



Williams College ECON 460:
 Women, Work, and the World Economy

Methods Monday 2: Research Designs in Economics

Professor: Pamela Jakiela

What Is a Paper?



Source: UC Berkeley

Prof. Romer says an economics paper needs:

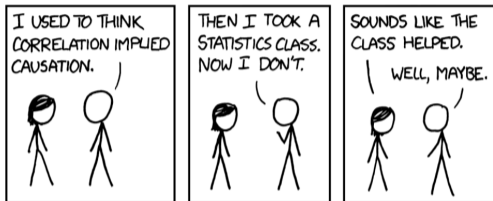
- A big question
- A **lever**
- Hard work

What constitutes a lever?

- A causal **identification strategy**
- A new source of data, measuring a new construct
- A new theoretical model (least relevant for us)

A research question is important, but what makes research an economics paper is not writing etc. but finding the lever

How Not to Estimate the Impact of X on Y



Source: xkcd

- Data Assignment 1 asked you to look at the relationship between two variables
 - ▶ Economists often call this type of analysis is “descriptive” or “observational” (and those adjectives are not compliments)
 - ▶ Correlations reflect **treatment effects** + **selection bias**, adding controls rarely fixes problem

Types of “Impact of X on Y ” Papers

- **Randomized experiments**
 - ▶ A **treatment** of interest is randomly assigned, as in a medical trial
 - ▶ When this is true, regressing Y on X does (more or less) tell us about the causal effect
- **Quasi-experimental research designs**
 - ▶ Difference-in-differences: compare changes in (non-random) treatment, comparison groups
 - ▶ Instrumental variables: find a source of **exogenous variation** in treatment (an **instrument**)
 - ▶ Regression discontinuity design: find a setting where access to program/policy depends on a continuous eligibility criterion with a strict cutoff, compare just above to just below
- **Natural experiments:** find a setting where policy is “as good as random”
 - ▶ Similar to IV but without two-stage least squares estimation to identify causal effect

Randomized Experiments (RCTs): Examples from the Syllabus

DO LABOR MARKET OPPORTUNITIES AFFECT YOUNG WOMEN'S WORK AND FAMILY DECISIONS? EXPERIMENTAL EVIDENCE FROM INDIA*

ROBERT JENSEN

Do labor market opportunities for women affect marriage and fertility decisions? We provided three years of recruiting services to help young women in randomly selected rural Indian villages get jobs in the business process outsourcing industry. Because the industry was so new at the time of the study, there was almost no awareness of these jobs, allowing us in effect to exogenously increase women's labor force opportunities from the perspective of rural households. We find that young women in treatment villages were significantly less likely to get married or have children during this period, choosing instead to enter the labor market or obtain more schooling or postschool training. Women also report wanting to have fewer children and to work more steadily throughout their lifetime, consistent with increased aspirations for a career. *JEL* Codes: I21, J12, J13, J16, J22.

ROLE MODELS IN MOVIES: THE IMPACT OF QUEEN OF KATWE ON STUDENTS' EDUCATIONAL ATTAINMENT

Emma Riley*

Abstract—This paper presents experimental evidence on the impact of a role model on secondary school students' exam performance in Uganda. Students were individually randomized to see either a movie featuring a female role model, Queen of Katwe, or to see a placebo movie. I find that treatment with the role model immediately before an important national exam leads to students performing better on their exams, particularly in math, with effects largest for female students. Female students exposed to the role model are more likely to remain in education in subsequent years, closing the gender gap with their male peers.

Should You Run an RCT for Your Empirical Project?

- Randomized experiments are difficult to implement, and expensive, and time consuming
 - ▶ Almost every economist I know tells PhD students and assistant professors not to run RCTs
- Ways you might base your empirical project on an existing RCT (not an exhaustive list):
 - ▶ Find information on communities in sample, link to another source of data (this is hard)
 - ▶ Example: Professor Ozier's paper on spillover effects of medication to treat intestinal parasites
 - ▶ Discover an RCT that was conducted but not (fully) analyzed (also hard)
 - ▶ Example: Baranov, Bhalotra, Biroli, and Maselko (2020) estimate the medium-term impacts of treating maternal depression by following up participants from an earlier RCT in Pakistan

