Air Pollution, Health Spending and Willingness to Pay for Clean Air in China

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Abstract

Understanding the health impact of air pollution and consumer willingness to pay (WTP) for clean air is critical for understanding the benefit of environmental regulations. Based on the universe of credit and debit card transactions in China from 2013 to 2015, this paper provides to our knowledge the first analysis of the impact of $PM_{2.5}$ on healthcare costs for the entire population of a developing country. To address potential endogeneity in pollution exposure, we construct an instrumental variable by modeling the spatial spillovers of $PM_{2.5}$ due to long-range transport. We incorporate the IV method into a distributed-lag model estimated with B-splines to flexibly capture the effect of past air pollution. Our analysis shows that $PM_{2.5}$ has significant impacts on health spending in both the short and medium term and that consumers exhibit avoidance behavior in spending. The annual reduction in national health spending from complying with the World Health Organization's annual standard of 10 $\mu g/m^3$ would amount to over \$40 billion, nearly 7% of China's total health spending in 2015. Our estimates suggest a lower bound of annual household WTP of \$9.25 for a 10 $\mu g/m^3$ reduction in $PM_{2.5}$.

Keywords: Air Pollution, Health Impact, Avoidance Behavior, Willingness to Pay

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1 Introduction

The health impact of air pollution and consumer willingness to pay (WTP) for clean air are important components of the overall benefit of environmental regulations. 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 quantify the causal impact of air pollution on health by using 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). This literature has mainly focused on mortality risk, in particular for infants, in the U.S. and Europe.

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, there is a lack of reliable data and rigorous studies on the benefit of pollution reduction in these countries. As a result, the dose-response relationship (between pollution exposure and health outcomes) estimated using data from developed countries are often used as inputs for evaluating environmental regulations in developing countries, raising the question of external validity of this approach (Arceo et al., 2015).

This study fills this gap in the literature by examining the impact of $PM_{2.5}$ on health spending in China. To do so, we combine hourly air pollution readings from all monitoring stations from 2013 to 2015 with the universe of credit/debit card transactions in China during the same period. This is to our knowledge the first comprehensive analysis of how air pollution affects health expenditures from all medical conditions for the entire population of a developing country.[1] The causal impact of air pollution on out-of-pocket health spending also provides a lower bound estimate of consumer WTP for improved air quality. The reliance on health spending to directly infer WTP is in contrast with the revealed preference literature that relies on the implicit trade-off between risk factors and

[1] A growing literature uses health insurance claims data to examine the impact of air pollution on health spending in the U.S. (Deschenes et al., forthcoming; Williams and Phaneuf, 2016; Deryugina et al., 2017). However, health insurance tends to be inadequately provided in developing countries.

prices in product choices.

There are a couple of key empirical challenges in identifying the causal effect of air pollution on health spending. The first challenge is the potential endogeneity in contemporaneous and lagged $PM_{2.5}$ that we use to capture pollution exposure. The endogeneity can arise from multiple sources, including unobservables that affect both the pollution level and consumer spending (e.g., economic conditions) and avoidance behavior in response to air pollution (e.g., reduced outdoor activities). In addition, there could be measurement errors in proxying pollution exposure using air quality monitoring data. The pollution level could vary across locations within a city, and the pollution exposure of the residents in a city ideally should be measured by the population weighted average of the pollution level in different parts of the city. However, monitoring stations are located sparsely and this prevents us from constructing population weighted averages. To the extent the measurement errors are classical, they would attenuate the estimates toward zero.

To deal with this challenge, we construct instrumental variables by modeling the spatial spillovers of $PM_{2.5}$ due to the property of long-range transport of fine particles that is affected by wind direction and speed. Our approach is in the same spirit of the source-receptor matrix in the atmospheric science literature that is used to predict air quality from various pollution sources.[2] Specifically, we use a parsimonious and transparent model of $PM_{2.5}$ concentration that allows us to disentangle the contribution of non-local and local sources. The model uses wind patterns, lagged pollution levels in other cities, and geographic information as inputs. We use this model to construct instruments for the observed $PM_{2.5}$ in that city as functions of $PM_{2.5}$ that is imported from non-local sources as well as prevailing wind patterns. The instruments we construct can be considered as various weighted sums of lagged $PM_{2.5}$ levels in other cities where the weights are a function of distance between the two cities, wind direction and speed in other cities. We show that the total amount of $PM_{2.5}$ imported from non-local sources is a linear combination of our instruments. To address the concern of spatial correlation of economic activities, we create a buffer zone of 150 km and only use pollution sources outside of the buffer zone in generating these instruments. Our results are robust to reasonable choices of the buffer zone and a variety of robustness checks to control for unobservables and spatial correlations in them.

Our identification strategy is different from the regression discontinuity (RD) approach based on the Huai River heating policy used in Chen et al. (2013); Ito and Zhang (2016); Ebenstein et al. (2017). The RD design is better suited to study the long-term impact such as on mortality by relying on the long-term cross-sectional variation in the data. This study focuses on the short- and medium-term impacts and the IV approach allows us to leverage rich spatial and temporal variations in our data. Our IV approach is similar to the identification strategy used in Williams

[2] In our model, we do not specify specific pollution sources (e.g., power plants), but instead use the pollution levels in other cities as the influencing factors for the pollution level of a given city.

and Phaneuf (2016) and Deryugina et al. (2017). The former constructs the IV based on air quality predictions from the EPA's source-receptor matrix using distant polluting facilities as inputs, while the latter uses daily wind direction in a county as exogenous shocks to local air pollution.

The second challenge in estimating the causal effect of pollution on health spending arises from the nature of the high-frequency data at the daily level. On the one hand, the data environment allows us to characterize the dynamic path of the impacts. On the other hand, the daily pollution measures exhibit high serial correlation. A direct OLS or IV estimation that includes many lagged terms leads to oscillating estimates that are imprecise. To take advantage of the rich data while addressing the high serial correlation, we propose a flexible distributed-lag model that extends the Almon technique (Almon, 1965) and uses finite-order B-splines to flexibly capture the effects of long lags. We incorporate the IV method in this framework to address endogeneity in contemporaneous and lagged air pollution measures.

Based on the OLS analysis of city-level daily health spending with a rich set of temporal and location fixed effects, a temporary increase of 10 μg/m^3 in $PM_{2.5}$ concentration that lasts for a week is associated with an increase of 0.19% in the total number of hospital and pharmacy transactions. A permanent elevation of 10 μg/m^3 in $PM_{2.5}$ concentration would raise the number of health transactions by 0.86%. The results from IV analysis indicate much stronger impacts: a temporary increase of 10 μg/m^3 in $PM_{2.5}$ would lead to a 0.61% increase in health transactions, while a permanent increase of the same magnitude would lead to a 2.65% increase in the number of transactions in healthcare. The impact of $PM_{2.5}$ differs across health facilities: spending in Children's hospitals is more than twice as responsive as that in other types of health facilities. For non-health spending, we find a negative impact of $PM_{2.5}$ in the short-term but no significant impact beyond two weeks. In addition, a projected worsening of air quality in the next day increases today's spending in both health and non-health categories. Taken together, these results provide evidence of avoidance behavior whereby consumers reduce outdoor activities (such as shopping) to mitigate pollution exposure.

The estimates of health impacts of $PM_{2.5}$ survive a variety of robustness checks including various parametric specifications of the medium-term impact, different buffer zones in constructing the IV, and the inclusion of other pollutants such as CO, SO_2 as well as the average of $PM_{2.5}$ in nearby cities. In monetary terms, a permanent reduction of 10 μg/m^3 in daily $PM_{2.5}$ would lead to total annual savings of at least 60 billion *yuan* ($9 billion) in health spending. Bringing down China's $PM_{2.5}$ to the World Health Organization's (WHO) annual standard of 10 μg/m^3 could lead to savings in health spending exceeding $42 billion, nearly 7% of the total health spending or 0.4% of China's GDP in 2015.

Our analysis on health spending helps quantify consumer WTP for improved air quality, a key policy parameter in the cost-benefit analysis of environmental regulations. Through a framework of consumer utility maximization, we show that consumer WTP for clean air can be bounded from below by the estimated impacts of air pollution on health spending. Our results suggest a lower bound of $9.25 for the annual household WTP for a 10 μg/m^3 reduction in $PM_{2.5}$, which is similar to the WTP estimates for PM_{10} reduction among Chinese households from Ito and Zhang (2016).

This study makes four contributions to the literature. First, to our knowledge, this is the first comprehensive study that analyzes the effect of pollution on health spending by the entire population of a developing country. Our analysis is made possible by a novel data set that is composed of the universe of credit card and debit card transactions in China from January 2011 to present. There are 2.7 billion credit and debit cards that contribute to 1.5 trillion *yuan* of economic activities. Besides covering fifty percent of out-of-pocket health spending in China, this data set also includes spending in three hundred non-health sectors.

Second, a common practice in evaluating the health impact of air pollution in developing countries is to take the dose-response function estimated in developed countries to interpolate the mortality or morbidity impact from reduced air pollution in developing countries (e.g. Lelieveld et al. (2015) and World Bank (2007)). This benefit-transfer approach may lead to large inaccuracies given the differences in air pollution levels, baseline health conditions, and access to health care between these two groups of countries. In contrast, our paper directly estimates the health impact of air pollution in a developing country, adding to the nascent literature using the same approach (Arceo et al., 2015; Chen et al., 2013; Greenstone and Hanna, 2014; He et al., 2016; Ebenstein et al., 2017). Different from other studies in this literature that mostly focus on mortality, the high-frequency nature of our data allows us to identify the short- and medium-term impacts on health spending. In addition, quantifying the benefits of reduced pollution by translating the reduced mortality or morbidity into monetary terms requires adopting concepts such as the *value of a statistical life* (VSL).[3] We benefit from directly observing health spending, which gets around such interpolations.

Third, traditionally, consumer WTP for improved air quality is estimated using the revealed preference approach that infers WTP based on the implicit trade-offs between risk levels and prices in consumer goods such as housing and consumer products (Chay and Greenstone, 2005; Bayer et al., 2009; Ito and Zhang, 2016). Resorting to the utility maximization framework, this approach typically invokes behavioral assumptions such as perfect information on the health impact of air pollution to infer consumer WTP. If consumers systematically underestimate the health impacts (for example due to a lack of awareness), the estimated WTP would be biased toward zero. Different from the revealed preference literature, this study uses realized health spending data and contributes to the growing literature on estimating health impacts and WTP for improved air quality with med-

[3] 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).

ical expenditures (Deschenes et al., forthcoming; Williams and Phaneuf, 2016; Deryugina et al., 2017). The approach of using health spending data to estimate WTP does not rely on the informational assumption: the estimates are derived from the fact that elevated pollution leads to illnesses which are then treated through healthcare spending. Whether or not consumers know that the underlying cause for their illnesses is pollution is immaterial for our estimates. The disadvantage of this approach is that the WTP estimates do not capture impacts through other channels such as on mortality and labor productivity, which the revealed preference approach should capture in theory under the assumption of perfect information.

Fourth, the rich spatial and temporal variations in our data allow us to examine both the short- and medium-term impacts of air pollution on health spending. The aforementioned studies using health insurance data all focus on the contemporaneous impact by using daily or quarterly data. We are interested in both the contemporaneous and future health consequences of pollution. However, as mentioned above, directly controlling for lagged daily measures leads to unstable estimates. Our flexible distributed-lag model with IVs is computational light and has several advantages over existing methods such as VARs or local projection methods. It delivers a smooth impulse response function, allows researchers to estimate both the short-term and long-run effects, and can easily incorporate instrumental variables. To our knowledge, our study is the first analysis in the environmental literature that uses this technique to estimate the short- and medium-term impacts with high frequency data.

The rest of the paper is organized as follows. Section 2 describes the data and the air pollution challenge in China. Section 3 provides a stylized model to illustrate that the estimated impact on health spending can be used as a lower bound for consumer WTP for clean air. Section 4 discusses our empirical framework and the identification strategy. Section 5 presents empirical results and Section 6 discusses our findings in relation to the literature. Section 7 concludes.

2 Data

Our analysis is based on three comprehensive micro-level datasets of air pollution, consumer spending by category, and meteorology conditions that each has a national coverage. Collectively, they form a daily city-level panel for more than 300 major Chinese cities from 2013 to 2015. This enables us to evaluate the impact of air pollution on spending in both the short- and medium-term, as well as heterogeneous impacts across pollution levels.

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. This unprecedented economic growth is largely propelled by fossil fuels, with coal accounting for about two-thirds of aggregate energy consumption and oil nearly twenty percent. China is by far the largest energy consumer, accounting for roughly a quarter of world's total energy consumption and half of world's coal consumption.

Fast economic growth and rising energy consumption have put an enormous pressure on the environment, with air, water, and soil pollution becoming the most serious challenges in China today that adversely affect human health, ecosystems, and the quality of life.[4] Improving air quality has become an important policy goal for the central government, which revised extensively the Environmental Protection Law in 2014 and implicitly defined goals of pollution abatement in both the 12th (2011 - 2015) and 13th (2016 - 2020) five-year plans.

Fine-scale air quality data at monitoring stations became publicly available in 2013. The Ministry of Environmental Protection (MEP) publishes hourly measures of $PM_{2.5}$, CO, SO_2, NO_2, and O_3. The number of monitoring stations and cities covered increases steadily from 1003 stations in 159 cities in 2013 to 1582 stations in 367 cities in 2015. We calculate the daily concentration of $PM_{2.5}$ and other pollutants at the city level by averaging data across monitoring stations within a city.

Figure 1 plots the three-year average of $PM_{2.5}$ from 2013 to 2015 for each city. The nationwide average during this period is 56 μg/m^3 (with a standard error of 46 μg/m^3), which is much higher than the annual average standard of 12 μg/m^3 that is set by the U.S. Environmental Protection Agency or 35 μg/m^3 by the China MEP.[5] There is considerable regional disparity. Cities in the northern and central China with a high concentration of manufacturing industries suffer from the most severe pollution, with many of them experiencing a three-year average $PM_{2.5}$ concentration of 90 μg/m^3 or higher. The less-developed regions in the west and wealthy regions in the south have better air quality. The latter, especially regions along the coast, has seen noticeable improvement in air quality as a result of shutting down or relocating polluting industries and reorienting the industry structure toward high tech and service industries.

One advantage of our empirical analysis is the rich variation in pollution measures both across cities and over time. To illustrate the time-series variation, we present in figure 3 the daily $PM_{2.5}$

[4] 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's total premature deaths in the same year. World Bank (2007) puts the health cost of air pollution at 1.2-3.8% of China's GDP in 2003.

[5] The EPA's daily standard is 35 μg/m^3 and annual standard is 12 μg/m^3. China's MEP sets limits on $PM_{2.5}$ for the first time in 2012 to take effect in 2016: the daily standard is 75 μg/m^3 and annual standard is 35 μg/m^3.

concentration for the nation (the top panel) and each of the four broad regions (the bottom panel).[6] In all regions of the country, the daily $PM_{2.5}$ concentration is higher than 35 $\mu g/m^3$, the official MEP standard, for most days. The northern regions have much more pronounced peaks in the winter than the southern region, largely because of the coal-fired central heating systems north of Huai River (Chen et al., 2013) The pollution level is trending downwards in all regions, driven by tightened government regulations, private and public investment in waste treatment, and changes in China's overall industry structure.

2.2 Consumer Spending

The second main database for our analysis is the universe of credit and debit card (or 'bank card') transactions in China settled through the UnionPay network. The Unionpay network is the only inter-bank payment network in China and is state owned. The network is the largest in the world in terms of both the number and value of transactions, ahead of Visa and Mastercard. There are in total 2.7 billion cards from 2013 to 2015 with transactions covering over 300 merchant categories.[7] The database includes eight trillion *yuan* of annual economic activities. We observe the location, time, merchant name, and amount for each transaction and we aggregate the data to daily spending by category by city from 2013 to 2015. To our knowledge, this is the most comprehensive and fine-scale data in temporal and spatial dimensions on consumer spending in China and we are the first to utilize them for academic research.

Health care in China is financed by out-of-pocket spending, health insurance, and government programs similar to the U.S. medicare. Medical expenses that are covered by the Chinese 'medicare' programs are often directly billed on medicare cards, most of which are settled through the UnionPay network and enter the database as regular transactions. Commercial health insurance companies usually require patients to pay for medical expenses first and get reimbursed later through filing claims. If consumers pay for these expenses via their bank cards, then these transactions will be included in our database.[8]

[6]The Northeastern region includes Heilongjiang, Jilin, Liaoning, and the northeastern part of Inner Mongolia. The Northern region includes Beijing, Tianjin, Hebei, Shanxi, Shandong, Henan, and the rest of Inner Mongolia. The Northwestern region includes Shanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Southern region includes Guangdong, Guangxi, Hainan, Guizhou, Yunnan, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Hubei, Hunan, Chongqing, and Sichuan. Tibet is excluded in the regional plots due to the sparse coverage.

