

Lecture 8

Outline of Lecture 8

- We will consider 2-level multi-level data where the outcome of interest is a level-1 binary variable
- PISA 2000
- Within the PISA 2000 data, we will
 - Consider logistic random intercept model to separate among and within-cluster effects
 - Review estimation and interpretation of contextual effects
 - Refresh our memory on the difference between marginal and random effects logistic model

Data Example: PISA

- 2000 Program for International Student Assessment (PISA)
- Conducted by the Organization for Economic Cooperation and Development (OECD 2000)
- Annual assessment of reading, mathematics and science proficiency (rotating)
- The 2000 survey assessed proficiency in reading of 15 year olds in 43 countries.
- Focus on US sample
- Complex survey design
 - We will look at this again later in the course

Data Example: PISA

id:	school id (numeric)
pass_read:	dummy variable for being proficient in reading (1: proficient, 0: not)
female:	dummy variable for student being female
isei:	international socioeconomic index
high_school:	dummy variable for highest education level by either parent being high school
college:	dummy variable for highest education level by either parent being college
test_lang:	dummy variable for English being spoken at home (NOTE: the reading proficiency test is administered in English)
one_for:	dummy variable for one parent being foreign born
both_for:	dummy variable for both parents being foreign born

Exploratory Data Analysis

id	school id (unique)
----	--------------------

type: numeric (long)

label: id

range: [1,148]

units: 1

unique values: 148

missing .: 0/2069

examples: 30 99160

57 99207

85 99249

116 99313

Exploratory Data Analysis

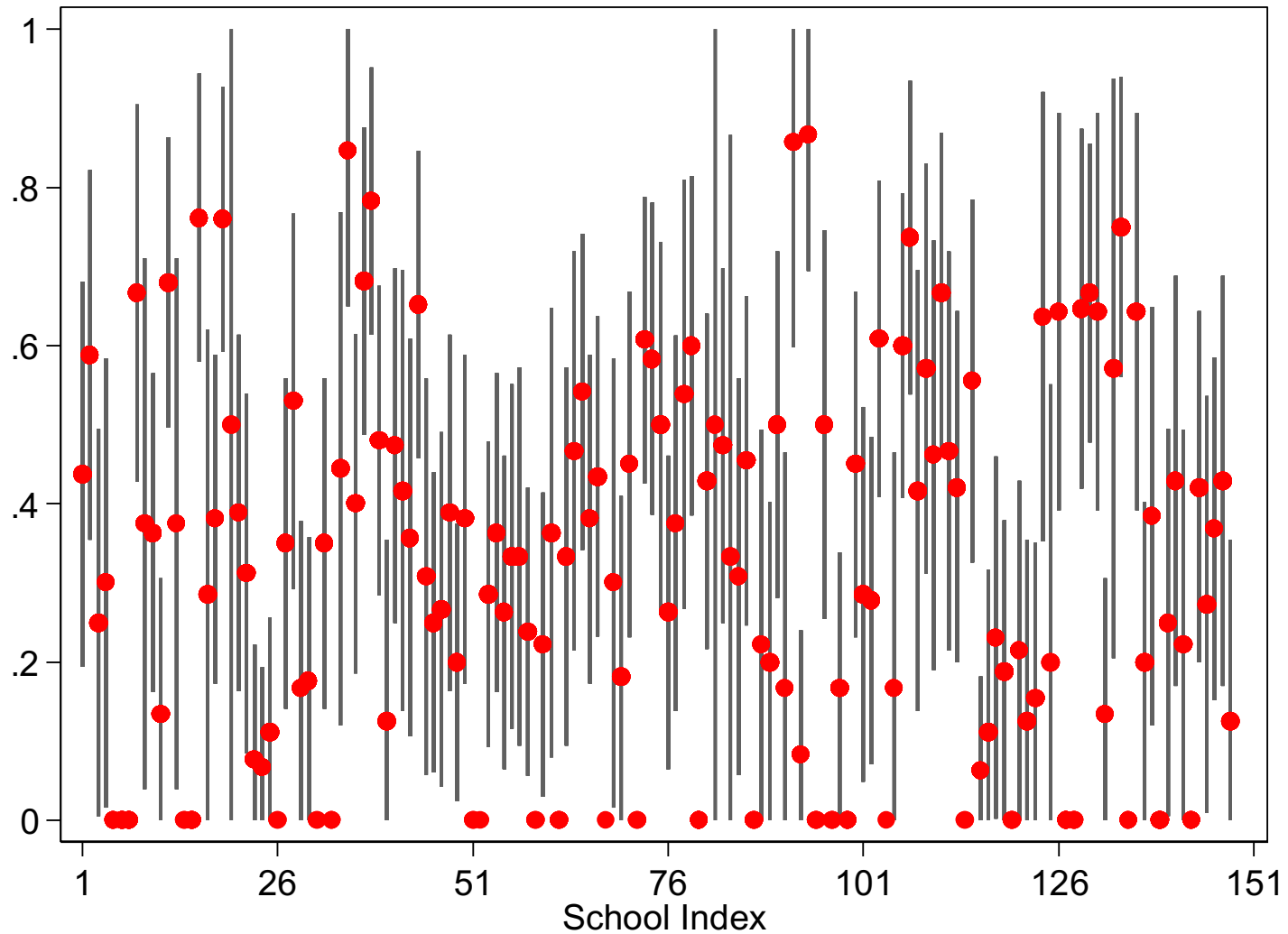
```
. bys id: gen copyid = _n
. bys id: egen n_student = count(id)
. summ n_student if copyid==1, detail
```

