Approaches to Multi-level Modelling in Tobacco Control Research and Evaluation

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Interdisciplinary Capacity Enhancement
advancing the science to reduce tobacco use

Rehaussement des compétences par l'interdisciplinarité
faire progresser la science pour réduire l'usage du tabac

Multiple Influences on Health

- Understanding health behaviours or health outcomes can involve studying factors at:
- The subject level
- The family level
- The school/clinic/hospital/physician level
- The community level
- …

Multiple Influences on Health Outcomes

- Studying factors at different levels has implications for:
- Measurement
- Design
- Analysis

Multi-levels – Examples from School-based Research

- Levels could include students, (in) schools, (in) communities, (in) provinces, etc.
- As well, must consider the role of time – follow-up of original students and/or schools

e.g. Project Impact (Lovato et al)

- Aim is to understand the relationship between **adolescent** tobacco use and:
- Individual characteristics
- School-based programs & policies
- Tobacco control programs in the community (bylaws)
- Factors in the community environment

Project Impact - Sample

- Grades 10 & 11, municipalities with a population > 10,000
- 28 districts randomly sampled (BC-6, MB-3, ON-8, QC-8, NF-3)
- Within districts, 4 schools randomly selected
- Target was 112 schools, 12,320 students
- Follow-up of Impact schools 2 years later

Project Impact - Data Collection

- School Smoking Profile
- Northrup Survey on School Policies
- Survey of School Prevention/Cessation Programs
- Impac Teen School Neighbourhood Scan
- Municipal by-laws
- Municipal smoking rates
- Legislation
- Tobacco control spending
- SES, etc.

Multi-level Studies

- Data on the **response** variable is obtained from the **lowest level (a subject measure) – we won't aggregate**
- Data on explanatory variables available at **all** levels

Multi-levels – Examples from School-based Research

- Aim is to model the response as a function of explanatory variables at different levels
    - Student – level variables: age, sex, number of friends who smoke, …
    - School – level variables: programs, policies, distance from retail outlets, …
    - Community – level variables: by-laws, media, distance from contraband cigarettes, …
    - Provincial – level variables: existence of province-wide strategy,…
    - And interactions
    - Role of multiple measurements across time on different levels must also be considered

Multiple Influences

- Developing statistical models to handle data from multiple levels requires
  - Time
  - Patience
  - Decent software
  - Sense of adventure
- We will focus on some of the challenges in developing “Multi-level Models” using school-based research in tobacco control as an example

Multi-level Models

- Standard regression models assume independence between observations
- Model for student i:

$$Y_i = \beta_0 + \beta_1 x_i + \beta_2 w_i + e_i,$$

x_i, w_i are covariates for subject i

β's are unknown parameters

e_i is a random variable that represents the combined effects of variables not modelled or controlled

