

Stata: a short history viewed through epidemiology

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2025 Stata Biostatistics and Epidemiology Virtual Symposium

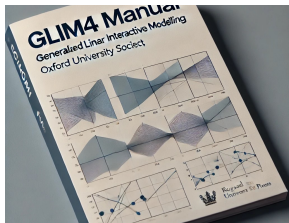
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- ▶ Given from a UK perspective
- ▶ Aims:
 - Pay tribute to influential contributors
 - Share some highlights
 - Offer reflections

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- 1 Some history
 - Before Stata
 - The 1990s
 - The 2000s
 - The 2010s
 - The 2020s

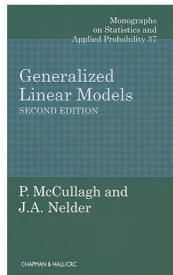
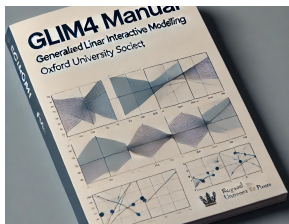
- 2 ...

- ▶ Dominant software: GLIM
(*Generalised Linear Interactive Modelling*)



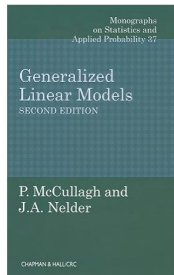
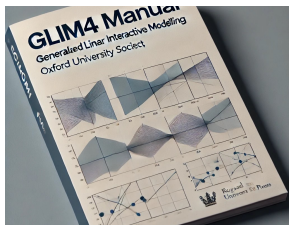
- ▶ Stemmed from a Royal Statistical Society WP
- ▶ Linked to the seminal book by McCulloch and Nelder
- ▶ Accessible on mainframe computers

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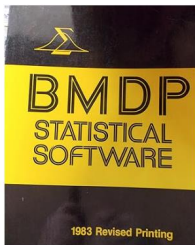
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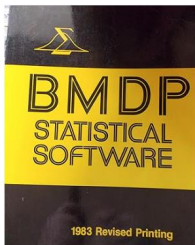
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- ▶ Biostatistics the US: BMDP (*Biomedical Data Package*)



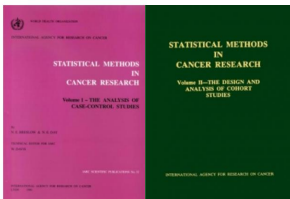
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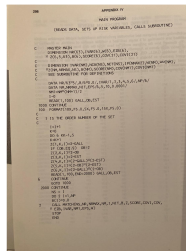
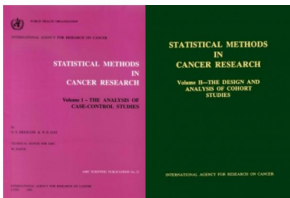
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► Reference books in epidemiology:



► Included several Fortran programs specific for analyses of epi studies (e.g. conditional logistic regression)

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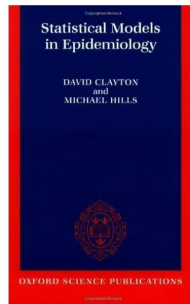
► Stata arrives!

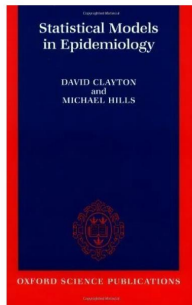


Commands in Stata 1.0 and Stata 1.1

append	dir	infile	plot	spool
beep	do	input	query	summarize
by	drop	label	regress	tabulate
capture	erase	list	rename	test
confirm	exit	macro	replace	type
convert	expand	merge	run	use
correlate	format	modify	save	
count	generate	more	set	
describe	help	outfile	sort	

► Developed for personal computers





Acknowledgments

The original version of `strate` was written by David Clayton (retired) of the Cambridge Institute for Medical Research and Michael Hills (1934–2021) of the London School of Hygiene and Tropical Medicine.

Acknowledgments

`stsplit` and `stjoin` are extensions of `lexis` by David Clayton (retired) of the Cambridge Institute for Medical Research and Michael Hills (1934–2021) of the London School of Hygiene and Tropical Medicine (Clayton and Hills 1995). The original `stsplit` and `stjoin` commands were written by Jeroen Weesie of the Department of Sociology at Utrecht University, The Netherlands

- ▶ London School of Hygiene and Tropical Medicine
- ▶ European Education Program in Epidemiology in Florence

Michael in Florence



Ana Timberlake



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- ▶ European Education Program in Epidemiology in Florence

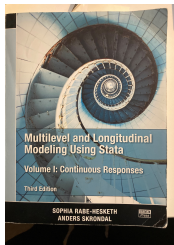
The Stata manuals ...

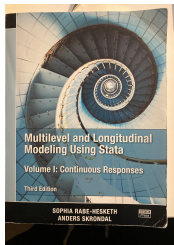


Michael's version!



