpay cards should be a good proxy for consumer health expenditure. For health expenditure, data is aggregated from the whole universe of transactions, but due to the size of the data set (about 100 GB for each day), our analysis on the control groups is based on a 1% card sample.[2] Tests are done by comparing health expenditure in the universe and the 1% card sample, in order to confirm its representativeness.

We analyze five categories of transactions for health spending (total health spending, hospitals, pharmacies, Renmin hospitals and children's hospitals) and two other categories (daily necessities and supermarket). Total health spending includes transactions at all hospitals, pharmacies, and other healthcare facilities (e.g. small health clinics). We separate hospitals and pharmacies from other healthcare facilities. In 2015, hospitals account for 83.5% of total health spending in our data, and 56.8% of transactions. Different from pharmacies in the U.S. such as Rite-Aid, most pharmacies in China only carry medicine and it is not common for pharmacies to sell daily necessities. Pharmacies account for 6.0% of total healthcare spending, and 31.0% of transactions in 2015. Within hospitals, we distinguish Renmin (or *people* by literal meaning) hospitals

[2]This sample includes all transactions for the randomly selected 1% of the cards. Cards included are stratified according to the month they first enter the database: for each month, 1% of cards that made their first transaction are randomly selected into the sample.

and children's hospitals from other hospitals. Renmin hospitals are state-owned general hospitals and tend to be the largest health care facilities in a city. There exists at least one Renmin hospital in each city. Children's hospitals in China accepts exclusively children as their patients. Birth centers and infant health centers are also included to account for the impact on infants. These two types of hospitals account for 24.1% and 4.2% of total health spending respectively, and 26.2% and 9.0% of total number of transactions in 2015.[3]

To implement falsification tests and examine avoidance behavior, we also analyze spending on daily necessities and in supermarkets. We define necessities based on United Nations' Classification of Individual Consumption According to Purpose (COICOP). Categories 01 (food and non-alcoholic beverages), 02 (alcoholic beverages, tobacco and narcotics), 03 (clothing and footwear), 09 (recreation and culture), and 11 (restaurants and hotels) are included. Inferring from the 1% sample, the category of daily necessities is more than three times as large as that for health spending in terms of both value and the number of transactions in 2015. In Chinese cities, residents go to supermarkets for groceries on a daily basis. This provides us with another proxy for daily consumption behavior. Spending in supermarket is over four times as large as health spending in value and over five times as large in the number of transactions in 2015.

2.3 Meteorology Data

As weather conditions may directly affect health outcomes [Deschenes et al., 2009], meteorology data is acquired from the Integrated Surface Database (ISD), hosted by Na-

[3] Among these categories, hospitals, pharmacies, necessities and supermarkets are classified directly by their merchant types in the dataset, while Renmin hospitals and children's hospitals are classified according to their names through keyword matching. Therefore, the identification for *Renmin* hospitals and children's hospitals are not exhaustive.

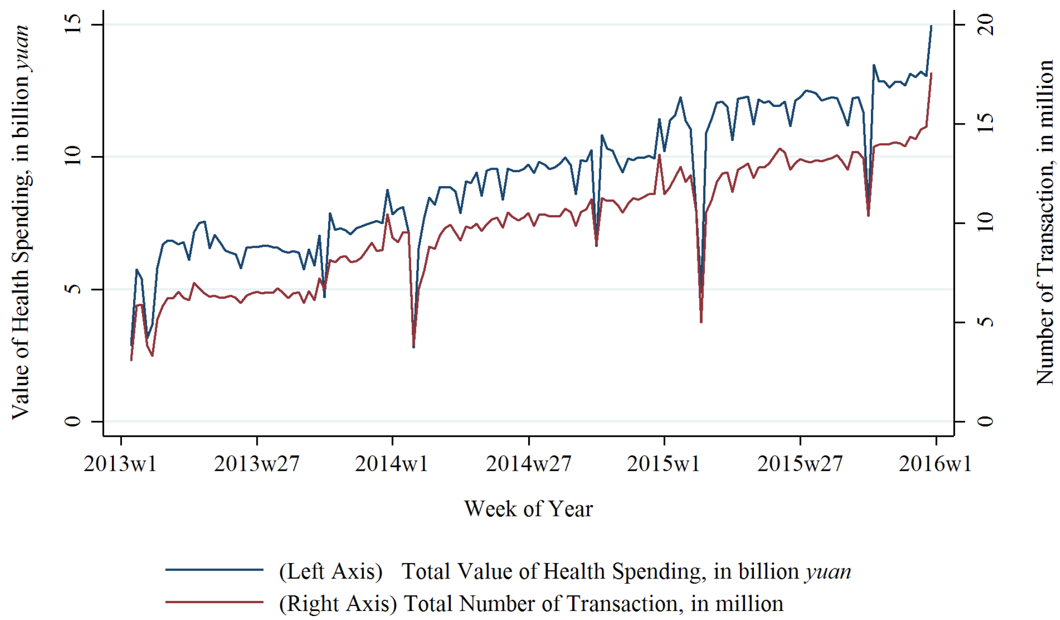


Figure 2.3: National Weekly Healthcare Spending, 2013 - 2015

tional Oceanic and Atmospheric Administration (NOAA). The dataset includes hourly measures of temperature, precipitation, wind speed and wind direction for 407 monitoring stations in China that are in operation during the time period of our study. To match cities with weather stations, a distance matrix is constructed using the geographic coordinates, and weather data from the closest station is then taken as that of the city.

For temperature and wind speed, we take the arithmetic mean from the hourly data as the daily measure. For precipitation, we find that the hourly data from ISD constantly suffers from measurement errors, with very few non-zero observations and possible underreports. Hence, additional daily precipitation data is collected from NOAA's Global Surface Summary of the Day (GSOD) database. Our reluctance of using GSOD as the main source of all other meteorology data originates from the fact that GSOD is summarized from hourly datasets using Greenwich Mean Time. While we have easily corrected for this in the hourly ISD database by a 8-hour lag, it is impossible to do so for GSOD without introducing additional errors. As a result, our daily precipitation data records the rainfall from 8 a.m. of the present day to 8 a.m. the next day. It is further transformed into a dummy variable to indicate rainfall, and included in the analysis as a control. Wind direction of the day is calculated by adding up 24 hourly vectors of wind, with hourly wind speed as the length of each vector[4]. It is later used in our model to account for heterogeneous spillovers from different pollution sources.

The summary statistics for all variables used in our study can be found in Table 2.1. The level of observation is city-day. The average daily $PM_{2.5}$ concentration was 56 $\mu g/m^3$ during 2013 and 2015 with the maximum being 985. The interquartile range was from 27 to 69. Out of the total city-day observations, the concentration level was above the U.S. daily standard of 35 $\mu g/m^3$ in 67% of the sample. The average daily number of transactions related to healthcare was 7,229 and the average spending is about 6.7 million *yuan*, based on the universe of card transactions.

[4] A similar measure of daily wind speed is also calculated, using the length of the summed vector. It is, however, very close to the arithmetic mean.

Table 2.1: Summary Statistics

	Mean	Std. Dev.	Min.	Max.	N
Pollution					
$PM_{2.5}$ Concentration, $\mu g/m^3$	56.33	46.37	0	985.18	198,246
Number of Transactions, Daily					
Healthcare Industry, Total	7,229.22	21,308.68	0	330,974	211,318
All Hospitals	4,122.72	14,503.94	0	237,525	210,539
Renmin Hospitals	1,060.60	2,800.44	0	40,332	203,407
Children's Hospitals	464.77	1,290.53	0	18,227	158,637
Pharmacies	2,245.33	7,063.37	0	96,336	210,001
Control Groups, *from 1% card sample*					
Daily Necessities	233.37	628.63	0	10,865	211,318
Supermarkets	393.44	990.30	0	15,224	210,493
Total Value of Transactions, Daily, *thousand yuan*					
Healthcare Industry, Total	6,701.80	17,818.97	0	301,108.70	211,318
All Hospitals	5,556.58	15,066.80	0	275,883.00	210,539
Renmin Hospitals	1,588.13	3,401.29	0	56,856.93	203,407
Children's Hospitals	363.93	843.39	0	10,324.36	158,637
Pharmacies	407.40	1,109.59	0	16,735.16	210,001
Control Groups, *from 1% card sample*					
Daily Necessities	236.93	551.38	0	9,532.49	211,318
Supermarkets	232.88	643.43	0	14,404.73	210,493
Weather					
Mean Temperature, $^{\circ}F$	60.11	18.92	-27.50	101.63	211,317
Percipitation, *inch*	0.13	0.42	0	15.60	211,318
Rain Dummy	0.36	0.48	0	1	211,318
Mean Wind Speed, *mph*	5.50	3.11	0	48.71	211,296
Wind Direction, *navigational bearing*	-	-	0	360	211,263

Notes: Sources of the data are Ministry of Environmental Protection, P. R. China, Integrated Surface Database (ISD), and Global Surface Summary of the Day (GSOD) Database. Data for control groups are calculated for the 1% card sample. Units for variables are displayed in *italics*, if possible. While calculating total value of transaction, transactions with value larger than 200,000 *yuan* ($29,000) are excluded. For wind direction, arithmetic mean and standard deviation do not have statistical meaning, and thus left out in the table.

CHAPTER 3

EMPIRICAL FRAMEWORK

In this section, we first present a parsimonious model that allows us to estimate the short- and long-term impacts of air pollution on health spending. We then discuss our identification strategy and the construction of the instrumental variable.

3.1 Theoretical Model

Air pollution affects human health mainly through its impact on respiratory and cardiovascular systems. Several decades of intense study in the epidemiology and more recently economics has shown an association between exposure to air pollution and increases in mortality and morbidity risks [Brunekreef and Holgate, 2002, Pope and Dockery, 2012]. Our empirical objective is to estimate the impact of exposure to air pollution on health spending. By focusing on health spending rather than health outcomes, our analysis tries to provide a direct measure of consumers WTP for clean air through improved health conditions.

Following a utility maximization framework of health production in Grossman [1972] where consumers chooses health care to alleviate the negative health impact of air pollution exposure, Deschenes et al. [2016] and Williams and Phaneuf [2016] show that the marginal effect of air pollution exposure on total health spending provides a lower bound of consumers WTP for improved air quality.[1] While the literature have largely neglected the role of avoidance and loss in the quality of life, we present a static

[1]Consumers can also engage in other types of defensive spending such as air purifiers or face masks or avoidance behavior such as stay indoors to reduce air pollution exposure. The spending on air purifiers or the lost utility from staying indoor more than otherwise should be part of the consumers WTP for clean air.

model below to account for both.

The problem can be written as

$$\max_{\{m,c_1,c_2\}} U[h, c_1, c_2, e(a, m + c_1)], \tag{3.1}$$

$$\text{s.t. } m + c_1 + c_2 = \bar{y}, \tag{3.2}$$

$$\bar{h} = h_0 + m - e(a, m + c_1), \tag{3.3}$$

where h is the health stock, h_0 is initial health stock, m is medical spending, c_1 is value of offline/outdoor transactions which expose consumers to air pollution, and c_2 is value of online transactions. Exposure $e(a, m+c_1)$ is a function of air quality and consumption offline/outdoors.[2] Income $\bar{y}$ and air quality (pollution level) a are exogenous, and $\bar{h}$ is a preset target health stock.

Health stock and consumption in non-medical categories can bring positive utility to the consumers. Moreover, the quality of life could still deteriorate as a result of exposure, even if health stock h has been fully replenished by medical spending after exposure. Thus, we include exposure e into the utility function U, and the disutility directly caused by exposure captures the loss in the quality of life.

The Lagrangian can be written as

$$\begin{aligned} L = &U[h, c_1, c_2, e(a, m + c_1)] + \lambda[\bar{y} - e(a, m + c_1) - c_1 - c_2 - k], \\ &\text{where } k = \bar{h} - h_0. \end{aligned} \tag{3.4}$$

[2]We assume the exposure from spending \$1 in each category is the same, which will be relaxed in the analysis later. For simplicity, exposure and health stock take a linear functional form and are normalized to dollar units.

And the FOC's are

$$\frac{\partial L}{\partial m} = U_h(\cdot)[1 - e_o(\cdot)] + U_e e_o(\cdot) - \lambda e_o(\cdot) = 0, \tag{3.5}$$
$$\frac{\partial L}{\partial c_1} = U_{c_1}(\cdot) + U_h(\cdot)[-e_o(\cdot)] + U_e e_o(\cdot) - \lambda[1 + e_o(\cdot)] = 0, \tag{3.6}$$
$$\frac{\partial L}{\partial c_2} = U_{c_2}(\cdot) - \lambda = 0, \tag{3.7}$$
$$\frac{\partial L}{\partial \lambda} = \bar{y} - e(a, m + c_1) - c_1 - c_2 - k = 0. \tag{3.8}$$

where U_h, U_{c_1}, U_{c_2} are derivatives of U w.r.t. each component of the utility function, and $e_o(\cdot)$ is the derivative of exposure e w.r.t. offline spending. Later, we denote the derivative of exposure e w.r.t. air pollution as $e_a(\cdot)$.

