Longitudinal data analysis: challenges and prospects in public health settings

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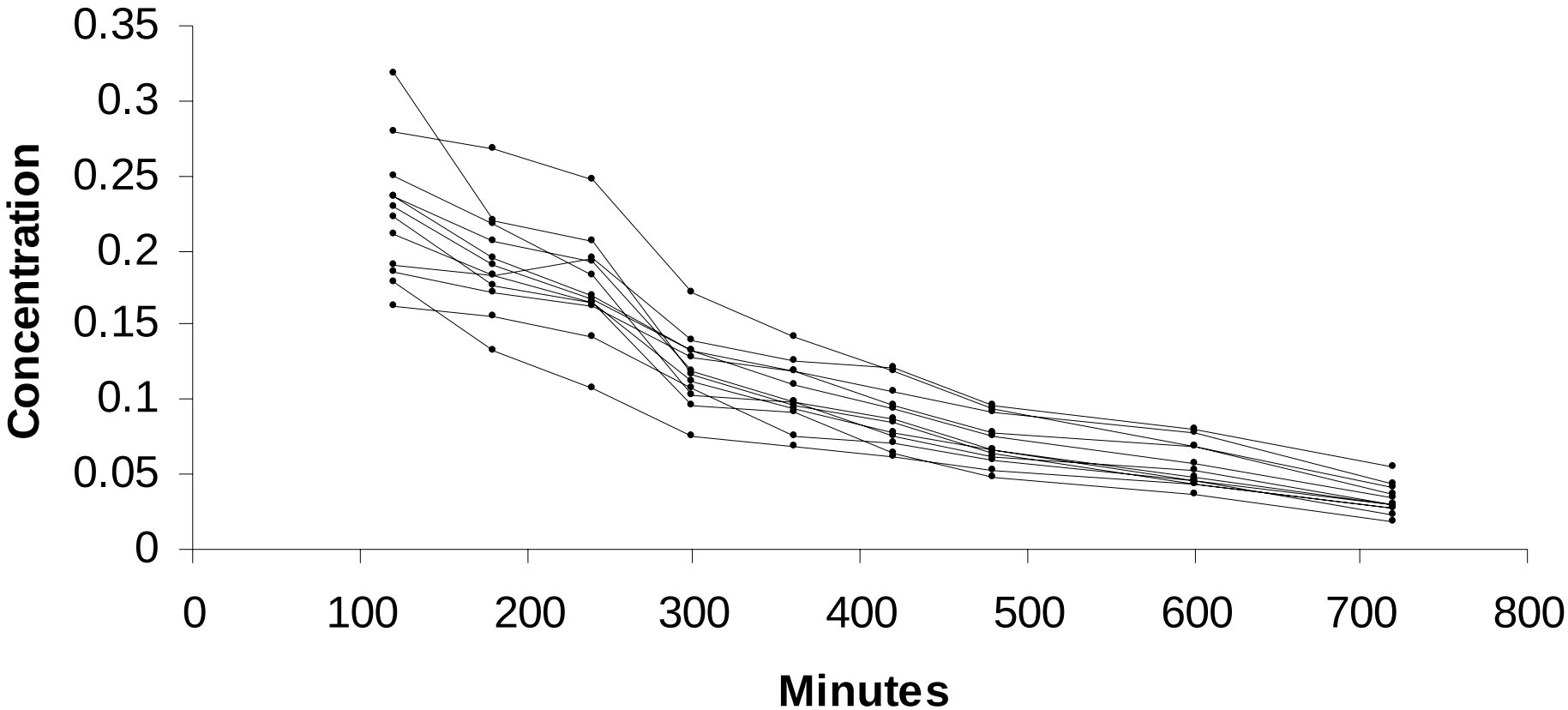
Training Course in Reproductive Health/ Sexual Health Research

