Instrumental Variables

September 2021

Lecture outline

- IV fundamentals (review)
- Hedonic regression (quick overview – Joe will take a deeper dive)
- IV meets hedonic regression meets air pollution - An EEE IV classic
- A frontier IV application: Health impacts of air pollution

Section 1

IV fundamentals

The plight of the quasi-experimentalist

"All instruments arrive on the scene with a dark cloud of invalidity hanging overhead. This cloud never goes entirely away, but researchers should chase away as much of the cloud as they can." Murray, 2006

From controlled experiments to quasi-experiments!

- In a field experimental setting, a well-designed and implemented experiment can ensure that the intervention or treatment of interest is independent of (or uncorrelated with) other confounding factors (at least in expectation).
- The unconfoundedness assumption poses more of a challenge in the absence of an experiment.
- When using non-experimental data to do causal inference, we are often concerned that one or more covariates are correlated with the error term. Some reasons why this might occur:

  1. Omitted time-varying variables
  2. Non-random selection into the data
  3. Simultaneity/reverse causality

Omitted variable bias with homogeneous treatment effects

Suppose an outcome variable of interest y_i is a linear function of a potentially endogenous explanatory variable x_i:

$$y_i = \beta x_i + \nu_i.$$

(Assume all variables are measured in deviations from means)

Suppose there exists a potential confounder A_i. If we could observe A_i we could include it in our model:

$$\begin{aligned} y_i &= \beta x_i + \gamma A_i + \mu_i, \\ E[x_i \mu_i] &= 0. \end{aligned}$$

If A_i is omitted, the β coefficient will confound the effects of x and A on y.

Identification strategy?

- Design an experiment to generate random variation in x,
- Take a trip to the instrument store. What are we looking for?

What makes a good instrument?

An instrumental variable satisfies the following conditions:

$$
\begin{aligned}
z_i &\perp \mu_i, A_i \qquad (1)\\
cov(z_i, x_i) &\neq 0. \qquad (2)
\end{aligned}
$$

The first condition:

- *Independence* implies that the assignment of the instrument is as good as random such that potential outcomes $Y_i(d, z)$ are independent of variation in the instrument.
- The *exclusion restriction* asserts that the effect of the instrument on the outcome works only through x.

The second condition can and should be evaluated directly.

Suppose we have an instrument..how do we use it?)

Indirect Least Squares

Refer to the equation we are ultimately interested in estimating as the **structural equation**:

$$y_i = \beta x_i + \nu_i$$

Refer to the regression of our endogenous regressor on our instrument as the **first stage** equation:

$$x_i = \pi_{11} z_i + \varepsilon_i$$

Substituting this first stage equation into the structural equation yields a **reduced form**:

$$\begin{aligned} y_i &= \beta(\pi_{11} z_i + \varepsilon_i) + \nu_i \\ &= (\beta\pi_{11}) z_i + (\beta\varepsilon_i + \nu_i) \\ &\equiv \pi_{21} z_i + \epsilon_i \end{aligned}$$

Indirect Least Squares (ILS)

The reduced form coefficient π_{21} gives us an unbiased estimate of how the change in x induced by an incremental change in z affects our outcome y:

$$\begin{aligned} y_i &= \beta(\pi_{11} z_i + \varepsilon_i) + \nu_i \\ &= (\beta\pi_{11}) z_i + (\beta\varepsilon_i + \nu_i) \\ &\equiv \pi_{21} z_i + \epsilon_i \end{aligned}$$

Except in the special case where a unit change in z induces a unit change in x, the reduced form coefficient π_{21} will not equal the underlying structural parameter of primary interest: β.

Indirect Least Squares and LATE

In this simple case, we can write down an expression for β in terms of population moments that we can observe:

$$\beta_{IV} = \frac{\pi_{21}}{\pi_{11}} = \frac{cov(y,z)}{cov(x,z)}.$$

These covariances can be consistently estimated given a random sample of $\{x, y, z\}$.

- In practice, the IV estimate can be biased even when the exclusion restriction is perfectly satisfied because it is the ratio of two random variables.
- If the exclusion restriction does not hold $\widehat{\beta}_{IV} = \beta + \frac{cov(z,\nu)}{cov(x,z)}$. Even small correlations between the instrument and the structural error can introduce severe bias if the instrument is weak.

Alternative approach: 2SLS

Lets stick with a simple linear relationship between a single potentially endogenous x variable and a single instrument. The first stage equation:

$$x_i = \pi_{11} z_i + \varepsilon_i$$

Note that the OLS estimate of π_{11} is $\frac{cov(x,z)}{var(z)}$. In the second stage, we can estimate the following using OLS:

$$y_i = \beta_{TSLS} \widehat{x_i} + \upsilon_i$$

This gets us to the same place:

$$\begin{aligned} \beta_{TSLS} &= \frac{cov(y, \widehat{\pi_{11}} z)}{var(\widehat{\pi_{11}} z)} = \frac{\widehat{\pi_{11}} cov(y,z)}{\widehat{\pi_{11}}^2 var(z)} = \frac{cov(y,z)}{\widehat{\pi_{11}} var(z)} = \frac{cov(y,z)}{\frac{cov(x,z)}{var(z)} var(z)} \\ &= \frac{cov(y,z)}{cov(x,z)} \end{aligned}$$

Advantages of 2SLS?

TSLS more convenient if there are additional exogenous regressors in the estimating equation (include in both the first and the second stage equations).

Return to ILS with multiple valid instruments for a single endogenous variable:

$$x_i = \pi_{11} z_{i1} + \pi_{12} z_{i2} + \varepsilon_i$$

Making the substitution:

$$\begin{aligned} y_i &= \beta(\pi_{11} z_{i1} + \pi_{12} z_{i2} + \varepsilon_i) + \nu_i \\ &= (\beta\pi_{11}) z_{i1} + (\beta\pi_{12}) z_{i2} + (\beta\varepsilon_i + \nu_i) \\ &= \pi_{21} z_{i1} + \pi_{22} z_{i2} + \mu_i \end{aligned}$$

No longer have a unique estimator of β. In the simple example above, $\widehat{\beta} = \pi_{21}/\pi_{11}$ or $\widehat{\beta} = \pi_{22}/\pi_{12}$.

