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Quasi-experiments in Nonmarket Valuation and Regulatory Analysis

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Understanding *Causality* in a Non-experimental World

- As applied social scientists, we are interested in the *causal relationship* between policy levers and outcomes.

- Causal relationships allow us to predict what will happen in alternative ("counterfactual") worlds.

Understanding *Causality* in a Non-experimental World

- The norm for identification of a causal effect in environmental economics literature based on observational data is regression analysis.

- Recent arguments suggest that the evidence to date is correlative, not causal.

  → Heart of critique is that the fundamental assumption of selection only on observables is likely invalid.

The Evaluation Problem

- We observe people (things) in one state of the world – treated or untreated – but never both.

- Solving the evaluation problem requires obtaining credible estimates of the *counterfactual*.

- What *would have happened* had you not been treated?

The Evaluation Problem

- Let Y_1 = outcome when treated
  Y_0 = outcome when not treated

- The impact of treatment on person i, Δ_i is:
$$\Delta_i = Y_{1i} - Y_{0i}$$

- However, never observe both Y_1 and Y_0 for the same person → the counterfactual is always missing!

The Evaluation Problem

- More generally, we seek:

$$\boldsymbol{\Delta = E(Y_{1i} \mid d_i=1) - E(Y_{0i} \mid d_i=1)}$$

where d=1/0 if individual is treated/untreated

- $E(Y_{1i} \mid d_i=1)$ is the EV of the outcome for those who are treated.
- $E(Y_{0i} \mid d_i=1)$ is the EV of the outcome for those who are treated, <u>had they not been treated</u>

The Evaluation Problem

- We can't know $E(Y_{0i} \mid d_i=1)$, so we use a control group:

$$\mathbf{\Lambda = E(Y_{1i} \mid d_i=1) - E(Y_{0i} \mid d_i=0)}$$

- $\Lambda = \Delta$ if:

$$E(Y_{0i} \mid d_i=0) = E(Y_{0i} \mid d_i=1)$$

→ mean independence must hold

The Evaluation Problem

- Ideally, one could experimentally vary treatment
  - Randomly assign eligible people/firms/units to treatment and control.
  - Two groups should be identical in observable & unobservable characteristics up to sampling error

  → i.e., we expect $E(Y_{0i} \mid d_i=0) = E(Y_{0i} \mid d_i=1)$ to hold!

The Evaluation Problem

- Less strictly, we only require conditional mean independence (CMI):

$$E(Y_{0i} \mid X, d_i=0) = E(Y_{0i} \mid X, d_i=1)$$

- Analogue in linear regression analysis:

$$E(u \mid X, d_i=0) = E(u \mid X, d_i=1)$$

where we also require:

$$E(u \mid X, D) = 0 \quad \textit{(a stronger condition)}$$

The Evaluation Problem

- The CMI assumption is key to understanding *selection bias* → an important threat to validity.

- *Selection* → correlation between assignment to treatment & outcomes in the absence of treatment.

The Evaluation Problem

- Different types of selection have different solutions.
  - selection on observables → matching methods
  - selection on unobserables → difference in differences if unobservables are time invariant

Difference-in-Differences (DD)

- Decompose outcome equation unobservable component into two pieces:

  $y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \rho\, D_{it} + \mu_i + \varepsilon_{it}$

  ρ = parameter of interest (D_{it} indicates treatment)
  μ_i = unobserved time-invariant fixed effect
  ε_{it} = transitory component of unobservable

  e.g., D_i is participation in job training program; and μ_i could be motivation

Difference-in-Differences (DD)

- Ignoring μ_i results in a biased estimate of ρ.

- But say, you have observations on treated and control groups over time (pre- and post-treatement) → μ_i can be differenced out.

