Ready to Roll? Practical Guidance on Whether and When to Aggregate Data in Health Policy Evaluation

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Slides are online!

slides.nickseewald.com/ichps2023.pdf

Individual-Level Data in Health Policy Evaluation

Many health policy evaluations start with individual-level data (e.g., insurance claims)

- Allows outcome or covariate construction
- Allows more choices about population of interest
  - Continuous enrollment requirements, samples with certain diagnoses, etc.

But many methods use/require *aggregated* data. Is that okay?

Individual-Level Data is Better, Right?

Intuition suggests that individual-level data would be better than aggregated data:

- More data is more information
- Adjust for individual-level confounding
- Appropriately account for nuanced functional forms

But “treatment” is at the state level.

Do Medical Cannabis Laws Change Opioid Prescribing?

- Cannabis is a potentially effective treatment for chronic non-cancer pain, but evidence is limited.
- Patients with chronic non-cancer pain are eligible to use cannabis under all existing state medical cannabis laws
- Some evidence of substitution among adults with chronic non-cancer pain

Question: What are the effects of state medical cannabis laws on receipt of opioid and non-opioid treatment among patients with chronic non-cancer pain?

Bicket, M. C., Stone, E. M., and McGinty, E. E. (2023). *JAMA Network Open*.

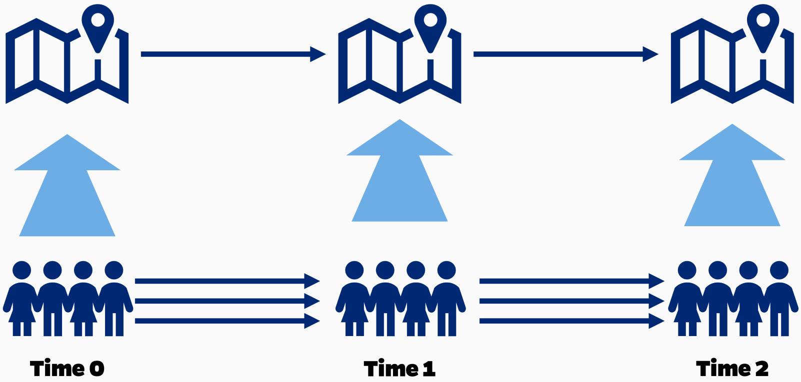
Medical Cannabis Study: Data

Data are individual-level commercial health insurance claims.

- Individuals included if they have a chronic non-cancer pain diagnosis in the pre-law period **and** are continuously enrolled in commercial health insurance for the full study period.

We have rich data on individual outcome trajectories, and think we should use it!

State-Time Aggregation




```
stats::aggregate(Y ~ state + time, data, mean)
```

Questions

1. Are difference-in-differences analyses using individual-level data **more efficient** than those using aggregate-level data?
2. Does individual-level data allow for **better control of confounding**?

Simulation Study: Generative Model

Idea: Simulate data from a simple but flexible data generative model and analyze using various approaches.

$$Y_{sit} = \beta_0 + \beta_1 t \beta_2 A_{st} + \beta_3 (t_k - t^*)_+ A_{st} + \eta^\top \mathbf{X}_{sit} + \gamma^\top \mathbf{X}_{sit} A_{st} \\ + b_{0,s} + b_{0,si} + b_{0,st} + \varepsilon_{sit}$$

- $A_{st} = \mathbb{1}\{\text{state } s \text{ is treated at time } t\}$
- t^* is the first post-treatment timepoint
- $\mathbf{X}_{sit}$ is a vector of covariates
- $b_{0,s}, b_{0,si}, b_{0,st}$ are state-, person-, and time-level random intercepts

Simulation Study: Generative Model

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$$Y_{sit} = \beta_0 + \beta_1 t \beta_2 A_{st} + \beta_3 (t_k - t^*)_+ A_{st} + \eta^\top \mathbf{X}_{sit} + \gamma^\top \mathbf{X}_{sit} A_{st} + b_{0,s} + b_{0,si} + b_{0,st} + \varepsilon_{sit}$$

- Random effects induce three distinct correlations:
  - Within-person correlation
  - Within-period correlation
  - Between-period correlation
- Time-varying treatment effects and effect heterogeneity are allowed
- Necessarily simpler than real data!

Simulation Study: Setting

Current focus has been on limited but common settings

- Continuously-enrolled sample (i.e., no changing case mix)
- Balanced panels
- Simultaneous treatment adoption
- Similar number of treated and control states (Rokicki et al. 2018)

Analytic approaches considered are "naive"

Rokicki, S. et al. (2018). *Medical Care*.

Question 1: Do we lose information in aggregated analyses?

A preview: OLS

OLS estimators are identical for individual- and aggregate-level data in a two-way fixed effects model

Individual-level model:

$$Y_{sit} = \beta_{0,s} + \beta_{1,t} + \beta_2 A_{st} + \varepsilon_{sit}$$

Aggregate-level model:

$$Y_{s\cdot t} = \beta_{0,s} + \beta_{1,t} + \beta_2 \bar{A}_{st} + \varepsilon_{st}$$

Differences might arise from clustering standard errors or introducing covariates.

