Valuing Environmental Externalities: Valuing Benefits - Air Pollution

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Big Picture: Social Cost of Air Pollution Externalities

In presence of externality, optimal policy typically entail a tax on emissions equal to marginal damages.

The key input in designing optimal environmental policy is the marginal damage associated with a given externality.

- Research community / policy makers have only a cursory understanding as to the social costs of air pollution externalities

There are **five main** challenges that researchers face in this arena

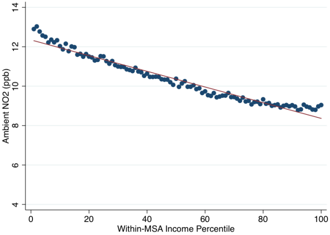
Challenge #1: Causal inference

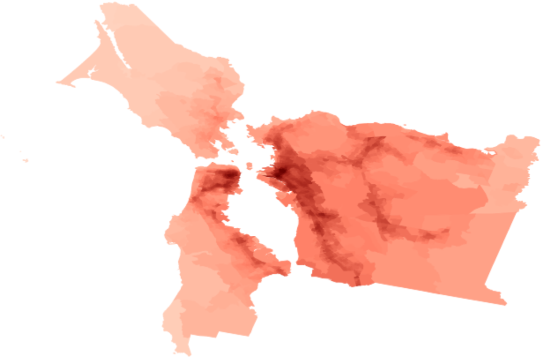
Air pollution exposure is not-randomly assigned

- Naive relationships between pollution and health are fraught with issues pertaining to omitted variable bias
- many reasons, observed and unobserved, why individuals whom live in polluted areas have worse health on average
    - ... and these may have nothing to do with air quality per se...

NO2 Levels in Bay Area

Census block NO2 levels and Census block per capita income:
<u>strongly correlated</u>

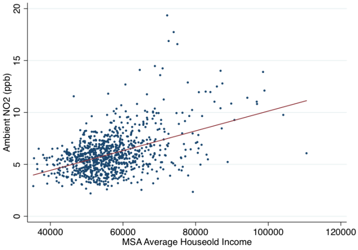


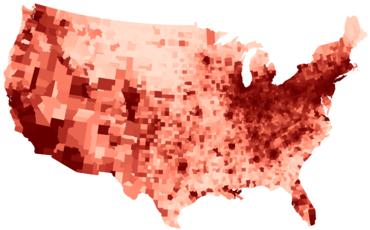


Causal? Or cause for concern?

NO2 Levels in United States

County level per-capita income and county level NO2 Levels: Strongly correlated





Causal? Or cause for concern?

Challenge #1: Causal inference

Fortunately, the recent economics, applied statistics, and epidemiology literature is beginning to make progress along this front

- Empirical techniques that come close to mimicking experimental research designs
- Well defined treatment and control groups designed to circumvent omitted variables problems
- We'll talk about some of these papers going forward (see e.g., Chay and Greenstone (2003), Schlenker and Walker (2015))

In doing so, this literature has introduced two additional challenges

Challenge #2: Multiple Pollutants that Are Correlated

Quasi-experimental research designs for a given air pollutant typically face the challenge that many air pollutants are correlated with one another

- Either directly via the original emitter of the pollution (e.g., cars emit both carbon monoxide and nitrogen dioxide),
- Or through chemical reactions in the atmosphere (e.g. ozone comes from reactions between nitrogen oxides and VOCs).

Difficult to attribute observed changes in health and/or welfare to any single pollutant (which is what optimal policy requires).

Challenge #3: Short Run vs. Long Run Exposure

Research exploiting quasi-experimental variation in air pollution often relies on short-run, high frequency variation in ambient air pollution levels

- Can be cleanly mapped into observable differences in health outcomes (e.g. Schlenker and Walker (2015)).
- Trading off strong internal validity with less strong external validity

Actual policy parameter often pertains to long run exposure

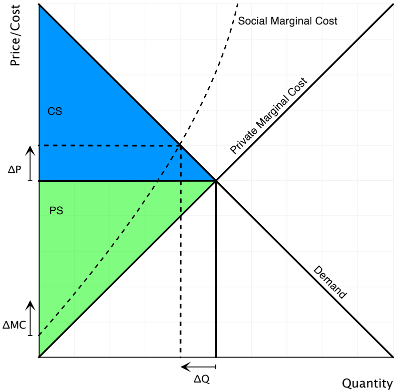
- Difficult to solve problems of causal inference while also recovering long-run, dose-response relationships
- Recent work on Huai River (Chen et al. 2013) is a step in this direction (e.g. quasi-experimental and focused on long-run)

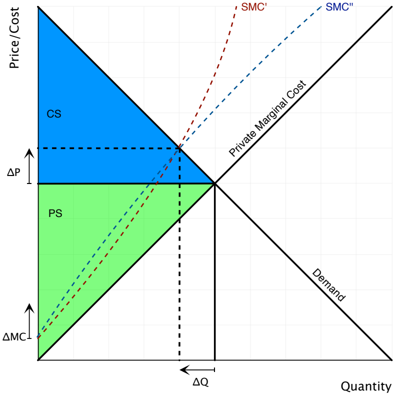
Challenge #4: Dose Response Function May Be Both Heterogeneous and/or Non-Linear.

Optimal policy requires an estimate of the marginal damage of the externality at the socially optimal level of output.

- If social costs are non-linear in level of externality, need to know the shape of the entire damage function.
- Much more difficult empirical problem: need useful (i.e. exogenous) variation in the air pollution over entire support of pollution distribution
- Adding heterogeneous dose-response functions on top of non-linearity further complicates picture

Challenge #4: Dose Response Function May Be Both Heterogeneous and/or Non-Linear.





Challenge #4: Dose Response Function May Be Both Heterogeneous and/or Non-Linear.

As we will see, the reason for the underlying heterogeneity in health impacts matters for thinking about overall social costs

- e.g. if people engage in defensive investments, these are costly and should factor into damage estimates (Grossman, 1972)
- Very difficult empirical problem attributing heterogeneity in dose-response to a single causal factor
    - Need exogenous variation in pollutant and explanatory factor (otherwise, correlated unobservables becomes a problem)

Challenge #5: Monetization

One of the most challenging aspects of identifying the social costs of an environmental externality is actually monetizing the costs.

- Typically estimate dose-response relationship between air pollution and mortality/morbidity and then monetize health costs
- e.g., attaching a value of a statistical life to observed increases in mortality and/or valuing increased hospital admissions by expenditures paid on health services (e.g., Medicare reimbursement rates)

Challenge #5: Monetization

Monetized health costs are an incomplete measure for 2 main reasons:

1. People's willingness to pay to avoid a negative health outcome may far exceed the hospital reimbursement costs.
2. Variety of additional social costs that come with pollution, not directly related to health

Other Costs of Air Pollution Not Captured by Dose-Response Estimates

Some examples (there are others):

- Amenity values associated with cleaner air (Chay and Greenstone 2003)
- Enhanced cognition and/or labor productivity (Neidell and Graff Ziven)
- Reduced school and workplace absenteeism (Currie et al.),
- Increased expenditures on defensive investments and/or medications (Deschenes, Greenstone, and Shapiro).

