# Discrete Choice and the Demand for Clean Air

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Discussion Paper 1

Willingness to Pay for Clean Air:

Evidence from Air Purifier Markets in China

Koichiro Ito and Shuang Zhang

# Motivation

- Valuation of non-market goods (and air quality in particular) is challenging but important.
- In the prior literature that investigates how people value air quality improvements, hedonic papers have focused on housing markets.
- Ito and Zhang (2019) take a different approach: analyze WTP for defensive investments in air purifiers in China.
- An interesting setting in which air pollution reductions are a salient attribute.
- Provide the first (?) revealed preference estimates of WTP for clean air in an emerging economy.

# Summary

- China is a very important setting to understand: High levels of air pollution and relatively low levels of investment in abatement.
- Primary challenge: Two key variables (pollution and price) are likely endogenous.
- Exploit a discontinuity in heating policy along China's Huai River to isolate quasi-random variation in air quality.
- Examine purchases of HEPA air filters north and south of river
- Estimate MWTP for reducing air pollution by 1 unit of PM10 for 1 year is about 1.34 USD per household (interpret this as a lower bound)

# Great (market level) data!!

- At the retail store level, collect product-level information on monthly sales, monthly average price, and detailed product attributes over January 2006 through December 2014.
- The product attributes include the information on each purifier's effectiveness to reduce indoor air pollution.
- Comprehensive transaction records of 690 air purifier products sold by 45 firms. Aggregate to the product-city level.
- Pollution data from air pollution monitors 2006-2014.
- Demographic data from the Chinese census (income, education, home size, et).

# Endogeneity concerns?

- Air pollution: Use a spatial regression discontinuity design which exploits discontinuous valuation in air pollution created by a policy-induced natural experiment at the Huai River boundary.
  - Provided city-wide coal-based heating for cities north of the river, which generated substantially higher pollution levels in the northern cities (Almond et al., 2009; Chen et al., 2013).
  - The policy-induced variation in air pollution has existed since the 1950s: long-lasting variation in pollution.

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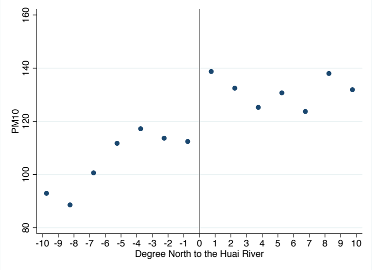
Figure 1: Huai River Boundary and City Locations

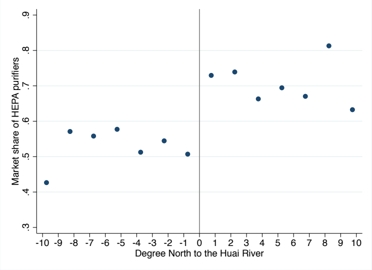

Notes: The line in the middle of the map is the Huai River-Qinling boundary. Each dot represents one city. There are 81 cities in our sample.

Figure 2: Regression Discontinuity Design at the Huai River Boundary

(a) PM10 in Winter




(b) Market Share of HEPA Purifiers in Winter




Note: Figure 2a plots the average $PM_{10}$ during winter (December to March) in 2006 to 2012 by 1.5 degrees of latitude north of the Huai River boundary. The vertical line at 0 indicates the location of the Huai river. Each dot represents cities at 1.5 degrees of latitude and corresponds to the middle point of the range on the x-axis. For example, the dot at 0.75 on the x-axis represents cities between 0 and 1.5 degrees of latitude

# Empirical strategy

- **Air pollution**: Spatial discontinuity because of the Huai River Policy. Observe the same product sold in regions with high versus low air pollution.
- **Purifier prices** are likely to be endogeneous (correlated with demand shocks/unobserved quality):
  - Include product and city fixed effects. But we might still worry if product-city unobservables are correlated with product-city prices
  - IV: Distance from each product's manufacturing plant (or its port if the product is imported) to each market captures variation in the transportation cost (supply-side price shifter).

# Demand for air purifiers

Consider that consumer $i$ in city $c$ has ambient air pollution $x_c$ (particulate matter). The consumer can purchase air purifier $j$ at price $p_{jc}$ to reduce indoor air pollution by $x_{jc} = x_c \cdot e_j$. We denote purifier $j$'s effectiveness to reduce indoor particulate matters by $e_j \in [0, 1]$. We observe markets for $c = 1, ..., C$ cities with $i = 1, ..., I_c$ consumers. The conditional indirect utility of consumer $i$ from purchasing air purifier $j$ at city $c$ is:

$$u_{ijc} = \beta_i x_{jc} + \alpha_i p_{jc} + \eta_j + \lambda_c + \xi_{jc} + \epsilon_{ijc}, \tag{1}$$

where $x_{jc}$ is the improvement in indoor air quality conditional on the purchase of product $j$, $p_{jc}$ is the price of product $j$ in market $c$, $\eta_j$ is product fixed effects that capture utility gains from unobserved and observed product characteristics, $\lambda_c$ is city fixed effects, $\xi_{jc}$ is a product-city specific demand shock, and $\epsilon_{ijc}$ is a mean-zero stochastic term. $\beta_i$ indicates the marginal utility for clean air, and $\alpha_i$ indicates the marginal disutility of price. The functional form for the utility function assumes that each variable, including the error term, enter the utility function linearly.