Usual assumption: $e_i \sim N(0,\sigma^2)$ and independent

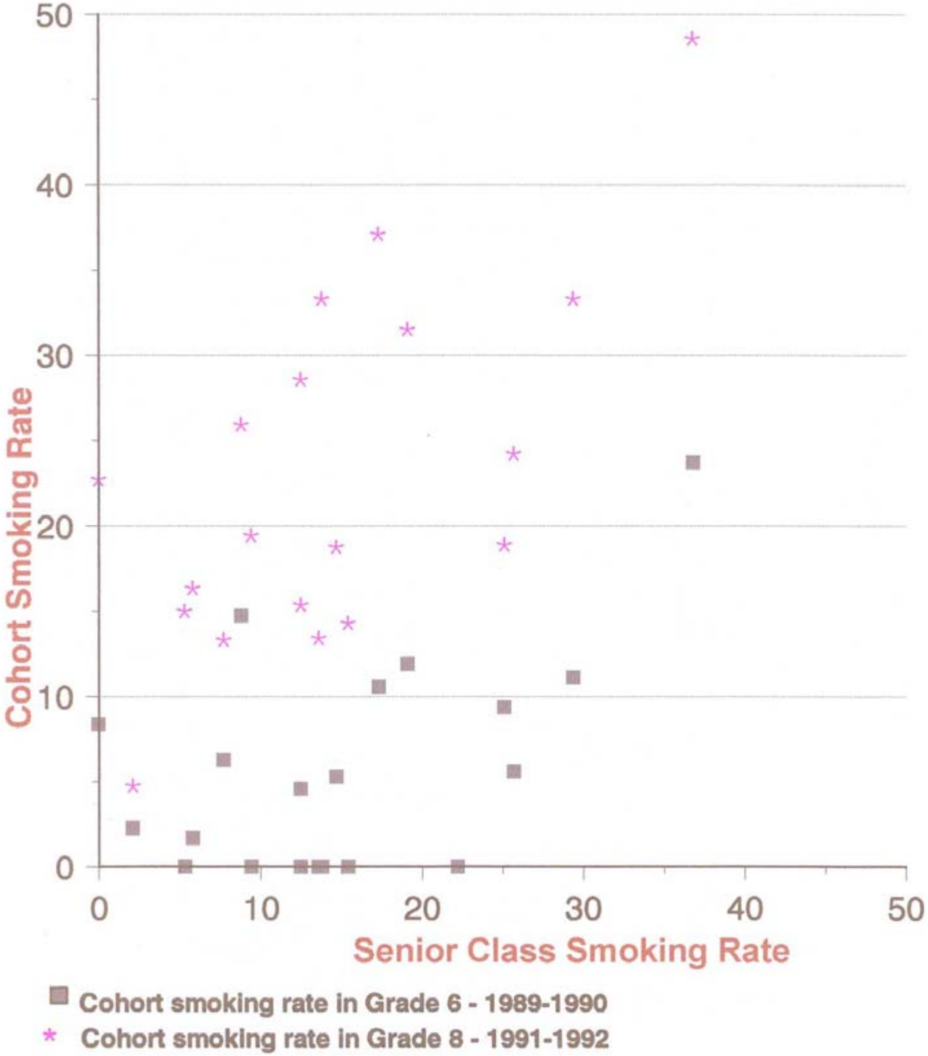
Multi-level Models

- Multi-level situations involve observations that are grouped in clusters
  - Students are clustered in schools (physical clustering)
  - Repeat observations on the same student are clustered within student (clustering in time)
  - Schools are clustered in communities (clustering in space)
- Clustering induces a correlation between observations in the same cluster
- Form of correlation is a modelling issue

Multi-Level Models

- Variation in smoking rates from school to school (cluster to cluster) is a fact of life
- Variation exceeds that which would be expected if children in the same schools were behaving independently (a la the binomial distribution)
- e.g. from WSPP3 (Cameron et al 1999)

Relation of School Risk* to Cohort Smoking Rates



* "School Risk" refers to the senior class (Grade 8) smoking rate measured when WSPP cohort students were in Grade 6.

Multi-Level Models

- Subjects in the same cluster are more similar than subjects in different clusters
- Correlation between students within schools leads to “extra-binomial” variation
- Ignoring leads to underestimating standard errors → calling estimates significant when not

Multi-level Models

- Need to account for the correlation between observations in the same cluster
- Two (common) ways to do this
    - Marginal Models (Population-Average Models)
    - Mixed Effects Models (Cluster-Specific Models)
- Important to understand the target of inference

Multi-Level Models

Type of Model	Target of Inference	Correlation	Procedure
Marginal Models	Population	Model for within-cluster association	GEE
Mixed Effects Models	Cluster (e.g. school)	Use random effects to induce correlation	Random effects models

Random Effects Models

- Illustration: Simple Structure – Simple Model
- k Students in n Schools
- Assume that the average value of the response will vary across schools – there is a school effect
- Need a parsimonious way to model this variability between schools
- Model with a random variable that represents the combined effects of variables that differ from school to school

Random Effects Models

- Model for student i in school (cluster) j

$$Y_{ij} = \beta_0 + b_{0j} + \beta_1 x_{ij} + \beta_2 w_{ij} + e_{ij},$$

where $b_{0j} \sim N(0,\sigma_s^2)$, and

$e_{ij} \sim N(0,\sigma^2)$ are assumed to be independent

- b_{0j} 's are the random effects – one per school
- b_{0j} 's represent the combined effects of those school-level variables that are not modelled or controlled
- We only estimate σ_s^2, so there is parsimony
- Adding b_{0j} 's induces a correlation between students in the same school
- x_{ij} and w_{ij} can be at individual or school level