In principal, each of these components should factor into damage function

- Each component is subject to the five challenges associated with estimating social costs: (1) causal inference, (2) multiple pollutants, (3) short-run versus long-run exposures, (4) non-linear damage functions, and (5) monetization or willingness to pay.

Social Costs of Air Pollution: Many Challenges Remain

Thus, the challenge in identifying the social costs of air pollution externalities remains large and incomplete.

Climate change impacts - somewhat “easier” to study:

- Lot’s of useful, seemingly exogenous variation in temperatures
- Much better idea of functional form, not really multiple pollutant challenges, endogeneity seemingly less of an issue (with modern research designs)
- Short-run/long-run still difficult, as is monetization, WTP (some recent progress here)

As a result, lot’s of recent progress on the social cost of carbon

- Comparatively much less work on the social cost of other forms of air pollution

Three Empirical Examples: Air Pollution and Health

1. Chay and Greenstone (2003): "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession"

2. Deryugina et al. (2016): "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction"

3. Chen et al. (2013) "Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy"

Chay and Greenstone: Pollution and Infant Mortality

1. What is the question, and why is it interesting?
2. Why is the existing literature crappy, non-existent, and/or unresolved?
3. What is this paper going to do to solve it?

Chay and Greenstone: Pollution and Infant Mortality

Linking Pollution and Infant Mortality

- Many studies linking infant mortality to pollution
  - Exposure of infants clearer (move less than adults)
  - Infants are susceptible subgroup
- Existing evidence
  - A lot of cross-sectional studies
  - Omitted variables problem
- Idea of this paper
  - Recession in 1980-1982 resulted in decrease in industrial output
  - Sharp drop in pollution
  - Varies by county

Linking Pollution and Infant Mortality

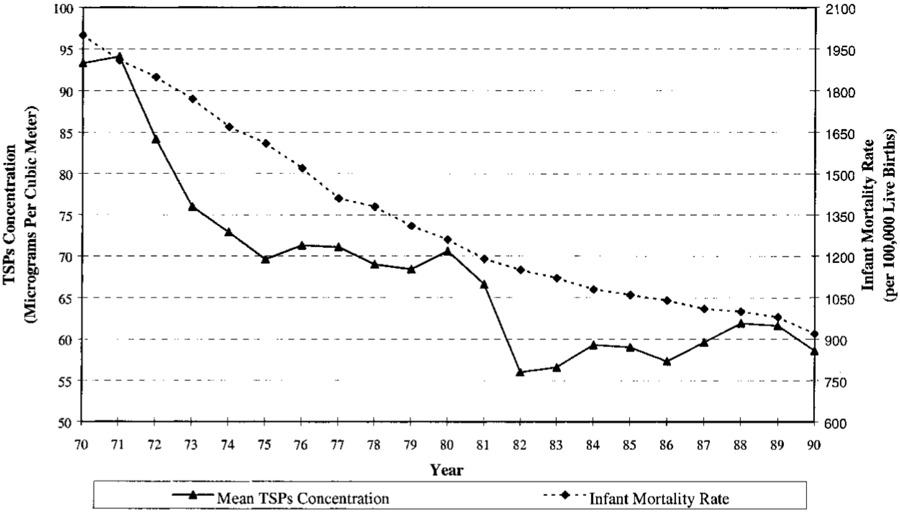


FIGURE I

National Trends in Total Suspended Particulates Air Pollution and Infant Mortality Rates

Linking Pollution and Infant Mortality

- Pollution reduction
  - Declining trend in 70s (Clean Air Act)
  - Reduction in early 80s (Recession)
- 1980-1982
  - Sharper reduction
  - Varies by county
- This paper
  - Mortality: number of deaths divided by number of births
  - Pollution: Total Suspended Particles (EPA monitors)
  - Income (BEA - REIS / Local Area Employment Statistics)
  - Sample of roughly 1200 counties

Cross-sectional Results

Replicate cross-sectional results

- Results vary by year

	Infant deaths due to internal causes (per 100,000 live births)				
	(1)	(2)	(3)	(4)	(5)
1978 Cross section	**1.51**	0.44	0.77	0.53	0.76
	(0.73)	(0.52)	(0.58)	(0.58)	(0.60)
	[1201, .02]	[1188, .41]	[1180, .48]	[1188, .53]	[1120, .48]
1979 Cross section	0.67	0.37	0.22	0.05	0.16
	(0.77)	(0.50)	(0.50)	(0.55)	(0.53)
	[1188, .02]	[1173, .42]	[1163, .51]	[1173, .53]	[1126, .50]
1980 Cross section	0.44	0.36	**1.08**	**1.04**	**1.06**
	(0.65)	(0.54)	**(0.48)**	**(0.51)**	**(0.49)**
	[1174, .02]	[1164, .47]	[1154, .54]	[1162, .57]	[1129, .54]
1981 Cross section	−0.19	−0.92	0.23	0.36	0.08
	(0.71)	(0.58)	(0.65)	(0.68)	(0.67)
	[1122, .01]	[1112, .42]	[1104, .47]	[1111, .51]	[1077, .47]
1982 Cross section	0.39	−0.20	1.14	1.52	1.14
	(1.06)	(0.69)	(0.87)	(0.86)	(0.93)
	[1104, .02]	[1098, .41]	[1091, .49]	[1098, .52]	[1062, .49]
1983 Cross section	1.72	0.64	**1.89**	**2.15**	**2.03**
	(1.23)	(0.61)	**(0.65)**	**(0.67)**	**(0.67)**
	[1076, .02]	[1067, .46]	[1060, .50]	[1067, .53]	[1036, .49]
1984 Cross section	−0.30	−0.09	−0.24	0.23	−0.41
	(0.78)	(0.53)	(0.68)	(0.73)	(0.70)
	[1029, .02]	[1023, .42]	[1016, .49]	[1023, .52]	[991, .47]
Income per capita	Y	Y	Y	Y	Y
Basic natality variables	N	Y	Y	Y	Y
Unrestricted natality	N	N	Y	Y	Y
Weather	N	N	Y	N	Y
State Medicaid	N	N	N	N	Y
Income assistance sources	N	N	N	N	Y
State effects	N	N	N	Y	N

