Program Evaluation with a Small Number of Sites:

An Intervention in California Schools to Reduce Obesity

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Goal

- We evaluate the effect of an obesity intervention in California schools that Francine Kaufman was involved in before she moved to Medtronic.
- While a form of random assignment was used, it was at the school level.
- Furthermore, the budget constraint only allowed for 4 treatment schools and 4 control schools.

Goal

- Complicated econometric issues arise here (and in other economic applications) because:
  i) We cannot randomize within sites.
  ii) Randomization has to be done over a small number of sites.
  iii) We need to calculate standard errors with a small number of sites/clusters.

- We will take a different tack than the standard epidemiology literature. It would have been difficult to do better in terms of sample design given the budget constraint.

- This is a project we started quite a while ago, and we are just getting back into it. So we are looking forward to your comments. (It’s not good for productivity when two of your co-authors go to the private sector.)

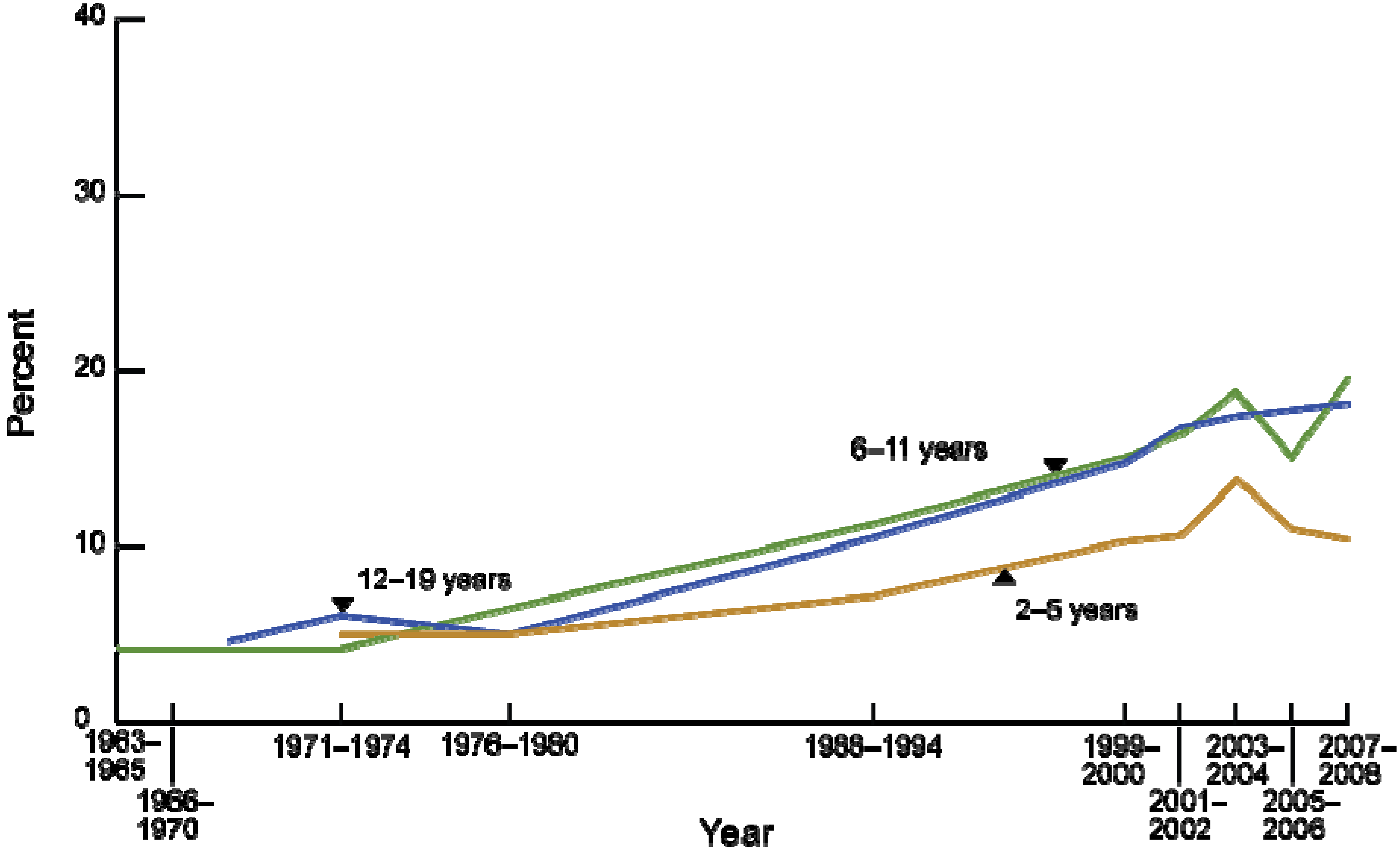
Background

- The last decades have seen dramatic increases in the prevalence of elevated weight and obesity in the U.S. population at large.