[7]There are seven major categories and 300 subcategories. The major categories are: retail; wholesale; direct sales; real estate and finance; residential and commercial service; hotel, restaurant, and entertainment; and education, health, and government service. Merchants are classified by these categories.

[8]The healthcare system and the insurance market in China have been improving with significant government support. In 2009, China's central government revealed plans to overhaul its healthcare system by providing 850 billion Yuan to develop the healthcare system between 2009 and 2011 and to increase the basic health insurance coverage from 65 percent to 90 percent by 2011. By 2011, the insurance coverage through three major government supported insurance programs reached nearly 95% and the reimbursement rate was about 44 to 68 percent depending on the insurance program (Yu, 2015).

Our data account for 31% of aggregate private healthcare spending in 2013, and as card penetration grew, the coverage rises to 51% in 2015, similar to the share of bank card transactions in other sectors. The high penetration of bank cards in retail spending in China is remarkable given its short history (the first credit card was issued in 1998 and it was not until late 2000s when consumers began to adopt bank cards. The official statistics from Central Bank of China (2015) show that bank card transactions accounted for 48% of overall spending on retail sales of consumer goods in the third quarter of 2015, increasing from only 17% in 2006. In the U.S., spending from credit and debit cards accounts for 55% of all consumer spending (Bagnall et al., 2014).

Figure 2 shows the spatial pattern of card adoption by plotting the number of active cards per capita (i.e., registered resident) by city in 2015. We assign each card to one primary city based on the location of its most frequent usage. The card adoption is higher in coastal or high-income cities. This could partially be driven by the fact that in high-income cities, there are likely more firms who own cards. In addition, some of the cards assigned to these cities could be owned by migrants and tourists who are not part of the population in the denominator of the variable.

Despite the richness and uniqueness of the credit and debit card transactions, they only cover about half of the healthcare spending in 2015 and they may not be representative of all the healthcare transactions. The card users are more likely to be urban residents, have higher income, and younger than the population average or those who seek medical treatment. In order to interpret the health impacts estimated based on our data as the population impacts, we need to assume that the health impacts are not correlated with the method of payments. To the extent that the elderly are less likely to use credit and debit cards while being more vulnerable to air pollution, the estimates based on our data may be a lower bound of the population impacts. However, the underestimation could be moderated by the fact that Chinese elderly tend to be cared for by the young who likely accompany them for hospital visit and pay the bill. In addition, rural and low-income residents likely have lower baseline health status. If this implies that air pollution has a more server health impact for them, our analysis would also underestimate the population impacts.

Health spending includes transactions at hospitals, pharmacies, and other healthcare facilities (e.g. small health clinics). In 2015, hospitals account for 83.5% of health spending in our data, and 56.8% of transactions. Different from pharmacies in the U.S. such as CVS or Walgreens, pharmacies in China only carry medicines and rarely sell daily necessities. Pharmacies account for 6.0% of total healthcare spending, and 31.0% of transactions in 2015. We separate hospitals and pharmacies from other healthcare facilities. Within hospitals, we distinguish People's hospitals and Children's hospitals from other hospitals. People's hospitals are state-owned general hospitals and tend to be the largest health care facilities in a city. Each city has at least one People's hospital. Children's hospitals accept mostly children patients. Birth centers and infant health centers are grouped into Children's hospitals. People's and Children's 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.[9]

In addition to health spending, we also analyze spending in non-health categories, such as daily necessities. We follow United Nations' Classification of Individual Consumption According to Purpose (COICOP) closely in defining necessity goods.[10] Relative to the health spending, total non-health spending is seven times as large and transact six times as frequent. Spending on daily necessities is three times as large and transact three times as frequent. A unique feature of Chinese consumers' shopping behavior is their frequent trips (often on a daily basis) for groceries at the supermarkets. We therefore use supermarket spending as another proxy for daily consumption, in addition to spending on necessities.[11] Spending in supermarkets is over four times as large as health spending in value and five times as frequent in 2015.

To illustrate the inter-temporal patterns, Figure 4 plots weekly healthcare spending and the number of transactions at the national level from 2013 to 2015. There is a significant drop in both the spending amount and the transaction frequency during holidays. In addition, both variables have more than tripled during our sample period due to the diffusion of bank cards. We control for these two salient features in our regression analysis through holiday fixed effects and city-specific time trends.

2.3 Meteorology Data and Summary Statistics

Besides pollution, weather conditions could also directly affect health outcomes (Deschenes et al., 2009). We obtain meteorology data from the Integrated Surface Database (ISD) that is hosted by National Oceanic and Atmospheric Administration (NOAA). The ISD dataset includes hourly measures of temperature, precipitation, wind speed and wind direction for 407 monitoring stations in China.[12] We match cities with the nearest weather station according to their geographic coordinates and compute daily temperature and wind speed from a simple average of the hourly data.

ISD's hourly measure of precipitation suffers from noticeable measurement errors, so we use daily precipitation from NOAA's *Global Surface Summary of the Day* database (GSOD) instead.[13] Wind direction of the day is calculated by adding up twenty-four hourly vectors of wind directions, where the length of each vector is the hourly wind speed.

Table 1 reports the summary statistics for all variables used in our study at the city-day level. The daily $PM_{2.5}$ concentration is on average 56 μg/m^3 between 2013 and 2015, where the in-

[9] We use hospital names and keyword matching to identify People's hospitals and Children's hospitals.

[10] United Nations' COICOP defines necessity goods as 1) food and non-alcoholic beverages, 2) alcoholic beverages, tobacco and narcotics, 3) clothing and footwear, 4) recreation and culture, and 5) restaurants and hotels.

[11] Since supermarkets sell a large variety of goods other than necessities, we exclude supermarkets in necessity spending.

[12] These stations cover most major Chinese cities from as early as the 1940s till now.

[13] GSOD reports daily precipitation using Greenwich Mean Time, which is the cumulative rainfall from 8 a.m. Beijing time to 8 a.m. the next day. We use this measure as our daily precipitation.

terquartile range is from 27 to 69 and the maximum is 985. Sixty-seven percent of these city-day observations record a concentration level that is above the U.S. daily standard of 35 μg/m^3. In terms of health spending, the average daily number of transactions is 7,229 per city, and the average daily spending is 6.7 million *yuan*.

3 Theoretical Model

Air pollution affects human health mainly through its impact on respiratory and cardiovascular systems. Several decades of study in epidemiology and more recently economics has associated exposure to air pollution with increases in mortality and morbidity risks (Brunekreef and Holgate, 2002; Pope and Dockery, 2012). Fine particles ($PM_{2.5}$) are especially detrimental to health as they can penetrate deep into lungs and carry toxins to other organs. High levels of $PM_{2.5}$ irritate respiratory and cardiovascular systems and can lead to aggravated asthma, lung disease, heart attacks, and stroke.

In this section we provide a theoretical model to illustrate the relationship between the estimated impact of $PM_{2.5}$ on health spending and consumer WTP for improved air quality. The seminal paper by Grossman (1972) first proposed the utility maximization framework of health production where consumers choose optimal health care spending to alleviate the negative impact of air pollution exposure. Following this tradition, Deschenes et al. (forthcoming) 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. The marginal effect provides a conservative estimate of WTP because consumers can engage in defensive spending such as purchases of air purifiers or face masks or avoidance behavior such as staying indoors. Air purifier spending or lost utility from staying indoors should constitute part of consumers' WTP for clean air but is not included in the marginal response of health spending. While the literature has largely neglected the role of avoidance behavior and reduction in quality of life, here we present a static model to account for both.

There is a continuum of consumers of measure 1. Each consumer i chooses health spending (m_i), non-health offline spending (c_i), and non-health online spending (o_i), subject to his budget constraint. The consumer is exposed to air pollution whenever he goes outdoors, and we assume that pollution exposure $e(a, m_i + c_i)$ is an increasing and convex function of the air pollution level a (which is exogenous to consumer i's spending) and spending activities $m_i + c_i$, but is not affected by online spending o_i.[14]

[14] We combine all non-health spending (except online spending) in c and assume each \$1 of spending results in the same amount of pollution exposure independent of purpose. Convexity implies that on more polluted days, the marginal impact of spending activities on pollution exposure is larger.

Consumer i has an endowed health stock h_0, which evolves as a result of exposure to air pollution and his own health spending that mitigates the negative consequences of pollution. Individuals differ in how sick they become when exposed. This is captured by $g_i(e_i)$, where $g_i \sim F_i$ is a non-decreasing function that is individual-specific and represents how much the individual's health stock changes with respect to e_i.[15] Thus the health stock equation can be written as:

$$h_i = h_0 + m_i - g_i(e_i)$$

Consumers have health insurance, with π denoting the premium and p the proportion of health spending that needs to be paid out-of-pocket.[16] Thus, if the consumer undergoes hospital treatments that cost a total of m_i, the consumer's out-of-pocket spending is equal to pm_i, where $p < 1$. Income $y(h_i)$ is composed of non-wage income y_0, which is exogenous and does not depend on health, and wage income $w(h_i)$, which is affected by health. Wage income is lower with diminished health, for example due to productivity loss or sick days. The budget constraint is:

$$y(h_i) \equiv y_0 + w(h_i) = \pi + pm_i + c_i + o_i$$

Consumer utility $U(h_i, c_i, o_i, e_i)$ depends on health stock (h_i), offline consumption (c_i), online spending (o_i), and pollution exposure (e_i). We allow utility to be both directly and indirectly affected by the pollution exposure. The indirect effect comes through reduction in health stock. The direct mechanism arises because consumers value the quality of life, which decreases with air pollution. Heavy haze and smoky air reduce consumers' utility even if their health stock is restored (i.e. held constant). For example, Levinson (2012) finds that people report lower levels of happiness on days with worse local air pollution.

Consumer i optimizes spendings to maximize utility, subject to his budget constraint and the rule of health stock evolution:

$$\begin{aligned}
&\max_{\{m_i, c_i, o_i\}} U[h_i, c_i, o_i, e(a, m_i + c_i)], \\
&\text{s.t. } y(h_i) \equiv y_0 + w(h_i) = \pi + pm_i + c_i + o_i, \\
&\text{and } h_i = h_0 + m_i - g_i(e(a, m_i + c_i)),
\end{aligned}$$

Our specification of the pollution exposure $e(a, m_i + c_i)$ makes it explicit that all offline spending, whether health-related or not, affects pollution exposure because it involves time spent out-

[15] An example is $g_i(e_i) = \alpha_i e_i$, where $\alpha_i \sim U[0,1]$. Individuals with $\alpha_i = 0$ remain healthy even after being exposed to air pollution; individuals with $\alpha_i = 1$ get very sick upon being exposed to air pollution, and experience a significant decline in their health stock.

[16] We assume that every consumer has health insurance. In 2011, nearly 95% of China's population was covered by one of the three major public health insurance programs (Yu, 2015).

doors.[17] This is the key difference between our model and those in Deschenes et al. (forthcoming) and Williams and Phaneuf (2016). In addition, our model incorporates utility from health (for example, through morbidity) and allows income to depend on health, both of which are absent in Williams and Phaneuf (2016)'s model.

The Lagrangian can be written as:

$$L_i = U[h_i, c_i, o_i, e(a, m_i + c_i)] + \lambda_i[y(h_i) - \pi - pm_i - c_i - o_i],$$

The first-order conditions are:

$$\begin{aligned}
\frac{\partial L_i^*}{\partial m_i} &= U_h(1 - g_i'(e_i)e_m) + U_e e_m + \lambda_i(y_h(1 - g_i'(e_i)e_m) - p) = 0, \\
\frac{\partial L_i^*}{\partial c_i} &= -U_h g_i'(e_i)e_c + U_c + U_e e_c - \lambda_i(y_h g_i'(e_i)e_c + 1) = 0, \\
\frac{\partial L_i^*}{\partial o_i} &= U_o - \lambda_i = 0, \\
\frac{\partial L_i^*}{\partial \lambda_i} &= y(h_i^*) - \pi - pm_i^* - c_i^* - s_i^* = 0.
\end{aligned}$$

where U_h, U_e, U_c, U_o are partial derivatives of the utility function with respect to health stock, pollution, consumption, and online spending, respectively. We assume $U_h > 0, U_c > 0, U_o > 0, U_e < 0$, since health and consumption are desirable but pollution is not. $e_m = e_c$ is the marginal impact of spending activities on pollution exposure e, which is allowed to be non-zero, as consumers are exposed to air pollution whether buying food or seeing a doctor.[18] The net impact of medical spending on health, $\frac{dh_i}{dm_i} = 1 - e_m$, is assumed to be positive, since the health benefit of medical treatment should be much larger than the incremental risk due to additional pollution exposure from hospital visits.[19] Exposure increases with pollution ($e_a > 0$). Finally, y_h is the effect of health on income, and is assumed to be positive.

Intuitively, when air quality worsens, medical spending should increase $\frac{\partial m_i^*}{\partial a} > 0$ and non-health spending should decrease $\frac{\partial c_i^*}{\partial a} < 0$. Appendix A discusses sufficient conditions for these patterns. $\frac{\partial c_i^*}{\partial a} < 0$ holds under fairly weak conditions of the utility function. $\frac{\partial m_i^*}{\partial a} > 0$ holds true as long as the health benefit from medical spending is much larger than any disutility from additional pollution exposure during the trip, which is likely to be true in practice.

Denote $V_i(a, h_0, y_0)$ as the indirect utility function and $L_i^*(a, h_0, y_0)$ as the optimal value of the

[17]In the short-term, consumer could reduce pollution exposure by delaying hospital visits or reducing time spent outdoors. In the long term, both m_i and c_i will respond to changes in pollution.

[18]We assume $e_m > 0, e_c > 0$, which seems reasonable.

[19]The optimal health spending is 0 if $1 - e_m < 0$.

Lagrangian. The marginal WTP for reduction in air pollution can be obtained as:

$$MWTP_i = -\frac{\frac{\partial V_i}{\partial a}}{\frac{\partial V_i}{\partial y_0}} = -\frac{\frac{\partial L_i^*}{\partial a}}{\frac{\partial L_i^*}{\partial y_0}}$$

As shown in Appendix A, individual i' marginal WTP can be expressed as:

$$MWTP_i = p\frac{\partial m_i^*}{\partial a} + y_h(-\frac{dh_i^*}{da}) + \frac{U_h}{\lambda_i}(-\frac{dh_i^*}{da}) + (-\frac{U_e}{\lambda_i})\frac{de_i^*}{da} + \frac{U_c - U_o}{\lambda_i}(-\frac{\partial c_i^*}{\partial a}) \tag{1}$$

Equation (1) illustrates the relationship between the impact of air pollution on health spending, given by $\frac{\partial m_i^*}{\partial a}$, and MWTP for improved air quality. Changes in an individual's out-of-pocket health spending provide a lower bound of his MWTP. The difference between the two quantities is determined by the last four terms in the equation. The first term, $y_h(-\frac{dh_i^*}{da})$, measures reduction in income due to lower productivity as a result of pollution ($\frac{dh_i^*}{da} < 0$). The second term $\frac{U_h}{\lambda_i}(-\frac{dh_i^*}{da})$ denotes the disutility from reduced health stock. The third term $(-\frac{U_e}{\lambda_i})\frac{de_i^*}{da}$ captures the monetized utility loss in the quality of life due to increased pollution exposure. Note that $\frac{de_i^*}{da}$ is the total derivative of exposure with respect to pollution: $\frac{de_i^*}{da} = e_a + e_m\frac{\partial m_i^*}{\partial a} + e_c\frac{\partial c_i^*}{\partial a}$, where $\frac{\partial m_i^*}{\partial a} > 0$ and $\frac{\partial c_i^*}{\partial a} < 0$. We posit that non-health spending is relatively inelastic to pollution, $|\frac{\partial m_i^*}{\partial a}| > |\frac{\partial c_i^*}{\partial a}|$, and hence $\frac{de_i^*}{da} > 0$. The last term $\frac{U_c - U_o}{\lambda_i}(-\frac{\partial c_i^*}{\partial a})$ denotes reduction in monetized utility due to the sub-optimal level of consumption distorted by pollution exposure. We assume $U_c - U_o > 0$, since otherwise consumers would choose a corner solution and set $c = 0$.