With the envelop theorem, we have

$$\begin{aligned} \frac{\partial L}{\partial a} &= -U_h e_a + U_e e_a - \lambda e_a \\ &= -e_a(U_h - U_e + \lambda) \\ &= -e_a(U_{c_1} - U_e). \end{aligned} \tag{3.9}$$

This is the marginal disutility brought by a one-unit increase in air pollution level. Then the marginal willingness-to-pay for a one-unit drop in air pollution level can be calculated by normalizing the disutility to the marginal utility of income $\frac{\partial L}{\partial \bar{y}} = \lambda$,

$$MWTP = -\frac{\frac{\partial L}{\partial a}}{\frac{\partial L}{\partial \bar{y}}} = \frac{e_a(U_h - U_e + \lambda)}{\lambda}. \tag{3.10}$$

Since $\bar{h}$ is preset, and $\bar{h} = h_0 + m - e(a, m + c_1)$, we take first derivative w.r.t a, as

$$0 = \frac{\partial m^*}{\partial a} - [e_a(\cdot) + e_o(\cdot)(\frac{\partial m^*}{\partial a} + \frac{\partial c_1^*}{\partial a})] \tag{3.11}$$
$$e_a(\cdot) = \frac{\partial m^*}{\partial a}[1 - e_o(\cdot)] - e_o(\cdot)\frac{\partial c_1^*}{\partial a}. \tag{3.12}$$

From the FOC's, we can derive

$$U_h - U_e + \lambda = \frac{\lambda - U_e}{1 - e_o}. \tag{3.13}$$

Plugging 3.12 and 3.13 into 3.10, we have

$$\begin{aligned} MWTP &= -\frac{\frac{\partial L}{\partial a}}{\frac{\partial L}{\partial \bar{y}}} \\ &= [\frac{\partial m^*}{\partial a} - \frac{e_o}{1-e_o}\frac{\partial c_1^*}{\partial a}](1 - \frac{U_e}{U_2}) \\ &= [\frac{\partial m^*}{\partial a} - \frac{U_{c_1} e_o}{\lambda}\frac{\partial c_1^*}{\partial a}](1 - \frac{U_e}{\lambda}), \end{aligned} \tag{3.14}$$

In Equation 3.14, $\frac{\partial m^*}{\partial a}$ is the response of medical spending to air pollution, and $\frac{\partial c_1^*}{\partial a}$ is the response of outdoor spending to air pollution. Intuitively, $\frac{\partial m^*}{\partial a} > 0$, $\frac{\partial c_1^*}{\partial a} < 0$. We assume $\frac{\partial h}{\partial m} = 1 - e_o(\cdot) > 0$, that is, the benefit from purchasing medicine or receiving medical treatment should outweigh the exposure during the trip. Also, $e_o(\cdot)$ is the marginal exposure of outdoor spending, and $e_o(\cdot) > 0$. And U_e is the marginal disutility of exposure as loss in life quality, and $U_e < 0$.

Equation 3.14 indicates that the marginal willingness-to-pay originates from extra medical spending to compensate for the harm of pollution ($\frac{\partial m^*}{\partial a}$), and additionally, the loss of utility as a result of decreased spending in c_1 to reduce exposure (- $\frac{e_o(\cdot)}{1-e_o(\cdot)}\frac{\partial c_1^*}{\partial a}$). This is then enhanced by consumer's belief that exposure by itself directly worsens the quality of life ($1 - \frac{U_e}{\lambda}$).

Only when the loss in quality of life is unaccounted for ($U_e = 0$) and exposure is not dependent on outdoor spending ($e_o = 0$), then we have $MWTP = \frac{\partial m^*}{\partial a}$.

If we relax the assumptions on the functional form of health stock h,

$$\bar{h} = h_0 + m - e(a; m, c_1, c_2, \cdots, c_r), \tag{3.15}$$

where $c_i (i = 1, \cdots, r)$ are spendings on r non-medical categories which do not affect health in ways other than through exposure, then

$$MWTP = [\frac{\partial m^*}{\partial a} - \frac{1}{1-e_m}\sum_{i=1}^{r} e_{c_i}\frac{\partial c_i^*}{\partial a}](1 - \frac{U_e}{\lambda}), \tag{3.16}$$

and again we have $\frac{\partial m^*}{\partial a}$ as a lower bound for marginal willingness-to-pay.

3.2 Distributed Lag Model and Almon Technique

To estimate the marginal effect of air pollution exposure on health spending, we postulate a distributed lag (DL) model of health spending with pollution exposure in multiple time periods as the key regressors.

Denote c as a city, t as a day and w as a week, the DL model is:

$$y_{ct} = \sum_{i=0}^{k} \beta_i p_{c,t-i} + \mathbf{x}_{ct}\alpha + \kappa_c t + \xi_c + \eta_w + \varepsilon_{ct}, \tag{3.17}$$

where y_{ct} is daily health spending in a city, and $p_{c,t-i}$ is contemporaneous or lagged pollution exposure. β's, the key parameters of interest, capture the short- and long-term impacts of pollution exposure on health spending. $\mathbf{x}_{ct}$ includes a rich set of controls such as weather variables, holiday fixed effects, day-of-week fixed effects, seasonalities, etc. $\kappa_c t$ is city-specific linear time trend, ξ_c is city fixed effect and η_w is week fixed effect. To ease exposition, we assume for a moment that pollution exposure x is observed by researchers but not by consumers. And consumers will seek medical treatment only because of health outcomes. This strong assumption allows us to abstract away measurement error and avoidance behavior, two important identification issues that we will return to in the next section.

If we put the issue of potential endogeneity in $p_{c,t-i}$ aside, the DL model can be estimated using OLS. But due to the high collinearity among $p_{c,t-i}$ especially with a large number of lags, OLS can provide imprecise estimates of β's. To reduce the number of parameters while allowing for potential long-term impact, Almon [1965] proposes a technique where β_i's are assumed to follow a polynomial function of order q. Take $q = 3$

as an example, that is

$$\beta_i = F(i) = \gamma_0 + \gamma_1 i + \gamma_2 i^2 + \gamma_3 i^3. \tag{3.18}$$

Then we can plug (3.18) back into (3.17), and rearrange,

$$\begin{aligned}
y_{ct} &= \sum_{i=0}^{k} \beta_i p_{c,t-i} + \mathbf{x}_{ct}\alpha + \kappa_c t + \xi_c + \eta_w + \varepsilon_{ct} \\
&= \gamma_0 p_{ct} + (\gamma_0 + \gamma_1 + \gamma_2 + \gamma_3) p_{c,t-1} + ... + (\gamma_0 + \gamma_1 i + \gamma_2 i^2 + \gamma_3 i^3) p_{c,t-i} + ... \\
&\quad + (\gamma_0 + \gamma_1 k + \gamma_2 k^2 + \gamma_3 k^3) p_{c,t-k} + \mathbf{x}_{ct}\alpha + \kappa_c t + \xi_c + \eta_w + \varepsilon_{ct} \\
&= \gamma_0 (p_{ct} + p_{c,t-1} + p_{c,t-2} + ... + p_{c,t-k}) \\
&\quad + \gamma_1 (0 \times p_{ct} + 1 \times p_{c,t-1} + 2 p_{c,t-2} + ... + k p_{c,t-k}) \\
&\quad + \gamma_2 (0^2 \times p_{ct} + 1^2 \times p_{c,t-1} + 4 p_{c,t-2} + ... + k^2 p_{c,t-k}) \\
&\quad + \gamma_3 (0^3 \times p_{ct} + 1^3 \times p_{c,t-1} + 8 p_{c,t-2} + ... + k^3 p_{c,t-k}) + \mathbf{x}_{ct}\alpha + \kappa_c t + \xi_c + \eta_w + \varepsilon_{ct}.
\end{aligned} \tag{3.19}$$

With this reformulation, we only need to estimate four coefficients γ's rather than k β's. The four key regressors would be:

$$\begin{aligned}
v_{1t} &= p_{ct} + p_{c,t-1} + p_{c,t-2} + ... + p_{c,t-k}, \\
v_{2t} &= \phantom{p_{ct} + {}} p_{c,t-1} + 2 p_{c,t-2} + ... + k p_{c,t-k}, \\
v_{3t} &= \phantom{p_{ct} + {}} p_{c,t-1} + 4 p_{c,t-2} + ... + k^2 p_{c,t-k}, \\
v_{4t} &= \phantom{p_{ct} + {}} p_{c,t-1} + 8 p_{c,t-2} + ... + k^3 p_{c,t-k}.
\end{aligned} \tag{3.20}$$

Additional restrictions can be applied to the key parameters γ's to further reduce the number of parameters. For example, assuming that pollution exposure from the future (forward one period) does not affect current health spending, then $\gamma_0 - \gamma_1 + \gamma_2 - \gamma_3 = 0$. Assuming that pollution exposure from too far back in time (beyond k lags) does not affect current health spending, $\gamma_0 + (k + 1)\gamma_1 + (k + 1)^2\gamma_2 + (k + 1)^3\gamma_3 = 0$. These assumptions can be applied individually or jointly in the estimation or they can be tested as linear restrictions. Once we impose the number of lags k, the order of polynomials q, and additional conditions on γ's, the estimation can be carried out in OLS and β's can then be calculated based on parameter estimates from OLS.[3]

3.3 Identification

3.3.1 Sources of Endogeneity

There are multiple potential sources of endogeneity in the previous empirical model. The first one is measurement error introduced by the aggregation of pollution data from monitoring stations to the city level. As population may not be evenly distributed within a city across different monitoring stations, the arithmetic mean of pollution levels for all stations within a city may not reflect the true exposure of the population. To illustrate this, consider a city composed of two areas: an urban core with a large population, and a suburban area with a smaller population - each with one monitoring station. An area-specific pollution shock to the urban core should have a larger impact to the city's aggregated health spending than a shock of the same magnitude but only specific to the suburban area. However, these two shocks will be reflected as shocks of the same magnitude to the city average pollution level. The aggregate therefore could introduce classical measurement error which could in turn lead to attenuation bias. Ideally, the aggregation should be a population-weighted average air quality, but this is impractical due to the mismatch between stations and respective administrative areas, and the large

[3]To improve efficiency, Almon [1965] initially proposes a weighting matrix from Weierstrass's Approximation and later Giles develops a simpler but numerically equivalent method, which we adopt in our estimation. See `http://davegiles.blogspot.com/2017/01/explaining-almon-distributed-lag-model.html`.

number of cities included in our study.[4]

The second potential source of endogeneity is avoidance behavior in both the short- and long-term. Consumers in China have increased awareness of air quality and its impact on health. $PM_{2.5}$ readings are easily accessible through cell phone apps or from government websites in recent years.[5] In the short term, during days of bad air pollution, consumers may reduce their outdoor activities, shift the timing of consumption (e.g. postponing visits to hospitals for conditions that are not related to air pollution), or undertake defensive measures such as wearing face masks and using air purifiers indoors [Mu and Zhang, 2016, Ito and Zhang, 2016, Sun et al., 2017]. These types of behavior, in response to contemporaneous air quality variations, could reduce health spending and render the pollution measure endogenous. Long-term air pollution trends could affect migration across cities as documented in the U.S. [Banzhaf and Walsh, 2008]. Consumers who are more vulnerable to air pollution or have a high valuation of clean air would choose to move away from more polluting cities. As a result, air pollution could be correlated with the error term (such as the stock of health status of the residents).

In a relatively short time period as in our data, location fixed effects could control for migration (the avoidance behavior in the long-run). However, the short-run avoidance behavior as responses to contemporaneous air pollution is more challenging to control for with location fixed effects. In addition, it is not obvious how the instrument variable strategy could address this source of endogeneity since this type of avoidance behavior is also direct result of air pollution. Based on spending on other categories such as daily necessities and at supermarkets, our analysis provides evidence of this type of short-term avoidance behavior. This leads us to argue that the estimated impacts of air quality

[4]Similarly, our daily pollution is the simple average over the hourly measures. The potential temporal heterogeneity of air pollution could also introduce measurement error.

[5]Hourly air pollution data in major Chinese cities are published on the website of the Ministry of Environment Protection and other non-governmental websites since 2013.

on health spending provides a lower bound of consumer WTP for clean air.

The third potential source of endogeneity is unobservables. Local shocks to health spending such as income shocks could be correlated with economic activities and hence with air quality. More importantly, time-varying local shocks such as big sport or political events could affect both the air pollution level or health spending (and consumer activities in general). These time-varying local shocks cannot be fully controlled for using location fixed effects and time fixed effects and could render the air quality variable endogeneous.

