Research Paper 27 | **2014**

AIR POLLUTION IN URBAN BEIJING: THE ROLE OF GOVERNMENT-CONTROLLED INFORMATION

C. RAVETTI, Y.POPP JIN, M. QUAN, Z. SHIQIU, T.SWANSON

Air pollution in urban Beijing: the role of government-controlled information

Chiara Ravetti* Yana Popp Jin† Mu Quan‡ Zhang Shiqiu§ Tim Swanson¶

August 21, 2014

Abstract

This paper looks at the problem of information control behind the unsustainable levels of air pollution in China. In particular, it focuses on a large urban area, Beijing, and it examines the role of the public, government-controlled information and the adaptation choices of households in response to signals about high pollution. Our analysis is based on a simple theoretical framework in which people migrate from rural areas to polluted cities, receiving a signal from the government about urban pollution; hence, they decide whether to adapt to pollution or not. We find that the government has no incentive to ensure sustainable air quality, as it can distort pollution information in order to attract cheap labour. We then analyse empirically two different air pollution indexes from different sources and agents' behaviour in an original household survey collected in Beijing. We find that the official air pollution values are systematically distorted, creating perverse incentives for households to react to bad air quality, especially for people who rely on government-controlled sources of information.

Keywords: Air Pollution; Government; Information; Averting Behaviour; Sustainability.

JEL Classification: Q53, Q56, Q58.

This research has received funding from the EU Seventh Framework Programme (FP7/2007-2013) under the grant agreement n. 266992 (GLOBAL IQ). All comments welcome.

*Corresponding author. Centre for International Environmental Studies (CIES), Graduate Institute of Geneva (IHEID), Maison de la Paix, Ch. Eugène-Rigot 2, CH-1211, Geneva, Switzerland *chiara.ravetti@graduateinstitute.ch.*

†Peking University, College of Environmental Sciences and Engineering, Beijing, China.

‡Peking University, College of Environmental Sciences and Engineering, Beijing, China.

§Peking University, College of Environmental Sciences and Engineering, Beijing, China.

¶Centre for International Environmental Studies (CIES), Graduate Institute of Geneva (IHEID), Maison de la Paix, Ch. Eugène-Rigot 2, CH-1211, Geneva, Switzerland

Introduction

Air quality affects in many different ways a country's economy and society, including its ecosystems, productive capacity and human health. However, many developing countries are still far from ensuring a sustainable amount of clean air,[1] especially in their urban centres. China is a striking example of this problem, as it prioritized over the years economic growth over pollution reduction, and has not managed insofar to ensure sustainable environmental quality.[2] In addition to the challenges of rapid urbanization and industrialization, however, Chinese people face a further difficulty in their path towards sustainability, since they live in a country tightly controlled by a single party, which may not have incentives to reduce air pollution. In particular, in China we observe that *information* about pollution is under the control that the Communist Party, through the national media. Any private effort to demand cleaner air or to defend against pollution could be diverted using information controls by the government. In this research, we analyse how this creates large difficulties in achieving sustainable air quality, i.e. at levels that are not beyond thresholds of significant health damage. To do so, we explore why the government may want to release misleading pollution data, if indeed there is evidence for this distorted signal, and how it can affects households' adaptive choices with respect to this crucial environmental issue in urban China.

Air quality is a key problem for Chinese cities: 7 out of 10 of the most polluted cities in the world are in China, Beijing being one of them [1]. Moreover, air pollution is not only a significant issue for the population of Chinese cities, but it also affects the surrounding ecosystems and can even be relevant at the global level for international actions such as climate change mitigation. [3]Nonetheless, it is fundamental to consider that the incentives that an autocratic government faces in dealing with local air pollution are quite different from those of a democratic country. In a single party regime with virtually full control of the media, the government may act as a stumbling block between environmental sustainability and the demand of the population, rather than as a solution.

In this study, we first model the behaviour of the (autocratic) social planner when choosing pollution levels and information about it, and that of households when choosing about labour provision in polluted cities and adaptation to bad air quality. Then we analyse how the Chinese government deals with pollution information: we examine the discrepancy between Chinese

[1] The concept of sustainability applied to air pollution relates mostly to its harmful effect on human health, i.e. a concentration of particulates and chemical substances sufficiently low not to cause in the population hazardous rates of airborne diseases. This concentration is usually measured in terms of air quality indexes, which are discussed in detail in section 3.1.

[2] Consider for instance the fact that, for the 10th Five-Year Plan period ($2001-2005$), almost half of the environmental protection targets set were not met. Some significant pollution indicators, such as sulfur dioxide (SO2) and particulate emissions, rose instead of falling as required by the plan [1].

[3] Since there exist many complementarities in the policies that reduce local and global pollutants ([52]), China could reap some tangible and localized benefits from reducing global emissions. This could provide a significant incentive for a developing country like China to participate in international climate change negotiation, while improving the domestic environment.

reported levels of pollution and those indicated by the US embassy in Beijing and we find that the two differ substantially, especially around important thresholds. Afterwards, we analyse the household dimension of the problem, focusing on the choice of various self-protecting measures, such as wearing a mask, reducing leisure time outdoor, or changing means of transportation. We identify the role of the information signal on those people who rely on the government information and consider it sufficient, as opposed to those who prefer to use the internet, those who do not care, and those who would like more information. We find that most households rely on the public (government controlled) media, and those who fully trust it are then those who, during high pollution days, take *less* protective actions.

The rest of the paper is organized as follows: the Background section contextualizes this research within the existing literature; then the Conceptual Framework section presents a basic model to think about government and households' interactions; next, the section on Government explores the evidence about data distortions in Beijing's air pollution index; and finally the section on Households moves to the private dimension and proposes some empirical findings about averting behaviour with different sources of information.

1 Background

The problem of air pollution damages to humans has been well studied from an environmental and health perspective. In the epidemiological literature, a positive relationship between air pollutants and adverse health outcomes has been identified consistently across a variety of studies in developed countries [55]. In the developing world, the research on mortality and morbidity outcomes of air pollution is scarcer, but to date a number of studies elicit exposure-response functions specific to poorer countries.[4] In mainland China, the key epidemiological studies have been summed up in a comprehensive meta-analysis by [5], to which we can add some recent cohort studies, such as [39] or [70] . Although the magnitude of the air-pollution effects varies across studies and pollutants, the literature mostly agrees that exposure to air pollution is damaging for health even in the short run.

This medical literature, however, assumes no adaptation mechanisms from the side of economic agents, and this can be problematic whenever the exact individual exposure to pollutants cannot be measured - as it is often the case in developing country's studies. Depending on people's awareness of the problem, there can be different attempts to avoid the negative consequences of bad outdoor air. Therefore, building on the well-established epidemiological relationship between pollution and airborne diseases, a number of papers have explored the socio-economic mechanisms that surround this relation. The key question is to what extent people can and want to defend themselves against the damages of pollution, and therefore would "buy" air quality.

For this purpose, two strands of microeconomic research have developed, tackling the problem in different, interlinked ways: a) the rich literature on stated willingness to pay for a public goods

[4] See, for example, [31] for Lebanon, [56] for Thailand, [11] for Brazil, [33] for India.

and for avoiding incurring the cost of illness, and b) various measures of averting behaviour and averting expenditures. The former can also be extended to the determinants of the value of a statistical life, and usually exploit an experimental approach focused on individual choices. Prominent examples in developing countries include [2] for Taiwan, [21] for Chile, [64] for a cross country comparison.

The literature on averting behaviour studies self-protective measures against environmental hazards: beginning with [30], it diffused the idea that people could allocate part of their income or efforts to risk-reduction. This is especially important whenever insurance markets are not perfect and in the presence of intangible values which have no market substitutes, such as good health ([58], [23]). Empirical research in this direction finds that indeed people combine market and non-market strategies to avoid uncertain damages ([58], [61], [66]). However this empirical literature encounters several methodological difficulties, due to the endogeneity of averting behaviour.

A small fraction of these studies focuses on aspects concerning the level of information that people can obtain regarding the risks and damages of a pollutant. This can be a substantial issue for developing countries, where the flow of information and data to the general population might be, for various reasons, less efficient [59]. For example, [41] noted that clean water can be effective in improving children's health (reducing diarrhoea), but it requires a level of knowledge and awareness of the mothers to reach the poorest children.[5]

The case of China is particularly interesting for the peculiar interplay between an environmental problem, air pollution, information regarding it, and household adaptation. In a context of tightly controlled data and media communication by the Communist Party, Beijing offers an interesting case study for the comparison between the official Chinese data on air pollution from the Ministry of Environmental Protection (MEP) and an alternative source of information about air quality, provided by the hourly tweet from the US embassy in Beijing. People living in the capital can therefore choose whether to trust the government or to look for alternative sources of information, such as the internet, self-perception of air pollution, word of mouth from other people, etc.