Our model encompasses that of Deschenes et al. (forthcoming), which abstracts away from pollution exposure associated with consumption ($e_c = 0$), as well as the utility loss of reduced quality of life ($U_e = 0$).[20] When $e_o = U_e = 0$, the FOCs indicates $U_c = U_o = \lambda$, and

$$MWTP_i = p\frac{\partial m_i^*}{\partial a} - y_h\frac{dh_i^*}{da} - \frac{U_h}{\lambda}\frac{dh_i^*}{da}.$$

In addition, if h_i is preset (i.e. kept at a subsistence level with $\frac{\partial h_i}{\partial a} = 0$) and income y is exogenous, as suggested by Williams and Phaneuf (2016), then our expression for the marginal

[20] In Deschenes et al. (forthcoming), $MWTP = w\frac{ds}{dc} + p_a\frac{\partial a}{dc} - \frac{U_s}{\lambda}\frac{ds}{dc}$, where w is wage rate (equivalent to y_h in our framework), s denotes number of sick days (equivalent to a negative change in health stock), a is defensive behavior, p_a is the price of taking defensive measures, and c is the concentration of pollutants (same as level of air pollution a in our framework.)

willingness-to-pay collapses to theirs:[21]

$$MWTP_i = p\frac{\partial m_i^*}{\partial a}.$$

The previous discussion focuses on individuals' MWTP. We now describe how to obtain a lower bound measure for the society's willingness to pay for pollution reduction. The society's willingness-to-pay has two components. First, each individual i is willing to pay at least $MWTP_i$ for a marginal reduction in pollution. Second, the net cost of providing insurance increases with the level of air pollution: for a marginal decrease in pollution, the change in the net cost equals the reduction in insurance pay-outs to individuals, or $(1-p)\int \frac{\partial m_i^*}{\partial a} dF_i$, where F_i denotes the distribution of pollution-induced health shocks across the population. China's health insurance programs are heavily subsidized by the government and the second component reflects the government's savings in supporting the health insurance market. A lower bound measure for the society's MWTP for pollution reductions is then given by the sum of individuals' MWTP plus reduction in the society's spending on insurance programs:

$$\begin{aligned} MWTP_{society} &\geq \int p\frac{\partial m_i^*}{\partial a} dF_i + (1-p)\int \frac{\partial m_i^*}{\partial a} dF_i \\ &= \int \frac{\partial m_i^*}{\partial a} dF_i \end{aligned}$$

Thus the change in aggregate medical spending in response to air pollution is a lower bound for the society's MWTP for reducing air pollution.

To summarize, the utility maximization framework illustrates that the impact of air pollution on health spending, the focus of our empirical analysis, provides a lower bound estimate for the society's MWTP for clean air, while the impact on out-of-pocket health spending provides a lower bound estimate for each individual's MWTP for clean air. The difference between MWTP and the impact of pollution on health spending can arise from four additional factors: reduced income from the loss of productivity, the disutility of reduced health stock (e.g., mortality risk), the disutility associated with reduction in the quality of life from increased pollution exposure, and the loss in utility due to consumption distortion (avoidance behavior). In the empirical analysis, we focus on quantifying the impact of air pollution on health spending ($\frac{\partial m_i^*}{\partial a}$), and use changes in non-health spending ($\frac{\partial c_i^*}{\partial a}$) to assess the importance of avoidance behavior.

[21] In Williams and Phaneuf (2016), $MWTP = p\frac{\partial m^*}{\partial a} + \frac{\partial \pi}{\partial a}$. They consider the case of a competitive insurance provider, and argue that in equilibrium insurance premiums will adjust in response to expected pollution. By contrast, in our setting, given that insurance reimbursement rates for China's public insurance programs are rarely adjusted year-to-year and are the same across cities despite large variance in pollution across cities, we find it more reasonable to assume that $\frac{\partial \pi}{\partial a} = 0$.

4 Empirical Framework

In this section, we first present a flexible econometrics model that allows us to estimate the short- and medium-term impacts of air pollution on health spending. Then we discuss our estimation strategy and the construction of instrumental variables.

4.1 Flexible Distributed-Lag Model

Air pollution has both short- and long-term consequences on health spending. Different from quarterly or annual data commonly used in the literature, our high-frequency data at the daily level allows us to characterize the path of health impacts from both contemporaneous and past air pollution exposure. We use the following distributed lag model (DL) to capture this relationship:

$$y_{ct} = \sum_{i=0}^{k} \beta_i p_{c,t-i} + \mathbf{x}_{ct}\alpha + \kappa_c t + \xi_c + \eta_w + \varepsilon_{ct} \tag{2}$$

where y_{ct} is daily health spending in a city, and $p_{c,t-i}$ is either contemporaneous ($i = 0$) or lagged pollution exposure ($i \geq 1$). $\mathbf{x}_{ct}$ includes a rich set of controls such as weather conditions, holiday fixed effects, day-of-week fixed effects, seasonality, etc. $\kappa_c t$ is city-specific linear time trend, ξ_c is city fixed effect, and η_w is week fixed effect. The key parameters of interest are β's, which capture the short- and longer-term causal impacts of pollution exposure on health spending.

Let us assume for a moment that there is no measurement error in pollution exposure $p_{c,t-i}$ and that there is no avoidance behavior or omitted variables (three important issues that we will return to in the next section), then the DL model can be estimated using OLS. But the linear estimation with a large number of lags is undesirable due to the high serial correlation among the lag terms $p_{c,t-i}$. The parameter estimates tend to be imprecise with artificial oscillations. To reduce the number of parameters that need to be estimated while allowing for flexible and smooth longer-term impacts, we extend Almon (1965) and specify β_i's as cubic B-spline functions of time with z segments, where z is a constant chosen by econometricians. The intuition is that any smooth function (here β_i can be treated as a function of time) defined on a closed interval $[a,b]$ can be uniformly approximated arbitrarily closely by basis splines. Take $k = 1$ as an example, in which case B-spline function collapses to a 3rd order polynomial:

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

where the contemporaneous effect of pollution on spending is captured by γ_0, the effect of yesterday's pollution is $\beta_1 = \gamma_0 + \gamma_1 + \gamma_2 + \gamma_3$, while the effect of pollution i days' in the past is $\beta_i = \gamma_0 + \gamma_1 i + \gamma_2 i^2 + \gamma_3 i^3$.

Plug (3) back into (2) and rearrange terms, we have:

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

With this reformulation, we only need to estimate four coefficients γ's rather than $k+1$ (the number of lags plus current day) coefficients. The four key regressors are:

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

where the first term is the sum of past pollution exposure, and the others are weighted sum of past exposure with the weights being polynomial terms of time.

This approach has several advantages over competing distributed lag models, the most popular one being the geometric decay model. One advantage of this approach is that these new regressors as defined in equation (4) exhibit much less multicollinearity than lags of $p_{c,t-i}$ themselves. Second, this model allows for much more flexible decaying patterns than those in geometric decay models. Third, it is straightforward to impose additional restrictions that either is generated by economic theories or reflect a prior knowledge of the data generating process. For example, if tomorrow's pollution exposure (forward one period) should not affect current health spending, then $\beta_{-1} = \gamma_0 - \gamma_1 + \gamma_2 - \gamma_3 = 0$. If pollution exposure beyond Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level. lags should not affect current health spending, then $\beta_{k+\tau} = \gamma_0 + (k+\tau)\gamma_1 + (k+\tau)^2\gamma_2 + (k+\tau)^3\gamma_3 = 0, \forall \tau \in \mathbb{N}$ and $\tau > 0$. These assumptions can be imposed individually or jointly as constraints in the estimation or they can be tested as linear restrictions. Fourth, this specification does not require instruments for the lagged dependent variable as in the geometric decay model, which is often challenging. Finally, we allow for arbitrary correlation between the contemporaneous error term and all of the past error terms, which is difficult in geometric decay models.

Once we choose the number of lags k, the order of polynomials q, the number of segments z, and additional conditions on γ's, the estimation can be carried out in (constrained) OLS and β's can then be calculated based on parameter estimates from OLS.

4.2 Identification

4.2.1 Sources of Endogeneity

There are multiple sources of potential endogeneity in the key variable of interest, pollution exposure. As is common in the literature on estimating the health impact of air pollution, our measure of pollution exposure likely suffers from measurement errors. This arises from the fact that pollution levels often vary across locations within a city and that we average the pollution data from monitoring stations to the city level. For example, among the 9 monitoring stations in the urban core of Beijing, the average difference between the maximum and minimum pollution level in a day is about 35 μg/m^3 in 2014 while the daily average at the city level is 87 μg/m^3. Since population is not evenly distributed within a city and the spatial distribution of monitoring stations does not align with residential areas, the arithmetic mean across all stations within a city may not accurately reflect the city population's exposure to pollution. An ideal measure should be population-weighted average of local air quality, but this is impractical due to the lack of air pollution data at the finer spatial level (e.g., city block or zip code) and many monitoring stations are located outside of population centers. In addition, our daily pollution is a simple average over hourly recordings and abstracts away the temporal variation. To the extent that the measurement errors are classical, our OLS estimates would suffer from the attenuation bias.[22]

Second, pollution exposure is potentially endogenous due to the avoidance behavior in both the short- and longer-term. Chinese consumers have increased awareness of air quality and its impact on health. $PM_{2.5}$ readings are becoming readily accessible through cell phone apps or from government websites in recent years.[23] In the short term, during days of severe air pollution, consumers may reduce outdoor activities, shift the timing of consumption (e.g. postpone visits to hospitals for non-acute conditions), 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

[22] Satellite data on Aerosol Optical Depth (AOD) offer an alternative measure of the ground level pollution with finer spatial resolutions (e.g., 3 km by 3 km from Terra satellite and 10 km by 10 km from Aqua). However, there are a lot of missing values at the daily level, in addition to noises from inferring $PM_{2.5}$ based on the AOD data.

[23] 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.

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 health stock of local residents).

In a short or medium time frame such as the one used in our analysis, location-specific time trend help control for migration and other long-run avoidance behavior. However, the short-run avoidance behavior as responses to contemporaneous air pollution is more challenging and cannot be absorbed by location fixed effects. In addition, it is not obvious that endogeneity arising from avoidance behavior could be addressed by the instrumental variable strategy since avoidance directly responds to air pollution (and hence will be correlated with shocks that affects air pollution). We use spending on daily necessities and at supermarkets to quantify avoidance behavior. Our results indicate that the avoidance behavior reduces spending in the short term (i.e., up to two weeks) through inter-temporal substitutions, but there is no significant aggregate impact over a longer period (a month or longer).

Another source of endogeneity in pollution measures is unobservables. Despite our rich set of controls for weather and local conditions (e.g., city specific time trend and seasonality), there is various temporal variation that can not be adequately controlled. For example, permanent local shocks to health spending, such as income shocks, could be correlated with economic activities and hence with air quality. Temporary local shocks, such as major sport and political events, could affect both the air pollution level and health spending (and consumer activities in general). These unobservables that are not absorbed by our location and trend/seasonality interactions render the air quality variable endogenous.

4.2.2 IV Construction

To address the concern of endogeneity, we exploit the spatial spillovers of $PM_{2.5}$ due to its long-range transportability to construct instruments. $PM_{2.5}$ particles are light, can travel at the speed of 10 mph, and often reside in the atmosphere for 3-4 days. Their region of influence is determined by the wind speed and direction. Based on atmospheric modeling, Zhang et al. (2015) document significant regional pollution transport in China. For example, nearly half of the pollution in Beijing originates from sources outside of the municipality. These results suggest that $PM_{2.5}$ from other cities could serve as exogenous shocks to the pollution level for a given city.

The approach of constructing instruments exploiting $PM_{2.5}$'s region of influence is in spirit similar to the source-receptor matrix constructed by the US EPA for air pollution prediction. We take each city as both a pollution source and a receptor, and develop a parsimonious model to predict the air pollution level of a given city based on lagged pollution levels in the same city and other cities, wind patterns (direction and speed), and distances between city pairs.[24] This model

[24] Williams and Phaneuf (2016) construct their IV for air pollution using pollutants 60 km away (or 120 km away)

allows us to estimate the contribution to the $PM_{2.5}$ level in a given city from non-local sources, i.e., $PM_{2.5}$ originated from other cities. We construct a buffer zone to minimize the correlation in unobserved regional economic shocks and only use cities outside of the buffer zone to construct the instruments.

Our identification assumption is that pollution shocks (e.g., economic activities) in regions outside of the buffer zone are not correlated with local shocks to spending. The assumption would be violated if economic shocks (e.g., increased demand for electricity induced by high temperature) in a given city affects production activities in other cities (e.g., electricity generation) outside of the buffer zone which then affect the pollution level in those cities. We address this concern in three ways. First, we test the robustness of our results to the buffer-zone radius in section 5 and show that the results are robust to different radii. Second, our instruments are weighted sums of *lagged* pollution levels in other cities, with the weights being a function of wind speed and direction as well as the distance between cities. To the extent that economic shocks in a given city affect production and hence pollution in other cities, this should induce correlation between the error term and future rather than lagged pollution levels in other cities. In addition, the exogenous variation in wind speed and direction should reduce such correlations. Third, in one of the robustness checks, we add the average $PM_{2.5}$ in other cities outside of the buffer zone but within the same region in the regressions to control for regional spillovers in economic activities. The parameter estimates on local $PM_{2.5}$ levels are very similar to those in the benchmark analysis.

In principle, our identification assumption implies that *any* function of pollution and weather conditions in cities outside the buffer zone is a valid instrument for pollution in city i. The set of such instruments, however, is very large and many of these instruments are likely to be quite weak. We therefore write down a simple model of air pollution transmission and use this model to guide our construction of instrumental variables.

Denote the pollution level of city i in time t as p_{it}. We model p_{it} as a function of past pollution and pollution from other cities:

$$p_{it} = \theta_1 p_{i,t-1} + \sum_{j \neq i} p^{+}_{j \to i,\, t} + \mu_{it}, \tag{5}$$

where θ_1 captures the amount of pollution that is carried over from the previous day and it can be affected by local meteorological conditions. $p^{+}_{j \to i,\, t}$ denotes the amount of $PM_{2.5}$ pollutants in city i at time t that are originated from city j, and μ_{it} is the error term. The contribution of non-local sources to the pollution level of a given city could be affected by a host of weather and topography conditions and is the subject of sophisticated air quality modeling. We use the following parsimonious model to capture the key feature that $PM_{2.5}$ pollutants dissipate over time and across

without exploiting wind patterns.

space as they move.

$$p^{+}_{j\to i,\ t+s_{ijt}} = \begin{cases} \cos\Phi\ p_{jt}\ f(d_{ij}, w_{jt}, w_{i,t+s_{ijt}}), \text{if } \cos\Phi > 0, \\ \\ 0, \qquad \text{otherwise.} \end{cases} \tag{6}$$

The above equation describes how $p^{+}_{j\to i,\ t+s_{ijt}}$, the amount of pollution that enters city i on day $t+s_{ijt}$ having originated from city j, is determined. Φ denotes the angle between the wind direction and the direction from city j to city i. We invoke a simple vector decomposition and assume that the amount of pollutants carried toward city i from city j is $\cos(\Phi)p_{jt}$ at speed $\cos(\Phi)S_{jt}$, where S_{jt} is the wind speed in city j. Pollution decays over time as it travels and only part of the pollution that was generated in city j and traveling in the direction of city i enters the atmosphere of city i. This is represented by $f(d_{ij}, w_{jt}, w_{i,t+s_{ijt}}) \in [0,1]$, which denotes the share of the pollution generated in city j that enters city i, and is a function of the distance between the two cities (d_{ij}), weather conditions in the source city at the time when the pollution was generated (w_{jt}) and weather conditions in the destination city at the time when the pollution enters its atmosphere ($w_{i,t+s_{ijt}}$). The number of days it takes pollutants to travel from city j to city i, s_{ijt}, is calculated as the following and rounded to the next smaller integer:

$$s_{ijt} = \left\lfloor \frac{d_{ij}}{\cos(\Phi)S_{jt}} \right\rfloor .$$

Figure 5a shows the wind-pollution vectors from over 300 cities on Dec. 5, 2013 (denoted as Day 0). Each arrow's length indicates the wind speed, rescaled to match the exact distance the arrow can travel in a day. The width of arrows indicates the level of $PM_{2.5}$ concentration at the source city. To illustrate how we predict city-day $PM_{2.5}$, Figure 5b shows all subvectors of pollutants that are blown towards Beijing on the same day. The pollution level of the receptor city, Beijing in this example, is predicted by pollutants carried through the subvectors that reach Beijing at time t, together with the lagged local pollution levels, as stated in Equation (5).

