Latent variable structural equation models for longitudinal and life course data using Mplus

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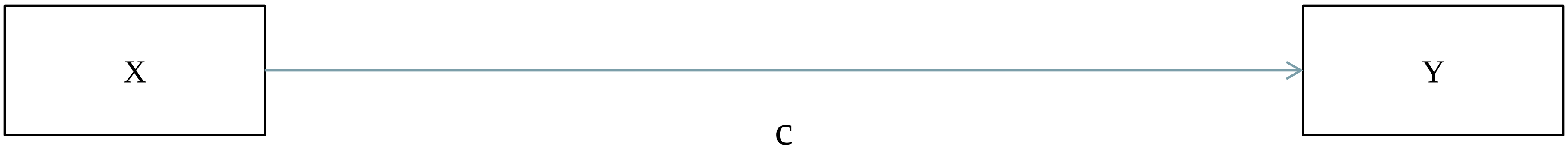
Intended learning outcomes

- By the end of this masterclass, you should be able to
  - Test a simple mediation model
  - Calculate direct and indirect effects
    - Cross-sectionally and longitudinally
  - Create a cross-lagged panel model
  - Distinguish between mediation, moderation, confounding, suppressor effects and antecedent variables
  - Build a life course structural equation model in Mplus
  - Introduce latent variables into path models

Morning session

DIRECT AND INDIRECT EFFECTS

X predicts Y



- Direct effect, quantified by c
  - Amount by which two participants who differ by one X unit are expected to differ on Y
- Linear regression
  - $Y = B_0 + B_1X+e$
- X measured without error, Y with error
  - Reliability and validity established prior to modelling

Aberdeen Children of the 1950s (ACONF)

Leon et al. (2006, *IJE*)

- Health from infancy to adulthood in Aberdeen
  - Participants born in Aberdeen 1950-1956
- Biological and social influences on health
  - Across the life-course
  - Between generations
- Birth records (father's social class)
- Cognitive ability test in 1962-1964 (IQ)
- Postal questionnaire 2001-2002 (education, health)
  - 81% still living in Scotland

Does childhood SES predict adult health?

Childhood SES 1950s → Self-rated health 2002

- Childhood SES
  - Father's occupational social class (range 1, 6)
- Self-rated health
  - Validated as a good proxy for actual health (range 1,4)
  - Treated as continuous

Mplus input file

- TITLE: ACONF
- DATA: FILE IS aconf.dat;
- VARIABLE: NAMES ARE id sex age health fsclass ed iq ediq verbal1 verbal2 maths english nomiss;
- MISSING ARE ALL (9999); !This is a comment
- USEVARIABLES ARE health fsclass;
- USEOBSERVATIONS (nomiss EQ 1);
- MODEL: health ON fsclass;
- OUTPUT: STAND;

Mplus output file

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
HEALTH ON				
FSCLASS	0.090	0.008	11.194	0.000
Intercepts				
HEALTH	2.763	0.026	108.308	0.000
Residual Variances				
HEALTH	0.588	0.010	56.022	0.000

- B = 0.09
  - One unit increase in childhood SES = 0.09 units increase in adult health
- β = 0.14
  - One SD increase in childhood SES = 0.14 SD increase in adult health

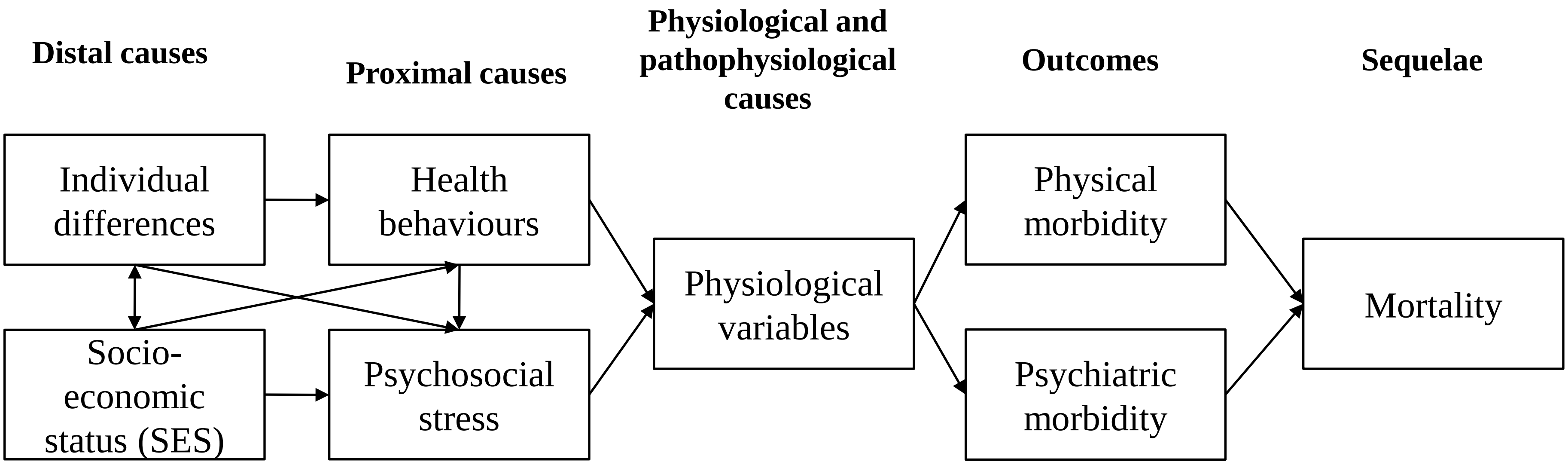
STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate
HEALTH ON	
FSCLASS	0.140

Life course approaches

- ‘When distal exposures operate through different levels of risk factors, their full impact may not be captured in traditional regression analysis methods in which both proximal and distal variables are included…Risk factors can also be separated from outcomes in time, sometimes by many decades’ (WHO, 2002, p.15)



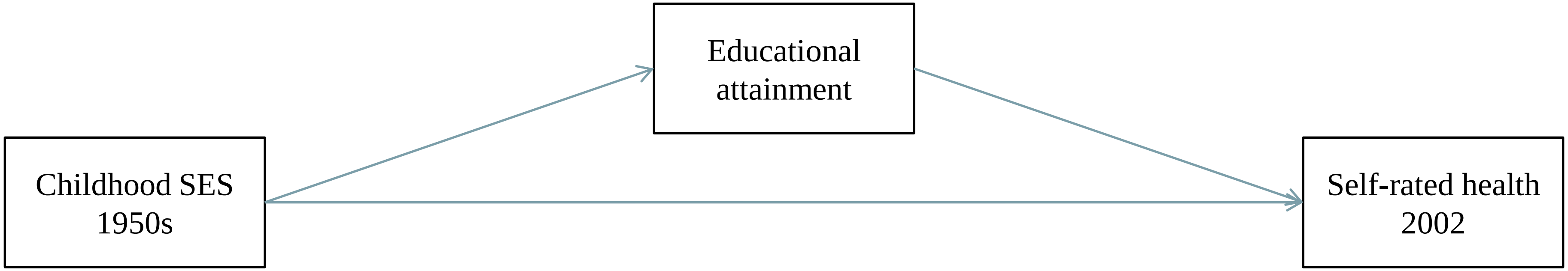
Life course models

- Biological, behavioural, and psychosocial processes operate across an individual's life course, or across generations, to influence the development of disease risk
- Multidisciplinary approach
  - Psychology, sociology, demography, epidemiology, anthropology, biology
- Socially patterned exposures during childhood, adolescence, and early adult life influence adult disease risk and socioeconomic position, and hence may account for social inequalities in adult health and mortality

Kinds of research questions

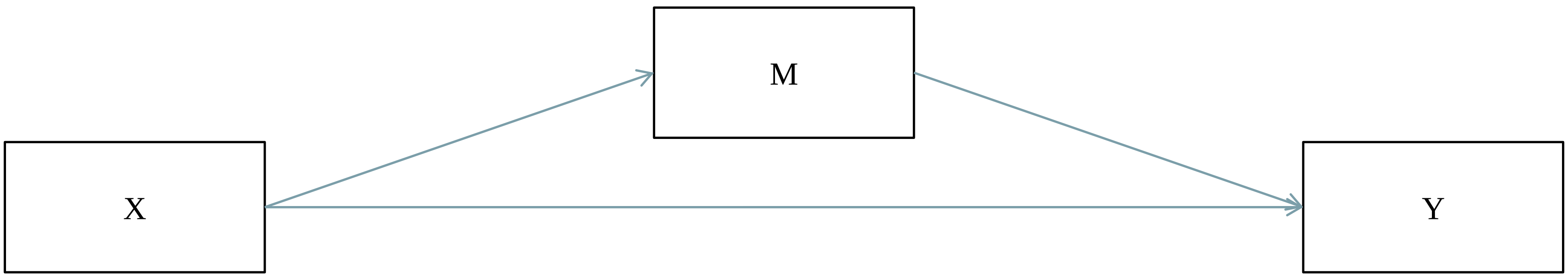
- Accumulation of risk
  - Life course exposures gradually accumulate, insult accumulation
- Birth cohort effects
  - Environmental change may show up several decades later
- Chains of risk
  - Sequence of linked exposures, one leads to another then another
- Critical period
  - Time window for development, biological programming
- Trajectory
  - Normative trajectories around which individuals vary, turn

Mediator



- Mediators are variables that lie on the causal chain
- Childhood SES could influence education, then health
- Also known as
  - Mechanisms
  - Explanatory variables
  - Intermediate variables
  - Causal confounders

Baron & Kenny (1986) approach



- Show that X and Y are correlated
- Show that X and M are correlated
- Regress Y on X and M
  - Full mediation if X is not associated with Y, controlling for M
  - Partial mediation if X and M are associated with Y

Mplus illustration

	Input syntax	B coefficient	Conclusion
Show that X and Y are correlated	X WITH Y;	0.13	✓
Show that X and M are correlated	X WITH M;	0.38	✓
Regress Y on X and M	Y ON X M;	0.05 (fsclass) 0.08 (ed)	✓ ✓

