Estimation of Small Area Causal Effects of Job Training Programs

Junni Zhang

Department of Business Statistics and Econometrics

Guanghua School of Management, Peking University, China

Joint Work with Jing Dong, Andy Dickerson, Sarah Brown

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Outline

- **Introduction and Motivating Example**
- **Propensity Score Matching with Small Areas**
- **Model Based Estimation of Small Area Causal Effects**

Introduction

- For decades, various job training programs have been used to help improve the labor market outcomes of participants.
- Evaluation of causal effects of job training programs (on employment, wages, and etc.) is an important issue that has generated a large literature bridging statistics and economics.

  e.g., Heckman and Robb 1984; Heckman and Hotz 1989; Angrist, Imbens and Rubin 1996; Heckman, Ichimura, Smith and Todd 1998; Dehejia and Wahba 1999; Abadie, Angrist and Imbens 2002; Aakvik, Heckman and Vytlacil 2005; Hotz, Imbens and Mortimer 2005; Hotz, Imbens and Klerman 2007; Zhang, Rubin and Mealli 2008, 2009; Lee 2009.

Introduction

- Most of previous research has focused on evaluating the average causal effects for the whole group of program participants. However, for different subgroups of participants, the average causal effects may be heterogeneous.

Motivating Example: The UK Labor Force Survey

- The Labor Force Survey (LFS) is a quarterly survey of the employment circumstances of the UK population. It is the largest household survey in the UK and collects information from individuals on issues related to employment and the personal characteristics.
- We use the LFS data on individuals who are employed at time t (the 1st observation of the individual, between the first quarter of 2007 and the last quarter of 2009) and also employed at t+1 (the 5th observation for the individual, which is 5 calendar quarters later), excluding those in Northern Ireland or outside UK, those containing missing data as well as some outliers. The data contains 29,493 observations.

Motivating Example: The UK Labor Force Survey

- Training Indicator Z: whether trained in last 13 weeks at time t, Z=1 (treated) or 0 (control)
- Outcome Y: $log(grsswk(t+1)) - log(grsswk(t))$, change in log gross weekly pay in main job

Motivating Example: The UK Labor Force Survey

- The average causal effects of Z on Y may differ by region, qualification and gender.

Region:		**Qualification:**		**Gender:**		
North East						
North West						
Yorks Humber						
Midlands		High				
East	$\times$	Medium	$\times$	Male	=	60 Small Areas
London		Low		Female		
South East						
South West						
Wales						
Scotland						

Motivating Example: The UK Labor Force Survey

Table 1: Number of Observations in Each Small Area (Male)

	Qualification Level					
	High		Medium		Low	
Region	#Treated	#Control	#Treated	#Control	#Treated	#Control
North East	94	112	99	176	37	147
North West	223	316	150	408	76	341
Yorks Humber	163	294	133	382	93	339
Midlands	309	471	266	599	112	593
East	126	253	129	318	68	279
London	214	439	122	252	68	234
South East	300	463	222	522	119	466
South West	198	270	140	342	61	309
Wales	107	143	58	157	21	110
Scotland	202	281	142	332	57	259

Motivating Example: The UK Labor Force Survey

Table 2: Number of Observations in Each Small Area (Female)

	Qualification Level					
	High		Medium		Low	
Region	#Treated	#Control	#Treated	#Control	#Treated	#Control
North East	144	109	103	168	51	166
North West	336	373	219	413	107	406
Yorks Humber	273	284	177	384	97	412
Midlands	427	462	322	635	182	616
East	235	265	156	298	92	395
London	268	365	101	217	77	224
South East	449	481	284	524	147	551
South West	300	270	199	382	94	336
Wales	181	117	93	144	35	141
Scotland	329	369	132	306	79	275