- ▶ Mixed effects models
- ▶ Missing data





gllamm — Generalized linear and latent mixed models

[Description](#)

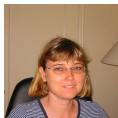
[Remarks and examples](#)

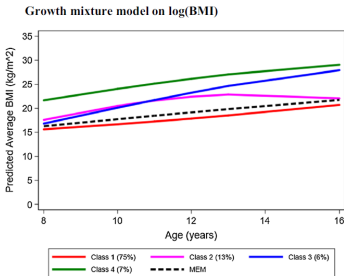
[References](#)

[Also see](#)

Description

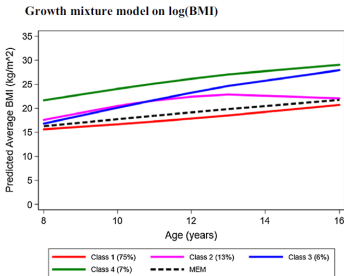
GLLMM stands for generalized linear latent and mixed models, and **gllamm** is a Stata command for fitting such models written by Sophia Rabe-Hesketh (University of California–Berkeley) as part of joint work with Anders Skrondal (Norwegian Institute of Public Health) and Andrew Pickles (King's College London).





Using *mixed*
and *gllamm*

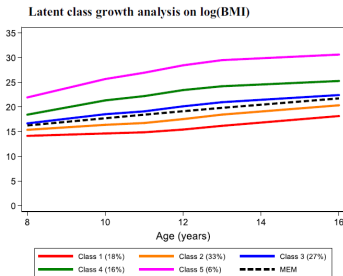
[Herle *et al.* EJE 2021]



Using *mixed*
and *gllamm*

[Herle *et al.* EJE 2021]

Using *mixed*
and *traj* (Jones and
Nagin, 2013)



- ▶ Increasing awareness of bias from ignoring missing data bias
- ▶ Rubin's Multiple Imputation approach and van Buuren's Multiple Imputation by Chained Equations were starting to gain traction

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ice, mim



The Stata Journal (2008)
8, Number 1, pp. 49-67

A new framework for managing and analyzing multiply imputed data in Stata

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Cancer and Statistical Methodology Groups
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London, UK

► Causal inference

- ▶ The currently dominant approach in biostatistics and epidemiology relies on potential outcomes (POs) [Rubin, 1974; Robins, 1986; Pearl, 1995]
- ▶ Adopting this approach, we are concerned with questions formulated as contrasts of outcomes that would occur under hypothetical interventions on the exposure:
"Would the outcome of an individual differ if they had/not had that exposure?"
- ▶ Robins proposed solutions for estimation of POs*:
 - (a) inverse probability weighting (IPW) (of marginal structural models)
 - (b) the g-computation formula
 - (c) g-estimation (of structural nested models)
- ▶ `teffects` implements (a) and (b) for time-fixed exposures

* Under assumptions of: no interference & consistency (i.e. SUTVA) and conditional exchangeability

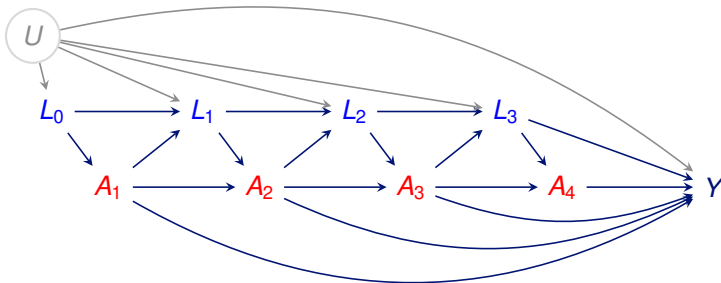
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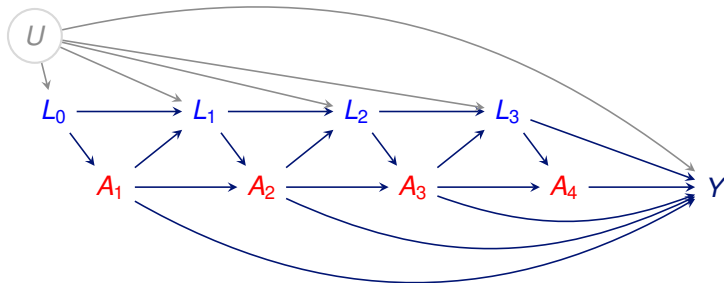
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Here the total causal effect of A involves L_1, L_2, L_3 , although these are also confounders for A_2, A_3, A_4 : standard regression modelling does not work!

