A DRAGON EATING ITS OWN TAIL: PUBLIC CONTROL OF AIR POLLUTION INFORMATION IN CHINA

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Abstract

This paper analyses the implications of state control over public information about air pollution. First, we model the incentives for a non-democratic government with control over the media to stir popular perception through biased public information. We then examine evidence of information misreporting in the context of Beijing, China. We show that official air pollution announcements diverge systematically from an alternative source of information, provided by the US Embassy. The distortion points at a manipulation of popular perception beyond political motives. Then, using an original household survey, we examine the effect of the distorted public signal on agents' behaviour. We find that households that depend upon government-controlled media are significantly less responsive to pollution peaks.

* *This is BAD. What is the 1 central contribution of this paper?*

Keywords: Information; Air Pollution; Government policy; Signal Extraction; Averting Behaviour.

JEL Classification: H41, Q53, Q56, Q58, I13.

1. Introduction

Information is power, and knowledge asymmetry can benefit those who control information. Often individual economic agents cannot afford to acquire complete data about the state of the world (Stiglitz, 2000). Hence the government can reduce knowledge asymmetries through public sector information, on issues ranging from meteorological forecasts, to inflation targets, to official socio-economic statistics (Morris and Shin, 2002; Cornand and Heinemann, 2008). Such information is a valuable public good that can influence the expectations and behaviour of private agents. However, if a government can exercise some degree of control over the media, this may create incentives to to limit or distort information to redirect public opinion and decentralized economic choices (Williams, 2009). Several studies identify the positive effects of independent public information and a free press (Brunetti and Weder, 2003; Besley and Prat, 2006), but what happens instead when the press is not free?

In this article, we investigate whether a government with control over public information would misrepresent environmental issues to its public, and to what effect. We explore these questions in the context of air pollution in Beijing, China. This country is an emblematic example of a nation where information is strictly controlled by the government.[1] We focus on urban air pollution to analyse environmental information control, because data about air quality is difficult to acquire individually: gathering precise information is costly and requires specialized technology (monitors) and knowledge, such as atmospheric science and epidemiological research to understand consequences for human health. Visibility, which can be used as a private proxy for pollution, is not a strong indicator for air quality, as it varies with wind and humidity, confounding for instance with fog (Lin et al., 2012).[2] Therefore, pollution information is provided in most countries by public state agencies.

In this article, we argue that a government with control over the media has direct economic incentives to manipulate the public perception of environmental hazards, limiting popular demands for better air quality. With a simple signal extraction model, we define the driving forces behind government

[1] Reporters Without Borders (2016) ranked China 176 out of 180 countries in its World Press Freedom Index. According to Djankov et al. (2003), 100% of TV, radio and the major newspapers in China are owned by the Chinese Communist Party.

[2] The US Environmental Protection Agency also notes that 'The same amount of pollution can have dramatically different effects on visibility, depending on existing conditions' (see https://www3.epa.gov/airtrends/aqtrnd95/vis.html).

information biases, and then we exploit unique data from the capital of China to illustrate the mechanism and consequences of this distorted information signal. We find evidence of misreporting around specific thresholds of air quality information in Beijing, which points at a manipulation of public perception. Moreover, looking at the the impacts of this distorted informational environment on household behaviour, we find that the agents that rely on government-controlled media are the most vulnerable to pollution.

This article contributes to the literature on how public information shapes expectations and economic outcomes. Much research has focused on impacts on macroeconomic variables or on government policies,[3] with fewer articles on environmental effects (Kennedy et al., 1994). Most of these works assume that the government or state agency only provides truthful information, or that the production of information by the media is separate from policy-makers (Dur and Swank, 2005; Angeletos and Pavan, 2007). Few articles highlight that governments might have an incentive to misreport data strategically (Michalski and Stoltz, 2013). In the case of China, a growing body of literature finds evidence of misreporting in pollution data (see Andrews, 2008, Chen et al., 2012 and Ghanem and Zhang, 2014, Jia, 2014, Stoerk, 2015). This literature highlights the political incentives for local government officials to present optimistic data to the central government, but does not consider the interplay of government's economic goals and households' expectations in this distorted information environment. Our work goes beyond this existing literature by analysing an important and relatively unexplored issue: the economic rationale for distorted public information and its potential consequences on households.

We proceed in three steps. First, we develop a model of state control over public information in an industrial urban area. The government faces a trade-off between higher output and health damages, both increasing with pollution levels within that city. However, the government has some control over public information, and can thereby manipulate air quality announcements to attract workers to the city, and to retain as their support. This model predicts that a negative bias - declaring that pollution is lower than in reality - ensues whenever the government places little weight over public health, while valuing highly the contribution of (cheap) labour to profits. Moreover, this bias can exacerbate as pollution increases, if the government perceives that public health damages are

[3]See for example Baeriswyl and Cornand, 2010 on central banks signals, or Mèon and Minne, 2014 on exchange rate regimes, and (Besley and Burgess, 2002; Gavazza and Lizzeri, 2009) for policy transparency and responsiveness.

not large relative to people's capacity to self-protect. Finally, the bias is even stronger when the informational environment gets noisier.

Then we illustrate our findings with a study of public information and air pollution in the capital city of China. Beijing offers a unique setting to analyse information signals about air pollution, because of an alternative source of data besides the official Chinese one: readings reported by the US Embassy. Comparing the two information sources, we find that the Chinese government downplays emissions' information as pollution increases, especially around emission levels where it can more strongly affect public opinion. A 10% increase in the most conservative measurement from the US index of pollution is associated with a 9% increment in the downward bias in the official pollution signal. In addition, once pollution crosses the threshold of 100 points, the bias becomes a further 34% more negative. This evidence suggests that the Chinese signal is distorted with the purpose of improving public perception of air quality. Finally, we examine the implications of these distorted signals at the household level. We employ an original household survey to show that agents who rely primarily on public information sources (publicly owned media such a television, radio and newspaper) are more directly influenced by public signals, and thus less capable of responding to pollution peaks.[4]

Our contribution is twofold: firstly, we find robust empirical evidence of the signal's bias in the case of China, supporting the mechanism of information manipulation described theoretically. Secondly, we illustrate in the case of Beijing how centralized control over public information hinders decentralized decision-making. More broadly, this article contributes to the understanding of a fundamental economic problem, the difficulty in public goods' provision, particularly in developing countries (Besley and Ghatak, 2006). Our analysis suggests that information control allows the government to manipulate the perception of pollution, and reducing the need for actual environmental public goods' provision.

The rest of the article proceeds as follows: section 2 presents a simple conceptual framework about

[4] A number of articles explored the mechanisms of self-protection against environmental risks. Economic agents can allocate resources or efforts to risk-reduction (Ehrlich and Becker, 1972), especially when insurance markets are incomplete and in the presence of intangible values, such as good health (Cook and Graham, 1977, Simmons and Kruse, 2000). Empirical research finds that people combine market and non-market strategies to avoid uncertain damages (Whitehead, 2005, Moretti and Neidell, 2011). Few studies specifically examine the role of information about environmental hazards whenever the flow of information is less efficient (Madajewicz et al., 2007, Jalan and Somanathan, 2008). Overall, these papers find that information can positively affect the response to environmental risks.

government and households' interactions through information; section 3 analyses empirically public information about Beijing's air pollution ; section 4 presents the household survey and the empirical findings about averting behaviour with different sources of information. Finally section 5 concludes.

2. Model

2.1. Information and expectations

We model two distinct groups of citizens, those who are relatively critical and well-informed, and those who are more passive with respect to information gathering and hence relatively uninformed.[5] Only the critical group updates expectations about pollution, correcting for an expected information bias, while the passive group wholly relies on any official source of information it can access. Individual agents cannot fully evaluate air quality, but they have some prior beliefs about its characteristics. The prior of the population about pollution in this economy is thus

$$\hat{p}_t = p^n + p_t \quad with \quad p_t \sim N(0, \sigma_p^2) \tag{1}$$

where p^n is some "natural" level of pollution, given by the geographic conformation and location of a city, and p_t captures emissions shocks that vary with meteorological conditions, traffic, economic activity, construction work, etc.[6] The overall pollution level on a given day is unknown to individual agents, because they are unable to measure the actual shocks p_t, but people have some prior about the distribution of these shocks. On the other hand we assume that the government agency can measure actual emissions in the economy, and so knows the true p_t. Given the actual level of pollution, the agency then releases announcements A_t about the quality of the air. We define the government announcement A to include a potential bias B:

$$A_t = p_t + B \quad with \quad B \sim N(\overline{B}, \sigma_B^2) \tag{2}$$

[5] For instance, we found that elderly people in Beijing seldom accessed the latest information technologies such as twitter or mobile apps.

[6] The government can shift p^n with environmental policy, but from the point of view of agents this is just an exogenous, unknown component of pollution.

Citizens do not know the actual bias of the government, but critical households have a prior over its distribution. This group forms updated expectations by solving a signal extraction problem: using their prior about the distribution of pollution and the bias, plus observations of the announcement over time $t = \{1, 2...T\}$, they update their expectations. However, a fraction $\lambda \in [0, 1]$ of the population is incapable of updating expectations concerning the bias. For them, expectations about pollution are just the announcements, $E(p) = A$, and the expectation about the bias is zero, $E(B) = 0$. This means that, on average, only $(1 - \lambda)$ of the bias is factored out of the announcement in the whole population, yielding the following aggregate expression for the popular beliefs concerning extant pollution given announcement A (derivation in the Appendix)

$$\lim_{T \to \infty} E(p) = \frac{A - (1 - \lambda) B}{z} \tag{3}$$

where z is a weight that captures how precisely the corrected announcement translates into expectations.[7] When z increases, the noise in the informational environment increases, and less of the announcement is transmitted to expectations. In other words, it is a measure of the the "effectiveness" of the informational environment, and how much the government can with its announcements affect expectations. Over time, aggregate expected pollution converges to the above expression, because $\lim_{T \to \infty} E(B) = B$ for those who update expectations (see Appendix). But as long as there are people who cannot fully update their priors about biases in the pollution announcements, i.e. $\lambda > 0$, expectations would never converge to the true value of pollution. From this signal extraction problem, we can derive the following proposition about the role of biased announcements in pollution expectations.

Proposition 1 - *An announcement A regarding emissions p that includes a bias B affects expectations about air pollution directly, as the announcement reaches the whole population, and indirectly, entering the bias-updating process of the critical group. The first effect is stronger than the second the higher the fraction λ of the population that does not update expectations, $\partial E(p)^2 / \partial B \partial \lambda > 0$.*

Proof - It follows straightforwardly from differentiating equation (3) with respect to B and λ.

[7] Precisely, this factor captures a combination of the variance from the announcement and the one from the pollution emissions $z \equiv W^2 \left(1/\sigma_p^2 + 1/W^2\right)$ where W^2 is the variance of $A - E(B)$.

2.2. Optimal bias of local government given competition among provinces

We now develop the basic structure concerning how local governments choose to release information on pollution, given that each government is competing with other similar jurisdictions within the federal structure. In doing so, we adapt the classic literature on tax competition to the particular circumstances of China (Bucovetsky, 1991; Wilson, 1995). In the literature on competitive governance units, the government is choosing the optimal level of tax, given mobile capital and/or labour. In the case of China, we consider how local governments might choose to affect the expectations of mobile labour units, given their responsiveness to expected pollution costs. The government units influence expectations about pollution levels, by choosing the optimal bias to include in their announcements concerning pollution levels, in the context of competition for labour with other provinces. For a broader model of such internal competitiveness, which also considers how local government choices influence the location of capital as well as labour, see Naso and Swanson (2017).

