

# Quasi-experiments in Nonmarket Valuation and Regulatory Analysis

Laura O. Taylor

Center for Environmental and Resource Economic Policy  
North Carolina State University

# 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  $i$ ,  $\Delta_i$  is:  
$$\Delta_i = Y_{1i} - Y_{0i}$$
- However, never observe both  $Y_1$  and  $Y_0$  for the same person  $\rightarrow$  the counterfactual is always missing!

# The Evaluation Problem

---

- More generally, we seek:

$$\Delta = \mathbf{E}(Y_{1i} \mid \mathbf{d}_i=1) - \mathbf{E}(Y_{0i} \mid \mathbf{d}_i=1)$$

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

- $\mathbf{E}(Y_{1i} \mid \mathbf{d}_i=1)$  is the EV of the outcome for those who are treated.
- $\mathbf{E}(Y_{0i} \mid \mathbf{d}_i=1)$  is the EV of the outcome for those who are treated, had they not been treated

# The Evaluation Problem

---

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

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

- $\Lambda = \Delta$  if:

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

→ 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  $E(Y_{0i} | d_i=0) = E(Y_{0i} | d_i=1)$  to hold!



# The Evaluation Problem

---

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

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

- Analogue in linear regression analysis:

$$E(u | X, d_i=0) = E(u | X, d_i=1)$$

where we also require:

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

# 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 unobservables → difference in differences if unobservables are time invariant

# Difference-in-Differences (DD)

---

- Decompose outcome equation unobservable component into two pieces:

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

$\rho$  = parameter of interest ( $D_{it}$  indicates treatment)

$\mu_i$  = unobserved time-invariant fixed effect

$\varepsilon_{it}$  = transitory component of unobservable

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

# Difference-in-Differences (DD)

---

- Ignoring  $\mu_i$  results in a biased estimate of  $\rho$ .
- But say, you have observations on treated and control groups over time (pre- and post-treatment)  $\rightarrow \mu_i$  can be differenced out.

# Difference-in-Differences (DD)

---

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

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

where  $\Delta$  is difference (i.e.,  $y_{it} - y_{is}$ ) and  $\delta_0$  is the difference in intercept ( $\beta_{0t} - \beta_{0s}$ )

- Estimate the difference ( $\rho$ ) in differences (t-s).
- Key assumption: selection depends only on  $\mu_i$  & not transitory factors that vary over time ( $\varepsilon_{it}$ )

# 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

$\beta$  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.,  
 $D_{1i} = 1 \text{ iff } Z_i \geq c$
- $y_{ijk} = \alpha_0 + \alpha_1 d_j + \alpha_2 d_k + \beta d_{jk} + Z_{ijk} \delta + \varepsilon_{ijk}$ 
  - 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-selection → 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

$$\rightarrow \text{VSL} = \$600 \times 10,000 = \$6 \text{ million}$$

# “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:

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

# “Value of a Statistical Life” (VSL)

---

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

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

- Say  $\beta = \$600 =$  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?

# Estimation Strategy

---

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

(i) Are they random?

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

# Estimation Strategy

---

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

(i) Are they random?

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

Results  $\Rightarrow$  no significant difference in observable characteristics of inspected and uninspected plants.

# Estimation Strategy

---

- (1) Are OSHA inspections a valid instrument for plant-level safety?
  - (ii) Do they affect plant-level risks?

# Estimation Strategy

---

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

(ii) Do they affect plant-level risks?

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

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



# Estimation Strategy

---

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

(ii) Do they affect plant-level risks?