The Stata Journal (2011)
11, Number 4, pp. 479–517

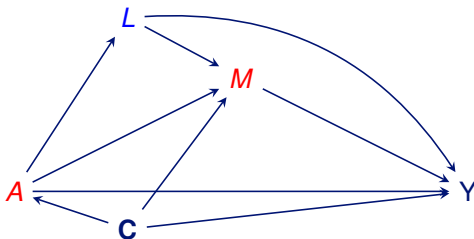
gformula: Estimating causal effects in the presence of time-varying confounding or mediation using the g-computation formula

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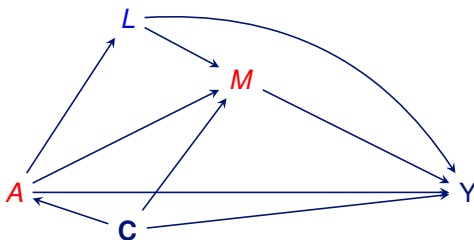
Simon N. Cousens
Centre for Statistical Methodology
London School of Hygiene and Tropical Medicine
London, UK





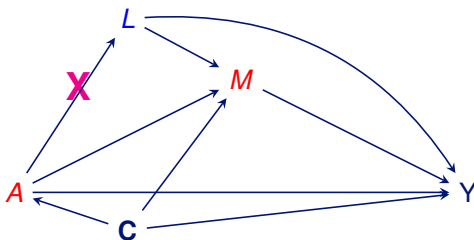
- ▶ `gformula` can be used to estimate natural and interventional effects
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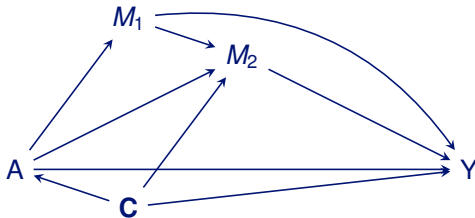
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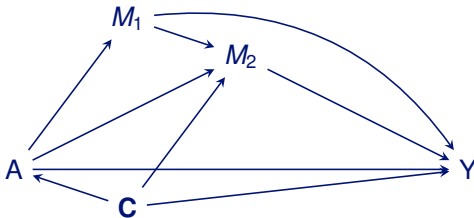
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Vansteelandt & Daniel “Interventional effects for mediation analysis with multiple mediators”, *Epidemiology* 2017



Vansteelandt & Daniel “Interventional effects for mediation analysis with multiple mediators”, *Epidemiology* 2017



Micali *et al.* “Maternal Prepregnancy Weight Status and Adolescent Eating Disorder Behaviors”, *Epidemiology* 2018

A: Prepregnancy maternal BMI

Y: Binge eating score at 13/14y

M_1 : Childhood growth 8-12y

M_2 : Maternal food avoidance at 8y

	Effect of Maternal overweight	
	Mean difference	95% CI
Total	0.25	0.18, 0.32
Direct	-0.02	-0.08, 0.05
Indirect via growth	0.28	0.23, 0.33
Indirect via environment	-0.02	-0.04, -0.01

- ▶ Administrative databases
- ▶ High-dimensional covariates

- ▶ Linked administrative data sources increasingly available for:
 - comparative effectiveness research
 - policy evaluations
- ▶ Recognition of biases potentially affecting such research:
 - Confounding and measurement error
 - Selection bias
 - Lack of positivity
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 - High dimensionality

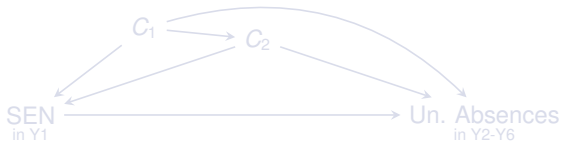
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- ▶ **Aim:** assess the impact of SEN provision on unauthorised absences for children with a certain health needs
- ▶ **Data:** ECHILD, linked educational and health records across England
- ▶ Many challenges including high-dimensionality of confounders
- ▶ Results with/without (correct) lasso selection (using `teLasso`)[‡]:

[‡]As developed by Chernozhukov (2018); Code to be deposited in GitHub 

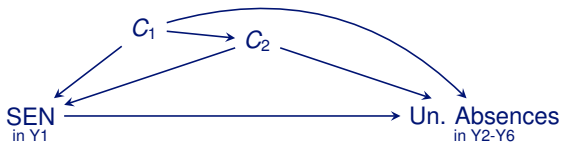
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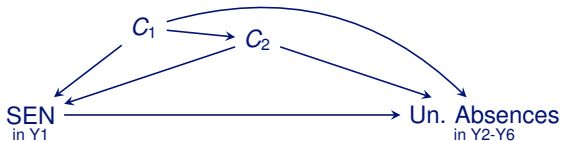
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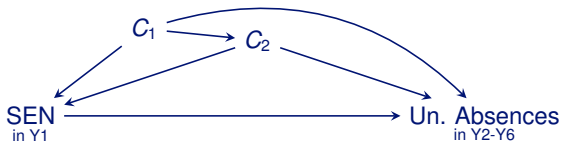
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	Effect of SEN in Y1	
	Rate Ratio	95% CI
Crude	1.22	1.11, 1.34
AIPW-lasso with int.	0.80	0.66, 0.95

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