Mobile labour units and their location choice

We assume that workers maximize their individual utility function, $U(c_i)$, where c_i is consumption that they can have in a location i (corresponding to a particular governance unit within the governmental structure of China, such as a province or large municipality). The workers all have identical preferences and the utility function is well behaved: $\partial U/\partial c_i > 0$ and $\partial^2 U/\partial c_i^2 < 0$. We further assume perfect mobility of the workforce, which implies utility equalization across locations: $U(c_i) = U(c_j) \;\; \forall i; j$.[8]

Workers' consumption depends on their wage, but also on the expected damages from pollution. This is because pollution damages can among other things hinder workers' productivity, result in absence from work and result in individual medical costs. The amount of a worker's damages associated with a given level of pollution is represented here by θ. So, workers' consumption in a given location i is equal to the announced wage w_i less the workers share of damages from expected pollution in locality i.

$$c_i = w_i - \theta E(p_i) \tag{4}$$

[8]This model abstracts from migration costs specific to China, such as the permanent residence registration system (hukou), land-sale policies, infrastructure, etc.

Assuming linear preferences, consumption in two different locations equalizes through workers' migration

$$w_i - \theta E(p_i) = w_j - \theta E(p_j) \tag{5}$$

Labour is paid its marginal productivity, namely

$$w_i = l'(L_i) \tag{6}$$

For purposes of simplifying the expressions, we will assume that production is quadratic in labour, so that $\Pi(L) = aL - b/2L^2$ and thus $\Pi'(L) = a - bL$. Total labour around a country is

$$\sum_{j}^{N} L_{j=1} = \overline{L} \tag{7}$$

With only two locations, the expression for labour in location i is then

$$L_i = \frac{\theta}{b}[E(p_j) - E(p_i)] + L_j \tag{8}$$

So, competition between production units will cause two locations to have identical population, unless the expected pollution in the two places differs, in which case there is an adjustment through migration to compensate for expected pollution costs.

This can be generalized with multiple locations from the point of view of location i as

$$L_i + \sum_{j=1}^{N-1} L_j = \overline{L} \tag{9}$$

Therefore

$$L_i + \sum_{j=1}^{N-1} \frac{\theta}{b}[E(p_j) - E(p_i)] + L_j = \overline{L} \tag{10}$$

$$L_i = \frac{\overline{L}}{N} - \frac{\theta}{bN}\left[(N-1)E(p_i) - \sum_{j=1}^{N-1} E(p_j)\right] \tag{11}$$

Again, this shows that if region i has higher expected pollution levels than the other regions j, it will lose workers to the others, and otherwise competition between locations will result in equalised population and production levels.

Local government choice of optimal bias in pollution announcements

In accord with the classic literature on competition between governance units within a federal structure, we assume that each local unit maximises its own objective function subject to competition with other jurisdictions. In the context here, the competition between governance units is for tax revenues deriving from levels of production, less the government's share of costs deriving from providing goods and services to the population in the locality. Here we will assume that these costs derive from providing healthcare related goods and services for the local population, and these costs increase with the size of the labour force and with the level of polluton. That is, an increase in the number of individuals exposed to the pollution associated with local production would increase the government's share of total health care costs. In this way, the government faces a trade-off between the number of workers it wishes to attract to the locality to provide labour (and hence production) and the number of individuals to which it provides some health care in the locality. The option of introducing a bias into the announced level of pollution provides the government with an instrument that enables it to attract labour to its locality, once pollution already exists, in excess of the number that would come if the true pollution level were to be known.

The objective function of each governance unit is then to maximise its tax revenues less the costs of government provided goods to the local population (e.g. medical/health care). This objective is optimised by competing for a supply of labour against other localities, given that revenues are a function of production and, as above, production is exclusively a function of labour.

$$max \;\; V_i = t_i R(L_i) - \phi L_i \tag{12}$$

subject to $L_i(w_i; E(p_i))$ where

$$E(p_i) = \frac{A - (1-\lambda)B}{z} = \frac{p - \lambda B}{z} \tag{13}$$

where V_i is the value function for the government, t_i is the tax rate on production revenues, R the level of revenue from production which derives directly from the supply of workers, and ϕ is the healthcare costs of local workers that is borne by the government.

The supply of labour to the locality is a function of wages and expected pollution levels, as described in the subsection above. Production Π and revenues R are then determined by the labour existing in the locality. As described above, the constraint relates to how the population forms expectations about pollution: from an announcement A, which a fraction λ of the people correct for a bias B, in an informational environment with some degree of noise z.

From this structure, it is now possible to calculate the optimal bias for any local government competing for labour supplies with other government units, when labour responds to expected pollution levels as well as wages. We will suppress subscripts for ease of exposition, and because the problem is assumed identical for each of the governance units.

The first order condition for the supply of labour given the bias in the announcement is as follows:

$$\frac{\partial L_i}{\partial B} = \frac{(N-1)}{N}\frac{\theta}{b}\frac{(1-\lambda)}{z} \tag{14}$$

Hence, the optimal bias for optimising revenue is found by optimising in respect to the total output produced by workers, $R \equiv Y = \Pi(L)$

$$\frac{\partial R}{\partial B} = a\frac{\partial L_i}{\partial B} - bL_i\frac{\partial L_i}{\partial B} \tag{15}$$

The first order conditions for an optimal bias are

$$ta\frac{\partial L_i}{\partial B} - tbL_i\frac{\partial L_i}{\partial B} = \phi\frac{\partial L_i}{\partial B} \tag{16}$$

which simplifies to

$$L_i = \frac{ta-\phi}{tb} \tag{17}$$

Using the labour equation:

$$L_i = \frac{\overline{L}}{N} - \frac{\theta}{bN}\left[(N-1)\frac{p-\lambda B}{z} - \sum_{j=1}^{N-1} E(p_j)\right] = \frac{ta-\phi}{tb} \tag{18}$$

and solving for B and simplifying yields:

$$B^* = \frac{1}{\lambda}\left[p + z\frac{N}{(N-1)}\left(\frac{ta-\phi}{t\theta}\right) - \frac{zb}{\theta(N-1)}\left(\overline{L} + \frac{\theta}{b}\sum_{j=1}^{N-1} E(p_j)\right)\right] \tag{19}$$

This result shows that a local governance unit has the incentive to distort information for the purpose of attracting workers to a locality, in numbers in excess of those who would come if the true level of pollution were known. This distortion in information is optimal for the government to the extent that tax revenues per labour unit (ta) exceed government labour cost (ϕL). When this is the case, it may be profitable for the government to attract workers to the locality, when it is not in the individual interests of the worker to come there (given w_i, p_i). But when perceptions of pollution are able to be distorted downward in this situation, the government achieves this net gain for each unit of labour that (from its own perspective) sub-optimally supplies labour within that locality.

For this reason, the size of the bias depends not only on the net gain to government from information distortion, but also on the capacity of government to distort perceived levels of pollution (i.e. the availability of other information sources, and the degree of noise within the system). Finally, the government's ability to gain from distortion is further constrained by the overall size of the labour pool and the level of pollution in other localities.

Proposition 2 - *The optimal bias B_i set by any governance unit for locality i becomes greater: A) to the extent that the net benefits from attracting labour are greater than zero (i.e. extent to which ta is greater than ϕ); and B) to the extent to which the characteristics of the locality render the population more susceptible to information manuipulation, which is the case when: 1) The overall level of pollution p is greater; 2) The proportion of the informed populace (1-λ) becomes greater; and 3) The size of the overall labour stock (that might be attracted) becomes smaller and the pollution in other jurisdictions becomes lower.*

In sum, the competition between governance units for labour supplies can explain why it is important to distort information concerning pollution levels. These distortions can be used to attract mobile labour supplies to polluted localities, when it is sub-optimal from the worker's perspective to go there. When the government can still gain from further supplies of labour in its locality (i.e. there is a net gain from taxes on production over the costs of supplying healthcare to the marginal worker), then the government has the incentive to attempt to attract that worker when it is against that person's individual interest.

3. Empirical analysis

In the previous section, we argue that a government with control over the media has an incentive to distort environmental information to attract labour. As an illustration of this phenomenon, we now examine public information about air pollution in Beijing. In the Chinese context, specific political forces may also play a role in the generation of public information - notably, local government officials may have incentives to report optimistic figures to the central government for personal career purposes. These political economy forces have been repeatedly identified in the literature on 'pollution for promotion' (Chen et al., 2012; Jia, 2014). Our theoretical model provides a more general framework for understanding public information distortions, abstracting from any specific political structure, highlighting the incentives to control popular opinions about environmental quality. Nonetheless, the empirical findings presented below are not in contrast with the pollution for promotion literature, as discussed in the Results section. At the same time, our empirical analysis points also at a direct control of citizens' perception of pollution risks, as suggested by our theoretical framework.

Following the discussion in the model, we formulate two testable hypotheses regarding public information distortions in an economy where the government controls the media. First of all, any distortion in government announcements should be related to both environmental (pollution) and informational conditions. More specifically, the results from Proposition 2 can be rearranged in the following reduced form expression:

$$B = \alpha_1 p_i + \alpha_2 z + \alpha_3 p z \tag{20}$$

where B is the bias, p is pollution and z a proxy for the informational environment. From the model, we can see that α_1 should be negative: simplifying from equation (19), it is simply $-1/\lambda$. The sign of α_2 is instead ambiguous, and depends on the number of workers relative to the value of these workers for production (precisely $(n(w)/k - \pi_N/ca)/2\lambda$). Finally, $\alpha_3 > 0$, capturing $d/2a\lambda$ from Proposition 3. In the following paragraph we detail how these elements are defined empirically.

Secondly, we can test if agents who fully rely on announcement without updating for potential biases (the fraction λ of the population) adopt less self-protective measures during pollution peaks, as they receive a downwards biased signal from the government. This hypothesis examines one of the key premises of the model, described in section 2.1: informed agents should adopt more self-protective behaviour with higher pollution than those who cannot update their expectations beyond the government announcements. We test the first hypothesis about the bias in this section, with a time series analysis of two signals about pollution. Then we examine the second hypothesis about the response to pollution signals with a household survey in Section 4.

3.1. Air quality signals and health risk perceptions

China's Ministry of Environmental Protection communicates to the public the state of air quality through an Air Pollution Index (API), with a format analogous to indexes used in the USA, Canada and the European Union. These indexes reflect international standards and health risks defined by the World Health Organization (WHO, 2005), and convey information about pollution risk through a simple rating of air quality. The signal needs to be understandable to the general public, thus it does not report the concentration of individual pollutants, but rather a color-coded scale ranging from green (lowest pollution) to dark red (highest pollution). Each colour corresponds to a description of the potential health damages associated with that pollution range and colour.

In Beijing, there exist a second source of information about air quality: the hourly Twit provided by the US Embassy. Table 2 in the Appendix compares the two measures, showing that the Chinese index uses as boundaries for particulate matter the same ones adopted in other countries following WHO recommendation.[9] In terms of health consequences, the two indicators convey the same colour-coded message: an index below 100 implies little risk of health damages (green); however,

[9] The value of an index is constructed using the same non-linear algorithm based on pollution concentration. At a given time, the index takes the highest value given by any of the pollutants that compose it:

$$AQI, API = max(I_1, I_2, ...I_n) \quad where \quad I_i = (C - C_{low})\frac{I_{high} - I_{low}}{C_{high} - C_{low}} + I_{low} \tag{21}$$

as the index rises between 100 and 200 (yellow) and 200-300 (orange), more people can be affected by pollution; and a signal above 300 is defined as a health alert (dark red), with all the population risking severe health consequences.