The only unknown in equation (6) is the form of the decay function $f(d_{ij}, w_{jt}, w_{i,t+s_{ijt}})$. We assume that the unknown decay function can be approximated by a polynomial function in variables $(1/d_{ij}, w_{jt}, w_{i,t+s_{ijt}})$:

$$p^{+}_{j\to i,\ t+s_{ijt}} = \begin{cases} \cos\Phi\ p_{jt}\ \sum_l \gamma_l u_l(1/d_{ij}, w_{jt}, w_{i,t+s_{ijt}}), \text{if } \cos\Phi > 0, \\ 0, \qquad \text{otherwise.} \end{cases}$$

where γ_l, $l = 1, ..., L$ are unknown parameters and $u_l(1/d_{ij}, w_{jt}, w_{i,t+s_{ijt}})$ denote various polynomial functions of $(1/d_{ij}, w_{jt}, w_{i,t+s_{ijt}})$.

We now describe how to use the above model to motivate the construction of instruments. Let r denote the radius of the buffer zone: for most of our results we assume a buffer zone of 150 km, but we also check that the results are robust to the choice of the buffer zone. The total amount of pollution imported from cities outside of the buffer zone, $\hat{p}_{it}^{far}$, is described by the following equation:

$$\hat{p}_{it}^{far} = \sum_{j:d_{ij}>r} p_{j\to i,\ t}^{+} \tag{7}$$

Plugging in $p_{j\to i,\ t}^{+}$ into the above equation, and interchanging the summation signs, we can write $\hat{p}_{it}^{far}$ as:

$$\begin{aligned}
\hat{p}_{it}^{far} &= \sum_{j:d_{ij}>r} p_{j\to i,\ t}^{+} \\
&= \sum_{j:d_{ij}>r} max(0, \cos\Phi) p_{j,t-s_{ijt}} \sum_{l} \gamma_l u_l(1/d_{ij}, w_{j,t-s_{ijt}}, w_{i,t}) \\
&= \sum_{l} \gamma_l \sum_{j:d_{ij}>r} max(0, \cos\Phi) p_{j,t-s_{ijt}} u_l(1/d_{ij}, w_{j,t-s_{ijt}}, w_{i,t}) \\
&= \sum_{l} \gamma_l Z_{it}^{l}
\end{aligned}$$

where $Z_{it}^{l} = \sum_{j:d_{ij}>r} max(0, \cos\Phi) p_{j,t-s_{ijt}} u_l(1/d_{ij}, w_{j,t-s_{ijt}}, w_{i,t})$.

This shows that $\hat{p}_{it}^{far}$, the total amount of pollution city i imports from cities outside the buffer zone, is a linear function in the known objects Z_l. As such, we follow the natural strategy of using Z_{it}^{l}, $l = 1, ..., L$, as instruments for p_{it}. These are valid instruments since they depend only on weather within city i, which we control for in our regressions, and on pollution and weather variables in cities outside of the buffer zone, which are uncorrelated with local shocks to spending by our identification assumption.

An alternative approach would have been to estimate the unknown parameters γ_l, use the above equation to construct $\hat{p}_{it}^{far}$, and then use $\hat{p}_{it}^{far}$ as an instrument for p_{it}. However any imprecision in the estimates of γ_l could then lead to a weaker first-stage prediction. The benefit of our approach of using Z_l directly as instruments is that we avoid having to estimate γ_l. [25]

Notice that although we do not estimate the air pollution transmission model directly, the model implies a number of restrictions on how pollution from outside the buffer zone reaches city i which we exploit. For example, if the prevailing wind conditions are such that it takes two days for pollution generated in city j to reach i, we would not expect any pollution generated in city j at

[25] As a robustness check, however, we have tried the alternative approach of estimating γ_l in order to construct $\hat{p}_{it}^{far}$. We have also constructed $\hat{p}_{it}^{far}$ using alternative functional forms for the decay function $f(d_{ij}, w_{jt}, w_{i,t+s_{ijt}})$, such as an exponential decay function. The results are similar to what we report in the paper, though the first-stage is slightly weaker.

time t to have any effect on $p_{i,t}$. Instead we should see this pollution show up only in $p_{i,t+2}$. Our IVs are constructed taking into account such considerations and are thus likely to out-perform naive approaches such as using the sum of pollution levels in all cities outside the buffer zone.

To examine the strength of our instruments, we regress city-daily $PM_{2.5}$ on our instruments together with other controls (e.g., city-specific trends and week fixed effects) as in equation (2). The number of observations is around 192,000 in total. The first-stage R^2 is 0.47. It is important to note that the goal of our first-stage model is not to maximize the accuracy of air quality predictions. Instead, we want to create an instrumental variable that is both predictive of local air pollution and at the same time exogenous to shocks to health spending. This is why we base our analysis on a relatively conservative definition of the buffer zone and exclude $PM_{2.5}$ from cities within 150 km in constructing the IV (although our results are robust to the choice of buffer radius).

5 Empirical Results

5.1 Short-Term Impact

Our empirical analysis begins with the contemporaneous effect of air pollution on health. In the discussion below, we use the log number of transactions as the dependent variable rather than the value of transactions as in the literature using transaction-level purchase data (Einav et al., 2014). The distribution of health spending rightly skewed with many large transactions (e.g., surgeries) that are unlikely caused by air pollution in the short run. In Appendix B, we report results using the value of transactions as the dependent variable. They are very similar in magnitude to those based on the number of transactions but less precise.

In all of 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 (i.e., interactions of city fixed effects and quarterly dummies) are added to the regression to control for trends in card adoption and seasonal diseases. We also add fixed effects for state holidays, working weekend, day of the week, as well as weather variables to control for their direct effects on spending. For example, people may reduce non-urgent hospital visits during holidays or on days with bad weather. All standard errors are clustered at the city level.

Table 2 summarizes the short-term impacts estimated with OLS. A 10 $\mu g/m^3$ increase in the daily $PM_{2.5}$ concentration is associated with a 0.11% increase in the total number of transactions on health care on the same day. Transactions in pharmacies and especially in Children's hospitals are more sensitive to air pollution, with an impact of 0.12% and 0.18%, respectively, from a 10 $\mu g/m^3$ increase in $PM_{2.5}$. The larger impact on Children's hospitals make intuitive sense since children are more vulnerable to air pollution. Similarly, when elevated air pollution aggravates symptoms for people with respiratory problems, they may go to pharmacies to purchase drugs without visiting hospitals.[26]

In contrast, a temporary increase in $PM_{2.5}$ reduces transactions in daily necessities and supermarkets. This could be due to two possibilities. The first is the effect of the budget constraint: if consumers have to spend more in heath care to mitigate the negative health impact of air pollution, they may have less to spend on non-health-related categories. The second possibility is avoidance behavior: consumers postpone or reduce shopping trips in response to poor air quality to reduce pollution exposure. We test these two possibilities in Section 5.5.

To graphically illustrate the relationship between pollution and spending, we plot the log number of transactions against $PM_{2.5}$ in Figure 6. All other controls (weather, city trend, etc.) are partialled out, so the figure displays the net effect of pollution on spending. For ease of presentation, we group $PM_{2.5}$ by percentiles and plot the in-group average of log number of transactions against each percentile of $PM_{2.5}$. In addition to the aggregate number of health transactions (top left corner), we also plot the relationship separately for People's hospitals, Children's hospitals, pharmacies, and two non-health categories (necessities and supermarkets). $PM_{2.5}$ has a positive relationship with spending in all health categories across all quantiles of $PM_{2.5}$. The data points tightly center around the fitted curve, which is consistent with the fact that our standard errors are small.

To address the issue of endogeneity and measurement errors, we instrument $PM_{2.5}$ using the instruments constructed from pollutants originated from outside of the 150 km buffer zone as discussed in Section 4.2. Table 3 reports results from IV regressions. The first-stage cluster-robust F-statistics on the instruments (reported in the last row of the table) vary from 52 to 62, suggesting a strong correlation between the instrument and the endogenous variable. The IV estimates are considerably larger than the OLS estimates, with most coefficients 3 to 7 times as large as their OLS counterparts. A 10 $\mu g/m^3$ increase in $PM_{2.5}$ in a day is associated with a 0.65% contemporaneous increase in transactions in the aggregate health care sector. The effect of air pollution on spending at Children's hospitals is the largest among different health care categories, and is nearly twice as large as that for the overall healthcare spending.

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). The bias toward zero in OLS estimates for both health and non-health spending is consistent with attenuation bias due to (classical) measurement errors in $PM_{2.5}$ as an imperfect proxy for population pollution exposure. The downward bias could also be driven by temporary local shocks that are positively correlated

[26] There is no distinction between prescription and over-the-counter medicines in China and medicines can be purchased without prescriptions from physicians. The Ministry of Human Resources and Social Security maintains the National Reimbursement Drug List (NRDL) and only the drugs on the list are covered by China's national medical insurance programs, some in full (type A drugs) and others partially (type B).

with air pollution such as economic activities or big events, which reduce health spending but increase non-health spending (more outdoor activities and fewer hospital visits).

Our database reported more than two billion transactions in hospitals and more than one trillion *yuan* ($153 billion) health spending in 2015. According to China's National Health Commission, the aggregate health expenditure, including both private and public spending, was more than four trillion *yuan* ($614 billion) in the same year. Therefore, a 10 μg/m^3 increase in $PM_{2.5}$ in a day could lead to millions more trips to healthcare facilities and billions added healthcare cost. As discussed below in more detail in Section 5.6, our estimated short-term impact include both the direct positive effect on health spending and the indirect negative effect through the avoidance behavior. Therefore, the direct effect of air pollution on health spending is likely larger.

5.2 Longer-Term Impact

Exposure to $PM_{2.5}$ could have longer-term health impacts. Directly estimating the coefficients of a large number of lagged $PM_{2.5}$ in equation (2) suffers from high serial correlation and imprecise estimates. Instead, we employ the flexible Distributed-Lag model discussed in Section 4.1 and allow pollution impacts to follow a smooth path of decay.

Table 4 reports the cumulative effects for different time periods across categories from the OLS regressions. Our benchmark specification uses 90 lags and three segments for the cubic B-splines. The standard errors are clustered at the city level and are reported in parentheses. The first column shows that a temporary surge of 10 μg/m^3 in $PM_{2.5}$ concentration increases today's number of transactions in all healthcare facilities by 0.03%. A permanent elevation of 10 μg/m^3 raises the number of transactions by 0.86%, eight times as large as the effect reported in Table 2 when only the contemporary $PM_{2.5}$ concentration is controlled. The longer-term impact on pharmacies is the largest while the impact on children's hospitals is statistically insignificant. The last two columns show a statistically significant negative impact on necessities and supermarket spending within two weeks, but not in the long run.

To deal with the endogeneity in $PM_{2.5}$, we use the instruments discussed in Section 4.2. Specifically we instrument for the local pollution on day s, p_{is}, using the instruments Z^l_{cs} that are functions of pollution in faraway sources that reach city i on day s. The contemporary and cumulative effects across different time spans are presented in Table 5.

Several important findings emerge from Table 5. First, the estimated longer-term impacts of $PM_{2.5}$ on health spending across all categories from 2SLS are positive and much larger than their OLS counterparts, consistent with the comparison for the short-term impact discussed in Section 5.1. Specifically, a permanent increase of 10 μg/m^3 in the $PM_{2.5}$ concentration raises the number of transactions in the health sector by 2.65%. Second, the impact on Children's hospitals is the largest and more than twice as large as the impact on aggregate health spending, consistent with the fact that children are among the most vulnerable group. Third, the effects on daily necessities and supermarket spending are all negative and appear to be short-lived.

To examine how the impact on spending changes overtime, Figure 7 plots the estimates of both current and past 90 days of pollution exposures for different categories.[27] The (dotted) solid part of each line indicates the impact being statistically (in)significant. There are several noticeable patterns. First, $PM_{2.5}$ has a positive impact on health spending in the short term across all health categories. The impact diminishes over time and becomes small and imprecise after three months. Second, air pollution has a negative impact on the spending on necessities and supermarkets in day zero, but the effect disappears after two weeks. This temporal reduction is inconsistent with the budget constraint hypothesis, since under a fixed budget, a permanent increase in health spending would lead to a permanent reduction in necessities and supermarkets. Instead, our result lends support to the hypothesis of avoidance behavior. We return to this issue in the next section.

Our results so far suggest that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ would lead to an increase in the number of health-related transactions in the long term by 0.8% from OLS and 2.6% from 2SLS. In terms of the value of transactions, the effect is about 0.5% from OLS (Table B1 in Appendix B) and 1.5% from 2SLS (Table B2 in Appendix B). The estimates are somewhat 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 which are not related to air pollution.[28] The smaller impact on the value of transactions makes intuitive sense in that elevated pollution could reduce the desire to go to hospitals for minor illnesses (and other outdoor activities), leading to a larger impact on transaction frequency. The heterogeneity across different types of healthcare facilities and the impact on non-health spending are similar to results using the number of transactions, but less precise.

5.3 Nonlinearity

Among the underlying concerns for the external validity of the benefit-transfer approach is the potential nonlinearity of the dose-response function. The pollution level observed in developing countries such as China and India is far greater than the prevailing level studied in the literature. The potential nonlinearity could lead to under- or over-estimation of the health costs of air pollution in developing countries based on the linear projections in the benefit-transfer approach (Lelieveld

[27] The number of lags for the optimal model should in theory differ across categories. For example, the effect of pollution on non-health categories appears to be short-lived, while for children's hospitals it could last for more than 3 months. To keep the results comparable, we impose the same lag structure on all categories.

[28] Our analysis focuses on transactions that cost less than 200,000 *yuan*. Among this sample, the 95th percentile of the transaction value is 6,000 *yuan* and the 99th percentile is 10,000 *yuan*.

et al. (2015) and World Bank (2007)). Despite of its important implications, there is a lack of empirical evidence on the nonlinearity of the dose-response function (Lelieveld and Pöschl (2017)). The rich spatial and temporal variation in our data allows us to examine the health impacts of $PM_{2.5}$ for a wide range of the pollution level.

To capture the nonlinearity, we use a one-segment spline for simplicity (instead of three segments in the benchmark analysis) and interact the intercept with $PM_{2.5}$ and its quadratic form. Figure 8a plots the estimated surface of the marginal response for varying levels of $PM_{2.5}$, and along the time path for three months. For each value of $PM_{2.5}$ the slice of the surface along the p-axis is the estimated spline as in Figure 7a. The surface is slightly tilted upwards with a higher marginal response for a higher pollution level. This suggests an increasing marginal impact of $PM_{2.5}$ on health spending. To further illustrate this, we collapse the time dimension by aggregating the marginal effect over three months ($\sum_t \beta_t$) to generate the 2D plot in Figure 8b. The plot shows that the marginal impact on health spending is increasing in $PM_{2.5}$ at a diminishing rate. The cumulative effect ranges from 2.16% when $PM_{2.5}$ is near zero, to 2.25% when the concentration reaches 150 μg/m^3 (i.e., the 90 percentile of the daily average). Overall, the nonlinearity is not strong and the curve in Figure 8b is almost flat. This allows us to extrapolate our estimates across a wide range of pollution levels in the discussion below.

5.4 Robustness Checks

We conduct a variety of robustness checks. Table 6 reports the cumulative impact for overall health spending under three different numbers of B-spline segments (1, 2, and 3) and five different numbers of lags (60, 90, 120 and 150). The estimates across different number of segments are very similar. We choose three segments (two knots) for our base specification since it is more flexible and yet still precisely estimated.[29] The cumulative impact tends to be smaller with 60 days of lags and larger with 120 days of lags than that with 90 days, but the difference is small. The cumulative impact using 30-day lags is considerably smaller. We prefer 90 lags because many of the estimated effects for lagged pollution are significant till around 90 days and start to lose significance for later periods.

Our second set of robustness checks is with regard to the radius size of the buffer zone in constructing the IV. We fix the radius at 150 km in the benchmark specification and assume that unobservables outside of the buffer zone of a city would not affect health spending in that city. There is an inherent trade-off in the choice of the radius. On the one hand, the larger the buffer zone, the easier it is for the exclusion restriction to hold; on the other hand, the bigger the radius, the weaker the correlation between the predicted $PM_{2.5}$ using non-local pollution and the observed

[29] Results from more than three knots suffer from the over-fitting problem and exhibit large swings over time.

$PM_{2.5}$ in a given city. Table 7 presents several choices of the buffer zone from 50 km to 300 km with an increment of 50 km. The top panel in the table reports the first-stage results. Generally, both the R^2 and the F-statistics decrease with the radius of the buffer zone, suggesting a weaker correlation between the IV and the endogenous variable as the buffer zone gets larger. The bottom panel shows the cumulative long-term impact on health spending, which varies from 2.4% to 2.9% across different radii when $PM_{2.5}$ increases by 10 $\mu g/m^3$ permanently. Our preferred specification with 150 km radius delivers an estimate that is in the middle of this range.

