

Beliefs, Information Trust, and Air Pollution

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- However, disclosed information is often imperfect
- Agents rely on their beliefs to fill information gaps and make decisions:
 - officially disclosed information
 - validity of the data → **information quality**
 - reliance on official information vs. external sources → **information trust**
- **Questions:**
 - To what extent do agents rely on official disclosures?
 - How much do agents value information quality?

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World Bank : 300 – 500m

Australia : 500m

Japan : 200m

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[1] “Areas within 10 kilometers of large waste incineration plants are contaminated with dioxins, posing significant health risks, especially to children.”

[2] “The old waste incineration plant was built less than 20 kilometers from residential areas. How can 350,000 residents live under such conditions?”

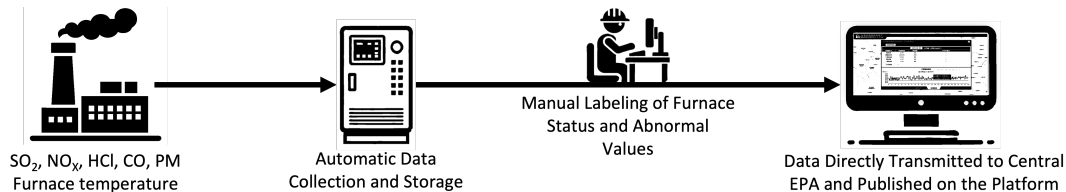
[3] “Qionghai City plans to build an incineration plant within 3 kilometers of residential areas... Could the government consider relocating it to an uninhabited area 20 kilometers away?”

This Paper: Waste Incineration and Housing Location Choices

- **Novel Setting - China:**

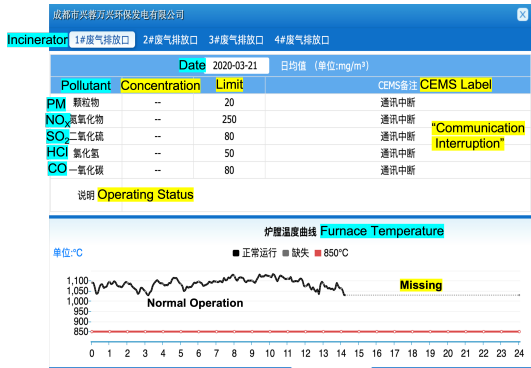
- largest number of waste-to-energy plants (918 plants, 2056 incinerators)
- first nationwide platform for WtE pollution disclosure (since Jan 2, 2020)
- plant details, **daily incinerator-level emission records**, **labels for abnormal records**

- By 2021, the platform had recorded over **60 million** visits

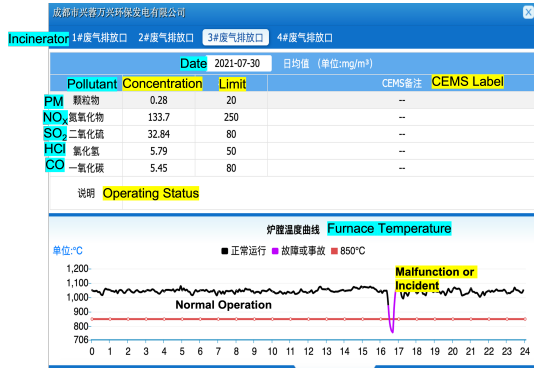


This Paper: Waste Incineration and Housing Location Choices

The data is not always valid: **15%** of daily records exhibit flaws



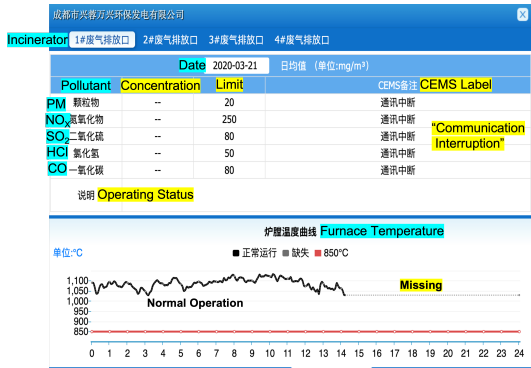
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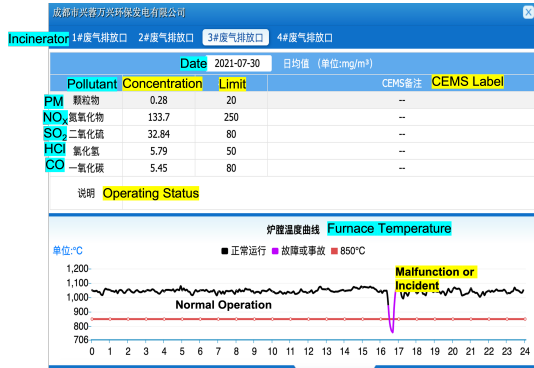
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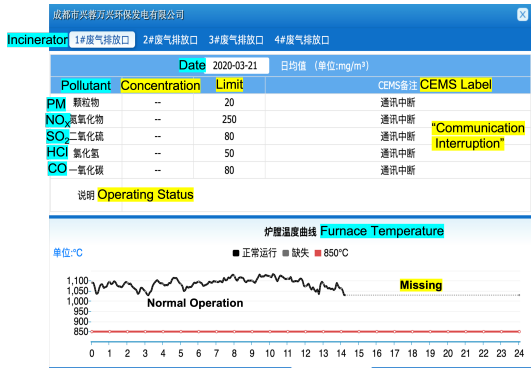