There are two important caveats when comparing the specific value of the two indexes at a point in time: one relating to spacial measurements of pollution, and the other to the chemicals included in the index. First of all, the Chinese measure comes from an aggregation of various monitors around the city, while the US measure refers the Embassy location in Chaoyang, in a relatively green neighbourhood. Secondly, the US measure focuses on PM2.5, particulate matter of fine diameter, while the Chinese index aggregates PM10 and other pollutants, such as NOx. This is probably they most important way the Chinese government withheld information from the population, as PM2.5 is more harmful for health than other pollutants. We compare only those days when the main pollutant for the Chinese index was PM10, which has been shown to be highly correlated with PM2.5 (Zhao et al., 2014; Liu et al., 2015). However, overall the two indexes are not exactly comparable in terms of their specific numerical value. Nevertheless, what is interesting for the purpose of our analysis is the end-point information signal seen by the population. Ultimately, a Beijing dweller can only observe the final information delivered by the government and possibly compare it to the one from the US Twit - even though not all Chinese people might have easy access to it, due to internet restrictions.

3.2. Air pollution data

We analyse four and a half years of daily pollution data measures in Beijing, both from official government announcements and from the US Embassy, starting from the first available date, 25 August 2008, up to January 2013. We do not consider further dates because recently the Chinese index has come under revision.[10] The two raw time series are shown in Fig. 2 and 3 in the Appendix. The mean value over this time period for the Chinese measure is a score of *Good*, while for the US index the average is classified as *Unhealthy*. The US index reaches peaks as high as 800 points and

where C is the concentration of pollutant i, I is the index value for that specific pollutant, and *high* and *low* indicate the boundaries of each category mentioned in Table 2 (Beijing Municipal Environment Monitoring Centre and US - Environmental Protection Agency 2006).

[10] In February 2012 (regulation HJ 633—2012), China defined a new air quality index that includes PM2.5 and ozone. This does not take effect nationwide until 2016, but Beijing already began piloting it in January 2013 (Ministry of Environmental Protection - Source: www.mep.gov.cn).

repeatedly crosses the level of 500 points during our time period, while the Chinese index goes above 300 points only in five occasions.

The time variation of the two indexes is not the same: the US Embassy data is more frequent, as it is reported hourly, while the Chinese one only daily. We can then experiment with different aggregation strategies over the 24-hours to compare the US and the Chinese index (see the Robustness section). To be extremely conservative, we use as our baseline the daily *minimum* of air pollution communicated by the US embassy. Fig. 1 below shows a snapshot of the two indexes during a short time period within our dataset. During this period, in August 2008, the Beijing Summer Olympic games took place, and economic activity and construction work were restricted to improve air quality in the city. Yet, despite these precautionary measures, if we compare the minimum pollution announcement from the US Embassy, which is located in a green and wealthy neighbourhood, to the official Chinese daily measure, we still see that the two sources of information often convey a different message in terms of health hazards.

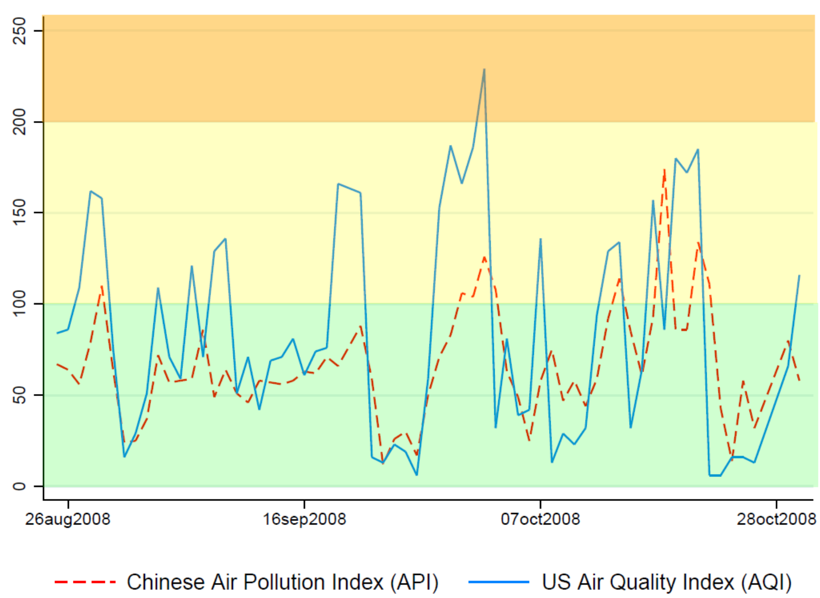

Figure 1: Index mismatch between Chinese and US index (daily minimum)

The difference of information signal in this specific time period could arise because the Chinese government had particular incentives to manipulate the data during the Olympic games. Thus, we must examine a longer time period to see if there is a systematic difference between the two sources of information. The difference on a given day could be partly due to random noise or measurement error in one or both signals. However we can test if there is a recurring pattern beyond a fixed gap between the indexes. To confirm our hypothesis of information control to influence public perception, we should not observe just a constant difference between the two time series, which could be due to monitors sensitivity, or even to their orientation towards a polluted street. We must examine if there are any systematic patterns that would suggest an intentional manipulation of public perception of air pollution. We turn in the next section to this analysis.

3.3. Empirical model

One crucial aspect of pollution indexes is how they translate into information for the population. Most people would not pay systematic attention to the exact value of an air pollution index and its minor variations. Most likely, the majority of the population just notices the colour on the health risks scale. The colour coding system is artificially overlapped on a continuous variable, the air quality index. It groups together ranges of values and imposes thresholds and discontinuities that do not exist intrinsically in the atmospheric concentration of pollution. For instance, a value of the index of 99 represents a pollution level very similar to a 101, but the first would be perceived by the population as clean air (green), and the second as mildly polluted (yellow). Viceversa, an index of 101 would be seen as virtually identical to a 149, because both fall in the yellow region. This discontinuous meaning of pollution indexe is useful to identify any potential manipulation of popular perception. All those issues that could influence the pollution measure (monitor sensitivity, measurement error, spatial variability, and so on) should be completely unrelated to the colour coding scale. Indeed, the discrepancy between the Chinese and US measure might depend on a variety of natural factors, but none of these should be significantly linked to the colour-coding scheme, unless there is some manipulation explicitly targeting popular perception.

Following the reduced form model in eq. (20), we estimate the following auto-regressive moving-average model by unconditional maximum likelihood:

$$G_t = \alpha + \beta ln(AQI)_t^{US} + \sum_{i=1}^{p} \gamma_i T_i + \sum_{i=1}^{p} \delta_i T_i ln(AQI)_t^{US} + \sum_{i=1}^{q} \phi_i G_{t-j} + \sum_{l=1}^{r} p_l \varepsilon_{t-l} + \eta_m + \sigma_y + \varepsilon_t$$

where the dependent variable G_t is the gap between the information signal provided by the Chinese government and the US one, namely $G_t \equiv ln(API)_t^{China} - ln(AQI)_t^{US}$, as a proxy for the bias.[11] Its average value is -0.1, indicating that the Chinese signal is slightly lower than the US one (see the summary statistics are reported in Table 3 in the Appendix). The dependent variable exhibits some significant autocorrelation, as shown by the autocorrelation and partial autocorrelation functions in Fig. 6 and hence requires careful modelling of the time-dependent components, to ensure that the remaining error term is white noise. The US index $ln(AQI)_t^{US}$ acts as a proxy for true air pollution shocks (p in the theoretical model) - this under the assumption that the US embassy does not have itself any systematic distortion in its signal.

T_i is a dummy variable equal to zero when the US measures of air pollution is below an information threshold, and to 1 above it, with $i \in [100, 200, 300]$. It captures the different "regions" of information about pollution damage: for example a value of the index above 300 means that the air is "Heavy Polluted" (dark red). Any significant action around these thresholds suggest some manipulation of the qualitative message that the index conveys. So, while the discrepancy between the US and the Chinese measure could derive from different monitoring techniques, a significant difference around these thresholds could not depend on them. Furthermore, we interact the thresholds with the US pollution index, $T_i \times ln(AQI^{US})$, following the theoretical model's predictions about the product of p and z in the optimal bias. Intuitively, we suspect that the incentive to introduce a bias should be stronger near the threshold, where the informational environment changes significantly, but then would diminish as pollution gets away from the crossing point. In order to capture persistence in shocks and in the stock of pollution and to correct for serial correlation over time, we include an autoregressive term G_{t-j}, with lags of the dependent variable, and some lags of the error term, ε_{t-l}.[12] Finally we include month and year fixed effects, η_m and σ_y, to capture any anomalous event in the dataset, like the Beijing Olympic games.[13]

[11] Or, equivalently, the natural log of the ratio of the two indexes, so that we can interpret effects as percentage changes.

[12] Our time series for air pollution are long and, according to Dickey-Fuller and Phillips-Perron tests for unit root, stationary (see tests in the Appendix). The underlying data-generating process may have some persistence (since high pollution can last few days), but not an extremely long memory. As we can see from Fig. 4 and 5 in the appendix, most of the autocorrelation seems to take place in the first period.

[13] We also checked for any seasonal component, but we found no evidence for it, and the log of the time series should take care of any heteroskedasticity in the variance.

3.4. Results

The results of different model specifications are presented in Table 4.[14] The negative and significant coefficient of the US index indicates that, whenever pollution (as registered by the US measurement) rises, the gap between the Chinese and US measure becomes more negative: a 10% increase in the minimum daily pollution measured by the US index makes the ratio of Chinese/US signals more negative by 9%. This result could be foreseen given the graphs showed before in Fig. 1: the Chinese pollution index does not increase as much as the US one, so whenever pollution raises, the ratio between the two indexes gets smaller. This confirms that the information provided by the Chinese government is more optimistic than the US one, but this could derive straightforwardly from the fact that the US reports PM2.5, which goes unaccounted for by the Chinese monitors.

More interestingly, beyond this linear relationship between the bias and pollution levels, we can observe an effect around the information thresholds. Crossing the 100 points threshold for the minimum daily observation of the US monitors has two effects: i) it directly reduces the ratio of indexes (intercept) by 0.44 and ii) this negative effect is somewhat hampered as pollution gets higher, as shown by the positive coefficient of the interaction term (slope). The combination of the two effects shows that the threshold has the strongest influence when immediately surpassing the crossing point of 100, but it gets slightly weaker as we move away from the thresholds and pollution increases. The magnitude of the second effect, however, is much smaller than the first. Overall, the combined effect of crossing the 100 points threshold is $-0.44+0.004$ x $ln(AQI)$, which ranges from -0.42 when the AQI is exactly 100 to -0.41 for higher pollution levels.[15] In terms of the percentage impact of the threshold dummy in this semi-logarithmic specification, we have a decline of around 34% in the ratio API/AQI .[16] The different columns of Table 4 show three different specifications of the model in terms of the number of autoregressive and moving average terms.[17]

[14]Other specifications with more autoregressive and moving average lags yield similar results, but we keep the most parsimonious models that guaranteed white noise error terms, according to a Portmanteau (Q) test that all autocorrelation coefficients are jointly equal to zero. Results for other lag structures are available upon request.

[15]A simple Wald test shows that both coefficients are jointly significant in the model estimated.