Motivating Example: The UK Labor Force Survey

Table 3: Covariates X measured at time t

Variable	**Description**
year	Year
qtr	Quarter
age	Age
hhchild	No. of dependent children in household under 19
house	Owned; Bought with mortgage; Part rent, Part mortgage; Rented; Rent free
eth	White; Mixed; Asian; Black; Chinese; Other
mar	Never married; Married; Civil partnership; Separated; Divorced; Widowed
sec	NS-SEC class (7 categories)
soc	Major occupation group (9 categories)
bushr	Basic usual hours
ttushr	Total usual hours in main job
netwk	Net weekly pay in main job
hourpay	Gross hourly pay
grsswk	Gross weekly pay in main job
parttime	Part-time job status
tempjob	Temporary job status
private	Private sector status

Motivating Example: The UK Labor Force Survey

- If the distributions of covariates for the treated and control groups are very different,
  - direct comparison of the treated and control groups is misleading; e.g. wrong comparison: male smokers vs. female nonsmokers
  - the treatment effect estimates resulting from regression models would rely heavily on extrapolation.

Motivating Example: The UK Labor Force Survey

$X = (X_1, X_2, ..., X_{45})$: 45 covariates;

$\bar{X}_{j,t}$: sample mean of X_j for treated group;

$\bar{X}_{j,c}$: sample mean of X_j for control group;

$S^2_{j,t}$: sample variance of X_j for treated group;

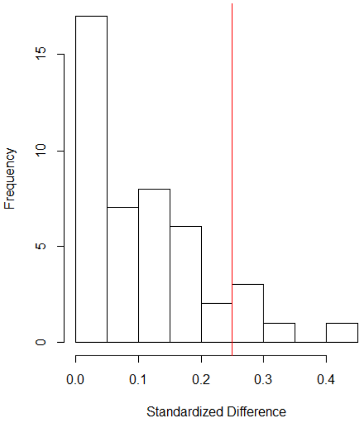
$S_{j,c}$: sample variance of X_j for control group;

Standardized difference of means of X_j:

$$T_j = |\bar{X}_{j,t} - \bar{X}_{j,c}| / \sqrt{0.5 S^2_{j,t} + 0.5 S^2_{j,c}}.$$

If $T_j > 1/4$, then X_j is treated as unbalanced (Cochran and Rubin, 1973; Rubin, 2001).

Figure 1: standardized differences (full sample)



Motivating Example: The UK Labor Force Survey

Table 4: Number of Unbalanced Covariates in Each Small Area (full sample)

	Qualification					
	High		Medium		Low	
Region	Male	Female	Male	Female	Male	Female
North East	5	3	7	4	11	14
North West	4	3	2	4	9	4
Yorks Humber	1	6	4	4	5	9
Midlands	1	7	3	3	5	8
East	1	1	3	4	7	9
London	0	4	3	4	2	11
South East	2	1	2	5	3	9
South West	4	7	4	3	5	11
Wales	4	6	4	8	10	13
Scotland	4	11	2	12	12	12

Total number: 329

Propensity Score Matching (General)

- Definition of Balancing Score: a (one-dimensional) balancing score b satisfies

$$\begin{aligned} & w \perp Z|b \\ & \iff f(w|Z=1,b) = f(w|Z=0,b), \end{aligned}$$

  where w is a set of observed covariates.

- Definition of Propensity Score: $e(w) = Pr(Z = 1|w)$.

- **Key Property of Propensity Score:** $w \perp Z|e(w)$.

Propensity Score Matching (General)

- Propensity score is often estimated by logistic regression

$$e(w) = \frac{exp(\gamma^\top w)}{1 + exp(\gamma^\top w)}$$

- 1:1 nearest neighbor matching can be used to select for each treated individual i the control individual with the smallest difference in estimated propensity score from individual i.

- Controls can be selected with or without replacement.

Propensity Score Matching with Small Areas

Problem: In order to reliably estimate causal effects within each small area defined by region×qualification×gender,

- we need to balance the distribution of covariates within each small area;
- to achieve good benchmarking, we also hope to balance the distribution of covariates
  - within each larger area defined by region×qualification, region×gender or qualification×gender;
  - within each larger area defined by region, qualification or gender;
  - for the full matched sample.