Random Effects Models

- $Y_{ij} = (\beta_0 + b_{0j}) + \beta_1 x_{ij} + \beta_2 w_{ij} + e_{ij}$, illustrates a "random intercepts" model
- "Cluster-specific"
- Like fitting a collection of models with the same regression parameters (β's) but where the intercept varies from school-to-school
- If three levels then two random effects
- Ordering of the levels is important in specifying the model and making inferences

Random Effects Models

"Intercepts and slopes as outcomes models"

- Can also allow the slopes to vary randomly from school-to-school
- Like fitting a regression model within each school – get estimates of an intercept and a slope for each cluster
- Then could regress these estimates on cluster (school) - level variables

e.g. Project Impact (Lovato et al)

- Data from the first wave of Project Impact:
- Approximately 24,000 students from 81 schools
- Significant between-school variability in smoking rates after adjusting for individual and school level variables
- Variables associated with adolescent smoking:
  - **School-level** policy, and observed environment (e.g. students smoking near school) variables
  - **Student-level** policy perception, and perception of the environment variables

Some Design Examples - Basic Set-Up

- Assume 2 Conditions
  - Intervention and Comparison
  - Multiple clusters (e.g. Schools) per Condition
  - Multiple subjects per cluster (e.g. students per school)
- Assume 2 Time Points
  - Pre - and Post – Intervention
- (Possible to Randomize to Condition – often not feasible)

Basic Set Up

Intervention	
Pre	Post
School 1	School 1
School 2	School 2
School 3	School 3
School 4	School 4
School 5	School 5
School 6	School 6
⋮	⋮
School n	School n

Comparison	
Pre	Post
School 1	School 1
School 2	School 2
School 3	School 3
School 4	School 4
School 5	School 5
School 6	School 6
⋮	⋮
School n	School n