[16]Calculated as $100[exp(-0.4)-1]$, following Halvorsen and Palmquist (1980). If we assumed a normal distribution of the errors, a consistent and almost unbiased estimator of the effect would be one that corrects for the variance of the estimated coefficient, as suggested by Kennedy (1981): $100[exp(-0.4-\frac{1}{2}v*(-0.4))-1]$, where $v*$ is the estimated variance. This however yields an almost identical result, a 33% fall.

[17]These models can be compared on the basis of the Akaike and the Bayesian Information Criterion, which are used for model selection through the relative goodness of fit. These criteria are only interpretable as relative measures to compare different models, they have no absolute meaning with respect to goodness of fit, as the classical R squared

The forecasts for the best fitting model are plotted in Figure 7 in the appendix, which shows how the model specified predicts the Chinese bias inside of the sample using previous information and the lags structure selected. The model follows closely the fluctuations in the bias.

3.5. Robustness

In the previous analysis we performed the most conservative comparison possible, confronting the Chinese signal with the *minimum* daily record of the US embassy. We find that the 100 information threshold is significant and its interaction with pollution has a positive sign, confirming the predictions of our model and indicating some manipulation of popular perception. However this result is also in accordance with the literature on strategic political manipulations of air pollution data: in particular, China applies a 'national environmental protection model city' award, based on various environmental measures, including a certain number of Blue Sky days with API below 100 points (Chen et al., 2012). This award could create incentives to manipulate specifically the 100 threshold. Up to 2012 Beijing never won the award,[18] so it is not clear if this political incentive exists there, but we cannot rule it out. The minimum US measurement rarely surpasses higher thresholds (93% of observations are below 200), so this might be the reason why only the 100 point threshold is significant. To see if the colour-coded information ranges have a further impact beyond these political incentives, we consider the *average* of all US observations during the day, and as a robustness check even the daily maximum. A graphical comparison between the US average and maximum daily value and the usual Beijing index is shown in Figure 8.

The results of the previous ARMA model are robust to these different specifications of the US index: we still find that as pollution raises the gap increases more or less by the same magnitude, and that the effect of the 100 points threshold is still downward, with the usual small opposite effect given by the interaction term.[19] Now however also the 200 and 300 thresholds starts playing a role. Considering the daily average of the US index (Table 5), crossing the 200 threshold has an effect

would have. Choosing the two models with lowest information criteria, namely the autoregressive and moving average models with one lag AR(1) and MA(1), we compute in-sample forecasts to see which of the chosen 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 select the most suitable lag structure among all the ones examined, which is the moving average one period lag, MA(1).

[18]See http://english.mep.gov.cn/inventory/Model_cities/

[19]For the US daily average the effect of T100 is around -25%, while for the daily maximum of -39%.

that cancels out with the one of crossing the 100 point threshold.[20] However, once we reach the 300 points threshold, the negative impact becomes substantial again, with approximately a 40% decrease for crossing the 300 points threshold (and naturally the previous two).[21] Similar effects occur with the daily maximum of the US index (Table 6), with an insignificant 200 threshold, but significant 100 and 300 points thresholds.

Overall, this analysis robustly shows that the Chinese signal about air quality systematically diverges from the measure of the US Embassy. In combination with the results from the theoretical model of an optimal government bias, we take this as suggestive evidence that indeed the government is introducing a downward bias, especially around significant information thresholds, to misguide popular perception about pollution. Part of the story could be driven by political incentives, but these would not explain the significant changes around the 300 threshold. The next section is dedicated to the analysis of household responses to pollution information in the context of this distorted air pollution signal.

4. Households

Households living in a polluted city like Beijing can respond to the environmental hazard presented by air pollution, by incurring a cost (monetary or in terms of time) to protect themselves. This decentralized response may be less effective than coordinated action from the state, and would depend, among other things, upon the general awareness of pollution peaks. In order to examine the behaviour of households with respect to pollution information, we collect household data through a survey in urban Beijing. We elicit the expenditure and time allocation regarding self-protective activities against pollution risks. A set of questions is dedicated specifically to sources of information. This allows us to identify which groups access specific signals during peak pollution days, and which ones are most likely to update their expectations over time. For a sample questionnaire, see the Appendix.

[20]The combined effect of crossing a level of 200 (and thus also the level of 100) is $-0.28+0.38+(0.003-0.001)\mathrm{x}ln(AQI)$, which is close to zero (for instance when AQI is exactly 100, it takes the value of 0.1).

[21]This is again calculated as $-0.28+0.38-0.53+(0.003-0.001+0.002)$ x $ln(AQI)$

4.1. Data

The survey was administered in August 2012 in three districts of Beijing, Haidian, Chaoyan and Dongcheng, for a total of 1672 individuals in 578 households. The sample selection was designed to represent accurately the total population: we applied 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.[22] The questionnaire inquired in detail about i) the socio-economic characteristics of the household, ii) various habits and self-protective behaviours: wearing masks, reducing time outdoor, changing means of transportation, doing preventive health checks,and using air purifiers, iii) how the family gathered information about air pollution, and iv) 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. Comparing various demographic characteristics of the sample with the Statistics Bureau of Beijing, the survey is in line with the characteristics of the total population, so the sample can be considered representative.

The data from the household survey varies in three dimensions: across individuals, within households and somewhat over time. For the time variation, respondents had to recall their averting behaviour choices in periods of extreme pollution peaks and over the rest of the year, which provides variation between 'normal' times and extreme pollution events. [23] The use of recall data to introduce this time dimension is not free from limitations, but it gives a sense of people's variation in behaviour vis-a-vis pollution peaks. We test in the following section whether the change in self-protective behaviour during extreme circumstances relates to the source of information used.

[22]The sampling probability for a given household was

$$p_0 \frac{[N_H]_{D_1}}{[N_h]_{TOT}} * p_1 \frac{[[N_H]_{S_1}]_{D_1}}{[N_h]_{D_1}} * p_2 \frac{1}{[[N_{C_1}]_{S_1}]_{D_1}} * \frac{x}{[[[N_H]_{C_1}]_{S_1}]_{D_1}} = c$$

where each term captures respectively the probability of a given district, street, community and household being chosen. Overall, the sampling design yielded a constant probability c for a household in any district, street or community to be selected.

[23]To distinguish between extreme and normal times, the respondents needed to recall the two worst episodes of air pollution in Beijing in the previous year, and to locate them in time. In the year before the survey, in fact, there were two major pollution alerts during hazardous pollution days. Only 66% of respondents had noticed the extremely polluted days in Beijing, indicating that even in those cases there was no widespread information about the pollution risks.

4.2. *Self protective behaviours and information*

Households should have a clear incentive to protect themselves from the damages of air pollution. The private cost of illness from airborne diseases in our sample is quite high: the average annual expenditure including medical costs, medicines and foregone wage is more than 3000 yuan, almost a month of average salary (see Table 7 in the Appendix). This indicates that air pollution imposes some significant costs on households, and there can be scope for rational self-protective actions. At the same time, though, the damage to the workforce of these airborne diseases is not large: on average workers suffered from 12 days per year of hindered activities due to sickness, but they lost less than one day a year of paid sick leave. So, according to our survey, the population bears substantial health costs, but without significant effects on labour force availability.

The survey captures in detail weekly exposure to outdoor pollution and self-protective behaviours. Table 8 in the Appendix illustrates the characteristics of the avertive choices considered. *Reducing time outdoor* captures the decision to spend less time outside for leisure and exercise purposes. *Transport change* implies a change in means of transportation, from those with high exposure to pollution (such as walking or biking) to relatively less-exposed forms of transport, such as using a car or a taxi. This is not a strategy that many people in Beijing can afford, as less than 6% of our sample adopts it in normal times. *Masks* are also a relatively infrequent behaviour, adopted by less than 20 % of the sample.[24] Finally, the questionnaire includes two different, more expensive long term strategies: *preventive medical checks* and *air purifiers*. The former considers medical check-ups of the respiratory system for which the person had to pay some medical costs. Buying an air purifier is an extremely infrequent behaviour, as air purifiers can cost up to 30,000 yuan. In the end, due to the scarce number of respondents who adopted this behaviour, we did not include this last option in the empirical model. These two strategies are quite different in nature from the previous behaviours, because they do not respond to pollution peaks and relate to long term perception of air pollution, rather than daily signals that indicate an alert.

The survey reports on the various modes of accessing public[25] pollution information in Beijing, and the rate of use of each source. Internet use for the purpose of collecting information about

[24] The questionnaire differentiates between common masks and more sophisticated ones, as there exist more expensive filters on the market that can block more particulate matter, but only few people used the higher quality masks (2-3 % of the sample).

[25] Personal monitoring devices were too expensive in 2012 to be relevant for our sample.

air pollution is limited. The vast majority of people interviewed relied on government controlled sources of information, such as television, radio or newspapers - see Table 9. The US Embassy measurements are freely available via Twitter every hour, and they can even be downloaded on a mobile device, however, since the internet in China is restricted, typically only young people are able to access this sort of information using virtual private networks. Furthermore, 70 % of our sample considers the information available on air pollution satisfactory and would not be interested in more information. Even after the worst pollution days in the previous year, only about a third started searching for more information about pollution peaks. For the majority of the population in Beijing, the government is the sole mean of accessing information on pollution.

Table 10 shows some conditional correlations to characterize information users. Individuals who use government media are generally older, whereas internet users are typically young people. Those who prefer to use self-perception are typically less educated, but there is no significant difference in educational attainments between internet users and those who rely on government media. Larger households 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: older people in large part, families of lower income.

4.3. Averting behaviour

Next, we analyse self-protective behaviours in response to high pollution depending on the source of information. We use a treatment-effect model, where the treatment is the government signal. Do people who rely on government information act differently during pollution peaks? Here we attempt to separate out the group of people that does not update beliefs from more critical individuals, and see if indeed the effect of public information is stronger for the former.

We apply a two-step procedure, with a bi-probit model - see Greene (2012), pp. 738-752 and Pindyck and Rubinfeld (1998), to examine how people responded to pollution peaks depending on their information sources.[26] We include in the first stage (eq. 23) a dummy variable, Λ, which takes

[26]The standard problem of missing observations is present in this case, as we cannot observe how a person behaves both with and without government information. We thus consider an average treatment effect (ATE), but given the non-random assignment of treatment we need to account for selection bias - as people choose what signal they want to listen to. A first improvement over this problem is to consider only within-individual changes, namely how the same person responds to different air pollution levels. Since many of the unobserved characteristics of a person remain constant under different pollution situations, this reduces the problem of omitted variables.

the value of 1 for those people who consider the information they have sufficient to understand the quality of the air, and zero otherwise. This variable captures the fraction of the population that, as in our theoretical model, is not likely to look for further information about pollution to adjust their expectations for any possible information bias.[27]

The two steps empirical model is specified as follows:

$$A_{ij} = \alpha_0 + \alpha_{h1} P_h + \mathbf{X_i} \alpha_{h2} + \mathbf{X_h} \alpha_3 + \eta_{it} \tag{22}$$

$$P_h = \beta_0 + \mathbf{X_i} \beta_{i1} + \mathbf{X_h} \beta_{h2} + \beta_3 \Lambda_h + \varepsilon_{it} \tag{23}$$

Averting behaviours, A, vary over individuals, i and over four possible activities, $j \in \{$masks, transport, time outdoor, health checks$\}$. With the exception of the last, the dependent variable is measured in changes, taking the value of one if a person switches to more averting behaviour in extremely polluted days compared to normal days. P is the use of public information controlled by the government, similarly to the previous specification: it takes the value of one when a person uses as principal source of information government-controlled public media (TV, radio, newspapers), zero otherwise. We add some further controls to the ones used previously: 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. We estimate a separate equation for each averting behaviour, rather than combining them in a multinomial logit, since these are not mutually exclusive behaviours.