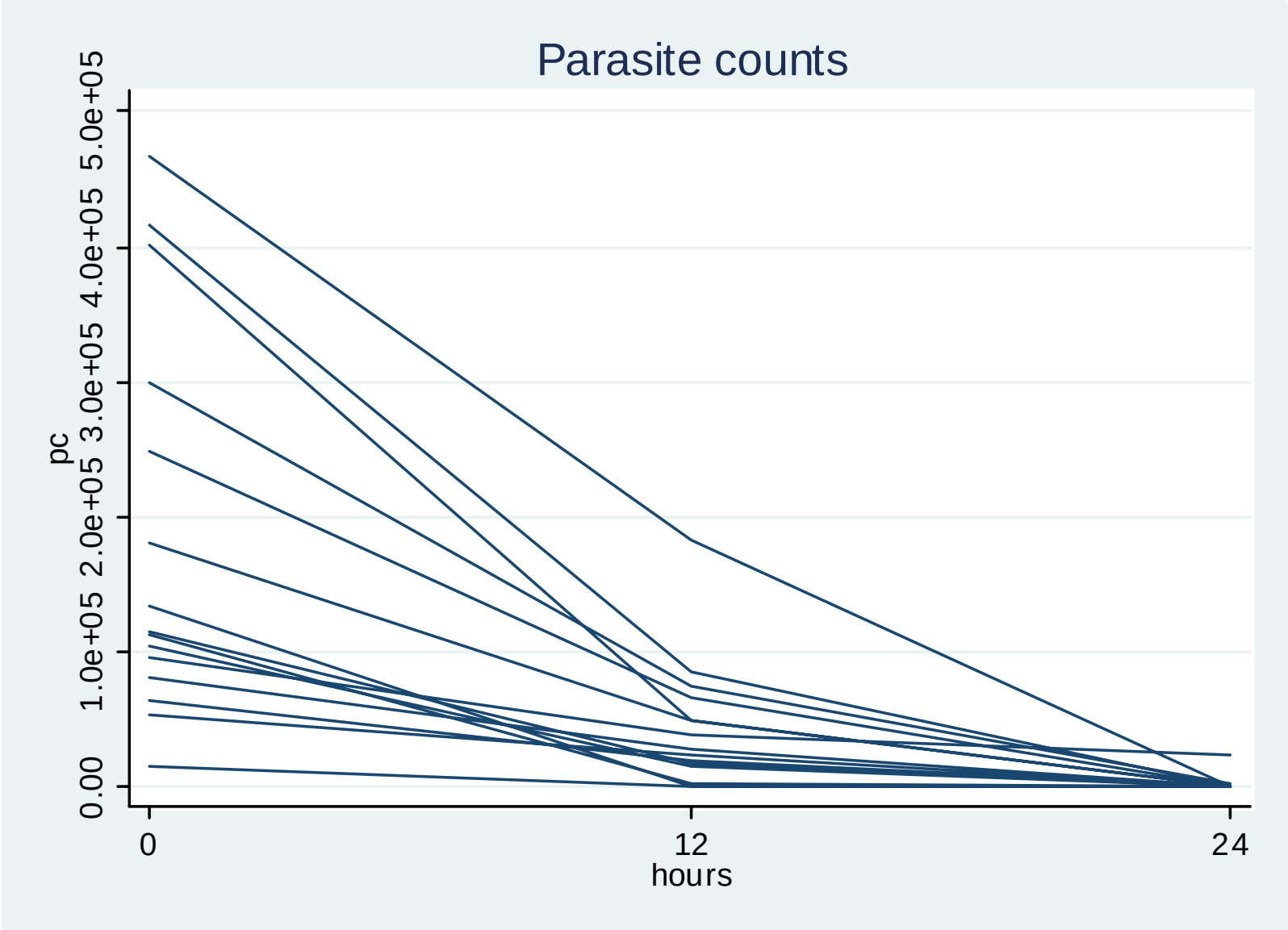
Geneva 2006

Classical clinical examples

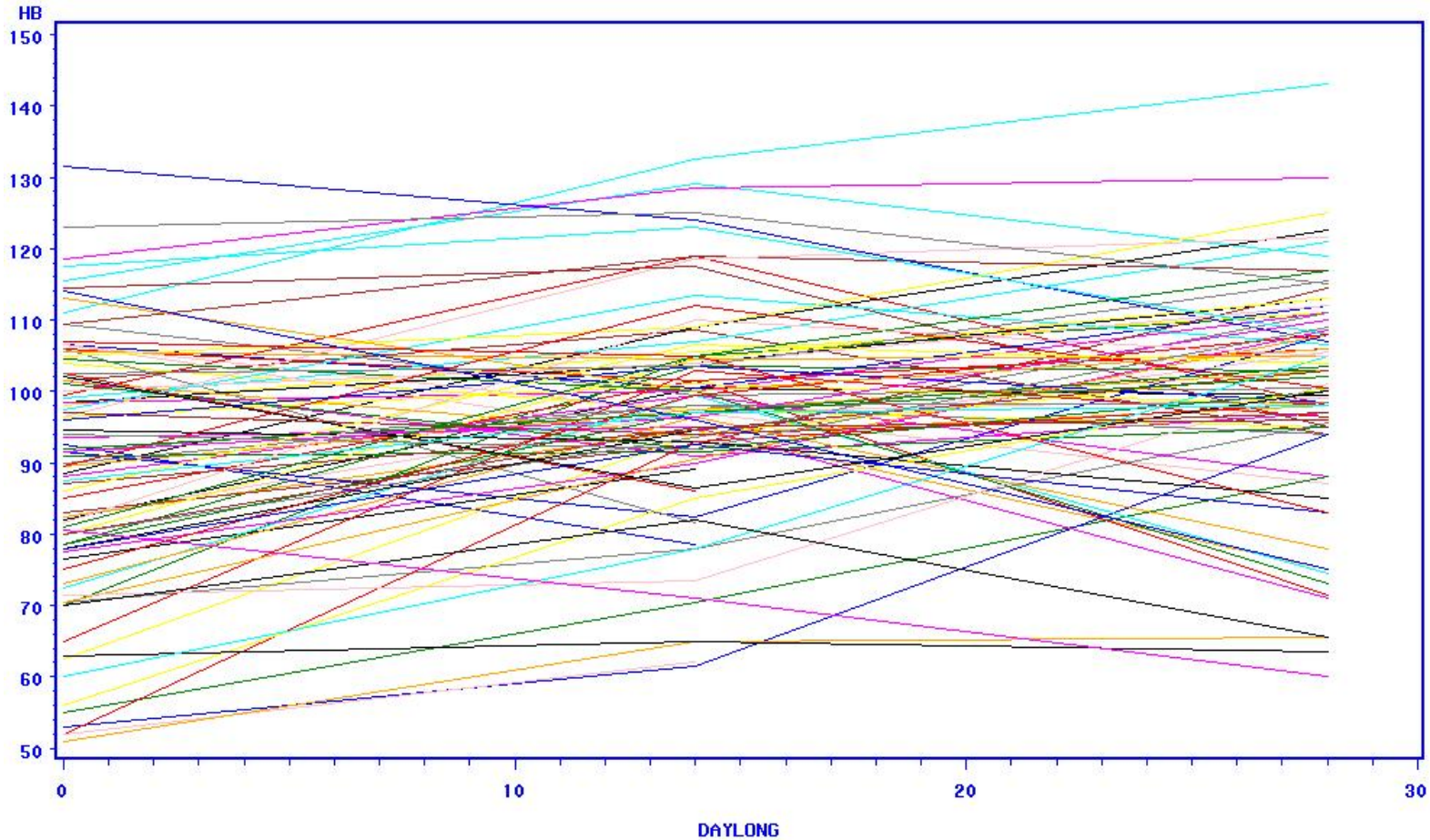
Pharmacokinetics
- a substans in Nexium



WHO rectal Artesmisinins



Haemoglobin levels after antimalarials, Tanzania



Specific characteristics

- Repeated measurements on several objects (individuals, families, villages)
- Normally the objects are followed over time, e.g. pharmacokinetics, measurements of performance, baseline/follow up.
- Separate intra- and inter object variances