# Market definition?

- Air purifiers last for 5 years and require periodic filter replacement.
- Authors have panel data, but the identifying variation is in the cross-section (air quality across region).
- So... they define markets in the cross-section (city)
- Market size = number of households in a city.
- Sum sales over 9 years of data and multiply by 5/9.
- Market share of outside option: $s_{0c} = 1 - \sum_j s_{jc}$.

# Empirical strategy

- Authors use a standard logit formulation and a random parameter logit formulation that allows heterogeneity in preferences for pollution and price.
- They can use the ratio of parameters on price and air pollution to estimate the WTP for an incremental improvement in air quality.
- Where is the identifying variation coming from?

# Standard logit

We begin with a standard logit model. Suppose that $\beta_i = \beta$ and $\alpha_i = \alpha$ for all consumer $i$ and that the error term $\epsilon_{ijc}$ is distributed as a Type I extreme-value function. Consumer $i$ purchases purifier $j$ if $u_{ijc} > u_{ikc}$ for $\forall k \neq j$. Then, the market share for product $j$ in city $c$ can be characterized by[8]

$$s_{jc} = \frac{\exp(\beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc})}{\sum_{k=0}^{J} \exp(\beta x_{kc} + \alpha p_{kc} + \eta_k + \lambda_c + \xi_{kc})}. \quad (2)$$

The outside option ($j = 0$) is not to buy an air purifier. We make a few assumptions to construct

Note how air quality improvements are modeled here:

- $x_{jc}$ is the air quality improvement associated with choice $j$ in city $c$.
- HEPA filters reduce PM by 99%. Non-HEPA do not remove small PM (but do remove VOCs and other)
- Thus, $x_{jc} = x_c \cdot HEPA$ .

# The Berry transformation (simple conditinal logit version)

Within the simple logit, share equations are easily manipulated (and estimating equations are now linear equations!)

Because $\ln s_{0c} = -\ln\left(\sum_{k=0}^{J}\exp(\beta x_{kc} + \alpha p_{kc} + \eta_k + \lambda_c + \xi_{kc})\right)$, the difference between the log market share for product $j$ and the log market share for the outside options is $\text{ln}s_{jc} - \text{ln}s_{0c} = \beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc}$., as shown by Berry (1994). Since $\ln s_{0c}$ is absorbed by city fixed effects, this equation is simplified to:

$$\text{ln}s_{jc} = \beta x_{jc} + \alpha p_{jc} + \eta_j + \lambda_c + \xi_{jc}, \tag{3}$$

where $\beta$ is the marginal utility for improvement in air quality, and $\alpha$ is the marginal disutility for price. The marginal willingness to pay (MWTP) for one unit of indoor air pollution reduction can be obtained by $-\beta/\alpha$.

# Identification recap (logit model)

$$lns_{jc} = \beta x_c H_j + \alpha p_{jc} + \eta_j +_c +\xi_{jc}$$

- Product FE absorb observed/unobserved non-price attributes
- City FE absorb city-level demand shocks.
- Identify $\beta$ off of the cross-city variation in air pollution.
- Identify $\alpha$ because prices vary across cities.
- Instrument for pollution and prices.

# Random parameter logit model

- Simple logit leads to a linear estimating equation. Great!
- But CL does not accommodate random variation in preferences/tastes.
- Random coefficient logit supports this preference heterogeneity...but involves non-linear estimation.
- Allow $\beta$ and $\alpha$ to vary in the population.

$$\beta_i = \beta_0 + \beta_1 y_i + u_i$$

$$\alpha_i = \alpha_0 + \alpha_1 y_i + \epsilon_i$$

# Predicted market shares now more complicated

$\mu_{jci} = (\beta_1 y_i + u_i)x_{jc} + (\alpha_1 y_i + e_i)p_{jc}$. Then, the market share for product $j$ in city $c$ can be evaluated using Monte Carlo integration assuming a number $n_c$ of individuals for city $c$ by:[10]

$$s_{jc} = \frac{1}{n_c}\sum_{i=1}^{n_c} s_{jci} = \frac{1}{n_c}\sum_{i=1}^{n_c} \frac{\exp(\delta_{jc} + \mu_{jci})}{\sum_{k=0}^{J} \exp(\delta_{kc} + \mu_{jki})}. \tag{5}$$

The important difference between equations (2) and (5) is that equation (5) now includes elements that vary by $i$. Therefore, the market share and $\delta_{jc}$ has to be calculated numerically by the fixed point iterations: $\delta_{.c}^{h+1} = \delta_{.c}^{h} + \ln S_{.c} - \ln s_{.c}$ for $h = 0, ..., H$ in which $s_{.c}$ is the predicted market share by equation (5) and $S_{.c}$ is the observed market share from the data. Once $\delta$ is obtained, $\xi_{jc}$

# Some methodological notes

- Random coefficient model requires non-linear estimation based on numerical optimization.
- Good practice to assess robustness to different starting values and search algorithms. These authors estimate 600 alternatives.
- Report tolerance levels for NFP iterations etc.