The first and central reason why we use a first stage with Λ is to identify those agents who not only use government information, but also believe completely in that signal and do not update expectations of a bias. This way, we can relate directly the averting behaviour to the distorted government signal, without much bias correction. In our theoretical model, this corresponds to the non-critical fraction of the population λ. In addition, we could argue that the first stage isolates the variation in the choice of public information that does not have to do with pollution peaks, but with

[27] In the household survey, this corresponds to those respondents who answered that information was enough to the question "*Do you think [your current choice of] information is enough for you or would you like more of it?*". Of course, those respondents who indicated they had enough information were not all users of government media for air quality news. However, in theory, these people are more likely to use government-controlled media (the easiest to access and most widespread type of information), and thus to be influenced by the biased signal.

how people consider information overall. In the theoretical model, we even assumed that the critical and non-critical groups of agents are exogenous. In practice, there could be a long term attitude towards media sources, a slow moving habit that determines if people search for extra information or are satisfied with what they get. Λ can then be seen as an instrument for using public sources of information and it could resolve potential issues of simultaneity in the second stage. We are cautious with a more causal interpretation of our results, but nonetheless we report the results for an IV-probit in Table 12.[28]

4.4. Results

Table 11 shows the results from a bi-probit estimation. In the first stage we note that Λ, the dummy capturing non-updating individuals, has a positive and significant correlation with the use of government-controlled media. Those people who consider sufficient the information they have are also more likely to choose government media, controlling for other factors. Then the second stage shows that this group of people who fully relies on media controlled by the Chinese Communist Party is less likely to switch to more averting behaviours during peak pollution days. This result is valid both in terms of time spent outdoors and for wearing masks.[29] A different story applies to preventive health checks: this behaviour correlate positively and significantly to the use of government media. This is not surprising, since preventive checks are not a response to peak pollution, but rather an ex-ante self-protective behaviour. Moreover, public servants in Beijing tent to have access to better health insurance and thus might do more preventive medical controls, even if they receive systematically biased air quality news.

In summary, in our sample of the population of Beijing, the individuals who rely uncritically on the government as a main source of information about air pollution are also more likely not to adopt short term self-protective behaviours during pollution peaks. Combining this result with the previous evidence that the government signal might contain a systematic bias, this suggests that the Chinese government is effectively distorting popular perceptions about air pollution risks in Beijing.

[28] Even if we can say that the instrument is relevant and significant, we cannot exclude that it correlates with some unobserved variables and $Corr(\Lambda, \eta_{it}) \neq 0$. At least the Wald test after IV-probit cannot reject the null hypothesis that the error terms in the second and first stage are uncorrelated ($H_0 : \rho = 0$).

[29] In the case of transport switch (third column), information does not play a significant role, since car ownership is a strong determinant of this behaviour. In this case, it is not the information signal and how much people can update expectations that matters, but the investment in an asset that allows for self-protective behaviour, in this case a car.

Overall these results fit well with the theoretical analysis, which suggested a mechanism for why and how a government should report optimistically low values for pollution. This evidence opens up many further questions about the joint provision of public information and other public goods, such as pollution abatement, when information can be manipulated. This could lead to interesting cross-countries comparisons, but we leave it for future research.

5. Conclusion

Centralizing certain decisions (how much you should know about pollution) makes people less able to take other decentralized decisions well. Quite obvious?

Much research has been conducted in analyzing how firms or individual agents may use information strategically. In this article, we argue that it is important that we extend this analysis to governments, which cannot always be assumed as impartial actors that work fully in the interest of their public. We illustrate this point in the context of Chinese air pollution, showing that a government with control over public media may have the incentive to introduce a bias in information signals, in order to maximize its own public support. Public information control enables the government to influence popular responses to pollution from production. In particular, the government may distort the perception of pollution risks, so as to retain a complacent workforce active in polluted cities. When such a government places a low weight on health costs, and the economy benefits significantly from cheap labour, then it will have an incentive to introduce a negative bias in pollution announcements. This bias increases with pollution and when the informational environment becomes more noisy. As a consequence, the population is less aware of pollution hazards, especially those households who rely completely on government-controlled media.

We illustrate this mechanism in an empirical analysis of the announced and experienced air quality in Beijing, China over the period 2008-2013. We analyse how the Beijing government provides public information about air pollution, and we found that the public signal is significantly downward biased as pollution increases. This bias is more pronounced around some critical thresholds, confirming the hypothesis that the government manipulates information in order to affect the perception of pollution. As a result, we find in an original household survey that those urban dwellers who rely on government-controlled media adopt fewer measures to protect themselves during pollution peaks.

Thus, the case of Beijing demonstrates that it can be optimal for a state with some control over both pollution and information to introduce a bias in its information signals, but at the cost of inducing less risk-averting behaviour.

The implication of this analysis is that in many other cases it could be interesting to look at how governments may use information strategically for their economic benefit. Whenever a government can control public information, there is a potential incentive for distorting popular perceptions about a public issue, and reduced incentives to do something about the problem. In the case of pollution, the government has fewer incentives for abatement or environmental regulation, because it can count on information control as a policy tool. This gives the government the power to shifts the costs of pollution to the population, so that they are experienced more as health damages than as production losses. A further issue to be explored is then that, in some developing countries, the problem with public goods' provision might not be the lack of capacity of the state, but rather the opposite, the excessive control of the government over certain aspects of the economy (such as information). In this system, this cycle of distorted information, reduced public responsiveness and possibly reduced provision of public goods is a self-reinforcing reality, similar to a snake, or in this case a dragon, eating its own tail.

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Bibliography

Andrews, S. Q. (2008), 'Inconsistencies in air quality metrics: 'Blue Sky' days and PM10 concentrations in Beijing', *Environmental Research Letters*, 3(3).

Angeletos, G. M. and Pavan, A. (2007), 'Efficient use of information and social value of information', *Econometrica*, 75(4), 1103 –1142.

Baeriswyl, R. and Cornand, C. (2010), 'The signaling role of policy actions', *Journal of Monetary Economics*, 57(6), 682 – 695.

Besley, T. and Burgess, R. (2002), 'The political economy of government responsiveness: theory and evidence from India', *Quarterly Journal of Economics*, 117, No. 4, 1415–1451.

Besley, T. and Ghatak, M. (2006), *Public goods and economic development*, In: Banerjee, A., Benabou, R. and Mookherjee, D., (Eds.) *Understanding Poverty*. Oxford University Press, Oxford.

Besley, T. and Prat, A. (2006), 'Handcuffs for the grabbing hand? Media capture and government accountability', *American Economic Review*, 96(3), 720–736.

Brunetti, A. and Weder, B. (2003), 'A free press is bad news for corruption', *Journal of Public Economics*, 87(78), 1801 – 1824.

Bucovetsky, S. (1991), 'Asymmetric tax competition', *Journal of Urban Economics*, 30(2), 167–181.

Chen, Y., Zhe, J. G., Naresh, K. and Guang, S. (2012), 'Gaming in air pollution data? Lessons from China', *The B.E. Journal of Economic Analysis and Policy*, 13(3), 1–43.

Cook, P. J. and Graham, D. A. (1977), 'The demand for insurance and protection: the case of irreplaceable commodities', *Quarterly Journal of Economics*, 91(1), pp. 143–156.

Cornand, C. and Heinemann, F. (2008), 'Optimal degree of public information dissemination', *Economic Journal*, 118(528), 718–742.

DellaVigna, S. and Kaplan, E. (2007), 'The Fox News effect: media bias and voting', *Quarterly Journal of Economics*, 122 (3)(12169), 1187–1234.

Djankov, S., McLeish, C., Nenova, T. and Shleifer, A. (2003), 'Who owns the media?', *Journal of Law and Economics*, 46(2), 341–81.

Dur, R. and Swank, O. H. (2005), 'Producing and manipulating information', *Economic Journal*, 115(500), 185–199.

Ehrlich, I. and Becker, G. S. (1972), 'Market insurance, self-insurance, and self-protection', *Journal of Political Economy*, 80(4), 623–48.

Gavazza, A. and Lizzeri, A. (2009), 'Transparency and economic policy', *Review of Economic Studies*, 76(3), 1023–1048.

Ghanem, D. and Zhang, J. (2014), 'Effortless perfection: do Chinese cities manipulate air pollution data?', *Journal of Environmental Economics and Management*, 68(2), 203 – 225.

Greene, W. H. (2012), *Econometric Analysis*, Prentice Hall, 7th ed. Upper Saddle River, NJ.

Halvorsen, R. and Palmquist, R. (1980), ‘The interpretation of dummy variables in semilogarithmic equations’, *American Economic Review*, 70, 474–475.

Hilbe, J. M. (1996), ‘Maximum-likelihood complementary log-log regression.’, *Stata Technical Bulletin Reprints, Stata Press*, 6, 129–131.

Jalan, J. and Somanathan, E. (2008), ‘The importance of being informed: experimental evidence on demand for environmental quality’, *Journal of Development Economics*, 87(1), 14 – 28.

Jia, R. (2014), ‘Pollution for promotion’, *Mimeo*, .

Kennedy, P. (1981), ‘Estimation with correctly interpreted dummy variables in semilogarithmic equations’, *American Economic Review*, 71(4).

Kennedy, P. W., Laplante, B. and Maxwell, J. (1994), ‘Pollution policy: the role for publicly provided information’, *Journal of Environmental Economics and Management*, 26(1), 31 – 43.

Lin, M., Tao, J., Chan, C.-Y., Cao, J.-J., Zhang, Z.-S., Zhu, L.-H. and Zhang, R.-J. (2012), ‘Regression analyses between recent air quality and visibility changes in megacities at four haze regions in China’, *Aerosol and Air Quality Research,*, 12, 1049–1061.

Liu, Z., Hu, B., Wang, L., Wu, F., Gao, W. and Wang, Y. (2015), ‘Seasonal and diurnal variation in particulate matter (PM10 and PM2.5) at an urban site of Beijing: analyses from a 9-year study’, *Environmental Science and Pollution Research*, 22(1), 627–42.

Madajewicz, M., Pfaff, A., van Geen, A., Graziano, J., Hussein, I., Momotaj, H., Sylvi, R. and Ahsan, H. (2007), ‘Can information alone change behavior? Response to arsenic contamination of groundwater in Bangladesh’, *Journal of Development Economics*, 84(2), 731 – 754.

Mèon, P. G. and Minne, G. (2014), ‘Mark my words: information and the fear of declaring an exchange rate regime’, *Journal of Development Economics*, 107(0), 244 – 261.

Michalski, T. and Stoltz, G. (2013), ‘Do countries falsify economic data strategically? Some evidence that they might’, *Review of Economics and Statistics*, 95(2), 591–616.

Moretti, E. and Neidell, M. (2011), ‘Pollution, health, and avoidance behavior: evidence from the ports of Los Angeles’, *Journal of Human Resources*, 46(1), 154–175.

Morris, S. and Shin, H. S. (2002), ‘Social value of public information’, *American Economic Review*, 92(5), 1521–1534.

Moscarini, G. (2007), ‘Competence implies credibility’, *American Economic Review*, 97(1), 37–63.

Naso, P. and Swanson, T. (2017), ‘Competition between governance units within a federal structure: Impacts on migration and pollution’, *CIES Working Paper (forthcoming)*, .