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

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

Results  $\Rightarrow \varphi = -3.35 (0.73)^{***}$  and  $\pi = -5.31 (1.38)^{***}$

# 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

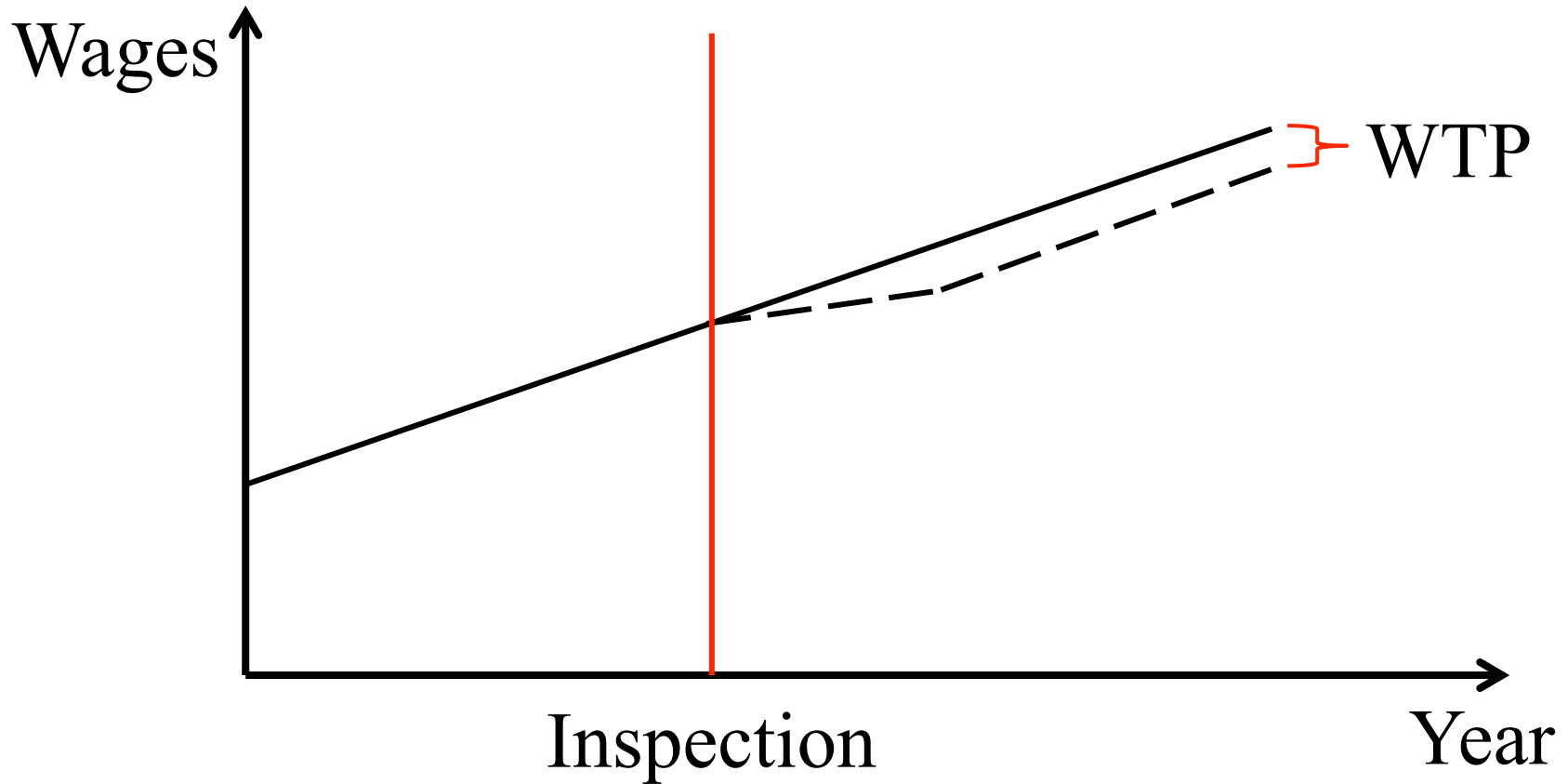
---

- Model:

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

- $FPI_{j,t}$  = 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
- $\gamma$  provides causal evidence for the existence of compensating wages for risk

