Empirical Methods, Fall 2025

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- What alternatives are there?
- What data would you want to answer this question?

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Examples:

- roosters and sunrise
- per capita cheese consumption and deaths by bedsheet entanglement
- education and income
- tax rates and income

More at https://www.tylervigen.com/spurious-correlations

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Identification problem: if variables are correlated, how can we establish whether one is causing the other?

Furthermore, we want to know the direction of causality **and** the strength of the effect (there may be *both* a causal relationship and correlation)

Extra challenge in economics: people optimize, which can offset or overstate a causal relationship

Randomization

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- Treatment and Control groups

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  Exogeneity: Treatment is independent of the potential outcomes.

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- The difference in outcomes is then the causal effect of the treatment

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Potential problems with randomization

Potential problems with randomization

- Do it wrong
- Attrition (leaving the study)
- External validity (volunteers special, experiments stylized)
- Cost (expensive to enforce)
- Ethical problems (See IRB)

Examples of randomized studies in Public Economics

- Randomized tax enforcement experiments — info provision, audits
- Effect of explaining EITC incentives on income/labor supply
- Randomizing various aspects of 1996 welfare reform (job training, work requirements, case worker assistance)
- Public health insurance (Medicaid) assigned by lottery in Oregon
- Universal Basic Income experiments

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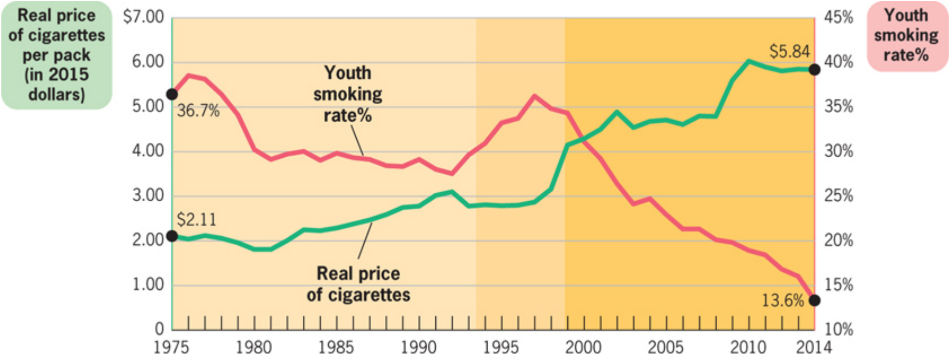
- **Panel data:** a lot of units that can be tracked over time

Time-series analysis

- Comparison of movement of variables over time
- Problem: too many things change over time, is 2003 a good control for 2004?
- Useful when there are sharp, repeated, and "isolated" changes in the treatment variable of interest

Price of cigarettes and youth smoking rate

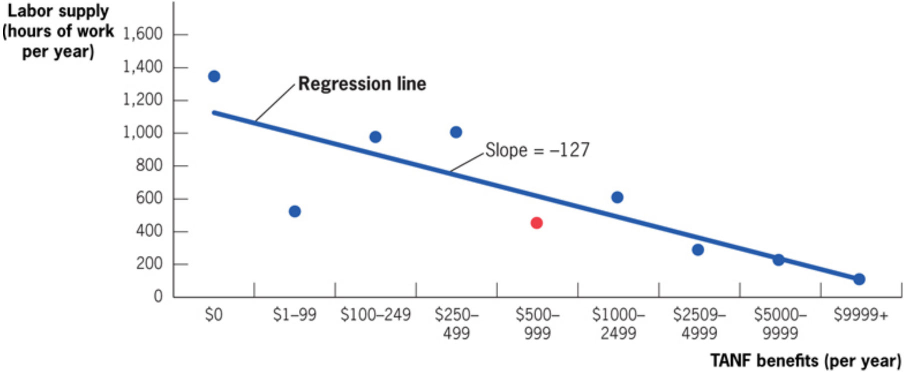


Gruber, *Public Finance and Public Policy*, Figure 3.1

Cross-sectional analysis

- Comparison of many individuals at one point in time
- Regression analysis: finding the best fitting relationship between the dependent variable (e.g., labor supply) and independent variables (e.g., welfare benefits, education, age)

Welfare benefits and labor supply



Gruber, *Public Finance and Public Policy*, Figure 3.4
What does the line capture?