Pindyck, R. S. and Rubinfeld, D. L. (1998), *Econometric Models and Economic Forecasts*, McGraw-Hill, 4th Ed. New York.

Reporters Without Borders (2016), ‘World press freedom index’, , .

Simmons, K. M. and Kruse, J. B. (2000), ‘Market value of mitigation and perceived risk: empirical results’, *Journal of Economics*, 26(1), 41–51.

Stiglitz, J. E. (2000), ‘The contributions of the economics of information to twentieth century economics’, *Quarterly Journal of Economics*, 115(4), 1441–1478.

Stoerk, T. (2015), ‘Statistical corruption in Beijing’s air quality data has likely ended in 2012’, *Grantham Research Institute on Climate Change and the Environment*, Working Paper No. 194.

Veldkamp, L. L. (2011), *Information Choice in Macroeconomics and Finance*, Princeton University Press.

Whitehead, J. (2005), ‘Environmental risk and averting behavior: predictive validity of jointly estimated revealed and stated behavior data’, *Environmental & Resource Economics*, 32(3), 301–316.

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

Williams, A. (2009), ‘On the release of information by governments: causes and consequences’, *Journal of Development Economics*, 89(1), 124 – 138.

Wilson, J. (1995), ‘Mobile labor, multiple tax instruments, and tax competition’, *Journal of Urban Economics*, 38(3), 333–356.

Zhao, C., Wang, Y., Wang, Y., Zhang, H. and Zhao, B. (2014), ‘Temporal and spatial distribution of PM2.5 and PM10 pollution status and the correlation of particulate matters and meteorological factors during winter and spring in Beijing’, *Huan Jing Ke Xue*, 35(2), 418–27.

Appendix

The expected bias (posterior) is a precision-weighted average of the prior and the signals that people have received up to time T, according to Bayes' law (see Veldkamp, 2011, p.12). We keep calculations as simple as possible by making three assumptions here: first of all, that the errors in the pollution process and the bias are independent; secondly, that announcement from the point of view of households are independently distributed; and finally, we assume that households consider the true bias time-invariant. When calculating expected pollution, we further assume that the fraction of uncritical people λ is independent of W and of the estimate of the bias $E(B)$.

$$E(B_T|A_1,A_2...A_T) = \left(\frac{1}{\sigma_B^2}\overline{B} + \frac{1}{\sigma_p^2}T\overline{A}\right) / \left(\frac{1}{\sigma_B^2} + T\frac{1}{\sigma_p^2}\right) \tag{24}$$

where $\overline{A} = \sum_{t=1}^{T} A_t/T$ is the average of all past announcements up to T, the present moment. The inverse of the variances gives the precision of the distribution of the priors. The higher the variance, the lower the weight that people assign to that variable in their updating process. Also, the more announcement they receive (higher T), the more weight they assign to announcements.

Then expected pollution emissions are the difference between the announcement and the expected bias, again weighted by the precision of the two (see Appendix). We can omit the T subscript.

$$E(p) = \left(\frac{A - E(B)}{W^2}\right) / \left(\frac{1}{\sigma_p^2} + \frac{1}{W^2}\right) \tag{25}$$

where W^2 is the variance of $A - E(B)$, the bias-adjusted announcement.[30] If agents can update their beliefs for a sufficiently long period of time, their expectations concerning announcements will converge to the true government bias. [31]

Estimation of the variance of $E[p|A-E(B)]$.

In order to obtain a precision-weighted estimate of p, conditional on the announcements corrected for the expected bias $A - E(B)$, we must know the variance of $A - E(B)$. First of all, we plug the expected bias of eq. (24) and rearrange:

[30]Similarly to DellaVigna and Kaplan (2007), this is $W^2 = \left(1/\sigma_B^2 - (T-1)/\sigma_p^2\right) / \left(1/\sigma_B^2 + T/\sigma_p^2\right)^2$. See derivation in the Appendix.

[31]This set-up is analogous to an output-gap model of an economy with a central bank deciding on inflation targeting and announcements. Similarly, here the government has control over real variables - pollution shocks - and nominal ones - announcements. For an example of a similar model in the context of a central bank and inflation, see Moscarini (2007).

$$
\begin{aligned}
A_T - E(B_T) &= A_T - \left(\frac{1}{\sigma_B^2}\overline{B} + \frac{1}{\sigma_p^2}T\overline{A}\right) / \left(\frac{1}{\sigma_B^2} + T\frac{1}{\sigma_p^2}\right) \\
&= p_T + B - \frac{\sigma_p^2\overline{B} + \sigma_B^2 \sum^T (p_t + B)}{\sigma_p^2 + T\sigma_B^2} \\
&= \frac{p_T(\sigma_p^2 + T\sigma_B^2 - \sigma_B^2) + B(\sigma_p^2 + T\sigma_B^2 - T\sigma_B^2) - \sigma_B^2\overline{B} - \sigma_B^2 \sum^{T-1} p_t}{\sigma_p^2 + T\sigma_B^2} \\
&= \frac{\sigma_p^2 + (T-1)\sigma_B^2}{\sigma_p^2 + T\sigma_B^2} p_T + \frac{\sigma_p^2}{\sigma_p^2 + T\sigma_B^2}(B - \overline{B}) - \frac{\sigma_B^2}{\sigma_p^2 + T\sigma_B^2}\sum^{T-1} p_t \\
&= \left(\frac{1}{\sigma_B^2}(B - \overline{B}) - \frac{1}{\sigma_p^2}\sum^{T-1} p_t\right) / \left(\frac{1}{\sigma_B^2} + \frac{1}{\sigma_p^2}T\right)
\end{aligned}
$$

In the last step we divide numerator and denominator by $\sigma_B^2\sigma_p^2$, and leave out the first term because since this is an estimate of contemporaneous $\hat{p}_T$, the variance does not depend on the p_T itself but only on previous values. The variance is then

$$
w^2 \equiv Var(A_T - E(B_T)) = \left(\frac{1}{(\sigma_B^2)} - \frac{(T-1)}{\sigma_p^2}\right) / \left(\frac{1}{\sigma_B^2} + \frac{1}{\sigma_p^2}T\right)^2
$$

Now we can calculate the expected value of pollution, given the announcements and the posterior about the bias:

$$
\begin{aligned}
E[p|A_T - E(B_T)] &= \left(\frac{1}{\sigma_p^2}E(p) + \frac{1}{w^2}(A_T - E(B_T))\right) / \left(\frac{1}{\sigma_p^2} + \frac{1}{w^2}\right) \\
&= \left(\frac{A_T - E(B_T)}{w^2}\right) / \left(\frac{1}{\sigma_p^2} + \frac{1}{w^2}\right)
\end{aligned}
$$

which is the expression for eq. (25).

Expected bias over time

For those people who update their expectations as they get announcements from the government, the limit of the expected bias goes to the true value of the bias as people observe more announcements. This can be shown easily, simplifying eq. (24) and multiplying numerator and denominator by T:

$$
\lim_{T\to\infty} E(B) = \frac{\overline{B}\sigma_p^2 + T\overline{A}\sigma_B^2}{\sigma_p^2 + T\sigma_B^2} = \frac{\overline{B}\sigma_p^2/T + \overline{A}\sigma_B^2}{\sigma_p^2/T + \sigma_B^2}
$$

Both terms divided by T go to zero as time rises, and we are left just with the mean of an increasingly large sum of announcement. And since we assumed that the mean of emissions shocks p equals zero and we are ignoring natural pollution, $p^N = 0$, this just converges to the true bias, B.

Optimal bias and pollution

The problem of the government in eq. (**??**) including its constraints can be written as

$$\underset{(p,B)}{max} \;\; V = \pi(p, n(w) - kE(p)) - c[dp - aE(p)]\, [n(w) - kE(p)] \tag{26}$$

Moreover, the government considers the expectations updating process about pollution and optimally responds to it. We plug eq. (3), and take the first order condition with respect to the bias B

$$\frac{\partial V}{\partial B}: \;\; B = \frac{z^2}{2cak\lambda^2}\left(\frac{can(w)z\lambda - kz\lambda\pi_N + (cdkz - 2cak\lambda)p}{z^2}\right)$$

which simplifies to the expression in eq. (19).

Plugging this back in eq. (26) and maximizing with respect to pollution, we can get also the optimal level of pollution, that the government can influence with environmental policies

$$p^* = \frac{1}{d}\left[h_1 \frac{n(w)}{k} + \frac{1}{c}\left(h_2 \pi_N - h_3\, \pi_p\right)\right] \tag{27}$$

where $h_1 \equiv \left(\frac{4a^2}{dz} - a\right)$, $h_2 \equiv \left(3 - \frac{4a}{dz}\right)$ and $h_3 \equiv \frac{2a}{kd}$.

The higher the pollution damages, d, the lower the optimal pollution. The optimal level of pollution depends on the marginal value of labour, the marginal value of pollution, and on the attractiveness of wages in this economy, respectively π_N, π_p and $n(w)$.

Noise in the informational environment

The effect of z on the optimal bias has an ambiguous sign. Specifically, this is

$$\frac{\partial B^*}{\partial z} = \frac{1}{2\lambda}\left[\left(\frac{n(w)}{k} - \frac{\pi_N}{ca}\right) + \frac{d}{a} p_t\right] \tag{28}$$

which depends on 1) the relationship between $n(w)$ and π_N, namely the relative attractiveness of wages and the profitability of workers, and 2) the pollution shocks, weighted by the ration of pollution damages to avertive capacity, d/a. The first element is likely to be largely negative in a developing country that uses labour intensively and where wages are not yet particularly high, but the second would go in the opposite direction, giving the ambiguous sign.