Recession-Induced Changes in Pollution

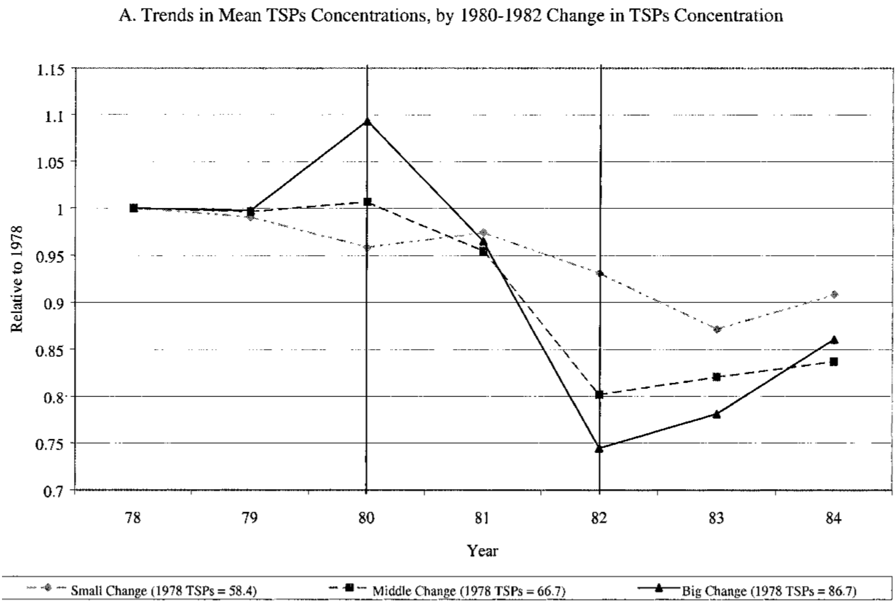
Some Prima-Facie Evidence

- Split counties into three sets
  - Big change: quartile with largest pollution changes
  - Small change: quartile with lowest pollution changes
  - Middle change: remaining counties

- Potential concern 1
  - Are these counties really random?
  - If "big change" counties are all in Midwest, no natural experiment (other confounding variables)

- Potential concern 2
  - Exclusion restriction: did other factors change through recession?
  - Less income?

Recession-Induced Changes in Pollution



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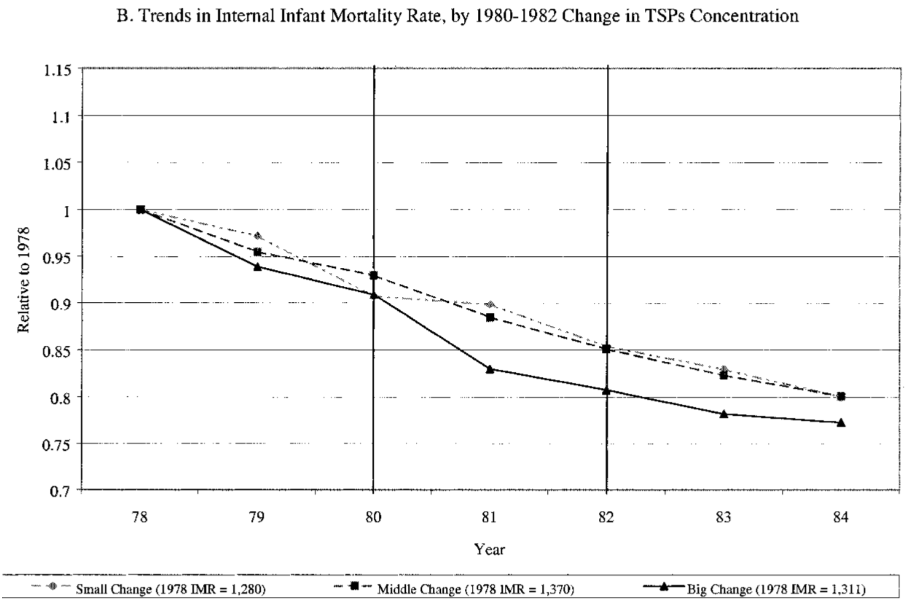

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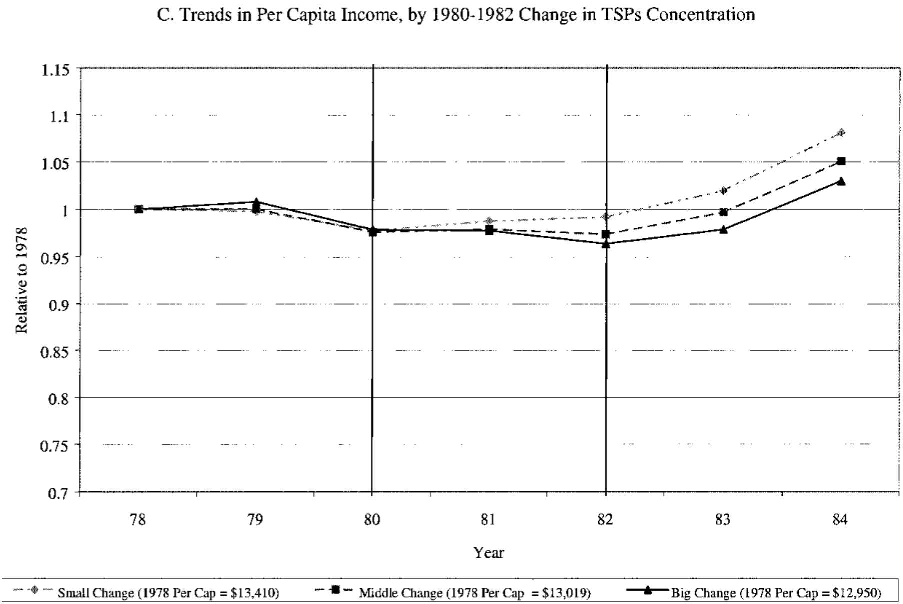

Recession-Induced Changes in Pollution

- Two models
  - Fixed effect
  - Instrumental variable (IV)
- Fixed effect
  - Allows for baseline difference among counties
  - But: how about differences in pre-recession trends?
- IV approach
  - Instrument changes in income and TSP with lagged levels
  - Sometimes includes state-by-year fixed effects

Fixed Effects: Refresher

This Paper: Uses a "fixed-effects estimator applied to the pooled three years of data from 1980-1982"

- What does this mean?

Why Fixed Effects?

- Headline reason is that they control for any observed or <u>unobserved</u> variable at the level of the fixed effect
  - Starts to make the CIA seem more plausible given ability to control for observables AND unobservables
- Isolates identifying variation to come from within a county over time (as opposed to across counties)
  - In presence of random effects, OLS estimand is weighted average of county specific slopes
  - For more details on OLS / IV weighting function see Angrist and Krueger Handbook of Labor Economics

Fixed Effects: Limitations

Effectively a control strategy rather than a "research design"

- "No causation without manipulation" (Holland 1986)
- "If you can't control/manipulate the underlying source of variation, at least understand where it is coming from"

Three main limitations to fixed effects research designs:

1. Unobserved time-varying shocks and/or differential trends (most serious problem)
2. Measurement error + attenuation bias
3. Time-invariant covariates: not identified (i.e. because it will effectively drop out of the fixed effect regression)

Recession-Induced Changes in Pollution

	Infant deaths due to internal causes (per 100,000 live births)							
	1978–1980 data		1982–1984 data		1980–1982 data		1978–1984 data	
	FE	IV	FE	IV	FE	IV	FE	IV
Mean TSPs	−0.96	4.68	0.66	0.54	**3.51**	**5.21**	**5.27**	**3.75**
	(0.67)	(4.00)	(0.87)	(2.87)	**(0.52)**	**(1.99)**	**(0.40)**	**(1.46)**
Income per capita	0.85	−1.69	−0.47	−0.21	0.00	−2.42	−0.31	−0.78
(1/10)	(0.15)	(1.01)	(0.09)	(0.29)	(0.19)	(1.26)	(0.07)	(0.40)
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year effects	N	Y	N	Y	N	Y	N	Y
R^2	0.70	0.00	0.69	0.00	0.71	0.00	0.58	0.00
Depend. var. mean	1276	−53.4	1088	−30.4	1170	−49.7	1179	−44.5
Sample size	3563	2172	3209	1994	3400	2099	7894	6265

Chay and Greenstone: Fixed Effects Model and Identifying Assumption

$$E[\Delta TSP_{ct}, \Delta\epsilon_{ct} | \Delta I_{ct}] = 0$$

Conditional on within-county changes in income, changes in TSP are as good as randomly assigned.