# WTP for clean air?

- Estimating equations support the estimation of $\beta$ and $\alpha$.
- The estimate of $\frac{-\beta}{\alpha}$ provides a lower bound on WTP...why?
- Limited understanding of the costs of air pollution exposure?
- Indoor air quality improvements are not the same as outdoor air quality improvements.
- Other avoidance behaviors possible.

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# Logit results (2SLS)

Panel B: Second stage of the RD design

| | Dependent variable: ln(market share) | |
|---|---|---|
| | (1) | (2) |
| PM10*HEPA ($\beta$) | 0.0299*** | 0.0302*** |
| | (0.0030) | (0.0032) |
| Price ($\alpha$) | -0.0048*** | -0.0048*** |
| | (0.0001) | (0.0001) |
| Observations | 7,359 | 7,359 |
| First-stage F-Stat | 285.16 | 292.01 |
| Control function for running variable | Linear*North | Quadratic |
| MWTP for 5 years (-$\beta/\alpha$) | 6.2077*** | 6.3100*** |
| | (0.6649) | (0.7130) |
| MWTP per year | 1.2415*** | 1.2620*** |
| | (0.1330) | (0.1426) |

Note: Panel A shows results for the reduced-form estimation in equation (8). All regressions include product fixed effects, city fixed effects, and longitude quartile fixed effects interacted with HEPA. Price is instrumented with the distance variables discussed in the text. Panel B shows results for the second-stage estimation in equation (9). PM10*HEPA and Price are instrumented with North*HEPA and the distance variables discussed in the text. We use the two-step linear GMM estimation with the optimal weight matrix. Standard errors are clustered at the city level. * significant at 10% level; ** significant at 5% level; *** significant at 1% level. We also report the Kleibergen-Paap rk Wald F-statistic. The Stock-Yogo weak identification test critical value for one endogenous variable (10% maximal IV size) is 16.38, and for two endogenous variables (10% maximal IV size) it is 7.03.

# Random Parameter Logit

Table 7: Random-Coefficient Logit Estimation Results

| Dependent variable: ln(market share) | | |
|---|---|---|
| | (1) | (2) |
| PM10 · HEPA | | |
| Mean coefficient ($\beta_0$) | 0.0459*** | 0.0498*** |
| | (0.0084) | (0.0092) |
| Interaction household income ($\beta_1$) | 0.0924*** | 0.0891*** |
| | (0.0224) | (0.0253) |
| Standard deviation ($\sigma_\beta$) | 0.0323*** | 0.0570*** |
| | (0.0117) | (0.0119) |
| Price | | |
| Mean coefficient ($\alpha_0$) | -0.0069*** | -0.0071*** |
| | (0.0007) | (0.0007) |
| Interaction with household income ($\alpha_1$) | 0.0028** | 0.0028** |
| | (0.0011) | (0.0011) |
| Standard deviation ($\sigma_\alpha$) | 0.0006 | 0.0005 |
| | (0.0007) | (0.0007) |
| Observations | 7,359 | 7,359 |
| Control function for running variable | Linear*North | Quadratic |
| GMM objective function value | 375.05 | 378.93 |
| MWTP per year: 5th percentile | 0.38 | 0.07 |
| MWTP per year: 10th percentile | 0.49 | 0.20 |
| MWTP per year: 25th percentile | 0.75 | 0.53 |
| MWTP per year: 50th percentile | 1.19 | 1.10 |
| MWTP per year: mean | 1.34 | 1.41 |
| MWTP per year: 75th percentile | 1.90 | 2.04 |
| MWTP per year: 90th percentile | 2.92 | 3.45 |
| MWTP per year: 95th percentile | 3.86 | 4.69 |

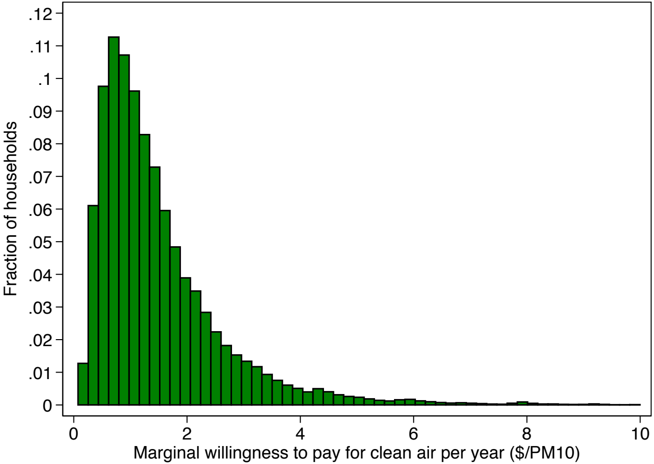
Note: This table shows the results of the random-coefficient logit estimation in equation (6). All regressions include product fixed effects, city fixed effects, and longitude quartile fixed effects interacted with HEPA. Column 1 uses a linear control for the running variable interacted with the North dummy variable, and column 2 uses a quadratic control for the running variable. Asymptotically robust standard errors are given