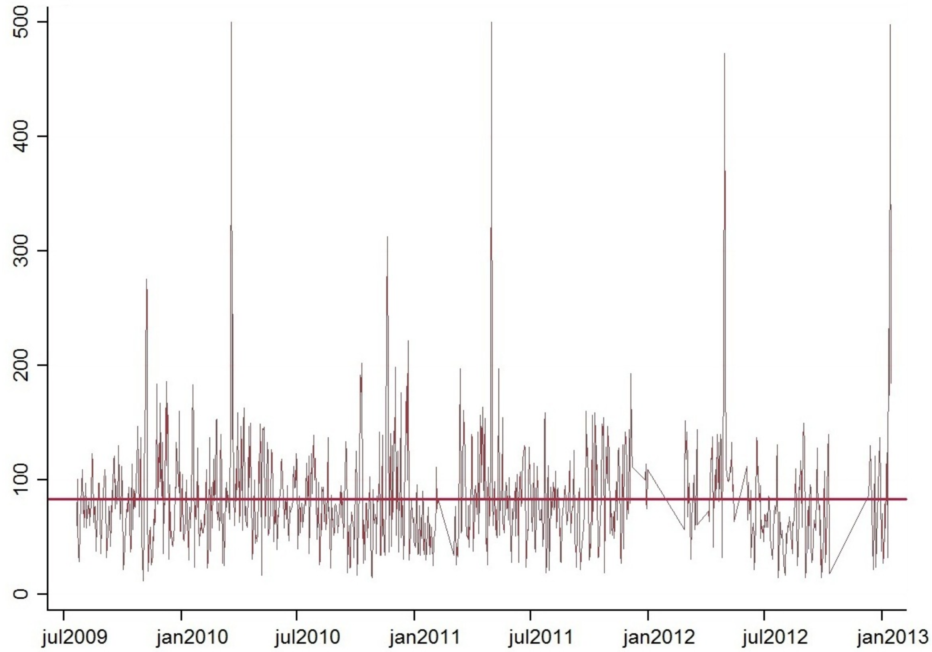


Figure 2: Chinese Daily Air Pollution Index

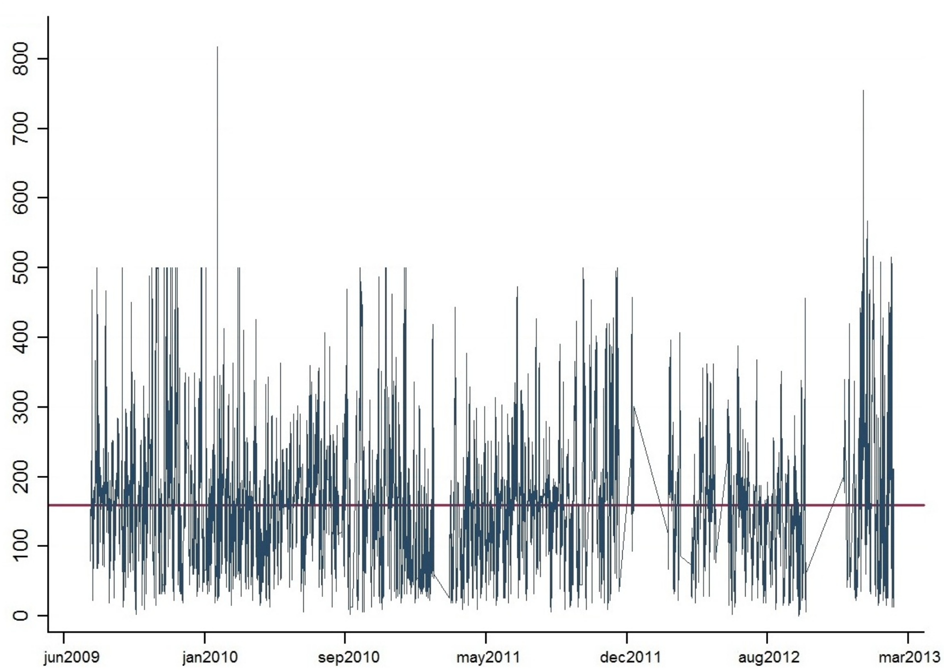


Figure 3: US Hourly Air Pollution Index

Table 1: Tests for stationarity of air pollution data

Dickey-Fuller test for unit root - Chinese API				Number of obs=1039
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-19.062	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

Phillips-Perron test for unit root - Chinese API				Number of obs=1039
Newey-West lags = 6				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-546.299	-20.7	-14.1	-11.3
Z(t)	-18.964	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

Dickey-Fuller test for unit root - US AQI				Number of obs=1039
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-16.045	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

Phillips-Perron test for unit root - US AQI				Number of obs=1039
Newey-West lags = 6				
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
Z(rho)	-405.843	-20.7	-14.1	-11.3
Z(t)	-15.786	-3.43	-2.86	-2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

The tests yield similar results when adding a trend

Table 2: Air pollution Indexes

Index and Definition			Health Implications	PM10 ($\mu g/m3$)		NOx ($\mu g/m3$)	
AQI US	API China			US	China	US	China
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
51-100 Moderate	51-100 Good		Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a small number of people who are unusually sensitive to air pollution.	50-150	50-150	0.03 - 0.14	50-150
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
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
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
	400-500				500-600		2100-2620
	500				600		2620

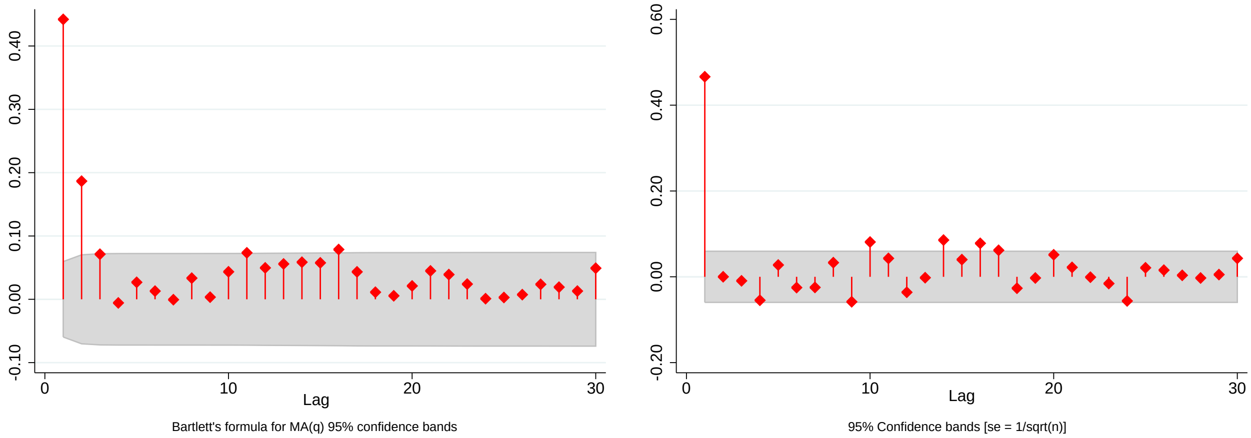
Source: own elaboration from US Environmental Protection Agency and China's Ministry of Environmental Protection.

Table 3: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Chinese Index	1083	82.9	45.9	12	500
US index (daily minimum)	1083	103.3	69.9	0	500
US index (daily average)	1083	158.6	78.2	9.1	528.1
US index (daily maximum)	1083	230.5	109.9	13	817
Log Chinese Index	1083	4.3	0.5	2.5	6.2
Log US index (daily min)	1082	4.3	0.8	1.1	6.2
Log US index (daily avg)	1083	4.9	0.6	2.2	6.3
Log US index (daily max)	1083	5.3	0.5	2.6	6.7
DEPENDENT VARIABLE - GAP					
Log Chinese - Log US (min)	1082	-0.1	0.7	-1.3	2.9
Log Chinese - Log US (avg)	1083	-0.6	0.4	-1.8	1.7
Log Chinese - Log US (max)	1083	-1	0.4	-2.6	1.7

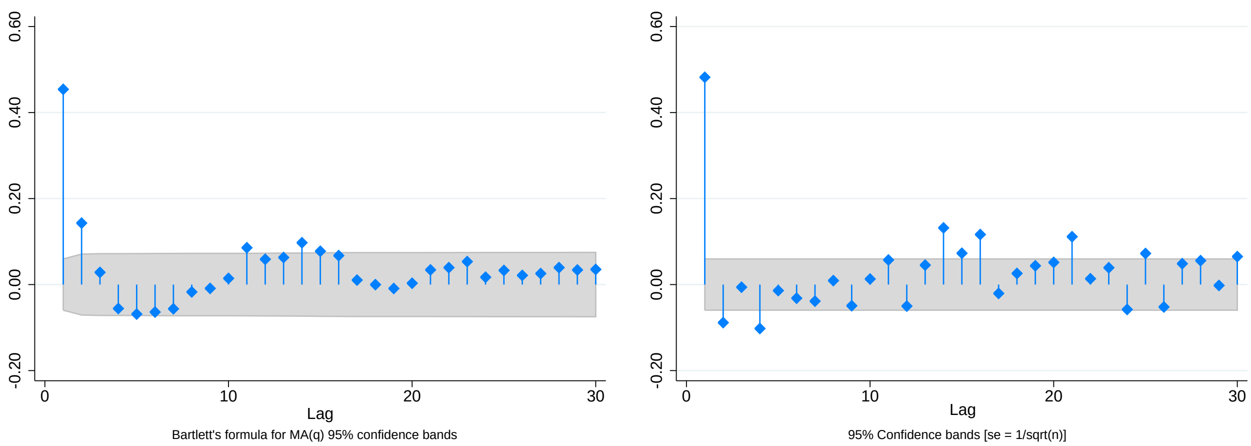
THRESHOLD DUMMIES

Threshold T	Obs	Mean	Mean T*AQI	Min	Max
Threshold 100 points - min	1083	.0.42	51.5	0	1
- avg	1083	0.5	80	0	1
- max	1083	.43	71.8	0	1
Threshold 200 points - min	1083	0.05	13.4	0	1
- avg	1083	0.2	46.3	0	1
- max	1083	0.2	63.2	0	1
Threshold 300 points - min	1083	0.01	3.8	0	1
- avg	1083	0.05	17.3	0	1
- max	1083	0.2	89.8	0	1



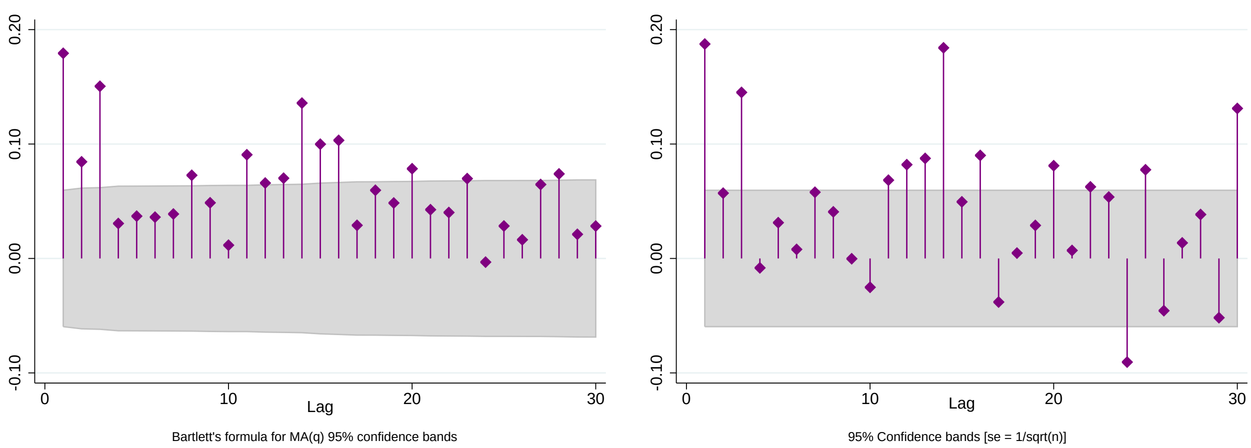
(a) AC (b) PAC

Figure 4: Autocorrelation and partial autocorrelation function Chinese API



(a) AC (b) PAC

Figure 5: Autocorrelation and partial autocorrelation function of US AQI



(a) AC (b) PAC

Figure 6: Autocorrelation and partial autocorrelation function of dependent variable

Table 4: Discrepancy between the Chinese and US Index (daily minimum)

	Dependent variable: Gap China - US minimum signal		
	(1)	(2)	(3)
US AQI (min)	−0.952***	−0.950***	−0.951***
	(0.02)	(0.02)	(0.02)
Min. AQI above T100	−0.441***	−0.449***	−0.442***
	(0.09)	(0.09)	(0.09)
Min. AQI above T200	−0.066	−0.037	−0.062
	(0.39)	(0.39)	(0.39)
Min. AQI above T300	0.333	0.308	0.326
	(0.93)	(0.95)	(0.93)
T100 * Min. AQI	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)
T200 * Min. AQI	−0.000	−0.000	−0.000
	(0.00)	(0.00)	(0.00)
T300 * Min. AQI	−0.001	−0.001	−0.001
	(0.00)	(0.00)	(0.00)
Constant	4.018***	4.010***	4.016***
	(0.14)	(0.14)	(0.14)
Month FE	YES	YES	YES
Year FE	YES	YES	YES
ARMA			
L.ar	0.235***		0.187
	(0.03)		(0.12)
L.ma		0.234***	0.052
		(0.04)	(0.13)
sigma			
Constant	0.276***	0.276***	0.276***
	(0.01)	(0.01)	(0.01)
Observations	876	876	876
AIC	290.799	291.657	292.729
BIC	414.958	415.817	421.664

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The lower panel shows the autoregressive moving average lags (ARMA) components.