Propensity Score Matching with Small Areas

We noticed a key property of a balancing score.

$$(w_1, w_2) \perp Z | b \iff \forall w_2, \; w_1 \perp Z | b, w_2.$$

Proof: Note that

$$f(w_1, w_2 | Z = 1, b) = f(w_1, w_2 | Z = 0, b)$$
$$\iff \forall w_2, \; f(w_1 | Z = 1, b, w_2) = f(w_1 | Z = 0, b, w_2).$$

Propensity Score Matching with Small Areas

$$\text{Implication of} \quad (w_1, w_2) \perp Z | b \implies \forall w_2, \quad w_1 \perp Z | b, w_2.$$

For each small area defined by region×qualification×gender, 16 candidate propensity score models can be used.

Model No.	Sample Used	Replacement
1,2	full sample	with/without
3,4	sample with the same region	with/without
5,6	sample with the same qualification	with/without
7,8	sample with the same gender	with/without
9,10	sample with the same region and qualification	with/without
11,12	sample with the same region and gender	with/without
13,14	sample with the same qualification and gender	with/without
15,16	sample within the small area	with/without

Propensity Score Matching with Small Areas

Implication of $\forall w_2, \;\; w_1 \perp Z | b, w_2 \quad \Longrightarrow \quad (w_1, w_2) \perp Z | b$:

If the distribution of covariates is well balanced within each small area defined by region×qualification×gender, then the distribution of covariates should also be balanced

- within each larger area defined by region×qualification, region×gender or qualification×gender;
- within each larger area defined by region, qualification or gender;
- for the full matched sample.

Propensity Score Matching with Small Areas

Notation:

- $m_s \in \{1, \cdots, 16\}$, the propensity score model no. for small area s.
- $M = \{m_1, \cdots, m_{60}\}$, the combination of models for all 60 small areas.
- Standardized differences of means of X_j achieved by matching with M:
  - $t_j(M)$: based on the full matched sample;
  - $t_{j,r}(M)$, $t_{j,q}(M)$, $t_{j,g}(M)$: based on the matched sample with region r, qualification q or gender g;
  - $t_{j,r,q}(M)$, $t_{j,r,g}(M)$, $t_{j,q,g}(M)$: based on the matched sample with region r and qualification q, region r and gender g, or qualification q and gender g;
  - $t_{j,r,q,g}(M)$: based on the matched sample with region r, qualification q and gender g.

Propensity Score Matching with Small Areas

We used conditional optimization with random updating order to search over the space of M in order to minimize one of the two following objective functions.

Propensity Score Matching with Small Areas

- **Objective Function 1:**

$$F1(M) = \sum_{j=1}^{45} t_j(M)$$

$$+ \sum_{r=1}^{10}\sum_{j=1}^{45} t_{j,r}(M) + \sum_{q=1}^{3}\sum_{j=1}^{45} t_{j,q}(M) + \sum_{g=1}^{2}\sum_{j=1}^{45} t_{j,g}(M)$$

$$+ \sum_{r=1}^{10}\sum_{q=1}^{3}\sum_{j=1}^{45} t_{j,r,q}(M) + \sum_{r=1}^{10}\sum_{g=1}^{2}\sum_{j=1}^{45} t_{j,r,g}(M) + \sum_{q=1}^{3}\sum_{g=1}^{2}\sum_{j=1}^{45} t_{j,q,g}(M)$$