Effect decomposition analysis

- Calculate percentage attenuation when proposed mediator is added to the model containing X and Y
- $100*[(B_{basic} – B_{basic+meditator})/B_{basic}]$
- 100*[(0.09-0.048)/0.09]
- =47%
- Education explains 47% of the association

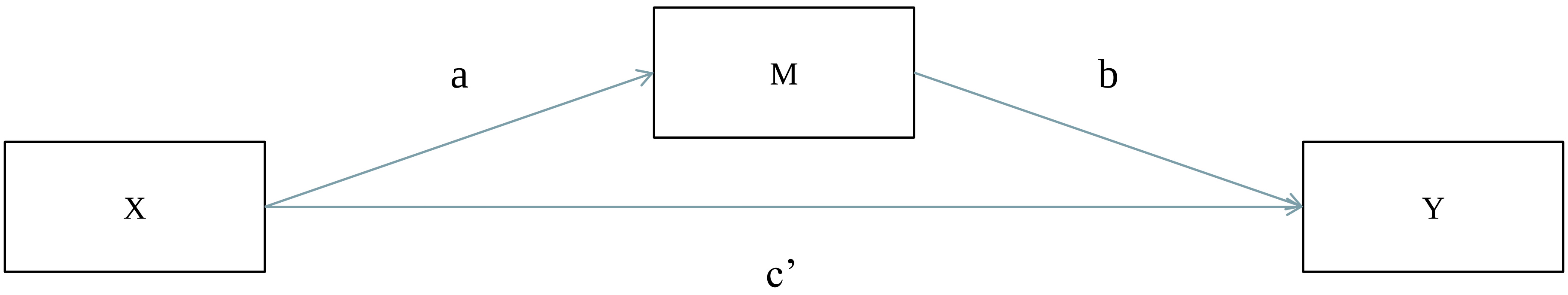
Problems with Baron & Kenny (1986) approach

- Multiple testing
  - Increases likelihood of type I error (false positive)
- Low power
  - Least likely to detect an indirect effect
  - Type II errors (false negative)
- Significance test not effect size
  - Does not show the size of the ‘indirect effect’
  - How much of the association happens through the mediator?
- Assumes X-Y have to be associated

Is your project over if Baron & Kenny (1986) will not sing?

- ‘Advisors tell their graduate students to start out a project establishing the basic effect. “Once you have the effect, then you can start looking for mediators and moderators”… Is the project not over until Baron and Kenny sing? Or can a project be declared over too soon because Baron and Kenny would not sing?... a ticket to the file drawer’ (Zhao, John & Chen, 2010)

Towards direct and indirect effects



- c = the total effect
- a*b = the indirect effect
  - Amount expected to differ on Y <u>through X's effect on M</u>, which in turn affects Y
- c' = the direct effect
- c = c' + ab (if variables are observed)
- ab = c – c' (indirect effect)

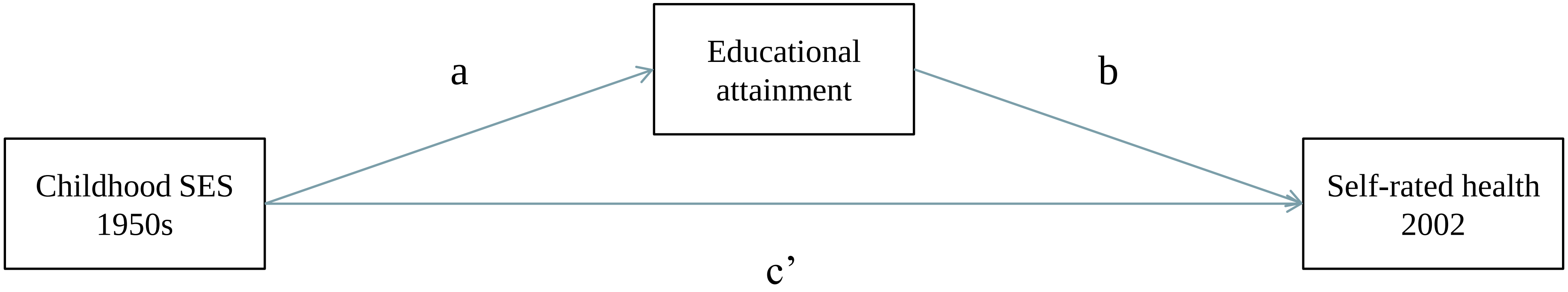
Effect sizes for indirect effects

- .01 small
- .09 large
- .25 medium
- Direct effect c’ is the part of the effect X on Y that is independent on the pathway through M
  - Proportion of total effect that is mediated (ab/c)
  - Ratio of mediated to direct effect (ab/c’)

Significance of the indirect effect: Sobel test

- Standard error of ab
- z-value = $a*b$/SQRT($b^2*s_a^2 + a^2*s_b^2$)
- Ratio of ab to its standard error = statistical significance
- Assumes normal distribution of indirect effect
- Sampling distribution of ab tends to be asymmetric, skewed and kurtotic
- Bootstrapping is an alternative

Does education mediate the association between childhood SES and adult health?

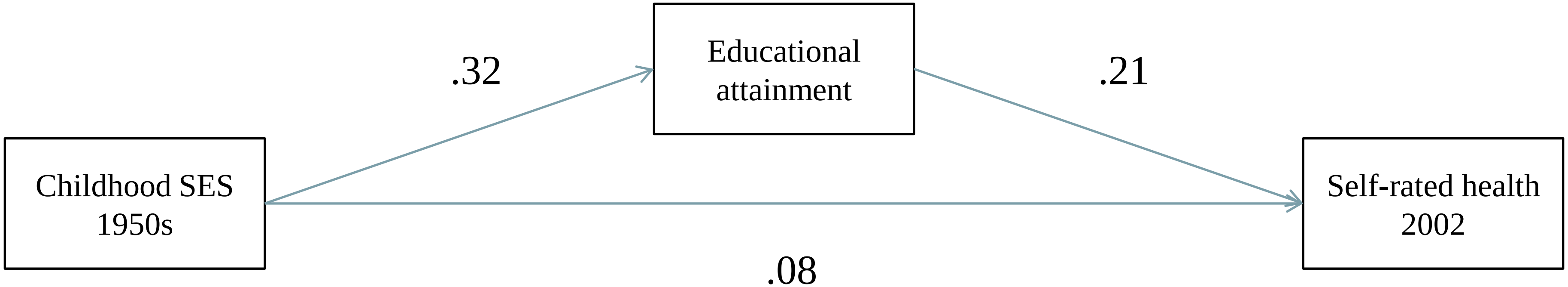



```
MODEL:
health ON ed fsclass;
ed ON fsclass;
MODEL INDIRECT:
health IND ed fsclass;
OUTPUT: STAND;
```

Mplus output file

```
STANDARDIZED MODEL RESULTS


STDYX Standardization


                    Estimate

 HEALTH   ON
    ED                 0.207
    FSCLASS            0.075

 ED       ON
    FSCLASS            0.315
```

```
MODEL RESULTS

                                                  Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

 HEALTH   ON
    ED                 0.076      0.005     16.019      0.000
    FSCLASS            0.048      0.008      5.785      0.000

 ED       ON
    FSCLASS            0.554      0.021     26.334      0.000

 Intercepts
    HEALTH             2.554      0.028     90.508      0.000
    ED                 2.752      0.066     41.409      0.000

 Residual Variances
    HEALTH             0.565      0.010     56.021      0.000
    ED                 3.986      0.071     56.025      0.000
```



Indirect effect

```
TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS


                                                    Two-Tailed
                    Estimate       S.E.  Est./S.E.    P-Value

Effects from FSCLASS to HEALTH

  Sum of indirect      0.042      0.003     13.686      0.000

  Specific indirect

    HEALTH
    ED
    FSCLASS            0.042      0.003     13.686      0.000
```

- One unit increase in childhood SES, 0.042 units increase in adult health through the effect of childhood SES on education (95% CI .037 to 0.47)

```
CONFIDENCE INTERVALS OF TOTAL, TOTAL INDIRECT, SPECIFIC INDIRECT, AND DIRECT EFFECTS


                  Lower .5%  Lower 2.5%   Lower 5%    Estimate    Upper 5%  Upper 2.5%   Upper .5%

Effects from FSCLASS to HEALTH

  Sum of indirect    0.034       0.036       0.037       0.042       0.047       0.048       0.050

  Specific indirect

    HEALTH
    ED
    FSCLASS          0.034       0.036       0.037       0.042       0.047       0.048       0.050
```

MODEL INDIRECT

- Provides indirect effects and standard errors
- STANDARDIZED option in OUTPUT provides standardized indirect effects
- ANALYSIS: BOOTSTRAP=1000
  – Bootstrapped standard errors (‘resampling’ technique)
- OUTPUT: CINTERVAL for confidence intervals
  – Symmetric, bootstrap or bias-corrected bootstrap
  – Allow for non-normality

Indirect and total effects in Mplus

- TOTAL = combination of direct effect and indirect effects
- TOTAL INDIRECT = combination of indirect effects
- SPECIFIC INDIRECT = indirect effects listed separately
- DIRECT EFFECTS = direct effects listed separately