- Is this plausible?
- How might one test this assumption?

Chay and Greenstone: Fixed Effects Model and Identifying Assumption

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Possible Solutions?

Recession Induced Changes in Pollution

Assuming linearity of the effects of TSPs, the quasi-experimental model in the ideal case is

$$(3) \qquad dy_{jt} = y_{j82} - y_{j80} = x_{j82}\beta - x_{j80}\beta + \epsilon_{j82} - \epsilon_{j80} = dx_{jt}\beta + d\epsilon_{jt}.$$

Below, we estimate this model using a fixed-effects estimator applied to the pooled three years of data from 1980–1982.

In the "almost ideal" situation, TSPs changes may be weakly correlated with changes in other factors, requiring the use of linear regression adjustment. Further, Figure IIB suggests that there are some differences across counties in infant mortality trends before the recession. Thus, we also estimate the following model:

$$(4) \qquad dy_{jt} = dx_{jt}\beta + dz_{jt}\theta + dw'_{jt}\Pi + d\epsilon_{jt}, \quad d\epsilon_{jt} = \lambda_{st} + du_{jt},$$

where λ_{st} are state fixed effects in infant mortality changes. Define $T_j^t = (x_{j1}, \ldots, x_{jt}, z_{j1}, \ldots, z_{jt})$; then the assumption $E(u_{jt}|T_j^t) = 0$ implies that the lag levels of TSPs and income can be used as instrumental variables for dx_{jt} and dz_{jt}. This condition, which presumes that the treatments are predetermined, is robust to differential trends and dynamic feedback from y to T of an unrestricted form. Consequently, it is much weaker than the strict exogeneity condition underlying identification of equation

Instrumental Variables: Refresher

To motivate, consider a simple linear model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u$$

where $E(u) = 0$, $Cov(x_j, u) = 0$, $j = 1, 2, ...K - 1$, but where x_k might be correlated with u

- i.e. explanatory variables x_1 through x_{K-1} are exogenous, and the last explanatory variable x_k is potentially endogenous
- u contains an omitted variable that is correlated with x_k

OLS estimation of this equation would lead to inconsistent estimators of all the β_j if $Cov(x_k, u) \neq 0$

Instrumental Variables: General solution to this problem

Instrumental Variables: Refresher

Need an observable variable z_1 that satisfies two conditions:

1. Instrument Relevance: z_1 is a strong predictor of the endogenous variable x_k, conditional on all other exogenous variables

$$x_k = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + ... + \theta_1 z_1 + \rho$$

   i.e. $\theta_1 \neq 0$

2. Instrument Exogeneity $Cov(z_1, u) = 0$

Instrumental Variables: Refresher

Under these assumptions, easy to show that β_k is identified using IV.

Write the system in matrix notation as

$$y = \boldsymbol{x}\boldsymbol{\beta} + u$$

where $\boldsymbol{x} = (1, x_2, x_3 ... x_k)$.

Let the $1 \times K$ vector of exogenous variables be $\boldsymbol{z} = (1, x_2, ... x_{k-1}, z_1)$.

IV assumptions tell us that $E(\boldsymbol{z}'u) = 0$, and if we multiply $\boldsymbol{z}$ through the regression equation and take expectations we get

$$[E(\boldsymbol{z}'\boldsymbol{x})]\boldsymbol{\beta} = E[\boldsymbol{z}'y] \quad \Rightarrow \quad \boldsymbol{\beta} = [E(\boldsymbol{z}'\boldsymbol{x})]^{-1} E[\boldsymbol{z}'y]$$

Instrumental Variables: Chay and Greenstone

What do we think about IV assumptions in this setting?

1. Instrument Relevance?
    - How to test/demonstrate?
2. Instrument Exogeneity?
    - How to test/demonstrate?

Recession-Induced Changes in Pollution

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Mean TSPs	−0.96	4.68	0.66	0.54	**3.51**	**5.21**	**5.27**	**3.75**
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Income per capita	0.85	−1.69	−0.47	−0.21	0.00	−2.42	−0.31	−0.78
(1/10)	(0.15)	(1.01)	(0.09)	(0.29)	(0.19)	(1.26)	(0.07)	(0.40)
County fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
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R^2	0.70	0.00	0.69	0.00	0.71	0.00	0.58	0.00
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Sample size	3563	2172	3209	1994	3400	2099	7894	6265

Interpreting Results

Mechanisms?

TABLE V
INSTRUMENTAL VARIABLES ESTIMATES OF EFFECTS OF MEAN TSPS ON INFANT BIRTH WEIGHT, 1980–1982

	Birth weight	Incidence in birth weight categories (per 100,000 live births)					
		$<$1500 g	$<$2000 g	$<$2500 g	$<$3000 g	$<$3500 g	$<$4000 g
Mean TSPs	−0.317	1.54	0.17	1.96	19.70	16.40	8.05
	(0.121)	(1.80)	(2.42)	(4.69)	(8.05)	(10.87)	(5.61)
Income per capita (1/10)	0.242	−1.51	−1.74	−6.20	−14.70	−12.80	−6.62
	(0.083)	(1.24)	(1.59)	(3.02)	(5.15)	(7.19)	(4.14)
Basic natality variables	Y	Y	Y	Y	Y	Y	Y
Unrestricted natality	Y	Y	Y	Y	Y	Y	Y
State-year effects	Y	Y	Y	Y	Y	Y	Y
Dependent var. mean	3337	1.2%	2.5%	6.9%	23.3%	60.4%	89.2%
Sample size	2075	2075	2075	2075	2075	2075	2075

Challenges in interpretation here?

Interpreting Results: Back of Envelope

4 million births per year in U.S.

1-$\mu g/m^3$ reduction $\Rightarrow$ 200 additional infants surviving past one year

VSL estimate: \$1.6 million $\Rightarrow$ \$320 million in estimated benefits (per year)

Valuing Damages Pertaining to Air Pollution

How does this paper stack up?

1. Causal inference,
2. Multiple pollutants,
3. Short-run versus long-run exposures,
4. Non-linear damage functions, and
5. Monetization or willingness to pay.