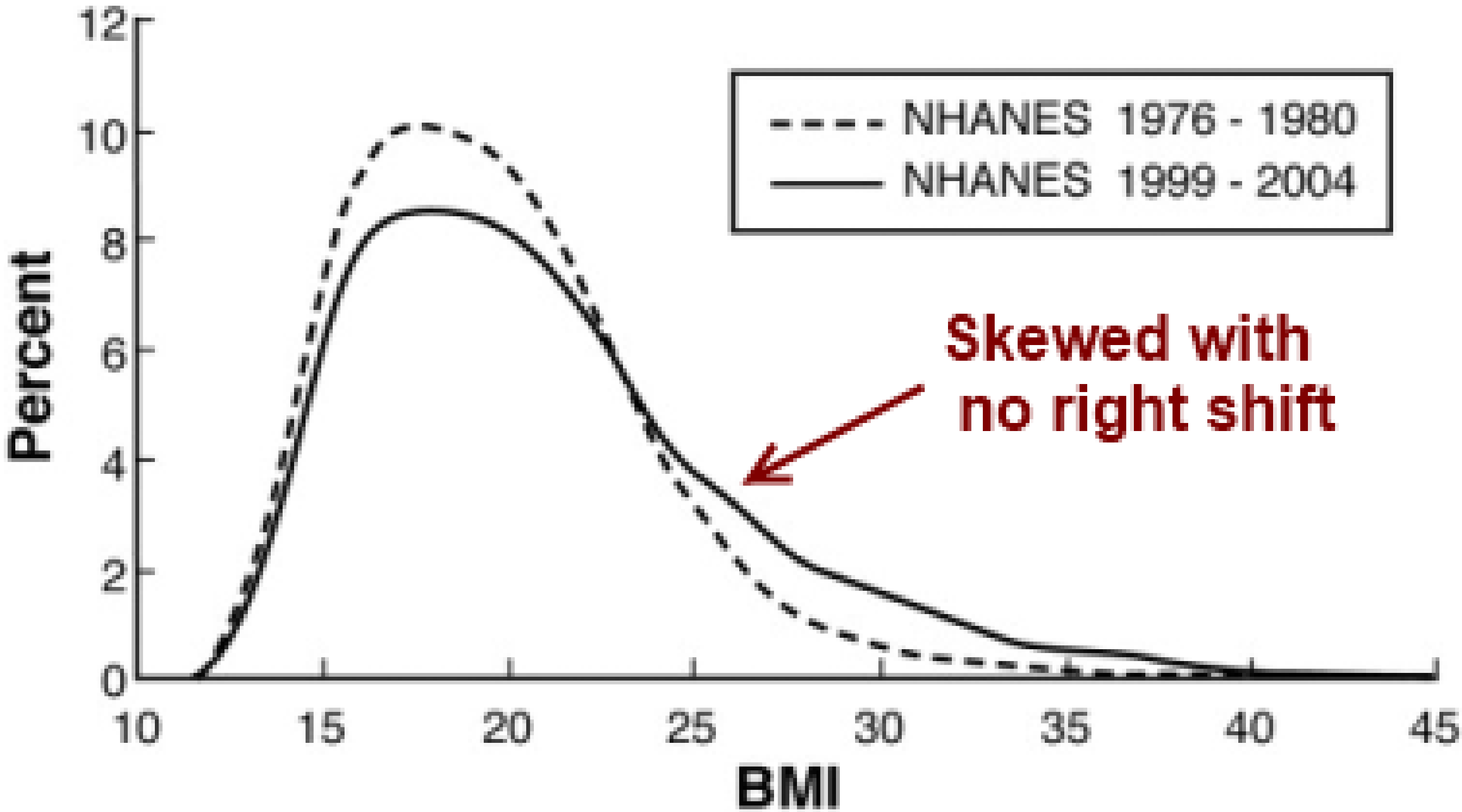
- Currently one-third of children in the U.S. are clinically overweight or obese (OO).

- If we look at only obesity among children over time, we see …

Figure 1. Trends in obesity among children and adolescents: United States, 1963–2008



NOTE: Obesity is defined as body mass index (BMI) greater than or equal to sex- and age-specific 95th percentile from the 2000 CDC Growth Charts.
SOURCES: CDC/NCHS, National Health Examination Surveys II (ages 6–11), III (ages 12–17), and National Health and Nutrition Examination Surveys (NHANES) I–III, and NHANES 1999–2000, 2001–2002, 2003–2004, 2005–2006, and 2007–2008.