The more instruments, the better?

The more instruments, the better?

- No!
- As the number of instruments included in the first stage gets large, the fit of that first stage improves for purely mechanical reasons and $\widehat{x}$ will start to approach x!
- Having a very large number of instruments (large relative to the sample size) is potentially a source of bias.
- Too many weak instruments tends to bias the 2SLS estimator towards the OLS estimator.

IV estimation when causal effects are heterogeneous

- If treatment effects vary in the population, we can only estimate average treatment effects for those whose treatment status is affected by the instrument.
- And we need another assumption in order to interpret our IV estimates as LATE estimates...

IV estimation when causal effects are heterogeneous

- If treatment effects vary in the population, we can only estimate average treatment effects for those whose treatment status is affected by the instrument.
- And we need another assumption in order to interpret our IV estimates as LATE estimates...

Monotonicity! (if treatment effects are homogeneous, then we need not worry about this because the treatment effects are the same across defier and complier populations).

Multiple instruments

- When treatment effects do not vary in the population, the over-identification tests make sense.
- And if different instruments capture the same (homogeneous) causal relationship, it makes good sense to combine multiple instruments to obtain more precise treatment effect estimates.
- But with heterogeneous treatment effects, different instruments can identify different local average treatment effects.
- Combining multiple instruments – now you are estimating a mixture of local average treatment effects.

Cloud chasing

- Writing IV papers has been likened to cloud chasing – chase them away doubts about your identification strategy with evidence.
- Although there is no formulaic approach to IV estimation and analysis, we can identify some basic steps and best practices.

Cloud # 1: IV estimation sheds light on uninteresting/poorly defined questions

- Pose a clear (and ideally interesting!) economic question.
- Make explicit the links between the parameter you are estimating and the underlying theory.
- If treatment effects are likely to vary in the population, think clearly about which units are affected by the exogenous variation in your instrument (and which units are out of reach).

Cloud #2 : Your instruments may be invalid

Absent an experiment, you can never be certain that your instruments are valid. But there is much you can do to build a convincing case:

- Clearly explain the nature of the omitted variables problem and why it might lead to biased estimates.
- Intuitively explain the rationale behind your IV strategy. Back up your arguments using graphs, tables, institutional details.
- Report the first stage results!
- Report the reduced form results! These do not suffer from the finite sample bias discussed above (recall this bias stems from estimation error in the first stage) and are proportional to the causal effect of interest.
- Think carefully about which units are affected by the instrument (and how to interpret the local average treatment effect).

Cloud # 3 : Weak instruments

The IV estimator is consistent but it is biased in small samples. Even small correlations between z_i and ν_i can cause severe bias if the instrument is weak

- Test whether the instruments are significant predictors of the potentially endogenous regressors. Report the F-statistic on the excluded instruments.
- If you are using multiple instruments, it is also good practice to report the just-identified estimates using your "best" instrument.

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Section 2

Hedonic valuation

What can we learn from revealed 'sorting'?

- Households sort across neighborhoods according to their wealth and preferences;
- Workers sort across jobs according to their qualifications and preferences;
- Drivers sort into vehicles according to their budget constraint and preferences. .

Insight: The act of sorting can reveal valuable information about consumer preferences for specific attributes and amenities that are not directly traded in markets.

The essence (of revealed preference) is figuring out what sort of behavior will reveal welfare measures when the levels of (quasi-fixed goods) change. Another way of looking at the problem is to ask what kinds of restrictions on preferences will allow a given type of behavior to reveal these values.

Of course, it is always possible to make assumptions about preferences that enable (us) to capture welfare measures from a given behavioral observation. The challenge is not so much the theoretical issue of whether there exists an assumption that will work. Rather, are there plausible and intuitively attractive stories about preferences that provide restrictions leading to the appropriate welfare measures?

Bockstael and McConnell (2007)

Neighborhood sorting and hedonic valuation

- The hedonic property value model is one of the most direct illustrations of how - with a little structure- private markets can reveal consumers' willingness to pay (WTP) for environmental quality.
- Many of the studies that helped establish modern best practices in hedonic valuation use data from housing markets.
- Primitives for the model consiste of supply for housing and the joint distribution of household preferences for income.

Why property markets?

- Housing/land markets provided a natural testing ground for equilibrium sorting models. And data are increasingly rich.
  - Particularly in urban areas, real estate markets are usually competitive and feature a large volume of transactions.
  - Property purchases are sizeable, so potential buyers presumably invest in collecting information about property and neighborhood characteristics.
  - The notion that property prices should reflect how people value attributes of the location and structure is intuitive and relatively non-controversial.
- Empirical analysis of housing markets rapidly expanding as high quality data linking property transactions to detailed property and neighborhood information becomes available.

Demand side (overview)

- Agents sort based on the basis of heterogeneous preferences and their understanding of the choice situation.
- Some forms of preference heterogeneity are related to observable features of consumers, their constraints, and their choices.
- Other forms of preference heterogeneity are not observable to us (the researcher).
  what the collection of those actions implies for market and non-market valuation.
- Absent market frictions (and assuming full information), spatial variation in amenities will be capitalized into housing prices.

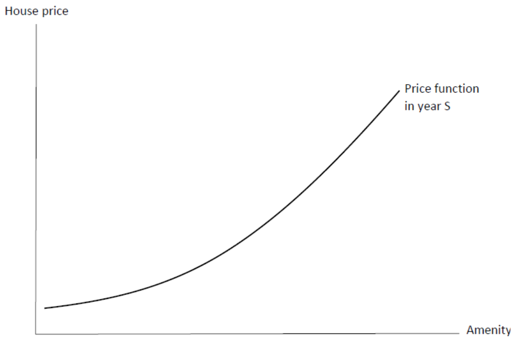
Supply side (overview)

- As heterogeneous agents sort, their collective behavior can influence the supply of amenities (e.g. school quality, racial composition, number of artisinal coffee shops).
- Sorting models that integrate descriptions of how these amenities are generated can, in principle, represent the attributes that define the choice alternatives available to agents as endogenous/part of the equilibrium outcome.
- Capturing these feedback loops is potentially important when assessing the equilibrium impacts of policies targeting environmental ammenity.
- But it also requires a ton of structure...which we'll not invoke today.