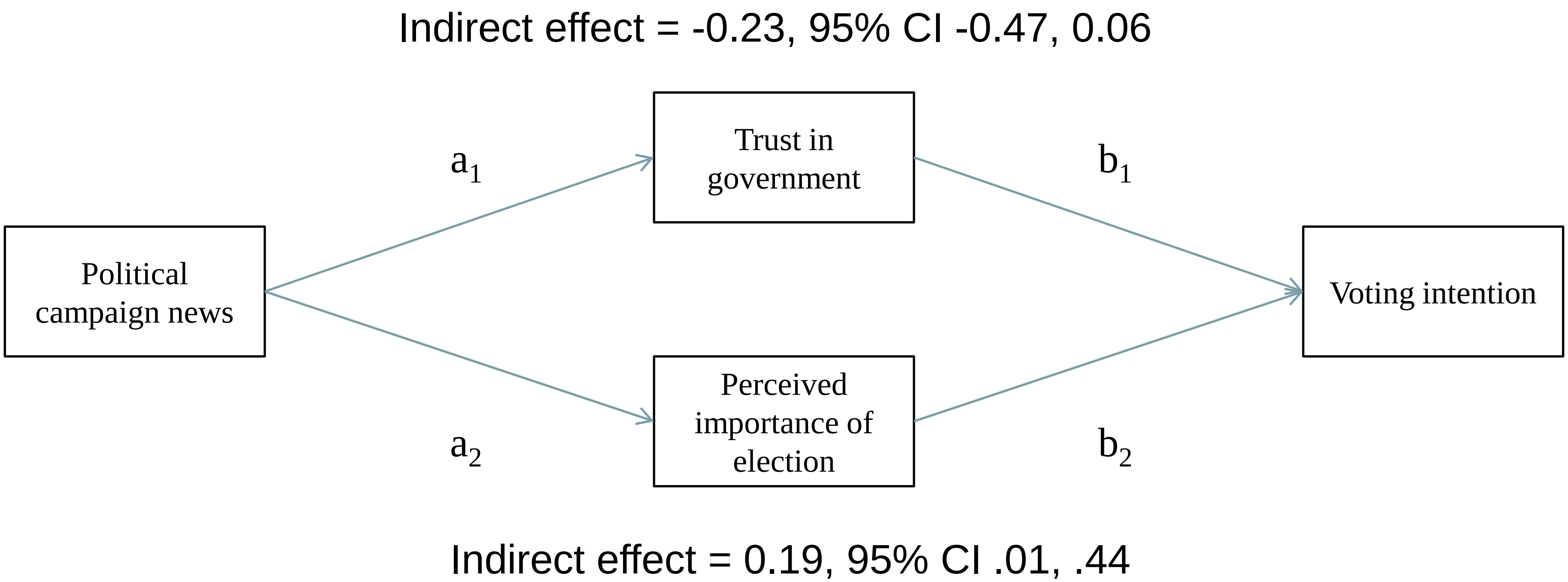
Do X and Y have to be associated?

- Indirect effects can exist without X-Y association
  - Calculate direct, indirect and total effects simultaneously
  - Do not use Baron & Kenny (1986) steps sequentially
- Total effect is sum of several pathways
  - The pathways may not have been elucidated by the researcher
- Indirect effects can have opposite signs
  - These can ‘cancel out’
  - Compare to main effect in 2 by 2 ANOVA
    - Simple effects could have opposite signs
    - Main effect can be non-significant

Two contrasting views

- ‘An intervening variable transmits the effect of an independent variable to a dependent variable’ MacKinnon et al., 2002
- ‘a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion’ Baron & Kenny (1986)
- Mediation as a special (restrictive) case of indirect effects
- Confounding, suppression and moderation can attenuate X-Y association
  - Other variables may contaminate the apparent association

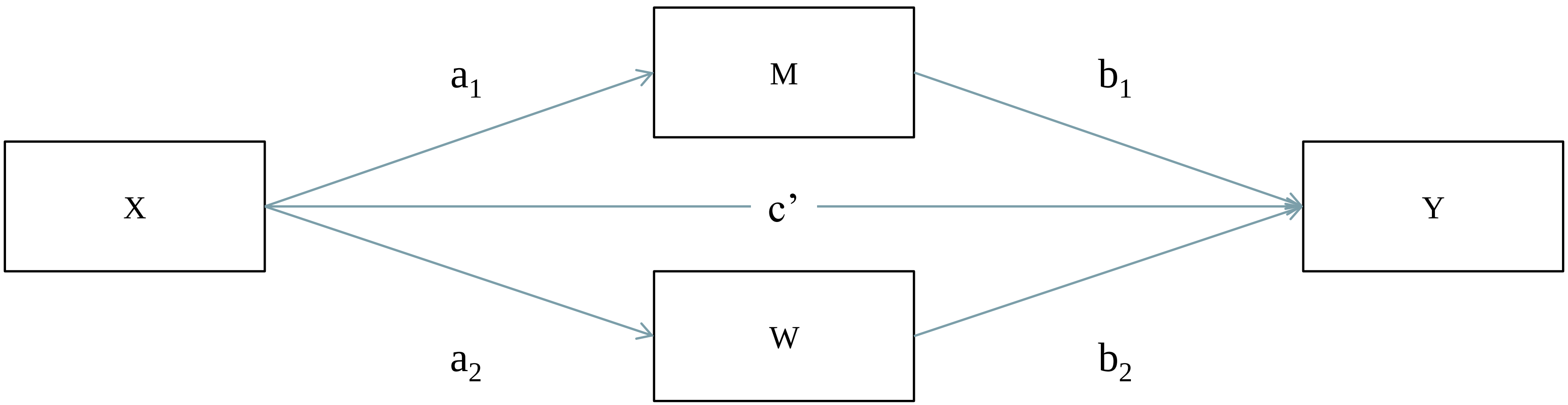
Example



- No association between X and Y
- Two mechanisms work in opposite directions

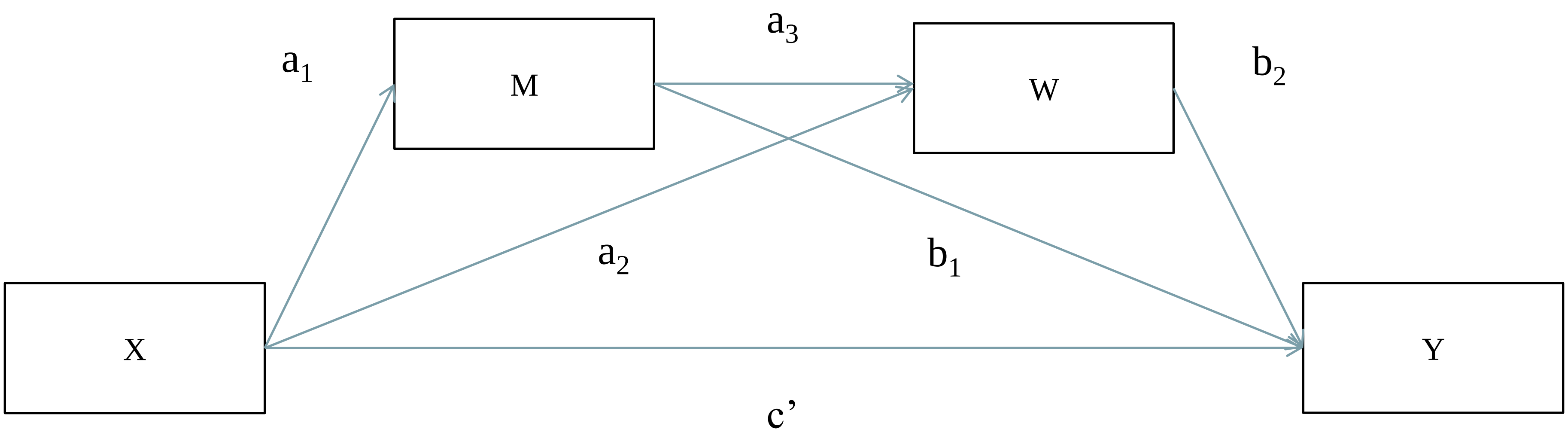
‘If you find a significant indirect effect in the absence of a detectable total effect, call it what you want – mediation or otherwise. The terminology does not affect the empirical outcomes. A failure to test for indirect effects in the absence of a total effect can lead you to miss some potentially interesting, important, or useful mechanisms by which X exerts some kind of effect on Y’ (Hayes, 2009)

Two mediators, single step model



- Total effect is c’ plus sum of indirect effect through M and indirect effect through W
- $c = c' \; a_1b_1 + a_2b_2$

Two mediators, multiple step

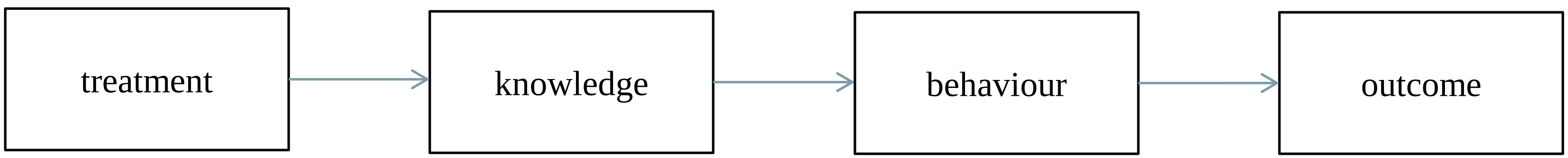


- $c = c' + a_1b_1 + a_2b_2 + a_1a_3b_2$

Indirect effects are important

- Explain why an association exists
- Show mechanisms
- Articulate assumptions explicitly
- Specify model in advance
  - Based on theory and prior research
- Allow model testing
- Identify possible points of intervention

Process analysis in interventions



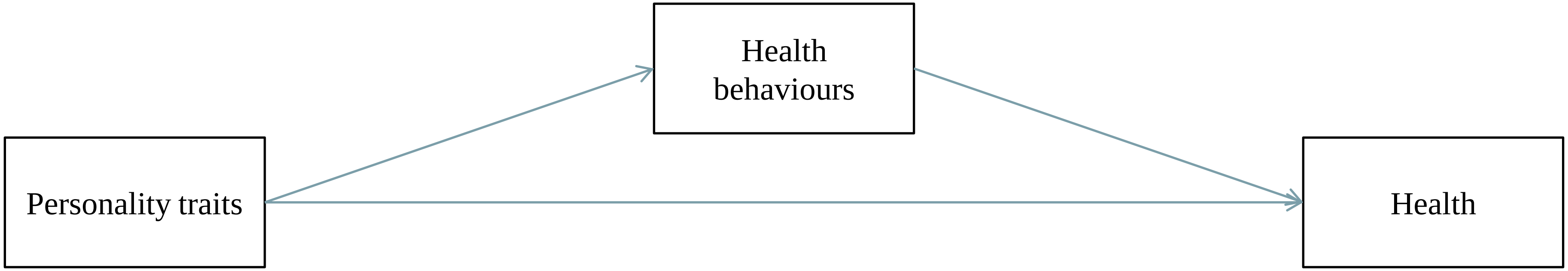
- Not whether but *how* an intervention produced the desired effects
- Treatment affects outcome
- Each variable affects the variable following it in the chain
- The treatment exerts no effect upon the outcome when the mediating variables are controlled
- If the hypothesized mediation process is sufficient