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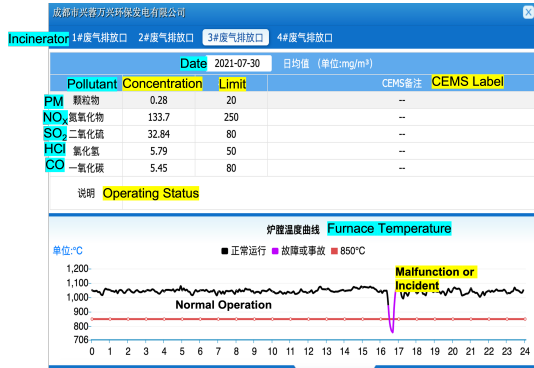
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⇒ Despite strict regulations, a few plants still falsely label to hide over-emissions

⇒ Household beliefs about emission should reflect interpretations of pollution levels

Estimate the beliefs using a Residential Sorting Model

- *Main ingredients:*
 - Household belief about plant emissions, influenced by information quality
 - $U(\text{Pollution at house } k, \text{Consumption, Housing services})$, budget constraint
- *Step 1:* Map plant emissions to pollution levels at all house locations
Gaussian plume model: perceived emissions $\rightarrow$ perceived pollution at house k
- *Step 2:* The expected indirect utility V_k
 - Integrate U w.r.t. belief $\rightarrow$ expected utility
 - Maximize w.r.t. consumption and housing services at house $k \rightarrow V_k$
- *The observation level:* Household chooses houses which maximizes V_k
 - $\Rightarrow$ a discrete choice model
 - $\Rightarrow$ ML estimation of parameters

Empirical Methodology - Emissions Beliefs

- **Overall emissions:** Pollution Index combining pollutants and furnace temperature.

$$\begin{array}{lcl} \log Q & \xrightarrow{\text{valid}} & [\log Q^o + \varepsilon^o] \sim \mathcal{N}(\log Q^o, \sigma_o^2) \\ & \xrightarrow{\text{flawed}} & \log Q^u \sim \mathcal{N}(\mu_u, \sigma_u^2) \end{array}$$

- **Assumption:** no systematic (log) bias in beliefs when records are valid
 - manipulating data is costly and difficult (Greenstone et al., 2022)
 - government values public reporting of emissions violations (Buntaine et al., 2024)
- $\Rightarrow \log Q^o = \text{average of valid records over the preceding 30 days}$

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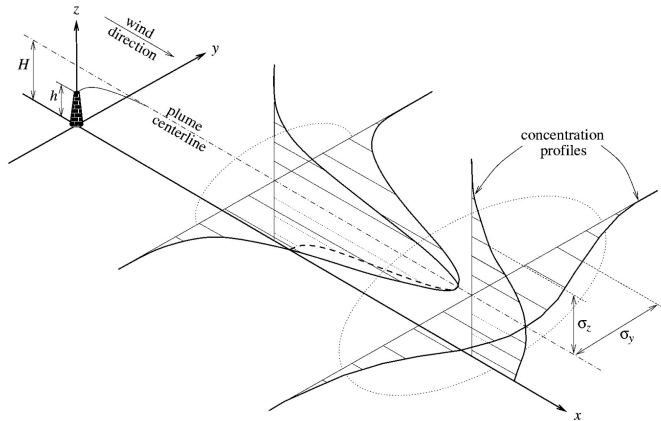
- **Information quality:** valid rate in the reference period (Info)

$$\log Q = \text{Info} \cdot [\log Q^o + \varepsilon^o] + (1 - \text{Info}) \cdot \log Q^u$$