# Implications?

- Use random-coefficient logit estimation results to calculate the mean/median of MWTP: USD \$ 1.19 \$1.34 .
- Estimates imply that a northern household is willing to pay USD \$32.70 per year to avoid the pollution increases induced by the Huai River policy.
- They can also calculate hh level MWTP as $-(\beta_0 + \beta_1 y_i + u_i)/(\alpha_0 + \alpha_1 y_i + \epsilon_i)$

# Distribution of MWTP?

Figure 3: Distribution of Marginal WTP for Clean Air




Note: This histogram is based on the random-coefficient logit estimation results in column 1 of Table 7 and household-level annual income from the 2005 census micro data.

# Policy implications

Table 8: Policy Implications

| | | |
|---|---|---|
| Panel A: Policy-relevant MWTP measures (\$ per 1 ug/m$^3$ annual reduction in $PM_{10}$) | | |
| | Household-level (\$) | Aggregate (\$) |
| In-sample estimate (from Table 7) | 1.34 | |
| Seven northern cities | 1.62 | 10.13 million |
| Nationwide | 1.26 | 0.45 billion |
| Panel B: Cost-benefit analysis: Heating reform in seven northern cities | | |
| Abatement cost (million \$) | 2.25 | |
| Estimated $PM_{10}$ reduction (ug/m$^3$) | 11.91 | |
| Total WTP (million \$) | 105.07 | |
| Benefit-cot ratio | 46.70 | |
| Panel C: Cost-benefit analysis: Replacement of coal power plants by wind or natural gas | | |
| | Wind | Natural gas |
| Estimated $PM_{10}$ reduction (ug/m$^3$) | 0.56 | 0.46 |
| Total WTP (billion \$) | 0.26 | 0.21 |
| MWTP for replacing coal-based electricity (\$/MWh) | 17.9 | 14.5 |

Note: This table shows policy-relevant MWTP measures and the cost-benefit analysis of two policies discussed in Section 6.

# Comments and considerations?

Discussion Paper 2

White Flight and Coming to the Nuisance

Can Residential Mobility Explain Environmental Injustice?

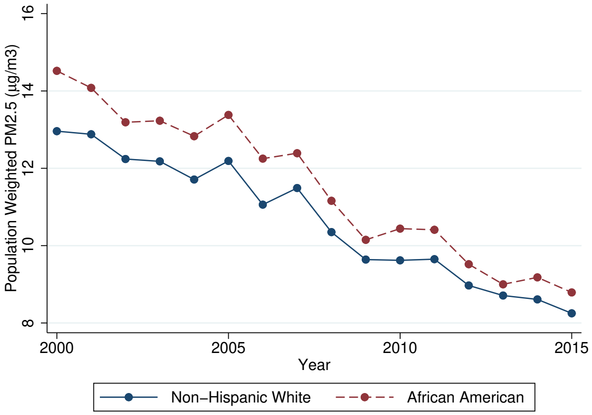
Depro et al.

# Disproportionate impacts of environmental risk/harm

- Early and influential studies by the General Accounting Office (1983) and the United Church of Christ (1987) demonstrated that poor and minority communities were disproportionately exposed to hazardous waste in many parts of the United States.
- Subsequent work in sociology, geography, public health documents an environmental risk exposure gap: e.g. Bullard (1994), Cole and Foster (2001), Bowen (2002), Mohai, Pellow, and Roberts (2009), London et al (2008).
- More recent work has documented variation in exposure to local air pollution, leveraging advances in remote sensing and local air quality modeling.

# Exposure to air pollution is unequal

Figure 1: Trends in Pollution Exposure by Race




This figure plots population-weighted average PM2.5 exposure by year separately by race.

Source: Currie et al. 2020.

# What is Environmental Justice?

" The fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies.

Fair treatment means that no population, due to policy or economic disempowerment, is forced to bear a disproportionate share of the negative human health or environmental impacts of pollution or environmental consequences resulting from industrial, municipal, and commercial operations or the execution of federal, state, local, and tribal programs and policies."

— EPA Office of Environmental Justice

# How to operationalize EJ concepts?

Policy objectives relating to the reduction of a social inequality or disparity can be hard to formalize/define (Cookson, 2017):

1. **Equality of what?** What is the “distribuendum”. Air pollution? Air pollution improvements? Health outcomes?
2. **Equality between whom?** Is the concern to reduce all variation in health/exposure? Or only that part of the variation that is considered unfair because it is related to a particular social characteristic of interest.
3. **Equality measured how?** Measuring inequality involves summarizing a many-valued distribution in terms of a single scalar inequality index.