12
10
8
6
4
2
0
Percent
10
15
20
25
30
35
40
45
BMI
NHANES 1976 - 1980
NHANES 1999 - 2004
Skewed with
no right shift

Background

- A major new study of more than 7,000 children has found that a third of children who were overweight in kindergarten were obese by 8^{th} grade. And almost every child who was very obese remained that way.

- The early onset of OO is important since it can lead to significant increases in morbidity and mortality due to increased risk for diabetes, coronary heart disease, atherosclerosis, hip fracture, and gout.

- This has spurred many interventions to address the problem. However, the effectiveness of such interventions is an open issue in the medical literature.

Intervention in California Schools

- Kids and Fitness (KnF) is a program developed by Children's Hospital in Los Angeles (CHLA) that has been shown to be effective in an outpatient hospital setting.

- KnF is an after-school intervention involving both parents and their children, with the aim of improving physical activity and nutrition habits by changing child and family behaviors.

- We evaluate a pilot intervention that introduces KnF into schools in the San Francisco (SF) and Los Angeles (LA) areas.

Intervention in California Schools

- KnF aims to teach children in grades 3-5, as well as their parents, about the benefits of healthy nutrition and physical activity.

- Children and one of their parents are expected to attend separate weekly, 90-120 minute sessions, for 6 weeks.

Intervention in California Schools

- The children's sessions covered topics related to nutrition, physical activity and behavior change, while the parents' sessions cover nutrition and behavior change.

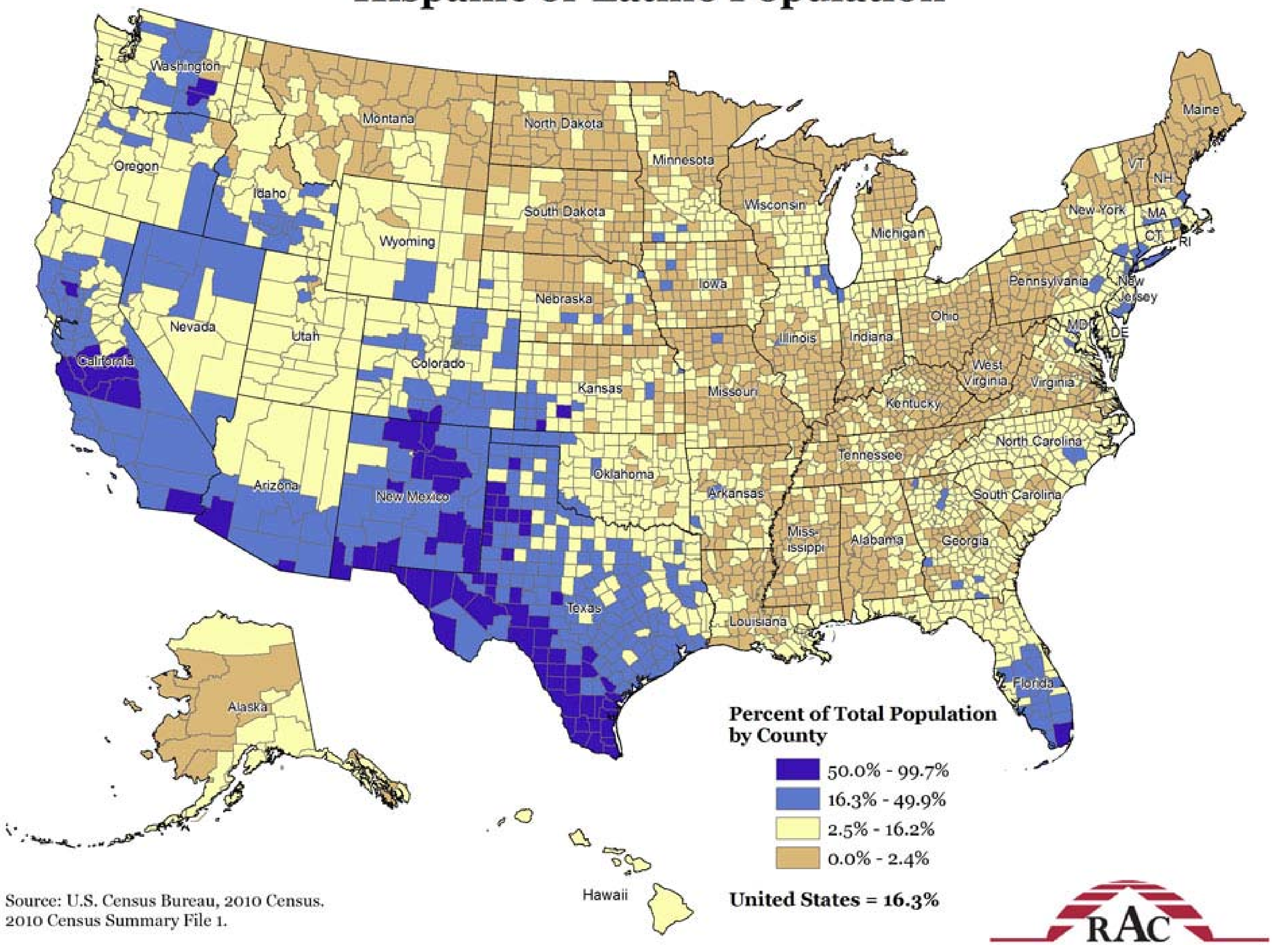
- At the end of each class, a healthy meal with appropriate portion sizes was served.

