Economics 174/274

Global Poverty and Impact Evaluation

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Lecture 9

Health and Economic Development

- Social scientists and policymakers traditionally thought of health purely as a measure of well-being, living standards
- Clearly, two of the objectives of development are:
  - to improve the material well-being of individuals, and
  - to enjoy this material well-being during longer life-spans
- Example:health/longevity components of human development index
  - Life expectancy
  - Infant/child survival rates

Health and Economic Development

- Alternative/complementary view: *health as human capital*
- Since the 1960s, however, economists have also started thinking of health as a form of human capital. If there is a return to the health of an individual, then investments in the health of the population may have important effects on economic development.
- In summary, individual health, as a form of human capital, may have important effects on development

Health and Economic Development

Key topics for this module

- The global disease burden
- Health as human capital - productivity-enhancing
- The impact of the HIV/AIDS epidemic in LDCs

Health and Economic Development

Definition of health according to the World Health Organization [WHO]:

"A state of complete physical, mental, and social well-being and not merely the absence of disease and infirmity."

- Despite outstanding achievements, the developing world continues to face great challenges as it seeks to continue to improve the health and education of its people
- Example: Child mortality rates in LDCs remain more than ten times higher than those found in rich countries
- These deaths generally result from conditions that are easily treatable (e.g., death from dehydration due to diarrhea)

Health and Economic Development

- Another measure of longevity: *life expectancy at birth*
- Note: these are coarse measures of health status of the population
  - Extension of life can provide extended years of vitality in one country while providing only additional years of extremely poor health or suffering in another.
  - Child (0-5 years) survival rates - do not measure health status of the general population past early childhood (although serves as a reasonable proxy)

The Global Disease Burden

- Major health problems in developing countries:
  - Diarrhea
  - Childhood diseases, including malaria, acute respiratory infections, parasitic worm infections, measles
  - Malnutrition (disease? or condition?)
  - HIV/AIDS

- These conditions (excluding HIV/AIDS) account for 70% of deaths among children less than five (5) years of age
- These health problems are particularly severe in Sub-Saharan Africa
  - Infant mortality $>$ 100 per 1,000 births in many countries

The Global Disease Burden

- Major health problems in developing countries: Diarrhea
- 4 million children under the age of 5 die each year from diarrhea
- Death due to dehydration
- Source(s): contaminated water (e.g. fecal matter, other)
- Deaths concentrated in early childhood (0-5 years)

The Global Disease Burden

- Treatment
  - Promotion of breastfeeding
  - Oral rehydration therapy
- Prevention
  - Access to (abundant) clean water (rural areas - protect springs)

The Global Disease Burden: Diarrhea

- Jalan and Ravallion examine whether access to piped water reduces diarrhea for children in rural India
- They use a large, representative cross-sectional survey for rural India implemented in 1993-1994
- An estimated 1.5 million child deaths per year in India due to diarrhea and other diseases related to poor water quality
- 1/5 of the population of rural India do not have access to safe drinking water (World Bank, 2000)
- Expanding access to piped water is considered an important development action in India

Jalan and Ravallion

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- How do we answer this question empirically?
- Can we simply compare households with and without piped water? Why not?
- Without random assignment, Jalan and Ravallion rely on propensity score matching

What is Propensity-Score Matching (PSM)?

- When a treatment cannot be randomized, the next best thing to do is to try to mimic randomization
- With matching methods, one tries to develop a counterfactual or control group that is as similar to the treatment group as possible in terms of observed characteristics.

What is Propensity-Score Matching (PSM)?

- We need to find a large group of nonparticipants who are observationally similar to participants in terms of characteristics not affected by the program
- Each participant is matched with an observationally similar nonparticipant, and then the average difference in outcomes across the two groups is compared to get the program treatment effect
- If one assumes that differences in participation are based solely on differences in observed characteristics, and if enough nonparticipants are available to match with participants, the corresponding treatment effect can be measured even if treatment is not random.

What is Propensity-Score Matching (PSM)?

- Issue: in practice, this can be quite hard
  - There may be many important characteristics!
  - A lot of bins - curse of dimensionality
  - Hard to find two individuals who match along all the characteristics

- It would be useful to create an "index" that aggregates all these characteristics
- Rosenbaum and Rubin proposed a solution
  - Compute everyone's probability (or propensity) of participating, based on their observable characteristics
  - Choose matches that have the same probability of participation as the treatments

What does PSM do?