Difference-in-Differences (DD)

- Let t = post-treatment and s=pre-treatment:

$$\Delta y_{it} = \delta_0 + \beta_1 \Delta X_{1it} + \ldots + \rho \Delta D_{it} + \Delta \varepsilon_{it}$$

where Δ is difference (i.e., $y_{it} - y_{is}$) and δ_0 is the difference in intercept ($\beta_{0t} - \beta_{0s}$)

- Estimate the difference (ρ) in differences (t-s).
- Key assumption: selection depends only on μ_i & not transitory factors that vary over time (ε_{it})

Difference-in-Differences (DD)

- Does this assumption hold?
  - The million dollar question (£0.74m)
  - When self-select into treatment?... maybe
  - Onus is on researcher to convince reader

More DD plus an RD

- Above requires panel data, the DD equivalent in repeated cross-sectional data is:

$$y_{ijt} = \alpha_0 + \alpha_1 d_t + \alpha_2 d_j + \beta\, d_{jt} + Z_{ijt}\delta + \varepsilon_{ijt}$$

i = observation

t = time period (after=1 or before=0)

j = group (treated=1 or not=0)

Z = vector of other control variables

β is the causal effect of treatment on outcomes (the effect of being in the experimental group, post-treatment).

More DD plus an RD

- Regression discontinuity design (RD), with a sharp design.
  - Assignment to treatment is determined by the value of a covariate relative to a threshold, e.g., $D_{1i} = 1$ iff $Z_i \geq c$

- $y_{ijk} = \alpha_0 + \alpha_1 d_j + \alpha_2 d_k + \beta\, d_{jk} + Z_{ijk}\delta + \varepsilon_{ijk}$

  i = observation (e.g., house)

  j = group (e.g., subdivision)

  k = boundary (e.g., school attendance or info disclosure zone)

Quasi & Natural Experiments

- Key assumption: no selection into treatment on time-varying factors.
- In situations of self-section → true?
- A strategy to alleviate? Quasi-experimental designs.

Quasi & Natural Experiments

- Quasi-experimental methods rely on variation in explanatory variables that are generated by policies or nature that is plausibly exogenous: i.e., plausible exogenous assignment to treatment.
  - Airport noise disclosures, cancer clusters, quirks in policies or programs (e.g., EPA & HRS scores)

- Key is to find exogenous variation in key explanatory variables & find comparison groups that are comparable.

Quasi & Natural Experiments

- A lot of important questions cannot be answered experimentally:
    - does mother's socio-economic affect birth weight?
    - does air quality affect mortality?
    - do environmental disamenities (hazardous waste sites, airport noise) lower property values around them?
    - does environmental quality affect learning outcomes?

or are hard/expensive to answer experimentally:

- do smaller class sizes improve learning outcomes?

Example 1:
The "Value of a Statistical Life" (VSL)

- Suppose mean WTP = \$600 per year
  to reduce the risk of death by 1/10,000

→ VSL = \$600 x 10,000 = \$6 million

“Value of a Statistical Life” (VSL)

- From a policy perspective (U.S.), the VSL is one of the (if not **the**) most important single benefit estimate generated by economists.

- Particularly important in environmental regulation (air quality), transportation safety, and some types of public health policies.

“Value of a Statistical Life” (VSL)

- VSL estimates used in policy primarily based upon hedonic wage estimates:

$$wage_{\mathrm{ik}} = \alpha + \beta\, risk_{\mathrm{k}} + WC_{\mathrm{i}}\gamma + JC_{\mathrm{k}}\varphi + \varepsilon_{\mathrm{ik}}$$

"Value of a Statistical Life" (VSL)

- VSL estimates used in policy primarily based upon hedonic wage estimates:

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- Say β = \$600 = annual average WTP

  → VSL = \$6 million (\$600 x 10,000)

“Value of a Statistical Life” (VSL)

- Over 45 studies implement hedonic wage models

- Post 2000, majority of estimates lie in \$8 to \$15 million range, but vary:
  - *\$2 million (Kochi, 2011)*
  - *\$15 million (Kniesner et al., 2012)*