The third set of robustness checks controls for other pollutants including O_3, SO_2, NO_2 and CO. Emission sources such as electricity generation and transportation produce both particulate matters and other pollutants, which also have harmful health impacts. Therefore, the estimated health impact from $PM_{2.5}$ could be confounded by other pollutants especially in OLS regressions. The IV strategy should address this issue to some extent in that it leverages the long-range transport property of $PM_{2.5}$ which is different for other pollutants especially O_3 and CO. That is, the predicted $PM_{2.5}$ should be less correlated with observed level of local pollutants. Table 8 reports estimates with these four pollutants as additional controls. The results for both health spending and non-health spending categories are very similar to those in Table 5 without controlling for other pollutants.[30]

The last set of robustness checks further addresses the concern of regional economic spillovers by controlling for the average level of $PM_{2.5}$ of nearby cities in the same region outside of the buffer zone. If regional economic activities have systematic spillover effects beyond the buffer zone, one might be concerned with the exogeneity of our IVs: local unobservables could be correlated with economic activities in other cities which are in turn correlated with pollution levels in other cities. Including the average level of $PM_{2.5}$ of nearby cities in the regressions could help control for economic activities in other cities. Table 9 presents estimation results with this additional control and the results are very close to the benchmark specifications without this control.

5.5 Avoidance Behavior

The analyses of both the short-term and longer-term impact suggest that elevated $PM_{2.5}$ leads to increased health spending and reduced non-health spending. This negative impact on non-health spending could be driven by two underlying mechanisms: the budget constraint or avoidance behavior. As we argued in Section 5.2, the short-lived nature of the negative consequences is inconsistent with the budget constraint hypothesis. In this section, we examine whether households engage in avoidance behavior to mitigate their pollution exposure.

A key insight of our analysis is that when consumers engage in avoidance behavior, expectations

[30]The correlation coefficient between $PM_{2.5}$ and O_3, SO_2, NO_2 and CO is -0.13, 0.55, 0.66, 0.03, respectively.

of *future* pollution levels should affect current consumption. For example, if consumers expect pollution to improve in the near future, they may postpone their consumption to avoid exposure today. On the other hand, an expectation of worse air tomorrow may encourage them to make the consumption in advance. To investigate this, we assume that the consumers have a *directional* perfect foresight, i.e. they have in their knowledge whether the next day's air quality is better or worse than today's.

We add the dummy variable $\mathbb{1}\{p_{\mathrm{i,t+1}} > p_{\mathrm{i,t}}\}$ in our baseline specification and report the results in Table 10. The coefficient on this dummy variable indicates a 0.41% increase in healthcare transactions when consumers anticipate worse air quality the next day. Interestingly, spending in necessities and supermarkets *increases* when next-day pollution is expected to deteriorate. The coefficient is also found to be larger for pharmacy than hospitals, where the transactions are less flexible for inter-temporal substitution. The estimated cumulative impact on health spending that is associated with a permanent reduction of 10 μg/m^3 of $PM_{2.5}$ is 2.71%, slightly higher than when we do not control for avoidance.

5.6 Discussion

Our preferred specifications show that a 10 μg/m^3 increase in $PM_{2.5}$ would lead to a 2.6% increase in the number of health-related transactions in the long term (Table 5) and a 1.5% increase in the value of transactions (Table B2). Credit and debit card transactions (i.e., bank card transactions) account for about half of the total spending in the health care industry, with the rest from cash transactions and government transfers. Assuming that the health impact is the same for non-bank-card spending, the 1.5% impact translates to more than 60 billion *yuan* ($9 billion) from a 10 μg/m^3 (about 18%) increase in $PM_{2.5}$. These numbers can directly inform the overall welfare cost of $PM_{2.5}$ and related policy discussions. For example, a 2016 report by OECD based on the benefit-transfer approach estimates that $PM_{2.5}$ and ground level ozone are associated with a $20 billion direct cost of health expenditure (due to morbidity) worldwide, with half of them accounted for by non-OECD countries.[31] With the average $PM_{2.5}$ level of 56 μg/m^3 and the recommended level of 10 μg/m^3 by WHO, a simple linear interpolation would imply a $42 billion in added health spending in China due to elevated $PM_{2.5}$ relative to the WHO recommendation. Even with the assumption that air pollution affects only health spending that is paid by bank cards and not health spending via cash or government transfers, the interpolation based on our estimates would still suggest a $21 billion impact on health spending. These results indicate that the OECD report significantly underestimates the health cost from outdoor air pollution, potentially up to an order of magnitude

[31] The report, titled "The Economic Consequences of Air Pollution", is available at http://www.oecd.org/env/air-pollution-to-cause-6-9-million-premature-deaths-and-cost-1-gdp-by-2060.htm.

for developing countries.

To better understand the size of our estimates, we compare our results with the findings in related literature in Table 11. In a study on preventive expenditure, Mu and Zhang (2016) estimate that face mask purchases increase by 5.45% for a 10-point increase in AQI, and 7.06% for anti-$PM_{2.5}$ masks. Given that the translation from $PM_{2.5}$ concentration to AQI is piecewise linear, a 10-point increase in AQI is equivalent to an increase of 7.5 $\mu g/m^3$ to 15 $\mu g/m^3$ in $PM_{2.5}$ concentration. This means that exposure to 10 $\mu g/m^3$ more $PM_{2.5}$ leads to an increase ranging between 3.6% and 7.3% in preventive spending.

Williams and Phaneuf (2016) use similar estimation methods and data and 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, which is equivalent to a 22% increase for 10 $\mu g/m^3$ more $PM_{2.5}$. According to China's National Health Commission, spending on respiratory diseases accounts for 8% of total health expenditure in 2012. Assuming all additional spending induced by air pollution is for respiratory diseases, our estimates translate to a 33% increase in respiratory-related spending, about one and a half times as large as the estimate from Williams and Phaneuf (2016).

Our estimates of the effect of air pollution on total health spending provide a lower bound of the social WTP for improved air quality in that the health spending impact does not take into account mortality, the quality of life, the loss of productivity as well as the cost of avoidance behavior. An increase in overall health spending of 60 billion *yuan* (or $9 billion) from a 10 $\mu g/m^3$ increase in $PM_{2.5}$ suggests that a lower bound for the social WTP is 145 *yuan* (or $22) per household for a reduction of $PM_{2.5}$ by 10 $\mu g/m^3$.

To estimate the consumers' private WTP for air quality, we need to account for the fact that the vast majority of consumers have health insurance and do not bear the full costs of their treatment. As the theoretical model in Section 3 illustrates, the consumer WTP is bounded below by the change in out-of-pocket spending resulting from a change in air quality. For urban residents, the proportion of health spending that has to be paid for out-of-pocket equals 32% for employees and 52% for non-employees. An increase in overall health spending of 60 billion *yuan* translates into 25 billion *yuan* (or $4.5 billion) additional out-of-pocket spending.[32] This implies a lower bound for consumer WTP of 60 *yuan* (or $9.25) per household for a 10 $\mu g/m^3$ reduction of $PM_{2.5}$.

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 price and quality (ability to remove more PM_{10}). Their WTP estimate for PM_{10} reduction could capture consumers' WTP for $PM_{2.5}$ as $PM_{2.5}$ constitutes the majority of harmful PM_{10}

[32]Due to the low penetration of credit and debit cards in rural areas, our sample primarily consists of urban residents. In 2011, there were 252 million urban employees and 221 million urban non-employees enrolled in China's public insurance programs (Yu (2015)). The population-weighted average proportion of health spending that must be covered out-of-pocket thus equals 41%.

pollutants and the higher-quality air purifiers (with HEPA filters) in their study can also effectively remove $PM_{2.5}$. Our analysis is in line with their estimates in a different context and without relying on the revealed preference approach. Their estimates should capture both the morbidity and mortality impact of PM_{10} to the extent that consumers are aware of their impacts while our estimates only capture the morbidity impacts.

Using the hedonic model for the U.S. housing market, Chay and Greenstone (2005) find that consumers are willing to pay \$450 - \$1,050 more in housing price (in 1982-84 dollars) for a one μg/m^3 reduction in TSP. With a 30-year time span and 5% annual discount rate, this translates to an annual WTP of \$72.9 - \$168.5 in 2015 dollars. Based on the discrete-choice framework that is also applied to the U.S. housing market, Bayer et al. (2009) estimate the annual household WTP to be \$23.9 - \$29.5 in 2015 dollars for one unit reduction in PM_{10}. These WTP estimates are substantially larger than ours for at least three reasons. First, the average household income in China during our data period is about one-eighth of that in the U.S., and the environmental quality is shown to be a luxury good (Kahn and Matsusaka, 1997). Second, our estimate of WTP reflects a lower bound and doesn't account for the impacts on mortality and the quality of life etc. as discussed above, while the WTP estimates using the revealed preference approach in both studies should in theory reflect those impacts (provided that consumers are well-informed and rational). Third, the difference could be partly due to the potential nonlinearity in the WTP schedule since the level of air pollution is drastically different between these two countries.

6 Conclusion

WHO's global air pollution database shows that the 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, past research from epidemiology and economics going back several decades has focused on the impacts of air pollution on human health (particularly mortality) in developed countries. This analysis examines the direct health cost from $PM_{2.5}$ based on the universe of credit and debit card transactions in China and provides a lower bound estimate of social 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 that allows us to isolate exogenous variations in local air quality using the spatial spillovers of $PM_{2.5}$. We propose a flexible distributed-lag model to estimate the temporal effect on health spending. Our 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 60 billion *yuan* ($9 billion) reduction in health spending annually, or 1.47% of total annual healthcare expenditure nationally. Our estimate of the direct health cost from $PM_{2.5}$ in China suggests that the recent report by OECD (2016) drastically underestimates worldwide impact of air pollution on health expenditure ($10 billion for all non-OCED countries).

In many major urban centers in Northern China, the annual average concentration of $PM_{2.5}$ is close to or even exceeds 100 μg/m^3, 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 $PM_{2.5}$ 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 could 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 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 it can 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.

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Figure 1: Three-Year Average $PM_{2.5}$ Concentration

2013 - 2015, $\mu g/m^3$

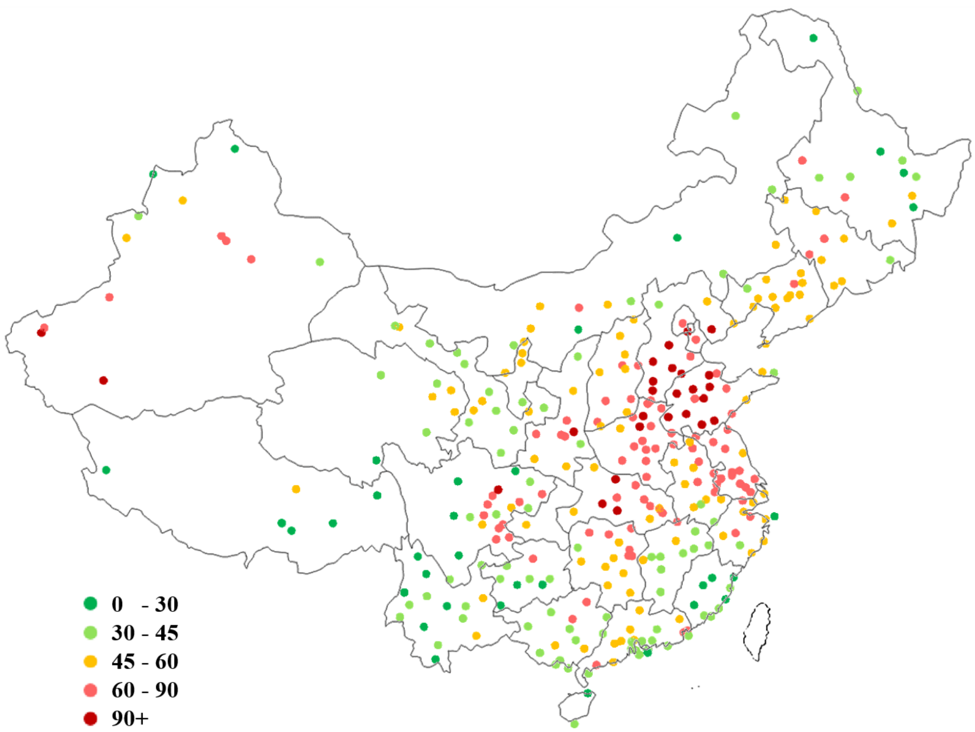
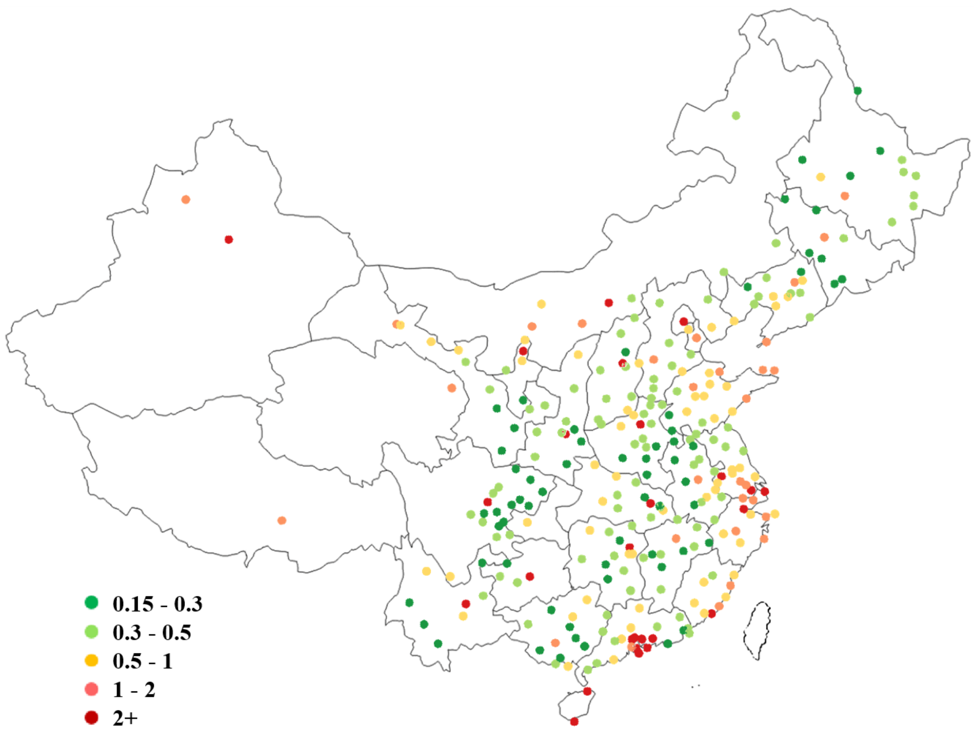


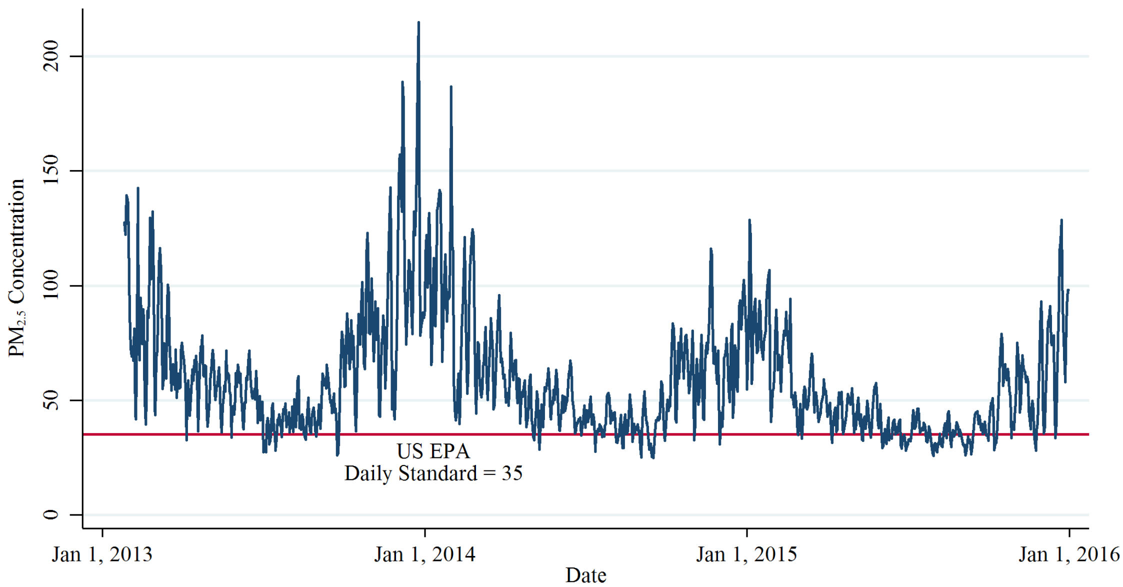
Figure 2: The Number of Active Cards per Capita, 2015



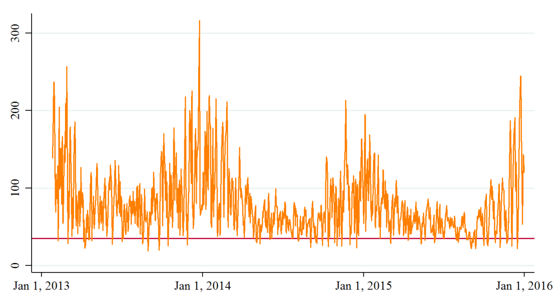
Notes: Active cards are defined as credit or debit cards that have been used at least once in the year. Each card is assigned to one primary city based on the location of its most frequent usage. Population measure is year-end registered population of each city.