Theory foundations: Hedonic property values

The implied relationship between the amenity and housing prices holding all other features constant.

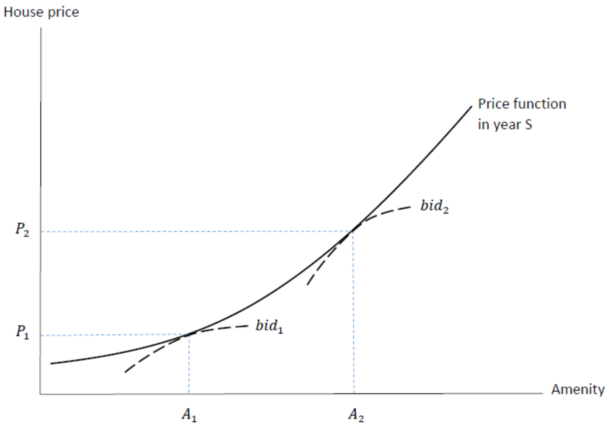
Fig 1a: The hedonic price function in amenity space



Theory foundations: Hedonic Price Function

Bid functions (which trace out max. WTP) differ across households with different incomes/preferences.

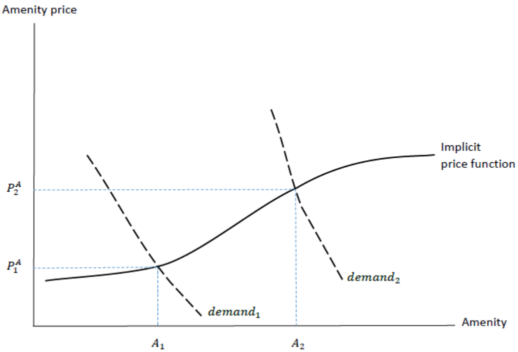
Fig 1b: The buyers' purchase decisions



Theory foundations: Implicit price function

- The slope of the bid function measures marginal WTP for an incremental increase in the attribute.
- Dashed demand curves are not observed by the econometrician. We only see intersection points.

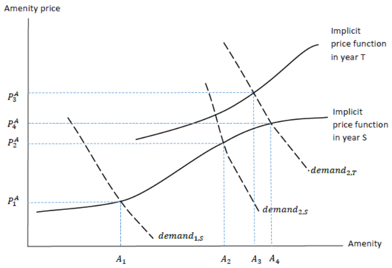
Fig 1c:The implicit price function reveals buyers' MWTP



Theory foundations: Something to think about...

Demand curves and implicit price functions change over time in response to changes in the distribution of the amenity.

Fig 1d: The implicit price function and MWTP change over time



When households experience wealth shocks, this can induce migration and alter the hedonic price function and its gradient (the implicit price function)...

From theory to empirics

Theory helps elucidate/define two empirical tasks:

1. First stage: Specify the hedonic price function $P(x, q)$. In theory, the partial derivative of the estimated hedonic price function yields participants' marginal willingness to pay for an incremental change in q.
    - In principle, we can estimate $P(x, q)$ using data on home prices, property attributes.
2. Second stage: Trace out the *demand function* in order to estimate how the marginal willingness to pay (MWTP) varies with the level consumed.
    - An essential step if we want to evaluate welfare implications of a non-marginal change....but more complicated!

First stage empirical challenges?

Specify a hedonic price function which relates variation in the unpriced amenity and variation in housing prices:

First stage empirical challenges?

Specify a hedonic price function which relates variation in the unpriced amenity and variation in housing prices:

- What is the spatial/temporal extent of the market over which the equilibrium price function is stable?
- How to measure variation in amenities?
- Perceived versus experience utility?
- Is observed variation exogenous in an econometric sense? Omitted variables?
- What is the functional form relationship between P and q, x.
- When can we expect changes in q to be capitalized in property values? Are consumers forward looking?

Bishop et al. (2019, REEP) offer an overview of best practices.

Market Definition

When specifying the hedonic price function $P(x, q)$, what is the right spatial extent of the market?

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When specifying the hedonic price function $P(x, q)$, what is the right spatial extent of the market?

- Model assumes a 'law of one price' - all houses with the same bundle of sell for the same price throughout the market.
- Narrowing the extent of the market will increase the chances that the law of one price – arbitrage between locations – holds empirically.
- Pooling data across large geographic areas can undermine the conceptual logic of the model.
- Trade-off?– narrowing the extent of the market limits observed variation in amenities AND limits your ability to value coarser amenities (such as climate, air quality).

Temporal aggregation?

When estimating the hedonic price function $P(x, q)$, can we pool data across years? Across decades?

Temporal aggregation?

When estimating the hedonic price function $P(x, q)$, can we pool data across years? Across decades?

- Over how long can we expect the same hedonic price function to hold?
- Stable conditions (e.g. business cycle, recession) are a consideration as there is unlikely to be arbitrage across time.
- Home buyers' MWTP can also evolve over time with changes in information and policy.

Spatially-aggregated data?

When estimating $P(x, q)$, researchers often regress mean housing prices on mean amenity levels. Problem?

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When estimating $P(x, q)$, researchers often regress mean housing prices on mean amenity levels. Problem?

- The derivative of the hedonic price function evaluated at the mean amenity need not equal the mean of the derivative of the hedonic price function (recall the implicit price function is the derivative of the hedonic price function).
- Median prices have been found to introduce measurement error that biases price-function parameter estimates (median prices can be poorly correlated with variation in local public goods). See, for example, Banzhaf and Farooque (2013).

Estimating amenity levels

Other concerns wrt measuring variation in q for the purpose of estimating $P(x, q)$?

Estimating amenity levels

Other concerns wrt measuring variation in q for the purpose of estimating $P(x, q)$?

- Revealed preference logic requires the analyst to characterize how buyers perceive amenity levels at each location.
- We need an objective measure of spatial variation in the amenity at high resolution.
- Complication 1: Sparse grid of amenity data (e.g. pollution monitors)
- Complication 2: Subjective beliefs. Perceived amenity may depart from actual.
- Complication 3: Dynamics. Purchase decisions may reflect expectations about the future evolution of amenity values (Bishop and Murphy 2018).