3.3.2 IV Construction

We construct an instrumental variable based on spatial spillovers of $PM_{2.5}$ due to its long-range transportability. $PM_{2.5}$ particles are light and reside in the atmosphere for 3-4 days. They can be transported by wind for 1000 miles or more.[6] Based on atmospheric modeling, Lin Zhang [2015] show significant regional pollution transport in China, for example, nearly half of the pollution in Beijing originates from sources outside of the city municipality. We predict $PM_{2.5}$ in a given city based on $PM_{2.5}$ in other cities that are sufficiently away to avoid correlation in unobservables such as regional economic shocks. The contribution of $PM_{2.5}$ in other cities to $PM_{2.5}$ in a given city depends on the wind speed and wind direction.

This approach is in the same spirit of the source-receptor matrix constructed by the US EPA to predict air pollution. Williams and Phaneuf [2016] explore this idea to construct their IV for air pollution with 60 km or 120 km as the boundary for economic

[6] Assuming a residence time of 4 days (96 hours) and an average transport speed of 10 mph, the transport distance will be 960 miles. The region of influence of $PM_{2.5}$ sources is determined by the wind speed and direction.

localness. Due to the lack of data on specific point and non-point sources to construct a source-receptor matrix, we take each city as a pollution source and a receptor and develop a model to predict the air pollution level of a given city based on the pollution data in other cities. To eliminate spatial correlation in local unobservables, we use 200 km as a buffer zone and our results are robust to this choice of distance.

Denoting the pollution level of city i in time period t as p_{it}, we enforce a simple structure on the pollution data

$$p_{it} = \theta p_{i,t-1} + \sum_{j \neq i} p^{+}_{j \to i,\ t} + \mu_{it}, \tag{3.21}$$

where θ governs the part of pollution that is carried over from the previous day, $p^{+}_{j \to i,\ t}$ denotes the contribution of city j to city i's pollution at time period t, and μ_{it} is the error term.

To compute $p^{+}_{j \to i,\ t}$, we invoke a simple vector decomposition (see Figure 3.1), where Φ is the angle between the direction that the wind blows towards, and the relative direction of city i w.r.t. city j. We assume that the amount of pollutant carried with the subvector and the speed that the subvector travels are decomposed proportionally, that is,

1. the amount of pollutant carried with the subvector towards city i (width of the arrow) is $\cos\Phi \; p_{jt}$, and
2. the speed at which the subvector travels (length of the arrow) is $\cos\Phi \; wsp_{jt}$, where wsp_{jt} is the wind speed.

Additionally, $\cos\Phi$ is set to zero when it is negative: in cases when wind blows towards the opposite direction, pollution from the source city should not contribute to that of the receptor city.

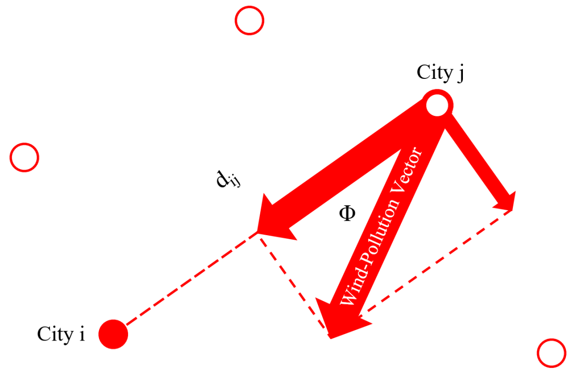


Figure 3.1: Wind-Pollution Vector Decomposition

As an illustration, Figure 3.2a shows the wind-pollution vectors from over 300 cities on Dec. 5, 2013 (denoted as Day 0). The arrows' lengths and directions indicate wind speeds and directions, with the lengths rescaled to match the exact distances they can cover in a day. The widths of arrows indicates the level of $PM_{2.5}$ concentration of the city from which the arrow originates. Figure 3.2b shows the subvectors towards Beijing after the decomposition.

Assuming constant travel speed and fixed direction, we can calculate the days needed for the subvector to reach city i, rounding down to the nearest integer with the *floor* function $\lfloor\ \rfloor$, that is

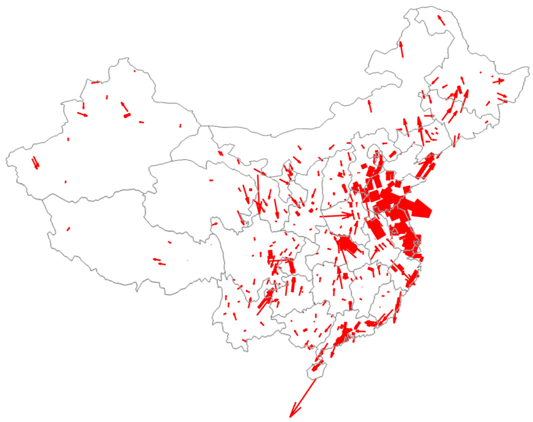
$$s = \left\lfloor \frac{d_{ij}}{\cos\Phi \, wsp_{jt}} \right\rfloor. \tag{3.22}$$

Considering that the pollutant the subvector carries will decay as it travels, we assume a spatial decay rate $(1-\delta)$ per 100 km traveled, and an additional temporal decay rate $(1-\gamma)$ per day traveled. Then we can derive the amount of leftover pollutant by the time the subvector reaches city i, at time $t+s$,

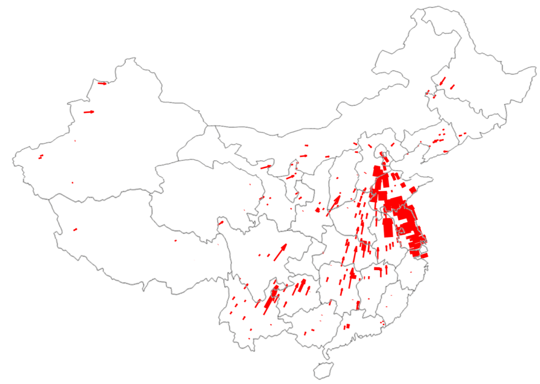
$$p^{+}_{j\to i,\ t+s} = \cos\Phi \, p_{jt} \, \delta^{\frac{d_{ij}}{100}} \gamma^{s}. \tag{3.23}$$

Figure 3.2c shows the movement and the decay of Day 0's subvectors in Day 1. And

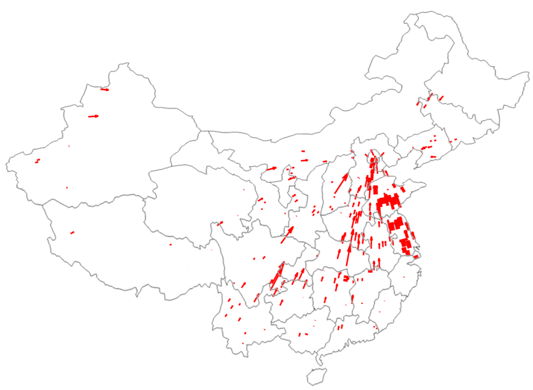
(a) Day 0: Wind-Pollution Vectors



(b) Day 0: Wind-Pollution Vectors (Decomposed)



(c) Day 0's Wind-Pollution Vectors in Day 1



(d) Day 0's & Day 1's Vectors in Day 1

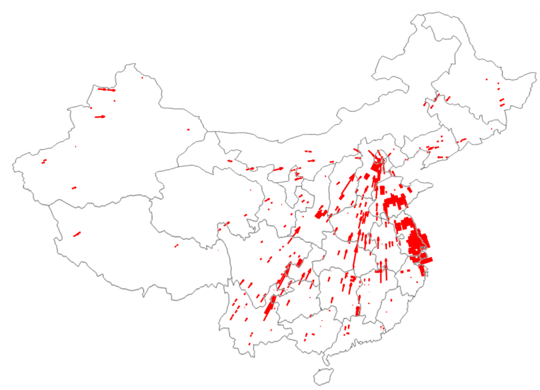


Figure 3.2: Wind-Pollution Vector Decomposition: Dynamic Illustration

Notes: Day 0 = Dec. 5, 2013. Subfigure 3.2a depicts the wind-pollution vector field on Day 0 from raw data, with vector's length indicating wind speed (rescaled to match distance travelled per day), pointing towards the direction where the wind blows to, and width indicating pollution level ($PM_{2.5}$ concentration) in the source city. In Subfigure 3.2b, the vectors are decomposed, and subvectors pointing towards Beijing are visualized. Subfigure 3.2c shows the position of subvectors in the Day 1, after a day's travel, with their widths indicating decayed pollution respectively. Subfigure 3.2d adds subvectors generated in Day 1 to the graph.

in Day 1, a new set of subvectors are generated, as illustrated in Figure 3.2d. Then the pollution level of the receptor city (in Figure 3.2, Beijing) can be partly predicted by pollutant carried through the subvectors that reaches the receptor in each day, and local pollution level of previous days, as stated in Equation 3.21.

As the result, pollution $\mathbf{P}$ can be predicted with a set of parameters δ, γ and θ, as

$$\widetilde{\mathbf{P}}(\delta, \gamma, \theta), \tag{3.24}$$

and the parameters can be estimated using Nonlinear Least Squares (NLS) by minimizing the sum of squared prediction errors (SSE) between actual air quality $\mathbf{P}$ and predicted air quality $\widetilde{\mathbf{P}}$,

$$\min_{\delta,\gamma,\theta} SSE = \sum_i \sum_t \mu_{it}^2 = (\mathbf{P} - \widetilde{\mathbf{P}})'(\mathbf{P} - \widetilde{\mathbf{P}}). \tag{3.25}$$

With the estimated parameters $\widetilde{\delta}, \widetilde{\gamma}$ and $\widetilde{\theta}$, we can construct $\widetilde{\mathbf{P}}_{far}$, taking into account only the contributions from cities more than 200 km away (see Figure 3.3),

$$\widetilde{p}_{it}^{far} = \sum_{d_{ij} > 200} p_{j \to i,\, t}^{+}, \tag{3.26}$$

and this *predicted non-locally generated pollution* serves as our instrument.

Although the model is parsimonious, it yields very reasonable predictions. In Figure 3.4, we plot the predicted level of pollution for Beijing against the observed data. Other than under-predicting some peaks, the predicted air quality follows true data very closely[7]. The instrument variable is small in scale, due to the decay parameters[8], but follows a similar trend.

[7]The underprediction for some peaks may be due to positive pollution shocks generated within the city, which is unaccounted for in the model, as we only allows decay for self-generated pollutants through $\theta p_{i,t-1}$.

[8]The model predicts that, after traveling 200 km, the leftover pollutant is at most 5.4% of the level at the origin.

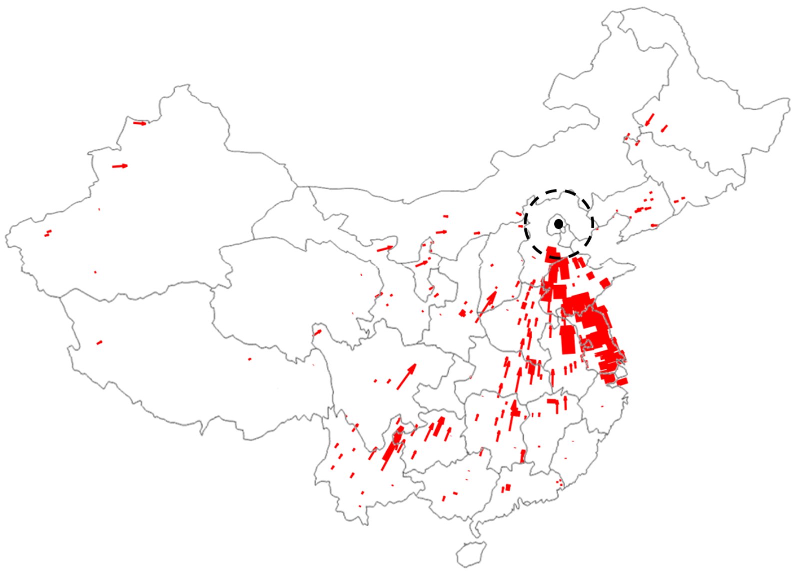


Figure 3.3: Wind-Pollution Vector Decomposition
From Cities Further Than 200 km

Notes: This graph is modified from Subfigure 3.2b, by excluding all subvectors originated from cities within a 200 km radius of Beijing. Black dot indicates the location of Beijing, and the dashed line circles the area with a radius of 200 km.