n_student			
Percentiles		Smallest	
1%	1	1	
5%	2	1	
10%	5	1	Obs 148
25%	9	2	Sum of Wgt. 148
50%	14.5		Mean 13.97973
		Largest	Std. Dev. 6.402029
75%	19	25	
90%	22	25	Variance 40.98598
95%	24	25	Skewness -.2412149
99%	25	28	Kurtosis 2.247757

Exploratory Data Analysis

Characteristic	Student % or mean (SD)	School Mean [min, Q1, Q3, max]
Female	54%	54% [0%, 46%, 64%, 100%]
Highest level of education		
Less than High-school	8%	5% [0%, 0%, 16%, 100%]
High-school	34%	33% [0%, 22%, 49%, 100%]
College	58%	57% [0%, 39%, 68%, 100%]
# foreign born parents		
0	83%	90% [0%, 67%, 100%, 100%]
1	5%	0% [0%, 0%, 8%, 50%]
2	12%	5% [0%, 0%, 20%, 100%]
English at home	92%	100% [0%, 86%, 100%, 100%]
ISEI	47 (17)	45 [25, 39, 51, 68]
Proficient in Reading	39%	33% [0%, 13%, 47%, 87%]

Partitioning Among vs. Within Variation of Binary Proficiency Outcome

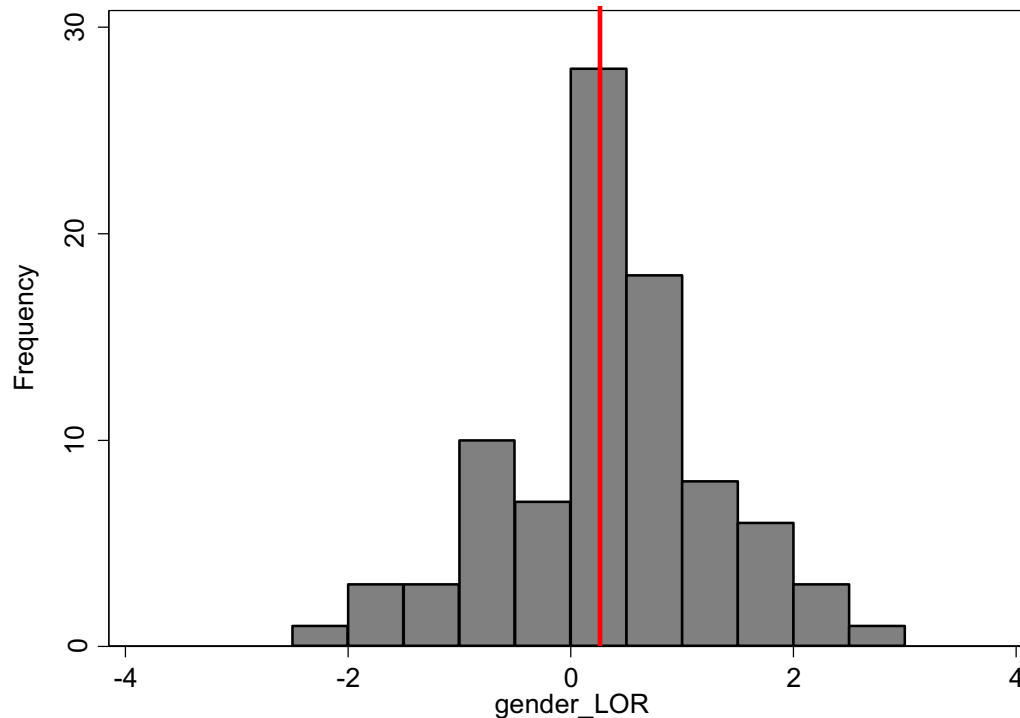


Within, Between and Contextual Effect

- Level-1 predictors
 - **Gender**
 - Highest level of education completed by parents
 - Number of foreign-born parents
 - **International socioeconomic index**
 - English as the primary language at home

Exploratory analysis of within-school gender effect

- Calculate the school-specific log odds ratio of reading proficiency comparing females to males