The contribution of our research is twofold: firstly, we want to explain why an autocratic government should decide to distort information about pollution, and then identify in the data if indeed the Chinese government manipulates air pollution information, by contrasting it with the US index. Secondly, we would like to examine how this distorted signal can reflect into household behavioural choices and attitudes towards pollution. In order to d that, we motivate our empirical analysis with a simple theory explaining the choices of households and of the government.

[5]See also [42] for the importance of information about environmental risks for averting behaviour, again in the case of water.

2 Conceptual Framework

We set up a stylized model to describe the interaction between an authoritarian municipal government, controlling pollution and information at the city level, and individuals, who form expectations about pollution in order to choose their labour provision and their response to bad air quality. This framework shows that it might be optimal for the local government to declare pollution to be *lower* than its actual levels, in order to attract people to work in the city. However, those urban dwellers who rely on the government signal might be less capable to avert the damages of pollution and fall sick more frequently.

2.1 Municipal government

The local government maximizes an objective function made of Y, the output produced, minus input costs, i.e. the wage bill, and health costs, cH per worker. We assume that the municipal government can fully capture the rents from production, as if all producing companies were state owned and profits accrued directly to the state - we therefore abstract from profits' taxation. This might be simplistic, but it depicts reasonably the large public sector and the high degree of public ownership in China. moreover, the government needs to pay wages in the public sector and to provide a basic sanitary system, which compensates people for illnesses through public health insurance, captured by c, for a given amount of health damages, H.

$$W = (Y - wN - cHN) \tag{1}$$

Output is produced using workers and some amount of pollution emissions.[6] The number of workers present in the city depends on a simple[36] (HT) mechanism, based on the wage differential between the city and other locations (rural areas, other cities), adjusted for unemployment. Moreover we assume an that expected pollution can deter some migrants from moving to polluted cities. Overall, we have

$$N = \underbrace{n(w_u \Pi - w_R)}_{HT} - kE(p))$$

where w_u and w_R are urban and rural wages, respectively, and Π the unemployment rate in the city.

For simplicity we abstract from unemployment rates and we scale wage units so that wages rural areas are zero. Therefore the number of workers is just

$$N = nw - kE(p)$$

[6] [25] discuss more specifically how pollution can be treated as an input or an output of production.

Output is produced with a Cobb-Douglas function using pollution and labour as inputs:

$$Y = p^{\alpha}\ N^{1-\alpha}$$

Finally we have a health production function, which depends on true pollution, but overall can be improved with some precautionary measures or protective behaviour, indicated by a) which depends upon perceived or expected pollution:

$$H = aE(p) - dp$$

where d is the parameter found in the empidemiological literature on dose response functions

The government maximizes the rents it can capture from this economy: all that is produced and does not go into wage payments or health costs remains to the municipal government.

2.2 Pollution and Information about pollution

The government has control over both sides of the problem: on the one hand, it can choose how much pollution to allow in the economy, while on the other it can control information about pollution, and therefore affect expectations.

Pollution in this economy is given by

$$p = p^n + \theta \ \ with \quad \theta \sim N(0, \sigma_\theta^2)$$

True pollution is unknown to people, who only know the average city level p^n; here we set it equal to zero without loss of generality, even if in China it is probably much higher than that. Agents know the distribution of pollution shocks, θ, which capture each period's emissions. The government can determine how much extra emissions to add every period to the economy.

Announcements are instead

$$A = \theta + \beta \quad with \quad \beta \sim N(\overline{\beta}, \sigma_\theta^2)$$

where β is the pollution bias of the government (again, unknown to households).

The game between the government and households unfolds in three stages:[7]:

[7] For an example of a game with two players similar to the set up described here, but applied to the context of central bank and an output-gap inflationary model, see [48].

1. The government observes past pollution, θ and makes an announcement about it to the public, A. This announcement can be biased.
2. People formulate their expectations, based on the announcement and on their past experience.
3. Finally, the government chooses the optimal pollution, θ, as best response to people's expectations.

2.3 Expectations

People form their expectations by solving a signal extraction problem: knowing the distribution of pollution shocks and government bias, and using their past observations of government announcements, they can form their expectations about i) the government pollution bias and ii) pollution. The expected bias is then

$$E(\beta) = \left(\frac{\overline{\beta}}{\sigma_\beta^2} + \frac{T\overline{A}}{\sigma_\theta^2}\right) / \left(\frac{1}{\sigma_\beta^2} + \frac{T}{\sigma_\theta^2}\right)$$

where $\overline{A} = \sum_{t=1}^{T} A_t/T$ is a weighted average of all past announcements.

The expected pollution shock, then, is obtained by updating any prior that the people have about pollution shocks (set to zero) with the government announcement adjusted for the expected bias

$$E(\theta) = \left(\frac{A - E(\beta)}{W^2}\right) / \left(\frac{1}{\sigma_\theta^2} + \frac{1}{W^2}\right)$$

where W^2 is the variance of the adjusted announcement, $A - E(\beta)$. [8]

We can see that whenever people receive the announcement that the air is not polluted, they can infer either that pollution shocks have indeed been minimal, or that the government has a downwards bias and instead the air is not so clean. If agents can update their beliefs for a sufficiently long time, their expectations will converge to the true bias. However not everyone may be able or willing to update fully, therefore we consider that only $(1 - \lambda)$ of the updated bias is incorporated in the final updated expectation

$$E(\theta) = \left(\frac{A - (1-\lambda)E(\beta)}{W^2}\right) / \left(\frac{1}{\sigma_\theta^2} + \frac{1}{W^2}\right) \tag{2}$$

[8] [28] show that this is $W^2 = \left(1/\sigma_\beta^2 + (T-1)/\sigma_\theta^2\right) / \left(1/\sigma_\beta^2 + T/\sigma_\theta^2\right)^2$

If the government can control the population very effectively, λ is very close to 1 and most people just consider the announcement to inform their expectations.

From this, we can derive two statements about the role of government biases in pollution expectations:

Proposition 1 - *Whenever the government biases announcements about air pollution, the bias affects expectations through two channels: directly, through the announcement A, and indirectly, entering the average of past announcements that form the expectations about the bias. Overall the first effect prevails on the second, so $\frac{\partial E(\theta)}{\partial \beta} > 0$, and this effect is greater the higher the incapacity to learn about the bias, lambda $\frac{\partial E(\theta)^2}{\partial \beta \partial \lambda} > 0$.*

Proof - *It follows straightforwardly from differentiating equation 2.*

This means that the larger the number of people the government can control (high lambda), the more effective the announcements are in pushing people's expectations away from true pollution. Over time, though the learning process, people can factor out more and more of the bias, but as long as there is a fraction of people who just fully believe the government, introducing a bias in the announcement is an effective policy tool.

Proposition 2 - *A negative bias results in $E(\theta) < \theta$, and viceversa.*

Proof - *By inspection again of equation 2, and given Proposition 1.*

2.4 Pollution

The government can then solve backwards the problem, by plugging the expectations about pollution in its best response pollution choice, derived from the maximization of the welfare function in equation (1).

using the above result on expectations we get

$$max \quad W = \theta^{\alpha}[nw - kE(\theta)]^{1-\alpha} - [w(nw - kE(\theta)] - [c(aE(\theta) - d\theta)(nw - kE(\theta)]$$

which yields as a solution

$$\theta^{BR} : \frac{\partial W}{\partial \theta} = 0 \implies \theta^{BR} = \frac{cd}{\alpha}\,[nw - kE(\theta] \;^{\alpha/\alpha - 1} \tag{3}$$

In this we can plug the expectations from Eq. 2 and find the optimal pollution choice.

$$\theta^{*} = \frac{cd}{\alpha}\left[nw - k\frac{A - (1-\lambda)E(\beta)}{(W^2/\sigma_{\theta}^2) + 1}\right]^{\alpha/\alpha - 1} \tag{4}$$

Proposition 3 - *For the government it is optimal to set a negative bias iff* $W(\theta > E(\theta)) > W(\theta \leq E(\theta))$. *This happens when the parameters of the model are such that*

$$\theta > \frac{nk}{n(a-n) + (d-a)a}$$

Proof - *Consider the loss function when* $E(\theta) = \theta - \epsilon$*, so that expectations are lower than real pollution (i.e. the government is creating a negative bias).* $L(\theta, E(\theta) = \theta - \epsilon) < L(\theta, E(\theta) = \theta + \epsilon)$ *iff* $\theta(a-n)n\epsilon - n\epsilon k + a(d-a)\theta a\epsilon < 0$*, as most of the quadratic terms cancel out, therefore we can simplify* ϵ *and get the above result.*

The above condition captures the costs and benefits for the government of creating a negative bias: if optimal pollution is relatively high, then it might be worthy using the information tool; if the damages of migrant workers and of averting behaviour, captured by n and$a$, interplaying with the other parameters, are not so large, then again the cost of a negative bias is worthy bearing.