Omitted variables (and related threats to identification)

- Amenities may be spatially correlated due to geography, voting on public goods provisions (e.g. wealthy households prefer better air quality and vote to increase public school funding).
- Important to isolate exogenous variation in the amenity of interest.
- Quasi-experimental approaches can offer a way to isolate exogenous variation in the amenity of interest... but sometimes compromise the ability to interpret econometric estimates as measures of MWTP.

Identification strategy?

Standard strategy: Analyze transactions before relative to after a change in the spatial distribution of the amenity.

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Standard strategy: Analyze transactions before relative to after a change in the spatial distribution of the amenity.

- Strength: mitigate omitted variable bias by isolating quasi-random variation over time... Problems?
- This assumes a stationary price function. But a quasi-experimental change in amenity levels could also cause the price function to adjust.
- A SUTVA violation! Prices of ‘control’ households are indirectly treated.
- Kuminoff and Pop (2014) show that when a price function shifts over time, the standard DID model will yield biased estimates of the price function and biased estimates of MWTP.

Hedonic regressions can generate valuable (albeit limited) insights

A large literature estimates MWTP for a variety of environmental ammenities.

- Data needed for first stage estimation increasingly available.
- Clever IV strategies can address omitted variables problems...but raise concerns about conflating moves along demand curves with moves across.

But if we want to evaluate discrete changes in amenities, we need to rely on second stage estimates which can be confounded by selection bias....

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Section 3

Air Quality and Housing Values (a classic EEE IV application)

Let's start with a classic

Does Air Quality Matter? Evidence from the Housing Market
Chay and Greenstone (2005)

- Exploit the structure of the U.S. Clean Air Act Amendments of 1970 to provide evidence on the capitalization of air quality into housing values.
- Use an IV strategy to estimate marginal willingness to pay (MWTP) for cleaner air (we will discuss the foundations of hedonic valuation next month).
- Test for preference-based sorting across space (we will come back to this in a few weeks).

Chay and Greenstone (2005)

3 main findings:

1. Conventional hedonic methods produce unreliable and misleading estimates.
2. Mid-1970s TSP non-attainment designations significantly increased housing values in non-attainment areas.
3. Provide evidence consistent with taste-based self-selection – suggests LATE may *underestimate* ATE.

What's the identification problem here?

- Researchers have estimated the *association* between property values and air pollution, regression-adjusted for differences in observable covariates.
- But omitted variables (e.g. more polluted areas tend to be more urbanized, offer more employment opportunities, urban amenities) may explain the wide variability in hedonic price estimates and perverse signs.

"I have entirely avoided... the important question of whether the empirical difficulties, especially correlation between pollution and unmeasured neighborhood characteristics, are so overwhelming as to render the entire method useless." *Ken Small, 1975*

Characterize the identification problem

The cross-sectional model predominantly used in the literature is

$$y_{c70} = \boldsymbol{X}'_{c70}\boldsymbol{\beta} + \theta T_{c70} + \epsilon_{c70}, \quad \epsilon_{c70} = \alpha_c + u_{c70}, \tag{2}$$

and

$$T_{c70} = \boldsymbol{X}'_{c70}\boldsymbol{\Pi} + \eta_{c70}, \quad \eta_{c70} = \lambda_c + v_{c70}, \tag{3}$$

where y_{c70} is the log of the median property value in county c in 1970, $\boldsymbol{X}_{c70}$ is a vector of observed characteristics, T_{c70} is the geometric mean of TSPs across all monitors in the county, and ϵ_{c70} and η_{c70} are the unobservable determinants of housing prices and TSPs levels, respectively. The coefficient θ is the "true" effect of TSPs on property values and is interpreted as the average gradient of the hedonic price schedule. For consistent estimation, the least-squares estimator of θ requires $E[\epsilon_{c70}\eta_{c70}] = 0$. If there are omitted permanent (α_c and λ_c) or transitory (u_{c70} and v_{c70}) factors that covary with both TSPs and housing prices, then the cross-sectional estimator will be biased.

Characterize the identification problem

With repeated observations over time, a "fixed-effects" model implies that first-differencing the data will absorb the county permanent effects, α_c and λ_c. This leads to

$$y_{c80} - y_{c70} = (\boldsymbol{X}_{c80} - \boldsymbol{X}_{c70})'\boldsymbol{\beta} + \theta(T_{c80} - T_{c70}) + (u_{c80} - u_{c70}) \qquad (4)$$

and

$$T_{c80} - T_{c70} = (\boldsymbol{X}_{c80} - \boldsymbol{X}_{c70})'\boldsymbol{\Pi} + (v_{c80} - v_{c70}). \qquad (5)$$

But identification requires that there are no unobserved, time varying shocks to pollution levels that co-vary with unobserved shocks to housing prices.

Instrumental solution

The Clean Air Act Amendment of 1970 establishes NAAQS for five criteria pollutants.

- Counties are designated as either attainment/non-attainment for each pollutant.
- Federal Total Suspended Particulates (TSP) standard violated if:
    1. Annual geometric mean exceeds 75 μ/m^3 or
    2. Second highest daily concentration exceeds 250 μ/m^3.
- TSP standards reduced pollution levels in non-attainment counties vis a vis attainment counties.

1969-1990 TSP concentrations (population weighted average)

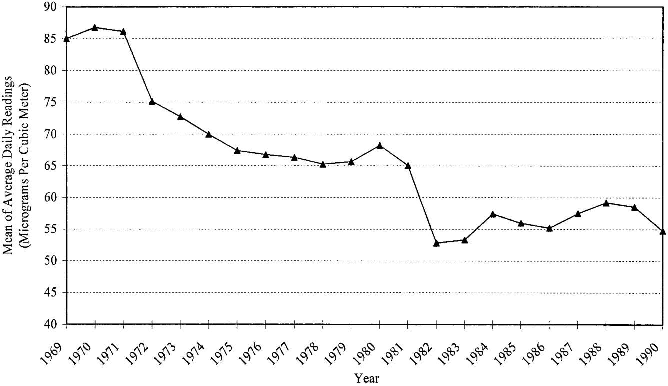


FIG. 1.—National trends in TSPs pollution, 1969–90. The data points are derived from the 169 counties that are continuously monitored in this period. These counties had a total population of approximately 84.4 million in 1980. The annual county means were calculated as the weighted average of the monitor-specific geometric means, where the weight is the number of monitor observations. The year-specific average is calculated as the weighted average of the county-specific means, where the weight is the 1980 population.