- PSM constructs a statistical comparison group by modeling the probability of participating in the program on the basis of observed characteristics unaffected by the program
- Participants are then matched on the basis of this probability, or propensity score, to nonparticipants
- The average treatment effect of the program is then calculated as the mean difference in outcomes across these two groups
- PSM is useful when only observed characteristics are believed to affect program participation
- That is, there is no selection bias based on unobservable characteristics

PSM Method in Theory

- PSM approach tries to capture the effects of different observed controls X on participation in a single propensity score or index
- In particular, we estimate the following model $P(X) = Pr(T = 1|X)$
- Rosenbaum and Rubin (1983) show that, under certain assumptions, matching on $P(X)$ is as good as matching on X

PSM Method in Theory

What are the necessary assumptions for a causal interpretation?

1. conditional independence
2. common support

Conditional independence

- **Conditional independence** states that given a set of observable covariates X that are not affected by treatment, potential outcomes Y are independent of treatment assignment T.
- If ${Y_i}^T$ represent outcomes for participants and ${Y_i}^C$ outcomes for nonparticipants, conditional independence implies

$$({Y_i}^T, {Y_i}^C) \perp T_i | X_i$$

- This assumption is also called *unconfoundedness*

Conditional independence

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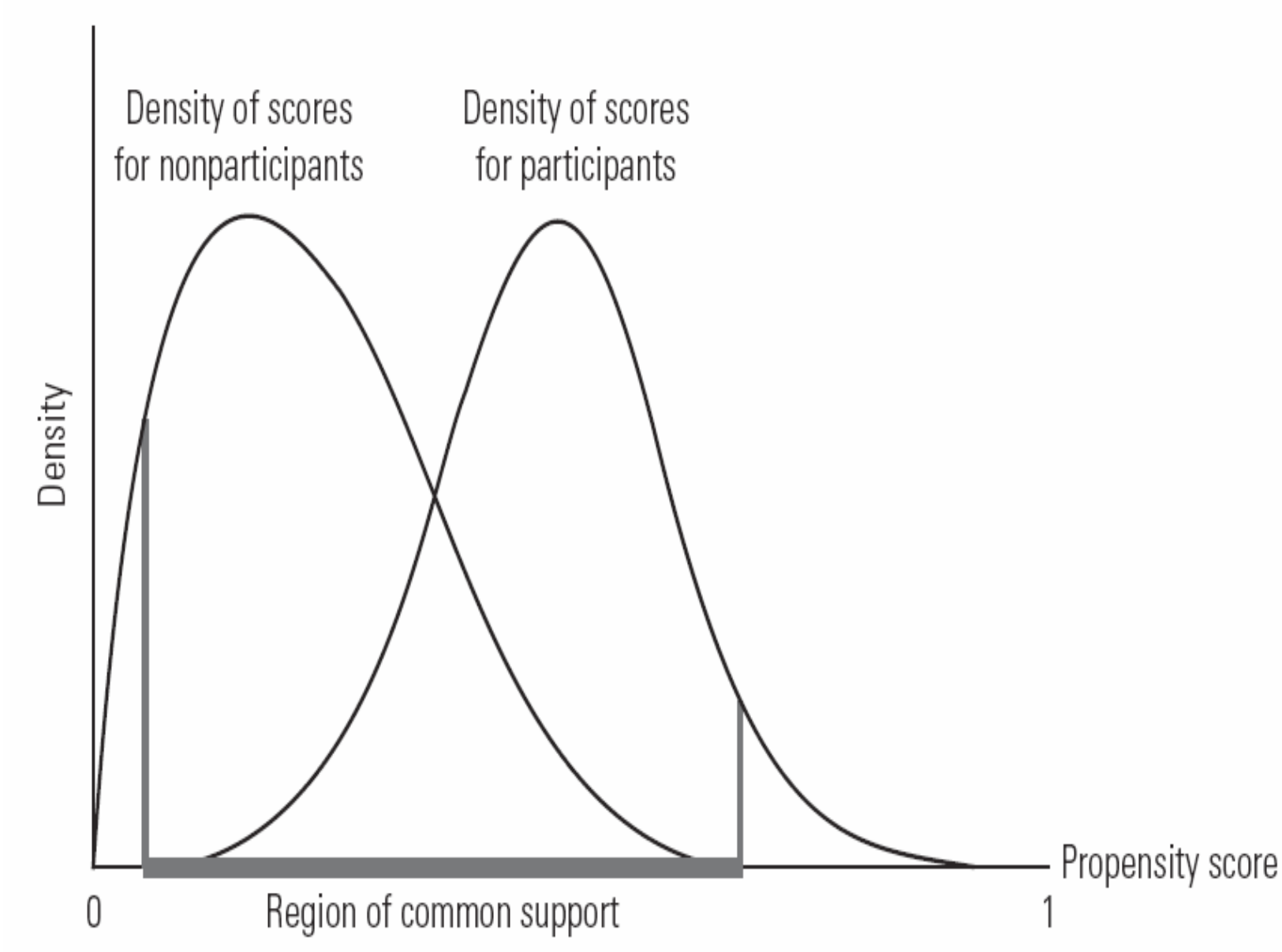
- Useful to have a lot of preprogram data (a lot of controls) and to understand the assignment mechanism