Key Shortcomings of Existing Hedonic Wage Studies

- Measurement error in available risk data
  - National average risk rates
- Omitted variable bias
  - Little known about workplace characteristics

$$wage_{ik} = \alpha + \beta\, risk_k + WC_i\gamma + JC_k\varphi + \varepsilon_{ik}$$

A Quasi-experimental Approach for Estimating the VSL

- Identify an exogenous instrument for risks at the place of employment:
  - *Randomized* Occupational Safety and Health Administration (OSHA) inspections (1987-1997)
  - Plants are either "violators" or "compliers"
  - If violations are found, plants must come into compliance (usually by 30 days)

Estimation Strategy

(1) Are OSHA inspections a valid instrument for plant-level safety?

(i) Are they random?

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$$\Delta = E[(X_t^I | industry_i, state_s) - E(X_t^{UI} | industry_i, state_s)]$$

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Results => no significant difference in observable characteristics of inspected and uninspected plants.

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(ii) Do they affect plant-level risks?

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(ii) Do they affect plant-level risks?

$$fatrate_{j,t} = a + PC_{j,t}\beta + T_t + P_j + \varphi V_{j,t} + \epsilon_{j,t},$$

$$accrate_{j,t} = a + PC_{j,t}\beta + T_t + P_j + \pi V_{j,t} + \epsilon_{j,t},$$

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Results => φ = -3.35 (0.73)*** and π = - 5.31 (1.38)***

Estimation Strategy

1. Difference-in-differences estimator comparing all inspected plants to all uninspected plants.

    » Post-inspection, do wages of *inspected plants* (safety improving) increase less than *uninspected plants*?

Estimation Strategy

- Model:

$$Wage_{j,t} = a + PC_{j,t}\beta + T_t + P_j + \gamma FPI_{j,t} + OI_{j,k,t}\delta + \epsilon_{j,t}$$

  - $Wage_{j,t}$ = average plant-level wage rate for production workers
  - $PC_{j,t}$ = vector of all observable plant characteristics
  - T_t = year fixed effects
  - P_j = plant specific fixed effects