3 Government

First of all, what measures and tools does the government use to communicate to a public audience the monitored levels of pollutants' concentration at a given point in time? Typically, public agencies monitor and diffuse the information about a city's pollution parameters through air quality indexes, providing a public good which otherwise is likely to be under-supplied by the private sector. The government has a pivotal role in determining the population's awareness of pollution risks, even on a daily basis.

3.1 Indexes of air pollution

The standard tools used in the USA, Canada, the European Union and many other countries to communicate to the general public the level of pollution are standardized indexes - Air Quality Indexes or AQI - that can easily convey information about the level of pollution through a simple rating of air quality. This is more understandable than reporting concentration of individual pollutants. The index score reported is then associated with the potential health damages that can derive from it. Generally cities and municipalities are required to report a simple scale, coloured to highlight the gravity of the environmental situation. China has also an Air Pollution Index (API) that is in many aspects similar to the one developed by the US Environmental Protection Agency (EPA). Both US AQI and Chinese API are non-linear in pollution concentration. A comparison is presented in Figure 3 in the Appendix.

The Chinese Air Pollution Index or the US Air Quality index on a given day corresponds to the highest index value given by any of the pollutants which compose it.

$$API = max(I_1, I_2, ...I_n) \tag{5}$$

In order to construct the index for an observed concentration C of pollutant **i**, the following formula is used:

$$I_i = (C - C_{low})\frac{I_{high} - I_{low}}{C_{high} - C_{low}} + I_{low} \tag{6}$$

where *high* and *low* indicate the boundaries of each category mentioned in Fig. 3 (Beijing Municipal Environment Monitoring Centre and US-EPA 2006). While the construction of the index is identical between the two countries, the boundaries of concentration for some of the pollutants are sometimes different (see for instance SOx), and between 100 and 300 some of the categories are defined differently. But generally, it is clear that a scale above 100 indicates the presence of pollution, and anything above 300 is highly polluted and hazardous.

3.2 Local incentives to distort information

The model of section 2 sets out a general framework to explain the incentives for the social planner to distort air pollution indexes. However the literature suggests also that some incentive to manipulate data may occur at the local level. The institutional framework of Chinese politics presents a strongly hierarchical relationship between local and central government. [9] This structure is based on a system of vertical bureaucratic control, which allows some flexibility at the local level, but no true decentralization [62]. Local government officers are responsible for economic targets and, more recently, also for some environmental performance evaluations, which however still represent a secondary concern [69].

It is therefore important to consider that there can be also *local* incentives for distorting information about environmental problems, to make them appear less significant to the central government. A clear incentive for such distortions comes from the National Environmental Protection Model City award, started in 2003, which prizes cities that, among other things, can achieve more than 85% of " blue sky days" in a year (API less than 100). Some evidence of this local effects has been found by [3] and [19], who analysed API data and found that air pollution data had been manipulated in various ways: from shifting monitoring stations to less polluted areas, to discontinuities just around the threshold of blue sky days .

[9] The observation that organization and hierarchy can generate different incentives and outcomes is not new, [46] for instance test this hypothesis with Chinese data on managers' incentives, using a broader model applicable to government structures.

3.3 Comparing the US AQI with Chinese API

Beijing is an excellent case study to search for distortions in the API, since it has the unique feature of having one useful counter-check to official data: the United States Embassy, which has its own monitor for particulate matter. Therefore, it is possible to conduct a comparative analysis of the two indexes produced by the Chinese and the US for the same time period, and see if the discrepancy between the two presents any pattern. Fig. 1 below shows a simple comparison of the two daily indexes during some months of 2008.

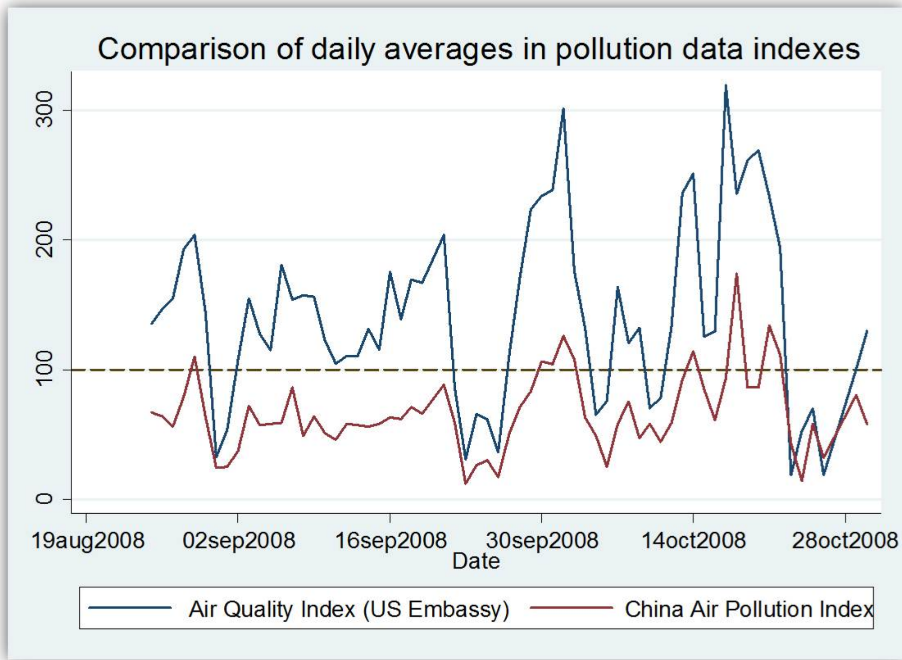

Figure 1: Mismatch between Chinese and US pollution indexes

Even from such a stylized graphical comparison, it is clear that the two indexes can take very different values in the same day. This could be due to some measurement error, but we notice that a pattern seems to exist. The Chinese index, in red, tends to be lower than the US one (blue) and rarely surpasses the blue sky day limit of an API of 100. Moreover, the Chinese index tends to be downward biased especially in highly polluted days, when the difference from the US AQI becomes greater, while for not so polluted days the two become more similar. Nonetheless, this the image depicts only a short period of time, so we extend our analysis to a longer time frame, from 2008 to 2013, the period for which data was available from both the two sources[10].

[10]Note that on December 14, 2012 the U.S. Environmental Protection Agency (EPA) strengthened the nation's air quality standards for fine particle pollution. This however falls at the very end of our sample, so should not

Note that the US embassy produces several measurements during the day, so it could also be a problem of how the data is aggregated. Even looking even at minimum daily values from the US AQI, the pattern still persists (see Fig.4 in the Appendix), but one of the robustness checks of our analysis will be to try different daily measures (average, minima, midday, etc.).

In order to gather more formal insights into any systematic ways in which the Chinese officials might manipulate Beijing's API, we conduct the following time-series analysis, to see how the US AQI can bee translated into the Chinese API. This under the assumption that the US embassy does not have itself any political incentive to distort pollution reporting (especially upwards, which would easily cause diplomatic tensions).

The time series model specification is the following:

$$\frac{API_t}{AQI_t} = \alpha + \beta_1 AQI_t + \beta_2 Politics_t + \sum_{i=1}^{p} \gamma_i Thresholds_i + \sum_{i=1}^{q} \phi_i \frac{API_{t-i}}{AQI_{t-i}} + \sum_{i=1}^{r} \theta_i \epsilon_{t-i} + \eta_m + \sigma_y + \epsilon_t$$

We take the two pollution indexes as logarithms, so to be able to measure the responsiveness of one to the other in terms of elasticities. Particularly we consider whether the AQI affects the ratio API/AQI in any significant ways. If the two indexes are very similar,[11] the ratio will take values close to one and the effect should be insignificant; the more discrepancy between the two, however, and the more of a (negative) significant impact we should observe.

We also include dummies for the various thresholds, such as the API at 100 which divides blue sky days from polluted ones, and the most noticeable ones in the AQI scale. Considering the way air quality indexes are constructed (see again Fig. 3 in the appendix) we include a threshold for T100, T200 and T300. In addition, to capture persistence in shocks and in the stock of pollution cumulated in the air, we add an autoregressive component and a moving average term, for which the exact number of lags can be determined comparing different models using standard time-series techniques. Finally, we add month and year fixed effects, in order to capture any particular event in our sample. Of course, following the above discussion on how the two pollution indexes are constructed, we consider only those days when PM10 is the main pollutant, since for SOx or NOx (or unknown main pollutant, as it is sometimes the case) the comparison would not be possible. The results of various autoregressive-moving average specifications are presented in Table 1.

affect the whole time series analysis and surely did not affect households' perceptions of air pollution. Also in China the current API is under revision and both English translations and tightness of standards are being modified: in February 2012 (regulation HJ 633—2012), China defined a new air quality index that includes PM2.5 and ozone. This will not take effect nationwide until 2016, but Beijing and many other cities have already started pilot uses of it. Source: * http://www.livefrombeijing.com/2013/01/demystifying-air-quality-numbers/ Ministry of Environmental Protection

[11] The two series are stationary according to a simple Dickey-Fuller test.