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Empirical Methodology - Gaussian Plume Model



Source: Stockie (2011)

$$\kappa(x, y, 0) = \frac{Q}{W} \exp[f(d)]$$

- W : wind speed
- $f(d)$:
decays with plant-house distance d ,
affected by angle relative to wind
direction θ
- W, θ : weighted by frequency in
the downwind region ▶ wind

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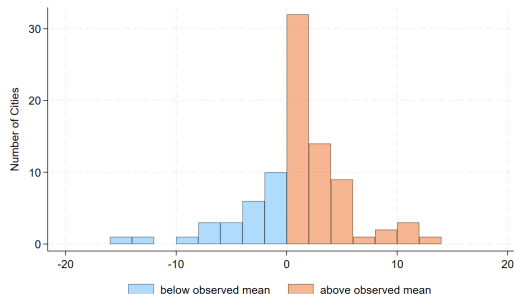
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Main Data Sources

- **Emissions from WtE Plants (2020-2022):**
 - plant details: geo-location, capacity, and start date
 - [daily] concentrations of five pollutants + [every five minutes] furnace temperature
 - 918 plants, totaling 2,056 incinerators by 2022
- **Secondhand house sales and listed properties in 92 cities:**
 - collected from *Beike*: largest platform for integrated online and offline real estate transactions and services in China
 - include list prices, supply dates, transaction prices and dates, locations, and characteristics (e.g., surface area, floor level, green space ratio)
 - 6 million
- **Household income: county-level**
 - per capita disposable income $\times$ average household size
 - 2021–2023 city-level statistical yearbooks and the 2020 Population Census.

Results - Pollution Beliefs and Information Trust

City-level divergence in pollution beliefs: $\hat{\Delta}_{\mu_u} = \hat{\mu}_u - \overline{\log Q^o}$

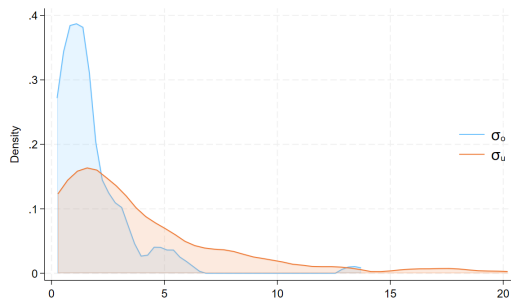


- 67/92 cities: perceive pollution as higher under flawed records
- **43** cities: statistically significant over-perceptions at the 5%

⇒ **“over-perception” cities**

Results - Pollution Beliefs and Information Trust

City-level uncertainty in pollution perceptions: $\hat{\sigma}_u$ and $\hat{\sigma}_o$



- uncertainty exists even with reliable information
 - $\hat{\sigma}_o$: concentrated around smaller values
 - $\hat{\sigma}_u$: broader with a larger mean
- greater uncertainty in the absence of valid records

Results - Potential sources of “over-perception”

- **Plant manipulation**

- external sources of *PM*_{2.5}
- compare days with flawed records with surrounding days
 - ⇒ No clear evidence of manipulation in over-perception cities

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- **Fundamental distrust**

- socio-economic and political factors
 - ⇒ Over-perception cities: ↑ NIMBY protests, ↓ local leadership, ↓ fines etc.

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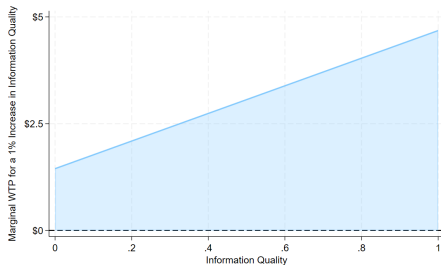
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- Divergence level: negatively correlated with long-term information quality

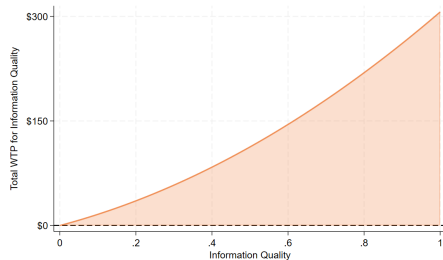
- ⇒ Information trust

Results - Willingness-to-Pay for Information Quality

$$\text{MWTP}_{i,k} = \frac{\frac{\partial V}{\partial \text{Info}}}{\frac{\partial V}{\partial M}} = \underset{\substack{\downarrow \\ 0.51}}{r_k^{dw}} \frac{\beta_Q (\mu_u - \log Q_k^o) - r_k^{dw} \beta_Q^2 \sigma_u^2 + r_k^{dw} \beta_Q^2 (\sigma_o^2 + \sigma_u^2) \text{Info}_k}{\beta_C + \beta_H} \underset{\substack{\downarrow \\ \$18,752}}{M_{i,j(k)}}$$