A Research Taxonomy for Interpreting Health Impact Papers

Several ways to probe the internal validity of a health paper

1. Pre-trends / event studies (i.e. is there "balance" in pre-period)
2. Post-trends in other observable characteristics that are correlated with health (e.g. education)
   - Maybe composition effects are driving entirety of results (i.e. people who live in area afterward are just healthier on average)
3. Placebo-like tests on things that shouldn't be affected by intervention (e.g. external causes of death)

Wrapping Up: Chay and Greenstone (2003)

This paper was hugely influential at the time:

- Clear example of cross-field arbitrage (Labor $\Rightarrow$ Health/Environment)
- One of first papers to use empirical tools from labor (e.g. fixed effects, IV) to answer question in environmental economics
- Paved the way for a lot of research(ers)

Modern Instrumental Variables:

- Always show OLS, Reduced Form, First Stage, and IV
- Strength of first stage? Overidentification tests?
- LATE/compliers/external validity

Some thematic criticisms:

- What does this have to do with economics? Is this epidemiology?

Deryugina et al. (2016). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction

What is the question and why is it interesting?

Why is the existing literature crappy, non-existent, or unresolved?

What are these researchers going to do to solve it?

Deryugina et al. (2016). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction

What is the question and why is it interesting?

- Effect of acute air pollution exposure on mortality, life-years lost, and health care utilization among the US elderly?

Why is the existing literature crappy, non-existent, or unresolved?

- Limited geographic coverage on detailed outcome data
- Treatment effect heterogeneity: if unhealthy people die then number of life years lost may differ substantially from using average life-year

What are these researchers going to do to solve it?

- Data on the universe of elderly Medicare beneficiaries
- Daily variation in wind direction to instrument pollution
- Predict remaining life expectancy for each individual (LASSO) and use as LHS... reduces life years lost calculations by 50+%

Treatment Effect Heterogeneity and Correlated Random Coefficients

Life expectancy of person i on day t, L_{it}

$$L_{it} = \alpha + \gamma PM2.5_{it} + e_{it}$$

Let $u_{it} = L_{it} - \hat{L}_{it}$, where $\hat{L}_{it}$ is predicted life expectancy

$$\hat{L}_{it} \quad = \alpha + \gamma PM2.5_{it} - u_{it} + e_{it}$$

Suppose there is treatment effect heterogeneity and consider random coefficients version of previous equation. Let $\bar{\gamma} = E(\gamma_i)$

$$\hat{L}_{it} \quad = \alpha + \bar{\gamma} PM2.5_{it} + (\gamma_i - \bar{\gamma}) PM2.5 - u_{it} + e_{it}$$

Treatment Effect Heterogeneity and Correlated Random Coefficients

$$\hat{L}_{it} = \alpha + \bar{\gamma} PM2.5_{it} + (\gamma_i - \bar{\gamma}) PM2.5 - u_{it} + e_{it}$$

Bias can arise in two cases: (note: text is different than this discussion)

1. $cov(PM2.5_{it}, \gamma_i PM2.5_{it}) \neq 0$, "self-selection bias"
2. $cov(PM2.5_{it}, u_{it}) \neq 0$, a bit unconventional (is measurement error in dependent variable correlated with pollution. Why?)

Large literature on **self-selection** bias in labor economics

- People who have larger returns to schooling more likely to attend
- Series of papers arguing that 2SLS still identifies γ (ATE) in presence of self-selection bias (under some - kinda strong - assumptions)
  - Heckman and Vytlacil (1998) and Wooldridge (1997, 2003, 2008)
- See Masten and Torgovitsky (2016) for recent CRC identification

Deryugina et al. (2016). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction

One goal of paper is to get better predictions of $\hat{L}_{it}$ to minimize u_{it}.

- Use health and demographic info from Medicare dataset to generate relatively precise predictions of counterfactual life expectancy
- Machine learning LASSO to predict life expectancy. Cox proportional hazard model with LASSO penalty term (Simon et al. (2011))

LASSO: Briefly

- Model selection with "regularization"
- Effectively choose variables/coefficients to minimize sum of squared residuals subject to a regularization constraint
- Regularization $\approx$ avoid "overfitting"
- Choose constraint or "tuning parameter" using cross-validation

Deryugina et al. (2016). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction

Hazard Rate: define h_t number of people who die at time t divided by number of living at time t

- Estimate of the probability of dying at time t conditional on surviving up to time t
- Standard specification of hazard model: Cox "proportional hazards"

$$h_t = \alpha_t \exp(\beta X)$$

- Here α_t is the non-parameteric "baseline" hazard rate in each period t and X is a set of covariates
- Semi-parameteric specification – allow hazards to vary freely across weeks and only identify coefficients off of variation across spells

Hazard Models

- Useful to rewrite expression as:

$$\log h_t = \log \alpha_t + \beta X$$

- Key assumption: effect of covariates proportional across all weeks

$$\frac{d \log h_t}{dX} = \beta = \frac{d \log h_s}{dX} \forall t, s$$

- If a change in a covariate doubles hazard in week 1, it is forced to double hazard in week 2 as well
- Restrictive but a good starting point; can be relaxed by allowing for time varying covariates X_t
- With hazard function estimates, can compute survival function and then integrate to get predicted life expectancy

Additional challenge - air pollution is endogenous

- Solution: wind direction as an IV for daily variation in pollution

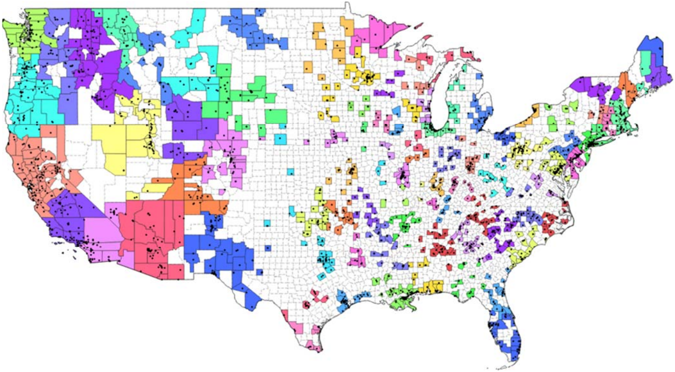

Figure 4. Counties assigned to each monitor group. Different colors correspond to different monitor groups. White corresponds to counties not assigned to any monitor group due to lack of monitors. Black dots represent PM 2.5 pollution monitors.

Deryugina, et al. (2016).

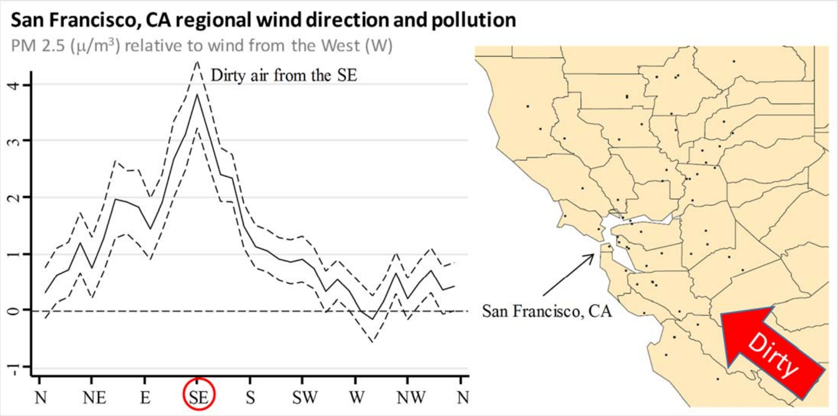

Figure 2. Relationship between daily average wind direction and PM 2.5 concentrations for counties in and around the Bay Area, CA. The left panel shows regression estimates of equation (A1) from the appendix, where the dependent variable is the county average daily PM 2.5 concentration and the key independent variables are a set of indicators for the daily wind direction falling into a particular 10-degree angle bin. Controls include county, month-by-year, and state-by-month fixed effects, as well as a flexible function of maximum and minimum temperatures, precipitation, wind speed, and the interactions between them. The dashed lines represent 95 percent confidence intervals based on robust standard errors. The right panel shows the location of the PM 2.5 pollution monitors (black dots) in the Bay Area that provided the pollution measures for this regression.