- Additionally, the children participated in 45-minute sessions of physical activity 3 times a week.

Treatment and Control Groups

- Schools in the SF and LA areas were asked if they wanted to participate in a pilot program introducing KnF in their school. Schools were only considered if:
  - i) they had large minority (Hispanic) student populations
  - ii) they were able to devote 90 minutes per week for the KnF classes
  - iii) they were willing to designate staff to be trained and teach KnF
  - iv) they had space for the physical activity component of KnF

Hispanic or Latino Population



Source: U.S. Census Bureau, 2010 Census.
2010 Census Summary File 1.

Note: Alaska and Hawaii not shown to scale

Rural Assistance Center

Treatment and Control Groups

- 4 pairs of comparable schools (2 in SF area and 2 in LA area) were chosen.
- When volunteering, schools knew that they could be assigned to either the Treatment group or the Control group. Schools did not know what the assignment rule was.
- The school that volunteered first received the Treatment in 2006.
- The school assigned to the Control group received KnF approximately one year after the intervention ended. This increases the cost of the intervention considerably.

Treatment and Control Groups

- The intervention had a $1.5 million budget (2005) that did not allow for more than 4 pairs.

- Students within the schools volunteered for the KnF program. Thus our treatment effects are for those who wanted to participate in KnF.

Outcomes and Groups of Interest

- Our focus is on the treatment effects for the students who were
  - clinically overweight or obese (OO)
  - at risk (AR) of becoming OO

- Our outcome variable is a child's BMI-Z score—BMI adjusted for gender and age. With the adjustment you can compare across gender and age.

Two Big Econometric Issues

1. Did we get approximate random assignment across individuals using only quasi randomization across these 4 pairs? In other words, given

$$Y_i = \gamma T_i + X_i \beta + \alpha_i + \sum_{p=1}^{4} \delta_{pt} D_{ip} + \varepsilon_i ,$$

   is $\operatorname{cov}(T_i, \varepsilon_i) = 0$?

2. How do we allow for within school correlation given a small number of schools (clustering issue)?

- To investigate whether we had approximate random assignment, we consider the difference in the means of the available observable variables between the treatment and control groups at the baseline conditional on pair dummies, and at the samples used to estimate the different treatment effects (which differ because of attrition.).

- But to carry out these tests, we need to address *the clustering issue.* There are four ways to deal with clustering:

1. A school random effects model, used e.g., by Ham et al. (J. Public Economics 2011).

$$Y_i = \gamma T_i + X_i \beta + \sum_{p=1}^{4} \delta_{pt} D_{ip} + \alpha_i + \eta_s + \varepsilon_i,$$

$$\operatorname{cov}(\alpha_j + \eta_s + \varepsilon_j, \alpha_i + \eta_s + \varepsilon_i) = \operatorname{cov}(\eta_s, \eta_s) = \sigma_\eta^2$$

$$\operatorname{cov}(\alpha_j + \eta_{s'} + \varepsilon_j, \alpha_i + \eta_s + \varepsilon_i) = \operatorname{cov}(\eta_s, \eta_{s'}) = 0 \qquad s \neq s'$$

- *Here you can do GLS or simply fix up the standard errors. We don't know how well it does with a small number of clusters.*
- *In this paper we show how you can use this approach to decide what level to cluster at. For example should we cluster at the school level or at the pair level? It's always a hard problem knowing a priori how far to extend the clustering.*

2. A variant of a bootstrap procedure.

   (See Cameron, Gelbach, and Miller (ReStat, 2008) for a definition of many different procedures, and how they perform in Monte Carlo experiments with different cluster sizes.)