Table 1: Chinese/US air pollution indexes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AQI	-0.79***	-0.79***	-0.79***	-0.79***	-0.79***	-0.79***	-0.79***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
AQI threshold(100)	-1.58***	-1.59***	-1.53***	-1.60***	-1.59***	-1.59***	-1.58***
	(0.30)	(0.30)	(0.31)	(0.30)	(0.30)	(0.30)	(0.31)
AQI threshold(200)	0.10	0.03	0.15	0.07	0.03	0.02	0.03
	(0.89)	(0.90)	(0.91)	(0.90)	(0.90)	(0.90)	(0.90)
AQI threshold(300)	-2.14**	-2.02*	-2.35**	-2.07*	-2.02*	-2.02*	-2.04*
	(1.05)	(1.06)	(1.06)	(1.06)	(1.07)	(1.07)	(1.07)
T100*avg. AQI	0.33***	0.33***	0.32***	0.34***	0.33***	0.33***	0.33***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
T200*avg. AQI	0.00	0.02	-0.01	0.01	0.02	0.02	0.02
	(0.16)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
T300*avg. AQI	0.38**	0.36*	0.41**	0.36*	0.35*	0.36*	0.36*
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Constant	3.05***	3.04***	3.04***	3.06***	3.04***	3.04***	3.04***
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)
ARMA							
L.ar	0.34***	0.32***			0.41*	0.34	-0.15
	(0.03)	(0.03)			(0.22)	(0.79)	(3.10)
L2.ar		0.05				0.04	0.29
		(0.03)				(0.27)	(1.36)
L.ma			0.30***	0.31***	-0.09	-0.02	0.47
			(0.03)	(0.03)	(0.22)	(0.80)	(3.10)
L2.ma				0.14***	0.02		-0.10
				(0.03)	(0.08)		(0.36)
sigma							
Constant	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	876	876	876	876	876	876	876
AIC	-197.63	-197.29	-183.31	-193.82	-195.32	-195.29	-193.30
BIC	-73.47	-68.35	-59.15	-64.89	-61.61	-61.58	-54.81

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The average value over the time period 2008-2013 of the dependent variable is 0.87, indicating that the Chinese API tends to be slightly smaller, on average, than the US index. The negative and significant coefficient of AQI indicates that, whenever pollution (as registered by the US AQI) rises, the effect on the ratio is unambiguously downwards: a 1% increase in the AQI causes a fall in the Chinese/US ratio of 0.8%. This result could be foreseen given the graphs showed before: the Chinese pollution index does not increase as much as the US one, so whenever pollution increases the ration between the two indexes goes down.

But perhaps more interestingly, thresholds play an important role in moving the asymmetric relation between the Chinese API and the US AQI. This gives a stronger indication of political will than the previous result, which could come from some differences in the measurements of the US Embassy. Both the 100 and 300 points thresholds are significant and large, as one could expect given the blue sky days policy and the dangerous health zone above 300. As foreseeable, the effect of being above 100 or 300 diminishes as the AQI increases (see the positive and significant effect of the interaction between thresholds and AQI): it is easier to downplay pollution levels just above the threshold (e.g. 101 or 302), to move to the category below, than values way above the threshold. Anyway, the interaction terms do not fully outweigh the negative coefficients of the thresholds T100 and T300, so there is always a temptation to reduce reported pollution when entering the dangerous levels of the scale.

The various specifications can be compared on the basis of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which are used for model selection by indicating the relative goodness of fit of various statistical models[12]. Choosing the two models with lowest information criteria, i.e. the MA (1) and the MA(2) models, we can compute in-sample forecasts to see which of the specified models performs best in terms of predictive power. Comparing the mean squared errors of our forecasts (or alternatively the absolute value of the predicted errors), we can select the most suitable model among all the ones examined, which is the moving average with one period lag, MA(1).

Overall, this analysis shows that the relationship between the Chinese reported Air Quality Index and the actual levels of pollution in Beijing during a given day do not match, and this suggests that, as hypothesized in the model, the benefits for the government of declaring that the air is cleaner outweigh the costs. The next section will then be dedicated to the analysis of household responses to this air pollution information for averting the health damages of pollution exposure.

[12]Note that these criteria are only interpretable as relative measures to compare different models, they have no absolute meaning relative to goodness of fit, as the classical R squared would have.

4 Households

Individuals who decide to live and work in Beijing can choose if and how to respond to the environmental and health hazard presented by air pollution, by virtue of incurring a cost (monetary or in terms of time) for protecting themselves and their families from the damages of pollution. [13] Furthermore, agents can decide how to obtain information about air pollution, either by relying on government controlled sources (TV, newspapers, radio), on their own perception of pollution (for instance basing their judgement on the visibility), or on alternative sources of information, which are still relatively less popular in China, such as the internet. Note that, for example, the US Embassy measurements are available hourly through an online tweet, which can even be downloaded on a mobile device as an application. The internet is quite restricted in China, but young people are nowadays able to access this sort of information through the web.

In order to examine the behaviour of households with respect to air pollution and health, we collected a household survey in urban Beijing, which elicits the expenditure and time allocation to averting activities. Particular attention is dedicated to information effects, in order to identify which groups are more capable of adapting during peak pollution days. The data is described below and an English version[14] of the questionnaire is included in the Appendix.

4.1 Household Survey

The household survey was administered in three districts of Beijing, Haidian, Chaoyan and Dongcheng, for a total of 1672 individuals (578 households). Due to time and financial constraints we could naturally survey only some districts, and within each district only some streets and some communities. Hence sample selection was designed to ensure representativeness using probability proportional to size (PPS) at the district and street level and random selection at the community and household level, so that all households in Beijing had equal chances of selection (see Equation 7).

$$\underbrace{p_0\,\frac{[N_H]_{D1}}{[N_h]_{TOT}}}_{\text{District choice (PPS)}} * \underbrace{p_1\,\frac{[[N_H]_{S1}]_{D1}}{[N_h]_{D1}}}_{\text{Street choice (PPS)}} * \underbrace{p_2\,\frac{1}{[[N_{C1}]_{S1}]_{D1}}}_{\text{Community choice (Random)}} * \underbrace{\frac{x}{[[[N_H]_{C1}]_{S1}]_{D1}}}_{\text{Household choice (Random)}} = c \tag{7}$$

[13]This decision is here conceptualized as an individual decision, but it could be extended to an and intra-household allocation of a public good, clean air, which can then translate into better health for the whole family. Each household member faces a trade-off between income and non-market activities (leisure, averting behaviour, taking care of children or elderly people, etc.). Within the household, agents bargain for who should dedicate more time to income or non-market tasks, depending on relative opportunity costs. For a formal analysis of the possible bargaining solutions inside the household, see a review of intra-household allocation model by [15]

[14]The survey was administered in Chinese, after numerous pilot tests for its understandability and repeated checks that the Chinese and English version corresponded exactly.

The questionnaire inquired in detail about a) the socio-economic characteristics of the household, b) various habits and averting behaviours (wearing masks, reducing time outdoor, changing means of transportation, doing preventive health checks - more detail about these below), c) how the family gathered information about air pollution and d) health of family members and particularly airborne diseases, cost of illness and insurance. The respondents (one per household) could only answer for themselves and for close family members who spent most of the time in the household. The average household size is around 3, which is reasonable given the one child policy. We also compare various demographic characteristics of our sample with data from the Statistics Bureau of Beijing (gender, age, education) and the sample is in line with the characteristics of the total population of those districts.

The data from the household survey varies over three dimensions: across individuals, within households and somewhat over time. We asked to the respondents to recall their averting behaviour choices in periods of extreme pollution peaks and over the rest of the year, which gives us variation between normal times and extreme pollution events. To define extreme and normal times, we asked the respondents if they could recall the two worst episodes of air pollution in Beijing in the previous year, and if they could locate them in time. In the year before the survey, in fact, there were two pollution alerts during extremely hazardous days. We defined an extremely polluted days those situations. Hence averting behaviour could optimally shift in such extreme circumstances, even if normally a person would not avert air pollution. The use of recall data to introduce this artificial time dimension is not free from limitations, but allows us to at least get a general sense of people's variation in behaviour in relation to pollution.

4.2 Stylized facts

4.2.1 Health and pollution

Preliminary analysis of the data indicates that for our sample we can observe the standard epidemiological correlation between air pollution and illness episodes outcomes (Fig. 2). This is interesting to observe, however it could be driven by a number of different factors, as medical experiments showed with more precise exposure data and physiological parameters. What is more interesting for the purpose of this study is to examine how the adaptive behaviour of the household comes into play and what is the role of information access.