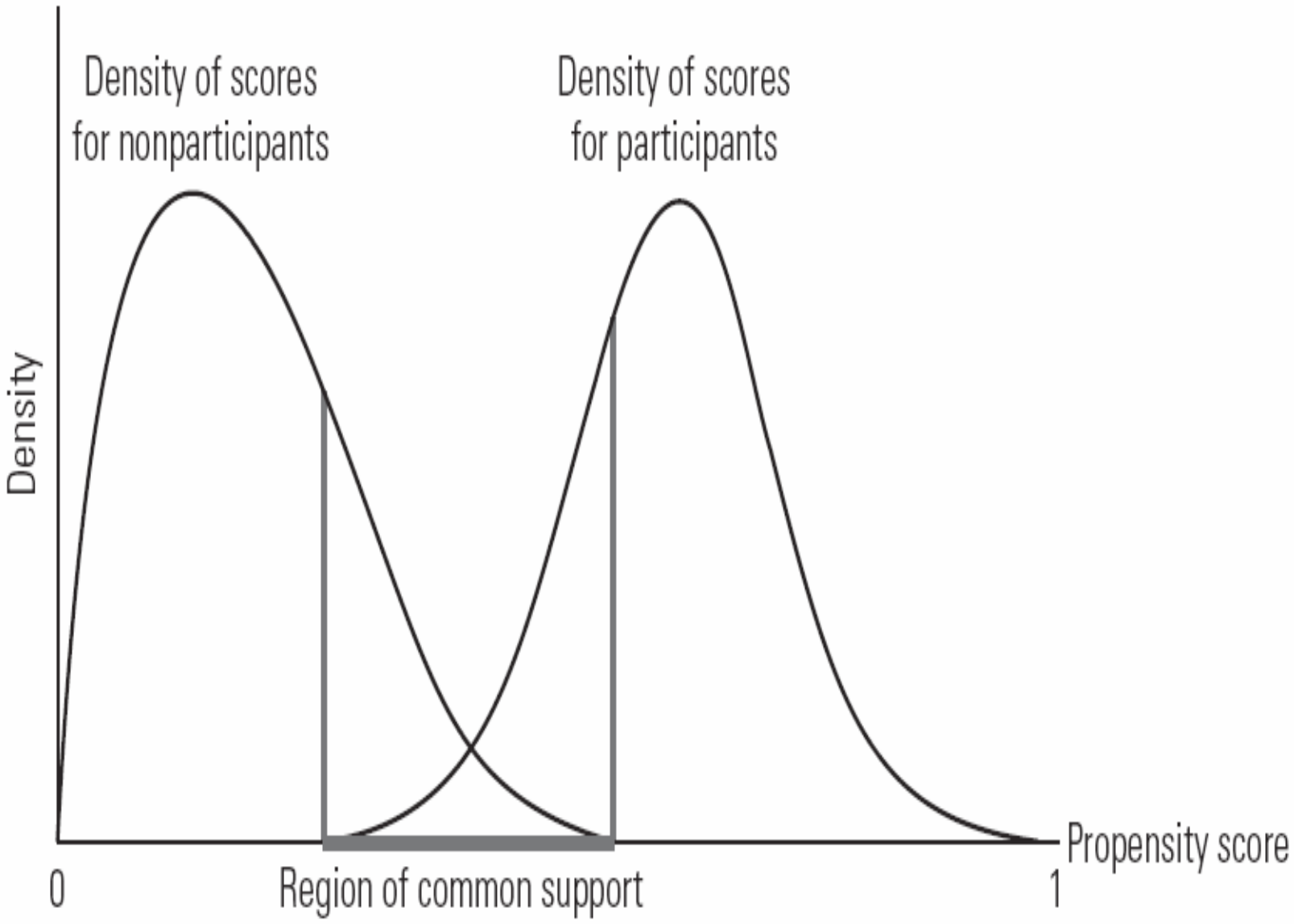
Common Support

- This condition ensures that treatment observations have comparison observations "nearby" in the propensity score distribution
- $0 < P(T_i = 1|X_i) < 1$
- the effectiveness of PSM also depends on having a large and roughly equal number of participant and nonparticipant observations so that a substantial region of common support can be found