The answers to these questions can yield different measures of equity

# What have environmental economists contributed to this conversation?

1. Research that analyzes inequality in exposure to local air pollution in the United States (e.g. Currie et al. 2020).
2. Research that investigates how policy interventions can impact/change patterns of environmental exposure (e.g. Cortes-Hernandes and Meng, 2019)
3. **Research that seeks to understand the role of markets/other mechanisms in generating/perpetuating inequities.**

*There are only two possible processes for explaining present-day disparities: (1) there has been a pattern, at the time of siting, of placing hazardous waste sites, polluting industrial facilities, and other locally unwanted land uses (LULUs) disproportionately in low-income and people of color communities, or (2) demographic changes after siting have led to disproportionately high concentrations of low-income and people of color around hazardous sites. These two processes have been termed respectively as 'disparate siting' and 'post-siting demographic change'. Which of these two processes has occurred, or whether both have, has not been firmly established.*
*Mohai and Saha, 2015*

Why do mechanisms matter?

# Economists have picked up this question and run with it..

Economics literature focuses on three possible explanations:

- Racial discrimination/siting
- Residential sorting
- Discrimination and 'steering' in housing markets?
- Collective action efficacy

Dorceta Taylor urges researchers to 'refine their methods to account for the complexity of EJ issues'.

# What can neighborhood choice tell us about environmental injustice?

> *Economic models of housing demand provide a useful framework for understanding how environmental injustice is related to residential mobility. Each year, more than 30 million people move from one home to another.*
>
> *Depro et al. 2015*

Models of utility-maximizing households trading off housing stock, neighborhood quality, and other (dis)amenities is at the heart of most residential sorting models.

# Estimating preferences (and preference heterogeneity) for environmental quality

- Early empirical work focused on proximity of disadvantaged populations to undesirable land uses (e.g. hazardous waste sites and landfills)
- More recent work focuses on polluting facilities (air and water).
- Analysis of geographically aggregated measures of exposure and neighborhood choice common due to confidentiality/data access considerations.
- Use of aggregated data on exposure presents some challenges....

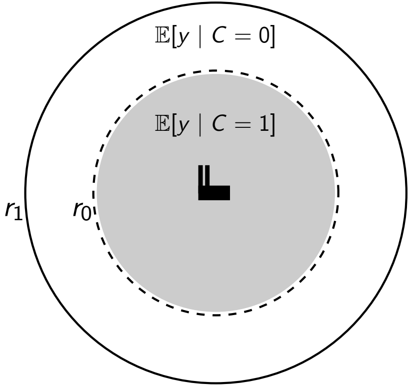
# 'Unit-hazard coincidence'

- Earlier environmental justice studies assumed that the population exposed to a nuisance coincides with those people living in the same geographic unit as the nuisance (e.g. zip code).
- The unit-hazard coincidence method compares the demographic characteristics of host geographic units, such as counties or zip codes, with the characteristics of their respective non-host units.
- Problems?

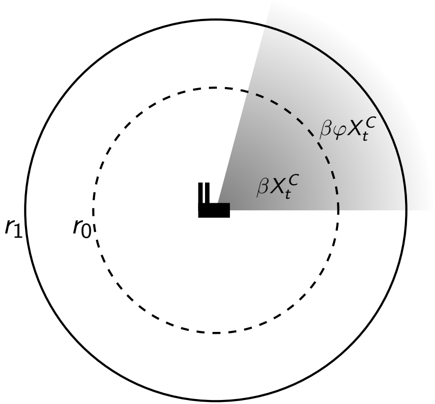
# 'Unit-hazard coincidence'

- Assumes environmental hazard is uniformly distributed within the spatial unit (e.g. county).
- When nuisances are located near geographical boundaries (often!), unit-hazard coincidence ignores exposures in adjacent areas that may be quite close by, while assigning exposure to parts of the coincident geographic unit that may be far from the nuisance
- Because geographic units designed to be similar in population size, standard unit-hazard coincidence assigns smaller exposure areas around urban facilities.

# Pollution is not uniformly distributed around a source!



# Prevailing wind direction



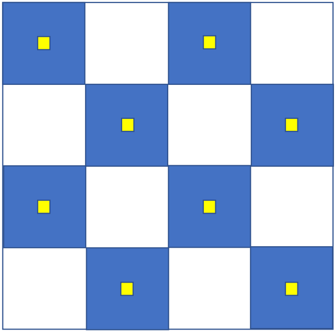

- Distance from source can be a crude proxy for true exposure!

# Ecological fallacy?

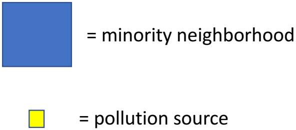
- When measuring the correlation between pollution and demographics, the ‘ecological fallacy’ can arise when inferring relationships between individual units (like households) from larger, more aggregated units (like counties) that contain those units.
- Relationship estimated using aggregate data is only equal to correlations at the micro-level if there are no correlated group-level effects.
- If peer preferences create segregation, positive correlations between race and exposure may be significant at local spatial scales but not at more aggregated scales.