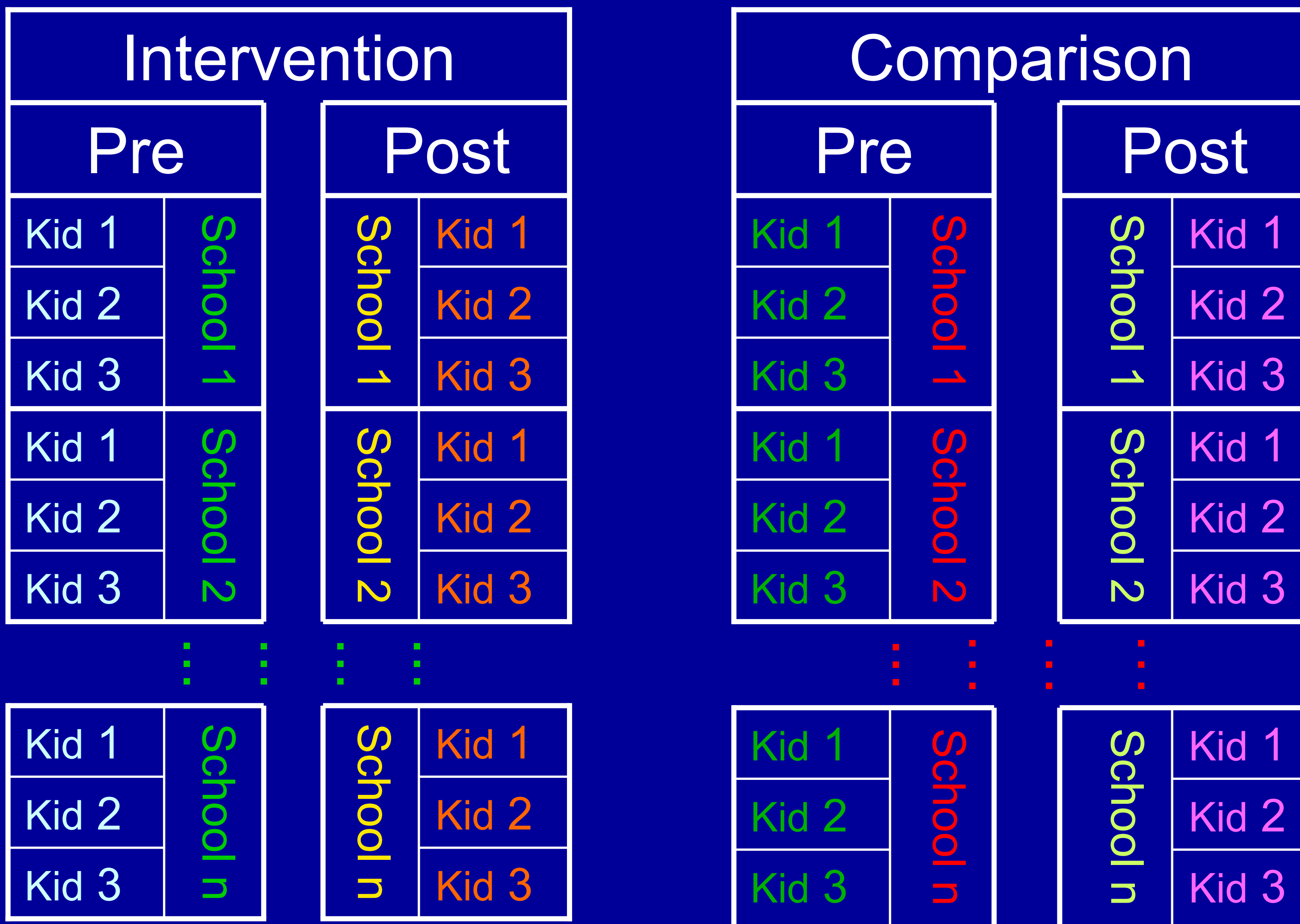
Some Design Choices

Design 1

- Different Schools at Pre- and Post-Test
- So ….. Different Students at Pre- and Post-Test
- E.g. Evaluation of Provincial Tobacco strategy with repeated cross-sectional surveys – comparison schools are from another province

Design 1

(Different Colours → Different Units)



Model for Design 1

Ordering

Kids in Schools in Times in Conditions

→

- Need to consider correlation between students in the same school
- Use school-level random effects to induce this correlation