Health and Lifestyle Survey (HALS) 1984

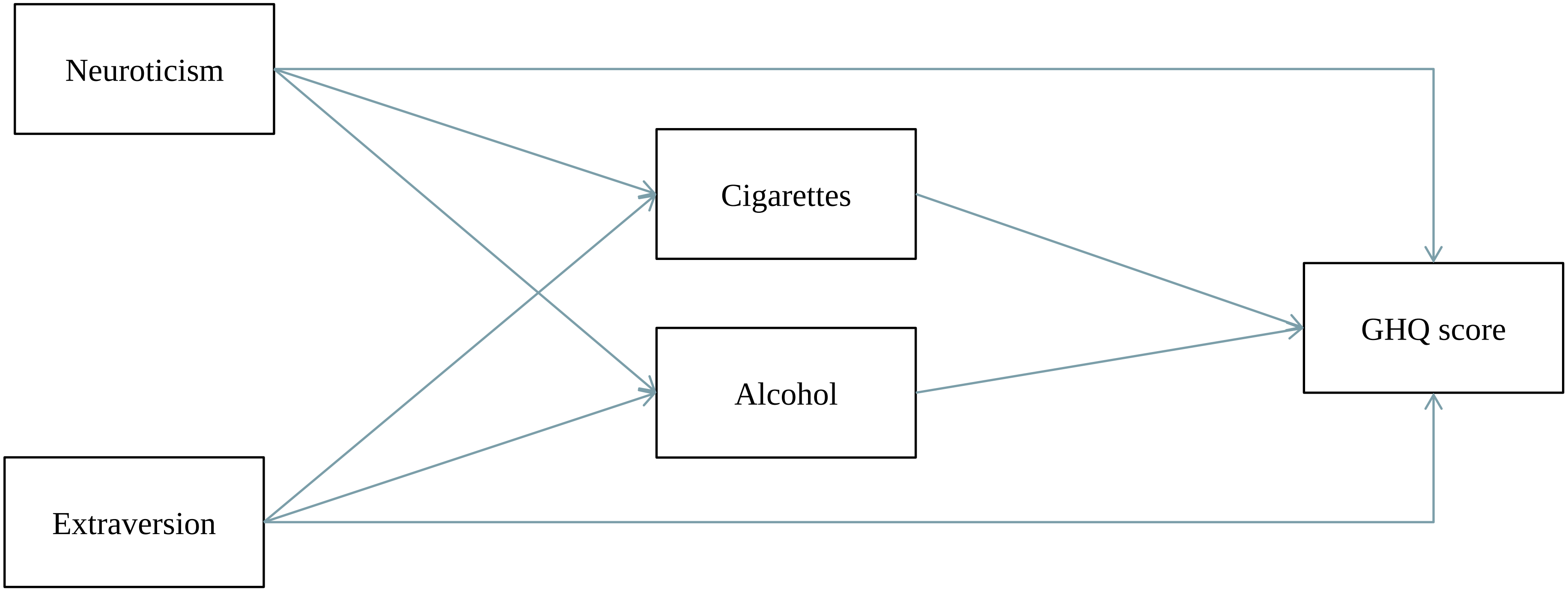
- Representative sample of 9003 adults in England, Wales and Northern Ireland 1984-1985 (HALS1), 1991-1992 (HALS2)
  - Baseline interview
  - Nurse home visit
  - Postal questionnaire
- Variables included: demographic, lifestyle, socio-economic, psychological health, personality traits, physical health

PRACTICAL SESSION

Mediation model in Mplus



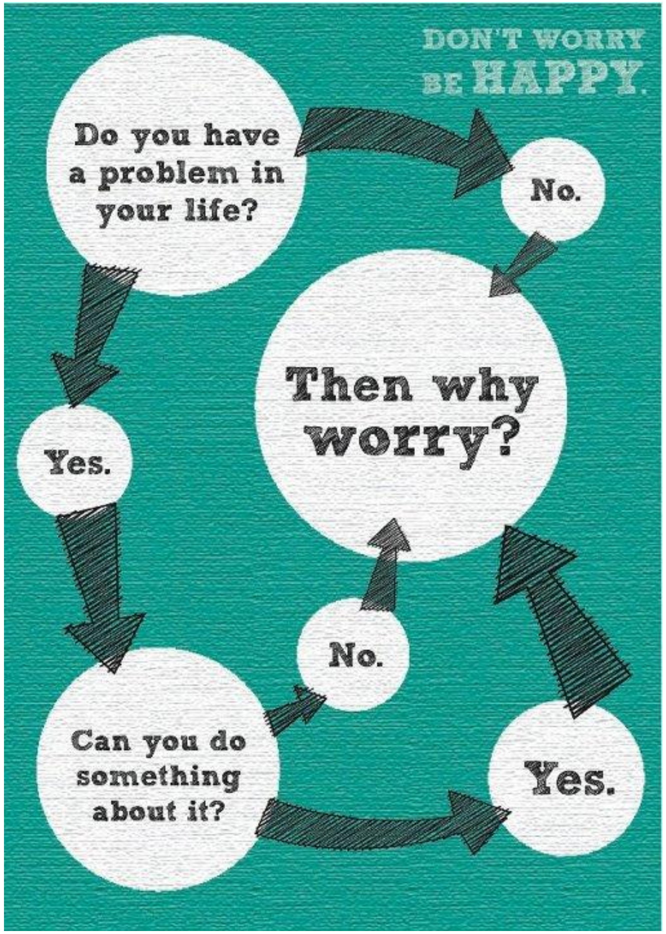
- 'Personality traits are associated with health habits...These habits, in turn, could mediate associations between personality and health' (Smith, 2006)
- Does smoking mediate the association between neuroticism (EPI score) and minor psychiatric morbidity (GHQ-30 score)?

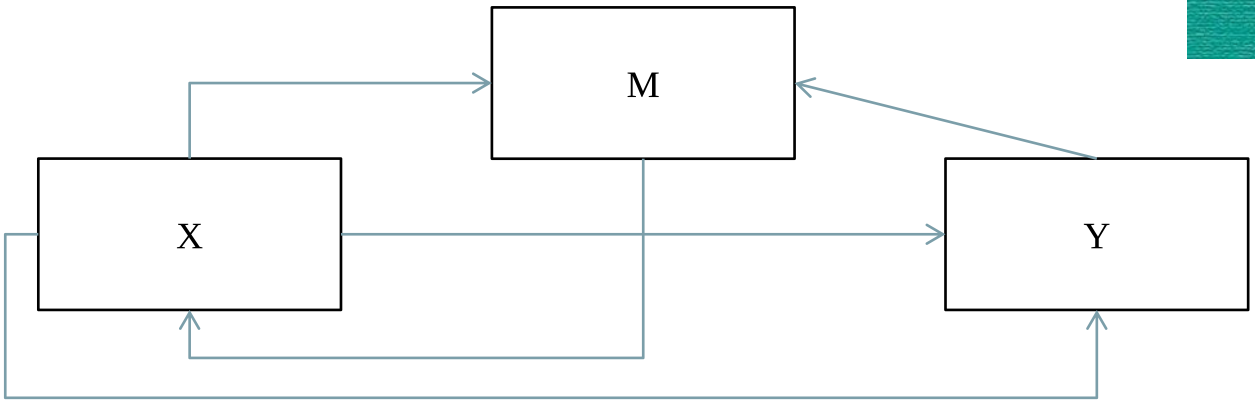


- Do cigarette smoking and/or alcohol units mediate the association between personality traits and minor psychiatric morbidity?

Some rules about pathways

- No loops
  - Pass through each variable once
- No going forward then backward
- Only one arrow from first to last variable





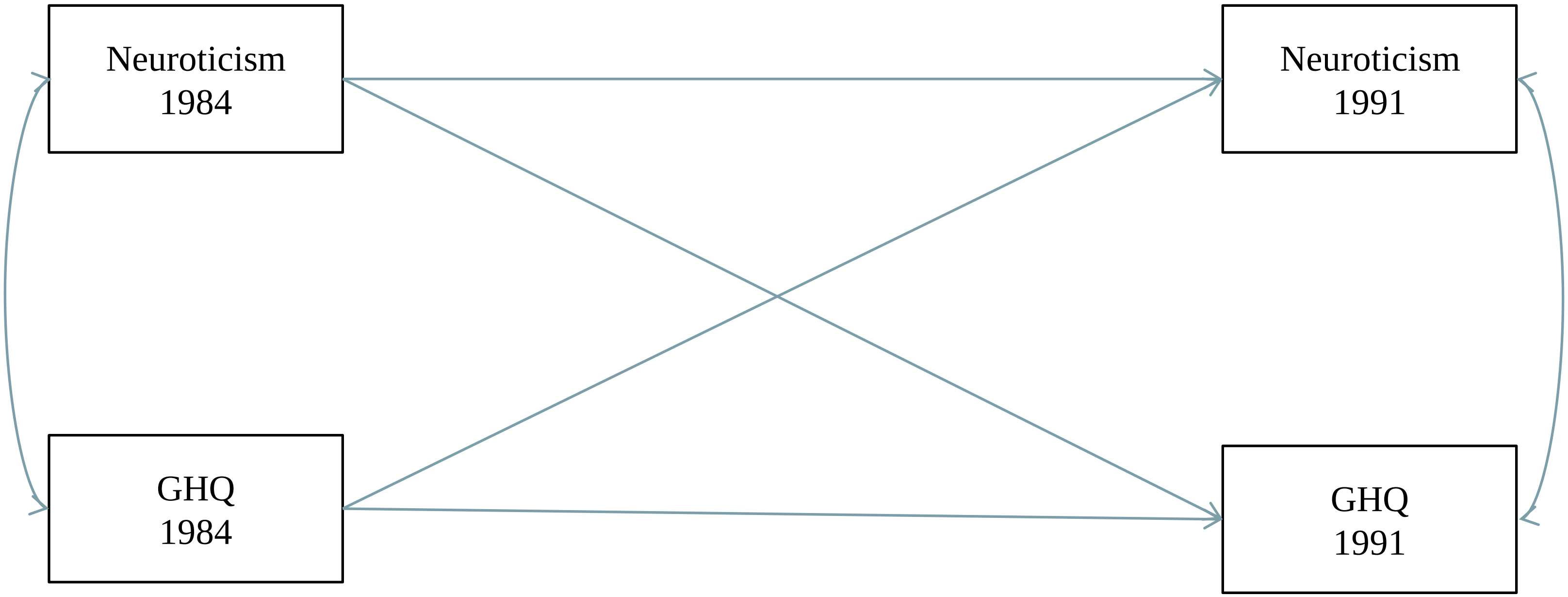
Limitations of simple mediation models

- Cross-sectional data
  - Causal relationships take time to unfold
  - Some proposed mediators (e.g. education) more plausible
- Previous levels of variables not controlled
- Magnitude of effect can depend on
  - Period (of time)
  - Span (of study, follow-up)
  - Lag (between waves)
- Consider timing not just temporal ordering