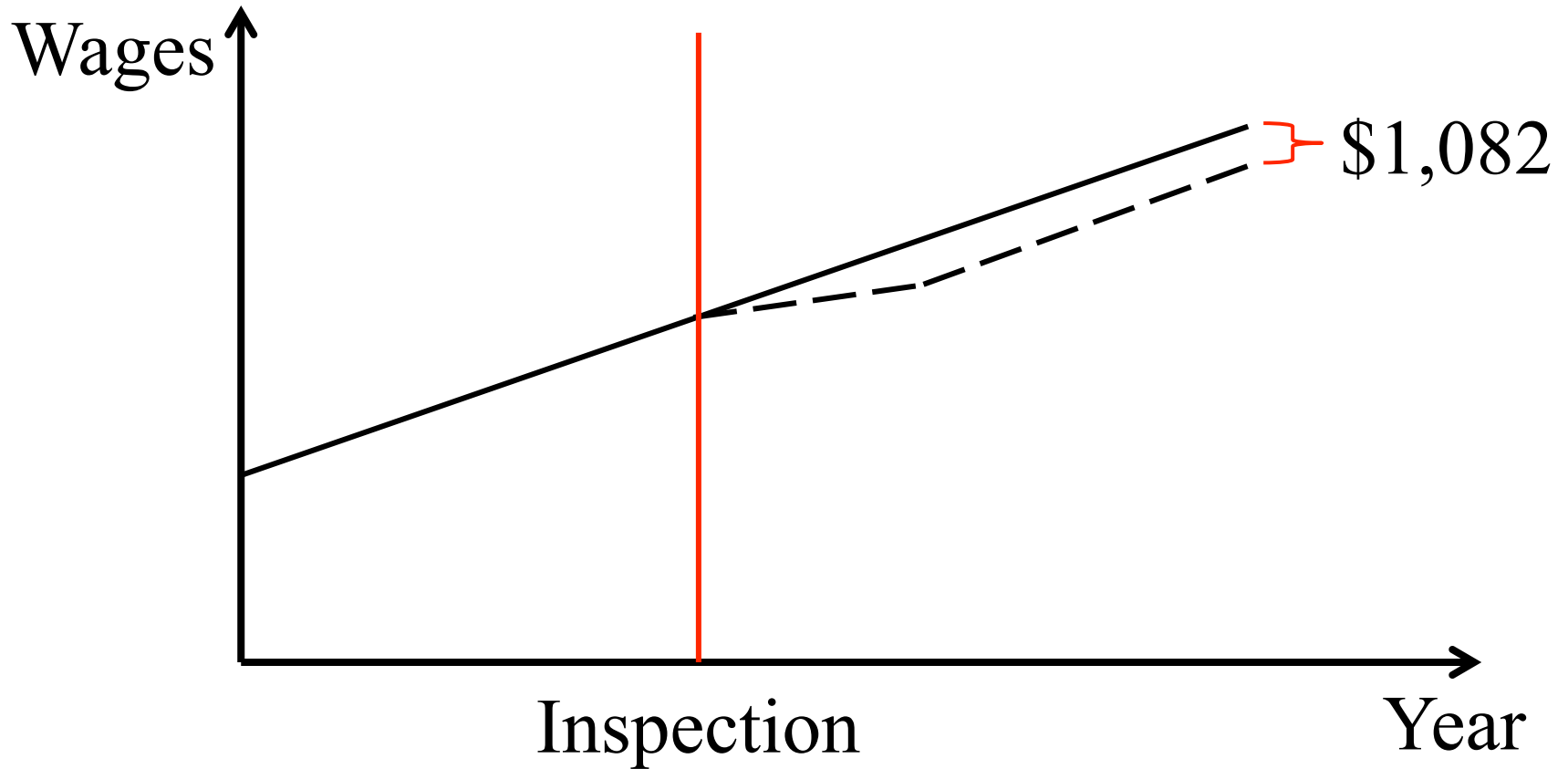
# Wage Adjustments



Uninspected ———

Inspected - - - -

# Wage Adjustments



Uninspected ———

Inspected - - - -

# 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 than 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.*