Difference-in-Differences

- In difference-in-differences (or diff-in-diff or DiD), we compare **changes** in outcomes between treatment and comparison groups that are (usually) not randomly selected
 - ▶ Pre-treatment vs. post-treatment outcomes for a(n eventually) treated group of individuals, states, countries, etc. and an untreated (i.e. not ever treated in your data) comparison group
- Identification assumptions (required for causal interpretation):
 - ▶ Selection bias reflects unchanging characteristics of units (e.g. people, states)
 - ▶ Time trends and period-specific shocks are common to treated, untreated units
 - ▶ Typically described as a **common trends** assumption:
 - ▶ In the absence of treatment, treated and untreated units were changing at the same rate
- Diff-in-diff is often possible when other identification strategies (RCT, RD) are not

Difference-in-Differences: Empirical Specifications

- Simplest possible 2×2 diff-in-diff specification (with two periods of data):

$$Y_{i,t} = \alpha + \beta T_i + \gamma Post_t + \delta T_i \times Post_t + \varepsilon_{it}$$

where:

- ▶ $Y_{i,t}$ is outcome for unit i in period t
- ▶ T_i is a dummy equal to one for units that are **ever** treated
- ▶ $Post_t$ is a dummy for time periods after treatment starts
- ▶ $T_i \times Post_t$ indicates the observations in your data that are actually treated (ever treated units in the post-treatment period)
- ▶ ε_{it} is a conditionally mean-zero error term

Difference-in-Differences: Empirical Specifications

- Often use individual (unit) fixed effects instead of ever-treated-group dummy:

$$Y_{i,t} = \alpha + \nu_i + \gamma Post_t + \delta T_i \times Post_t + \varepsilon_{it}$$

where:

- ▶ $Y_{i,t}$ is outcome for unit i in period t
- ▶ ν_i is a vector of individual fixed effects for states, people, whatever
- ▶ $Post_t$ is a dummy for time periods after treatment starts
- ▶ $T_i \times Post_t$ indicates the observations in your data that are actually treated (ever treated units in the post-treatment period)
- ▶ ε_{it} is a conditionally mean-zero error term

Difference-in-Differences: Empirical Specifications

- With only two periods, we can also use the change in outcomes as the dependent variable:

$$\Delta Y_{i,t} = \alpha + \delta T_i + \varepsilon_{it}$$

where:

- ▶ $\Delta Y_{i,t}$ is the change in outcomes for unit i , pre vs. post
 - ▶ T_i is a dummy equal to one for units that are **ever** treated
 - ▶ ε_{it} is a conditionally mean-zero error term
- Don't need individual fixed effects (with only two periods) because they are differenced out

Difference-in-Differences: Empirical Specifications

- If you have many periods of data (which is good!), you can also use time fixed effects:

$$Y_{i,t} = \alpha + \nu_i + \phi_t + \delta T_i \times Post_t + \varepsilon_{it}$$

where:

- ▶ $Y_{i,t}$ is outcome for unit i in period t
 - ▶ ν_i is a vector of individual fixed effects for states, people, whatever
 - ▶ ϕ_t is a vector of time period fixed effects
 - ▶ $T_i \times Post_t$ indicates the observations in your data that are actually treated (ever treated units in the post-treatment periods)
 - ▶ ε_{it} is a conditionally mean-zero error term
- If treatment starts at different times in different locations/units, life is more complicated

Difference-in-Differences: Examples

“Momma’s Got the Pill”: How Anthony Comstock and *Griswold v. Connecticut* Shaped US Childbearing

By MARTHA J. BAILEY*

The 1960s ushered in a new era in US demographic history characterized by significantly lower fertility rates and smaller family sizes. What catalyzed these changes remains a matter of considerable debate. This paper exploits idiosyncratic variation in the language of “Comstock” statutes, enacted in the late 1800s, to quantify the role of the birth control pill in this transition. Almost 50 years after the contraceptive pill appeared on the US market, this analysis provides new evidence that it accelerated the post-1960 decline in marital fertility. (JEL J12, J13, K10, N31, N32)

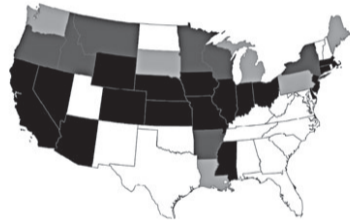


FIGURE 4. GEOGRAPHIC DISTRIBUTION OF COMSTOCK SALES LAWS BY TYPE CIRCA 1960

Notes: No shading: states with no laws mentioning the “prevention of conception.” Light gray: states banning only advertising or the distribution of information (Table 1, columns 2 and 3). Dark gray: states banning advertising and the sale of contraceptives but with physician exceptions (Table 1, columns 3 and 4). Black: states with sales bans and advertising bans with no exceptions for physicians (Table 1, columns 3 and 4)