Longitudinal mediation models

- Autoregressive
  - Cross-lagged panel model
- Cross-sectional and autoregressive
  - X, M and Y within wave and across waves
- Latent growth curve model

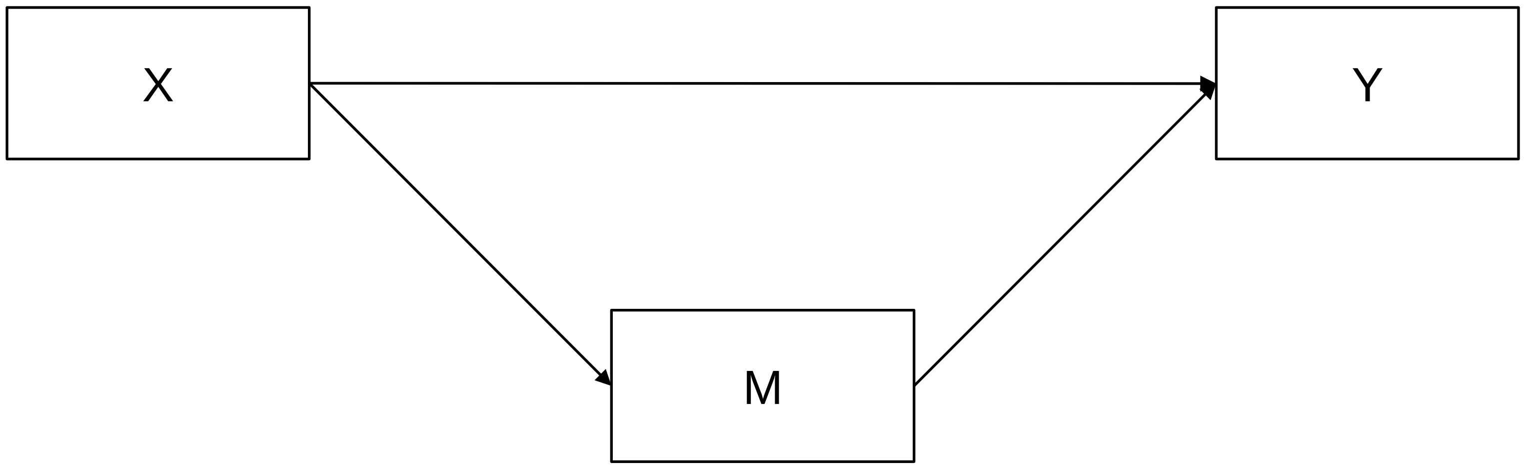
Practical exercise 2



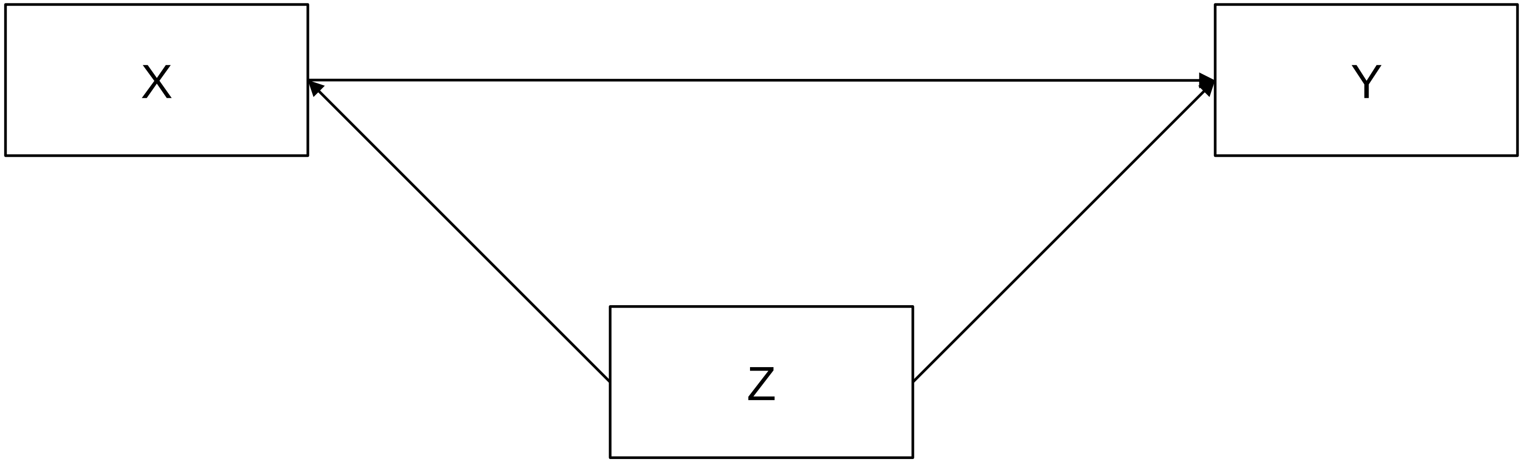
Limitations of the cross-lagged panel model

- Does not explicitly consider passage of time
- Seconds or decades later?
- Effect take time to develop
- Interval too short (effect not happened yet)
- Interval too long (effect faded)