Table 3.1: Results of First Stage Regression

	$PM_{2.5}$
IV: Predicted Non-Locally Generated $PM_{2.5}$, ¿200 km	0.96***
	(0.06)
N	219747
R^2	0.412
F	220.11

Notes: The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Reported R^2 including controls. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

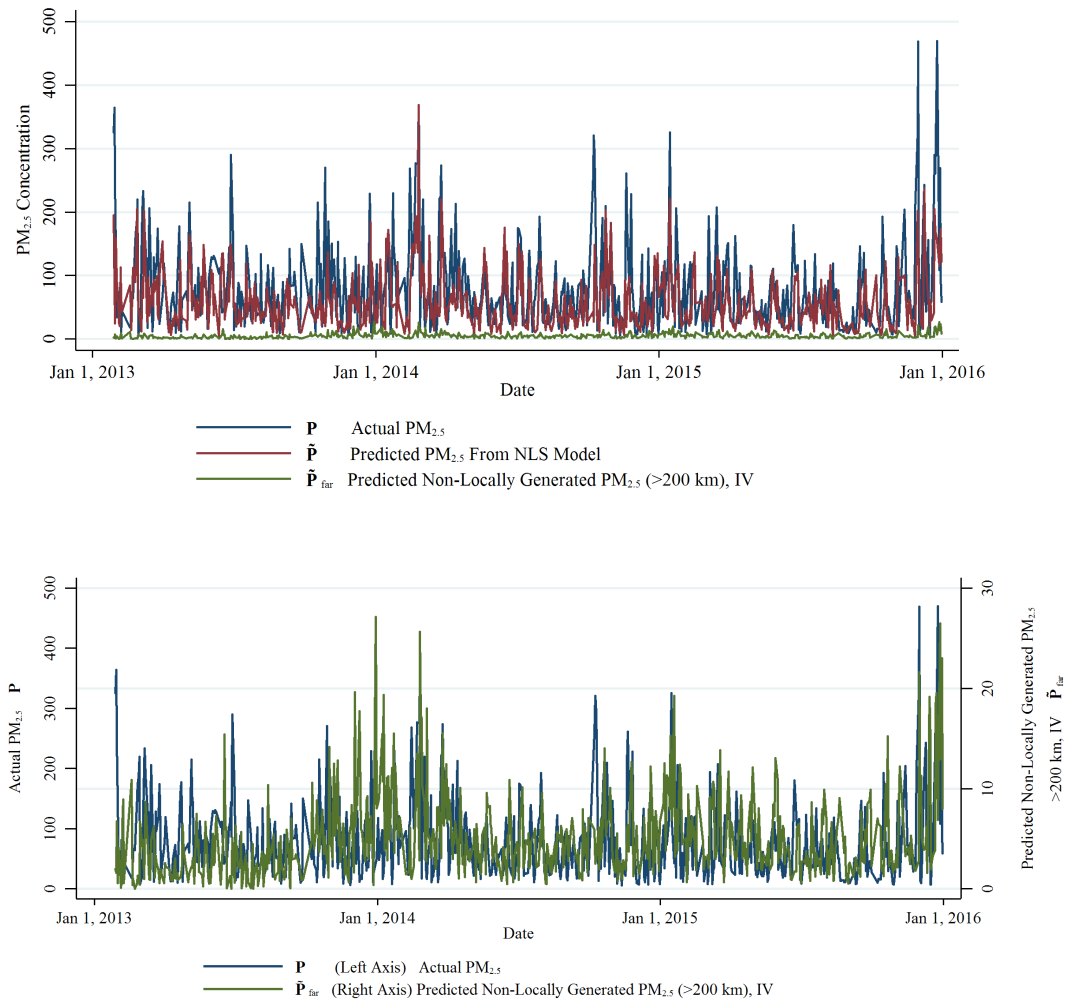


Figure 3.4: Actual and Predicted Level of Daily Air Pollution
Beijing, Jan. 2013 - Dec. 2015

Overall, the first-stage result reports a cluster-robust F-statistic[9] of 220, and an R^2 of 0.412 (Table 3.1). Although the F-statistic will shrink as the number of observation drops after merging in the UnionPay data, it is still well above the rule of thumb to reject the weak IV hypothesis. Since the dependent variable and independent variable in the first stage regression are of the same unit (μg/m^3), a coefficient estimate close to 1 also indicates a good prediction from our dynamic model: by design, when the end-impact of imported pollution (from cities more than 200 km away) increase by 1 unit, local

[9]In cases where the i.i.d. assumption is dropped and cluster standard errors are specified, Cragg-Donald Wald statistics are no longer valid, and Kleibergen-Paap Wald rk F-statistic is reported.

pollution should respond roughly by a 1-unit rise.

CHAPTER 4

EMPIRICAL RESULTS

4.1 Short-Term Impact

Our analysis starts by estimating contemporary effects of air pollution on health. In our regressions, we use the number of transaction (log-transformed) as the dependent variable, rather than the total value. In our dataset, total spending is equivalent to a weighted sum of transactions, weights being their individual value. Transactions with very large values (e.g., surgeries) are unlikely to be caused by air pollution at least in the short run but would affect the value much more so than the number of transactions. We report additional results in Appendix B using expenditure as the dependent variable for the purpose of robustness checks and supporting our discussions in Section 4.4. The results from using expenditure provide are very similar in magnitude to those based on the number of transactions but less precise.

In all the regressions, we include city fixed effects to control for time-invariant unobservables and week fixed effects to control for nationwide shocks. City-specific time trend and city-specific seasonality are added to the regression to control for trends in card adoption and seasonal pollution patterns. We also add holiday, spring festival, working weekend and day-of-week fixed effects, as well as weather variables to control for their direct effects on spending. For example, people may reduce their non-emergency hospital visits during holidays or bad weather.

Table 4.1: Impact of Air Pollution from OLS

	Health Spending					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$ (10000μg/m^3)	1.00***	0.87***	1.33***	0.98***	1.79***	-0.52**	-0.21
Current Day	(0.18)	(0.21)	(0.25)	(0.21)	(0.55)	(0.24)	(0.20)
N	189641	189075	188568	183214	144508	189228	188995

Notes: The dependent variable is log(number of transactions). The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day FEs (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). $PM_{2.5}$ is measured in 10000 μg/m^3. The coefficient on that variable indicates the percentage change in the number of transactions per 100 μg/m^3 increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4.1 summarizes the OLS regression results for the short-term impacts. The results suggest that an increase in daily $PM_{2.5}$ concentration is associate with an increase in the number of transactions in hospitals and pharmacies, and a decrease in transactions in daily necessities and supermarkets. The parameter estimates imply that a 10 μg/m^3 increase in daily $PM_{2.5}$ is associated with a 0.1% increase in the total number of transactions for health spending on the current day. Transactions in pharmacies and especially in children's hospitals are more sensitive to air pollution, with an impact of 0.13% and 0.18% from a 10 μg/m^3 increase in $PM_{2.5}$. The larger impact in pharmacies and children's hospitals make intuitive sense: children are more vulnerable to air pollution; and when elevated air pollution aggravates symptoms for people with respiratory problems, they may go to pharmacies to purchase drugs without visiting hospitals. The negative impact on transactions in daily necessities and supermarkets suggests avoidance behavior, people reducing shopping trips in response to bad air quality to reduce exposure.

To address the potential endogeneity due to measurement error or unobservables, we instrument $PM_{2.5}$ using the predicted $PM_{2.5}$ from other cities outside of the 200 km buffer zone as discussed in Section 3.3.2. Table 4.2 reports results from IV regressions. The F-statistics on the IV from the first-stage are reported in the last row, suggesting a strong first stage. Compared with the results from OLS in Table 4.1, the estimated impacts from the IV regressions are considerably larger, with most coefficients being 5 to 10 times larger than their OLS counterparts. A 10 μg/m^3 increase in $PM_{2.5}$ in a day is associated with a 0.61% increase in the number of transactions in the health care sector. The effect of air pollution on children's hospital is the largest among different health care categories, nearly three times larger than that for the health care sector. The coefficients estimates on the two controls group also become much larger in magnitude relative to those from OLS.

Table 4.2: Impact of Air Pollution from IV

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$ (10000 μg/m^3)	6.09***	8.86***	2.63	8.95***	22.76***	-8.84***	-3.88**
Current Day	(2.23)	(2.68)	(2.60)	(2.70)	(8.56)	(2.60)	(1.89)
N	189641	189075	188568	183214	144508	189228	188995
F	160.2	159.3	158.7	152.0	126.3	159.9	159.5

Notes: The dependent variables are log(number of transactions). The instrument is predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away. The controls are City FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficient on $PM_{2.5}$ indicates the percentage change in the number of transactions per 100 μg/m^3 increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported in the last row and it is cluster-robust at the city level.

The large difference between OLS and 2SLS results on the health impact of air pollution is common in this literature [Knittel et al., 2015, Schlenker and Walker, 2015, Williams and Phaneuf, 2016] and the downward bias could be caused by the following two factors. First, unobservables that are positively correlated with air pollution such as busy economic activities or big events could lead to reduced health spending. Second, classical measurement error in $PM_{2.5}$ as an imperfect proxy for pollution exposure could lead to attenuation bias. Although the IV could not fully address the avoidance behavior which is a response to local air pollution, the variation in local air pollution generated by the spatial spillovers of $PM_{2.5}$ from other cities is only a small part of the variation on overall air pollution as shown in Figure 3.3. This could also help explain the downward bias of the OLS estimates. This may also help explain the relatively large increase in 2SLS results for children's hospital: the avoidance behavior might be larger if children are sick while spending at pharmacies or non-emergency hospital visits by adults could be subject to more avoidance behavior in response to bad air pollution.

In 2015, there were more than two billion transactions in hospitals and the total out-of-pocket health spending exceeded one trillion *yuan* ($145 billion). Including government and social problems, the total health spending was more than three trillion *yuan* ($435 billion).[1] Therefore, a 0.61% increase in total health spending would amounts to 18 billion *yuan*. This will be further discussed in Section 4.4. The estimate is likely a lower bound on the true impact of air pollution due to the the avoidance behavior suggested by the results on the two control groups.

As health is a stock variable that can be affected by previous exposure to air pollution, we include the weekly $PM_{2.5}$ concentration before the current day. The results are presented in Tables 4.3 for OLS and Table 4.4 for 2SLS where both $PM_{2.5}$ variables are instrumented. The OLS estimates on the current day $PM_{2.5}$ by and large are similar to those in Table 4.2 across all categories. The coefficient estimates on the weekly $PM_{2.5}$ are significant in most categories and have a larger magnitude than the current day but not seven times as large, suggesting a decreasing impact over time. The 2SLS results

[1] *Source*: National Bureau of Statistics and National Health Commission, P. R. China.

are interesting in that all the coefficients on the current day $PM_{2.5}$ in health spending categories turn negative, the same sign as the coefficient estimates on the two control groups. The coefficient estimates on the weekly $PM_{2.5}$ in the health care categories are all positive and much larger in magnitude than those on the current day $PM_{2.5}$. Opposite to this, the coefficient estimates on the weekly $PM_{2.5}$ for the two control groups are smaller in magnitude than those on the current day and not significant. The avoidance behavior is likely to occur on current day rather than responding to pollution in previous days.

The results from 2SLS in Table 4.4 point to the following: (1) there is avoidance behavior in spending including both health spending and other spendings as shown by the coefficient estimates on on the current day $PM_{2.5}$; (2) the air pollution has a longer-term impact on health beyond the current day, which we explore more systematically in the next section.

Table 4.3: Impact of Air Pollution from OLS

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$, Current Day	0.82***	0.74***	0.95***	0.69***	1.63***	-0.34	-0.23
	(0.14)	(0.16)	(0.21)	(0.17)	(0.38)	(0.22)	(0.18)
Mean $PM_{2.5}$, Past 1w	1.26***	0.89	2.56***	2.01***	1.07	-1.23***	0.10
	(0.45)	(0.55)	(0.52)	(0.56)	(1.43)	(0.46)	(0.40)
N	189641	189075	188568	183214	144508	189228	188995

Notes: The dependent variables are log(number of transactions). The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficient on that variable indicates the percentage change in the number of transactions per 100 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 4.4: Impact of Air Pollution from IV

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$, Current Day	-4.67**	-3.96	-4.07	-1.15	-5.63	-7.01***	-3.39
	(2.35)	(2.61)	(3.34)	(2.60)	(8.48)	(2.63)	(2.33)
Mean $PM_{2.5}$, Past 1w	8.77***	10.43***	5.45	8.11***	22.57*	-1.50	-0.40
	(2.89)	(3.39)	(3.57)	(3.02)	(12.43)	(2.52)	(1.89)
N	189641	189075	188568	183214	144508	189228	188995
F	114.3	114.2	114.3	111.2	92.83	114.3	114.2

Notes: The dependent variables are log(number of transactions). The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, for the current day and past one week. The controls are City FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficient on that variable indicates the percentage change in the number of transactions per 100 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

4.2 Longer-Term Impact

Our analysis from previous section suggests that $PM_{2.5}$ could have health impact beyond one week. We have tried to include $PM_{2.5}$ of many lags directly into the equation to explore the longer-term impact, but the large serial correlation in $PM_{2.5}$ renders poor numerical property of this method. Instead, we employ the Almon technique by allowing the coefficients on current-day pollution and its lags to follow a polynomial path of decay. The classic specification of the Almon technique entails three parts: the number of lags k, the order of polynomials q, and additional end-point restrictions. In our model, we do not impose any end-point restrictions so as to allow for a flexible functional form, though we do refer to *a prior* knowledge to decide the lag length and the degree of polynomial.