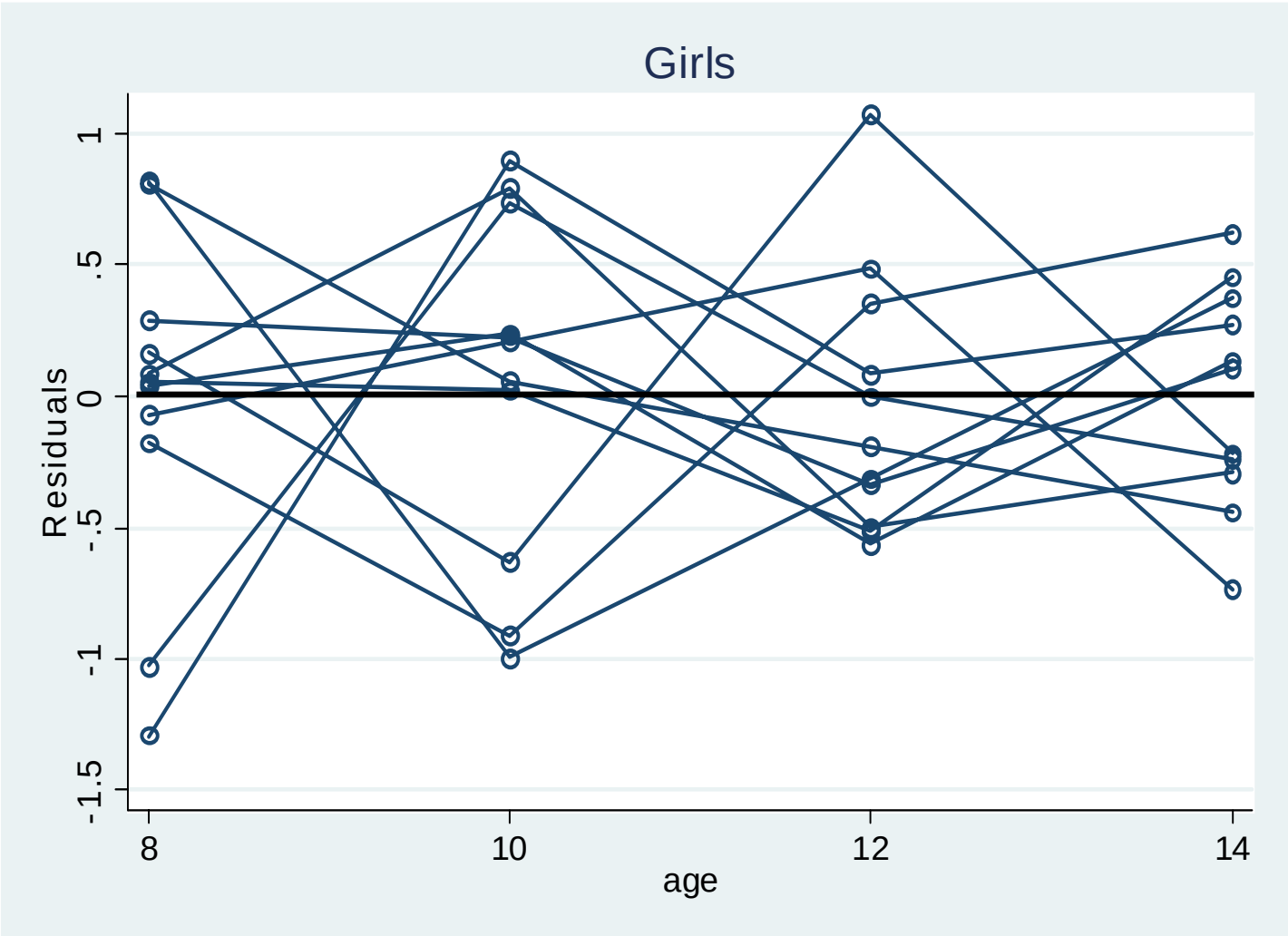
Longitudinal analysis

- It is a matter of correctness and richness

Correctness

- uncorrelated and normally distributed residuals

Don´t forget model diagnostics!