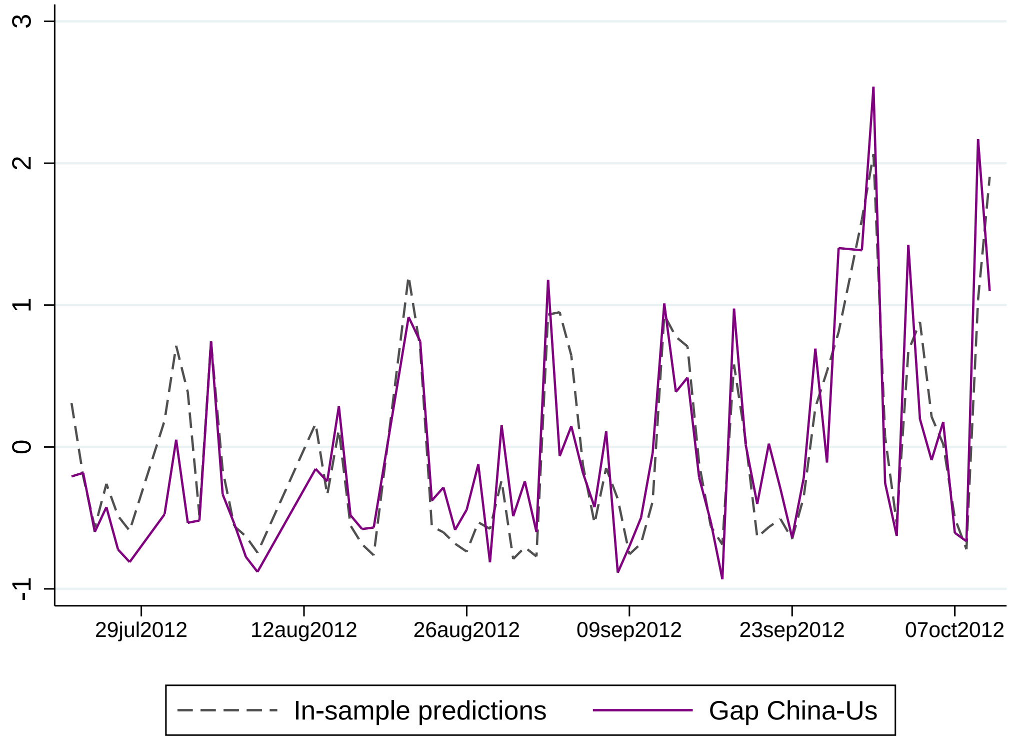


Figure 7: Model performance in predicting the bias

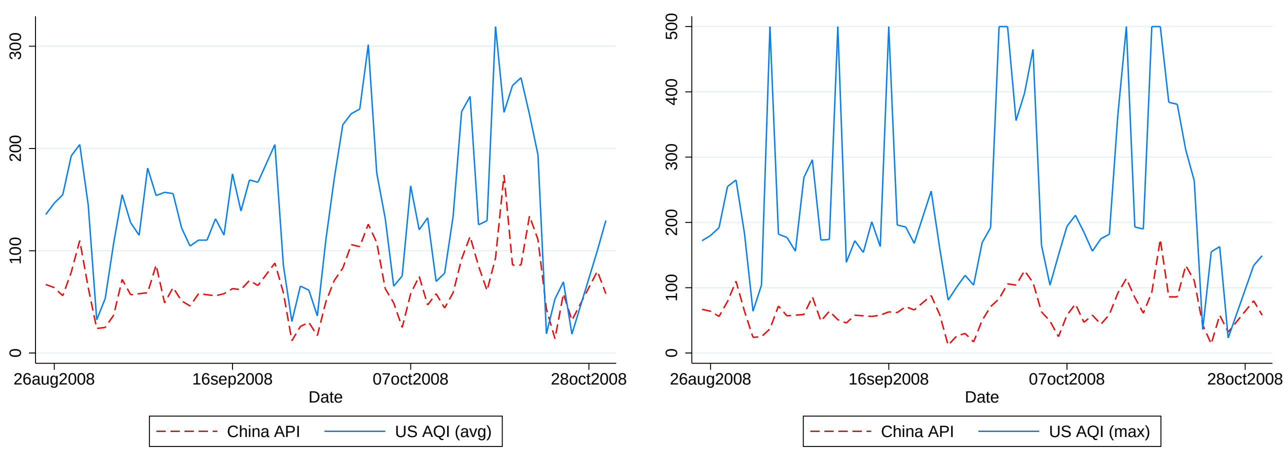


Figure 8: Difference of Chinese API from average and maximum daily values of US index

Table 5: Discrepancy between the Chinese and US Index (daily average)

	Dependent variable: Gap China - US average signal		
	(1)	(2)	(3)
US AQI (avg)	−0.926***	−0.925***	−0.924***
	(0.08)	(0.08)	(0.08)
Avg. AQI above T100	−0.280***	−0.284***	−0.296***
	(0.07)	(0.07)	(0.08)
Avg. AQI above T200	0.384**	0.385**	0.394**
	(0.18)	(0.18)	(0.18)
Avg. AQI above T300	−0.534*	−0.541*	−0.553*
	(0.30)	(0.30)	(0.30)
T100 * Avg. AQI	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)
T200 * Avg. AQI	−0.001*	−0.001*	−0.001*
	(0.00)	(0.00)	(0.00)
T300 * Avg. AQI	0.002*	0.002*	0.002*
	(0.00)	(0.00)	(0.00)
Constant	3.754***	3.749***	3.745***
	(0.35)	(0.35)	(0.35)
Month FE	YES	YES	YES
Year FE	YES	YES	YES
ARMA			
L.ar	0.146***		−0.345*
	(0.03)		(0.20)
L.ma		0.143***	0.482**
		(0.03)	(0.19)
sigma			
Constant	0.244***	0.244***	0.244***
	(0.00)	(0.00)	(0.00)
Observations	876	876	876
AIC	72.629	73.187	75.427
BIC	196.788	197.347	204.362

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The lower panel shows the autoregressive moving average lags (ARMA) components.

Table 6: Discrepancy between the Chinese and US Index (daily maximum)

Dependent variable: Gap China - US maximum signal			
	(1)	(2)	(3)
US AQI (max)	−1.030***	−1.033***	−1.033***
	(0.11)	(0.11)	(0.11)
Max. AQI above T100	−0.522***	−0.522***	−0.529***
	(0.15)	(0.15)	(0.15)
Max. AQI above T200	0.226	0.223	0.236
	(0.20)	(0.21)	(0.20)
Max. AQI above T300	0.387**	0.382**	0.389**
	(0.17)	(0.17)	(0.17)
T100 * Max. AQI	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)
T200 * Max. AQI	−0.001	−0.001	−0.001
	(0.00)	(0.00)	(0.00)
T300 * Max. AQI	−0.001*	−0.001*	−0.001*
	(0.00)	(0.00)	(0.00)
Constant	4.037***	4.049***	4.057***
	(0.47)	(0.46)	(0.48)
Month FE	YES	YES	YES
Year FE	YES	YES	YES
ARMA			
L.ar	0.237***		0.449***
	(0.03)		(0.13)
L.ma		0.211***	−0.227
		(0.03)	(0.14)
sigma			
Constant	0.240***	0.241***	0.240***
	(0.00)	(0.00)	(0.00)
Observations	876	876	876
AIC	49.327	54.807	49.103
BIC	173.486	178.966	178.038

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The lower panel shows the autoregressive moving average lags (ARMA) components.

A2 - Household Survey

Table 7: Private cost of illness

	Direct costs	Days of work lost	Paid sick leave	Days of inactivity	Indirect costs[32]	Total
Airborne diseases	2514 yuan	1.4	0.5	9	812 yuan	3326 yuan
All illnesses	5184 yuan	18	13	53	305 yuan	5489 yuan

Table 8: Characteristics of averting behaviours

	Frequency	Observations
Everyday's life		
Cancel outdoor activities	58%	1621
Change means of transportation	6%	1602
Wear a mask	11%	1618
Peak pollution times		
Cancel outdoor activities	77%	1240
Change means of transportation	12%	1231
Wear a mask	18%	1245
Change of behaviour		
Reduce time outdoor	23%	1239
Transport change	5%	1224
Mask	9%	1238
Other behaviours		
Preventive health checks	73%	1626
Air purifier	23%	1639

[32]Non-medical costs (wage loss) are computed multiplying the wage by the days at home, net of those covered by sick-leave: wage $\times$ (days lost - sick leave).

Table 9: Information about air pollution

What is the main source of information about air pollution you use?		What did you do after the peak pollution days last year?	
Government sources (TV, radio, newspapers)	77 %	Nothing	39%
Internet (PC or mobile device)	6 %	I started worrying more about air pollution	25%
Self-perception, other people	17 %	I look for more information	9%
Doesn't care	0.1 %	I worry more about air pollution and look for more information about it	27%

Table 10: Sources of Information

	Government media	Govt vs. Internet	Govt vs. Self-perception	Internet[33]
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

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[33] For the first three columns we use a logit specification. For the determinants of internet, since the occurrence of a positive value is quite rare, we use a complementary log-log specification to account for the asymmetric nature of the dependent variable (Hilbe, 1996).

Table 11: Self-protective Behaviours and Information (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)	
	Government media			
Λ - 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.

Table 12: Self Protective Behaviours and Information (IV-Probit)

	Outdoor Δ	Mask Δ	TransportΔ	Health checks	Air purifier
Government media	−2.25***	−2.74***	−2.01*	−1.42	1.79
	(0.86)	(0.44)	(1.06)	(1.23)	(1.29)
Smoker	−0.21*	−0.40**	0.04	−0.20*	0.08
	(0.11)	(0.17)	(0.15)	(0.12)	(0.12)
Worker	−0.01	0.31*	0.22	−0.06	0.15
	(0.13)	(0.19)	(0.21)	(0.14)	(0.16)
Children	0.03	0.11	−0.37*	0.22	0.57**
	(0.16)	(0.19)	(0.21)	(0.17)	(0.27)
Household Income	0.04	−0.21	−0.77	2.67**	1.31
	(1.00)	(0.82)	(1.21)	(1.12)	(0.82)
Car			0.63***		
			(0.19)		
	Government media				
Smoker	−0.06**	−0.05*	−0.06**	−0.05*	−0.05*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Worker	0.02	0.02	0.03	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Children	−0.05	−0.04	−0.08*	−0.03	−0.03
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Household Income	−0.16	−0.16	−0.33	−0.08	−0.08
	(0.26)	(0.27)	(0.29)	(0.23)	(0.23)
Λ - Sufficient info	0.08**	0.08**	0.09**	0.08**	0.08**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Car			0.10***		
			(0.04)		
athrho	0.82	1.22**	0.76	0.47	−0.76
	(0.54)	(0.52)	(0.59)	(0.50)	(0.64)
lnsigma	−1.12***	−1.12***	−1.13***	−1.11***	−1.11***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Street Controls	Yes	Yes	Yes	Yes	Yes
Observations	1103	1103	1093	1353	1356
Wald Test p value	0.13	0.02	0.20	0.34	0.24

Clustered standard errors in parentheses (household). $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$