To check the robustness of our results, we test several possible combinations of the number of lags and the order of polynomials. Figure 4.1 plots the estimates for several combinations from OLS. The dotted part in each line indicates that the estimated lagged impact for the corresponding period is not statistically significant at 5% level. The results show that the effect of air pollution diminishes over time and is too imprecise to detect after two or three months. Specifications with too many lags (over 150) or too short (less than 60) would lead to imprecise and large swings in parameter estimates. Once the length of lags is set at 100, we choose the order of polynomials to be five which maximizes the adjusted R^2. Although individual parameters differ across specifications with different order of polynomials and lags, the aggregate impact is quite robust for specifications with orders from three to six and lags from 60 to 150 as we discuss below.

Table 4.5 reports the cumulative effects for different time periods across categories with the standard errors in parenthesis from OLS. The first column shows that an increase in the $PM_{2.5}$ concentration has a smaller positive impact on the number of transactions in all healthcare facilities in the immediate short term but a much larger impact during the longer term of 100 days. The impact on pharmacies is the largest in the longer term while the impact on children's hospital is not statistically significant. This is contrary to the results on short-term impacts from 2SLS in Table 4.4. This non-intuitive result could be due to endogeneity, which we address below. The last two columns show a negative effect on necessities and supermarket shopping, although not statistically significant.

Figure 4.2 shows the time path of impacts for different categories from OLS.[2] The dotted part of each line indicates the impact being statistically insignificant. There are two patterns from these lines. First, air pollution has positive impact of health spending

[2]The optimal specification of oder of polynomials and lags may differ. For example, spending in children's hospital should be estimated with fewer lags based on our estimation results. To keep the results comparable, we impose the same lag-order structure on all categories.

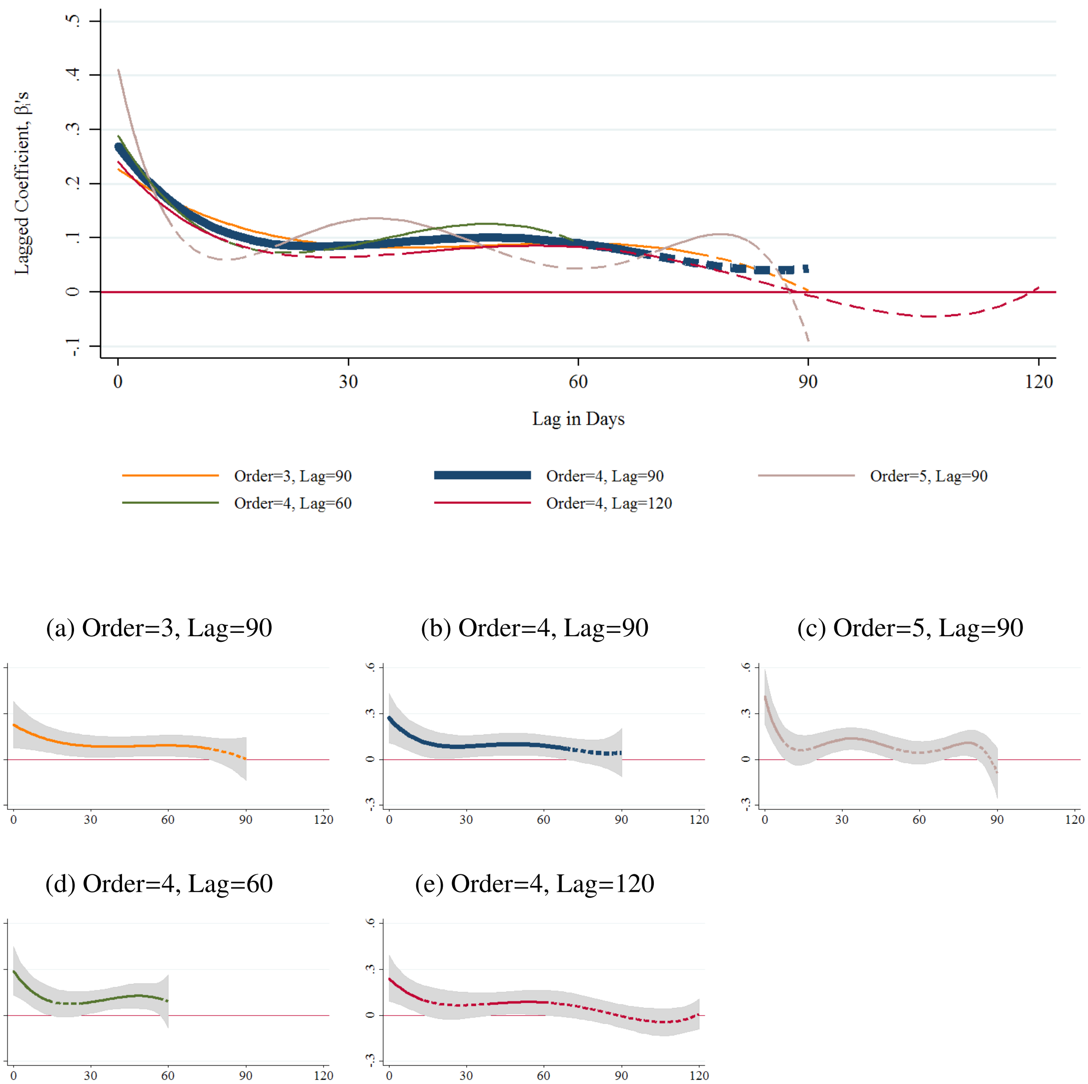


Figure 4.1: Impact of Air Pollution on Number of Transaction from OLS, Total Healthcare Industry, Various Order-Lag Specifications

Notes: The coefficients indicate the percentage change in number of transactions per 100 μg/m^3 increase in PM$_{2.5}$ concentration. Solid line indicates $p < 0.05$ for β_i. Gray areas are 95% confidence intervals.

Table 4.5: Cumulative Effect of Pollution, Almon Estimation from OLS (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.27***	0.22**	0.44***	0.30***	0.56***	-0.32***	-0.21***
	(0.08)	(0.09)	(0.11)	(0.11)	(0.21)	(0.10)	(0.08)
Current + Past 3d	0.97***	0.78**	1.65***	1.11***	1.72**	-1.03***	-0.70***
	(0.29)	(0.33)	(0.38)	(0.37)	(0.79)	(0.33)	(0.26)
Current + Past 7d	1.71***	1.29**	3.02***	2.01***	2.36	-1.51***	-1.11***
	(0.51)	(0.59)	(0.65)	(0.59)	(1.51)	(0.52)	(0.43)
Current + Past 14d	2.63***	1.76*	4.98***	3.09***	2.11	-1.65**	-1.34**
	(0.80)	(0.96)	(1.00)	(0.84)	(2.77)	(0.72)	(0.64)
Current + Past 28d	3.88***	1.97	8.14***	3.98***	1.23	-1.49	-0.88
	(1.25)	(1.51)	(1.64)	(1.38)	(4.95)	(1.15)	(1.10)
Current + Past 56d	6.54***	2.62	14.10***	4.70**	5.74	-2.74	0.31
	(1.87)	(1.96)	(2.94)	(2.36)	(7.43)	(2.10)	(1.80)
Current + All Lags	8.63***	3.37	18.08***	5.92*	3.77	-0.82	0.22
	(2.73)	(2.76)	(4.24)	(3.59)	(11.44)	(2.69)	(2.14)

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficients indicate cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

in the short term across all categories. The impact diminishes over time and becomes imprecise after two months. Second, air pollution has negative impact on the spending of the two control groups and the impact is short-lived, consistent with avoidance behavior, rather than being driven by budget constraint, i.e., an increase in health spending would lead to a decrease in other spending when the budget is fixed for these categories of spending.

To deal with the endogeneity in $PM_{2.5}$, we apply the IV estimation within the Almon framework by transforming the lagged instrument variables in the same way as the regressor (as shown in Equation 3.20). Estimates on the cumulative effects across differ-

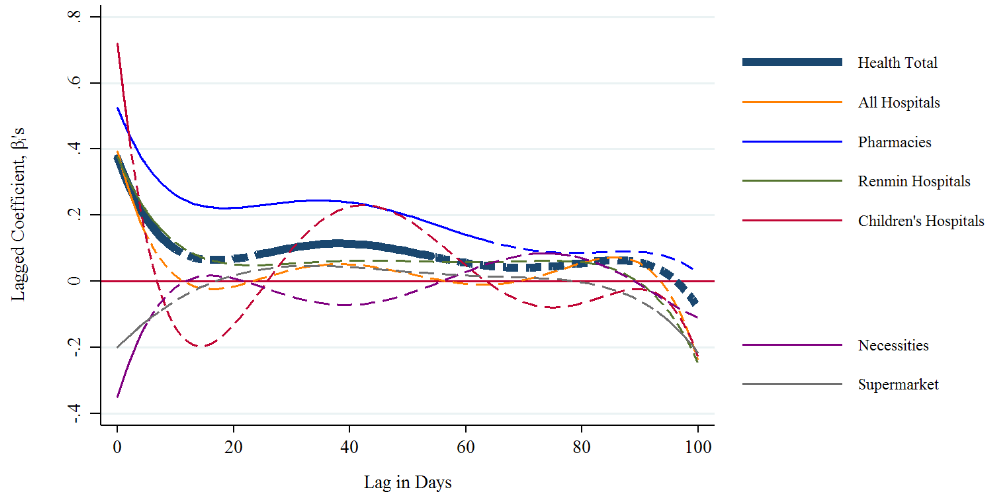
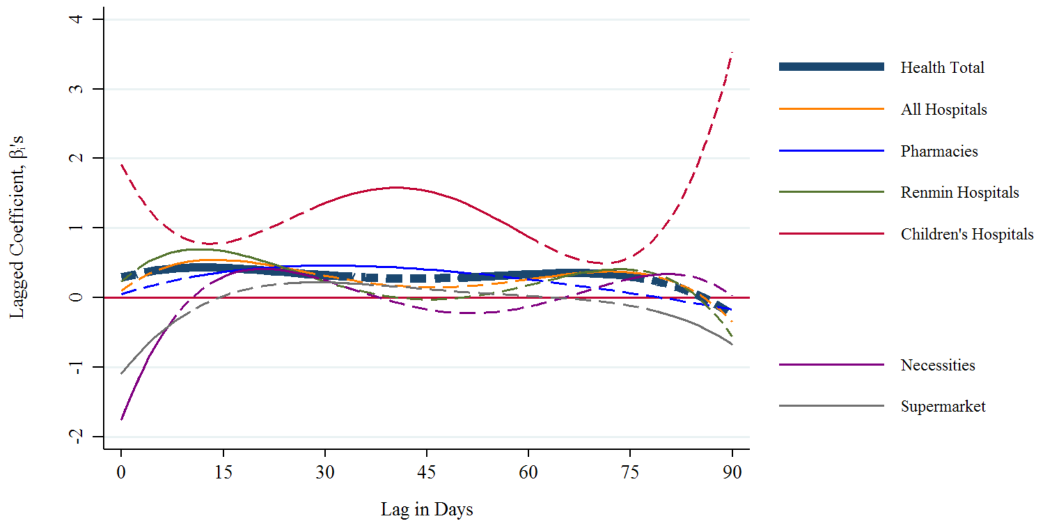


Figure 4.2: Impact of Air Pollution on Number of Transactions from OLS (Order=5, Lag=100)

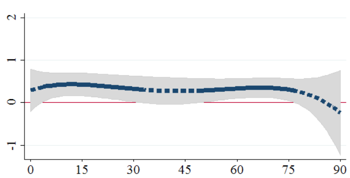
Notes: The coefficients indicate the percentage change in number of transactions due to per 100 μg/m^3 increase in $PM_{2.5}$ concentration.

ent time spans are presented in Table 4.6. Several important findings emerge from Table 4.6. First, the estimated long-term impact of air pollution on health spending across all categories from 2SLS are positive and much larger than those from the OLS results, consistent with the comparison from the short-term impact discussed in the previous section. Second, the largest impact is in children's hospitals, consistent with the fact that children are among the most vulnerable group from air pollution. This finding is also consistent with the results from Tables 4.2 and 4.4. Third, the effect on the daily necessities and supermarket spending is negative and much shorter-lived and does not seem to persist longer then two weeks: the aggregate impact becomes smaller and statistically insignificant. The time paths of impact for different categories are presented in Figure 4.3. The pattern is less clear for pharmacies and children's hospitals. The spending on necessities and supermarkets shows a strong negative impact in the immediate short term.