Figure 3: Daily $PM_{2.5}$ Concentration

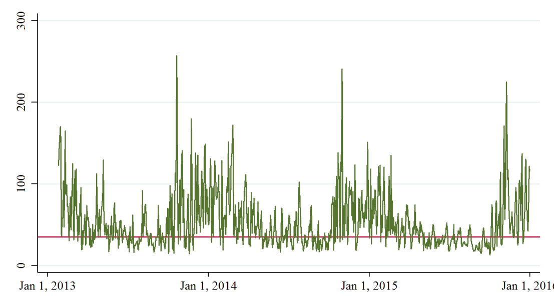
Jan. 2013 - Dec. 2015
National and Regional Average, μg/m^3



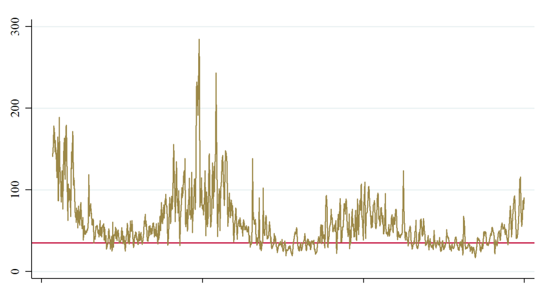
(a) Northern Region



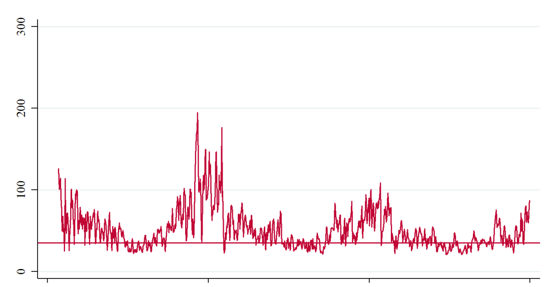
(b) Northeastern Region



(c) Northwestern Region



(d) Southern Region



Notes: The Red line in all subfigures indicates the daily standard set by US EPA: 35 μg/m^3.

Figure 4: National Weekly Healthcare Spending, 2013 - 2015

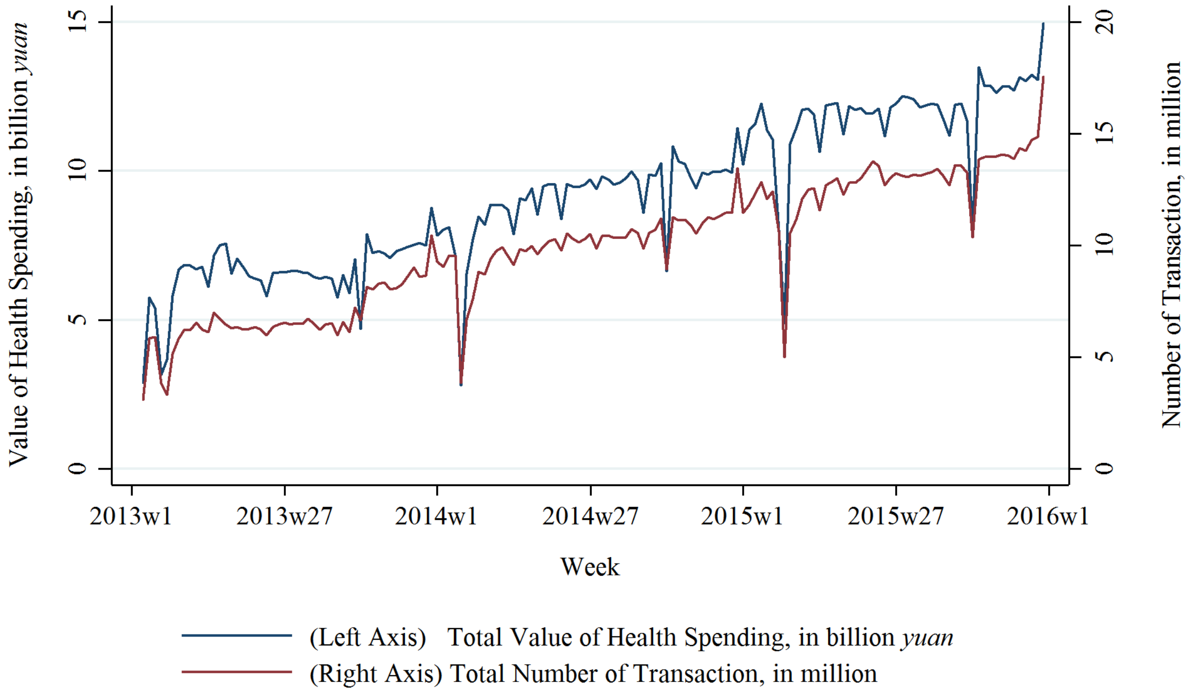
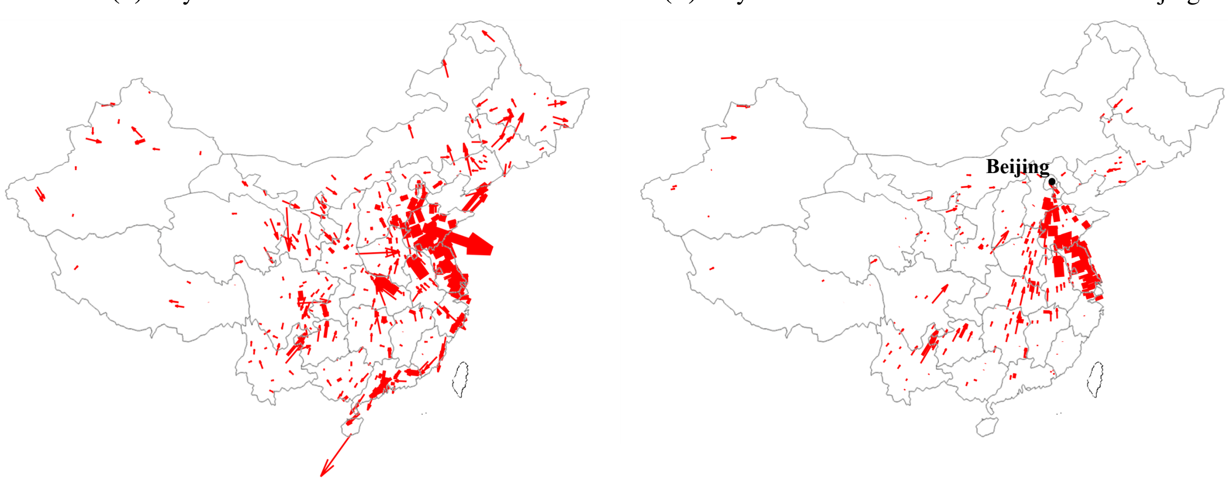


Figure 5: Wind-Pollution Vector Decomposition

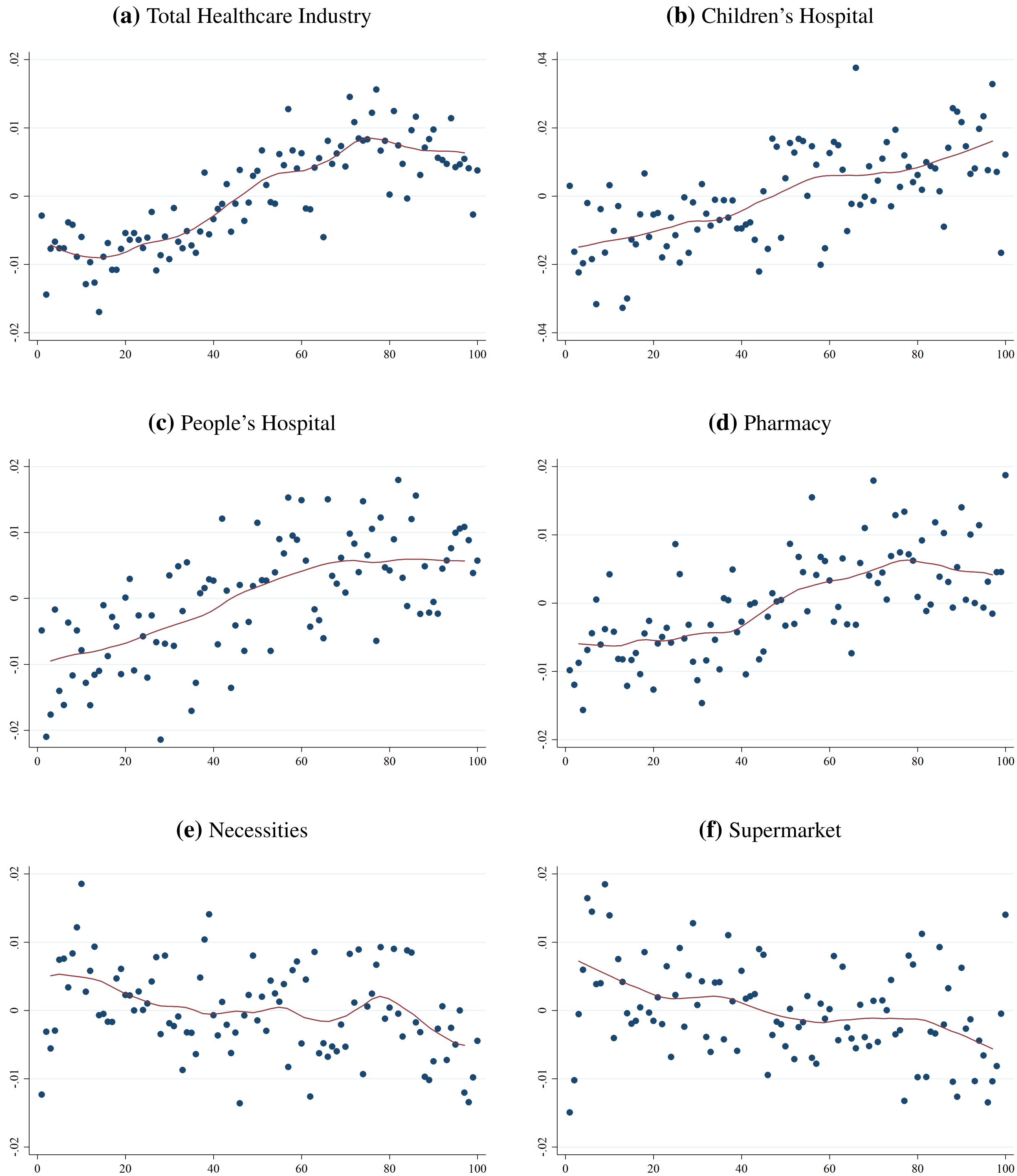
(a) Day 0: Wind-Pollution Vectors

(b) Day 0: Wind-Pollution Vectors toward Beijing



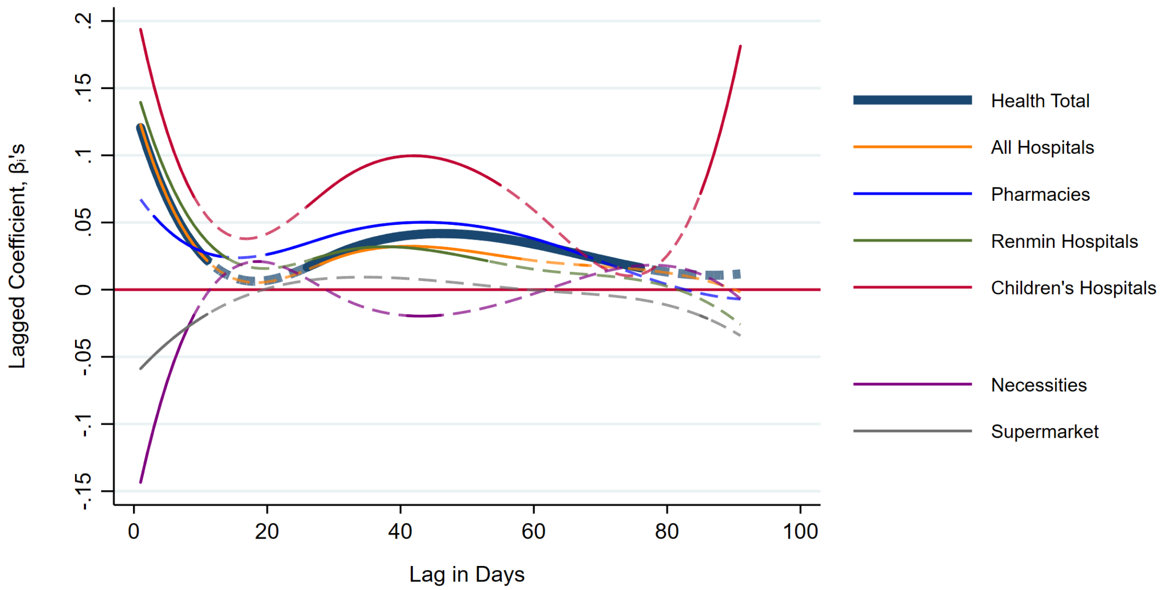
Notes: Day 0 = Dec. 5, 2013. Subfigure 5a depicts the wind-pollution vector fields on Day 0 from raw data, with each vector's length indicating wind speed (rescaled to match the distance traveled per day) and width indicating $PM_{2.5}$ concentration level in the source city. Subfigure 5b plots the decomposed subvectors pointing towards Beijing.

Figure 6: Residuals of Log Number of Transactions v. $PM_{2.5}$ Concentration, by Category

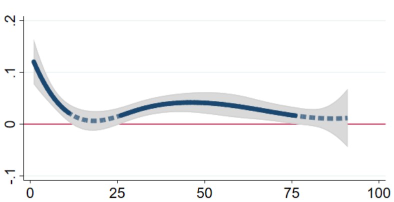


Notes: Each dot denotes the in-group average residuals, partialing out city FEs, weekly FEs, city-specific time trend, city-specific seasonality, day-of-week FEs, dummies for holidays and working weekends), and weather controls (temperature, precipitation, wind speed). Groups are binned by percentiles of the x-axis variable, $PM_{2.5}$.