Difference-in-Differences: Examples

Women's inheritance rights reform and the preference for sons in India[☆]

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ARTICLE INFO

JEL classification:
O12
K11
O21

Keywords:
inheritance rights
ultra-sonid
female foeticide
sex selection
son preference
gender
India

ABSTRACT

We investigate whether legislation of equal inheritance rights for women modifies the historic preference for sons in India, and find that it exacerbates it. Children born after the reform in families with a firstborn daughter are 3.8–4.3 percentage points less likely to be girls, indicating that the reform encouraged female foeticide. We also find that the reform increased excess female infant mortality and son-biased fertility stopping. This suggests that the inheritance reform raised the costs of having daughters, consistent with which we document an increase in stated son preference in fertility post reform. We conclude that this is a case where legal reform was frustrated by persistence of cultural norms. We provide some suggestive evidence of slowly changing patri-locality norms.



Fig. 1. The Five Reforming States (in green) and rest of India (in blue). Note: The southern state of Andhra Pradesh split into two states - Andhra Pradesh and Telangana - in 2014. For the purposes of our analysis, these two are considered together as the undivided state of Andhra Pradesh that reformed in 1986. (For interpretation of the reference to colour in this figure legend, the reader is referred to the Web version of this article.)

Should You Use Diff-in-Diff for Your Empirical Project?

- Diff-in-diff is a promising approach when a policy is implemented in different places at different times, or implemented in some places but not in other reasonably similar places
 - ▶ Both the U.S. and India have sufficiently decentralized governance to allow for this
- Sometimes a policy change takes effect everywhere, but will only impact some areas
 - ▶ Example: Professor Godlonton's work on informal birth attendants in Malawi
- Diff-in-diff is useful when:
 - ▶ You know of a policy change you want to study
 - ▶ You know of a data set with observations before and after the policy change, and with some variation in who was impacted by the policy (e.g. based on geography, age, gender etc.)

Instrumental Variables

- You'd like to run the regression

$$Y_i = \alpha + \delta T_i + \varepsilon_{it}$$

to estimate the impact of treatment T_i on Y_i , but you “can't” because of selection bias

- An **instrument** is a variable that:
 - ▶ Predicts take-up of treatment T_i (first-stage)
 - ▶ Is as-good-as-random (exogeneity)
 - ▶ Doesn't have a direct effect on Y_i (exclusion restriction)
- If you have a good instrument, then (and only then) you can use **instrumental variables**

Instrumental Variables: Specifications

- IV estimated via two-stage least squares (2SLS) given instrument Z_i :

$$T_i = \alpha + \beta Z_i + \nu_i \quad \text{[first stage]}$$

$$Y_i = \gamma + \delta_{IV} \hat{T}_i + \varepsilon_i \quad \text{[second stage]}$$

- We can also look at the impact of our instrument on the outcome (through treatment):

$$Y_i = \alpha + \lambda T_i + \nu_i \quad \text{[“reduced form”]}$$

- IV estimate (from 2SLS second stage) is ratio of reduced form λ to first stage β

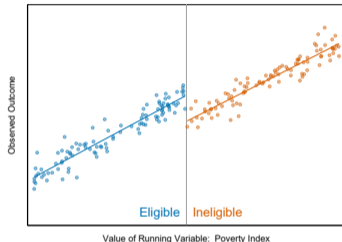
Instrumental Variables: Examples

- Weather as an instrument for the size of political rallies:
 - ▶ A famous paper by Madestam, Shoag, Veuger, and Yanagizawa-Drott (2013) shows that the Tea Party movement was stronger, and Republicans subsequently increased their vote share, in places where there as good weather on April 15, 2009 (the day of the first rally)
 - ▶ Magdalena Larreboure and Felipe González have a working paper showing similar effects of weather on the day of a protest from the 2017 Women's March on the 2018 House elections
- Sex composition of children as an instrument for future births:
 - ▶ Angrist and Evans (1998) use the sex composition of a couples' first two children (same sex?) to instrument for subsequent fertility, estimating impacts on labor supply

Should You Use IV for Your Empirical Project?