   - *(We could, and probably should, have a brown bag meeting to discuss their paper.)*

Example of standard bootstrap for clustering with 100 clusters:

(i) Sample with replacement from all the clusters (i.e., take all the individuals in the cluster) until you have a new sample with 100 clusters. Estimate your parameter of interest $\hat{\gamma}_1$ using the regression above on this new sample.

(ii) Repeat point (i) 1,000 times to get $(\hat{\gamma}_1, \hat{\gamma}_2, ..., \hat{\gamma}_{1000})$, and use the $V(\hat{\gamma})$ for your standard errors.

- *Only more complicated versions do well with a small number of clusters; otherwise you still have the problem of over-rejection.*

3. The usual (sandwich) clustering formula that underlies the Stata cluster command.

$$Y_i = \gamma T_i + X_i\beta + \sum_{p=1}^{4} \delta_{pt} D_{ip} + \alpha_i + \eta_s + \varepsilon_i,$$

$$\text{cov}(\alpha_j + \eta_s + \varepsilon_j, \alpha_i + \eta_s + \varepsilon_i) = \sigma_{ij}^2 \quad \textit{if } i, j \text{ go to the same school}$$

$$\text{cov}(\alpha_j + \eta_{s'} + \varepsilon_j, \alpha_i + \eta_s + \varepsilon_i) = 0 \qquad \textit{otherwise.}$$

- *Usually use it to just fix up the standard errors. It's not expected to do well with a small number (<15) of clusters in that it will tend to over-reject the null hypothesis that the coefficients are zero.*

- *Again, we face the issue of how far to extend the clustering, e.g., at the school level or at the pair level.*

4. A school fixed effects model.
   - Advocated by Imbens and Wooldridge in their (excellent) online lecture notes when the number of clusters is small.
   - This approach is often used in experimental economics where clustering is extremely controversial (German Critique).

Data and Summary Statistics

- In total, 323 students took part in the study. 160 students received the intervention, while the remaining 163 students were in control schools.

- The program began in October 2006**,** and a child's height, weight and calculated BMI-Z score were measured:
  - at the start of the program (baseline)
  - at the conclusion of the 6-week intervention
  - 3 months after the conclusion of the program
  - 6-8 months after conclusion of the program

Data and Summary Statistics

- Demographic variables were also collected at baseline, and we focus on seven covariates in our analysis.
    - Two variables are specific to the child (gender and age).
    - Five variables are specific to the parent (BMI, age, working status, high school completion (or GED equivalent), and marital status).
- Column 1 of Table 1 presents the summary statistics for the 297 (out of 323) child-parent pairs with data on the complete set of covariates. Columns 2 and 3 of Table 1 present the summary statistics for children in the AR group and the OO group respectively upon whom we focus our analysis. We have 53 and 155 students in the AR and OO subgroups respectively.

Table 1: Sample Means and Standard Deviations

Group	Entire Population	At-Risk (AR)	Overweight-Obese (OO)
# Observations	297	53	155
Child BMI-Z Score	1.031 (1.044)	0.803 (0.159)	1.856 (0.48)
Percent Male	0.448 (0.498)	0.453 (0.503)	0.490 (0.502)
Child's Age	9.892 (1.105)	10.106 (1.087)	9.854 (1.071)
Parent's BMI	31.424 (6.287)	30.738 (6.675)	32.592 (6.104)
Parent's Age	35.202 (6.457)	35.736 (6.472)	34.458 (6.095)
Parent Working (Yes-No)	0.438 (0.517)	0.472 (0.504)	0.406 (0.493)
Parent High School Grad (Yes-No)	0.370 (0.484)	0.396 (0.494)	0.329 (0.471)
Parent Married (Yes-No)	0.717 (0.451)	0.736 (0.445)	0.729 (0.446)