Deryugina, et al. (2016).

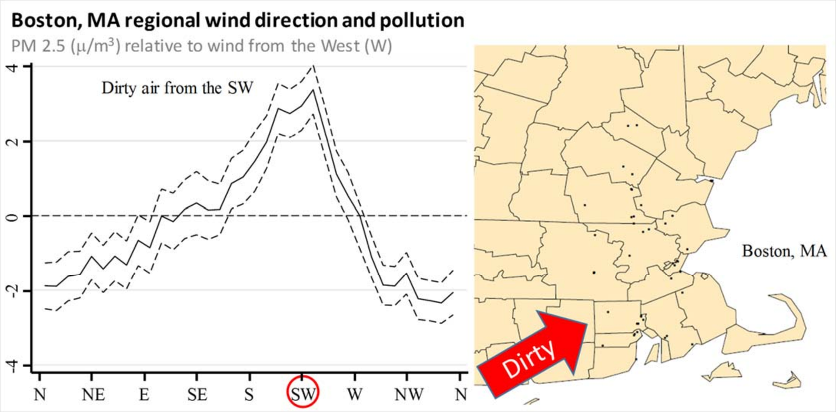

Figure 3. Relationship between daily average wind direction and PM 2.5 concentrations for counties in and around the Boston Area, MA. The left panel shows regression estimates of equation (A1) from the appendix, where the dependent variable is the county average daily PM 2.5 concentration and the key independent variables are a set of indicators for the daily wind direction falling into a particular 10-degree angle bin. Controls include county, month-by-year, and state-by-month fixed effects, as well as a flexible function of maximum and minimum temperatures, precipitation, wind speed, and the interactions between them. The dashed lines represent 95 percent confidence intervals based on robust standard errors. The right panel shows the location of the PM 2.5 pollution monitors (black dots) in the Boston Area that provided the pollution measures for this regression.

OLS-Fixed Effects regression

$$
\begin{aligned}
Y_{cdmy} &= \beta \mathrm{PM2.5}_{cdmy} + f(Temp_{cdmy}, Prcp_{cdmy}, WS_{cdmy}) \\
&+ \sum_{t=d+1}^{d+2} [\gamma_t \mathrm{PM2.5}_{ctmy} + f_t(Temp_{ctmy}, Prcp_{ctmy}, WS_{ctmy})] \\
&\sum_{t=d-1}^{d-2} \gamma_t \mathrm{PM2.5}_{ctmy} + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_{cdmy},
\end{aligned}
\tag{1}
$$

First stage regression

$$
\begin{aligned}
\mathrm{PM2.5}_{cdmy} &= \sum_{g=1}^{100} \sum_{b=0}^{2} \beta_b^g 1[G_c = g] \times WINDDIR_{cdmy}^{90b} + f(Temp_{cdmy}, Prcp_{cdmy}, WS_{cdmy}) \\
&+ \sum_{t=d+1}^{d+2} [g_t(1[G_c = g] \times WINDDIR_{ctmy}) + f_t(Temp_{ctmy}, Prcp_{ctmy}, WS_{ctmy})] \\
&+ \sum_{t=d-1}^{d-2} g_t(1[G_c = g] \times WINDDIR_{ctmy}) + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_{cdmy}.
\end{aligned}
\tag{2}
$$

How many endogenous variables? How many instruments?

Deryugina, et al. (2016).

OLS-Fixed Effects regression

$$
\begin{aligned}
Y_{cdmy} &= \beta \mathrm{PM2.5}_{cdmy} + f(Temp_{cdmy}, Prcp_{cdmy}, WS_{cdmy}) \\
&+ \sum_{t=d+1}^{d+2} [\gamma_t \mathrm{PM2.5}_{ctmy} + f_t(Temp_{ctmy}, Prcp_{ctmy}, WS_{ctmy})] \\
&\sum_{t=d-1}^{d-2} \gamma_t \mathrm{PM2.5}_{ctmy} + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_{cdmy},
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&+ \sum_{t=d-1}^{d-2} g_t(1[G_c = g] \times WINDDIR_{ctmy}) + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_{cdmy}.
\end{aligned}
\tag{2}
$$

How many endogenous variables? How many instruments?

- 86,700 weather controls/indicators + county, state-month, and month-year FE

Deryugina, et al. (2016).

Table 2: OLS and IV estimates of effect of PM 2.5 on elderly mortality, by age group

	(1) 65+	(2) 65-69	(3) 70-74	(4) 75-79	(5) 80-84	(6) 85+
Panel A: OLS estimates						
PM 2.5 ($\mu g/m^3$)	0.098***	0.042***	0.022	0.033	0.137***	0.423***
	(0.021)	(0.015)	(0.019)	(0.023)	(0.037)	(0.074)
Dep. var. mean	393	138	205	326	531	1,170
Effect relative to mean, percent	0.025	0.030	0.011	0.010	0.026	0.036
Observations	1,600,846	1,600,846	1,600,846	1,600,846	1,600,846	1,600,846
Adjusted R-squared	0.249	0.080	0.086	0.084	0.081	0.115
Panel B: IV estimates						
PM 2.5 ($\mu g/m^3$)	0.605***	0.263***	0.312***	0.307***	0.775***	2.050***
	(0.065)	(0.071)	(0.075)	(0.106)	(0.177)	(0.264)
F-statistic	241.115	232.367	236.416	241.909	247.716	256.311
Dep. var. mean	391	134	201	318	514	1,132
Effect relative to mean, percent	0.155	0.196	0.155	0.097	0.151	0.181
Observations	1,600,846	1,600,846	1,600,846	1,600,846	1,600,846	1,600,846

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Table reports OLS and IV estimates of equation (1) from the main text. Standard errors (in parentheses) clustered by county. Dependent variable is the 3-day mortality rate per million beneficiaries in the relevant age group. All regressions include county, month-by-year, and state-by-month fixed effects; flexible controls for temperatures, precipitation, and wind speed; and two leads of these weather controls. OLS (IV) estimates also include two lags and two leads of PM 2.5 (instruments). Estimates are weighted by the number of beneficiaries in the relevant age group.

Deryugina, et al. (2016).