- Do you have an instrument?!?
 - ▶ Is it exogenous?
 - ▶ Does it satisfy the exclusion restriction? Really?
 - ▶ Exclusion restrictions cannot be tested, which is both good and bad
 - ▶ If you want to know if your idea for an instrument is convincing and satisfies the exclusion restriction, explain it to a professor who teaches ECON 255 and see if their face lights up
- You also need a **strong** first-stage relationship
 - ▶ This can be tested empirically
 - ▶ A rule-of-thumb is that your first-stage F-statistic should be at least 10 if not much higher

Regression Discontinuity



Assignment to treatment depends on a continuous variable (like an index, score, or vote share) with a sharp, known cutoff; those just above and just below the cutoff are otherwise similar

- Idea is to control flexibly for the **running variable**, estimate the jump at the cutoff

Regression Discontinuity: Empirical Specifications

- The RD specification is a linear regression estimating the impact of being above or below the discontinuity while simultaneously controlling directly for the running variable

$$Y_i = \alpha + \delta D_i + \beta X_i + \gamma X_i \times D_i + \varepsilon_{it}$$

where:

- ▶ Y_i is outcome for unit i
 - ▶ D_i is a dummy for being above (or below) the cutoff, and hence treated
 - ▶ X_i is the value of the running variable
 - ▶ ε_{it} is a conditionally mean-zero error term
- The key issue is choice of **bandwidth** around the discontinuity (to include in analysis)
 - Also important to demonstrate absence of manipulation around the discontinuity

Regression Discontinuity: Examples

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Can gender quotas in candidate lists empower women? Evidence from a regression discontinuity design [☆]

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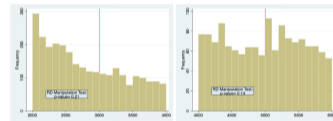
Keywords:
Gender quotas
Regression discontinuity design
Women in politics

ABSTRACT

We provide a comprehensive analysis of the short- and medium-term effects of gender quotas in candidate lists using evidence from local elections in Spain. In the context of a closed list system with proportional representation, quotas were introduced in 2007 in municipalities with more than 5000 inhabitants, and were extended in 2011 to municipalities with more than 3000 inhabitants. Using a Regression Discontinuity Design, we find that quotas increased the share of women in candidate lists by around 8 p.p. and among council members by 4 p.p. However, within three rounds of elections, we do not observe any significant variation in several proxies of politicians' quality, the probability that women reach powerful positions such as party leader or mayor, or the size and composition of public finances. Overall, our analysis suggests that quotas in candidate lists fail to remove the barriers that prevent women from playing an influential role in politics.

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(a) Years 2002-2005



(b) Years 2006-2015

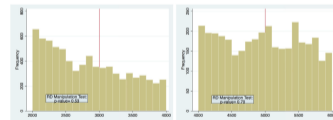


Fig. 5. Histograms of population. Note: Histograms of population in bins of 100 individuals for municipalities with a population close to the 3000 threshold (left-hand side) and municipalities with a population close to the 5000 threshold (right-hand side). Each figure also reports the result from the density test proposed by Cattaneo et al. (2015) performed at the corresponding cutoff.

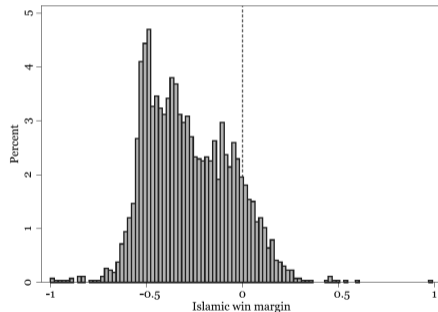
Regression Discontinuity: Examples

Econometrica, Vol. 82, No. 1 (January, 2014), 229–269

ISLAMIC RULE AND THE EMPOWERMENT OF THE POOR AND PIOUS

BY ERIK MEYERSSON¹

Does Islamic political control affect women's empowerment? Several countries have recently experienced Islamic parties coming to power through democratic elections. Due to strong support among religious conservatives, constituencies with Islamic rule often tend to exhibit poor women's rights. Whether this reflects a causal relationship or a spurious one has so far gone unexplored. I provide the first piece of evidence using a new and unique data set of Turkish municipalities. In 1994, an Islamic party won multiple municipal mayor seats across the country. Using a regression discontinuity (RD) design, I compare municipalities where this Islamic party barely won or lost elections. Despite negative raw correlations, the RD results reveal that, over a period of six years, Islamic rule increased female secular high school education. Corresponding effects for men are systematically smaller and less precise. In the longer run, the effect on female education remained persistent up to 17 years after, and also reduced adolescent marriages. An analysis of long-run political effects of Islamic rule shows increased female political participation and an overall decrease in Islamic political preferences. The results are consistent with an explanation that emphasizes the Islamic party's effectiveness in overcoming barriers to female entry for the poor and pious.