Table 2A: School Means and Std Devs – At Risk Group

	Pair 1		Pair 2		Pair 3		Pair 4	
	KnF	**Control**	**KnF**	**Control**	**KnF**	**Control**	**KnF**	**Control**
N	**7**	**8**	**10**	**5**	**9**	**7**	**5**	**8**
Child Enrollment BMI Z Score	0.8085 (0.062)	0.8012 (0.066)	0.733 (0.044)	0.912 (0.054)	0.8122 (0.036)	0.6485 (0.034)	0.826 (0.055)	0.8787 (0.073)
Percent Male	0.4285 (0.202)	0.125 (0.125)	0.4 (0.163)	0.2 (0.2)	0.5555 (0.175)	0.2857 (0.184)	0.6 (0.244)	0.875 (0.125)
Child Age	9.6857 (0.465)	9.5125 (0.297)	10.07 (0.244)	10.24 (0.282)	10.511 (0.398)	10.357 (0.414)	10.86 (0.400)	10.062 (0.521)
Parent BMI	29.2 (0.428)	30.857 (2.906)	28.41 (1.471)	25.98 (1.591)	31.555 (2.303)	31.928 (2.709)	29.86 (2.203)	35.175 (3.301)
Parent Age	33.285 (2.243)	34.375 (2.698)	33.4 (1.462)	36.2 (2.634)	38.888 (2.306)	32.571 (2.091)	34 (1.264)	39.5 (2.878)
Parent Working	**0**	**0.25 (0.163)**	**0.4 (0.163)**	**0.8 (0.2)**	**0.5555 (0.175)**	**0.4285 (0.202)**	**0.4 (0.244)**	**0.75 (0.163)**
Parent High School Grad	**0**	**0.375 (0.182)**	**0.5 (0.166)**	**0.5 (0.288)**	**0.3333 (0.166)**	**0.5 (0.223)**	**0.4 (0.244)**	**0.75 (0.163)**
Parent Married	0.4285 (0.202)	0.875 (0.125)	0.8888 (0.309)	0.4 (0.244)	0.75 (0.163)	0.6666 (0.210)	1 (0)	1 (0)

Table 2B: School Means and Std Devs – OO Group

	Pair 1		Pair 2		Pair 3		Pair 4	
	KnF	**Control**	**KnF**	**Control**	**KnF**	**Control**	**KnF**	**Control**
N	**13**	**28**	**18**	**14**	**22**	**21**	**25**	**17**
Child Enrollment BMI Z Score	1.8492 (0.134)	1.8424 (0.087)	1.9485 (0.121)	1.9582 (0.103)	2.1068 (0.101)	1.6986 (0.097)	1.7480 (0.091)	1.7811 (0.093)
Percent Male	0.3571 (0.132)	0.4333 (0.092)	0.5000 (0.114)	0.7058 (0.113)	0.6000 (0.100)	0.3636 (0.104)	0.5769 (0.098)	0.4117 (0.123)
Child Age	9.8571 (0.230)	9.4300 (0.145)	9.8100 (0.178)	10.247 (0.274)	9.4960 (0.230)	9.6636 (0.195)	10.530 (0.288)	9.8588 (0.218)
Parent BMI	33.800 (1.413)	33.075 (1.085)	34.483 (1.888)	31.147 (1.135)	31.754 (1.000)	31.385 (1.312)	31.461 (1.259)	35.241 (1.523)
Parent Age	33.428 (1.759)	33.266 (1.308)	36.050 (0.927)	35.294 (1.462)	34.227 (1.287)	35.227 (1.559)	35.769 (1.332)	34.235 (1.041)
Parent Working	**0.5000 (0.138)**	**0.3000 (0.085)**	**0.2500 (0.099)**	**0.6470 (0.119)**	**0.1666 (0.077)**	**0.3181 (0.101)**	**0.4000 (0.100)**	**0.7647 (0.106)**
Parent High School Grad	**0.4285 (0.137)**	**0.1666 (0.069)**	**0.2500 (0.099)**	**0.4285 (0.137)**	**0.3750 (0.100)**	**0.3181 (0.101)**	**0.2400 (0.087)**	**0.6470 (0.119)**
Parent Married	0.6428 (0.132)	0.7500 (0.083)	0.8000 (0.155)	0.6250 (0.125)	0.8750 (0.068)	0.5909 (0.107)	0.8400 (0.074)	0.7647 (0.106)

Balancing Tests

Let X_{ij} denote the j^{th} observable baseline variable for family *i*,

T_{ij} denote a dummy variable equal to 1 if family *i* is in the treatment group and zero otherwise, and

D_{ip} denote a dummy variable equal to 1 if family *i* is in school pair *p*, and zero otherwise, *p=1,…,4*.

Then for each *j* we run the regression

$$X_{ij} = \phi_j T_i + \sum_{p=1}^{4} \theta_{pj} D_{ij} + u_{ij},$$

and test the null hypothesis that $\phi_j = 0$. The advantage of setting it up this way is you don't have to treat the u_{ij} as independent.