Example of Common Support



Example of Poor Balance and Weak Common Support



Common support

- Treatment units will therefore have to be similar to non-treatment units in terms of observed characteristics unaffected by participation;
- Some non-treatment units may have to be dropped to ensure comparability.
- However, sometimes a nonrandom subset of the treatment sample may have to be dropped if similar comparison units do not exist
- This may create possible sampling bias in the treatment effect.
- Examining the characteristics of dropped units may be useful in interpreting potential bias in the estimated treatment effects

Estimating the treatment effect with PSM

1. Estimating a Model of Program Participation
2. Defining the Region of Common Support and Balancing Tests
3. Matching Participants to Nonparticipants
4. Computing the treatment effect

Estimating a Model of Program Participation

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- $E(u_i|X) = 0$ because of conditional independence

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- $Pr(T_i = 1|X_i) = \beta_0 + \beta_1 X_i$
- But this is just the linear probability model, which we have already estimated! (OLS estimation when the dependent variable is binary)

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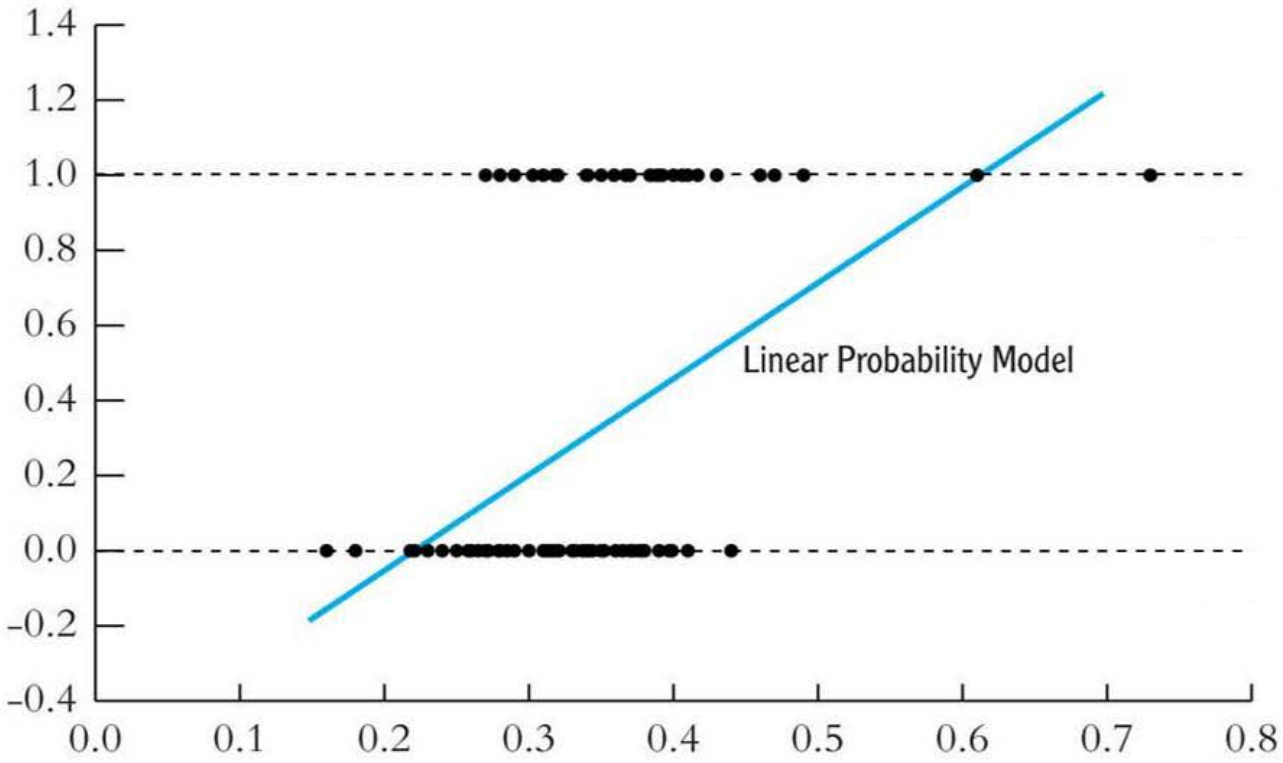