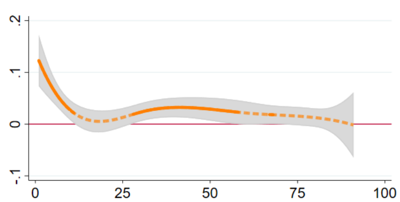
Figure 7: Impact of Air Pollution on Number of Transactions from IV with 90 Lags



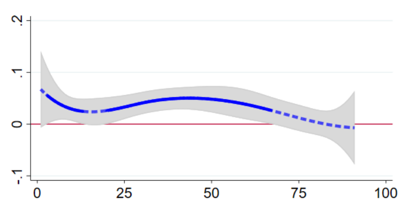
(a) Health Total



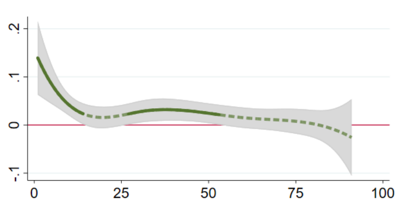
(b) All Hospitals



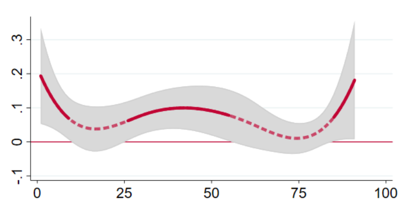
(c) Pharmacies



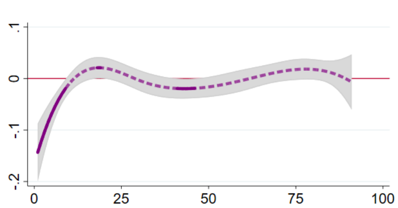
(d) People's Hospitals



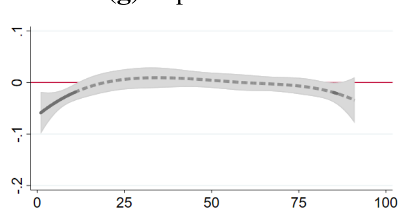
(e) Children's hospitals



(f) Necessities



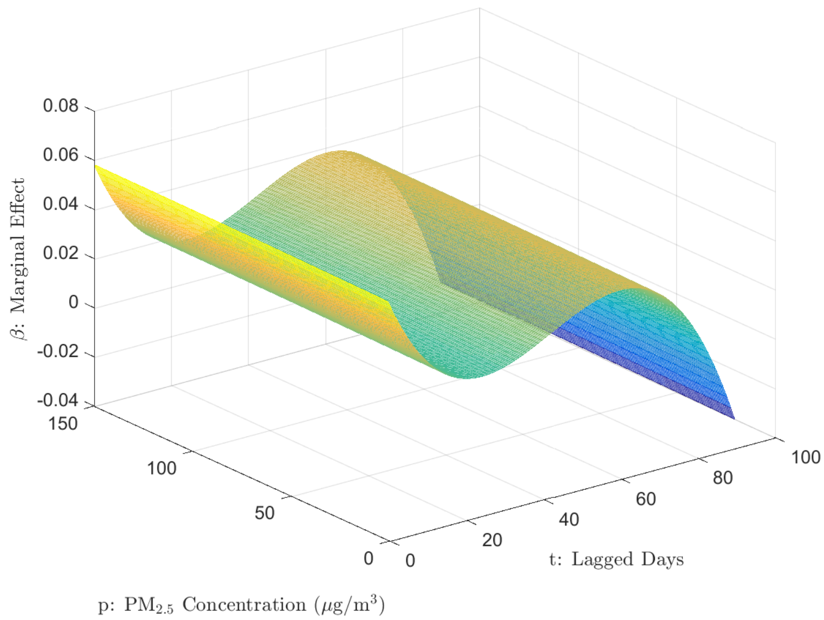
(g) Supermarkets



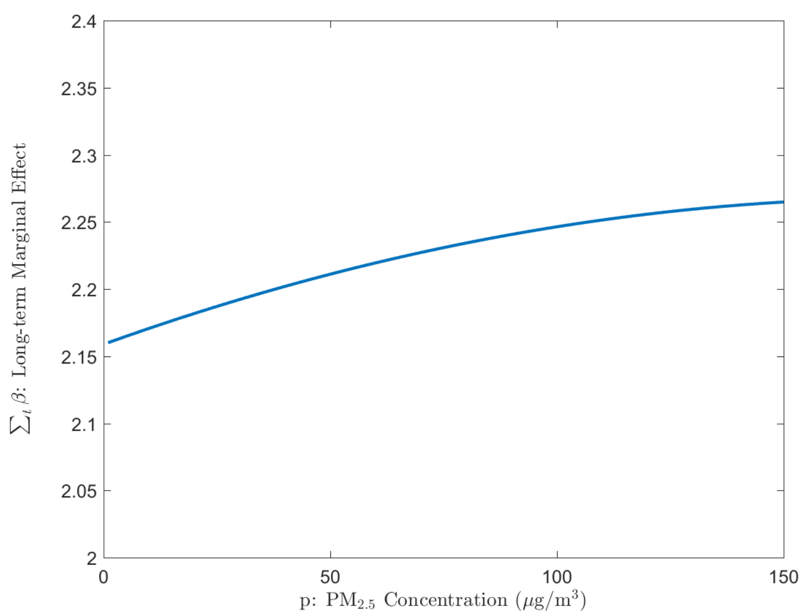
Notes: The y-axis indicates the percentage change in the number of transactions per 10 μg/m^3 increase in $PM_{2.5}$ concentration. The x-axis (from left to right) refers to current pollution, pollution in the previous day, previous t day, etc. Solid line indicates significance at 0.05 level. Gray areas are 95% confidence intervals. The y-axis for Children's Hospitals in subfigure (e) is scaled differently from other subfigures.

Figure 8: Impact of Air Pollution on Number of Transactions from IV: Nonlinearity

(a) 3D Illustration of Nolinearity



(b) 2D Illustration of Nolinearity



Notes: The y-axis in (a) indicates the percentage change in the number of transactions for a 10 $\mu g/m^3$ increase in $PM_{2.5}$ on a given day. The t-axis (from 0 to 90) refers to current pollution, pollution in the previous day, previous *t* day, etc. The y-axis in (b) indicates the percentage change in the number of transactions for a 10 $\mu g/m^3$ increase in $PM_{2.5}$ persistently during the last three months. The p-axis denotes different levels of pollution.

Table 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	7,229.2	21,308.6	0	330,974	211,318
All Hospitals	4,122.7	14,503.9	0	237,525	210,539
People's Hospitals	1,060.6	2,800.4	0	40,332	203,407
Children's hospitals	464.7	1,290.5	0	18,227	158,637
Pharmacies	2,245.3	7,063.3	0	96,336	210,001
Comparison Groups, *from 1% card sample*					
Daily Necessities	233.3	628.6	0	10,865	211,318
Supermarkets	393.4	990.3	0	15,224	210,493
Total Value of Transactions, Daily, *thousand yuan*					
Healthcare Industry, Total	6,701.8	17,818.9	0	301,108.7	211,318
All Hospitals	5,556.5	15,066.8	0	275,883.0	210,539
People's Hospitals	1,588.1	3,401.2	0	56,856.9	203,407
Children's hospitals	363.9	843.3	0	10,324.3	158,637
Pharmacies	407.4	1,109.5	0	16,735.1	210,001
Comparison Groups, *from 1% card sample*					
Daily Necessities	236.9	551.3	0	9,532.4	211,318
Supermarkets	232.8	643.4	0	14,404.7	210,493
Weather					
Mean Temperature, $^\circ F$	60.11	18.92	-27.50	101.6	211,317
Precipitation, *inch*	0.13	0.42	0	15.6	211,318
Mean Wind Speed, *mph*	5.50	3.11	0	48.7	211,296
Wind Direction, *navigational bearing*	-	-	0	360	211,263

Notes: Data sources include China's Ministry of Environmental Protection, Integrated Surface Database (ISD), and Global Surface Summary of the Day (GSOD) Database. Data for comparison groups are calculated from a subsample with randomly selected 1% of bank cards. Transactions with value larger than 200,000 *yuan* ($29,000) are excluded from total value of transactions. The arithmetic mean and standard deviation of wind directions do not have statistical meaning and are left out in the table.

Table 2: OLS Estimates of the Pollution Impact on Health Spending: Contemporaneous Effects

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$, Current Day	0.11***	0.11***	0.12***	0.13***	0.18***	-0.06***	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)
N	192,586	191,814	191,277	185,773	146,224	192,035	191,766

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, dummies for holidays and working weekends, and weather controls (temperature, precipitation, wind speed). Each column reports the percentage change in the number of transactions per 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 3: IV Estimates of the Pollution Impact on Health Spending: Contemporaneous Effects

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$, Current Day	0.65***	0.73***	0.60***	0.77***	1.13***	-0.09	-0.10
	(0.09)	(0.11)	(0.15)	(0.13)	(0.37)	(0.15)	(0.12)
N	192,586	191,814	191,277	185,773	146,224	192,035	191,766
First-stage F	61.93	61.77	61.78	59.47	52.32	61.92	61.97

Notes: The dependent variable is log(number of transactions). The IVs are various functions of non-local $PM_{2.5}$ imported from cities more than 150 km away. Same controls as in Table 2. Each column reports the percentage change in the number of transactions per 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentration. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table 4: Cumulative Effect of Pollution, OLS with 90 Lags

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.03***	0.04***	0.05***	0.04***	0.06***	-0.03***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Current + Past 3d	0.12***	0.11***	0.18***	0.13***	0.19**	-0.11***	-0.07**
	(0.03)	(0.03)	(0.04)	(0.04)	(0.08)	(0.03)	(0.03)
Current + Past 7d	0.19***	0.16***	0.32***	0.21***	0.25*	-0.16***	-0.11***
	(0.05)	(0.06)	(0.07)	(0.06)	(0.15)	(0.05)	(0.04)
Current + Past 14d	0.25***	0.16	0.49***	0.30***	0.20	-0.16**	-0.13**
	(0.08)	(0.10)	(0.10)	(0.08)	(0.28)	(0.07)	(0.06)
Current + Past 28d	0.38***	0.18	0.80***	0.39***	0.12	-0.15	-0.09
	(0.13)	(0.15)	(0.16)	(0.14)	(0.50)	(0.12)	(0.11)
Current + Past 56d	0.66***	0.27	1.42***	0.47**	0.57	-0.27	0.03
	(0.19)	(0.20)	(0.29)	(0.24)	(0.74)	(0.21)	(0.18)
Current + All Lags	0.86***	0.34	1.81***	0.59*	0.38	-0.08	0.02
	(0.27)	(0.28)	(0.42)	(0.36)	(1.14)	(0.27)	(0.21)
N	141,794	141,657	141,567	137,853	110,259	141,770	141,652

Notes: The dependent variable is log(number of transactions). The effect of current and past air pollution is estimated using Flexible Distributed-Lag Model with 90 lags and 3 evenly-split segments. Same controls as in Table 2. Each row reports cumulative percentage change in the dependent variable in response to a 10 $\mu g/m^3$ increase in $PM_{2.5}$ for the corresponding period. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 5: Cumulative Effect of Pollution, IV with 90 Lags

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.12***	0.12***	0.07*	0.14***	0.19***	-0.14***	-0.06***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.07)	(0.03)	(0.02)
Current + Past 3d	0.40***	0.40***	0.23*	0.47***	0.65***	-0.45***	-0.21***
	(0.07)	(0.08)	(0.12)	(0.13)	(0.23)	(0.09)	(0.07)
Current + Past 7d	0.61***	0.62***	0.39**	0.75***	1.04***	-0.64***	-0.34***
	(0.10)	(0.12)	(0.18)	(0.19)	(0.36)	(0.13)	(0.10)
Current + Past 14d	0.74***	0.75***	0.57***	0.97***	1.40***	-0.63***	-0.45***
	(0.14)	(0.16)	(0.21)	(0.22)	(0.50)	(0.16)	(0.12)
Current + Past 28d	0.91***	0.90***	0.99***	1.24***	2.12***	-0.44*	-0.41**
	(0.22)	(0.25)	(0.30)	(0.27)	(0.79)	(0.23)	(0.21)
Current + Past 56d	1.97***	1.71***	2.31***	2.01***	4.65***	-0.85**	-0.23
	(0.42)	(0.47)	(0.54)	(0.46)	(1.56)	(0.41)	(0.36)
Current + All Lags	2.65***	2.18***	2.80***	2.13***	6.37***	-0.55	-0.57
	(0.68)	(0.71)	(0.89)	(0.75)	(2.33)	(0.58)	(0.47)
N	141,794	141,657	141,567	137,853	110,259	141,770	141,652
First-stage F	38.35	38.36	38.37	39.69	47.79	38.29	38.29

Notes: The dependent variable is log(number of transactions). The effect of current and past air pollution is estimated using Flexible Distributed-Lag Model with 90 lags and 3 evenly-split segments. The IVs are various functions (both current and lagged) of non-local $PM_{2.5}$ imported from cities more than 150 km away. Same controls as in Table 2. Each row reports cumulative percentage change in the dependent variable in response to a 10 $\mu g/m^3$ increase in $PM_{2.5}$ for the corresponding period. Standard errors in parentheses, clustered at the city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table 6: IV Cumulative Effects of Pollution: Different Number of Lags and Segments

	Lag k				
Segments z	30 days	60 days	90 days	120 days	150 days
1	1.18***	2.12***	2.42***	2.60***	2.58*
	(0.25)	(0.51)	(0.69)	(0.98)	(1.48)
2	1.41***	2.26***	2.67***	2.80***	2.62*
	(0.25)	(0.52)	(0.69)	(0.95)	(1.43)
3	1.28***	2.16***	2.65***	2.74***	2.41*
	(0.25)	(0.49)	(0.68)	(0.93)	(1.40)

Notes: The dependent variable is log(number of transactions). Each row indicates the number of segments for the cubic B-splines. Each column reports the cumulative percentage change in the dependent variable in response to a 10 μg/m^3 increase in $PM_{2.5}$, over different number of days. Same IV and controls as in Table 5. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.

Table 7: IV Cumulative Effects of Pollution: Different Buffer Zone Radii

	Radius for the Buffer Zone					
	50 km	100 km	150 km	200 km	250 km	300 km
First Stage Regression						
N	192,586	192,586	192,586	192,586	192,586	192,586
R^2	0.502	0.486	0.474	0.467	0.464	0.462
IV Regression						
Total Long-Term Effect	2.56***	2.42***	2.65***	2.86***	2.86***	2.88***
	(0.78)	(0.60)	(0.68)	(0.71)	(0.72)	(0.70)
First-stage F	34.48	46.69	38.35	34.14	35.36	35.33

Notes: The dependent variable is log(number of transactions). Each column uses a different buffer zone radius in constructing the instruments and reports the cumulative percentage change in the dependent variable in response to a 10 μg/m^3 increase in $PM_{2.5}$ over 90 days. Same controls as in Table 5. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics are reported in the last row and are cluster-robust at the city level.

Table 8: IV Cumulative Effects of Pollution: Controlling for O_3, SO_2, NO_2 and CO

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.09***	0.09***	0.05	0.12***	0.16**	-0.16***	-0.05**
	(0.02)	(0.03)	(0.04)	(0.04)	(0.08)	(0.03)	(0.02)
Current + Past 3d	0.32***	0.31***	0.16	0.40***	0.56**	-0.51***	-0.18***
	(0.07)	(0.08)	(0.12)	(0.13)	(0.24)	(0.09)	(0.07)
Current + Past 7d	0.50***	0.49***	0.29	0.65***	0.91**	-0.73***	-0.31***
	(0.11)	(0.12)	(0.18)	(0.19)	(0.37)	(0.14)	(0.10)
Current + Past 14d	0.64***	0.63***	0.48**	0.89***	1.27**	-0.71***	-0.44***
	(0.14)	(0.16)	(0.22)	(0.23)	(0.50)	(0.16)	(0.13)
Current + Past 28d	0.84***	0.82***	0.93***	1.19***	2.01**	-0.49**	-0.44**
	(0.22)	(0.25)	(0.31)	(0.27)	(0.79)	(0.23)	(0.20)
Current + Past 56d	1.87***	1.60***	2.24***	1.91***	4.51***	-0.88**	-0.30
	(0.43)	(0.47)	(0.55)	(0.46)	(1.55)	(0.41)	(0.36)
Current + All Lags	2.55***	2.07***	2.73***	2.01***	6.21***	-0.55	-0.69
	(0.69)	(0.72)	(0.91)	(0.76)	(2.34)	(0.58)	(0.46)
N	141,779	141,642	141,552	137,838	110,244	141,755	141,637
First-stage F	39.76	39.85	39.75	41.61	50.98	39.71	39.71

Notes: The dependent variable is log(number of transactions). The same IVs as in Table 5 are used. In addition to controls in Table 5, daily average concentration levels of O_3, SO_2, NO_2 and CO are included. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table 9: IV Cumulative Effects of Pollution: Controlling for Regional Economic Spillover

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.11***	0.10***	0.05	0.13***	0.19***	-0.15***	-0.05***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.07)	(0.03)	(0.02)
Current + Past 3d	0.35***	0.34***	0.17	0.44***	0.64***	-0.46***	-0.19***
	(0.07)	(0.08)	(0.12)	(0.13)	(0.23)	(0.09)	(0.07)
Current + Past 7d	0.55***	0.54***	0.31*	0.71***	1.03***	-0.66***	-0.32***
	(0.11)	(0.13)	(0.18)	(0.19)	(0.37)	(0.14)	(0.10)
Current + Past 14d	0.70***	0.68***	0.50**	0.95***	1.39***	-0.65***	-0.43***
	(0.14)	(0.17)	(0.21)	(0.23)	(0.51)	(0.16)	(0.13)
Current + Past 28d	0.89***	0.87***	0.96***	1.23***	2.13***	-0.46**	-0.41*
	(0.22)	(0.25)	(0.30)	(0.27)	(0.80)	(0.23)	(0.21)
Current + Past 56d	1.94***	1.66***	2.27***	1.99***	4.66***	-0.86**	-0.22
	(0.42)	(0.47)	(0.54)	(0.46)	(1.57)	(0.41)	(0.36)
Current + All Lags	2.62***	2.15***	2.76***	2.12***	6.37***	-0.56	-0.56
	(0.68)	(0.72)	(0.89)	(0.76)	(2.34)	(0.59)	(0.47)
N	138,390	138,254	138,164	134,544	107,345	138,366	138,250
First-stage F	37.53	37.49	37.54	38.91	45.28	37.49	37.48