Building an instrument

How to leverage CAA NAAQS to construct an instrument?

Building an instrument

How to leverage CAA NAAQS to construct an instrument?

- These authors focus on TSP because TSP are the most visible form of air pollution (i.e. more likely to affect housing values).
- They use 1975 non-attainment status as an instrument for changes in TSP concentrations.
- They work to provide evidence in support of the validity of their instrument.

LATE versus ATE?

LATE versus ATE?

- If there is heterogeneity across individuals in tastes for clean air/susceptibility to pollution impacts, individuals may self-select into locations on the basis of unobserved differences.
- If individuals with lower WTP for air quality sort to areas with worse air quality, then authors identify the average MWTP for a non-random subpopulation.
- Authors suggest that, for this reason, the LATE likely biased down vis a vis ATE in this context.... thoughts?

The first stage:

$$T_{c80} - T_{c70} = (\boldsymbol{X}_{c80} - \boldsymbol{X}_{c70})'\boldsymbol{\Pi}_{TX} + Z_{c75}\Pi_{TZ} + (v_{c80} - v_{c70})^{\circ} \tag{6}$$

and

$$Z_{c75} = 1(T_{c74} > \overline{T}) = 1(v_{c74} > \overline{T} - \boldsymbol{X}'_{c74}\boldsymbol{\Pi} - \lambda_c), \tag{7}$$

where Z_{c75} is the regulatory status of county c in 1975, $1(\cdot)$ is an indicator function equal to one if the enclosed statement is true, and $\overline{T}$ is the maximum concentration of TSPs allowed by the federal regulations.[21] Nonattainment status in 1975 is a discrete function of TSPs concentrations in 1974. In particular, if T_{c74}^{avg} and $T_{c74}^{\max}$ are the annual geometric mean and second-highest daily TSPs concentrations, respectively, then the actual regulatory instrument used is $1(T_{c74}^{\text{avg}} > 75\ \mu\text{g/m}^3$ or $T_{c74}^{\max} > 260\ \mu\text{g/m}^3)$.

The reduced form:

$$y_{c80} - y_{c70} = (\boldsymbol{X}_{c80} - \boldsymbol{X}_{c70})'\boldsymbol{\Pi}_{yX} + Z_{c75}\Pi_{yZ} + (u_{c80} - u_{c70})^{\circ}, \tag{8}$$

The IV estimator is exactly identified by the ratio of two reduced form parameters

Under what conditions does 2SLS provide a consistent estimate?

Under what conditions does 2SLS provide a consistent estimate?

$\Pi_{TZ} \neq 0$: Authors can directly show this.

$E[Z_{c75}(u_{c80} - u_{c70}] = 0$: Unobserved price shocks from 1970-80 are orthogonal to transitory shocks to 1974 TSP levels.

1970-1980 change in TSPs by attainment status in 1975

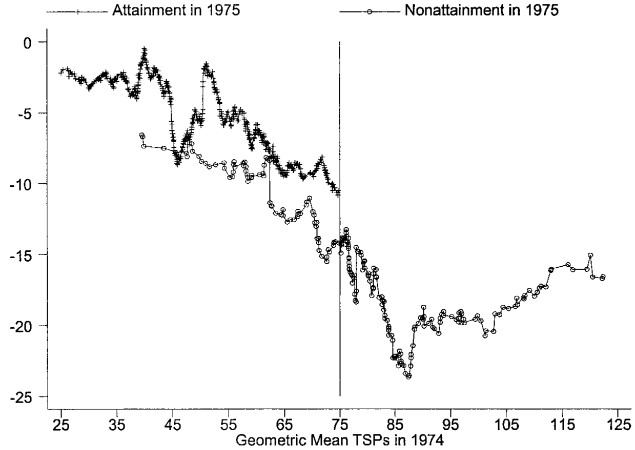


FIG. 4.—1970–80 change in mean TSPs by 1975 nonattainment status and the geometric mean of TSPs in 1974.

Graphical evidence that non-attainment designation generated reductions in TSP over the 1970-1980 period.

Graphical preview of the reduced form

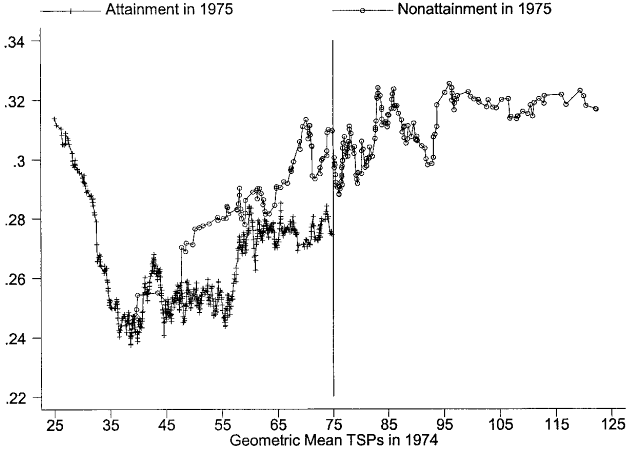


FIG. 5.—1970–80 change in log housing values by 1975 nonattainment status and the geometric mean of TSPs in 1974.