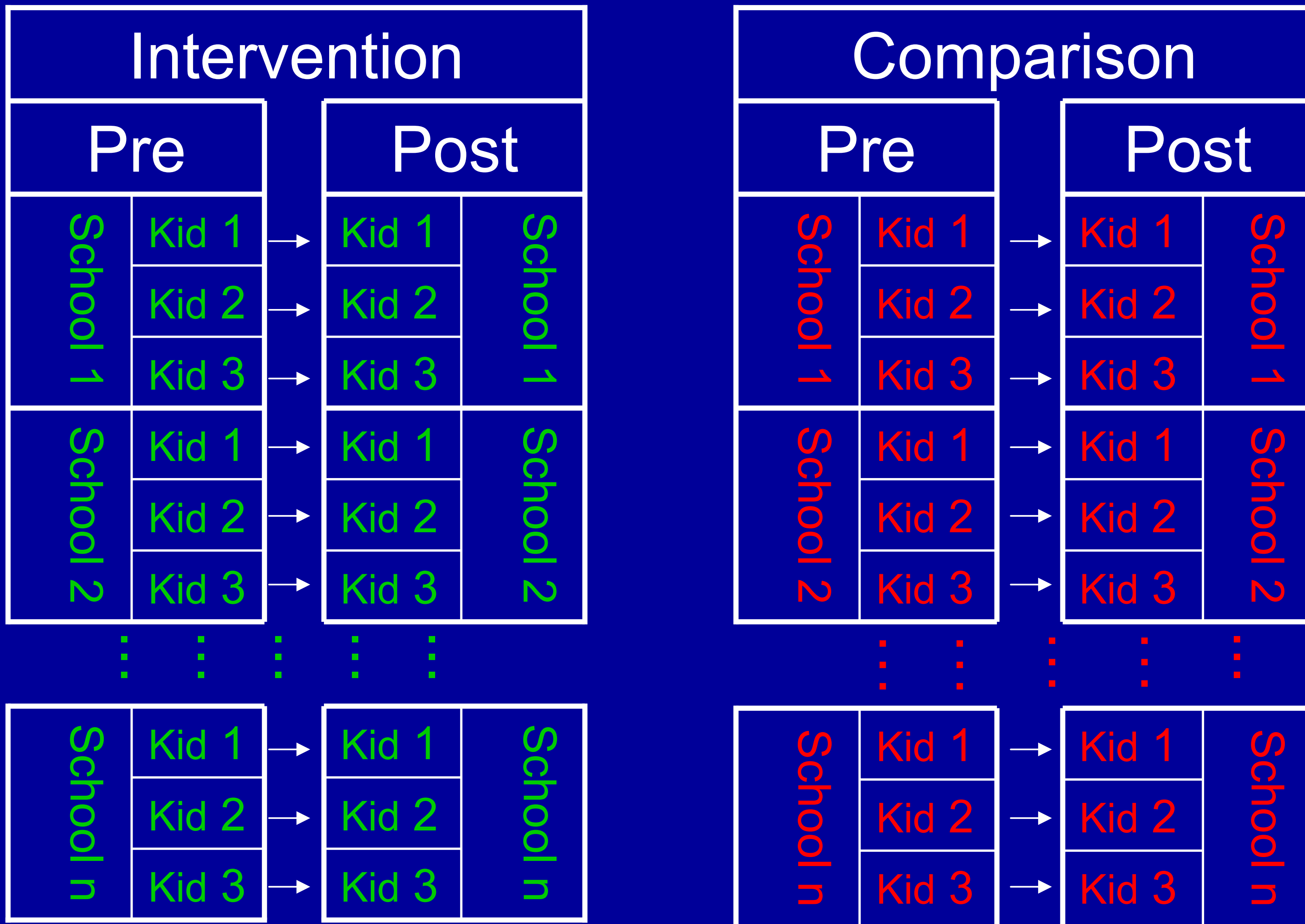
Some Design Choices

Design 2

- Same Schools at Pre- and Post-Test
- Students followed longitudinally from Pre-Post test
- Common randomized design – schools randomly assigned to intervention or comparison
- e.g. WSPP3 – (Cameron et al, 1999)

Design 2

Same colour → Same Unit



Model for Design 2

Ordering:

Times in Kids in Schools in Conditions

We need two types of random effects

- child-level random effects to induce correlation between measurements on the same child
- school-level random effects to induce correlation between students in the same school