Estimating a Model of Program Participation

- The problem is the probability of $T = 1$ is modeled as linear: $Pr(T_i = 1|X_i) = \beta_0 + \beta_1 X_i$
- We want instead: $0 < Pr(T = 1|X) < 1$ for all X(Common support assumption)
- This requires a nonlinear functional form for the probability

Estimating a Model of Program Participation

Two common options

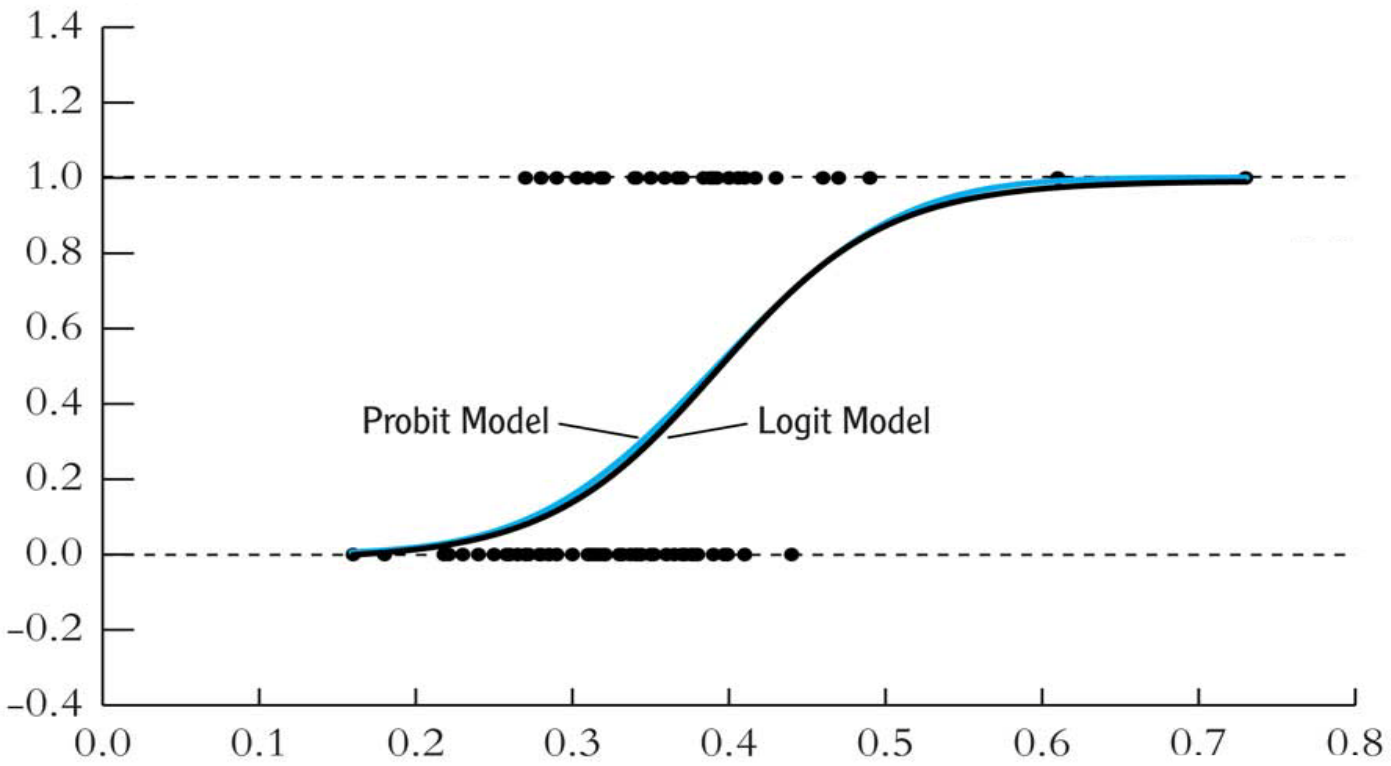
1. Probit:

$$Pr(T_i = 1|X_i) = \Phi(\beta_0 + \beta_1 X_i)$$

2. Logit:

$$Pr(T_i = 1|X_i) = \frac{1}{1 + \exp^{-(\beta_0 + \beta_1 X_i)}}$$

Estimating a Model of Program Participation



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- We also want a specification that achieves a good degree of balance (thus we should be careful to overfit the model)

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- We also want a specification that achieves a good degree of balance (thus we should be careful to overfit the model)
- This is not a behavioral model!