First stage

TABLE 4
ESTIMATES OF THE IMPACT OF MID-DECADE TSPs NONATTAINMENT ON 1970–80 CHANGES IN TSPs POLLUTION AND LOG HOUSING VALUES

	(1)	(2)	(3)	(4)
	A. Mean TSPs Changes			
TSPs nonattainment in 1975 or 1976	−9.96	−10.41	−9.57	−9.40
	(1.78)	(1.90)	(1.94)	(2.02)
F-statistic TSPs nonattainment*	31.3	29.9	24.4	21.5
	(1)	(1)	(1)	(1)
R^2	.04	.10	.19	.20

- Mid-decade nonattainment status is associated with an 11 −− 12 percent reduction in TSPs.
- This estimate is insensitive to a wide set of controls.
- F-statistic ranges between 22 and 31 depending on the specification

Reduced form

	B. Log Housing Changes			
TSPs nonattainment in 1975 or 1976	.036	.022	.026	.019
	(.012)	(.009)	(.008)	(.008)
F-statistic TSPs nonattainment*	8.5	6.2	9.3	6.4
	(1)	(1)	(1)	(1)
R^2	.01	.56	.66	.73
County Data Book covariates	no	yes	yes	yes
Flexible form of county covariates	no	no	yes	yes
Region fixed effects	no	no	no	yes
Sample size	988	983	983	983

NOTE.—See the notes to previous tables. In panel A the dependent variable is the difference between the 1977–80 and 1969–72 averages of mean TSPs concentrations. The mean is $-7.82\ \mu g/m^3$. In panel B the dependent variable is the difference between 1980 and 1970 log housing values, and its mean is 0.27. Standard errors (in parentheses) are estimated using the Eicker-White formula to correct for heteroskedasticity.

* Numbers in parentheses in rows with F-statistics are numerator degrees of freedom.

- TSP non-attainment designations associated with substantial improvements (2-3 percent increase) in property values.
- These reduced form findings are important in their own right.

Main Event

TABLE 5
INSTRUMENTAL VARIABLES ESTIMATES OF THE EFFECT OF 1970–80 CHANGES IN TSPS POLLUTION ON CHANGES IN LOG HOUSING VALUES

	(1)	(2)	(3)	(4)
	A. TSPs Nonattainment in 1975 or 1976			
Mean TSPs (1/100)	−.362	−.213	−.266	−.202
	(.152)	(.096)	(.104)	(.090)
Sample size	988	983	983	983
	B. TSPs Nonattainment in 1975			
Mean TSPs (1/100)	−.350	−.204	−.228	−.129
	(.150)	(.099)	(.102)	(.084)
Sample size	975	968	968	968
	C. TSPs Nonattainment in 1970, 1971, or 1972			
Mean TSPs (1/100)	.072	−.032	−.050	−.073
	(.058)	(.042)	(.041)	(.035)
Sample size	988	983	983	983
County Data Book covariates	no	yes	yes	yes
Flexible form of county covariates	no	no	yes	yes
Region fixed effects	no	no	no	yes

NOTE.—See the notes to previous tables. The coefficients are estimated using 2SLS. The first row of panels A–C indicates which instrument is used. From panels A to C, the instruments are an indicator equal to one if the county was nonattainment for TSPs in either 1975 or 1976, an indicator equal to one if the county was nonattainment for TSPs in 1975, and an indicator that equals one if the county was nonattainment for TSPs in either 1970, 1971, or 1972, respectively. Standard errors (in parentheses) are estimated using the Eicker-White formula to correct for heteroskedasticity.

- Using the 1975 non-attainment indicator as an instrument, a 1 percent decrease in TSP leads to a 0.2 percent increase in housing prices.
- Translating this to levels, a 1 μ/m^3 increase in TSP decreases house prices by \$243 (in 2001 dollars).
- If preferences are homogeneous and linear (implying a constant MWTP for clean air), authors can evaluate the 10-unit reduction in mean TSPs in non-attainment counties: They estimate an increase in mean housing value of \$2,400 (and an aggregate value increase of \$45 billion!).
- Thoughts? Concerns??

Section 4

Frontier application: Health costs of air pollution

Health Costs of Air Pollution

- An estimated 4.2 million premature deaths globally are linked to ambient air pollution (WHO 2020).
- Federal air pollution regulations are among the most controversial interventions mandated by the U.S. government.
- Estimated mortality effects of PM2.5 comprise the largest component (by far) of benefits in regulatory cost benefit analysis of major pollution regulations.
- Estimating the causal effects of PM2.5 on health is complicated by a host of factors, including omitted variable bias and measurement error...
- Credible estimates of the value of cleaner air are essential inputs to policy evaluation/analysis.

What's the identification problem here?

- Researchers have estimated the *association* between pollution exposure and health outcomes, regression-adjusted for differences in observable covariates.
- But omitted variables (e.g. changes in economic activity that are correlated with pollution and health outcomes) potentially confound the interpretation.
- Selection also an issue if sensitive (unsensitive) people move away (towards) the risk.

Mortality and Medical Costs of Air Pollution

- Deryugina et al. (2020) presents the first large-scale, quasi-experimental estimates of the causal effects of *short-term*, *acute* PM2.5 exposure on mortality and medical costs.
- Authors harness wind-generated variation in pollution across a broad geographic and temporal scale.
- Combine the universe of Medicare beneficiaries (97 percent of population over 65) with novel IV strategy to estimate causal effects of exposure variation on mortality.

Innovations

- Overcome identification and statistical power challenges by exploiting daily variation in wind direction which generates variation in pollution exposure.
  - This strategy allows them to harness plausibly exogenous variation across a broad geographic scale and over a long time period.
- Rich data allows them to explore heterogeneity in exposure effects across sub-populations.
- Develop a new approach to estimating the life-years lost due to air pollution exposure.
  - Use ML techniques to incorporate >1000 variables from Medicare health histories to more accurately predict counterfactual life expectancy.

Preview of findings

- 1 $\mu g/m^3$ increase in PM2.5 exposure for one day causes 0.61 deaths per million elderly individuals over three day window.
- Increases in PM2.5 leads to more ER visits, hospitalizations, in-patient spending.
- Accounting for rich medical history reduces life years lost estimate by 55% relative to standard approach that conditions on age and gender.
- 1 $\mu g/m^3$ increase in PM2.5 exposure for one day causes loss of 2.7 liife-years per million elderly individuals over three day window.