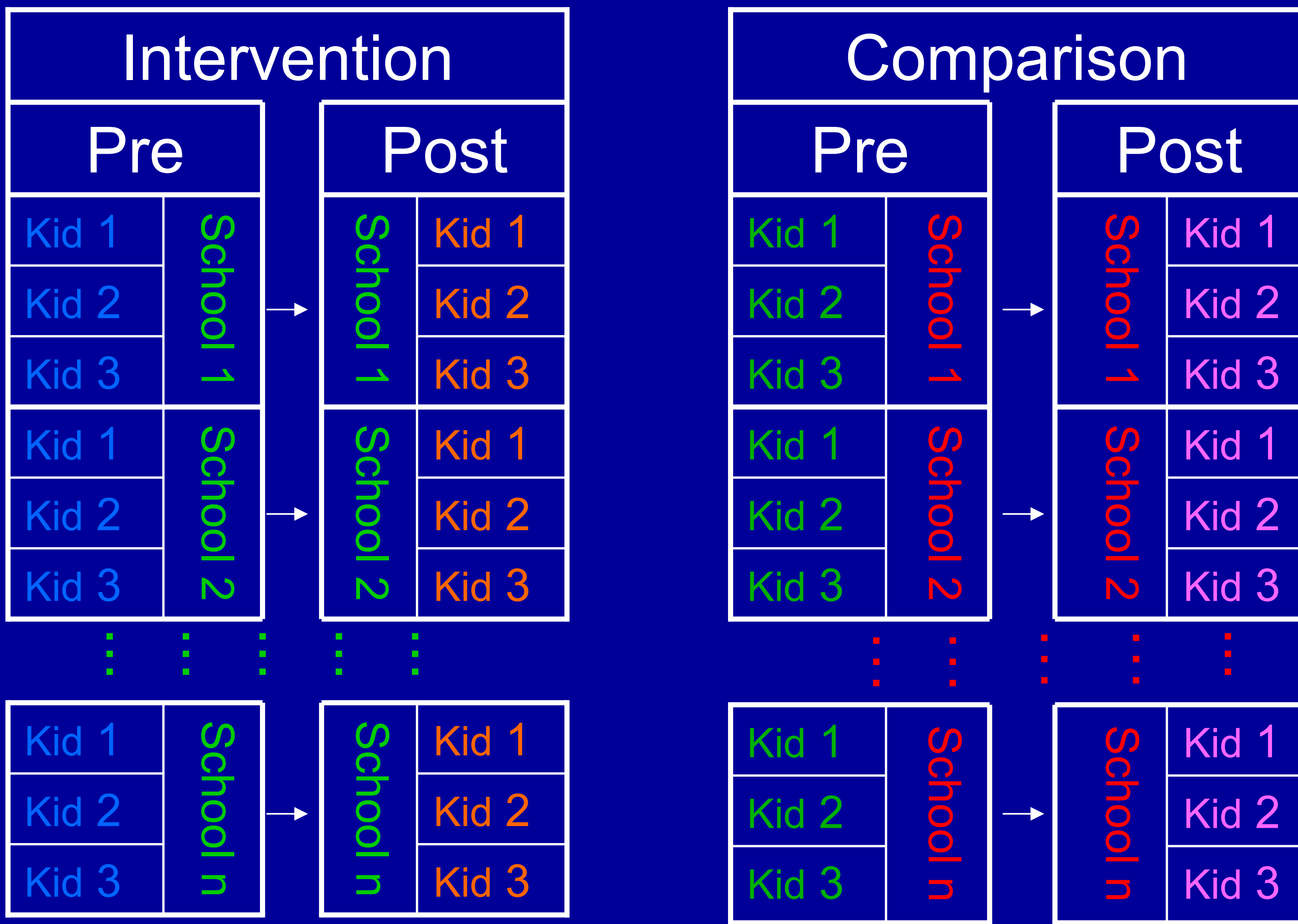
Some Design Choices

Design 3

- Same Schools at Pre- and Post-Test
- Different Students or (no linking of students) from Pre- to Post-Test
- e.g. Evaluation of Tobacco Control Policies in PEI (Murnighan, et al); Project Impact (Lovato, Brown, et al); WSPP4 – (Brown, Cameron, Manske et al)

Design 3

(Same colour → Same Unit)



Model for Design 3

Ordering:

Kids in Times in Schools in Conditions

→

- We need random effects for schools – the same effect at both times for a school
- We also need other random effects for schools at each time

Generalized Linear Models with Random Effects

- Extensions to logistic models are available
- e.g. logistic model with random effects:

$$Y_{ij} \sim \text{Binomial}(n_{ij}, p_{ij}), \text{ with}$$

$$\log(p_{ij}/(1-p_{ij})) = \beta_0 + b_{0j} + \beta_1 x_{ij} + \beta_2 w_{ij},$$

$$\text{where } b_{0j} \sim N(0, \sigma_s^2),$$

- Computations become more complicated
  - No closed form expressions
  - Involves numerical approximations

Sources of Explanatory Variables at Second level (Schools)

- Data from secondary sources
    - Statistics Canada data by postal code
- Data from administrative records
    - School size, % students bussed
- Data from school officials
    - Interviews, questionnaires
- Data from all students
    - Aggregated to level of school
- Data from selected students
    - E.g. older students to predict younger student behaviour