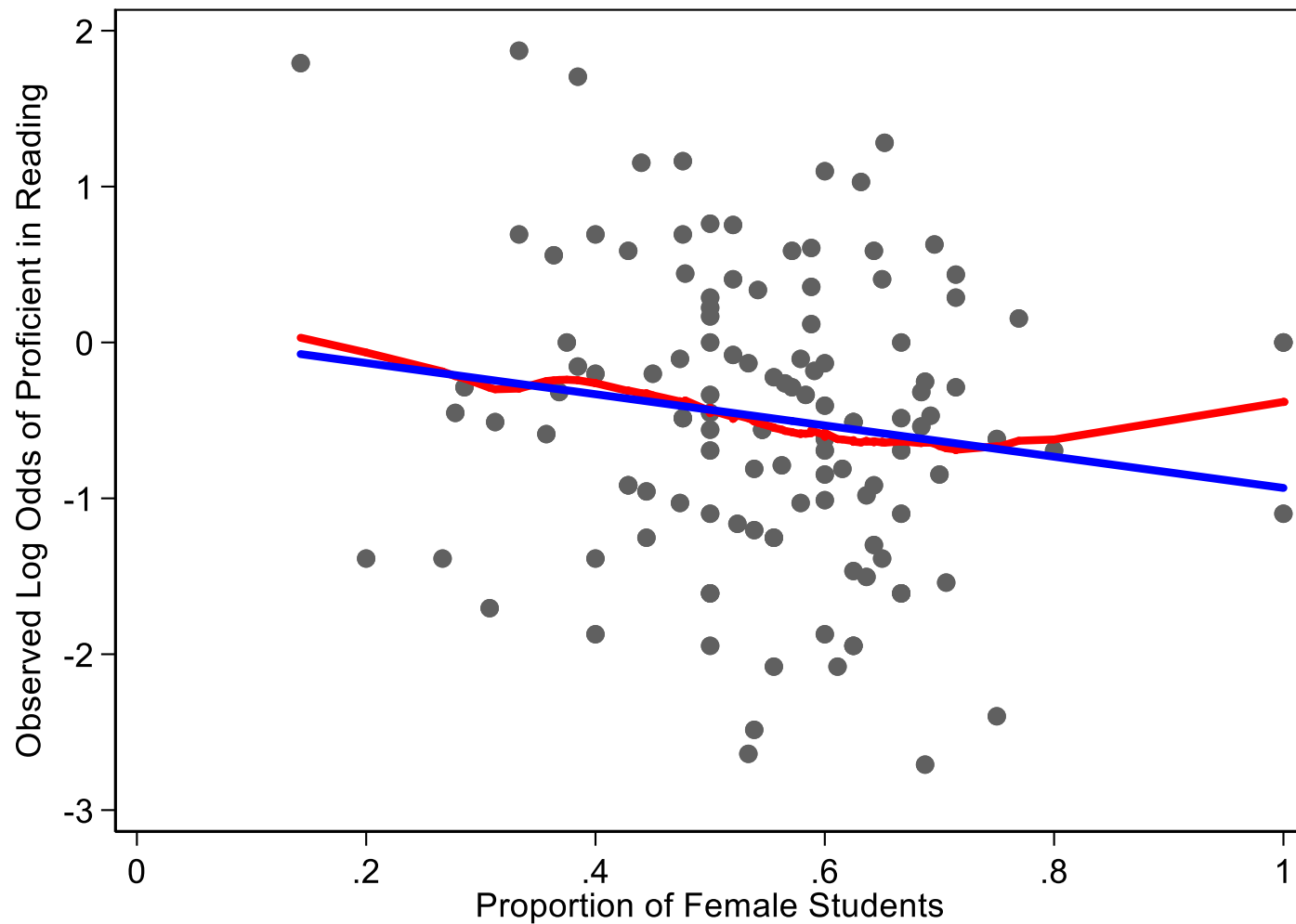


Mean = 0.32

Odds Ratio = $\exp(0.32) = 1.38$

Within school
comparison of the odds
of reading proficiency
comparing females to
males

Exploratory analysis of between-school gender effect



Separation of Within- and Among-Cluster (School) Effects

$$\text{Model 1: } \text{LogOdds}(Y_{ij} = 1|X_{ij}) = \alpha_{1i} + \beta_1 X_{ij}$$

$$\text{Model 2: } \text{LogOdds}(Y_{ij} = 1|X_{ij}, \bar{X}_{i.}) = \alpha_{2i} + \beta_2 X_{ij} + \gamma_2 \bar{X}_{i.}$$

$$\text{Model 3: } \text{LogOdds}(Y_{ij} = 1|X_{ij}, \bar{X}_{i.}) = \alpha_{3i} + \beta_3 (X_{ij} - \bar{X}_{i.}) + \gamma_3 \bar{X}_{i.}$$

$$\text{Model 4: } \text{LogOdds}(Y_{ij} = 1|X_{ij}, \bar{X}_{i.}) = \alpha_{4i} + \beta_4 (X_{ij} - \bar{X}_{i.})$$

$$\text{Model 5: } \text{LogOdds}(Y_{ij} = 1|X_{ij}, \bar{X}_{i.}) = \alpha_{5i} + \gamma_5 \bar{X}_{i.}$$

Where

$$\text{LogOdds}(Y_{ij} = 1|X_{ij}) = \text{Log} \left(\frac{\text{Pr}(Y_{ij} = 1|\alpha_{1i}, X_{ij})}{\text{Pr}(Y_{ij} = 0|\alpha_{1i}, X_{ij})} \right) = \alpha_{1i} + \beta_1 X_{ij}$$

$$\alpha_{ki} \sim N(\alpha_k, \tau_k^2), \text{ for each model } k$$

Results: Gender Effect

Model	$\exp(\beta_k)$	$\exp(\gamma_k)$
1	1.65 (1.35, 2.01)	
2	1.68 (1.37, 2.05)	0.46 (0.13, 1.66)
3	1.68 (1.37, 2.05)	0.78 (0.22, 2.74)
4	1.68 (1.37, 2.05)	
5		0.78 (0.22, 2.69)

Model 1 interpretation: For a given school, the odds of being reading proficient are 1.65 times greater for female than male student.

The attempt here is to estimate the “within-school effect” but the result can be confounded by the “among-school effect”

- If the among-school effect is very different from the within-school effect, then the within estimate can be markedly different than the true within-school effect, **confounded differences among schools**.

Results: Gender Effect

Model	$\exp(\beta_k)$	$\exp(\gamma_k)$
2	1.68 (1.37, 2.05)	0.46 (0.13, 1.66)
3	1.68 (1.37, 2.05)	0.78 (0.22, 2.74)
4	1.68 (1.37, 2.05)	

Models 2, 3 and 4 estimate the within-school gender effect!