# Ecological fallacy?

Ecological Fallacy: Incorrectly draw conclusions about individual-level behavior from group-level behavior.



Using small geography, pollution perfectly correlated with race.

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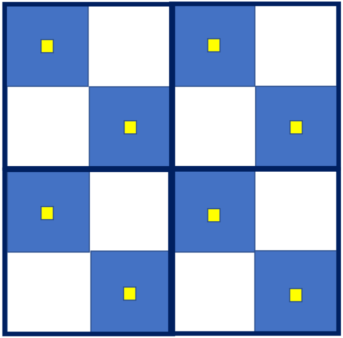
# Ecological fallacy



Using the larger geographical definition, there is no correlation between race and pollution.

# What drives race-income pollution correlations?

- Standard approach:. Following an (exogenous?) change in pollution exposure, look for evidence of 'nuisance-driven' residential mobility.
- A number of studies find little evidence that disadvantaged populations 'come to nuisance' and thus conclude that siting is the issue (e.g. Oakes et al. 1996; Pastor et al. 2001; Morello-Frosch et al. 2002).
- But *changes* in demographics may appear uncorrelated with *changes* in pollution, even if cross-sectional correlations are driven by sorting..

# White Flight and Coming to the Nuisance

- Depro et al (2014) argue that traditional DID empirical models are not actually identified.
- Without additional structure, *individual* sorting behavior cannot be identified using aggregate changes in population flows.
- This paper questions the strength of the prior evidence arguing that siting (versus residential mobility) explains inequalities in exposure.

# An under-appreciated identification problem

Authors argue that geographically aggregated population statistics cannot be used as evidence for or against the hypothesis that people of color 'come to the nuisance'.

- Let $pop_t^j$ measure population in location $j$ in time $t$ (t=A, B).
- Let $P_{jk}$ denote the probability that an individual in location $k$ and period $A$ chooses to reside in location $k$ in period $B$.
- Market dynamics described by the following system of equations:

$$\begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix} \begin{pmatrix} pop_1^A \\ pop_2^A \\ pop_3^A \end{pmatrix} = \begin{pmatrix} pop_1^B \\ pop_2^B \\ pop_3^B \end{pmatrix}.$$

# What's the problem?

$$\begin{pmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,3} \\ P_{3,1} & P_{3,2} & P_{3,3} \end{pmatrix} \begin{pmatrix} pop_1^A \\ pop_2^A \\ pop_3^A \end{pmatrix} = \begin{pmatrix} pop_1^B \\ pop_2^B \\ pop_3^B \end{pmatrix}.$$

- Past work has looked at changes in population of a particular subgroup ($pop_j^B - pop_j^A$). Look at how these changes evolve after a change in environmental risk.
- Elements of the P matrix provide the true measure of how the change in exposure impacts the tendency of a subgroup to make a move.

# Traditional Models of Residential Mobility are not Identified

- The elements of the $P$ matrix provide a measure of how a change in exposure associated with a move affects the tendency of individuals to make that move.
- But the *vector* of changes in how a sub-population is distributed across neighborhoods over time, $\Delta pop_j$ does not identify the elements of this matrix!
- Without additional structure, there is not a one-to-one mapping between the $P_{jk}$ matrix and observed changes in aggregate populations.

# Conventional approach can be misleading

Authors show how very different underlying transition probabilities can generate the same aggregate changes in population shares. Consider a simple example where amenity levels are not changing but populations are moving: $\alpha_1 = 0; \alpha_2 = 0.5; \alpha_3 = 1$. Regress elements of P on the change in amenity:

**Example 1:**

$$\begin{pmatrix} 0.00 & 0.60 & 0.60 \\ 0.50 & 0.25 & 0.20 \\ 0.50 & 0.15 & 0.20 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \quad \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}.$$

Slope coefficient = −0.0583 [0.666] (coming to the nuisance).

**Example 2:**

$$\begin{pmatrix} 0.50 & 0.10 & 0.10 \\ 0.30 & 0.50 & 0.30 \\ 0.20 & 0.40 & 0.60 \end{pmatrix} \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 1.8 \\ 2.2 \\ 2.0 \end{bmatrix} \quad \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix} = \begin{bmatrix} 0.0 \\ 0.5 \\ 1.0 \end{bmatrix}.$$

Slope coefficient = 0.0833 [0.276] (fleeing the nuisance).

# Empirical analysis

- Use National Air Toxics Assessment (NATA) data, historical census tract-level statistics, and other neighborhood attributes (e.g. school quality, crime rates).
- Calculate the correlation between the within-percentages of each race group and NATA cancer risk measures for 1,989 LA census tracts.
- Compare changes in tract-level demographics (racial percentages in particular) over the period 2000-2010 with a variety of 2000 tract attributes (following earlier work).