Overall there seems to be scope for averting behaviour, given that the private cost of illness obtained for our sample was quite high: from airborne diseases, the average annual expenditure including medical costs, medicines and foregone wage[15] was more than 3000 yuan, almost a month of average salary. Table 2 illustrates the breakdown of costs.

[15] Wage loss is computed multiplying the wage by the days at home, net of those covered by sick-leave: wage x (days lost-sick leave).

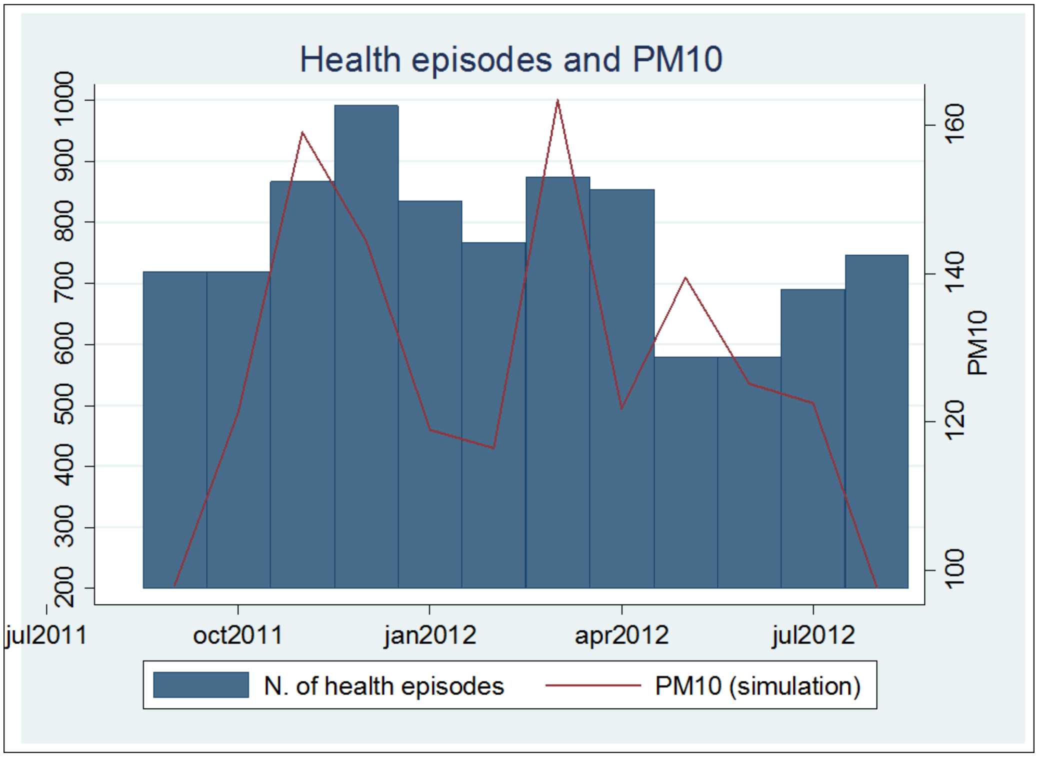

Figure 2: Correlation between PM_{10} and number of disease episodes

Table 2: Private cost of illness

	Direct costs	**Days of work lost**	**Paid sick leave**	**Days of inactivity**	**Indirect costs**	**Total costs**
Average (airborne diseases only)	2514 yuan	1.4	0.5	9	812 yuan	3326 yuan
Average (including other illnesses)	5184 yuan	18	13	53	305 yuan	5489 yuan

4.2.2 Averting behaviours

The averting behaviours we consider range from activities that are mostly time consuming to more expensive ones. Some are undertaken by almost everybody, while other ones are rarely adopted. Table 3 below illustrates the characteristics of the averting choices, their correlation with income and also, following the original literature on self-protection versus market protection, with insurance.

Reducing time outdoor means spending less time outside for leisure and for exercise purposes, so it captures changes in the free-time schedule of a person. This behaviour was much more frequent during extremely polluted days (77 % of our sample declared they did it). Transport change instead implies moving from means of transportation with very high exposure to pollution (i.e. walking or bicycle) to relatively safer ones, such as using a car or a taxi. The percentage of people adopting this behaviour in the extremely polluted days almost doubles, but still this is not a common strategy that people choose

Table 3: Characteristics of averting behaviours during a normal day

AVERTING BEHAVIOUR	FRENQUENCY	INCOME	INSURANCE
Reduce time outdoor	58 %	0.01	-0.02
Transport change	6 %	-0.01	0.03
Mask	11 %	0.1 **	0.01
Preventive health checks	62 %	0.1 ***	0.1 **

or can afford. Facial masks are also a relatively infrequent behaviour. We looked also at the use of protective masks, and asked the respondents also to mention if they choose a common, paper mask or a more sophisticated one (there exist more expensive masks on the market that can filter much more efficiently particulate matter), but only few people used the higher quality masks (2-3 % of the sample). Finally, a different, more expensive strategy is considered: going for preventive medical checks, and here we consider only those check-ups for which the person had to pay some individual contribution. The price paid for preventive health checks annually ranged from 10 to 15,000 yuan. The latter behaviour clearly correlate more strongly with income and hence also to private insurance expenditure. It is quite different in nature from the previous adaptation strategies, because it does not respond to pollution peaks, but rather is undertaken in advance.

4.2.3 Information about pollution

Internet usage for the purpose of collecting information about air pollution is still limited. The vast majority of people interviewed relied on government controlled sources of information, such as TV, radio or newspapers - see Table 4. Furthermore, 70 % of our sample considers the information available on air pollution sufficient. Therefore, it seems that the government can exert a direct influence on the choices of a large fraction of the population when deciding what data to publish for the API.

Table 4: Different sources of information about air pollution

SOURCE OF INFORMATION	FREQUENCY
Government sources (TV, radio, newspapers)	77 %
Internet (PC or mobile device)	6 %
Self-perception, other people	17 %
Doesn't care	0.1 %

4.2.4 Awareness of the problem

Despite not being a primary goal of the survey (e.g. we did not use any experimental setting to elicit the exact value that our interviewees give to clean air), from a number of answers we can get a sense about their level of awareness of the environmental problem posed by air pollution and how much people give importance to it. For instance, the fact that only 66 % of respondents had noticed and remembered the extremely polluted haze days in Beijing already indicates that the individual perception and interest in the issue might be still relatively limited. For those who did recognize the bad haze days, Table 5 shows how people reacted afterwards:

Table 5: What did you do after the peak pollution days last year?

Nothing	38 %
I started worrying more about air pollution	25 %
I look for more information	9 %
I worry more about air pollution and look for more information about it	27 %
Other	1 %

4.3 Empirical model

Starting from these stylized facts, we can analyse the determinants of averting behaviour and of the choice of source of information.

4.3.1 Information

First of all, we want to characterize the agents that use government media as opposed to the internet or neither of the two. This can tell us what groups are more affected by the government's signal. We set a general empirical model of information, as follows:

$$Info_h = \beta_0 + Individual\ X_i\beta_1 + Household\ X_h\beta_2 + \beta_3 Income_h + \epsilon_{it} \tag{8}$$

and we test this using as a dependent variable different types of information sources. Such a specification may pose some problems in terms of reverse causality, so we prefer a parsimonious model that uses only exogenous observables. Overall, we will be cautious in making any causal statement, since there could be biases arising also from potential omitted variables. The individual controls are age, gender, education level and smoking status (to capture somehow risk attitude towards pollution and lung diseases). At the household level we have income and household size.

First of all, we consider as left-hand-side variable the binary choice between using or not government controlled media to check air pollution information. The dependent variable is then a dummy equals to 1 if the respondent said that (s)he use TV, radio or newspapers as a source of information, and zero otherwise (so if he uses internet or no information about pollution at all, or self-perception). Then we distinguish between government media versus internet users, and government media versus self-perception users, to see what is driving the results. We also look at internet users versus everyone else.[16]

The results are displayed in Table 6. People who use government media are generally older, and this is driven by the internet users, who are generally younger, and more educated (but this is instead determined by those who prefer to use self-perception to know about air pollution, as they tend to have lower education status). Interestingly, smokers declare to use the internet more than anything else. Larger households (families) rely a lot more on government sources than on the internet. Finally, income is strongly correlated with internet usage. This gives us an initial picture of those people who typically rely on the government's information.

Table 6: Internet vs Government information

	Government media	Govt vs. Internet	Govt vs. Self	Internet
Age	0.01***	0.04***	0.00	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)
Male	0.06	0.13	0.03	-0.15
	(0.10)	(0.17)	(0.11)	(0.15)
Education	0.15**	-0.08	0.22***	0.13
	(0.06)	(0.12)	(0.07)	(0.11)
Smoker	-0.48***	-0.69***	-0.41*	0.56**
	(0.18)	(0.27)	(0.21)	(0.25)
Migrant	-0.46	0.16	-0.61	-0.30
	(0.35)	(0.89)	(0.37)	(0.80)
Household size	0.25**	0.69**	0.12	-0.67**
	(0.11)	(0.32)	(0.12)	(0.29)
Household Income	-2.13	-5.66***	-0.10	5.45***
	(1.45)	(1.93)	(1.90)	(1.63)
Constant	-0.76	-0.51	-0.04	-0.13
	(0.50)	(0.96)	(0.57)	(0.84)
Observations	1490	1260	1408	1490

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[16] For the determinants of internet, since the occurrence of a 1 is quite rare, we use a complementary log-log specification to account for the asymmetric nature of the dependent variable ([38]).