Defining the Region of Common Support and Balancing Tests

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Defining the Region of Common Support and Balancing Tests

- Find the regions of distribution where the propensity score for treatment and control overlap
- Drop the observations where there is no common support
- Check the characteristics of non-participants that were dropped to see how much sampling bias may have occurred
- Conduct balancing tests within each quantile of the propensity score distribution. Make sure the X's are balanced between treatment and control: $\hat{P}(X|T=1) = \hat{P}(X|T=0)$

Matching Participants to Nonparticipants

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- Do we only match those with the same probability? Or do match those whose probabilities are close? What does it mean to be close? We need a metric.
- There are many different matching criteria one could use to assign participants to non-participants on the basis of the propensity score

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  - Imposes a threshold or tolerance on the maximum propensity distance
  - Potential issue: higher number of dropped nonparticipants is likely $\rightarrow$ increasing the chance of sampling bias

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  - Overall impact is a weighted average of these interval impacts (weighted by share of participants)
- Kernel and local linear matching
  - Nonparametric technique uses a weighted average of all nonparticipants to construct the counterfactual match for each participant

Matching Participants to Nonparticipants

Regression methods

- Estimate the following regression:

$$Y_i = \beta_0 + \beta_1 T_i + \beta_2 \hat{P}(X) + \beta_3 (T_1 \times (\hat{P}(X) - E[\hat{P}(X)])) + u_i$$

- Estimate the following regression: $Y_i = \beta_0 + \beta_1 T_i + \delta X_i + u_i$ using weighted least squares
- Weights are 1 for participants and $\frac{\hat{P}(X)}{1-\hat{P}(X)}$ for non-participants

PSM

STATA EXAMPLE

Back to Jalan and Ravallion

- Main question: Is a child less vulnerable to diarrhoeal disease if he/she lives in a household with access to piped water?
- Do children in poor, or poorly educated, households realize the same health gains from piped water as others?

Jalan and Ravallion

- propensity-score matching (PSM) methods to estimate the causal e0ects of piped-water on child health in a cross-sectional sample without random placement

- Two groups: those households that have piped water $D_i = 1$ and those that do not $D_i = 0$

- Radius and nearest neighbor matching: The nearest neighbor to the ith participant is defined as the non-participant that minimizes $[p(x_i) - p(x_j)]^2$ over all j in the set of non-participants, then uses 5 nearest
- $p(x_k)$ is the predicted odds ratio of observation $k \rightarrow$ $p(x_k) = \frac{\hat{P}(x_k)}{1-\hat{P}(x_k)}$
- Matches were accepted if $[p(x_i) - p(x_j)]^2 < 0.001$

Jalan and Ravallion

Estimate of the impact: Let ΔH_j denote the gain in health status for child j

$$\Delta H = \sum_{j=1}^{T} \omega_j \left(h_{j1} - \sum_{j=1}^{C} W_{ij} h_{ij0} \right)$$

- ω_j - sampling weights
- W_{ij} - weights applied in claculating the average
- h_{ij0} - outcome indicator of the ith non-treated matched to the jth treated
- h_{j1} - post-intervention health indicator

Jalan and Ravallion

- Nationally representative survey collecting detailed information on education and health status of 33,000 rural households from 1765 villages covering 16 states of India
- Access to piped water - an indicator for whether the household reports access to piped water from a tap either inside or outside the house
- Outcome variable - prevalence of diarrhea among children under 5 years of age and the reported illness duration

Summary stats

Table 1

Access to piped water across the income distribution and by education

Income quintiles (stratified by household income per person)	Number of observations	Percentage of people with piped water	Households with piped water stratified by highest education of female members				
			Illiterate	At most primary	At most matriculation	Higher secondary or more	Full sample
Bottom 20th percentile	6581	27.18	768	655	251	33	1707
20–40th percentile	6508	25.40	674	590	274	29	1567
40–60th percentile	6543	26.96	667	560	371	60	1658
60–80th percentile	6694	29.62	660	602	462	90	1814
Top 20th percentile	6904	33.63	665	593	638	185	2081
Full sample	33230	28.62	3434	3000	1996	397	8827