Should You Use RD for Your Empirical Project?

- RD requires a policy or treatment where eligibility depends on a cutoff
 - ▶ More like an RCT than DD or IV: no debate about whether something is an RD
- If you think you know of a potential RD, you need to check for:
 - ▶ Manipulation around the cutoff (endogenous selection invalidates an RD design)
 - ▶ Sufficient data around the cutoff (sample restricted to narrow bandwidth)
- Key to many quasi-experimental designs is knowing about policies, policy changes, and other sources of variation in institutional arrangements that allows for impact evaluation
 - ▶ Look for information on policy changes in existing papers

When to Write a “New Data” Paper

- Economists write “descriptive” papers which introduce new sources of data; in such cases, summary statistics (e.g. on gender gaps) and simple correlations are of inherent interest
 - ▶ Whether new data is interesting is subjective (unfortunately, it can help if you are famous)
- How might you find a new source of data?
 - ▶ By running a lab experiment (or similar)
 - ▶ By building a data set from archival or secondary sources
 - ▶ By gaining access to a new(ish) source of “big data” (e.g. from a firm)
 - ▶ By scraping (or otherwise collecting) data from the web
- These types of papers are often motivated by a theoretical model (“test of theory”) or a hypothesis from another discipline (“bringing new data to an old question”)

New Data Papers: Examples

MANAGEMENT SCIENCE

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Gender Differences in Willingness to Guess

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We present the results of an experiment that explores whether women are less willing than men to guess on multiple-choice tests. Our test consists of practice questions from SAT II history tests; we vary whether a penalty is imposed for a wrong answer and the salience of the evaluative nature of the task. We find that when no penalty is assessed for a wrong answer, all test takers answer every question. But, when there is a penalty for wrong answers, women answer significantly fewer questions than men. We see no differences in knowledge of the material or confidence in the test takers, and differences in risk preferences explain less than half of the observed gap. Making the evaluative aspect of the test more salient does not impact the gender gap. We show that, conditional on their knowledge of the material, test takers who skip questions do significantly worse on our test.

Data, as supplemental material, are available at <http://dx.doi.org/10.1287/mnsc.2013.1776>.

Keywords: economics; behavior; behavioral decision making; microeconomic behavior; education systems
History: Received December 17, 2012; accepted May 8, 2013, by Uri Gneezy, behavioral economics. Published online in *Articles in Advance* October 7, 2013.

Table 4 Mean Number of Questions Skipped by Treatment and Gender

	Male means	Female means	<i>p</i> -value ^a men vs. women
Unframed	2.000	3.679	0.008
Low penalty	(3.259)	(4.452)	
SAT framed	1.063	2.035	0.033
Low penalty	(1.702)	(3.336)	
<i>p</i> -value ^a Unframed vs. SAT	0.042	0.008	

^aFrom Fisher–Pitman permutation tests for two independent samples, testing the null of equality.

New Data Papers: Examples

Gendered Language

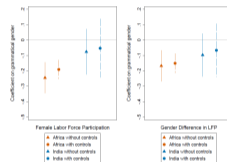
Pamela Jakiela and Owen Ozier*

January 26, 2022

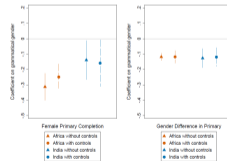
Abstract

Languages use different systems for classifying nouns. *Gender languages* assign nouns to distinct sex-based categories, masculine and feminine. We construct a new data set, documenting the presence or absence of grammatical gender in more than 4,000 languages which together account for more than 99% of the world's population. We find a robust negative relationship between prevalence of gender languages and women's labor force participation and educational attainment both across and within countries. We also demonstrate that grammatical gender is associated with both weaker legal support for women's equality and reduced female bargaining power within the household.