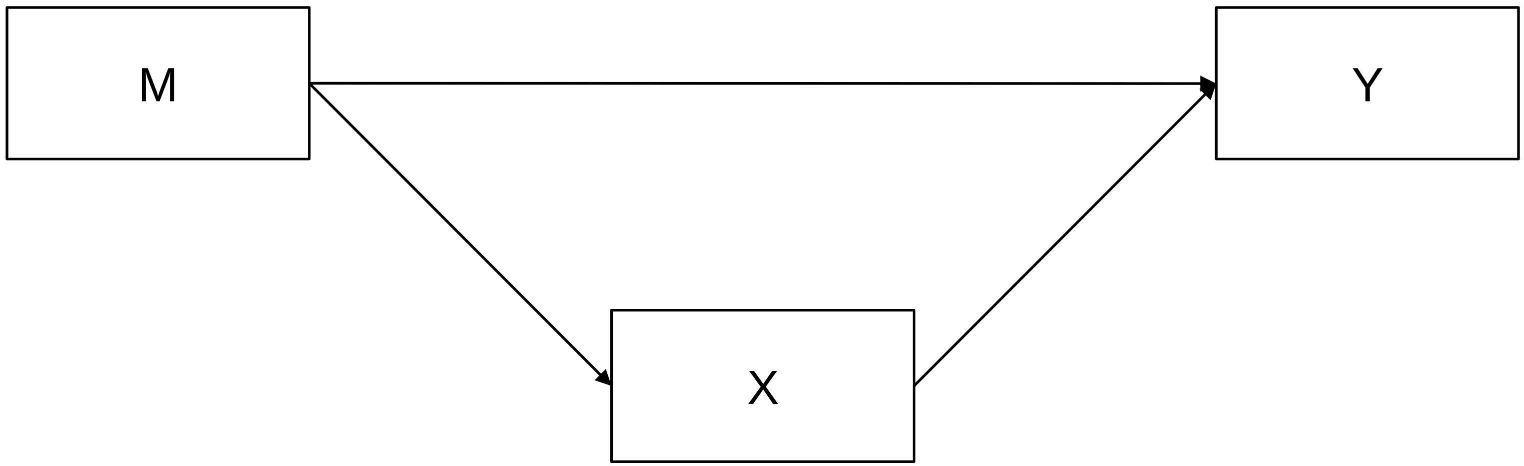
Mediation



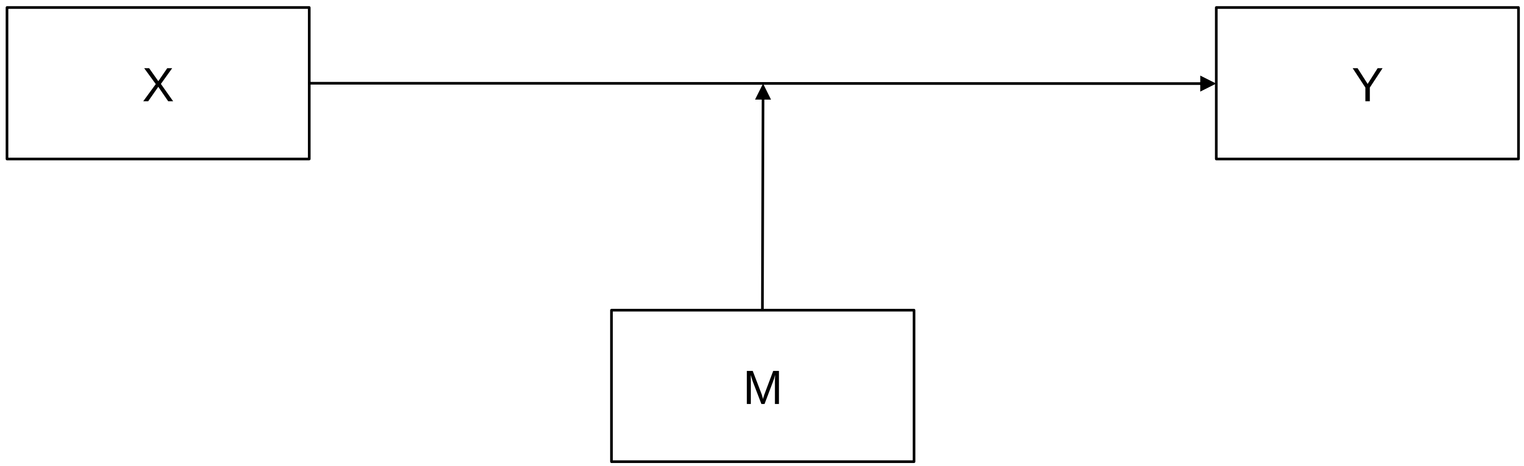
Confounding



Antecedent variable



Moderator

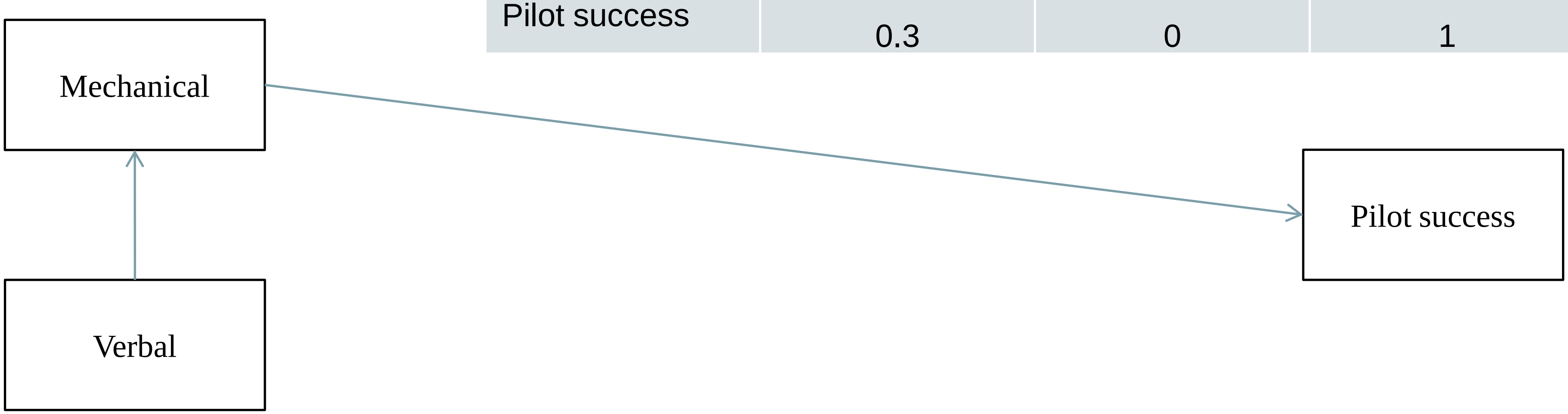


Suppressor effects

- Association between X-Y usually decreases when adding a confounder or mediator
  - If it increases, this could indicate suppression
  - Also known as 'negative confounding'
- If regression coefficient larger than correlation, also indicates suppression
- Also known as 'inconsistent mediation'
  - at least one indirect effect has a different sign than other indirect or direct effects in a model

Suppression

Horst (1941)	Mechanical	Verbal	Pilot success
Mechanical	1		
Verbal	0.5	1	
Pilot success	0.3	0	1



- Verbal associated with mechanical
- Verbal not associated with success
- Mechanical B = 0.4
- Verbal B = -0.2
- Verbal ability is required for mechanical test

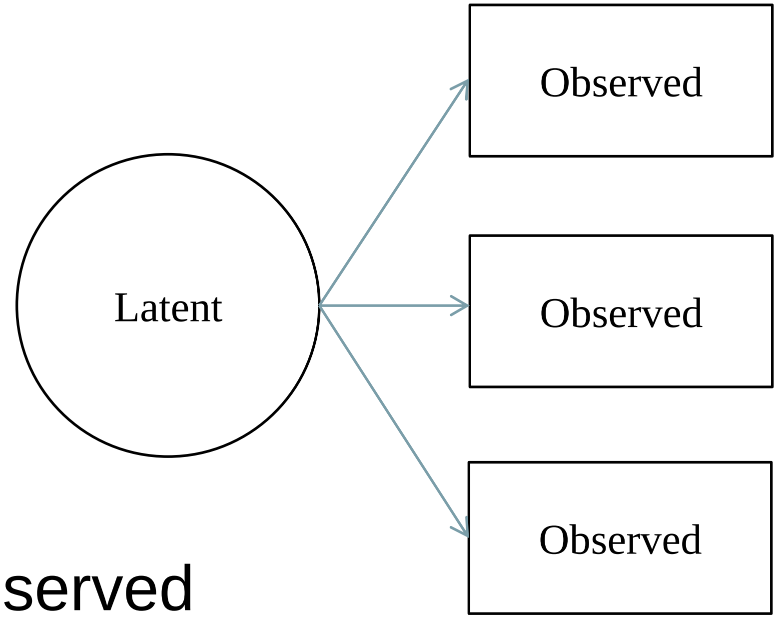
Afternoon session

LATENT VARIABLES

Measurement error

- Measurement error attenuates correlations
  - In X variables, attenuates regression coefficients
  - In Y variables, increases standard errors
- Latent variables are used to address measurement error
  - If known, we can specify what it is
  - If unknown, we can estimate from multiple indicators

Latent variables



- Captures covariation between observed variables
  - Intelligence, personality, SES
- Latent variable is common cause of indicators
- Advantages
  - Reduces measurement error
  - Address collinearity
  - Invoke theoretical constructs

Other names for latent variables

- Hypothetical variables
- Hypothetical constructs
- Factors
- Unobservable variables
- Unmeasured variable influenced by causal indicators
- Phantom variables
- Variables which exist only in the mind of social scientists

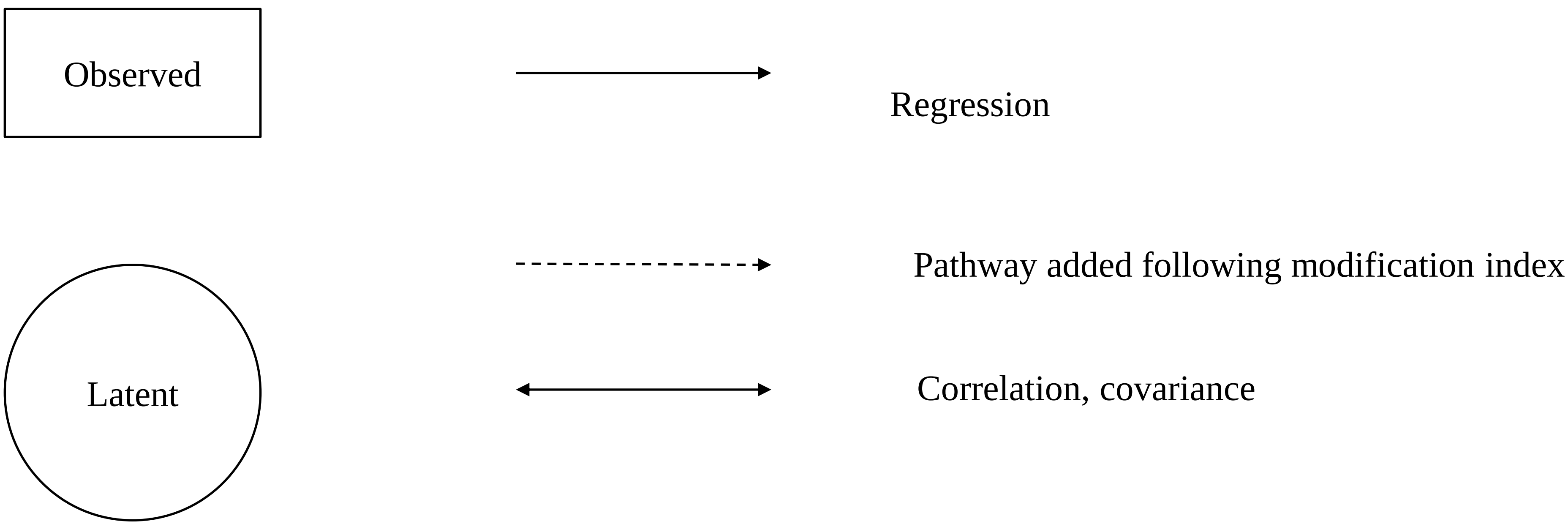
Theoretical status of latent variables

- Formal
  - Syntax: Defined by x1, x2, x3
  - Semantics: 1 unit increase in f1, X unit increase in Y
- Empirical
  - Does the model fit the data?
- Ontological
  - The latent exists independent of measurement (entity realism), observable in the future (e.g. atoms)
  - The latent variable is constructed (constructivist)
  - Operationalist (numerical track, empirical only)