Propensity score

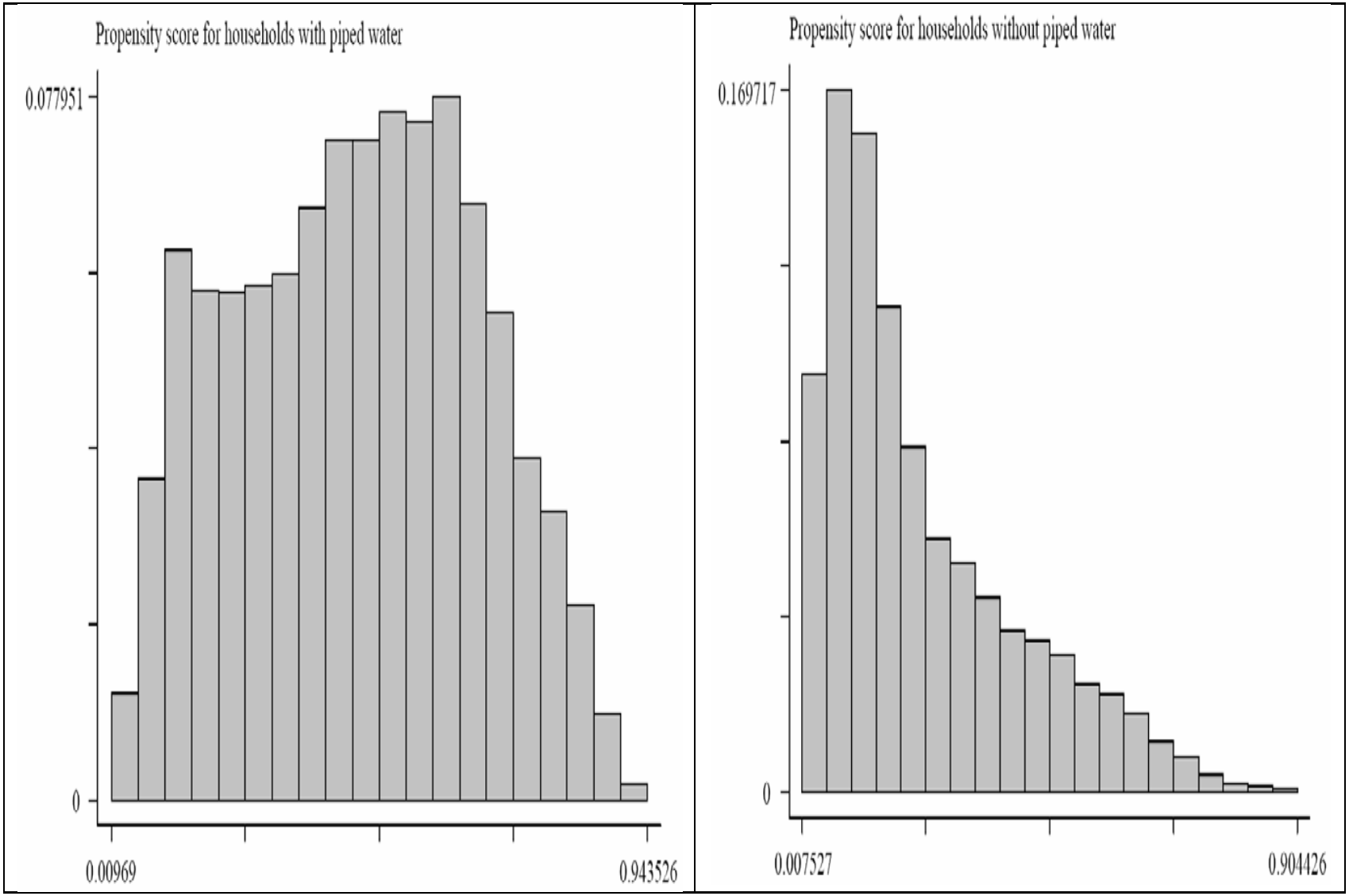
Table 2
Logit regression for piped water

	Coefficient	t-statistic
Village variables		
Village size (log)	0.08212	4.269
Proportion of gross cropped area which is irrigated: > 0.75	−0.04824	−1.185
Proportion of gross cropped area which is irrigated: 0.5–0.75	0.19399	4.178
Whether village has a day care center	−0.07249	−2.225
Whether village has a primary school	−0.08136	−1.434
Whether village has a middle school	−0.09019	−2.578
Whether village has a high school	0.26460	7.405
Female to male students in the village	0.10637	3.010
Female to male students for minority groups	−0.07661	−2.111
Main approachable road to village: pucca road	0.19441	3.637
jeepable/kuchha road	−0.00163	−0.033
Whether bus-stoop is within the village	0.11423	2.951
Whether railway station is within the village	0.00920	0.179
Whether there is a post-office within the village	0.02193	0.550
Whether the village has a telephone facility	0.33059	9.655
Whether there is a community TV center in the village	0.09859	2.661
Whether there is a library in the village	−0.04153	−1.116
Whether there is a bank in the village	0.19084	4.655
Whether there is a market in the village	0.31690	6.092
Student teacher ratio in the village	0.00242	5.295