# Correlation between race and NATA total cancer risk (2000)

Table 2. Correlation between Race and NATA Total Cancer Risk (Year 2000)

| | NATA Cancer | % Asian | % Black | % Hispanic | % White |
|---|---|---|---|---|---|
| NATA cancer | 1.000 | | | | |
| % Asian | .0254 | 1.000 | | | |
| % black | .1156 | −.2249 | 1.000 | | |
| % Hispanic | .3967 | −.3167 | −.0800 | 1.000 | |
| % white | −.4676 | −.0507 | −.3509 | −.7936 | 1.000 |

Note.—NATA = National Air Toxics Assessment.

Table reports correlations between within-tract percentages of each race group and NATA cancer risk for 1989 census tracks in Los Angeles.

# Standard analysis of residential mobility

- Compare changes in tract-level demographics (racial percentages in particular) over the period 2000-2010 with a variety of 2000 tract attributes (following Pastor et al. 2001).
- Consider how changes in racial percentages between 2000-2010 are driven by 2000 tract-level attributes (assuming these are predetermined and uncorrelated with unobservable determinants of migration).
- Control for a host of other neighborhood attributes, racial pre-trends, etc.

# Traditional regression-based strategy

Table 3. Traditional Housing Market Dynamics Model

| | White | | | Hispanic | | |
|---|---|---|---|---|---|---|
| Variable | Baseline | FE Neighborhood | Own-Race Pre-trend | Baseline | FE Neighborhood | Own-Race Pre-trend |
| **NATA total cancer risk** | **7.69e−05*** ** | **4.20E−05** | **6.48e−05*** ** | **−9.84e−05*** ** | **−6.61e−05** ** | **−4.24e−05* ** |
| TRI facilities | −3.07e−04* | −2.48E−04 | −3.13e−04* | −5.19e−04*** | −3.33e−04* | −3.45e−04** |
| API | −7.64E−06 | −1.50e−05* | −8.15E−06 | −1.75e−05** | 2.29E−06 | −6.12E−06 |
| Violent crime rate | 5.04e−06** | 7.85e−06*** | 5.09e−06** | 3.25E−06 | 1.43E−06 | 1.95E−06 |
| Median income | 1.49E−08 | 5.35E−08 | 1.77E−08 | −1.77e−07*** | −1.88e−07*** | −1.86e−07*** |
| % built before 1980 | −1.23e−04*** | −8.02e−05* | −1.14e−04*** | 1.11e−04*** | 4.52E−05 | 8.03E−06 |
| Median home value | 5.54E−09 | 3.05E−10 | 1.87E−09 | 6.41E−09 | 3.62E−09 | 1.61e−08** |
| % detached | −2.54E−05 | −4.89e−05* | −4.07E−05 | −1.70E−05 | 2.34E−05 | 3.85E−05 |
| % under 18 | 5.84E−05 | 1.09E−04 | 1.48E−04 | 6.75e−04*** | 6.36e−04*** | 2.02e−04* |
| % high school dropout | 4.30e−04*** | 4.08e−04*** | 2.94e−04*** | −4.12e−04*** | −4.95e−04*** | −5.40E−05 |
| % college graduate | 1.05E−04 | 1.75E−04 | 2.94E−05 | −3.62e−04*** | −5.41e−04*** | −1.68E−04 |
| % white | 1.45e−02*** | 1.55e−02** | 9.81e−03* | −2.05e−02*** | −3.10e−02*** | −6.41E−03 |
| % Asian | 6.47e−02*** | 6.67e−02*** | 6.49e−02*** | −1.25e−02** | −2.60e−02*** | 4.98E−03 |
| % black | 6.50e−02*** | 6.60e−02*** | 5.91e−02*** | 6.18E−03 | −1.09e−02* | 1.74e−02*** |
| Δ% white (1990–2000) | | | 2.47e−02*** | | | |
| Δ% Hispanic (1990–2000) | | | | | | 9.67e−02*** |
| Constant | −5.10e02*** | −4.98e−02*** | −4.13e−02*** | 5.90e−02*** | 6.17e−02*** | 3.34e−02*** |
| *N* | 1,989 | 1,989 | 1,989 | 1,989 | 1,989 | 1,989 |

Note.—Cancer risk = Total cancer risk, NATA 2005 read *X* in a million; violent crime = violent crime rate per 100,000 inhabitants, three nearest areas to centroid 2005; TRI facilities = average number of facilities with TRI emissions 2004–6 within 1 mile tract buffer; API = CA Academic Performance Index, API Base, three nearest elementary schools to centroid in 2005. FE = fixed effects.

**Traditional EJ residential mobility analysis compares changes in aggregate tract-level demographics with pre-period attributes (e.g. Pastor et al. 2001)**

# Implications?

- These authors find that increasing NATA risk from lowest to highest value in 2000 increases white share in the census tract by 4%. Hispanic share *decreases*.
- Appears inconsistent with the residential mobility hypothesis.
- One interpretation? Minorities are not coming to the nuisance. Earlier papers thus conclude disproportionate siting must be driving correlation between cancer and race.