For a given school (i.e. conditioning on the school-specific random intercept), the odds of being proficient in reading for girls are 68 percent greater than the odds for males.

The odds of being proficient in reading for girls are 1.68 times the odds for males **from the same school.**

Results: Gender Effect

Model	$\exp(\beta_k)$	$\exp(\gamma_k)$
2	1.68 (1.37, 2.05)	0.46 (0.13, 1.66)

$$\text{Model 2: } \text{LogOdds}(Y_{ij} = 1 | X_{ij}, \bar{X}_i) = \alpha_{2i} + \beta_2 X_{ij} + \gamma_2 \bar{X}_i.$$

Comparing two schools with the same random effect value, the school with more females has a lower rate (population odds) of being proficient in reading ($\exp(\gamma_k) < 1$).

NOTE: the calculated proportion of females goes from 0 to 1. So the contextual effect of 0.46 is really comparing the scenario where we go from an all boys school to an all girls school.

- We can rescale the contextual effect, by taking $\exp(\gamma_k/10) = 0.93$.

Comparing two schools that differ in the proportion of female students by 10% and have the same random effect values, a girl from the school with the higher proportion of female students has odds of being proficient in reading that are 7 percent smaller than a girl from the other school.

Results: Gender Effect

Model	$\exp(\beta_k)$	$\exp(\gamma_k)$
2	1.68 (1.37, 2.05)	0.46 (0.13, 1.66)
3	1.68 (1.37, 2.05)	0.78 (0.22, 2.74)
5		0.78 (0.22, 2.69)

The between-cluster effect of gender is estimated to be negative!
i.e. the school log odds of being proficient in reading decreases as the proportion of females in the school increases, holding the school random effect constant (e.g. school).

Again, we can rescale $\exp(\gamma_k)$ so that we are describing the between effect for a 10% increase in the proportion of female students.

Increasing the proportion of female students by 10% in a given school decreases the school-odds of reading proficiency by 2% ($0.78^{0.1} = 0.98$)

Results: Gender Effect

Model	$exp(\beta_k)$	$exp(\gamma_k)$
2	1.68 (1.37, 2.05)	0.46 (0.13, 1.66)
3	1.68 (1.37, 2.05)	0.78 (0.22, 2.74)
5		0.78 (0.22, 2.69)

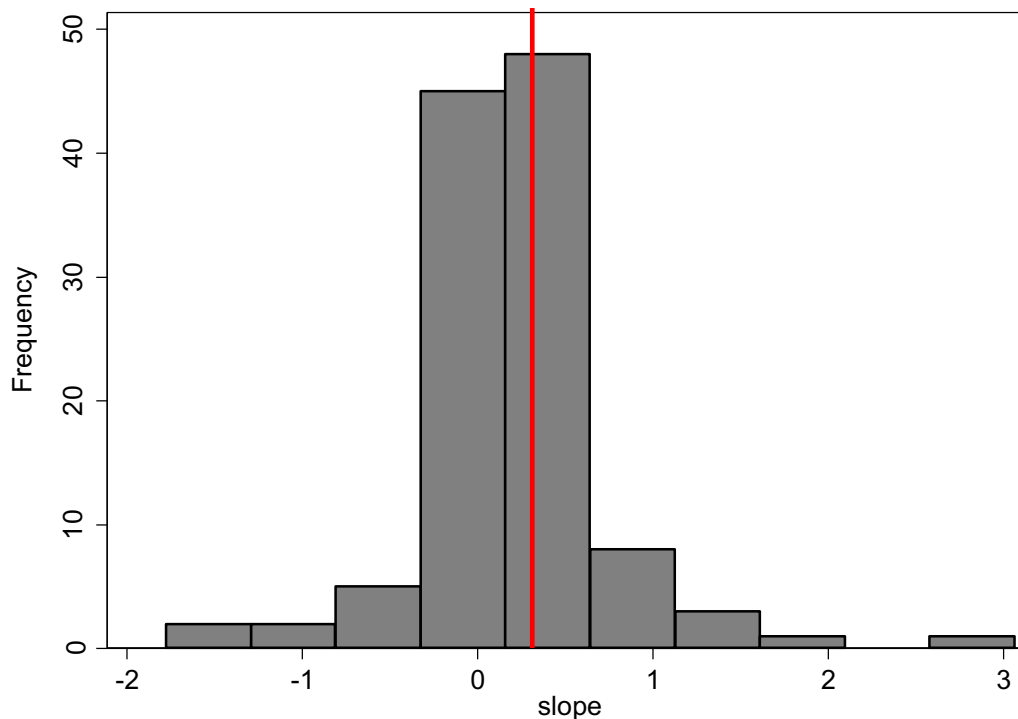
Summarize the within and between-cluster effects of gender.