4.3.2 Averting behaviour

In order to analyse averting behaviours, we can specify a similar model as the one above, but as soon as we include information sources we might introduce an endogeneity problem, as it is not clear whether it's the information source that determines the averting choice, or viceversa those who, for some unobserved reason, prefer to avert more use a particular information tool. Therefore we try to overcome this problem through a two stage model, with the determinants of information sources in the first stage (Eq. 10) identifying those who not only use the public media, but also consider it sufficient (i.e. fully rely on it).

$$Avert_{ik} = \alpha_0 + Individual\ X_i\alpha_1 + Household\ X_h\alpha_2 + \alpha_3\mathbf{Media_h} + \eta_{it} \tag{9}$$

$$\mathbf{Media_h} = \beta_0 + Individual\ X_i\beta_1 + Household\ X_h\beta_2 + \beta_3 Sufficient_h + \epsilon_{it} \tag{10}$$

Averting behaviours vary over k, covering masks, transport, time outdoor and preventive health checks. With the exception of the latter, the dependent variable is measured in changes (i.e. if a person switches to more averting behaviour in extremely polluted days compared to normal days). Beyond the controls used in the previous specification, we add other controls: a dummy for workers, to distinguish individuals with more time flexibility from those with less; a control for car ownership in the transport specification, which may be particularly important as a sunk investment in averting; and a dummy for households with children, which could be possibly more careful about the health damages of pollution. Moreover we need to control for whether the person was the survey respondent or not, because when talking about family members, respondent knew less and tended to downplay their capacity to avert.

Table 7 shows that, first of all, the first stage probit predicts quite well whether a person uses publicly controlled public media, thanks to the sufficiency variable. Then those who use TV, radio and newspapers controlled by the Communist Party are less likely to switch to more averting behaviours during peak pollution days, both in terms of time spent outdoors and for wearing masks. In the case of transport, information does not play a significant role, but we can see that car ownership is a very strong determinant of this behaviour. It is harder for people to adopt safer means of transport if they do not own a car. A different story applies to preventive health checks: those do not respond to the information signal negatively, but on the contrary correlate positively and significantly to it. This is not surprising, however: preventive checks do not need to be done distinguishing between peak pollution days and cleaner ones.

These results fit well with what was suggested in section 3 about government reporting optimistic values for pollution: since we identify here people who use such information and consider it sufficient for their choices, clearly these people will not be alerted much in high pollution days, and therefore, even for those behaviours they can easily modify, such as time outdoor and masks, they will be less likely to implement them.

Table 7: Averting Behaviours Bi-Probit

	Outdoor (Δ)	Mask (Δ)	Transport(Δ)	Health checks
Smoker	-0.21*	-0.46**	0.04	-0.10
	(0.13)	(0.20)	(0.15)	(0.11)
Worker	-0.06	0.35*	0.21	-0.06
	(0.14)	(0.20)	(0.24)	(0.12)
Children	0.17	0.29	-0.18	0.28*
	(0.15)	(0.18)	(0.24)	(0.15)
Household Income	-0.05	-0.33	0.06	3.09***
	(1.02)	(1.08)	(1.35)	(0.73)
Public Media	-1.37***	-2.18***	-0.45	1.73***
	(0.48)	(0.56)	(0.50)	(0.29)
Car			0.57***	
			(0.21)	
Sufficient info	0.39**	0.37**	0.38**	0.29**
	(0.16)	(0.17)	(0.17)	(0.13)
Smoker	-0.34**	-0.33**	-0.29**	-0.28**
	(0.13)	(0.13)	(0.13)	(0.12)
Worker	0.06	0.06	0.09	0.08
	(0.16)	(0.16)	(0.17)	(0.14)
Children	-0.22	-0.17	-0.17	-0.02
	(0.20)	(0.20)	(0.21)	(0.18)
Household Income	-0.15	0.16	-0.42	-1.15
	(1.10)	(1.08)	(1.03)	(0.77)
Observations	1147	1146	1133	1428

Clustered standard errors (household) in brackets. * (p<0.10), ** (p<0.05), *** (p<0.01)
Respondent, Age, Male, Education controls and Constants not reported.

5 Conclusion

The above analysis shows that the Chinese government does not have much incentive to improve air quality to sustainable levels, as it can give an information signal about pollution that is lower than actual values. In particular, we find that it can simply reduce the Air Quality index some points below certain critical thresholds for human health. As a result, those urban dwellers who rely fully on this government controlled source of information adopt less averting measures to protect themselves during peak pollution days. We propose that the mechanism behind government's choice of distorting information is a simple social planner's problem, in which the government tries to attract workers to polluted cities. Announcing that the air is clean might be costly if people avert less and total medical costs rise, but this happens only indirectly and for a fraction of the population, while the migrant workforce directly contributes to output. Therefore it is optimal for an autocratic government to use this information tool, even if this induces less averting behaviour.

These results indicates that, whenever an autocratic country can exercise ample government control over the media, it is not unlikely that this will sacrifice environmental sustainability in order to achieve higher output production. This in turn will spill onto the households that take less self-protective actions. Unless there is some process of learning about pollution, this situation is just going to perpetrate itself, as long as urban production requires immigrant cheap workers and pollution emissions. In this system, as there is no pressure from below to start tackling pollution, the cycle of incorrect information and distorted adaptation incentives continues, similarly to a snake (or better in this case a dragon) eating its own tail. In the future, it is likely that the Chinese population will pressure more the government to disclose the true levels of pollution, so to increase the credibility cost to the Communist Party of manipulating information. But as we have shown here, it will require quite a substantial effort to overcome the benefits that the government can currently reap from this information tool.

For further extensions of this analysis, it would be interesting to model and to explore empirically a mechanism for interaction between several cities and rural areas, rather than focusing just on one city, Beijing, and an urban versus rural model. If some migrants communicate back to rural areas the true level of pollution, the cost of cheating about pollution might increase over time for the government; or people could move across cities depending on their income levels and job opportunities, coupled with air quality. It could even be that the role of the government not only consist of allocating migrants, but also firms and productive activities. Furthermore, it would also be interesting as a future extension of this work to consider a general equilibrium framework, in which migration flows can affect wages as well, so that the government could trade pollution off for income payments, and maybe even for different levels of health insurance. But for this, a different set of data would be needed, possibly about a wider range of rural and urban dwellers.

Bibliography

[1] Asian Development Bank ADB. Country environmental analysis for the people's republic of china. *Country Environmental Analysis Series*, May, 2007.

[2] Anna Alberini, Maureen Cropper, Tsu-Tan Fu, Alan Krupnick, Jin-Tan Liu, Daigee Shaw, and Winston Harrington. Valuing health effects of air pollution in developing countries: The case of taiwan. *Journal of Environmental Economics and Management*, 34(2):107–126, October 1997.

[3] Steven Q. Andrews. Inconsistencies in air quality metrics: 'blue sky' days and pm10 concentrations in beijing. *Environmental Research Letters*, 3, No. 3, 2008.

[4] Patricia F. Apps and Ray Rees. Collective labor supply and household production. *Journal of Political Economy*, 105(1):pp. 178–190, 1997.

[5] Kristin Aunan and Xiao-Chuan Pan. Exposure-response functions for health effects of ambient air pollution applicable for china – a meta-analysis. *Science of The Total Environment*, 329(1–3):3 – 16, 2004.

[6] Timothy J. Bartik. Evaluating the benefits of non-marginal reductions in pollution using information on defensive expenditures. In Joseph Herriges and Catherine L. Kling, editors, *Revealed Preference Approaches to Environmental Valuation*, volume 0 of *Book chapters suthored by Upjohn Institute researchers*, pages 459–475. W.E. Upjohn Institute for Employment Research, June 2008.

[7] Gary S. Becker. A theory of the allocation of time. *The Economic Journal*, 75(299):pp. 493–517, 1965.

[8] Henrik Brnnum-Hansen Jakob Hjort Bnlkke Esben Meulengracht Flachs Bjrn Serstrm, Marie Kruse and Jan Srensen. A method to assess the potential effects of air pollution mitigation on healthcare costs. *Journal of Environmental and Public Health*, vol. 2012, 2012.