Table 4: IV estimates of effect of PM 2.5 on elderly life-years lost, using different survival models

		Life-years lost regressions			
	(1) All-age mortality	(2) None	(3) Age, sex	(4) Age, sex, chronic conditions	(5) LASSO
PM 2.5 ($\mu g/m^3$)	0.746***	8.625***	5.925***	3.539***	2.693***
	(0.085)	(0.978)	(0.757)	(0.562)	(0.521)
F-statistic	239	239	239	239	239
Dep. var. mean	462	5,338	3,624	2,444	2,245
Effect relative to mean, percent	0.162	0.162	0.163	0.145	0.120
LYL per decedent	NA	11.557	7.847	5.292	4.861
LYL per complier	NA	11.557	7.939	4.742	3.608
Observations	1,518,549	1,518,549	1,518,549	1,518,549	1,518,549

Significance levels: * 10 percent, ** 5 percent, *** 1 percent. Table reports IV estimates of equation (1) from the main text. Standard errors (in parentheses) clustered by county. The dependent variable in column 1 is the 3-day mortality rate per million continuously enrolled fee-for-service (FFS) Medicare beneficiaries. The dependent variable in columns 2-5 is life-years lost (LYL) over 3 days for the same group. The headings in columns 2-4 display the variables used to predict life expectancy when using a traditional Cox proportional hazards model. Column 5 displays results when life expectancy is predicted using a Cox proportional hazards model that is estimated using a LASSO machine learning algorithm with over one thousand predictors. LYL per decedent is calculated by dividing the average LYL in the sample by the average mortality rate. LYL per complier is calculated by dividing the columns estimate by the mortality effect reported in column 1. All regressions include county, month-by-year, and state-by-month fixed effects, as well as flexible controls for temperatures, precipitation, and wind speed; two leads of the weather controls; and two leads and lags of the instruments. Estimates are weighted by the number of continuously enrolled FFS beneficiaries.

Implications

Between 1999-2011, national reduction in PM 2.5 levels of 3.65 μg/m^3

- Estimates imply reduction in elderly deaths of 55,000 per year and reduction in life-years lost by 150,000 per year
- Assuming value of $100,000 per statistical life-year implies a corresponding benefit of $15 billion per year
- Estimating life-years lost using average life expectancy increases estimate to $47 billion (+220%)

Comments:

- Identifying variation?
- Leads/lags and other tests of internal validity (e.g. placebo)
- Non-linearities and other forms of treatment effect heterogeneity
- Short-run versus long-run dose response

A Brief History of Air Pollution and Health Literature

The Tradeoffs Between Internal and External Validity

Pollution-Health v1.0: Cross-sectional comparisons

- Correlated unobservables, omitted variables $\Rightarrow$ Internal validity questionable. Bad stuff!

Pollution-Health v2.0: Fixed Effects/Panel/IV Estimators

- "Fix" internal validity at expense of external validity
- LATE concerns, short run responses $\neq$ long run responses

Pollution-Health v3.0: Chen et al. (2013)

- Emerging literature finding balance between internal/external validity
- Focus on long-run, dose-response damage functions
- See also Anderson (2016)

Chen et al. 2013

China's more than six-decade long government-subsidized central heating system only provides heat to the homes in the north

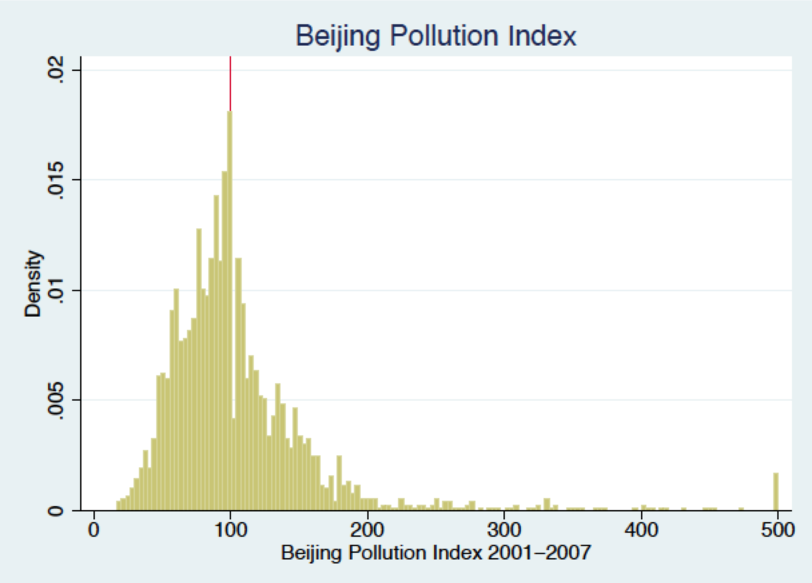
- North of a dividing line that traces Huai River and Qinling Mountain near, where temperatures fall far below freezing in the winter.
- Most heating is done by coal $\Rightarrow$ higher particulate levels

Chen et al. 2013: Geographic regression discontinuity

- Exploit design to make inferences about long-run pollution
- Those on either side of line should be similar to one another
- Identifying assumption: conditional on controls, the only difference in mortality comes from the policy's effect on air pollution

Initial concerns? Skepticism?

Chinese Air Pollution Data



Chen et. al 2013

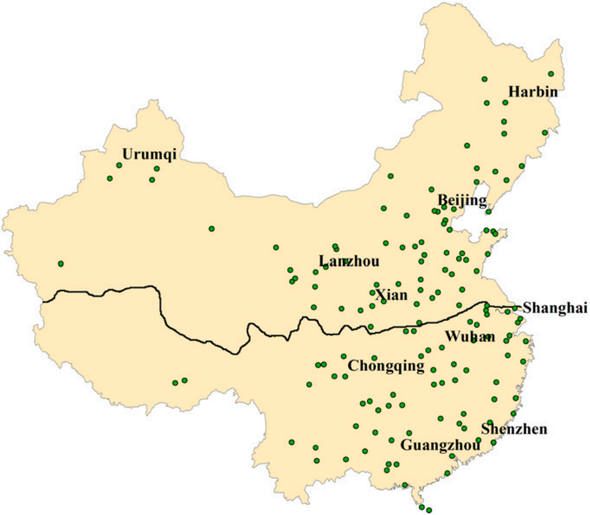


Fig. 1. The cities shown are the locations of the Disease Surveillance Points. Cities north of the solid line were covered by the home heating policy.