Propensity score

Household variables		
Whether household belongs to the Scheduled Tribe	−0.21288	−4.203
Whether household belongs to the Scheduled Caste	−0.01045	−0.288
Whether it is a Hindu household	−0.24195	−1.709
Whether it is a Muslim household	−0.21631	−1.427
Whether it is a Christian household	0.40367	2.426
Whether it is a Sikh household	−0.86645	−4.531
Household size	0.00337	0.571
Utilization of landholdings: used for cultivation?	0.17109	1.914
Whether the house belongs to the household	−0.18988	−2.854
Whether the household owns other property	0.00181	0.044
Whether the household has a bicycle	−0.26514	−8.243
Whether the household has a sewing machine	0.01183	0.252
Whether the household owns a thresher	−0.05790	−0.577
Whether the household owns a winnower	0.21842	1.820
Whether the household owns a bullock-cart	−0.25900	−5.430
Whether the household owns a radio	0.01036	0.251
Whether the household owns a TV	0.08095	1.335
Whether the household owns a fan	0.01336	0.321
Whether the household owns any livestock	−0.07780	−2.339
Nature of house: Kuchha	−0.10004	−2.775
Pucca	0.12039	2.709
Condition of house: Good	0.00230	0.036
Livable	0.09268	1.756

Overlap


Propensity score for households with piped water
0.077951
0
0.00969
0.943526
Propensity score for households without piped water
0.169717
0
0.007527
0.904426

Overlap

- Prior to matching
  - with piped water - average p-score: 0.5495
  - without piped water - average p-score: 0.1933
- After matching
  - with piped water - average p-score: 0.3743
  - without piped water - average p-score: 0.3742
- 650 treatment households lost due to inability to find match

Impact

Table 3

Impacts of piped water on diarrhea prevalence and duration for children under five

	Prevalence of diarrhea		Duration of illness	
	Mean for those with piped water (st. dev.)	Impact of piped water (st. error)	Mean for those with piped water (st. dev.)	Impact of piped water (st. error)
Full sample	0.0108	−0.0023*	0.3254	−0.0957*
	(0.046)	(0.001)	(1.650)	(0.021)
Stratified by household income per capita (quintiles)				
1 (poorest)	0.0155	0.0032*	0.4805	0.0713
	(0.055)	(0.001)	(2.030)	(0.053)
2	0.0136	0.0007	0.4170	0.0312
	(0.051)	(0.001)	(1.805)	(0.051)
3	0.0083	−0.0039*	0.2636	−0.1258*
	(0.038)	(0.001)	(1.418)	(0.042)
4	0.0100	−0.0036*	0.3195	−0.1392*
	(0.044)	(0.001)	(1.703)	(0.048)
5	0.0076	−0.0068*	0.1848	−0.2682*
	(0.042)	(0.001)	(1.254)	(0.036)

Impact

Table 3

Impacts of piped water on diarrhea prevalence and duration for children under five

	Prevalence of diarrhea		Duration of illness	
	Mean for those with piped water (st. dev.)	Impact of piped water (st. error)	Mean for those with piped water (st. dev.)	Impact of piped water (st. error)
Stratified by highest education level of a female member				
Illiterate	0.0131	−0.0000	0.3588	−0.0904*
	(0.053)	(0.001)	(1.710)	(0.036)
At most primary school educated	0.0112	−0.0015	0.3502	−0.0465
	(0.045)	(0.001)	1.739)	(0.036)
At most matriculation educated	0.0074	−0.0065*	0.2573	−0.1708*
	(0.038)	(0.001)	(1.476)	(0.039)
Higher secondary or more	0.0050	−0.0080*	0.1880	−0.2077*
	(0.027)	(0.002)	(1.158)	(0.076)

*Indicates significance at the 5% level or lower.

Conclusions

- They find significantly lower prevalence and duration of the disease for children living in households with piped water as compared to a comparison group of households matched on the basis of their propensity scores
- They find no evidence of significant gains for the poorest 40% in terms of incomes
- Health gains from piped water tend to be lower for children with less well-educated women in the household
- Income poverty and lack of education and knowledge may well constrain the potential health gains from water infrastructure improvements.
- The incidence of health gains need not favor children from poor families even when facility placement is pro-poor.