# BLP meets neighborhood choice

- Basic idea: use a RUM model with a spatial analog to the BLP instruments to explain observed choices among individual houses or housing types
- Given prices and house/neighborhood characteristics, each household makes the location choice that maximizes its utility.
- Utility-maximizing choice is determined by preferences for observed housing characteristics and idiosyncratic preferences.
- Derive choice probabilities using the RUM framework (and logit assumptions) Choose parameters that match choice probabilities to market shares.

# Structural model of neighborhood dynamics

To better understand the preferences underlying neighborhood dynamics, impose more structure:

$$pop_j^B = \sum_{k=1}^{N} P_{j,k} pop_k^A. \tag{4}$$

Next, specify the mean utility from living in location $k$ ($\delta_k$) as a function of observable attributes of that location ($X_k$), a scalar attribute that is unobserved by the econometrician ($\xi_k$), and a vector of parameters ($\beta$):

$$\delta_k = f(X_k, \xi_k; \beta). \tag{5}$$

The utility an individual $i$ receives from living in location $k$ is given by

$$U_{i,k} = \delta_k + \eta_{i,k}, \tag{6}$$

where $\eta_{i,k}$ refers to the idiosyncratic utility specific to that individual and location. The change in utility an individual $i$ currently living in location $k$ receives from moving to location $j$ is therefore given by

$$U_{i,j} - U_{i,k} = (\delta_j - \delta_k) - \mu MC_{j,k} + (\eta_{i,j} - \eta_{i,k}), \tag{7}$$

where $MC_{j,k}$ is our measure of moving costs described in section 2.4. If $j = k$, $MC_{j,k} = 0$, meaning that the change in utility from staying in one's current location is zero.

# What about those moving costs?

- Moving costs are an important consideration as they can explain why households don't move.
- Authors reference an earlier paper by Bieri et al. who document moving costs (closing costs, physical moving costs, etc).
- They assume moving costs increase with housing value and adjust for renters versus owners.
- An important calibration exercise as variation helps pin down marginal utility of income..

# Derive a system of share equations:

If $\eta_{i,k}$ is independently and identically distributed Type I extreme value, then the probability that an individual in location $k$ would find it optimal to move to location $j$ is given by the familiar logit functional form. Applying this probability to all individuals in location $k$ yields an equation for the share who move to each location $j$:

$$s_{j,k} = \frac{e^{(\delta_j - \delta_k - \mu MC_{j,k})}}{\sum_{l=1}^{N} e^{(\delta_l - \delta_k - \mu MC_{l,k})}}. \tag{8}$$

Similarly, the share of individuals in location $k$ who would find it optimal to remain in that location is given by

$$s_{k,k} = \frac{1}{\sum_{l=1}^{N} e^{(\delta_l - \delta_k - \mu MC_{l,k})}}. \tag{9}$$

# Estimation?

Estimate the model separately for each race group (allowing structural error/mean utility to vary across race groups)

1. First stage solves for $\delta$ vector (given a guess at $\mu$) that best matches observed (race-specific) neighborhood shares using contraction mapping trick.
   - With converged $\delta$ values search for the values of $\mu$ that equate observed and actual $\%Stay$.
2. Regress these race-specific deltas on neighborhood attributes (including pollution exposure).
3. The values of the $\delta_{kr}$ are not directly comparable across race groups. Normalize by marginal utility of income $\mu$ for each group so that they are comparable(?!)

# Estimation results

- Find economically and statistically significant differences in Hispanic and white MWTP to avoid an incremental increase in cancer risk.
- Relative to whites, Hispanics residential location choices reveal a smaller WTP for risk reduction.
- These results are more consistent with (but not necessarily proof of) a residential mobility explanation for observed race and pollution correlations.

# Implications?

- Results imply that hispanic households are less willing to trade other forms of consumption to avoid cancer risk.
- Over the long run, individuals making sorting decisions with different MWTP for risk reductions will yield residential patterns that reflect those differences.
- This sorting could counteract the effects of policies mandating equitable site placement?

Thoughts? Discussion?

# Christensen and Timmins(2019)

- Authors document evidence of discrimination in the characteristics of neighborhoods towards which individuals are steered.
- Paper finds that minority homebuyers are systematically steered to neighborhoods with higher concentrations of toxic contamination and pollution than their white counterparts.
- People of color are often presented with housing options that are disproportionately lower in environmental quality than are those given to similar white buyers.
- This discriminatory 'steering' can contribute substantially to the disproportionate number of minority households found in high poverty neighborhoods.

# What does steering imply for discrete choice modeling?

- The utility maximization assumptions underlying hedonic and residential sorting models may not hold.
- If different types of households have different choice sets (or if some households must exert more effort to access certain choices), what does this imply for the interpretation of estimated taste parameters?
- What other factors are standard discrete choice models missing?
- Discuss!