Chen et. al 2013

Table 1. Summary statistics

Variable	South (1)	North (2)	Difference in means (3)	Adjusted difference in means (4)	*P* value (5)
Panel 1: Air pollution exposure at China's Disease Surveillance Points					
TSPs, $\mu g/m^3$	354.7	551.6	196.8***	199.5***	<0.001/0.002
SO_2, $\mu g/m^3$	91.2	94.5	3.4	−3.1	0.812/0.903
NO_x, $\mu g/m^3$	37.9	50.2	12.3***	−4.3	<0.001/0.468
Panel 2: Climate at the Disease Surveillance Points					
Heating degree days	2,876	6,220	3,344***	482	<0.001/0.262
Cooling degree days	2,050	1,141	−910***	−183	<0.001/0.371
Panel 3: Demographic features of China's Disease Surveillance Points					
Years of education	7.23	7.57	0.34	−0.65	0.187/0.171
Share in manufacturing	0.14	0.11	−0.03	−0.15***	0.202/0.002
Share minority	0.11	0.05	−0.05	0.04	0.132/0.443
Share urban	0.42	0.42	0.00	−0.20*	0.999/0.088
Share tap water	0.50	0.51	0.02	−0.32**	0.821/0.035
Rural, poor	0.21	0.23	0.01	−0.33*	0.879/0.09
Rural, average income	0.34	0.33	0.00	0.24	0.979/0.308
Rural, high income	0.21	0.19	−0.02	0.27	0.772/0.141
Urban site	0.24	0.25	0.01	−0.19	0.859/0.241
Predicted life expectancy	74.0	75.5	1.54***	−0.24	<0.001/0.811
Actual life expectancy	74.0	75.5	1.55	−5.04**	0.158/0.044

The sample (n = 125) is restricted to DSP locations within 150 km of an air quality monitoring station. TSP ($\mu g/m^3$) in the years 1981–2000 before the DSP period is used to calculate city-specific averages. Degree days are the deviation of each day's average temperature from 65°F, averaged over the years 1981–2000 before the DSP period. The results in column (4) are adjusted for a cubic in degrees of latitude north of the Huai River boundary. Predicted life expectancy is calculated by OLS using all of the demographic and meteorological covariates shown. All results are weighted by the population at the DSP location. One DSP location is excluded due to invalid mortality data. *Significant at 10%, **significant at 5%, ***significant at 1%. Sources: China Disease Surveillance Points (1991–2000), *China Environment Yearbook* (1981–2000), and World Meteorological Association (1980–2000).

Chen et. al 2013

First stage and reduced form:

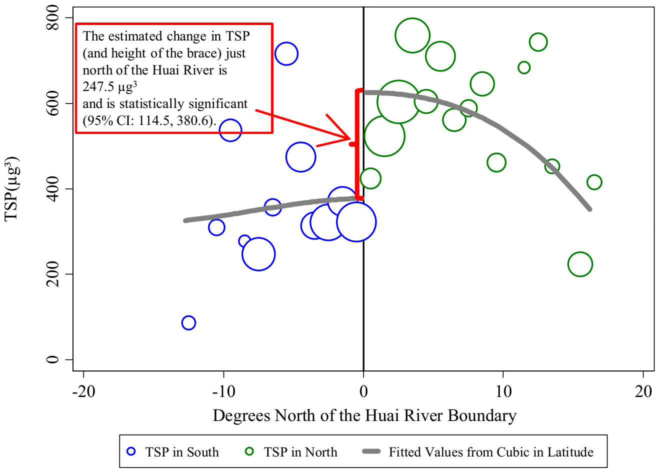
$$TSP_j = \alpha_0 + \alpha_1 N_j + \alpha_2 f\left(L_j\right) + X_j \kappa + \nu_j \qquad \textbf{[2a]}$$

$$Y_j = \delta_0 + \delta_1 N_j + \delta_2 f\left(L_j\right) + X_j \phi + u_j, \qquad \textbf{[2b]}$$

IV/2SLS:

$$Y_j = \beta_0 + \beta_1 T\hat{S}P_j + \beta_2 f\left(L_j\right) + X_j \varGamma + \varepsilon_j, \qquad \textbf{[2c]}$$

Chen et. al 2013



Chen et. al 2013

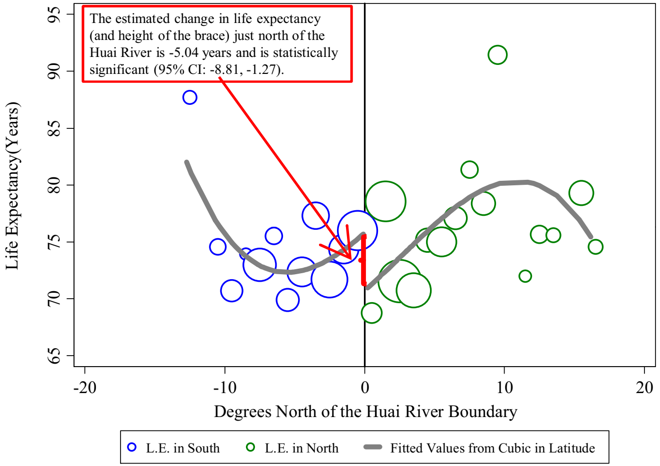


Fig. 3. The plotted line reports the fitted values from a regression of life expectancy on a cubic in latitude using the sample of DSP locations, weighted by the population at each location.

Chen et. al 2013

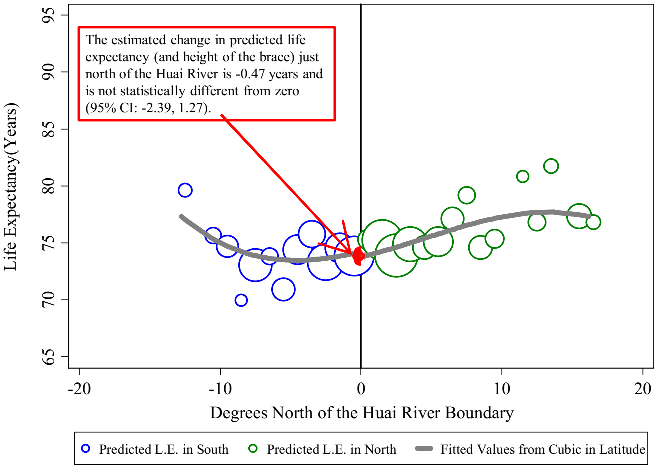


Fig. 4. The plotted line reports the fitted values from a regression of predicted life expectancy on a cubic in latitude using the sample of DSP locations, weighted by the population at each location. Predicted life expectancy is calculated by OLS using demographic and meteorological covariates (excluding TSPs).

Chen et. al 2013

Headline Findings: ambient concentrations of TSPs are about 184 $\mu g/m^3$ or 55% higher in the north.

- estimates suggest life expectancies are about 5.5 y lower in north stemming from increased cardiorespiratory mortality
- long-term exposure to an additional 100 ?g/m3 of TSPs is associated with a reduction in life expectancy at birth of about 3.0 y
    - 500 million residents of Northern China losing more than 2.5 billion life years of life expectancy.

Lingering concerns?

- Other institutional changes that co-vary with border?
- Defensive investments (see Ito and Zhang 2016)?
- Are these marginal damages?

Chen et. al 2013

This paper generated a bit of controversy in the blogosphere:

- See Here (link), Here (link), and Here (link)
- Basic message is that results are sensitive to polynomial order
- General movement in the RD literature to remove researcher "degrees of freedom": optimal bandwidth (Imbens and Kalyanaraman 2011) + local linear regression.

Social Costs of Air Pollution: Many Challenges Remain

Thus, the challenge in identifying the social costs of air pollution externalities remains large and incomplete.

Climate change impacts - somewhat "easier" to study:

- Lot's of useful, seemingly exogenous variation in temperatures
- Much better idea of functional form, not really multiple pollutant challenges, endogeneity seemingly less of an issue (with modern research designs)
- Short-run/long-run still difficult, as is monetization, WTP (some recent progress here)

As a result, lot's of recent progress on the social cost of carbon

- Comparatively much less work on the social cost of other forms of air pollution