[9] Alok K. Bohara, Michael McKee, Robert P. Berrens, Hank Jenkins-Smith, Carol L. Silva, and David S. Brookshire. Effects of total cost and group-size information on willingness to pay responses: Open ended vs. dichotomous choice. *Journal of Environmental Economics and Management*, 35(2):142–163, March 1998.

[10] J. Bousquet, N.G. Khaltaev, A.A. Cruz, and World Health Organization. *Global Surveillance, Prevention And Control Of Chronic Respiratory Diseases: A Comprehensive Approach*. Nonserial Publication. World Health Organization, 2007.

[11] Alfesio L.F. Braga, Paulo H.N. Saldiva, Luiz A.A. Pereira, Joaquim J.C. Menezes, Gleice M.S. Conceição, Chin A. Lin, Antonella Zanobetti, Joel Schwartz, and Douglas W. Dockery. Health effects of air pollution exposure on children and adolescents in são paulo, brazil* *Pediatric Pulmonology*, 31(2):106–113, 2001.

[12] Brian W. Bresnahan, Mark Dickie, and Shelby Gerking. Averting behavior and urban air pollution. *Land Economics*, 73(3):pp. 340–357, 1997.

[13] B.W. Bresnahan and M. Dickie. Averting behavior and policy evaluation. *Journal of Environmental Economics and Management*, (397e), 1995.

[14] Martin Browning, Francois Bourguignon, Pierre-Andre Chiappori, and Valerie Lechene. Income and outcomes: A structural model of intrahousehold allocation. *Journal of Political Economy*, 102(6):1067–96, December 1994.

[15] Martin Browning, Pierre-Andre Chiappori, and Valerie Lechene. Distributional effects in household models: Separate spheres and income pooling. *The Economic Journal*, 120(545):786–799, 2010.

[16] Martin Browning and Mette Gortz. Spending time and money within the household. *The Scandinavian Journal of Economics*, 114(3):681–704, 2012.

[17] Edward Calthrop and David Maddison. The dose-response function approach to modelling the health effects of air pollution. *Energy Policy*, 24(7):599 – 607, 1996. <ce:title>Valuing air pollution damage</ce:title>.

[18] M. Carter and E. Katz. *Intrahousehold Resource Allocation in Developing Countries: Methods, Models and Policies.*, chapter Separate Spheres and the Conjugal Contract: Understanding the Impact of Gender-Biased Development. 1997.

[19] Yuyu Chen, Ginger Zhe Jin, Naresh Kumar, and Guang Shi. Gaming in air pollution data? lessons from china. *NBER Working Paper No. 18729*, (18729), January 2013.

[20] Pierre-Andre Chiappori. Collective labor supply and welfare. *Journal of Political Economy*, 100(3):437–67, June 1992.

[21] Luis A. Cifuentes, Jose Joaquin Prieto, and Jorge Escobari. Valuing mortality risk reductions at present and at an advanced age: preliminary results from a contingent valuation study in chile. *Mimeo, Pontifical Catholic University of Chile, Santiago*, 2001.

[22] Roger D. Congleton. Political institutions and pollution control. *The Review of Economics and Statistics*, 74(3):pp. 412–421, 1992.

[23] Philip J. Cook and Daniel A. Graham. The demand for insurance and protection: The case of irreplaceable commodities. *The Quarterly Journal of Economics*, 91(1):pp. 143–156, 1977.

[24] Philip J. Cook and Daniel A. Graham. The demand for insurance and protection: The case of irreplaceable commodities. *The Quarterly Journal of Economics*, 91(1):pp. 143–156, 1977.

[25] Brian R. Copeland and M. Scott Taylor. Trade, growth, and the environment. *Journal of Economic Literature*, 42(1):7–71, March 2004.

[26] Paul N. Courant and Richard C. Porter. Averting expenditure and the cost of pollution. *Journal of Environmental Economics and Management*, 8(4):321–329, December 1981.

[27] M. L. Cropper. Measuring the benefits from reduced morbidity. *The American Economic Review*, 71(2):pp. 235–240, 1981.

[28] Stefano DellaVigna and Ethan Kaplan. The fox news effect: Media bias and voting. Working Paper 12169, National Bureau of Economic Research, April 2006.

[29] Avinash K. Dixit. *Optimization in Economic Theory*. Number 9780198772101 in OUP Catalogue. Oxford University Press, 1990.

[30] Isaac Ehrlich and Gary S Becker. Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80(4):623–48, July-Aug. 1972.

[31] M. El-Fadel and M. Massoud. Particulate matter in urban areas: health-based economic assessment. *Science of The Total Environment*, 257:133–146, 2000.

[32] US Environmental Protection Agency (EPA). Guideline for reporting of daily air quality air quality index (aqi). *EPA-454/B-06-001*, May 2006, 2006.

[33] Andrew Foster and Naresh Kumar. Health effects of air quality regulations in delhi, india. *Atmospheric Environment*, 45:1675–1683, 2011.

[34] Michael Grossman. On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2):pp. 223–255, 1972.

[35] James Hammitt and Kevin Haninger. Valuing fatal risks to children and adults: Effects of disease, latency, and risk aversion. *Journal of Risk and Uncertainty*, 40(1):57–83, February 2010.

[36] John R Harris and Michael P Todaro. Migration, unemployment & development: A two-sector analysis. *American Economic Review*, 60(1):126–42, March 1970.

[37] Jerry A. Hausman and William E. Taylor. Panel data and unobservable individual effects. *Econometrica*, 49(6):pp. 1377–1398, 1981.

[38] J. M. Hilbe. Maximum-likelihood complementary log-log regression. *Stata Technical Bulletin Reprints, Stata Press*, 6:129131, 1996.

[39] Linwei Tian Xiaorong Wang Lap Ah Tse Wilson Tam Tze Wai Wong Hong Qiu, Ignatius Tak-sun Yu. Effects of coarse particulate matter on emergency hospital admissions for respiratory diseases: A time-series analysis in hong kong. *Environmental Health Perspectives*, 120(4):572576, 2012.

[40] Bryan Hubbell and Jeffrey L. Jordan. Joint production and averting expenditure measures of willingness to pay: Do water expenditures really measure avoidance costs? *American Journal of Agricultural Economics*, 82(2):427–437, 2000.

[41] Jyotsna Jalan and Martin Ravallion. Does piped water reduce diarrhea for children in rural india? *Journal of Econometrics*, 112(1):153–173, 2003.

[42] Jyotsna Jalan and E. Somanathan. The importance of being informed: Experimental evidence on demand for environmental quality. *Journal of Development Economics*, 87(1):14 – 28, 2008.

[43] V. Kerry Smith and William H. Desvousges. Averting behavior: Does it exist? *Economics Letters*, 20(3):291–296, 1986.

[44] Michael J. Lamla and Samad Sarferaz. Updating Inflation Expectations. KOF Working papers 12-301, KOF Swiss Economic Institute, ETH Zurich, March 2012.

[45] Jia Li, Sarath K Guttikunda, Gregory R Carmichael, David G Streets, Young-Soo Chang, and Virginia Fung. Quantifying the human health benefits of curbing air pollution in shanghai. *Journal of Environmental Management*, 70(1):49 – 62, 2004.

[46] Eric Maskin, Yingyi Qian, and Chenggang Xu. Incentives, information, and organizational form. *The Review of Economic Studies*, 67(2):pp. 359–378, 2000.

[47] Enrico Moretti and Matthew Neidell. Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *Journal of Human Resources*, 46(1):154–175, 2011.

[48] Giuseppe Moscarini. Competence Implies Credibility. *American Economic Review*, 97(1):37–63, March 2007.

[49] Matthew J. Neidell. Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations. NBER Working Papers 14209, National Bureau of Economic Research, Inc, July 2008.

[50] Mark M Pitt and Mark R. Rosenzweig. Estimating the intrahousehold incidence of illness: Child health and gender-inequality in the allocation of time. *International Economic Review*, 31(4):969–80, 1990.

[51] Mark M. Pitt, Mark R. Rosenzweig, and Md. Nazmul Hassan. Productivity, health, and inequality in the intrahousehold distribution of food in low-income countries. *The American Economic Review*, 80(5):pp. 1139–1156, 1990.

[52] Karen Pittel and Dirk T.G. Rubbelke. Climate policy and ancillary benefits: A survey and integration into the modelling of international negotiations on climate change. *Ecological Economics*, 68(1-2):210–220, December 2008.

[53] John Quiggin. Risk, self-protection and ex ante economic value–some positive results. *Journal of Environmental Economics and Management*, 23(1):40–53, July 1992.

[54] John Quiggin. Risk and self-protection: A state-contingent view. *Journal of Risk and Uncertainty*, 25(2):133–45, September 2002.

[55] Cizao Ren and Shilu Tong. Health effects of ambient air pollution - recent research development and contemporary methodological challenges. *Environmental Health*, 7(1):56, 2008.