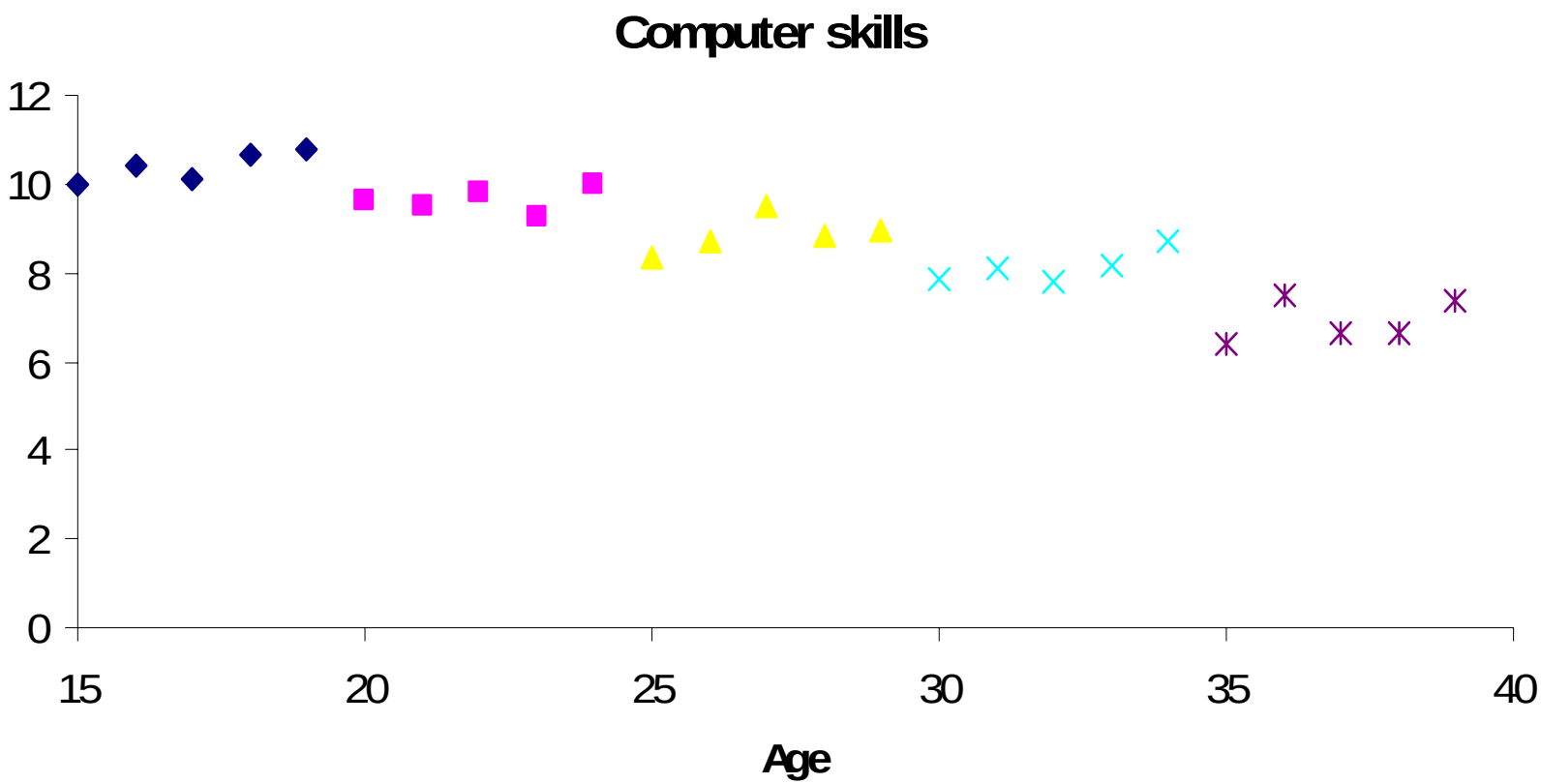


Richness

- to make inference about the individual as well as the group

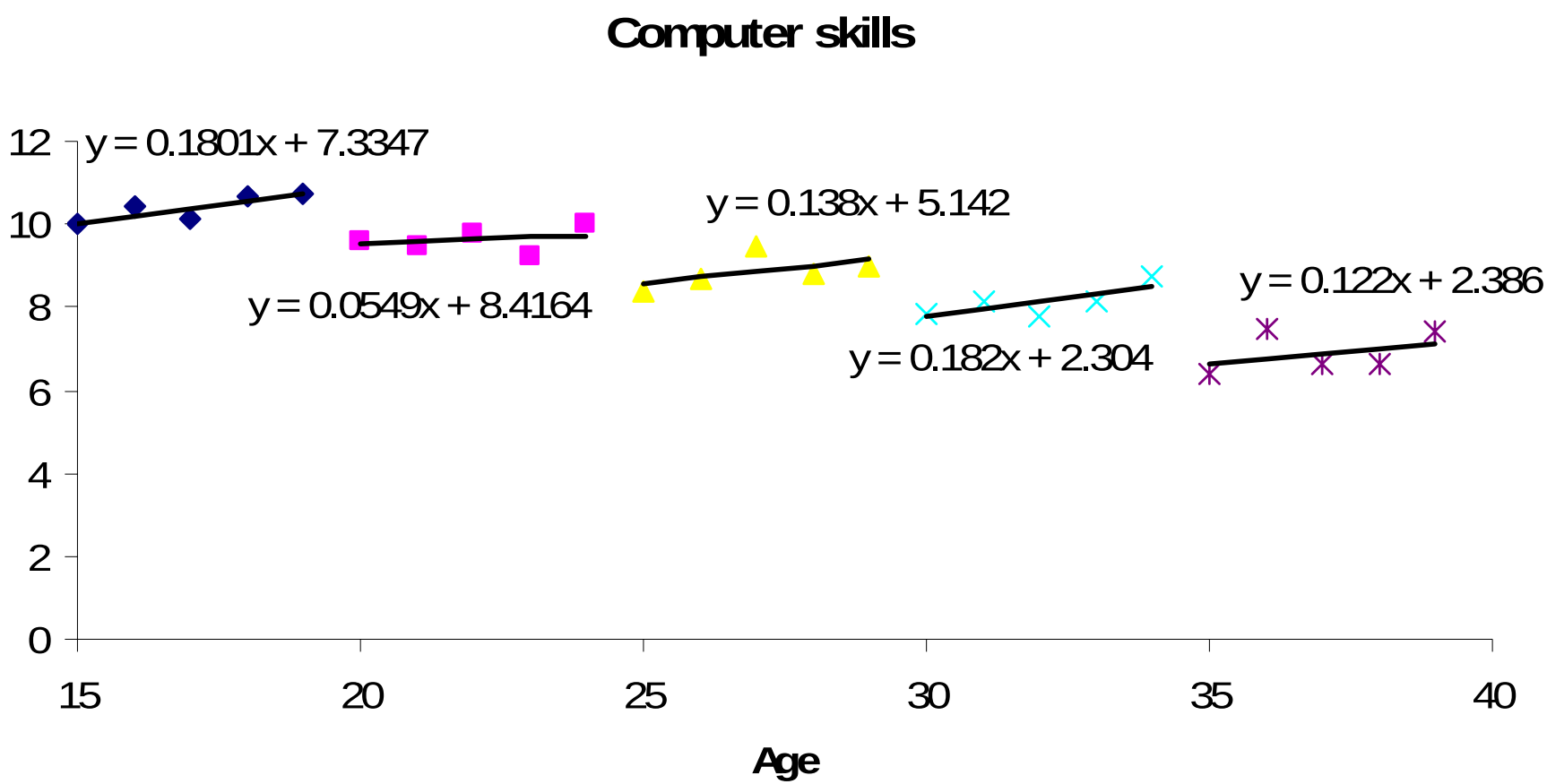

Computer skills
12
10
8
6
4
2
0
15
20
25
30
35
40
Age

But, repeated measurements on individuals



Now increasing with age within an individual

– Separate individual from group effect



BRAC

- Both classical longitudinal studies and pre/post control group designs

Targeted intervention for the ultra-poor: does it make any difference in their health-seeking behaviour?

Syed Masud Ahmed, Max Petzold, Zarina Nahar Kabir, Göran Tomson

Table: Proportion seeking 'formal allopathic' care

	Intervention	Control	Estimated intervention effect
HHs seeking 'formal allopathic' care[a] (15 days recall)			
Baseline (2002)	22.7	25.0	
Post intervention (2004)	38.7	31.8	9.20

Intervention effect: (38.7-22.7) – (31.8-25.0) = 9.20

But how to calculate CIs and control for confounding?

	Intervention	Control	Estimated intervention effect	95% CI	p value