$$+ \sum_{r=1}^{10}\sum_{q=1}^{3}\sum_{g=1}^{2}\sum_{j=1}^{45} t_{j,r,q,g}(M)$$

- **Objective Function 2:**

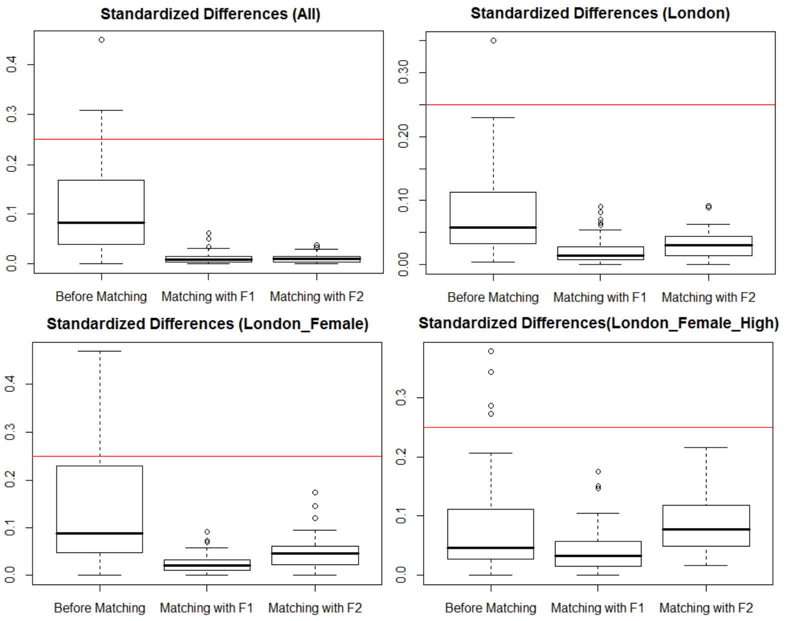
$$F2(M) = \sum_{j=1}^{45} I\{t_j(M) \geq \frac{1}{4}\}$$

$$+ \sum_{r=1}^{10}\sum_{j=1}^{45} I\{t_{j,r}(M) \geq \frac{1}{4}\} + \sum_{q=1}^{3}\sum_{j=1}^{45} I\{t_{j,q}(M) \geq \frac{1}{4}\} + \sum_{g=1}^{2}\sum_{j=1}^{45} I\{t_{j,g}(M) \geq \frac{1}{4}\}$$

$$+ \sum_{r=1}^{10}\sum_{q=1}^{3}\sum_{j=1}^{45} I\{t_{j,r,q}(M) \geq \frac{1}{4}\} + \sum_{r=1}^{10}\sum_{g=1}^{2}\sum_{j=1}^{45} I\{t_{j,r,g}(M) \geq \frac{1}{4}\} + \sum_{q=1}^{3}\sum_{g=1}^{2}\sum_{j=1}^{45} I\{t_{j,q,g}(M) \geq \frac{1}{4}\}$$

$$+ \sum_{r=1}^{10}\sum_{q=1}^{3}\sum_{g=1}^{2}\sum_{j=1}^{45} I\{t_{j,r,q,g}(M) \geq \frac{1}{4}\}$$

Propensity Score Matching with Small Areas



Propensity Score Matching with Small Areas

Results of matching with F1:

- All covariates are balanced
  - for the full matched sample;
  - for the matched sample with the same region, qualification or gender;
  - for the matched sample with the same qualification and gender.
- 1 covariate is unbalanced for Yorks&Humber$\times$high;
- 1 covariate is unbalanced for South West$\times$high;
- 6 covariates are unbalanced for Wales$\times$low;
- 1 covariate is unbalanced for Yorks&Humber$\times$female.

Propensity Score Matching with Small Areas

Table 5: Number of Unbalanced Covariates in Each Small Area

	Qualification					
	High		Medium		Low	
Region	Male	Female	Male	Female	Male	Female
North East	4	2	0	2	3	3
North West	2	0	0	0	2	0
Yorks Humber	1	1	0	0	1	0
Midlands	0	0	0	0	0	0
East	0	0	0	0	3	0
London	0	0	0	0	0	0
South East	0	0	0	0	0	0
South West	0	0	0	0	0	0
Wales	1	1	1	1	12	6
Scotland	0	0	0	0	0	0

Propensity Score Matching with Small Areas

Notice that the propensity score matching stage uses only covariates on the individuals, designing the nonexperimental study as would be a randomized experiment, without access to the outcome values.

Now we can move to outcome analysis.