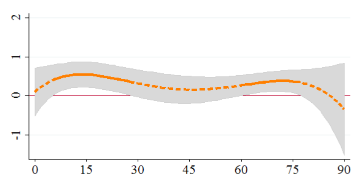
The results we focused on are based on the specification with five orders of poly-



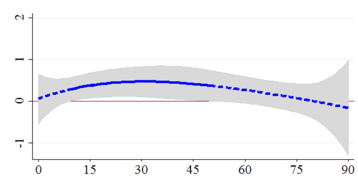
(a) Health Total



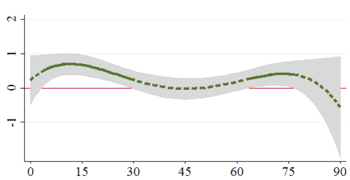
(b) All Hospitals



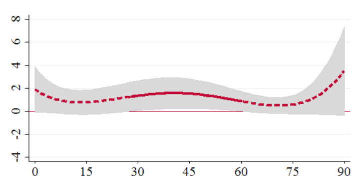
(c) Pharmacies



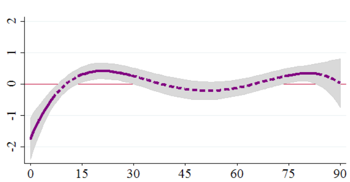
(d) Renmin Hospitals



(e) Children's Hospitals



(f) Necessities



(g) Supermarkets

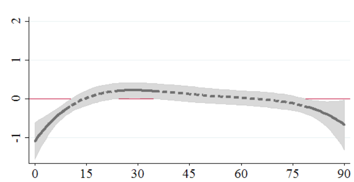


Figure 4.3: Impact of Air Pollution on Number of Transactions from IV (Order=4, Lag=90)

Notes: The coefficients indicate the percentage change in number of transactions per 100 μg/m^3 increase in PM$_{2.5}$ concentration. Solid line indicates p $<$ 0.05 for β_i. Gray areas are 95% confidence intervals. Coefficients for Children's Hospital in (e) and Necessities in (f) are scaled differently from other subfigures.

Table 4.6: Cumulative Effect of Pollution from IV (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.29	0.10	0.05	0.23	1.92*	-1.75***	-1.08***
	(0.26)	(0.31)	(0.31)	(0.37)	(1.00)	(0.34)	(0.24)
Current + Past 3d	1.30	0.80	0.38	1.41	6.59*	-5.56***	-3.65***
	(0.88)	(1.09)	(1.02)	(1.21)	(3.49)	(1.12)	(0.78)
Current + Past 7d	2.88*	2.42	1.17	3.74*	11.05*	-8.01***	-5.74***
	(1.50)	(1.85)	(1.66)	(1.94)	(5.98)	(1.75)	(1.19)
Current + Past 14d	5.89**	6.10**	3.34	8.55***	16.81*	-7.80***	-6.84***
	(2.32)	(2.88)	(2.44)	(2.74)	(9.41)	(2.31)	(1.51)
Current + Past 28d	11.31***	12.60**	9.34**	15.56***	30.91*	-2.57	-4.62**
	(4.06)	(4.97)	(4.28)	(4.05)	(16.89)	(3.35)	(2.21)
Current + Past 56d	19.50**	18.31**	20.84**	17.21***	71.11**	-4.11	-0.61
	(7.78)	(9.19)	(8.91)	(6.51)	(33.46)	(6.40)	(3.90)
Current + All Lags	27.17**	26.03*	23.59	23.81*	109.79**	0.48	-6.21
	(12.88)	(15.01)	(15.25)	(12.74)	(52.66)	(9.41)	(5.61)
F	29.78	29.81	29.72	29.68	25.00	29.77	29.75

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficients indicate the cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

nomials and 100 lags. Tables A.1, A.2, A.3, and A.4 in Appendix present the results for different order-lag combinations (4 & 100, 6 & 100, 5 & 60, and 5 & 150) from OLS. Tables A.5, A.6, A.7, and A.8 in Appendix show the results for the corresponding specifications from 2SLS. The key findings are robust across different specifications: (1) there is positive and statistically significant impact on health spending across categories and the effect is observed over a period of three months; (2) the results from 2SLS are much larger than those from OLS, although the directions of impact are the same; and (3) the impact on the two control groups is negative and large in the immediate short term and tends to be short-lived, suggesting avoidance behavior.

Table C.1 in Appendix reports the cumulative impact for overall health spending under three different orders of polynomials (3, 4, and 5) and five different numbers of lags (30, 60, 90, 120 and 150). The estimates across the three different orders are very close. The results are slightly more sensitive to the lag structure. The cumulative impact is smallest with 30 days of lag and largest with 150 days of lag but the results are similar across the three other lag structures, suggesting the impact does not persist longer than three months. In addition, the estimates become imprecise with lags longer than 90 days.

4.3 Avoidance Behavior

In previous analysis, we assume future pollution level does not affect current-day spending, and thus it is left out in our regression. However, if consumers can predict the pollution level of future days to some extent, they may change their consumption patterns by intertemporal substitution. For example, if they expect pollution to get better in future days, they may postpone their consumption to avoid exposure today. On the other hand, an expectation of worse air may encourage them to make the consumption in advance.

To capture this, we try to mimic consumers' prediction on future air with an OLS model. We regress next-day pollution level $\mathbf{P_{-1}}$ on the variables reflecting the information we believe that are available to the consumers when they make the (maybe unconscious) prediction . The regressors include current-day variables, such as current-day pollution level $\mathbf{P_0}$, weather, special day dummies ((holiday, spring festival, working weekend), city FEs and weekly FEs, city-specific seasonality, linear trend, and day-of-week FEs. Additionally, we included variables reflecting next-day information, such as next-day weather expectation[3], next-day special day dummies[4], day-of-week dummies (which are perfect collinear with current-day).

Predicted next-day air $\widehat{\mathbf{P}}_{-1}$ from the OLS model has a correlation of 0.788 with actual next-day air quality $\mathbf{P}_{-1}$. We further generated a dummy variable indicating if the predicted next-day air $\widehat{\mathbf{P}}_{-1}$ is worse (denoted value 1) than the mean air quality of current day and past 7 days. If taking this dummy as the criteria, the OLS prediction has a total accuracy of 85%. However, the model is more accurate in cases when next-day air is better (with an accuracy of 88.8%), and less accurate at predicting worsening air (with an accuracy of only 74.8%). This echoes with our intuition, since most of the next-day information corresponds with shocks that reduces pollution level (weather conditions like rainfall and stronger wind), and is less predictive for shocks to the opposite direction (congestion combined with calm wind, for example). This is summarized in the Table 4.7.

Table 4.7: Accuracy of Prediction from OLS Model, Next-Day Pollution Level

		Actually Worse			
		0	1	Total	Accuracy
Predicted Worse	0	265,027	23,342	288,369	91.9%
	1	33,271	69,302	102,573	67.6%
	Total	298,298	92,644	390,942	
	Accuracy	88.8%	74.8%		85.5%

Notes: Dummy variable 1_{worse} is defined as worse than the mean pollution level of current day and past 7 days. The regressors for the prediction include current-day information, such as pollution level, weather, special day dummies (holiday, spring festival, working weekend), city FEs and weekly FEs, city-specific seasonality, linear trend, and day-of-week FEs; next-day information, such as next-day weather expectation, special day dummies,and day-of-week dummies. We use next-day weather variables in place of their expectations.

We then include the dummy $1_{\text{Predicted Worse}}$ and the predicted next-day air quality $\widehat{\mathbf{P}}_{-1}$

[3]Given the high accuracy of weather forecast in the very short term, we use next-day weather variables in place of their expectations.

[4]Consumers should know, for example, if tomorrow is a holiday.

into our baseline Almon IV estimation respectively, and the results are presented below in Tables 4.8 and 4.9. Our main conclusion on the health effect is not affected by including the additional variable. When $1_{\text{Predicted Worse}}$ is included in the regression, the result indicates 0.85% more transactions for total healthcare industry when residents of the city anticipates worse air, compared with the default - better air.

One thing to note is that the indicators for avoidance ($1_{\text{Predicted Worse}}$ or $\widehat{\mathbf{P}}_{-1}$) are by design correlated with current-day air quality, and the estimation of the effect could be inaccurate as it is mixed with health effects. For example, when $1_{\text{Predicted Worse}} = 0$ and current-day transaction increases, it is also indicated that the past week's air quality is relatively worse, and transactions for healthcare industries should rise as a result. Similarly, when $\widehat{\mathbf{P}}_{-1}$ is large, it is more likely that pollution is also severe for current day and past days, mixing the effect of avoidance with short-term health impacts. The Almon estimation cannot guarantee a clear separation between the two effects, which could explain some counter-intuitive results for health-related consumption in Table 4.9, Columns (1) to (5).

However, by analyzing the control groups, where there is no health effect, we can always find a positive correlation between next-day pollution level and current-day spending, an evidence for intertemporal substitution. The size of avoidance behavior, in Table 4.9, Columns (6) and (7), is almost as big as the negative effect of pollution from current day and previous 2 to 3 days.

4.4 Discussion

The estimation results suggest that a 10 μg/m^3 increase in $PM_{2.5}$ would lead to an increase in the number of health-related transactions in the long term by 2.7% from 2SLS

Table 4.8: Cumulative Effect of Pollution from IV, with Dummy $1_{\text{Predicted Worse}}$ (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1_{\text{Predicted Worse}}$, %	0.85***	0.53	0.72**	0.70**	1.45	0.25	0.15
	(0.27)	(0.33)	(0.29)	(0.28)	(1.10)	(0.27)	(0.19)
Current Day	0.42	0.18	0.16	0.34	2.14*	-1.71***	-1.06***
	(0.29)	(0.35)	(0.33)	(0.39)	(1.14)	(0.36)	(0.25)
Current + Past 3d	1.76*	1.09	0.76	1.79	7.36*	-5.43***	-3.57***
	(0.99)	(1.23)	(1.10)	(1.30)	(3.99)	(1.21)	(0.83)
Current + Past 7d	3.64**	2.89	1.81	4.37**	12.33*	-7.79***	-5.60***
	(1.68)	(2.09)	(1.80)	(2.11)	(6.84)	(1.91)	(1.28)
Current + Past 14d	6.90***	6.72**	4.19	9.38***	18.51*	-7.50***	-6.65***
	(2.59)	(3.22)	(2.66)	(2.98)	(10.60)	(2.53)	(1.64)
Current + Past 28d	12.29***	13.21**	10.16**	16.37***	32.55*	-2.28	-4.45*
	(4.32)	(5.30)	(4.50)	(4.29)	(18.01)	(3.54)	(2.32)
Current + Past 56d	20.42**	18.87**	21.61**	17.97***	72.55**	-3.84	-0.45
	(8.01)	(9.49)	(9.10)	(6.68)	(34.38)	(6.57)	(3.97)
Current + All Lags	28.05**	26.58*	24.33	24.54*	111.14**	0.74	-6.05
	(13.09)	(15.28)	(15.41)	(12.88)	(53.47)	(9.56)	(5.68)
F	29.55	29.59	29.49	29.52	25.02	29.54	29.52

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficients indicate the cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

and and 0.8% from OLS. In terms of the impact on value of transactions, the effect is about 0.4% from OLS (Table B.1 in Appendix B) and 2.3% from 2SLS (Table B.2 in Appendix B). The estimates are less precise than those based on the number of transactions. This is likely due to the larger noise inherent in the value of health spending. For example, some of largest incidences of health transactions are likely to be surgeries

Table 4.9: Cumulative Effect of Pollution from IV, with Predicted Next-Day $PM_{2.5}$ (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Next-Day $PM_{2.5}$, Predicted	0.31	-0.11	2.77***	-0.98	-4.29	4.38***	3.34***
	(0.89)	(1.13)	(0.94)	(1.09)	(3.69)	(1.03)	(0.82)
Current Day	0.32	0.16	-0.03	0.34	2.11*	-1.87***	-1.20***
	(0.28)	(0.35)	(0.33)	(0.40)	(1.12)	(0.36)	(0.26)
Current + Past 3d	1.40	1.01	0.09	1.77	7.32*	-5.98***	-4.05***
	(0.98)	(1.21)	(1.10)	(1.32)	(3.91)	(1.20)	(0.86)
Current + Past 7d	3.06*	2.77	0.74	4.33**	12.41*	-8.69***	-6.40***
	(1.67)	(2.06)	(1.80)	(2.12)	(6.69)	(1.88)	(1.31)
Current + Past 14d	6.16**	6.59**	2.83	9.32***	18.98*	-8.68***	-7.73***
	(2.57)	(3.18)	(2.64)	(2.96)	(10.42)	(2.48)	(1.66)
Current + Past 28d	11.72***	13.19**	9.02**	16.36***	33.83*	-3.36	-5.46**
	(4.34)	(5.29)	(4.52)	(4.23)	(18.08)	(3.50)	(2.33)
Current + Past 56d	20.18**	19.15**	20.83**	18.26***	73.85**	-4.55	-1.10
	(8.06)	(9.50)	(9.14)	(6.65)	(34.65)	(6.53)	(4.02)
Current + All Lags	28.06**	27.07*	23.80	25.02*	112.72**	0.45	-6.45
	(13.18)	(15.32)	(15.49)	(12.84)	(53.88)	(9.49)	(5.71)
F	29.46	29.51	29.41	29.42	25.28	29.44	29.44

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). The coefficients indicate the cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

which are not related to air pollution.[5] These transactions would reduce the precise of estimation to a larger extent in the regressions focusing on the value of spending rather than the number of transactions.