Estimation Strategy

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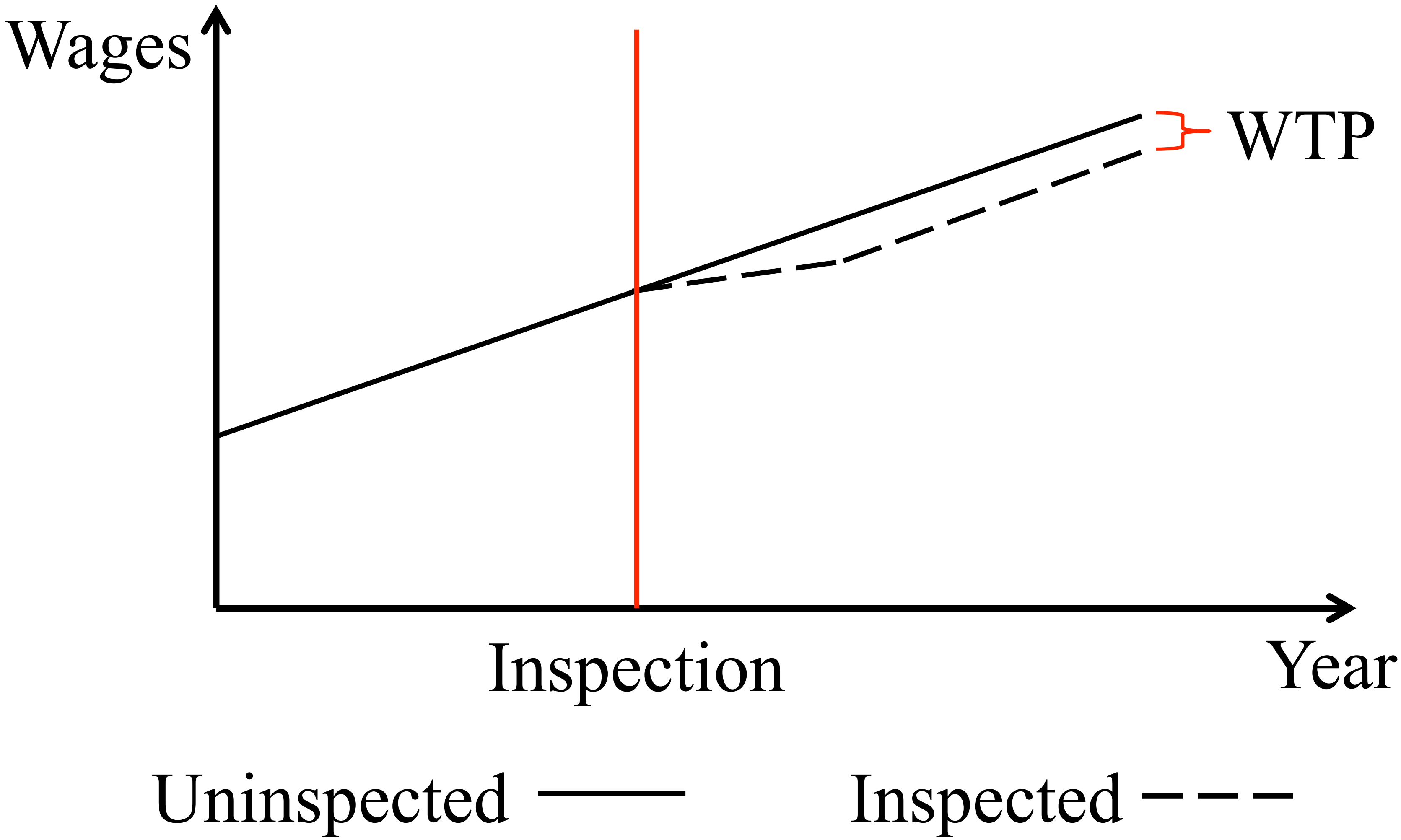
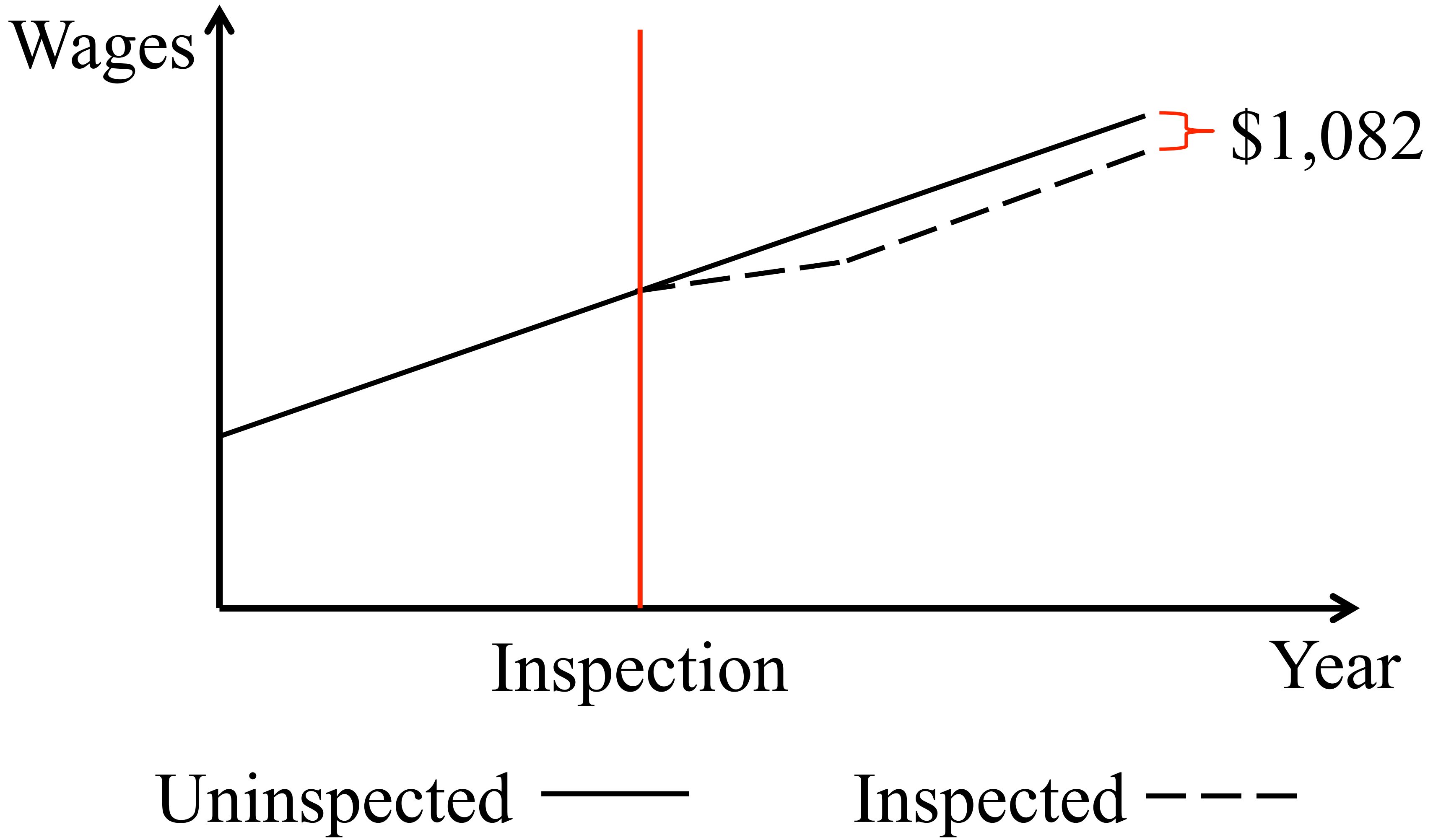
$$Wage_{j,t} = a + PC_{j,t}\beta + T_t + P_j + \gamma FPI_{j,t} + OI_{j,k,t}\delta + \epsilon_{j,t}$$