[56] Songsak Sakulniyomporn, Kuskana Kubaha, and Chullapong Chullabodhi. External costs of fossil electricity generation: Health-based assessment in thailand. *Renewable and Sustainable Energy Reviews*, 15(8):3470–3479, 2011.

[57] Jason F. Shogren and Thomas D. Crocker. Risk and its consequences. *Journal of Environmental Economics and Management*, 37(1):44–51, January 1999.

[58] Kevin M. Simmons and Jamie Brown Kruse. Market value of mitigation and perceived risk: Empirical results. *The Journal of Economics*, 26(1):41–51, 2000.

[59] E. Somanathan. Effects of information on environmental quality in developing countries. *Review of Environmental Economics and Policy*, 2010.

[60] Jon Strand. Public-good valuation and intra-family allocation. *Environmental and Resource Economics*, 38:527–543, 2007.

[61] John Talberth, Robert P. Berrens, Michael Mckee, and Michael Jones. Averting and insurance decisions in the wildland-urban interface: Implications of survey and experimental data for wildfire risk reduction policy. *Contemporary Economic Policy*, 24(2):203–223, 04 2006.

[62] Kai-yuen Tsui and Youqiang Wang. Between separate stoves and a single menu: Fiscal decentralization in china. *The China Quarterly*, 177:71–90, 2 2004.

[63] Mi-Jung Um, Seung-Jun Kwak, and Tai-Yoo Kim. Estimating willingness to pay for improved drinking water quality using averting behavior method with perception measure. *Environmental and Resource Economics*, 21:285–300, 2002.

[64] W Kip Viscusi and Joseph E Aldy. The value of a statistical life: A critical review of market estimates throughout the world. *Journal of Risk and Uncertainty*, 27(1):5–76, August 2003.

[65] Wentao Wang, Toby Primbs, Shu Tao, and Staci L. Massey Simonich. Atmospheric particulate matter pollution during the 2008 beijing olympics. *Environmental Science & Technology*, 43(14):5314–5320, 2009.

[66] John Whitehead. Environmental risk and averting behavior: Predictive validity of jointly estimated revealed and stated behavior data. *Environmental & Resource Economics*, 32(3):301–316, November 2005.

[67] WHO. *Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide. Global update 2005. Summary of risk assessment.* World Health Organization, 2005.

[68] Jing Wu, Yongheng Deng, Jun Huang, Randall Morck, and Bernard Yeung. Incentives and outcomes: Chinas environmental policy. Working Paper 18754, National Bureau of Economic Research, February 2013.

[69] Chenggang Xu. The fundamental institutions of china's reforms and development. *Journal of Economic Literature*, 49(4):1076–1151, 2011.

[70] Pengfei Zhang, Guanghui Dong, Baijun Sun, Liwen Zhang, Xi Chen, Nannan Ma, Fei Yu, Huimin Guo, Hui Huang, Yungling Leo Lee, Naijun Tang, and Jie Chen. Long-term exposure to ambient air pollution and mortality due to cardiovascular disease and cerebrovascular disease in shenyang, china. *Respiration*, 84 (5)(6):360–368, 06 2012.

APPENDIX

Index and Definition			Health Implications	PM10 (μg/m^3)		SOx		NOx		Other pollutants
AQI US	API China			US	China	US (ppm)	China(μg/m3)	US	China(μg/m3)	US
0 – 50 Good	0-50 Excellent		Air quality is considered satisfactory, and air pollution poses little or no risk	0-50	0-50	0 - 0.03	0-50	Under revision	0-80	Ozone (8 hour and 1 hour), Carbon monoxide, PM2.5
51 -100 Moderate	51-100 Good		Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.	>50-150	50-150	>0.03 - 0.14	50-150		80-120	
101-150 Unhealthy for sensitive groups	100-200	Slightly polluted	Members of sensitive groups may experience health effects. The general public is not likely to be affected.	>150-250	150-350	>0.14 - 0.22	150-800		120-280	
151-200 Unhealthy		Light polluted	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects	>250-350		>0.22 - 0.30				
201-300 Very Unhealthy	200-300	Moderately polluted Moderate - heavy polluted	Health warnings of emergency conditions. The entire population is more likely to be affected.	>350-420	350-420	>0.30 - 0.60	800-1600		280-565	
300+ Hazardous	300-400	Heavy polluted	Health alert: everyone may experience more serious health effects	>420-600	420-500	>0.60 - 1.0	1600-2100		565-750	
	400-500				500-600		2100-2620		750-940	
	500				> 600		> 2620		> 940	

Figure 3: US versus China's pollution indexes (Source: own elaboration from US EPA and MEP)

Robustness: minima

Since the US air pollution index is constructed from hourly observations, we might want to check if the official Chinese air quality index is somehow closer to the US Embassy one when using daily minima, or other forms of aggregation. A graph of comparison between the US minimum value and the usual Beijing index is shown in figure 4.

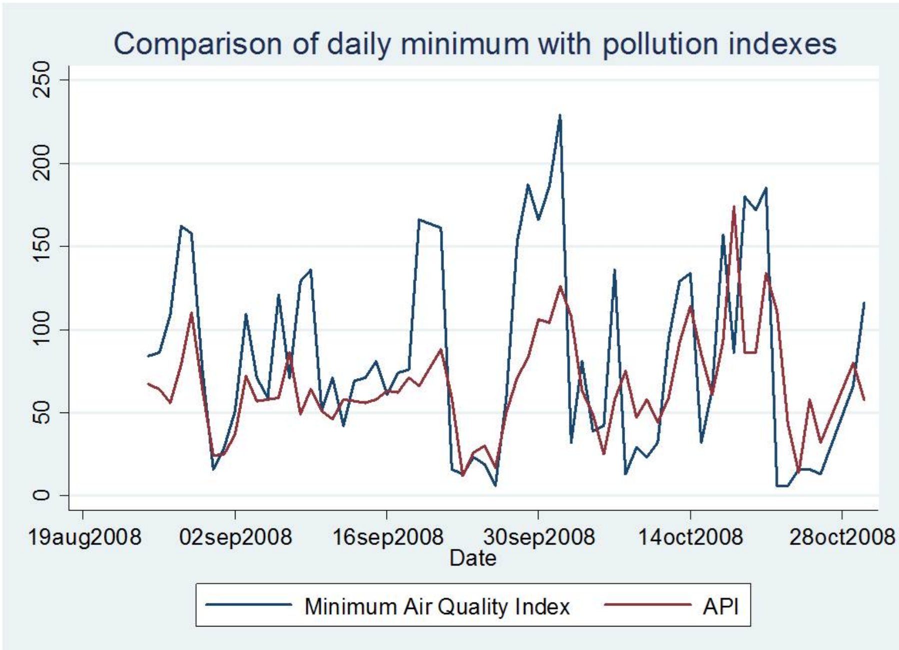

Figure 4: Mismatch even with daily minima

The results are also robust when we use instead the maximum daily observation for the US Embassy data.

Table 8: Chinese/USA air pollution indexes (minimum of US hourly observations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
min. AQI	-0.92***	-0.92***	-0.92***	-0.92***	-0.92***	-0.92***	-0.92***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
AQI threshold(100)	-1.86***	-1.86***	-1.81***	-1.86***	-1.86***	-1.86***	-1.85***
	(0.29)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)	(0.30)
AQI threshold(200)	0.41	0.35	0.47	0.37	0.34	0.34	0.35
	(0.87)	(0.87)	(0.88)	(0.88)	(0.87)	(0.88)	(0.88)
AQI threshold(300)	-2.56**	-2.48**	-2.78***	-2.52**	-2.48**	-2.48**	-2.49**
	(1.04)	(1.05)	(1.05)	(1.05)	(1.05)	(1.05)	(1.05)
T100*avg. AQI	0.40***	0.40***	0.39***	0.40***	0.40***	0.40***	0.40***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
T200*avg. AQI	-0.05	-0.04	-0.06	-0.05	-0.04	-0.04	-0.04
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
T300*avg. AQI	0.45**	0.44**	0.49***	0.44**	0.44**	0.44**	0.44**
	(0.18)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)
Constant	3.69***	3.69***	3.68***	3.70***	3.69***	3.69***	3.69***
	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
ARMA							
L.ar	0.34***	0.32***			0.44	0.43*	-0.15
	(0.03)	(0.03)			(0.97)	(0.23)	(2.22)
L2.ar		0.04			-0.00		0.27
		(0.03)			(0.32)		(0.91)
L.ma			0.30***	0.32***	-0.11	-0.11	0.47
			(0.03)	(0.03)	(0.97)	(0.23)	(2.22)
L2.ma				0.12***		-0.00	-0.09
				(0.03)		(0.08)	(0.21)
sigma							
Constant	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***	0.21***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	876	876	876	876	876	876	876
AIC	-159.64	-158.62	-147.24	-155.81	-156.64	-156.64	-154.73
BIC	-35.48	-29.68	-23.08	-26.87	-22.93	-22.93	-16.25

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$