Notes: The dependent variable is log(number of transactions) and the same IVs as in Table 5 are used. In addition to controls in Table 5, we include the average level of pollution in other cities outside of the buffer zone but within the same region, to control for regional economic spillovers. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table 10: IV Cumulative Effects of Pollution: Controlling for Avoidance

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}\{P_{+1} > P_0\}$	0.41***	-0.15	0.95***	-0.11	0.29	0.36**	0.95***
	(0.11)	(0.13)	(0.19)	(0.20)	(0.32)	(0.15)	(0.14)
Current Day	0.13***	0.13***	0.07*	0.15***	0.20***	-0.14***	-0.05***
	(0.02)	(0.03)	(0.04)	(0.04)	(0.07)	(0.03)	(0.02)
Current + Past 3d	0.41***	0.41***	0.25**	0.49***	0.68***	-0.44***	-0.18***
	(0.07)	(0.08)	(0.12)	(0.13)	(0.24)	(0.09)	(0.07)
Current + Past 7d	0.63***	0.63***	0.42**	0.78***	1.09***	-0.63***	-0.31***
	(0.11)	(0.12)	(0.18)	(0.19)	(0.37)	(0.13)	(0.10)
Current + Past 14d	0.77***	0.77***	0.60***	1.01***	1.48***	-0.63***	-0.43***
	(0.14)	(0.16)	(0.22)	(0.23)	(0.51)	(0.16)	(0.13)
Current + Past 28d	0.95***	0.94***	1.03***	1.29***	2.25***	-0.45*	-0.41*
	(0.22)	(0.25)	(0.31)	(0.27)	(0.80)	(0.23)	(0.21)
Current + Past 56d	2.02***	1.77***	2.34***	2.07***	4.82***	-0.88**	-0.24
	(0.43)	(0.47)	(0.54)	(0.46)	(1.59)	(0.42)	(0.37)
Current + All Lags	2.71***	2.27***	2.83***	2.22***	6.57***	-0.60	-0.60
	(0.69)	(0.72)	(0.90)	(0.75)	(2.38)	(0.59)	(0.48)
N	141,272	141,136	141,046	137,347	109,862	141,248	141,132
First-stage F	37.76	37.79	37.77	38.88	45.27	37.72	37.70

Notes: The dependent variable is log(number of transactions). Same IV as in Table 5. Besides controls used in Table 5, the dummy variable indicating whether pollution level of next day is worse than current day is also included to control for avoidance behavior. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table 11: 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 $\mu g/m^3$)	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 $\mu g/m^3$ 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 $\mu g/m^3$ 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 $\mu g/m^3$ TSP	WTP: \$450-\$1,050 in housing price
Bayer et al. (2009)	1 $\mu g/m^3$ PM_{10}	WTP: \$149-\$185 in housing price
Ito and Zhang (2016)	1 $\mu g/m^3$ PM_{10}	WTP: \$1.1 per household per year
Our estimation		
OLS	10 $\mu g/m^3$ $PM_{2.5}$	0.9% in hospital visits and pharmacy purchases, 0.5% in total health expenditure
IV	10 $\mu g/m^3$ $PM_{2.5}$	2.6% in hospital visits and pharmacy purchases, 1.5% in total health expenditure WTP: \$9.25 per household annually

Appendices

A Derivation of Marginal Willingness-to-Pay for Clean Air

In this section, we show how to derive the expressions for the marginal willingness to pay for pollution reductions described in Section 3. Recall that individual i's maximization problem can be written as:

$$\max_{\{m_i, c_i, o_i\}} U[h_i, c_i, o_i, e(a, m_i + c_i)],$$
$$\text{s.t. } y(h_i) \equiv y_0 + w(h_i) = \pi + pm_i + c_i + o_i,$$
$$\text{and } h_i = h_0 + m_i - g_i(e(a, m_i + c_i)),$$

The Lagrangian can be written as:

$$L_i = U[h_i, c_i, o_i, e(a, m_i + c_i)] + \lambda_i[y(h_i) - \pi - pm_i - c_i - o_i],$$

The first-order conditions are:

$$\frac{\partial L_i^*}{\partial m_i} = U_h(1 - g_i'(e_i)e_m) + U_e e_m + \lambda_i(y_h(1 - g_i'(e_i)e_m) - p) = 0,$$
$$\frac{\partial L_i^*}{\partial c_i} = -U_h g_i'(e_i)e_c + U_c + U_e e_c - \lambda_i(y_h g_i'(e_i)e_c + 1) = 0,$$
$$\frac{\partial L_i^*}{\partial o_i} = U_o - \lambda_i = 0,$$
$$\frac{\partial L_i^*}{\partial \lambda_i} = y(h_i^*) - \pi - pm_i^* - c_i^* - o_i^* = 0.$$

where U_h, U_c, U_o are the derivatives of the utility function with respect to each component of the utility function, and $y_h = \frac{\partial y_i}{\partial h_i}$ is the marginal effect of health stock on income.

How does an increase in air pollution a affect the consumer's health and non-health spending decisions? Because air pollution a affects a consumer's wage income, a effectively governs the relative prices of non-health consumption c_i and health consumption m_i with respect to online spending o. The intuition is that when air pollution is high, the effective price of consuming one unit of c is not just the amount spent on the good, but also the additional income lost from the increased exposure to air pollution.[33] An increase in a therefore corresponds to an increase in the relative price of c_i and a decrease in the relative price of m_i. The "price" effect causes c_i to decrease

[33]To see this more formally, notice that the consumer's net income left over after purchasing c_i is equal to $y(h_i) - c_i$. Differentiating that with respect to c_i, we see that a 1-unit increase in consumption reduces the consumer's net income available for spending on other goods by $y_h e_c + 1$, which is therefore the effective price of consumption with respect to online spending. Since e_c is increasing in a, it follows that the price of consumption is increasing in a.

and m_i to increase.

There is also an income effect: the reduction in income causes both c_i and m_i to decrease. Finally, a directly lowers the consumer's utility by decreasing the health stock, h_i, and by increasing exposure e_i. Assuming that consumption and health are complements, the marginal utility of consumption is non-decreasing in h_i and non-increasing in e_i. Thus a decrease in h_i and an increase in e_i caused by an increase in a lead to a further decrease in c_i. Thus, taking into account all of these effects, an increase in air pollution unambiguously causes c_i to decrease.

The effect of an increase in a on m_i is theoretically ambiguous, because the income and price effects work in opposite directions, and because the consumer is trading off improvements in health stock h_i (which increases utility) against increased exposure to pollution e_i (which lowers utility). As long as income effects are not too large and the effect of medical spending on health stock h_i dominates the increased exposure e_i from going out to visit the doctor, m_i should be increasing in a.

We now derive the marginal willingness to pay for pollution reduction. Denote $V_i(a, h_0, y_0)$ as the indirect utility function and $L_i^*(a, h_0, y_0)$ as the optimal value of the Lagrangian. The marginal WTP for reduction in air pollution can be obtained as:

$$MWTP_i = -\frac{\frac{\partial V_i}{\partial a}}{\frac{\partial V_i}{\partial y_0}} = -\frac{\frac{\partial L_i^*}{\partial a}}{\frac{\partial L_i^*}{\partial y_0}}$$

By the Envelope Theorem,

$$\begin{aligned} \frac{\partial L_i^*}{\partial a} &= -U_h g_i'(e_i) e_a + U_e e_a - \lambda_i y_h g_i'(e_i) e_a - \lambda_i \pi'(a) \\ &= U_e e_a - g_i'(e_i) e_a (U_h + \lambda_i y_h) - \lambda_i \pi'(a) \\ \frac{\partial L_i^*}{\partial y_0} &= \lambda_i \end{aligned} \tag{8}$$

Taking the total derivatives of both the health stock h_i and exposure e_i with respect to a, we obtain the following equations:

$$\frac{dh_i^*}{da} = \frac{\partial m_i^*}{\partial a} - g_i'(e_i) e_a - g_i'(e_i) e_c \left(\frac{\partial m_i^*}{\partial a} + \frac{\partial c_i^*}{\partial a}\right) \tag{9}$$

$$\frac{de_i^*}{da} = e_a + e_c \left(\frac{\partial m_i^*}{\partial a} + \frac{\partial c_i^*}{\partial a}\right) \tag{10}$$

Rearranging terms, we obtain the following relations:

$$\lambda_i p = U_e e c_c + (U_h + \lambda_i y_h)(1 - g_i'(e_i) e_c) \tag{11}$$

$$U_c - U_o = -U_e e_c + (U_h + \lambda_i y_h) g_i'(e_i) e_c \tag{12}$$

Plugging these equations into equation (8), we obtain[34]:

$$\begin{aligned}
\frac{\partial L_i^*}{\partial a} &= U_e\big(\frac{de_i^*}{da} - e_c(\frac{\partial m_i^*}{\partial a} + \frac{\partial c_i^*}{\partial a})\big) + \big(\frac{dh_i^*}{da} - \frac{\partial m_i^*}{\partial a} + g_i'(e_i)e_c(\frac{\partial m_i^*}{\partial a} + \frac{\partial c_i^*}{\partial a})\big)\big(U_h + \lambda_i y_h\big) - \lambda_i \pi'(a) \\
&= U_e\frac{de_i^*}{da} + (U_h + \lambda_i y_h)\frac{dh_i^*}{da} - \frac{\partial m_i^*}{\partial a}\big[-U_e e_c + (U_h + \lambda_i y_h)(1 - g_i'(e_i)e_c)\big] + \\
&\quad \frac{\partial c_i^*}{\partial a}\big[-U_e e_c + (U_h + \lambda_i y_h) g_i'(e_i)e_c\big] - \lambda_i \pi'(a) \\
&= -\lambda_i p \frac{\partial m_i^*}{\partial a} + \frac{dh_i^*}{da}\big(U_h + \lambda_i y_h\big) + U_e\frac{de_i^*}{da} + (U_c - U_o)\frac{\partial c_i^*}{\partial a} - \lambda_i \pi'(a)
\end{aligned}$$

The marginal WTP for individual i is then equal to:

$$\begin{aligned}
MWTP_i &= -\frac{\frac{\partial L_i^*}{\partial a}}{\frac{\partial L_i^*}{\partial y_0}} \\
&= -\frac{U_e e_a - g_i'(a)(U_h + \lambda_i y_h) - \lambda_i \pi'(a)}{\lambda_i} \\
&= p\frac{\partial m_i^*}{\partial a} + \frac{d\pi}{da} + y_h(-\frac{dh_i^*}{da}) + \frac{U_h}{\lambda_i}(-\frac{dh_i^*}{da}) + (-\frac{U_e}{\lambda_i})\frac{de_i^*}{da} + \frac{U_c - U_o}{\lambda_i}(-\frac{\partial c_i^*}{\partial a})
\end{aligned}$$

We assume that premiums cannot adjust in response to pollution: $\frac{d\pi}{da} = 0$. This seems reasonable in the context of China, where the insurance reimbursement rates for the 3 major public insurance programs are fixed by the government and don't depend on individuals' pollution exposure. The MWTP for individual i can be simplified as:

$$MWTP_i = p\frac{\partial m_i^*}{\partial a} + y_h(-\frac{dh_i^*}{da}) + \frac{U_h}{\lambda_i}(-\frac{dh_i^*}{da}) + (-\frac{U_e}{\lambda_i})\frac{de_i^*}{da} + \frac{U_c - U_o}{\lambda_i}(-\frac{\partial c_i^*}{\partial a})$$

To derive the social MWTP, we additionally need to calculate how much the cost of providing insurance changes in response to air pollution. For any level of air pollution a, the net payment that the insurance program has to make to individual i equals $(1-p)m_i$. Each individual i also pays a fixed premium π into the insurance program. The insurance program's net cost therefore equals:

$$C = (1-p)\int m_i dF_i - \pi$$

where $\int m_i dF_i$ is the aggregate medical spending in the economy. When the premium is invariant to pollution, the change in the cost of providing insurance due to a change in pollution equals:

$$\frac{dC}{da} = (1-p)\int \frac{\partial m_i^*}{\partial a} dF_i$$

[34] In the first line, we plug in (9) and (10). In the second line, we re-arrange and collect terms. To get to the third line, we plug in (11) and (12).

B Additional Regression Results using the Value of Transactions

Table B1: OLS Estimates of Pollution Impact on Value of Transactions with 90 Lags

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.01	0.01	0.02	0.01	-0.01	-0.03	-0.02
	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
Current + Past 3d	0.04	0.04	0.08	0.04	-0.07	-0.10	-0.07
	(0.03)	(0.04)	(0.05)	(0.05)	(0.10)	(0.07)	(0.06)
Current + Past 7d	0.07	0.07	0.15*	0.07	-0.16	-0.15	-0.10
	(0.05)	(0.06)	(0.09)	(0.07)	(0.18)	(0.10)	(0.10)
Current + Past 14d	0.12	0.09	0.27**	0.10	-0.31	-0.17	-0.10
	(0.08)	(0.10)	(0.13)	(0.10)	(0.34)	(0.14)	(0.14)
Current + Past 28d	0.19	0.12	0.46**	0.12	-0.37	-0.17	-0.09
	(0.13)	(0.15)	(0.21)	(0.17)	(0.63)	(0.21)	(0.22)
Current + Past 56d	0.31*	0.09	1.02***	0.00	0.40	-0.28	0.01
	(0.17)	(0.19)	(0.37)	(0.27)	(0.88)	(0.34)	(0.36)
Current + All Lags	0.49*	0.21	1.14**	-0.04	0.43	0.10	0.20
	(0.25)	(0.26)	(0.51)	(0.41)	(1.31)	(0.47)	(0.48)
N	141,794	141,656	141,566	137,854	110,257	141,757	141,641

Notes: The dependent variable is log(value of transactions). Same controls as in Table 5. Each row reports cumulative percentage change in the dependent variable in response to a 10 $\mu g/m^3$ increase in $PM_{2.5}$ for the corresponding period. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. The Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.

Table B2: IV Estimates of Pollution Impacts on Value of Transactions with 90 Lags

	Health-Related Consumption					Comparison Groups	
	Health	All Hospital	Pharmacy	People's	Children's	Necessities	Supermarket
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Current Day	0.07***	0.07**	0.01	0.10**	0.01	-0.12**	-0.04
	(0.02)	(0.03)	(0.05)	(0.05)	(0.09)	(0.05)	(0.05)
Current + Past 3d	0.23***	0.25***	0.04	0.34**	0.05	-0.38**	-0.16
	(0.08)	(0.08)	(0.15)	(0.15)	(0.30)	(0.17)	(0.17)
Current + Past 7d	0.36***	0.38***	0.04	0.54**	0.13	-0.55**	-0.36
	(0.11)	(0.13)	(0.21)	(0.23)	(0.45)	(0.24)	(0.25)
Current + Past 14d	0.42***	0.46***	0.03	0.69**	0.33	-0.56**	-0.68**
	(0.15)	(0.17)	(0.24)	(0.27)	(0.59)	(0.27)	(0.31)
Current + Past 28d	0.43*	0.44	0.29	0.79***	1.09	-0.34	-0.99**
	(0.25)	(0.29)	(0.34)	(0.30)	(0.88)	(0.34)	(0.43)
Current + Past 56d	1.04**	0.83	1.64***	1.15**	4.07**	-0.32	-0.95
	(0.47)	(0.54)	(0.61)	(0.47)	(1.72)	(0.58)	(0.75)
Current + All Lags	1.47**	1.08	1.96**	1.20	6.12**	0.54	-0.66
	(0.70)	(0.78)	(0.96)	(0.83)	(2.61)	(0.87)	(1.04)
N	141,794	141,656	141,566	137,854	110,257	141,757	141,641
First-stage F	38.35	38.38	38.37	39.68	47.79	38.26	38.30

Notes: The dependent variable is log(value of transactions). Same IV and controls as in Table 5. Each row reports cumulative percentage change in the dependent variable in response to a 10 μg/m^3 increase in $PM_{2.5}$ for the corresponding period. Standard errors in parentheses, clustered at city level. Significance levels are indicated by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. The Kleibergen-Paap Wald rk F-statistics is reported in the last row and is cluster-robust at the city level.