Comments on regression analysis

- Econometric method to find the best fitting relationship: regression

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- Results that it yields
  - coefficient estimate $\hat{\beta}$ — slope of the relationship (127 in the example)
  - standard error often in parentheses (e.g. 127 (25)), confidence interval, significance level of β — the precision of the estimate.
  - In the TANF example, 95% confidence interval is approximately $(78, 176)$ from $(\hat{\beta} - 1.96 \cdot \text{SE}, \hat{\beta} + 1.96 \cdot \text{SE})$

Problems with regression analysis

- Regression describes a relationship: $X \uparrow 1 \Leftrightarrow Y \uparrow \beta$ (on average)
- Causality is *ceteris paribus*, "all else equal" $X \uparrow 1 \Rightarrow Y \uparrow \beta$ (on average)
- Interpretation of β depends on the research design and assumptions
- Observations may differ by Z, which affects Y $\Rightarrow$ not "all else equal"
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- Do you have non-causal explanations for the TANF result?
- For example: single mothers who work less (regardless of benefits) may also be the ones receiving higher benefits $\Rightarrow$ correlation (**endogeneity**)

Potential "solutions" to identify causality with regressions

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- This is the goal of the "causal inference" toolkit

Causal inference toolkit

What are some ways to do causal inference?

Causal inference toolkit

- **Randomized experiments** – the gold standard
- **Instrumental variables** – a variable that is correlated with the treatment but not the outcome (except through the treatment)
- **First differences** – comparing the same unit before and after a treatment
- **Difference-in-difference** – comparing the difference between treatment and control before and after a treatment
- **Regression discontinuity** – comparing units just above and below a threshold that are otherwise similar

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- We can never be 100% certain that all sources of bias are dealt with

Difference-in-difference — example

Using Quasi-Experimental Variation

Arkansas

	1996	1998	Difference
Benefit guarantee	$5,000	$4,000	–$1,000
Hours of work per year	1,000	1,200	200

Louisiana

	1996	1998	Difference
Benefit guarantee	$5,000	$5,000	$0
Hours of work per year	1,050	1,100	50

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By how much did the EITC increase labor supply?

Difference-in-difference — example

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Results suggest that \$1,000 (\$1,000-\$0) reduction in benefits caused an increase in hours of work by 150 ($150 = 200 - 50$)

Difference-in-difference EITC (Eissa et al. 2006)

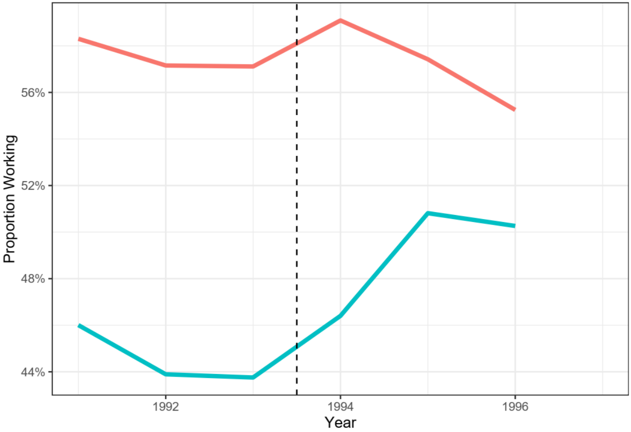
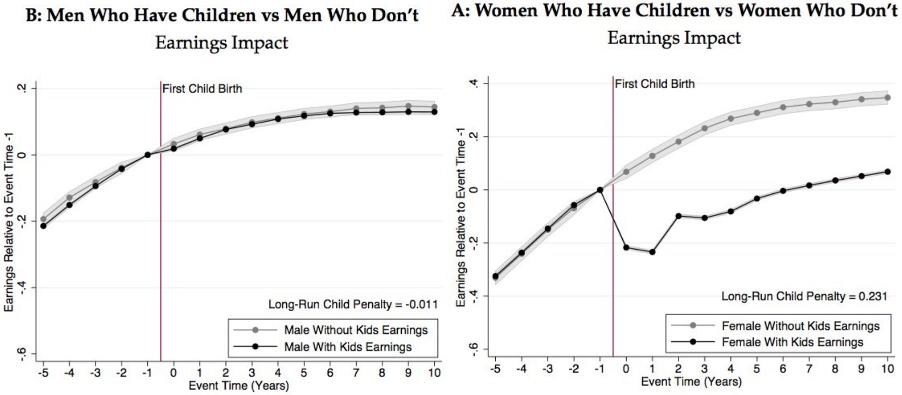