PM2.5 Overview

Figures

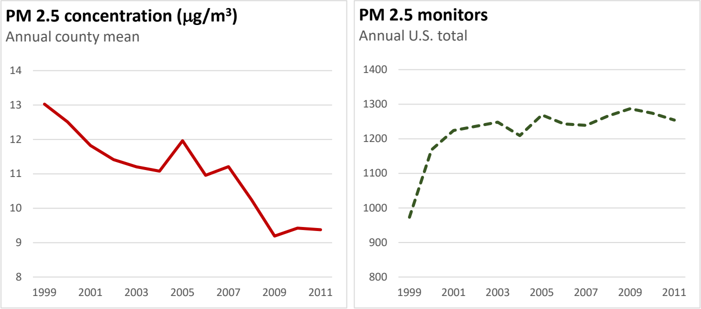
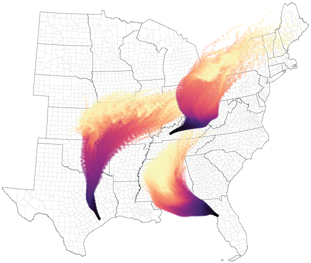


Figure 1. Trends in PM 2.5 air pollution and monitoring, 1999-2011. Figure displays annual county means for PM 2.5 concentration (left panel), and the nationwide total number of PM 2.5 monitors (right panel).

Regulatory limits on ambient PM2.5 concentrations are enforced using measurements collected by a sparse network of regulatory-grade air pollution monitors (US EPA).



- A very large fraction of local PM is caused by emissions from non-local sources.
- Pollution transport can be highly stochastic - wind/temperature/precip.
- Authors show that the relationship between PM and wind direction is strong.

Medicare administrative data

- Tracks detailed health data for over 97 percent of Americans over 65.
- Detailed information about every death, every hospital visit, nursing home stay is tracked and recorded.
- Indicators for the presence of 27 chronic conditions and extensive health history.
- Health care utilization and costs also reported by providers.
- 80 percent of counties do not have EPA monitors. Study focuses on individuals living in monitored counties: approx. 70 percent of the elderly Medicare population.

Isolating variation in PM2.5

The key causal relationship we would like to estimate is the effect of short-run fluctuations in fine particulate matter on mortality, health, and health care spending, net of any potentially confounding factors. This relationship can be represented by the following regression equation:

$$Y_{cdmy} = \beta \text{PM2.5}_{cdmy} + X'_{cdmy}\boldsymbol{\gamma} + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_{cdmy}, \tag{1}$$

where the dependent variable is one of several possible outcomes in county c on day d in month m and year y. The parameter of interest is β, the coefficient on daily PM 2.5 levels.

- High granularity supports high-dimensional fized effects: flexibly control for geography (county), time (statexmonth, monthxyear).
- Concerns?

- OLS specification contains county FE to control for time-invariant cross-county differences.
- Month fixed effects to capture seasonality; month-by-year FE to control flexibly for time-varying shocks (e.g. medicare policy changes).
- But OLS estimates still prone to bias because pollution exposure is not randomly assigned and prone to measurement error.

How to harness the wind?

What dimensions of wind direction do they use to instrument for air pollution (and why?)

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- PM2.5 in a given location is significantly determined by contributions from regional upwind sources.
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- PM2.5 in a given location is significantly determined by contributions from regional upwind sources.
- **Why don't the authors use prevailing wind direction?** because the predictability could cause individuals to sort upwind/downwind (sorting bias). Use variation attributed to departures in wind from prevailing direction (thus focus on acute versus chronic exposure).
- **Why pool effects across monitors?** Because county pollution monitor reading is a crude proxy for air quality throughout the county, authors estimates a common effect of county wind direction for spatial clusters of 20 monitors.

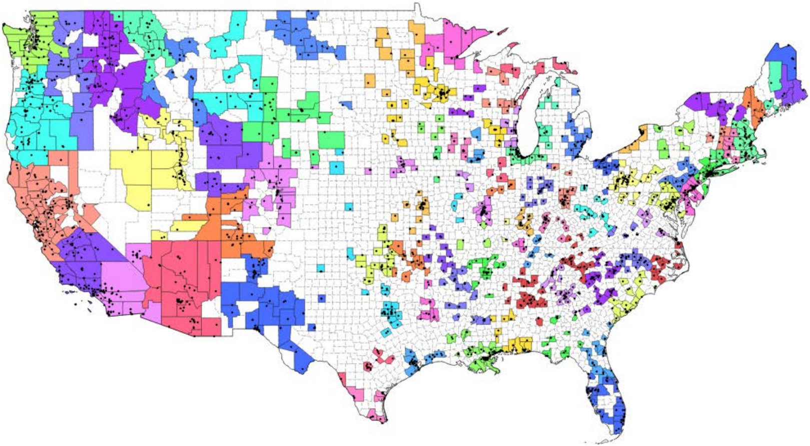

Figure 4. Counties assigned to each monitor group. Different colors correspond to different monitor groups. White corresponds to counties not assigned to any monitor group due to lack of monitors. Black dots represent PM 2.5 pollution monitors.

Pollution transport that affects monitor readings in a way that is not representative of ambient pollution levels will generate measurement error and bias.

First stage

instrument for pollution. Because the effect of wind direction on PM 2.5 levels varies by geography, as illustrated by Figures 1 and 2, we allow the effect of the wind instruments in our first stage to also vary according to geography. The specification for our first stage is:

$$\text{PM2.5}_{cdmy} = \sum_{g=1}^{100} \sum_{b=0}^{2} \beta_b^g 1[G_c = g] \times WINDDIR_{cdmy}^{90b} + X'_{cdmy}\boldsymbol{\sigma} + \alpha_c + \alpha_{sm} + \alpha_{my} + \epsilon_c. \quad (2)$$

- The variable $1[\ G_c = g\ ]$ is an indicator for county being classified into monitor group g.
- The coefficient on the interaction between these two variables, β_b^g, is thus allowed to vary across 100 different geographic regions g and 3 wind direction bins b.
- With such a large number of instruments, they report (large) F-statistics.

Under what conditions does 2SLS provide a consistent estimate?

1. **Strong first stage**: $\beta_b^g \neq 0$: Authors can directly show this.
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2. **Exclusion restriction?**

   Assumption: After flexibly controlling for many fixed effects and climatic variables, changes in a county's daily wind direction are unrelated to changes in the county's mortality or health care use except through their influence on air pollution.

   Changes in wind direction affect health outcomes only via pollution exposure.