  - $FPI_{j,t} = 1$ for plants receiving a federal programmed OSHA inspection post inspection
  - $OI_{j,k,t}$ = vector of dummy variables for other OSHA inspections of type k
  - γ provides causal evidence for the existence of compensating wages for risk

Wage Adjustments



Wage Adjustments



Constructing the VSL

- Results indicate a VSL = \$2.2 million (2011\$)
- Range is \$2.2 to \$3.8 million (stat. sig.)

  - US EPA currently uses \$8.2 million

  - Viscusi, 2004 (blue collar): \$9.9 million

  - EU in 2000 suggested €1.0m (range 0.65 – 2.5)
    → \$1.7m (range \$1.3 – \$4.4) in 2011\$

Summary

- Estimate VSL that:
  - is grounded in measures of risks at the place of employment
  - relies on ***exogenous*** variation in workplace risk
  - results are substantially lower then existing estimates from similar samples

Wrap-up

- Payments for Energy Conservation
  – use quirk of eligibility rule (service date start) as a random assignment rule to treatment (finds payments to achieve a 20% reduction only were causal for 5%-10% of total)
- Does downzoning increase property values?
  – Water supply watershed protection act
- Daylight savings saves energy?
  – Australian Olympics / Indiana

Wrap-up

- Does cleanup of hazardous waste increase property values?
  - Quirk in superfund funding policy
- Does airport noise affect property values?
  - Information disclosure
- Value of water in agricultural production?
  - Surprise moratorium in a watershed
- Air quality impacts on neonatal health?
  - Installation of toll stop & wind direction.

Final words

If you cannot experimentally control
the variation in your data,
you should at least understand it.

Final words

Experiments are not, however, a substitute for thinking.