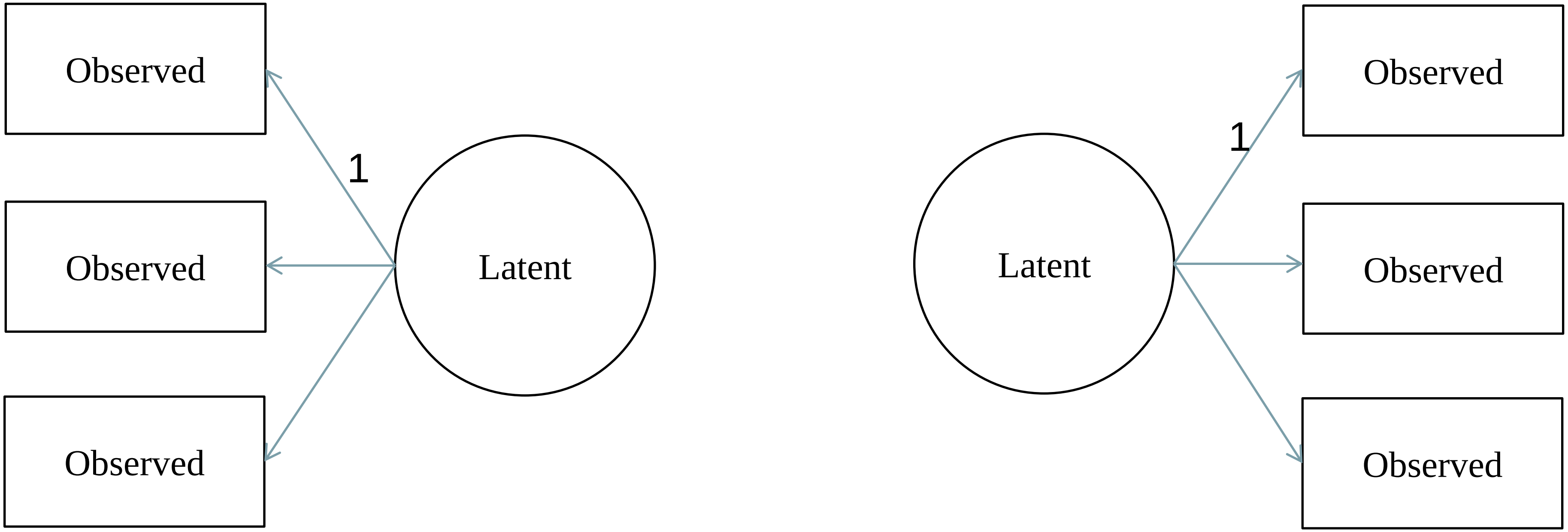
Latent variable units

- There are no units
- Two solutions
  - Fix a path coefficient to 1 (default = first)
  - Fix variance of latent variable to 1
    - Standardizes the latent so that 1 unit = 1 SD or z score