Panel A: Labor Force Participation



Panel B: Primary School Completion



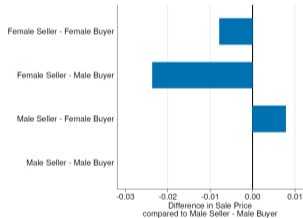
New Data Papers: Examples

The Gender Gap in Housing Returns
Paul Goldsmith-Pinkham and Kelly Shue
NBER Working Paper No. 26914
March 2020
JEL No. D14,D31,G4,G51,J16,R2

ABSTRACT

Housing wealth represents the dominant form of savings for American households. Using detailed data on housing transactions across the United States since 1991, we find that single men earn 1.5 percentage points higher unlevered returns per year on housing relative to single women. The gender gap grows significantly larger after accounting for mortgage borrowing: men earn 7.9 percentage points higher levered returns per year relative to women. Approximately 45% of the gap in housing returns can be explained by gender differences in the location and timing of transactions. The remaining gap arises primarily from gender differences in execution prices: data on repeat sales reveal that women buy the same property for approximately 2% more and sell for 2% less. Women experience worse execution prices because of differences in the choice of initial list price and negotiated discount relative to the list price. Gender differences in upgrade and maintenance rates, and preferences for housing characteristics and listing agents appear to be less important factors. Overall, the gender gap in housing returns is economically large and can explain 30% of the gender gap in wealth accumulation at retirement.

Figure 6: Transaction price by seller-buyer gender pairing



Note: This figure plots the average difference in log transaction prices for each possible seller-buyer gender pair, relative to transactions involving single male sellers and single male buyers. These estimates come from a regression of the form in Table 4 column 4, but allowing for the buyer and seller gender group indicators to interact. We plot only the coefficients representing single male or female buyers and sellers, with male seller-male buyer as the omitted base coefficient.

New Data Papers: Examples

AEA Papers and Proceedings 2018, 108: 175–179
<https://doi.org/10.1257/pandp.20181101>

GENDER ISSUES IN ECONOMICS

Gendered Language on the Economics Job Market Rumors Forum[†]

By ALICE H. WU*

Women are underrepresented in math-intensive fields (Ceci et al. 2014; Kahn and Ginther 2017), and analysts have noted that the representation gap is as large or larger in economics than in STEM (science, technol-

issues. Anonymity presumably eliminates social pressures that constrain participants' speech in other public settings, leading to a record of postings that reveal what participants believe but would not otherwise openly express.

TABLE 1—TOP 10 WORDS MOST PREDICTIVE
OF FEMALE/MALE

Most female		Most male	
Word	ME	Word	ME
Hotter	0.422	Homo	-0.303
Pregnant	0.323	Testosterone	-0.195
Plow	0.277	Chapters	-0.189
Marry	0.275	Satisfaction	-0.187
Hot	0.271	Fieckers	-0.181
Marrying	0.260	Macroeconomics	-0.180
Pregnancy	0.254	Cuny	-0.180
Attractive	0.245	Thrust	-0.169
Beautiful	0.240	Nk	-0.165
Breast	0.227	Macro	-0.163

Notes: The model was trained on a 75 percent sample of gendered posts that contain only female or only male classifiers from the comprehensive list. ME—the marginal effect of word w is the change in probability that a post is discussing a female, when it contains an additional word w . The words that predict *Female (Male)* are sorted in descending (ascending) order of the ME.

Should You Write a New Data Paper for Your Empirical Project?

- Can you find a new source of data that speaks to a relevant topic?
 - ▶ Anonymous lab/internet experiment
 - ▶ Scraping the web (e.g. percent female faculty by department)
 - ▶ Archival data sources that you've used in other classes

What Next?

You need to submit a Project Group and Topic Statement by September 30

- The composition of your group for the empirical project
- The big question you are interested in exploring
- Any thoughts you have about possible levels or contexts of particular interest

I'll respond by sending you several papers to read on closely related topics

- Papers will illustrate potential data sources, examples of relevant or related policies, and (when possible) suggestions on where you might start looking for exogenous variation
- In practice, most of you will settle on two-way fixed effects (policy phase-in)
- Start thinking (now!) about connections between big questions and levers

Widely Used Data Sources

- World Development Indicators
- American Community Survey (ACS)
- Demographic and Health Surveys (DHS)
- IPUMS
- Panel Study of Income Dynamics (PSID)
- National Longitudinal Survey of Youth (NLSY)
- Afrobarometer
- India Human Development Survey
- World Banks Living Standard Measurement Surveys (LSMS)
- Replication files from recently published papers

The End!