- 1) The within-school effect of being female is positive
- 2) The estimated contextual effect of gender is 0.
 - This implies that the within- and between-effects of gender are the same.
 - You can test this within Model 3!

```
. test female_center = mean_female  
  
( 1)  [eq1]female_center - [eq1]mean_female = 0  
  
      chi2( 1) =      1.40  
      Prob > chi2 =      0.2373
```

Within-school effects of socioeconomic index

- Fit a school specific logistic regression model for reading proficiency as a function of ISEI (scaled per 10 point increase)

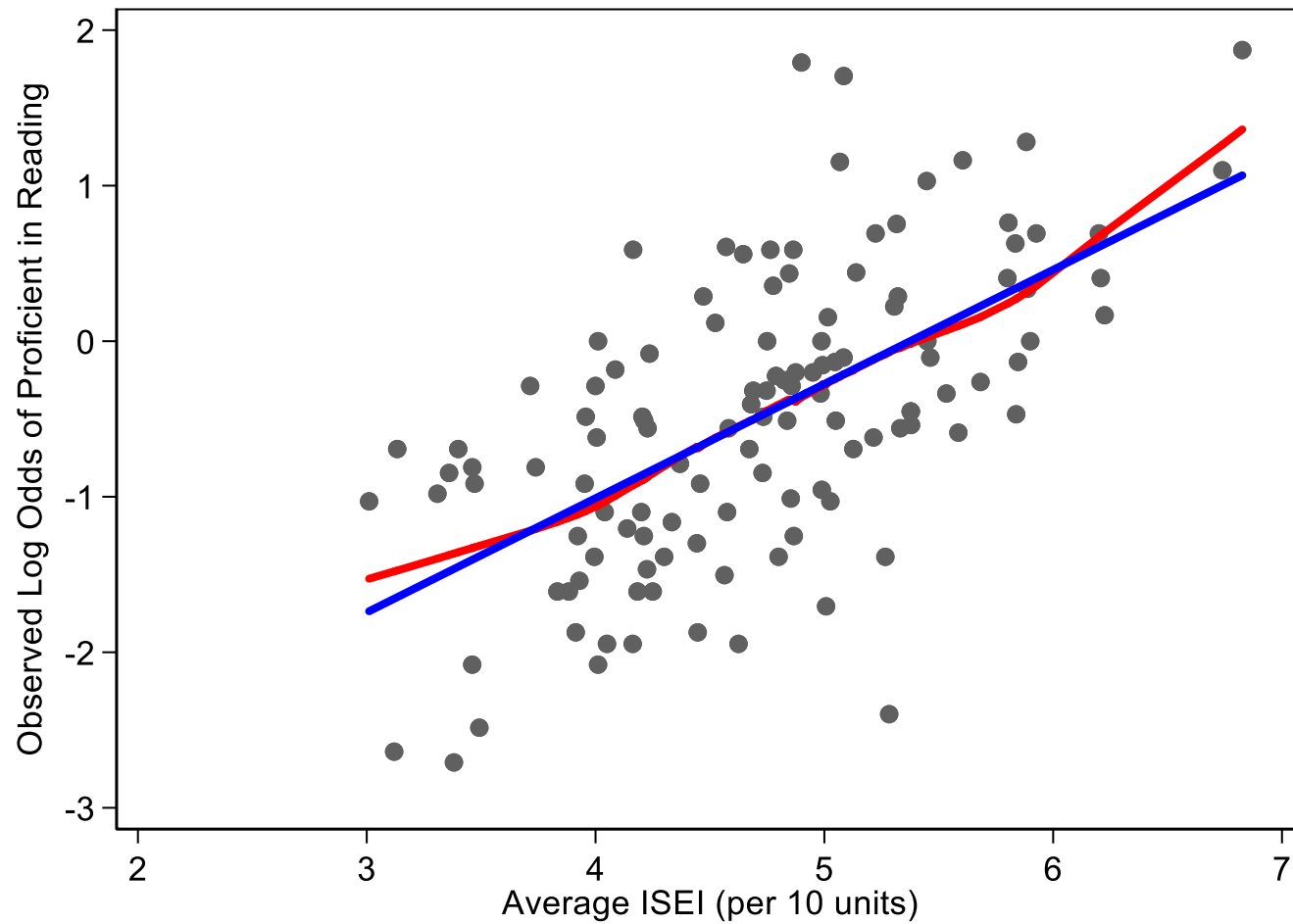


Mean = 0.20

$\text{Exp}(0.20) = 1.20$

Increase in odds of
reading proficiency
per 10 point increase
in ISEI

Between-school effects of socioeconomic index



Results: ISEI Effect

Model	$exp(\beta_k)$	$exp(\gamma_k)$
1	1.29 (1.21, 1.37)	
2	1.20 (1.13, 1.28)	2.03 (1.69, 2.43)
3	1.20 (1.13, 1.28)	2.44 (2.05, 2.90)
4	1.21 (1.13, 1.28)	
5		2.41 (2.03, 2.85)

Some observations:

- 1) The between-school effect is roughly twice the size of the within-school effect (Model 3) and statistically significantly different ($p < 0.001$)
- 2) Contextual effect is positive and statistically significant
- 3) Model 1 total effect is larger than the within-school effect due to the large/positive between-school effect.

Results: ISEI Effect

Model	$exp(\beta_k)$	$exp(\gamma_k)$
2	1.20 (1.13, 1.28)	2.03 (1.69, 2.43)
3	1.20 (1.13, 1.28)	2.44 (2.05, 2.90)

Interpretations:

1. Within a school, the estimated odds of being reading proficient increase by 20 percent per 10-point increase in the ISEI.