Model Based Estimation of Small Area Causal Effects

Notation:

- for individual i, $\tilde{X}^{(i)} = (1, Z^{(i)}, X^{(i)}, R^{(i)}, Q^{(i)}, G^{(i)})$, where $R^{(i)}$, $Q^{(i)}$ and $G^{(i)}$ respectively denote the region, qualification and gender of individual i;
- $\tilde{X}$ is the matrix of $\tilde{X}^{(i)}$;
- β: fixed effect parameters, $\beta = (\beta_0, \beta_Z, \beta_X, \beta_R, \beta_Q, \beta_G)$;
- V: 120 small areas random effects, 60 for treated and 60 for control;
- A: a known design matrix;
- ε: individual random effects.

- General ANOVA Model

$$Y = \tilde{X}\beta + AV + \varepsilon \tag{3}$$

Where $V \sim N(0, U)$, $\varepsilon \sim N(0, E)$.

- We apply the hierarchical Bayesian approach to the general ANOVA models, assuming the following flat prior on model parameters:

$$f(\beta) \propto 1;$$

$$f(\text{unique element of } U \text{ or } E) \propto 1.$$

Model Based Estimation of Small Area Causal Effects

- **Model 1**: the variance parameters for the small area random effects and the individual random effects are the same for the treated and control groups.
- **Model 2**: the variance parameters for the small area random effects and the individual random effects are different for the treated and control groups.
- **Model 3**: there is no small area random effect, and the variance parameters for the individual random effects are different for the treated and control groups.

Model Based Estimation of Small Area Causal Effects

- For model checking, we used two methods:
    - deviance information criterion (Spiegelhalter et al., 2002);
    - sampled posterior p-value (Johnson 2004, 2007; Gosselin 2011).

  Model 2 performs better than the other two and fits the data well.

- The causal effect of Z on Y for small area s ($s = 1, \cdots, S$) is estimated by

$$\beta_Z + V_{s,t} - V_{s,c}.$$

Model Based Estimation of Small Area Causal Effects

Table 6: 95% Credible Interval of Small Area Causal Effects (Male)

	Qualification Level		
Region	High	Medium	Low
North East	(-0.023,0.058)	(-0.037,0.044)	(-0.034,0.056)
North West	(0.001,0.071)	(-0.036,0.043)	(-0.026,0.065)
Yorks Humber	(-0.018,0.060)	(-0.034,0.047)	(-0.012,0.073)
Midlands	(-0.021,0.046)	(-0.003,0.067)	(-0.034,0.048)
East	(-0.036,0.043)	(-0.042,0.041)	(-0.044,0.043)
London	(-0.013,0.061)	(-0.025,0.056)	(-0.030,0.059)
South East	(0.006,0.073)	(-0.031,0.042)	(-0.033,0.048)
South West	(-0.013,0.060)	(-0.030,0.048)	(-0.010,0.079)
Wales	(-0.041,0.043)	(-0.015,0.078)	(-0.033,0.064)
Scotland	(-0.013,0.059)	(-0.013,0.066)	(-0.022,0.065)

Model Based Estimation of Small Area Causal Effects

Table 7: 95% Credible Interval of Small Area Causal Effects (Female)

	Qualification Level		
Region	High	Medium	Low
North East	(-0.026,0.053)	(-0.021,0.058)	(-0.007,0.082)
North West	(0.008,0.078)	(-0.005,0.071)	(-0.039,0.048)
Yorks Humber	(0.002,0.071)	(-0.044,0.034)	(-0.024,0.059)
Midlands	(-0.037,0.027)	(-0.011,0.055)	(-0.035,0.042)
East	(-0.023,0.051)	(-0.029,0.048)	(-0.026,0.058)
London	(-0.046,0.026)	(-0.018,0.072)	(-0.042,0.045)
South East	(-0.050,0.015)	(-0.026,0.044)	(-0.018,0.060)
South West	(-0.020,0.049)	(-0.044,0.032)	(-0.037,0.053)
Wales	(-0.035,0.044)	(-0.016,0.070)	(-0.020,0.074)
Scotland	(0.004,0.070)	(-0.018,0.062)	(-0.021,0.065)

Thank you!