We take 2.3% as the long-term impact of a 10 $\mu g/m^3$ increase in $PM_{2.5}$ on health spending. Credit/debit transactions account for about half of the total spending in the

[5]Our analysis focus on transactions with amount less than 200,000 *yuan*. Among this sample, the 95 percentile of the transaction value is 6,000 *yuan* and the 99 percentile is 10,000.

health care industry with the rest from cash transactions and government transfers. Assuming that the impact is the same for non-credit/debit card spending, this estimate translates to more than 75 billion *yuan* ($11 billion), about 2.3% of the annual healthcare expenditure in China from a 10 μg/m^3 (about 18%) increase in $PM_{2.5}$. To compare our results with findings in previous literature, we summarized the reported dose-response relationship in Table 4.10 below.

In a research focusing on preventive expenditure, Mu and Zhang [2016] report that mask purchases increase by 54.5% for a 100-point increase in AQI, and 70.6% for anti-$PM_{2.5}$ masks. Given that the translation from $PM_{2.5}$ concentration to AQI is piecewise linear, a 100-point increase in AQI is equivalent to an increase of 75 μg/m^3 to 150 μg/m^3 in $PM_{2.5}$ concentration. This means that exposure to 10 μg/m^3 more $PM_{2.5}$ leads to an increase ranging between 3.6% and 7.3% in preventive spending.

Table 4.10: Summary of Dose-Response Relationships from Literature

Source	Dose, additional	Response
Mu and Zhang [2016]	100-point AQI	54.5% increase in masks purchases, 70.6% in anti-$PM_{2.5}$ masks
Williams and Phaneuf [2016]	1 std. dev. $PM_{2.5}$ (3.78 μg/m^3)	8.3% more spending on asthma and COPD
Schlenker and Walker [2015]	1 std. dev. pollution	17% more asthma and total respiratory problems, 9% heart problems
Arceo et al. [2015]	1 μg/m^3 PM_{10} 1 ppb CO	0.23 per 100,000 increase in infant mortality 0.0046 per 100,000 increase in infant mortality
He et al. [2016]	10 μg/m^3 PM_{10} (roughly 10%)	8.36% in all-cause mortality rate 285,000 premature deaths each year
Chay and Greenstone [2003]	1% TSP	0.35% in infant mortality rate nationwide
Chay and Greenstone [2005]	1 μg/m^3 TSP	WTP: $329 in housing price
Bayer et al. [2009]	1 μg/m^3 PM_{10}	WTP: $149-$185 for U.S. household
Ito and Zhang [2016]	1 μg/m^3 PM_{10}	WTP: $1.1 per household
Our estimation		
OLS	10 μg/m^3 $PM_{2.5}$	0.8% in hospital visits and pharmacy purchases, 0.5% in total health expenditure
IV	10 μg/m^3 $PM_{2.5}$	2.7% in hospital visits and pharmacy purchases, 2.3% in total health expenditure $25 per household annually

For Williams and Phaneuf [2016], whose estimation methods and data are more similar to ours, they find that a one-standard-deviation change in $PM_{2.5}$ (roughly 3.78 $\mu g/m^3$ for their data) leads to 8.3% more spending on asthma and COPD (or 22% for 10 $\mu g/m^3$ more, equivalently). To make our results comparable, we refer to statistics recorded by the National Health Commission, that spending on respiratory diseases accounts for 8% of total health expenditure[6]. Assuming all additional spending induced by air pollution are for respiratory diseases, then our estimation translates to about 31% to 53% increase in respiratory-related spending, more than twice as large as the estimate from Williams and Phaneuf [2016].

Our estimates provide a lower bound of consumer WTP for improve air quality in that the health spending does not take into account the (negative) impact on the quality of life. In addition, the estimates do not reflect the costly avoidance behavior which we find from spending on the two control groups. The impact of 75 billion *yuan* (or \$11 billion) from a 10 $\mu g/m^3$ increase in $PM_{2.5}$ implies a lower bound for consumer WTP of 160 *yuan* (or \$25) per household for a reduction of $PM_{2.5}$ by 10 $\mu g/m^3$. Using a discrete choice framework to estimate the demand of indoor air purifiers in China, Ito and Zhang [2016] estimate a WTP of \$1.1 for a one unit reduction in PM_{10} based on the trade-off between the high price and the better quality (ability to remove more PM_{10}). With hedonic pricing model, Chay and Greenstone [2005] find that consumers are willing to pay \$329 more in housing price for a 1 $\mu g/m^3$ decrease in TSP. With 30-year time span and 5% annual interest rate, this translate to an annual payment of \$20. Bayer et al. [2009] estimated the willingness-to-pay to be \$149-\$185 for U.S. household for 1 $\mu g/m^3$ decrease in PM_{10}, around \$10 annually.

[6] For 2012, the most recent year available, and for hospital stays only.

CHAPTER 5
CONCLUSION

World Health Organization's global urban ambient air pollution database shows that world's most polluted cities in terms of $PM_{2.5}$ in 2016 were all from developing countries such as China, India, Iran, Pakistan, Philippines, and Saudi Arabia. The database also shows that 98% of cities in low- and middle-income countries with more than 100,000 residents do not meet WHO air quality guidelines. However, developed countries have been the focus of several decades of research on the impacts of air pollution on human health (particularly mortality) from epidemiology and economics. This analysis examines the morbidity impact of $PM_{2.5}$ based on the universe of credit and debit card transactions in China and provides a lower bound estimate of consumer WTP for improved air quality that can be used as an input for the cost-benefit analysis of environmental regulations.

To address the potential endogeneity in the air pollution measure, we develop an air quality prediction model in the spirit of the US EPA's source-receptor matrix whereby we consider each city as a source and a receptor at the same time. The model allows us to tease out plausibly exogenous variations in local air quality from the spatial spillovers due to the long-range transport of $PM_{2.5}$. The IV results, three to four times larger than those from OLS, suggest that a 10 μg/m^3 decrease in $PM_{2.5}$ would lead to at least 75 billion *yuan* ($11 billion) reduction in health spending annually, amounting to one percent of total annual health care expenditure nationally. The annual average concentration of $PM_{2.5}$ is about 60 μg/m^3 with the measure exceeding 100 in many major urban centers in Northern China, compared to the WHO recommended level of 10 μg/m^3. The National Plan on Air Pollution Control developed by the State Council in 2013, for the first time as a national policy, set a goal of reducing $PM_{2.5}$, for example by 25%, 20% and 15%

in 2017 relative to the 2012 levels in Beijing-Tianjin-HeBei, Yangtze River Delta, and Pearl River Delta regions. The findings from this study imply that the targeted reductions would lead to significant economic benefit.

We offer to our knowledge the first national-level analysis of the impact of air pollution on health spending in a developing country context. The air pollution level in many large urban centers in developing countries is often an order of magnitude higher than that observed in developed countries. As urbanization continues and development pressure rises, air pollution could be further exacerbated before they get better. The full impacts of air pollution on economic growth through channels such as human capital accumulation, productivity, talent loss due to migration, and foreign direct investments are interesting and important areas for future research.

APPENDIX A

ALMON ESTIMATION, ALTERNATIVE SPECIFICATIONS, OLS

Table A.1: Cumulative Effect of Pollution, Almon Estimation, OLS (Order=4, Lag=100)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.27***	0.22**	0.44***	0.30***	0.39*	-0.25**	-0.22***
	(0.08)	(0.09)	(0.1)	(0.1)	(0.21)	(0.1)	(0.07)
Current + Past 3d	0.97***	0.79**	1.64***	1.09***	1.20	-0.83***	-0.74***
	(0.27)	(0.32)	(0.36)	(0.35)	(0.8)	(0.32)	(0.25)
Current + Past 7d	1.71***	1.33**	3.02***	1.92***	1.65	-1.31**	-1.19***
	(0.48)	(0.58)	(0.62)	(0.59)	(1.57)	(0.53)	(0.42)
Current + Past 14d	2.62***	1.83*	5.03***	2.87***	1.47	-1.65**	-1.48**
	(0.78)	(0.97)	(0.99)	(0.89)	(2.94)	(0.76)	(0.67)
Current + Past 28d	3.80***	1.98	8.32***	3.72**	0.66	-1.81	-1.16
	(1.27)	(1.59)	(1.63)	(1.45)	(5.4)	(1.21)	(1.17)
Current + Past 56d	6.19***	2.29	14.15***	5.10**	4.26	-2.78	-0.16
	(1.93)	(2.15)	(2.93)	(2.35)	(8.22)	(2.19)	(1.89)
Current + All Lags	8.25***	2.94	18.55***	5.90	3.10	-1.91	-1.46
	(3.01)	(3.25)	(4.59)	(4.17)	(13.35)	(2.91)	(2.38)

Notes: The effect of air pollution for the past 100 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 μg/m^3 more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.2: Cumulative Effect of Pollution, Almon Estimation, OLS (Order=6, Lag=100)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.38***	0.39***	0.57***	0.35***	0.47**	-0.31***	-0.21**
	(0.09)	(0.11)	(0.12)	(0.12)	(0.21)	(0.12)	(0.1)
Current + Past 3d	1.25***	1.22***	1.95***	1.22***	1.55**	-1.01***	-0.73**
	(0.3)	(0.36)	(0.4)	(0.38)	(0.78)	(0.35)	(0.29)
Current + Past 7d	1.95***	1.71***	3.26***	2.06***	2.22	-1.51***	-1.16***
	(0.49)	(0.58)	(0.65)	(0.6)	(1.53)	(0.53)	(0.44)
Current + Past 14d	2.58***	1.78*	4.92***	2.90***	1.80	-1.69**	-1.46**
	(0.77)	(0.95)	(0.99)	(0.9)	(2.93)	(0.78)	(0.69)
Current + Past 28d	3.65***	1.72	8.22***	3.58**	-0.07	-1.62	-1.20
	(1.28)	(1.62)	(1.63)	(1.44)	(5.44)	(1.22)	(1.17)
Current + Past 56d	6.45***	2.72	14.30***	5.34**	5.44	-3.09	-0.10
	(1.9)	(2.11)	(2.94)	(2.38)	(8.18)	(2.2)	(1.91)
Current + All Lags	8.26***	2.96	18.58***	5.89	2.98	-1.90	-1.46
	(3.01)	(3.25)	(4.6)	(4.21)	(13.38)	(2.91)	(2.37)

Notes: The effect of air pollution for the past 100 days are estimated allowing polynomial decay with an order of 6. The dependent variables are log number of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.3: Cumulative Effect of Pollution, Almon Estimation, OLS (Order=5, Lag=60)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.48***	0.46***	0.77***	0.60***	0.61***	-0.26**	-0.11
	(0.09)	(0.12)	(0.12)	(0.13)	(0.21)	(0.12)	(0.09)
Current + Past 3d	1.33***	1.23***	2.14***	1.80***	1.91***	-1.03***	-0.50*
	(0.27)	(0.35)	(0.37)	(0.38)	(0.73)	(0.33)	(0.27)
Current + Past 7d	1.75***	1.50***	2.87***	2.60***	2.79**	-1.77***	-0.92**
	(0.47)	(0.56)	(0.6)	(0.6)	(1.36)	(0.49)	(0.42)
Current + Past 14d	2.24***	1.56*	3.95***	3.35***	3.14	-1.96***	-1.00
	(0.76)	(0.92)	(0.95)	(0.94)	(2.47)	(0.68)	(0.63)
Current + Past 28d	4.05***	2.10	8.14***	4.21***	1.97	-1.01	-0.33
	(1.25)	(1.51)	(1.61)	(1.57)	(4.53)	(1.04)	(1.05)
Current + Past 56d	7.08***	3.19	14.29***	5.73**	3.30	-1.88	1.19
	(1.86)	(2.04)	(2.64)	(2.37)	(7.44)	(1.89)	(1.66)
Current + All Lags	7.16***	2.68	15.11***	5.47**	2.60	-2.57	-0.18
	(1.98)	(2.16)	(2.81)	(2.51)	(8.06)	(1.99)	(1.73)