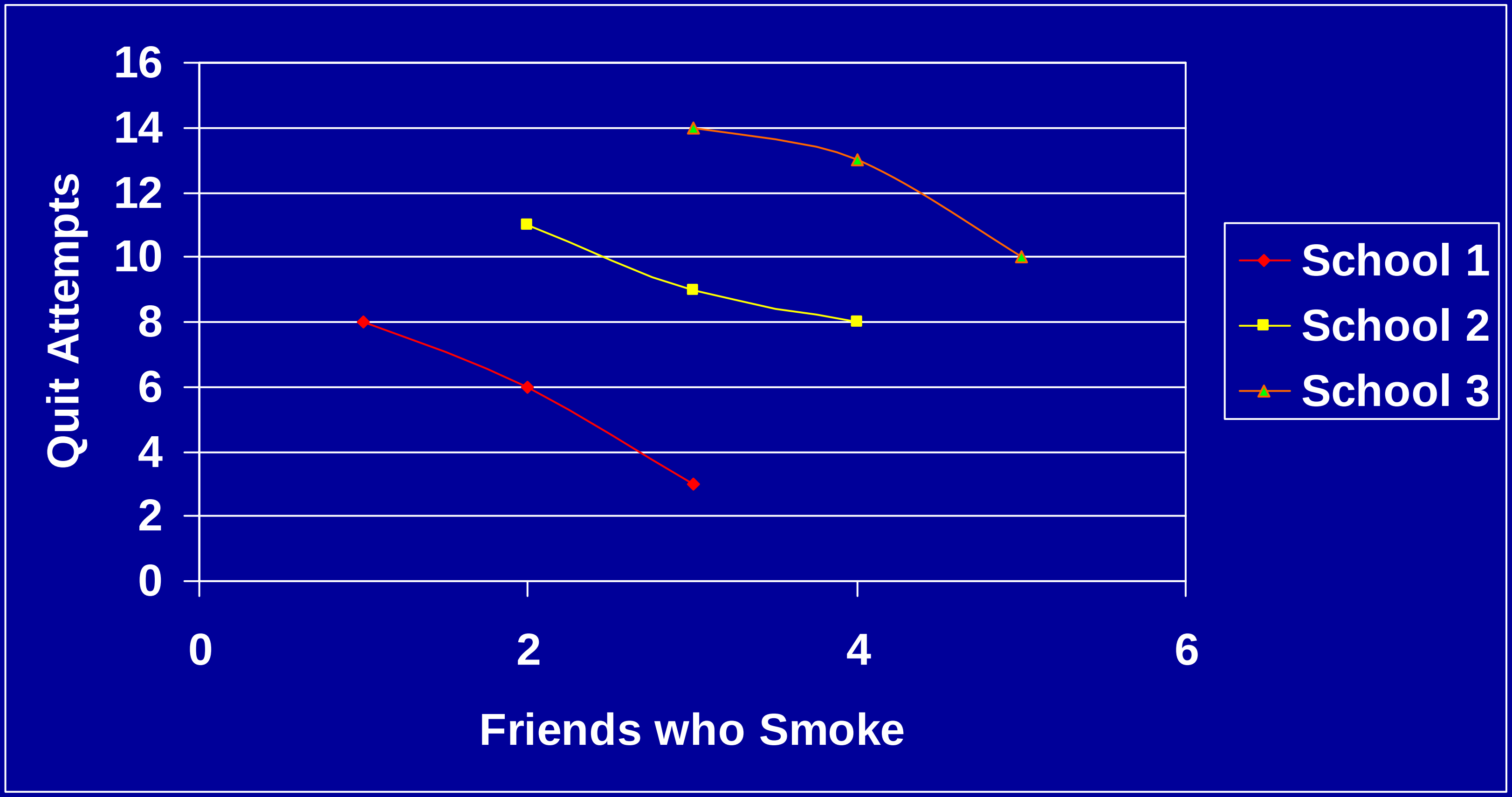
Higher Level Variables

- Objective measures at the level of school, community, etc. are problematic (e.g. “school environment”)
- Temptation to aggregate from level(s) below (i.e. average student responses to get measure for school)
- Does “Average perception = Reality”?
- What makes most sense theoretically (e.g. student perception of policy **or** actual policy?)