Table 3: Balancing Tests:
Regression of Initial Characteristics on Treatment Status

Group	At-Risk (AR)	Overweight/Obese (OO)
Child BMI-Z Score	-0.020 (0.043)	0.089 (0.057)
Percent Male	0.056 (0.084)	0.036 (0.065)
Child's Age	0.227 (0.154)	0.14 (0.155)
Parent's BMI	-1.071 (1.287)	-0.371 (1.031)
Parent's Age	0.345 (0.625)	0.345 (0.625)
Parent Working	-0.316[a] (0.063)	-0.184[b] (0.078)
Parent High School Grad	-0.192[a] (0.061)	-0.076 (0.107)
Parents Married	-0.046 (0.102)	0.114[c] (0.066)

Notes: Standard errors clustered at the school level.

Significance: *a* denotes 1% level, *b* denotes 5% level, *c* denotes 10% level.

- Since we have attrition at each evaluation time should also do the balancing tests for those 3 samples but the results are the same as in Table 3 above.

- Based on these results we conclude that quasi-random assignment at the school level does not imply random assignment at the individual level. We proceed on the basis that we have random assignment in first differences.

- Let t denote which BMI-Z scores we are considering; $t=1,2,3$ denotes the respective post-baseline interview period and t=0 denotes the baseline period.

- Let Y_{it} denote the child's BMI-Z score in the relevant period *t*, *(t=0,1,2,3).*

- Assume that the baseline BMI-Z score is given by

$$Y_{i0} = \alpha_i + X_{i0}\beta_0 + \varepsilon_{i0}, \qquad (1)$$

where X_{i0} is a vector of other (i.e., besides BMI) baseline variables and α_i is a child-specific fixed effect.

- Next assume that the BMI-Z score in *t=1,2,3* is given by

$$Y_{it} = \gamma_t T_i + X_{i0}\beta_t + \alpha_i + \sum_{p=1}^{4} \delta_{pt} D_{ip} + \varepsilon_{it}, \qquad (2)$$

- Note that we let the treatment effect γ_t differ across *t* since the effect of the program may decay with length of time since the intervention.

- We also allow the effects of the demographic variables and the pair dummies to differ by interview period.

- Subtracting (1) from (2) for each *t* yields

$$\Delta Y_{it} = Y_{it} - Y_{i0} = \gamma_t T_i + X_{i0}(\beta_t - \beta_0) + \sum_{p=1}^{4} \delta_{pt} D_{ip} + \varepsilon_{it} - \varepsilon_{i0}$$

$$= \gamma_t T_i + X_{i0}\mu_t + \sum_{p=1}^{4} \delta_{pt} D_{ip} + v_{it}.$$

  - Now our identifying assumption is that the treatment dummies are not correlated with any child specific trends reflected by the error term v_{it} after allowing for pair specific trends. This is an exactly (untestable) identifying assumption.
  - Question of whether we need to allow for X_{i0} or pair dummies in differences.

Standard Errors

Since individual fixed effects imply school fixed effects, we have implicitly used the Imbens-Wooldridge approach for a small number of clusters, so there is no need for additional clustering.

Table 4: Treatment Effects on BMI-Z Score

	At the Program End		*3 Months After Program End*		*6-8 Months After Program End*	
Percentile	AR	OO	AR	OO	AR	OO
N	42	111	41	110	36	92
Treatment	-0.161[b] (0.069)	-0.066[b] (0.026)	-0.275[b] (0.115)	-0.047 (0.033)	-0.224 (0.156)	0.027 (0.051)

Notes: Standard errors are **not** clustered.

Regression includes all variables in Table 2 except initial BMI-Z score.

Significance: *a* denotes 1% level, *b* denotes 5% level, *c* denotes 10% level.

Only effects are for the At Risk group.

Conclusions

1. Randomizing at the school level does not seem to insure randomization at the school level. This is true whether or not we incorporate the loss of data due to attrition.

2. The program seems to help the At Risk children but not the children who are already overweight or obese.

Future Work

i) Other approaches to adjusting the standard errors for a small number of clusters, e.g. Cameron et al, Ham et al.

ii) Ignore time changing coefficients – then another way to test the Random Assignment at the individual level is to estimate the following systems by individual and school two-way Random Effects and by individual Fixed Effects, and then compare the results using a Hausman test.

RE vs. FE: Six Week Model

$$Y_{i0} = \alpha_i + \mu_s + X_{i0}\beta + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i0},$$

$$Y_{i1} = \gamma_1 T_i + \alpha_i + \mu_s + X_{i0}\beta + \alpha_i + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i1},$$

Then we ask whether we get the same treatment effect using a Hausman test. We can carry out the same test for the 3 month and 6-8 month treatment effects.