HHs seeking 'formal allopathic' care[a] (15 days recall)					
Baseline (2002)	22.7	25.0			
Post intervention (2004)	38.7	31.8	9.20	4.25 – 14.18	<0.001

- Utilize effect modification / interaction in a regression
- Add confounders, it is regression
- Observe the dependency over time!
- Difficulties when having binary data

Nutrition – Farhana Haseen

- Design: Pre/post intervention control group design
- Measured on family level
- Energy intake as outcome
- Did the intervention make a difference?
- Other covariates (confounders)?

Energy intake related to sex?

- Phase: 0=Baseline, 1=Follow up
- Stup: 0=Control, 1=Intervention
- Interventiontime: Interaction Phase*Stup
- Sex: 0=Female, 1=Male

ene_p_	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
phase	25.9684	65.70378	0.40	0.693	-102.8086	154.7454
stup	12.70908	67.54684	0.19	0.851	-119.6803	145.0985
interventi~t	362.267	92.06088	3.94	0.000	181.831	542.703
sex_	25.67868	50.29746	0.51	0.610	-72.90254	124.2599
_cons	1671.512	134.0944	12.47	0.000	1408.692	1934.333

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ene_p_	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
phase	27.59011	64.86322	0.43	0.671	-99.53946	154.7197
stup	5.718676	67.27671	0.09	0.932	-126.1412	137.5786
interventi~t	505.1664	104.5445	4.83	0.000	300.263	710.0699
sex_	-48.51439	57.13399	-0.85	0.396	-160.4949	63.46617
sexint	-306.7489	110.9452	-2.76	0.006	-524.1975	-89.30039
_cons	1790.904	140.6727	12.73	0.000	1515.191	2066.617

Data collection

- If process, how to measure and how to model process between measurements?
- When did the event stop? Recurrent events/episodes, how to count? Varying severeness
- Recall bias
- Varying covariates (e.g. education)

Data organisation

- If dates, give start date and date for measurement/survey
- Give all covariates, also shifting
- Wide or long format? Wide is sparse, but long is what we need. Reshape. Use numbered variable names. Be consequent.

Remember

- both a challenge and a richness