Notes: The effect of air pollution for the past 60 days are estimated allowing polynomial decay with an order of 5. The dependent variables are log number of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.4: Cumulative Effect of Pollution, Almon Estimation, OLS (Order=5, Lag=150)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.27***	0.32***	0.34***	0.39***	0.51**	-0.31***	-0.40***
	(0.09)	(0.09)	(0.13)	(0.13)	(0.22)	(0.11)	(0.09)
Current + Past 3d	0.98***	1.11***	1.31***	1.28***	1.78**	-1.07***	-1.34***
	(0.3)	(0.31)	(0.45)	(0.42)	(0.8)	(0.37)	(0.3)
Current + Past 7d	1.72***	1.85***	2.51***	1.93***	2.97**	-1.77***	-2.14***
	(0.52)	(0.53)	(0.77)	(0.68)	(1.45)	(0.61)	(0.5)
Current + Past 14d	2.64***	2.55***	4.42***	2.14**	4.02	-2.41***	-2.63***
	(0.79)	(0.85)	(1.18)	(0.96)	(2.48)	(0.91)	(0.81)
Current + Past 28d	3.92***	2.99**	7.76***	1.50	4.10	-2.75*	-1.97
	(1.3)	(1.46)	(1.92)	(1.64)	(4.6)	(1.63)	(1.55)
Current + Past 56d	6.32***	3.92*	12.49***	3.06	3.52	-3.74	-1.09
	(2.15)	(2.27)	(3.44)	(3.08)	(8.56)	(3)	(2.62)
Current + All Lags	6.42	3.00	13.05*	4.45	0.93	2.36	-3.42
	(4.95)	(5.1)	(7.29)	(7.79)	(19.74)	(4.64)	(3.96)

Notes: The effect of air pollution for the past 150 days are estimated allowing polynomial decay with an order of 5. The dependent variables are log number of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.5: Cumulative Effect of Pollution, Almon Estimation, IV (Order=4, Lag=100)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.56**	0.50	0.08	0.65**	1.46	-1.34***	-0.96***
	(0.26)	(0.31)	(0.28)	(0.31)	(1.01)	(0.29)	(0.23)
Current + Past 3d	2.08**	1.97*	0.45	2.64**	5.28	-4.39***	-3.30***
	(0.89)	(1.09)	(0.97)	(1.08)	(3.58)	(0.98)	(0.75)
Current + Past 7d	3.82**	3.90**	1.24	5.27***	9.49	-6.54***	-5.34***
	(1.53)	(1.9)	(1.61)	(1.81)	(6.24)	(1.58)	(1.17)
Current + Past 14d	6.35***	7.09**	3.32	9.52***	15.91	-6.81***	-6.69***
	(2.38)	(3)	(2.45)	(2.7)	(10.04)	(2.19)	(1.54)
Current + Past 28d	10.88***	12.66**	9.24**	15.68***	30.97*	-2.35	-4.93**
	(4.18)	(5.19)	(4.4)	(4.12)	(18.39)	(3.38)	(2.34)
Current + Past 56d	20.48**	20.79**	20.79**	20.47***	71.30*	-1.34	-0.65
	(8.29)	(9.96)	(9.5)	(6.89)	(37.78)	(6.55)	(4.08)
Current + All Lags	27.96*	29.41*	22.82	28.04*	121.27*	3.84	-7.54
	(14.66)	(17.35)	(17.31)	(14.97)	(63.37)	(10.19)	(6.46)
F	23.72	23.79	23.65	24.04	20.91	23.72	23.69

Notes: The effect of air pollution for the past 100 days are estimated allowing polynomial decay with an order of 4. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

Table A.6: Cumulative Effect of Pollution, Almon Estimation, IV (Order=6, Lag=100)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.54	0.84	-0.16	0.50	3.41**	-1.23**	-0.77*
	(0.53)	(0.62)	(0.62)	(0.74)	(1.72)	(0.53)	(0.4)
Current + Past 3d	1.96	2.82	-0.19	2.16	10.18**	-4.36***	-2.75**
	(1.49)	(1.78)	(1.72)	(2.08)	(4.96)	(1.52)	(1.11)
Current + Past 7d	3.59*	4.71*	0.54	4.63*	14.40**	-6.97***	-4.69***
	(1.97)	(2.41)	(2.21)	(2.67)	(7.02)	(2.01)	(1.41)
Current + Past 14d	6.14**	7.45**	2.93	9.08***	18.33*	-7.44***	-6.28***
	(2.45)	(3.09)	(2.59)	(2.98)	(10.07)	(2.34)	(1.56)
Current + Past 28d	11.05**	13.37**	8.91*	15.71***	34.89*	-1.24	-4.77*
	(4.69)	(5.84)	(4.94)	(4.84)	(21.02)	(3.72)	(2.5)
Current + Past 56d	20.01**	21.17**	20.19**	19.60***	74.35**	-3.07	0.07
	(8.18)	(9.84)	(9.24)	(7.26)	(37.2)	(6.63)	(4.04)
Current + All Lags	27.88*	30.33*	22.17	27.62*	126.98*	4.09	-7.00
	(15.18)	(18.07)	(17.79)	(16.11)	(66.3)	(10.51)	(6.51)
F	13.33	5.41	27.48	11.06	6.11	16.90	50.06

Notes: The effect of air pollution for the past 100 days are estimated allowing polynomial decay with an order of 6. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

Table A.7: Cumulative Effect of Pollution, Almon Estimation, IV (Order=5, Lag=60)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	-0.86	-0.67	-0.13	0.09	-1.85	-2.03***	-1.17**
	(0.57)	(0.62)	(0.78)	(0.57)	(1.87)	(0.66)	(0.55)
Current + Past 3d	-1.31	-0.52	-0.22	1.32	-1.61	-6.27***	-3.48**
	(1.33)	(1.46)	(1.86)	(1.53)	(3.86)	(1.66)	(1.37)
Current + Past 7d	0.74	2.18	0.27	4.05*	5.06	-8.78***	-4.82***
	(1.49)	(1.74)	(1.95)	(2.09)	(3.85)	(1.94)	(1.49)
Current + Past 14d	5.28**	7.18***	2.57	8.70***	16.15**	-8.56***	-5.15***
	(2.13)	(2.64)	(2.22)	(2.71)	(7.94)	(2.2)	(1.47)
Current + Past 28d	9.86***	11.71***	9.96***	13.29***	26.78**	-3.56	-3.11
	(3.47)	(4.26)	(3.67)	(3.58)	(13.54)	(3.05)	(2.32)
Current + Past 56d	20.87***	21.48**	21.08***	15.04**	72.63**	-2.71	2.13
	(7.19)	(8.57)	(8.01)	(6.05)	(31.59)	(6.54)	(4.07)
Current + All Lags	24.93***	25.08**	25.21**	17.43**	86.81**	-2.89	1.04
	(9.04)	(10.7)	(10.15)	(7.65)	(38.97)	(7.59)	(4.35)
F	28.38	28.24	28.31	27.21	19.10	28.40	28.17

Notes: The effect of air pollution for the past 60 days are estimated allowing polynomial decay with an order of 5. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

Table A.8: Cumulative Effect of Pollution, Almon Estimation, IV (Order=5, Lag=150)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.42**	0.70***	-0.20	0.79**	0.51	-1.57***	-1.38***
	(0.2)	(0.25)	(0.27)	(0.32)	(0.75)	(0.34)	(0.28)
Current + Past 3d	1.58**	2.59***	-0.33	2.96***	2.43	-5.04***	-4.71***
	(0.7)	(0.88)	(0.9)	(1.08)	(2.69)	(1.11)	(0.92)
Current + Past 7d	2.99**	4.72***	0.33	5.47***	5.75	-7.34***	-7.53***
	(1.27)	(1.63)	(1.46)	(1.79)	(5.19)	(1.75)	(1.39)
Current + Past 14d	5.23**	7.71**	2.94	9.01***	13.08	-7.25***	-9.29***
	(2.38)	(3.05)	(2.45)	(2.68)	(10.64)	(2.38)	(1.76)
Current + Past 28d	9.56*	12.65**	9.56*	14.09***	30.74	-2.06	-7.01**
	(5.14)	(6.39)	(5.42)	(4.45)	(23.99)	(3.95)	(2.91)
Current + Past 56d	18.49*	22.91*	15.97	21.54**	68.97	-1.71	-4.23
	(10.1)	(12.34)	(11.07)	(8.39)	(47.11)	(7.96)	(5.69)
Current + All Lags	32.90	45.99	7.36	35.77	193.12	11.19	-27.75*
	(29.7)	(35.47)	(32.34)	(29.66)	(141.27)	(19.23)	(14.24)
F	8.71	8.72	8.57	8.24	8.64	8.73	8.67

Notes: The effect of air pollution for the past 150 days are estimated allowing polynomial decay with an order of 5. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

APPENDIX B

ADDITIONAL REGRESSION RESULTS WITH VALUE OF TRANSACTIONS

Table B.1: Cumulative Effect of Pollution, Almon Estimation, OLS (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.07	0.05	0.22	0.02	-0.09	-0.40**	-0.23
	(0.09)	(0.10)	(0.16)	(0.14)	(0.28)	(0.19)	(0.18)
Current + Past 3d	0.29	0.24	0.84	0.17	-0.55	-1.24**	-0.73
	(0.30)	(0.35)	(0.53)	(0.46)	(0.99)	(0.63)	(0.61)
Current + Past 7d	0.63	0.54	1.56*	0.50	-1.46	-1.72*	-1.03
	(0.52)	(0.60)	(0.88)	(0.71)	(1.82)	(1.00)	(0.99)
Current + Past 14d	1.20	1.01	2.62**	1.10	-3.10	-1.66	-1.04
	(0.82)	(0.95)	(1.29)	(0.98)	(3.38)	(1.38)	(1.43)
Current + Past 28d	1.94	1.28	4.60**	1.30	-3.82	-1.51	-0.84
	(1.25)	(1.47)	(2.05)	(1.68)	(6.24)	(2.07)	(2.20)
Current + Past 56d	3.02*	0.89	10.23***	-0.10	4.11	-2.93	0.08
	(1.72)	(1.90)	(3.72)	(2.69)	(8.83)	(3.44)	(3.63)
Current + All Lags	4.87*	2.11	11.39**	-0.39	4.31	0.99	2.03
	(2.51)	(2.59)	(5.12)	(4.06)	(13.09)	(4.68)	(4.78)

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are total values of transactions. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.2: Cumulative Effect of Pollution, Almon Estimation, IV (Order=4, Lag=90)

	Health-Related Consumption					Control Groups	
	Health	All Hospital	Pharmacy	Renmin	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.07	-0.05	-0.54	0.21	1.50	-2.33***	-1.61***
	(0.33)	(0.37)	(0.53)	(0.43)	(1.15)	(0.57)	(0.56)
Current + Past 3d	0.47	0.14	-1.59	1.14	4.73	-7.34***	-5.49***
	(1.14)	(1.26)	(1.74)	(1.43)	(3.97)	(1.86)	(1.84)
Current + Past 7d	1.36	0.96	-1.93	2.81	7.03	-10.34***	-8.82***
	(1.92)	(2.13)	(2.74)	(2.25)	(6.67)	(2.88)	(2.86)
Current + Past 14d	3.39	3.13	-0.48	5.99*	9.20	-9.53***	-11.09***
	(2.95)	(3.30)	(3.83)	(3.06)	(10.12)	(3.67)	(3.78)
Current + Past 28d	7.43	7.26	6.06	9.83**	20.20	-2.32	-9.11*
	(5.14)	(5.78)	(6.48)	(4.36)	(17.39)	(4.90)	(5.39)
Current + Past 56d	14.50	12.32	20.86*	9.11	68.28*	-3.47	-0.15
	(9.82)	(10.88)	(12.07)	(7.02)	(34.92)	(8.89)	(9.69)
Current + All Lags	23.39	19.38	24.80	15.93	110.56**	10.25	2.64
	(15.45)	(17.14)	(18.93)	(13.22)	(55.66)	(13.37)	(14.82)
F	29.78	29.81	29.72	29.68	25.00	29.74	29.74

Notes: The effect of air pollution for the past 90 days are estimated allowing polynomial decay with an order of 4. The dependent variables are total values of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates cumulative effect on the number of transaction in percentage, from an exposure to 100 $\mu g/m^3$ more $PM_{2.5}$ for the corresponding length of time listed in the first column. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported for cluster-robustness.

APPENDIX C

ALMON ESTIMATION, ALTERNATIVE SPECIFICATIONS, IV

Table C.1: Total Long-Term Effect of Pollution, Almon Estimation, IV, Healthcare Industry

	Lag k				
Order q	30 days	60 days	90 days	120 days	150 days
3	15.12***	26.43***	27.70**	28.49	32.91
	(5.10)	(9.34)	(12.63)	(20.74)	(30.01)
4	18.81***	27.61***	27.17**	27.89	32.66
	(6.29)	(10.26)	(12.88)	(20.49)	(29.96)
5	16.48***	24.93***	28.42**	26.38	32.90
	(4.71)	(9.04)	(12.38)	(19.64)	(29.70)

Notes: The effect of air pollution for current day and the past k days are estimated allowing polynomial decay with an order of q. The dependent variables are log number of transactions. The instruments are predicted non-locally generated $PM_{2.5}$, from cities more than 200 km away, transformed by the same method as the regressor. The controls are city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, special day dummies (holiday, spring festival, working weekend), current-day weather controls (mean temperature, rain dummy, mean wind speed). Coefficients indicates total long-term effect on the number of transaction in percentage, from an exposure to 100 μg/m^3 more $PM_{2.5}$ for the corresponding length of time listed in the given specification. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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