2. For a given school, increasing the school average ISEI would result in higher odds of reading proficiency. Odds increase by a factor of 2.44 per 10-point increase in the school-average ISEI.
3. Consider two students in the same school that have the same ISEI, the student who comes from the school with higher average ISEI has increased odds of being proficient in reading.

Marginal vs. Conditional Estimates

- Fit Model 2 using logistic regression model, no random effects
- Estimation based on GEE assuming exchangeable within-school correlation structure.
- Compare the estimates from those obtained using the random intercept logistic model.
 - The RI coefficients in general will be larger in absolute value
 - The inferences (estimate/se), CI, tests) will be similar if the marginal model you specify induces the same/similar correlation structure.

Marginal vs. Conditional Estimates

Model	$exp(\beta_k)$	$exp(\gamma_k)$
RI	1.20 (1.13, 1.28) $z = 5.96$	2.03 (1.69, 2.43) $z = 7.69$
GEE	1.19 (1.12, 1.26) $z = 5.95$	1.94 (1.64, 2.30) $z = 7.73$

- In the GEE model, the within effect has the same interpretation as for the RI model.
 - Condition on a school!
- In the GEE model, the contextual effect now does not require that the schools have similar “random effects” only that the schools have mean ISEI that differs by 10 units.

Summary of Lecture 8

- Consider logistic random intercept models to separate between and within-cluster effects
 - Similar decomposition of effects as in the linear model case
- Random effects logistic models will produce estimates that are greater in absolute value than their corresponding marginal model friends
 - Conditional interpretation
 - In two-level data, can fit a marginal model assuming exchangeable within cluster correlation