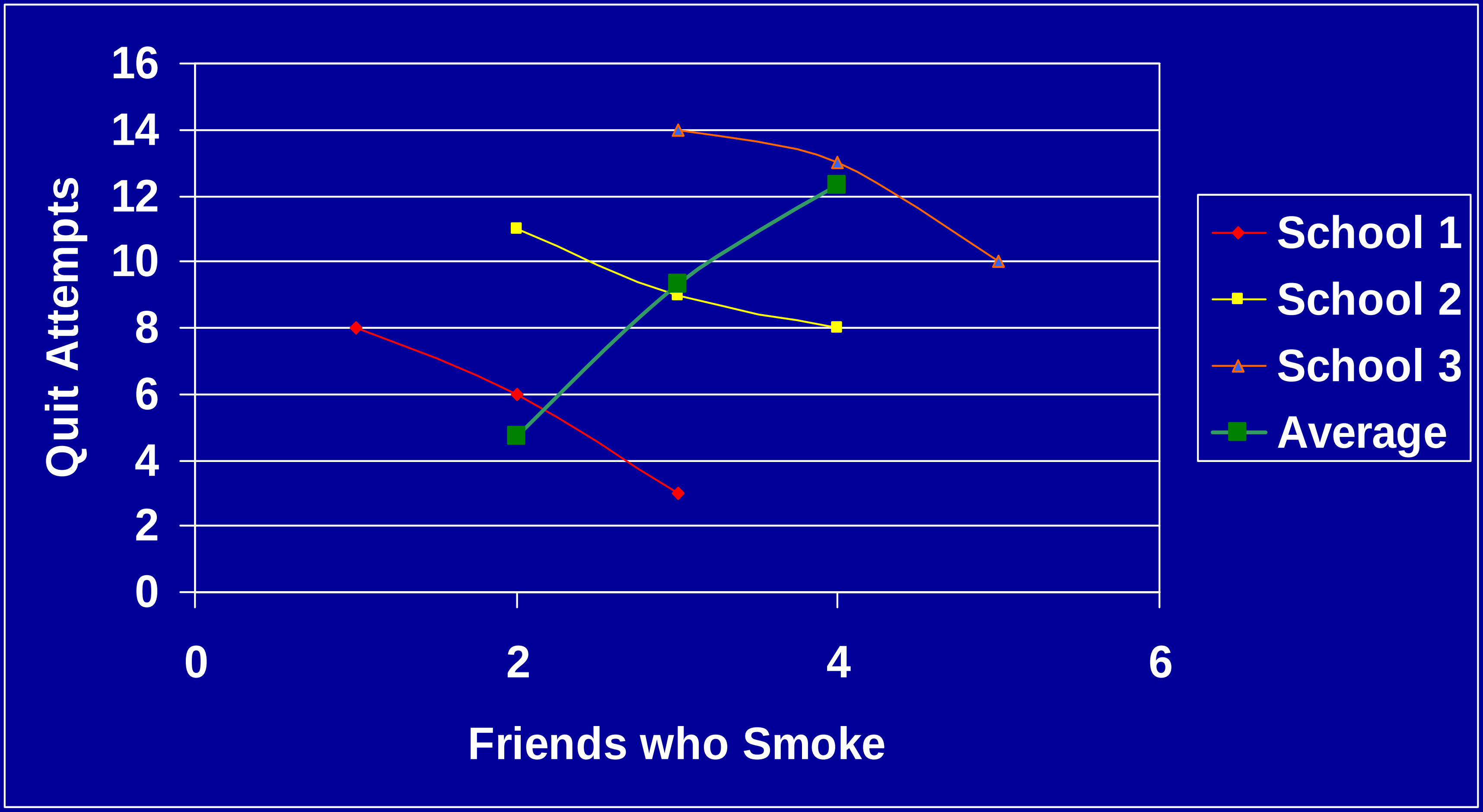
Higher Level Variables

- Could use average values from some students in schools as higher level variable (e.g. smoking rates in older students in school – WSPP3)
- Need to be careful in interpretation
- “Ecological fallacy”

Ecological Fallacy



Ecological Fallacy



Ecological Fallacy

Issues with Multi-level Models

- Measurement: Easy to imagine variables at higher levels – hard to operationalize in practice
- Power: More higher-level units more important than more lower-level units
- Fitting: How many levels are feasible? Software limitations (e.g. SAS – NLMIXED)

Issues with Multi-level Models

- Complicated Models: Interactions with variables at different levels may be important
- Extending Models: Desire to look at other outcomes (e.g. multi-state models, or bivariate outcomes)
- Model Reduction: Lots of variables! How to do variable selection in this context? By level? ….
- Missing Data: can occur at multiple levels, too

Conclusions

- Some form of multi-level modelling is necessary to handle correlation between observations within levels
- Measurement of higher level explanatory variables is tricky
- Often easier to imagine these models than to fit them
- Area of active research in (bio)statistics

Conclusions

- Multi-level Models: Panacea or Pandora's Box???

"All models are wrong. Some are useful"
(G.E.P. Box)