Clustered Standard Errors, No Covariates

Moderate within- and between-person correlation: $\text{ICC}_{\text{person}} = 0.5$, $\text{ICC}_{\text{state}} = 0.4$.
2000 simulations, 500 individuals per state

	Bias	SE	95% Coverage
Individual data, OLS SE	0.000	0.014	0.971
Individual data, person-clustered SE	0.000	0.013	0.955
Individual data, state-clustered SE	0.000	0.012	0.928
Aggregate data, OLS SE	0.000	0.013	0.953
Aggregate data, state-clustered SE	0.000	0.013	0.954

Question 2: Do individual-level models allow better control of confounding?

Confounding in Difference-in-Differences

"Only covariates that differ by treatment group and are associated with outcome *trends* are confounders in diff-in-diff."

- Time-invariant covariates are confounders if they have time-varying effects on the outcome
- Time-varying covariates are confounders if they have time-varying effects on the outcome or evolve differently in treated and control groups.

Zeldow, B. and Hatfield, L. A. (2021). *Health Services Research*.

Time-Invariant Covariate, Time-Invariant Effect

$$Y_{sit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3 X_{si} + b_{0,s} + b_{0,si} + \epsilon_{sit}$$

	Bias	SE	RMSE	95% Coverage
Individual, unadj., OLS SE	0.000	0.030	0.013	1.000
Individual, unadj., person-clustered SE	0.000	0.013	0.013	0.942
Individual, unadj., state-clustered SE	0.000	0.012	0.013	0.922
Individual, adj., OLS SE	0.000	0.014	0.013	0.965
Individual, adj., person-clustered SE	0.000	0.013	0.013	0.942
Individual, adj., state-clustered SE	0.000	0.012	0.013	0.922
Aggregated, unadj., OLS SE	0.000	0.013	0.013	0.942
Aggregated, unadj., state-clustered SE	0.000	0.013	0.013	0.945

Time-Invariant Covariate, Time-Varying Effect

$$Y_{sit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3 X_{si} + \beta_4 t X_{si} + b_{0,s} + b_{0,si} + \epsilon_{sit}$$

	Bias	SE	RMSE	95% Coverage
Individual, unadj., OLS SE	5.182	0.043	5.182	0.000
Individual, unadj., person-clustered SE	5.182	0.075	5.182	0.000
Individual, unadj., state-clustered SE	5.182	1.410	5.182	0.000
Individual, adj., OLS SE	0.000	0.027	0.015	0.999
Individual, adj., person-clustered SE	0.000	0.015	0.015	0.959
Individual, adj., state-clustered SE	0.000	0.015	0.015	0.917
Aggregated, unadj., OLS SE	0.000	0.017	0.016	0.954
Aggregated, unadj., state-clustered SE	0.000	0.017	0.016	0.930

Time-Varying Covariate, Time-Invariant Effect

$$Y_{sit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3 X_{si} + \beta_4 X_{sit} + b_{0,s} + b_{0,si} + \epsilon_{sit} \qquad X_{si} \sim \mathcal{N}(\mu, \Sigma)$$

	Bias	SE	RMSE	95% Coverage
Individual, unadj., OLS SE	0.000	0.025	0.024	0.963
Individual, unadj., person-clustered SE	0.000	0.018	0.024	0.833
Individual, unadj., state-clustered SE	0.000	0.024	0.024	0.934
Individual, adj., OLS SE	0.000	0.022	0.013	0.999
Individual, adj., person-clustered SE	0.000	0.013	0.013	0.958
Individual, adj., state-clustered SE	0.000	0.012	0.013	0.934
Aggregated, unadj., OLS SE	0.000	0.025	0.024	0.962
Aggregated, unadj., state-clustered SE	0.000	0.026	0.024	0.960
Aggregated, adj., OLS SE	0.000	0.013	0.013	0.956
Aggregated, adj., state-clustered SE	0.000	0.013	0.013	0.962

Time-Varying Covariate, Time-Varying Effect

$$Y_{sit} = \beta_0 + \beta_1 t + \beta_2 A_{st} + \beta_3 X_{si} + \beta_4 t X_{sit} + b_{0,s} + b_{0,si} + \epsilon_{sit}$$

X_{sit} is linear in time

	Bias	SE	RMSE	95% Coverage
Individual, unadj., OLS SE	9.949	0.037	9.949	0.000
Individual, unadj., person-clustered SE	9.949	0.018	9.949	0.000
Individual, unadj., state-clustered SE	9.949	0.024	9.949	0.000
Individual, adj., OLS SE	-0.001	0.059	0.082	0.845
Individual, adj., person-clustered SE	-0.001	0.081	0.082	0.940
Individual, adj., state-clustered SE	-0.001	0.079	0.082	0.935
Aggregated, unadj., OLS SE	9.949	0.071	9.949	0.000
Aggregated, unadj., state-clustered SE	9.949	0.215	9.949	0.000
Aggregated, adj., OLS SE	0.005	0.146	0.145	0.956
Aggregated, adj., state-clustered SE	0.005	0.133	0.145	0.895

Results

What we've seen so far:

- Differences in efficiency, if they exist, are small
- Seemingly quite similar bias control
- Individual-level data is harder to work with than aggregated data
- Individual-level data might be better if you're adjusting for complicated time-varying confounders

Conclusions

We think this is a question of **design** vs. **analysis**.

- Individual-level data is incredibly useful in *the design stage* of a policy evaluation!
  - Better sample identification, feature construction, outcome construction, etc.
- In *the analysis stage* (with diff-in-diff), aggregate-level data is more ergonomic and seems more or less the same.

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- **Maybe you??**

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