Table 2—OLS and IV Estimates of Effect of PM 2.5 on Elderly Mortality, by Age Group

	65+ (1)	65–69 (2)	70–74 (3)	75–79 (4)	80–84 (5)	85+ (6)
Panel A. OLS estimates						
PM 2.5 (μg/m^3)	0.095	0.041	0.029	0.022	0.142	0.425
	(0.021)	(0.014)	(0.018)	(0.022)	(0.036)	(0.072)
Dependent variable mean	385	131	197	312	508	1,127
Effect relative to mean, percent	0.025	0.032	0.015	0.007	0.028	0.038
Observations	1,980,549	1,980,549	1,980,549	1,980,549	1,980,549	1,980,549
Adjusted R^2	0.254	0.080	0.085	0.082	0.077	0.110
Panel B. IV estimates						
PM 2.5 (μg/m^3)	0.685	0.267	0.329	0.348	0.877	2.419
	(0.061)	(0.066)	(0.068)	(0.098)	(0.159)	(0.246)
F-statistic	298	285	292	303	309	315
Dependent variable mean	385	131	197	312	508	1,127
Effect relative to mean, percent	0.178	0.204	0.167	0.111	0.173	0.215
Observations	1,980,549	1,980,549	1,980,549	1,980,549	1,980,549	1,980,549

Notes: Table reports OLS and IV estimates of equation (1) from the main text. Dependent variable is the three-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. Standard errors, clustered by county, are reported in parentheses.

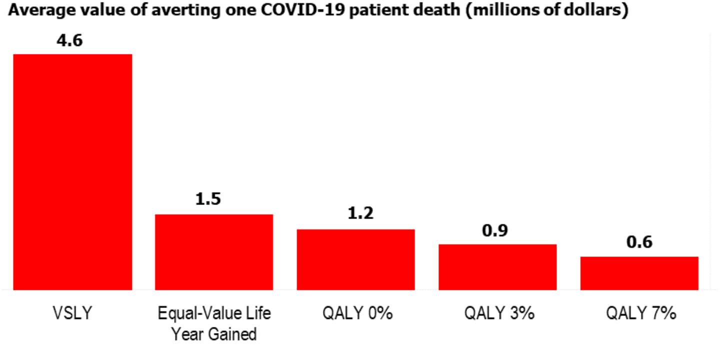
Mortality impacts

- IV estimates are substantially (5-14) times larger than OLS, suggesting that OLS estimates are biased... what's the mechanism?
- IV estimates imply that each 1 $\mu g/m^3$ increase in daily exposure causes 0.61 additional deaths per million elderly over the following 3 days (a 0.15 percent increase)
- IV estimates show a monotonic relationship between mortality estimates and age.

Life years lost

- Using the same VSL estimate for all deaths may overstate true cost if individuals who are impacted have short life expectancies.
- Estimating life-years lost is challenging because counterfactual life expectancy is unobserved.
- Prior studies condition on age and/or sex.
- This approach will overstate life-years lost if individuals who are impacted have shorter life expectancies than the conditional average.

The value of averting a single COVID-19 death depends heavily on the value of life method used



VSLY=Value of Statistical Life Year: $311,194 x undiscounted years of life expectancy
Equal-Value Life Year Gained: $100,000 x undiscounted years of remaining life expectancy
QALY 0%=$00,000 x undiscounted quality-adjusted years (QALYs) of remaining life expectancy
QALY 3%=$100,000 x QALYs of remaining life expectancy discounted at 3%
QALY 7%=$100,000 x QALYs of remaining life expectancy discounted at 3%

Life years lost innovation

- Authors exploit detailed Medicare claims data.
- Machine learning techniques allow them to use 1,062 variables when predicting individual life expectancies.
- Use LASSO to predict the life expectancy of every Medicare beneficiary.
- Aggregate life-years lost relative to counterfactual expectancies for all decedents in each county. Estimate life-years lost per million beneficiaries.

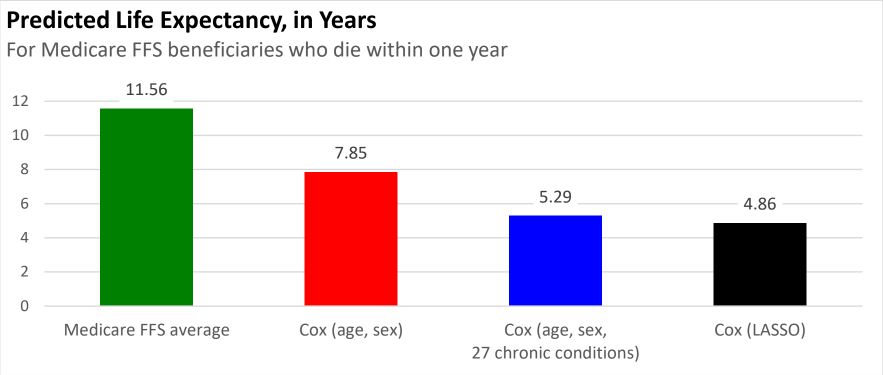


Figure 5. Average life expectancy for continuously enrolled fee-for-service Medicare beneficiaries who later die within one year, 2001-2011. Life expectancy for each beneficiary is estimated as of January 1 of the calendar year of death. Estimates for "Medicare FFS average" are produced by MLE estimation of survival model (6) with no covariates. Estimates for "Cox (age sex)" and "Cox (age sex cc) are produced by estimating the survival model (6) using age and gender, and age, gender and 27 chronic conditions, as predictors, respectively. Estimates for "Cox (LASSO)" are produced by machine learning estimation of the survival model (7) with 1,062 included regressors.

LASSO provides the most accurate predicted conditional average life expectancy.

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.

Better survival models predict lower life expectancy for decedents on average and a more accurate distribution of life expectancies among decedents.

Policy implications?

- Average PM2.5 level decreased by 3.65 $\mu g/m^3$ between 1999-2011.
- Estimates imply this saved 147,098 life-years annually in 2011.
- Value a life year at \$100,000, this amounts to \$15 billion.
- If authors condition only on age and sex when constructing counterfactual life expectancy, benefits are \$32 billion.

Comments? Thoughts?