(a) MWTP for 1% Increase in Info

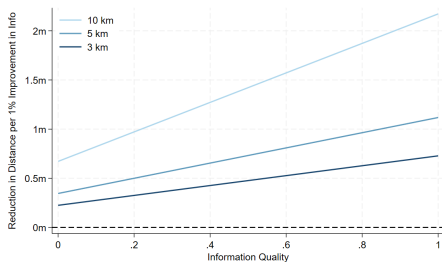


(b) TWTP

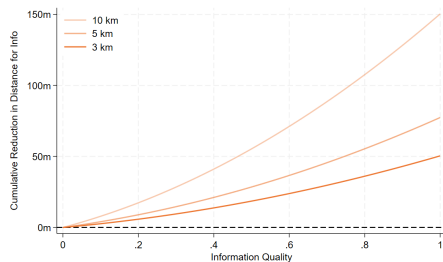
⇒ MWTP for current level (0.85) = **\$1.23** → TWTP for increasing to 1 = **\$19.54**

Results - Substitution Effects Between Info and Distance

$$|\text{MRS}_{d,\text{Info}}| = \frac{\frac{\partial V}{\partial \text{Info}}}{\frac{\partial V}{\partial d}} = \frac{\beta_Q \cdot (\log Q^o - \mu_u) + r^{dw} \cdot \beta_Q^2 \cdot [\sigma_u^2 - (\sigma_o^2 + \sigma_u^2) \cdot \text{Info}]}{\beta_d \cdot f^{(1)}(d)}$$



(a) MRS for 1% Increase in Info



(b) Cumulative Substitution Effects

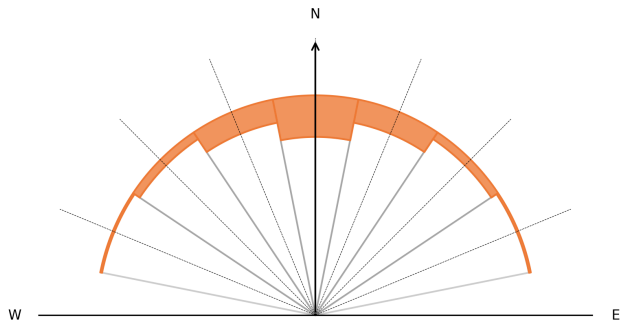
⇒ if located exactly 5 km downwind from the plant

MRS for current level (0.85) = 1.06m → CSE for increasing to 1 = 16.82m

Results - Substitution Effects Between Info and Distance

If wind consistently blows true north, for houses 5 km from the plant

⇒ reduction in surface area = $86,648 \text{ m}^2$



Inward Shift Under Improved Info

Conclusion

- **Main results**

- Flawed records increase perceived pollution and uncertainty, even with technical explanations
- Distrust is rooted more in institutional factors than in deliberate manipulation by plants
- Degrading information quality generates sizable economic costs

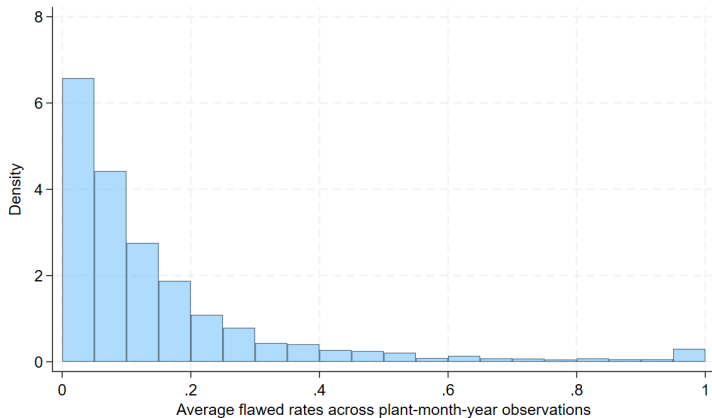
- **Implications**

- Households do not take disclosures at face value
- Poor-quality records can erode trust and weaken, or even reverse, intended policy effects

References I

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Empirical Methodology - Emissions Beliefs



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