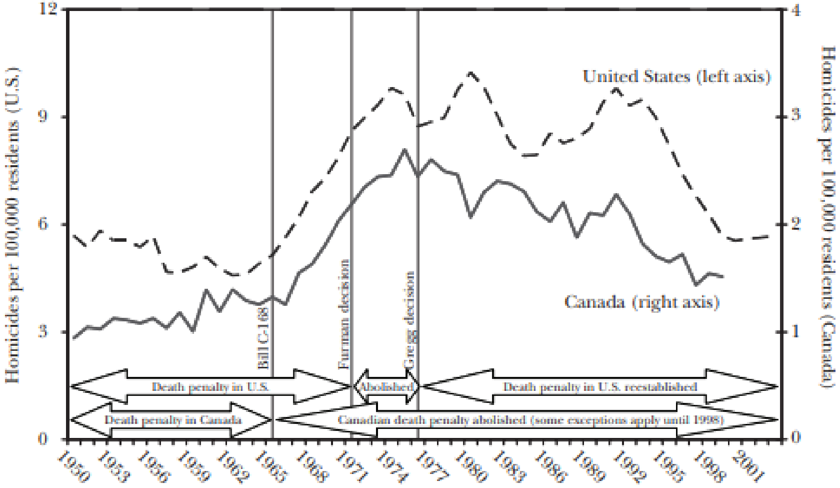
Figure 1: Difference-in-difference of the 1996 EITC increase on labor supply. The blue shows employment participation of single mothers, the red shows single women. Author's calculations using data compiled by Nick Huntington-Klein.



Source: Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and Gender Inequality: Evidence from Denmark." American Economic Journal: Applied Economics, 11 (4): 181–209.

[The event: Having a child in Denmark for men and women.]

(U.S. and Canada rates on the left and right y-axes, respectively)



Source: Donohue and Wolfers (2005).

Source: Donohue and Wolfers (2005) via Angrist and Pischke (2010) shows the homicidal crime rate of US and Canada track similarly despite changes to death penalty – suggesting that the death penalty had little effect on crime.

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Key assumptions:

- No manipulation at the threshold
- Nothing else changes at the threshold

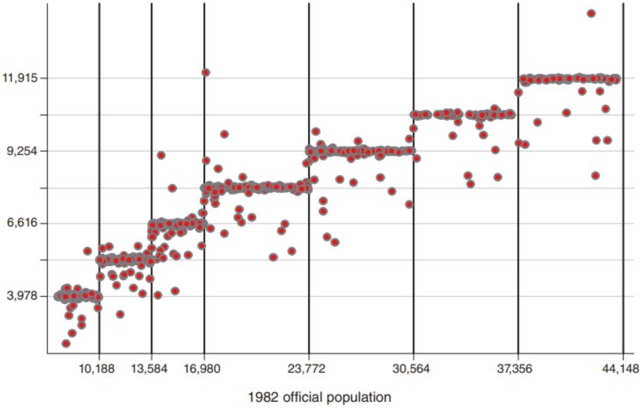

FIGURE 1. FPM TRANSFERS, 1982–1985 (*,000 2008 Reais*)

Source: Litschig, Stephan, and Kevin M. Morrison. 2013. "The Impact of Intergovernmental Transfers on Education Outcomes and Poverty Reduction." American Economic Journal: Applied Economics, 5 (4): 206–40.

Brazilian Municipality level data. X-axis is population binned by percentage points away from a threshold for receiving increased transfers due to a spending formula. Y-axis is amount of Fundo de Participação dos Municípios transfers received.

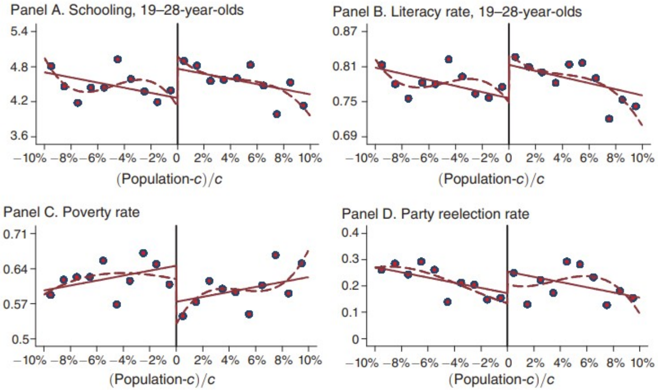

Figure 5. Impacts on Schooling, Literacy, Poverty, and Party Reelection

Source: Litschig, Stephan, and Kevin M. Morrison. 2013. "The Impact of Intergovernmental Transfers on Education Outcomes and Poverty Reduction." American Economic Journal: Applied Economics, 5 (4): 206–40.

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Structural Estimation

- We've covered "reduced form" methods.
- Structural estimation targets underlying utility or technology functions ("structural parameters").
- Imposes economic theory-based restrictions (e.g., negative substitution effect).
- Regression finds the best-fit line; structural estimation fits a model-based shape.
- Advantage: Explores more policy experiments.
  - Simulates untested policies.
  - Potentially more "externally" valid.
- Disadvantage: Imposes more assumptions on data.

Overview

- Correlation $\neq$ causation
- Multivariate regression with controls only goes so far
- Randomized experiments are the gold standard
- Causal inference toolkit uses natural experiments to identify causality
- Structural estimation uses economic theory to identify causal effects