RE vs. FE: Whole Model

Alternatively we could look at all the equations at once, and again we ask whether we get the same treatment effects using a Hausman test.

$$Y_{i0} = \alpha_i + \mu_s + X_{i0}\beta + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i0},$$

$$Y_{i1} = \alpha_i + \mu_s + \gamma_1 T_i + X_{i0}\beta + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i1},$$

$$Y_{i2} = \alpha_i + \mu_s + \gamma_2 T_i + X_{i0}\beta + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i2},$$

$$Y_{i3} = \alpha_i + \mu_s + \gamma_3 T_i + X_{i0}\beta + \sum_{p=1}^{4} \delta_p D_{ip} + \varepsilon_{i3}.$$

Appendix A Tables:
Balancing Tests for Samples Used at
6 weeks, 3 months, and 6-8 months

Table 3: Regression of Initial Characteristics on Intervention Assignment (All observations in sample at 6 weeks)

	At-Risk (AR)	Overweight Obese (OO)
n	42	111
Child BMI Z Score	0.001 (0.044)	0.098 (0.065)
Percent Male	0.123 (0.092)	-0.023 (0.129)
Child Age	0.294 (0.153)*	-0.087 (0.193)
Parent BMI	-1.878 (1.798)	-0.526 (1.403)
Parent Age	-1.074 (1.929)	1.111 (0.485)**
Parent Working	-0.260 (0.072)***	-0.180 (0.096)*
Parent Completed High School	-0.165 (0.053)***	-0.232 (0.1)**
Parent Married	-0.053 (0.102)	-0.020 (0.07)

Table 3: Regression of Initial Characteristics on Intervention Assignment (All observations in sample at Post review time)

	At-Risk (AR)	Overweight Obese (OO)
n	41	110
Child BMI Z Score	-0.016 (0.06)	0.118 (0.077)
Percent Male	0.146 (0.137)	0.067 (0.129)
Child Age	0.205 (0.19)	0.101 (0.112)
Parent BMI	-1.518 (1.577)	-0.546 (1.055)
Parent Age	-2.010 (1.79)	1.039 (0.727)
Parent Working	-0.397 (0.118)***	-0.129 (0.104)
Parent Completed High School	-0.352 (0.047)***	-0.099 (0.112)
Parent Married	0.063 (0.153)	0.150 (0.113)

Table 3: Regression of Initial Characteristics on Intervention Assignment (All observations in the sample at Follow Up review time)

	At-Risk (AR)	Overweight Obese (OO)
n	36	92
Child BMI Z Score	0.006 (0.052)	0.103 (0.045)**
Percent Male	0.107 (0.129)	0.205 (0.117)*
Child Age	0.189 (0.29)	0.098 (0.12)
Parent BMI	-1.677 (0.81)**	-1.170 (1.236)
Parent Age	-2.850 (2.43)	0.182 (0.182)
Parent Working	-0.382 (0.111)***	-0.120 (0.096)
Parent Completed High School	-0.339 (0.109)***	-0.149 (0.101)
Parent Married	-0.257 (0.12)**	0.076 (0.1)

Appendix Table B:
Full Set of Estimates for Treatment Effect Equation

	At the end of the course		3 Months after the course end		6-8 Months after the course end	
Group	AR	OO	AR	OO	AR	OO
Intervention	-0.161 (0.049)	-0.066 (0.032)	-0.279 (0.086)	-0.049 (0.048)	-0.201 (0.159)	0.0254 (0.043)
Male	-0.005 (0.023)	-0.007 (0.020)	0.0547 (0.072)	-0.025 (0.032)	-0.076 (0.080)	0.0661 (0.050)
Child Age	-0.035 (0.024)	-0.002 (0.008)	-0.050 (0.040)	-0.035** (0.015)	-0.029 (0.037)	0.018** (0.008)
Parent BMI	0.0042 (0.003)	-0.002* (0.001)	0.0046 (0.006)	0.0013* (0.000)	0.0192*** (0.005)	0.0014 (0.003)
Parent Age	0.0028 (0.002)	-0.000 (0.002)	-0.001 (0.010)	0.0051** (0.002)	0.0115 (0.012)	0.0027 (0.003)
Parent Working	-0.024 (0.068)	-0.022* (0.012)	-0.080 (0.073)	-0.042 (0.049)	-0.056 (0.196)	0.0083 (0.053)
Parent HS Grad	-0.052 (0.055)	0.0295 (0.021)	-0.060 (0.108)	0.0270 (0.026)	0.0118 (0.122)	-0.000 (0.057)
Parent Married	0.0812 (0.091)	0.0018 (0.019)	0.0002 (0.082)	0.0335 (0.021)	-0.168* (0.099)	0.0177 (0.067)

Note: Standard errors clustered at the school level