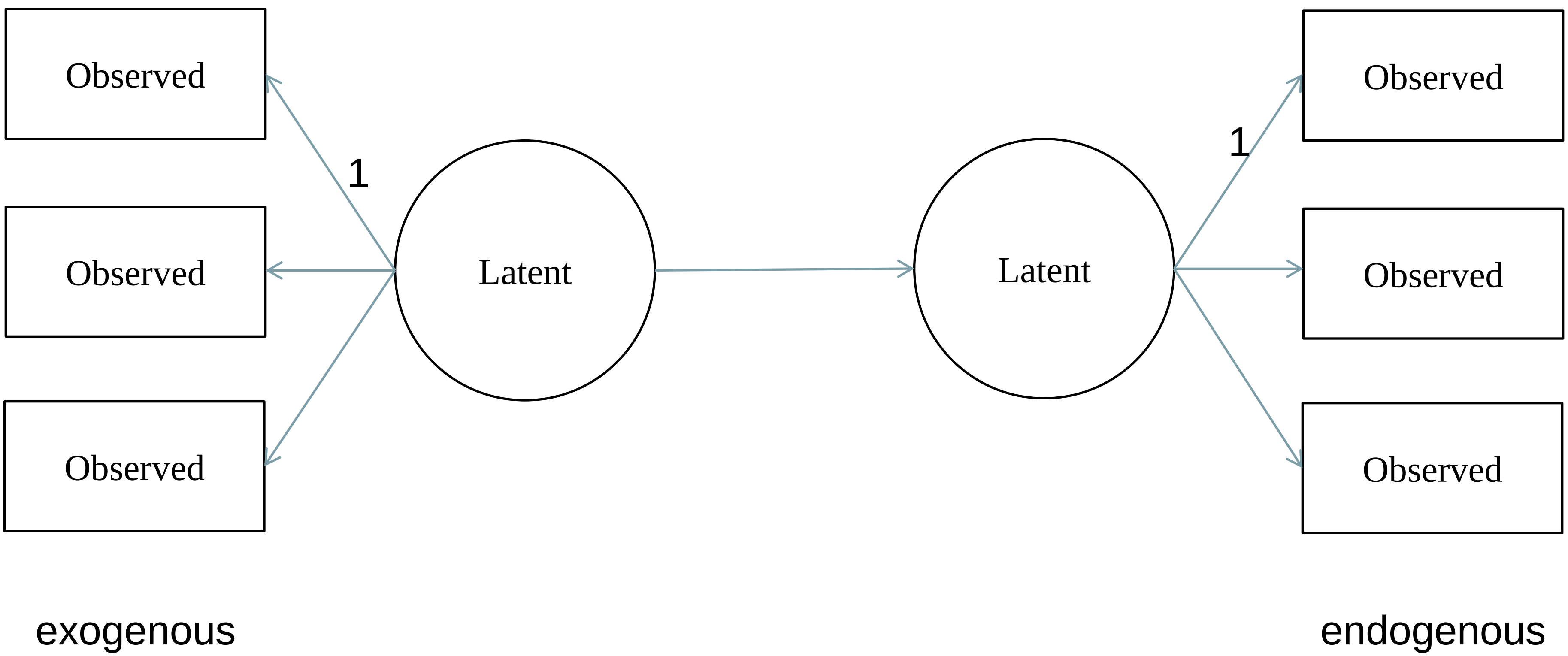
Path diagram notation



Measurement model



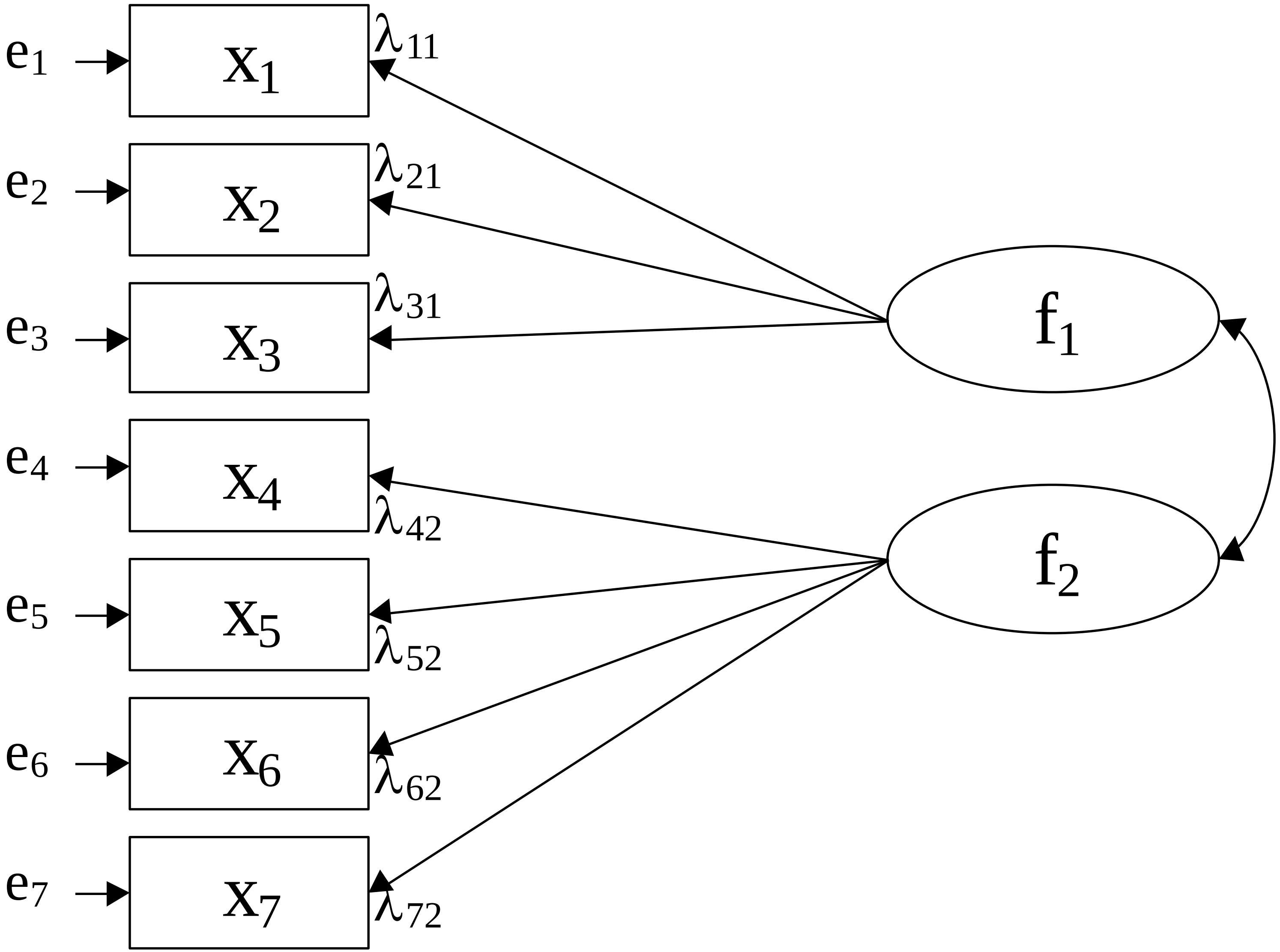
Structural model



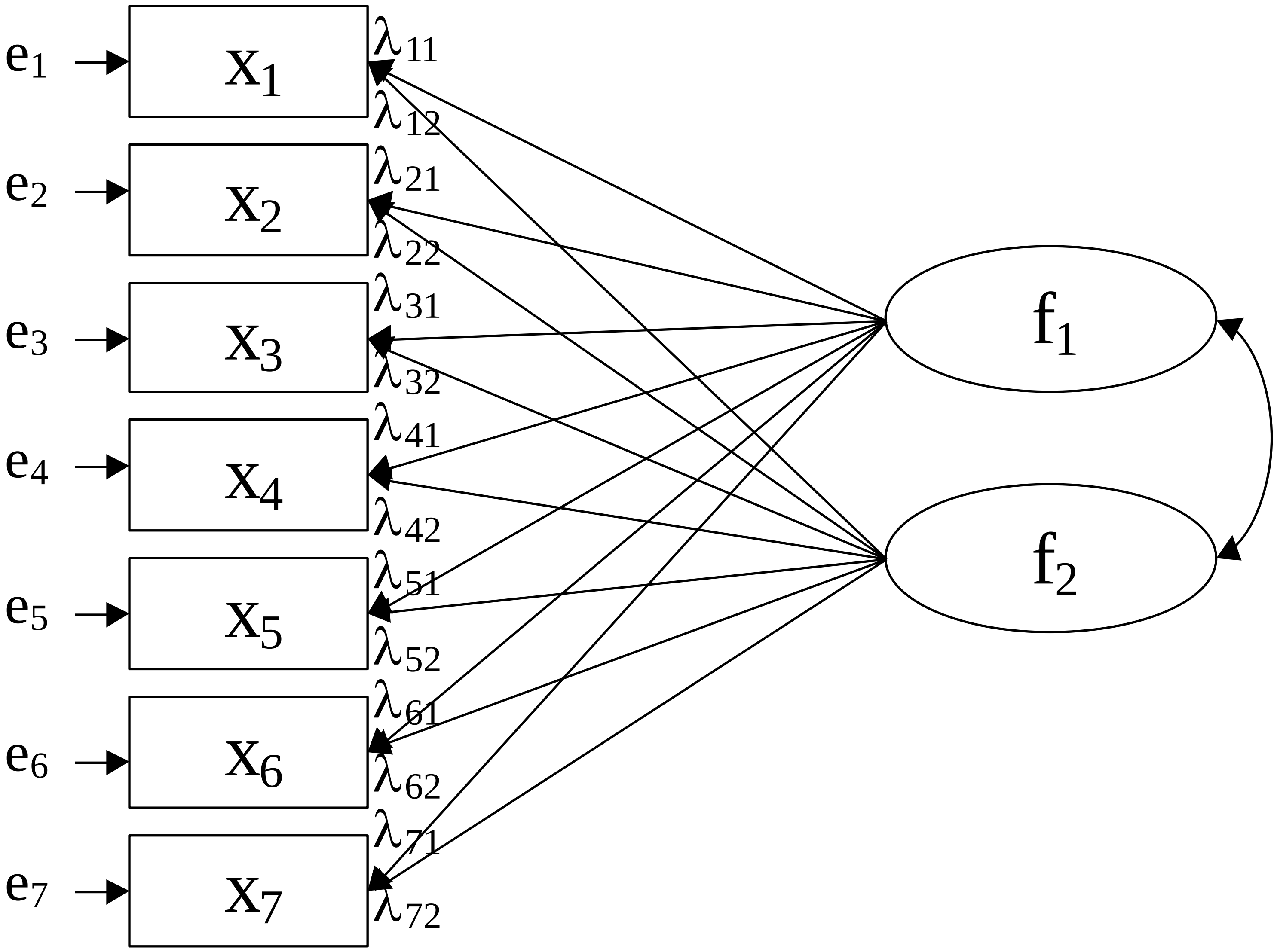
Confirmatory Factor Analysis

- Prior knowledge about factors
- More advanced stage of research
- Factors assumed to have caused correlations
- Specify exact model in advance
- Do the data fit the hypothesized model?
- Theory testing (CFA), not hypothesis generation (EFA)

Confirmatory factor analysis (CFA)



Exploratory factor analysis (EFA)



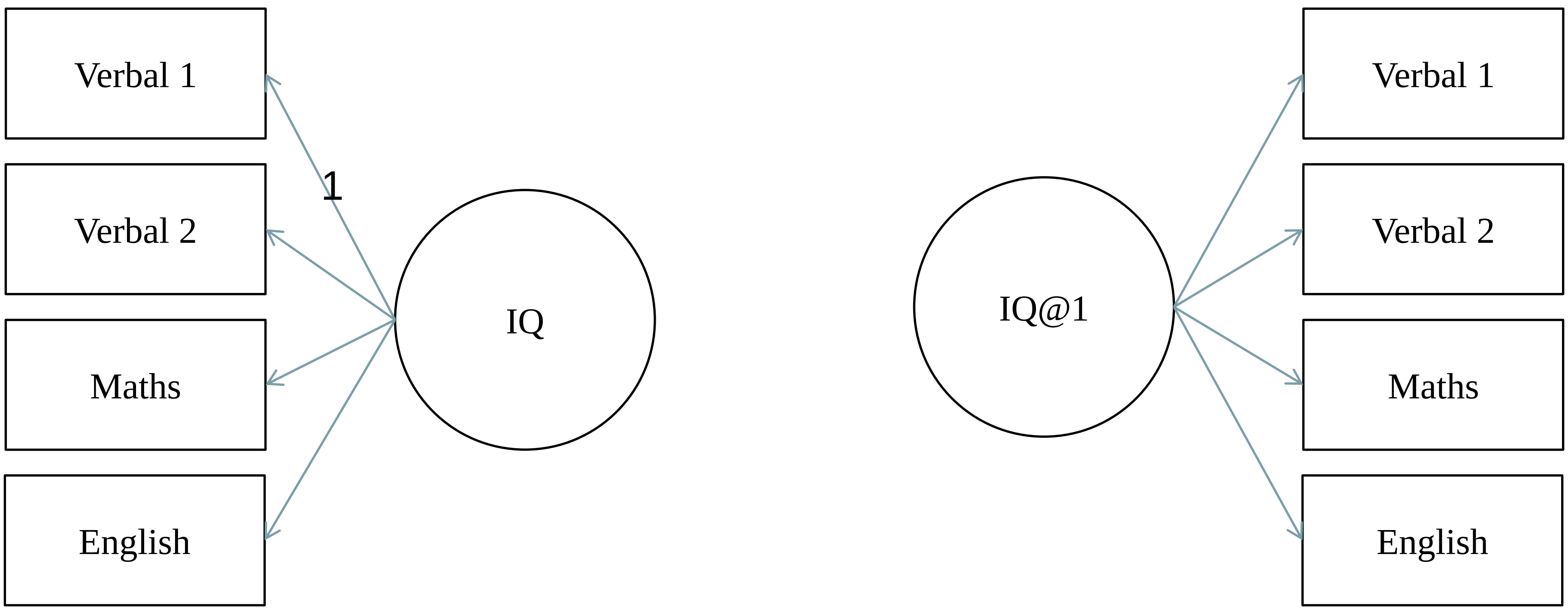
Causal inference

- Factors reflect underlying processes that create variables
  - Implies that factors cause variables
- EFA
  - What underlying processes could have produced the correlations?
  - Useful in theory development
- CFA
  - Are correlations consistent with hypothesized factor structure?
  - Useful in theory testing

Measurement model steps

- Latent variables defined by observed variables
- At least three, preferably more
- Choose method for setting metric
  - MODEL: iq BY verbal1 verbal2 maths english;
  - MODEL: iq BY verbal1* verbal2 maths english; iq@1;
- Model testing using confirmatory factor analysis
- Test each latent variable separately for fit
- Build up to the full model

Intelligence as a latent variable (ACONF)



Mplus defaults for CFA

- Factor loading of first variable after BY is fixed to one
- Factor loadings of other variables are estimated
- Residual variances are estimated
- Residual covariances are fixed to zero
- Variances of factors are estimated
- Covariance between the exogenous factors is estimated

Model fit

```
MODEL FIT INFORMATION

Number of Free Parameters                       12

Loglikelihood

          H0 Value                      -19857.073
          H1 Value                      -19822.425

Information Criteria

          Akaike (AIC)                   39738.146
          Bayesian (BIC)                 39819.082
          Sample-Size Adjusted BIC       39780.949
            (n* = (n + 2) / 24)

Chi-Square Test of Model Fit

          Value                             69.296
          Degrees of Freedom                     2
          P-Value                           0.0000

RMSEA (Root Mean Square Error Of Approximation)

          Estimate                           0.073
          90 Percent C.I.                    0.059  0.088
          Probability RMSEA <= .05           0.004

CFI/TLI

          CFI                                0.997
          TLI                                0.992

Chi-Square Test of Model Fit for the Baseline Model

          Value                          24469.993
          Degrees of Freedom                     6
          P-Value                           0.0000

SRMR (Standardized Root Mean Square Residual)

          Value                              0.005
```

Model results

MODEL RESULTS

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
IQ BY				
VERBAL1	1.000	0.000	999.000	999.000
VERBAL2	1.021	0.007	149.069	0.000
MATHS	0.933	0.009	105.188	0.000
ENGLISH	0.961	0.008	113.417	0.000
Intercepts				
VERBAL1	0.178	0.012	14.598	0.000
VERBAL2	0.178	0.012	14.597	0.000
MATHS	0.141	0.013	11.236	0.000
ENGLISH	0.147	0.013	11.773	0.000
Variances				
IQ	0.817	0.017	48.893	0.000
Residual Variances				
VERBAL1	0.116	0.003	35.759	0.000
VERBAL2	0.081	0.003	28.043	0.000
MATHS	0.226	0.005	44.573	0.000
ENGLISH	0.185	0.004	42.828	0.000

STANDARDIZED MODEL RESULTS

STDYX Standardization

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
IQ BY				
VERBAL1	0.936	0.002	441.251	0.000
VERBAL2	0.956	0.002	536.532	0.000
MATHS	0.871	0.004	243.046	0.000
ENGLISH	0.896	0.003	298.185	0.000

Modification indices

- english WITH verbal2;

```
MODEL MODIFICATION INDICES

NOTE:  Modification indices for direct effects of observed dependent variables
regressed on covariates may not be included.  To include these, request
MODINDICES (ALL).

Minimum M.I. value for printing the modification index    10.000

                            M.I.     E.P.C.  Std E.P.C.  StdYX E.P.C.

WITH Statements

VERBAL2  WITH VERBAL1      24.109    -0.020     -0.020       -0.204
MATHS    WITH VERBAL1      69.938     0.029      0.029        0.176
MATHS    WITH VERBAL2      14.253    -0.013     -0.013       -0.096
ENGLISH  WITH VERBAL1      14.258    -0.013     -0.013       -0.089
ENGLISH  WITH VERBAL2      69.963     0.030      0.030        0.244
ENGLISH  WITH MATHS        24.115    -0.017     -0.017       -0.085
```

Goodness of fit indices

- χ^2 (not recommended N>200)
- χ^2/df ratio (no agreed standard)
- TLI (.90 good, >.95 better)
- CFI (.90 good, >.95 better)
- RMSEA (<.05 ‘close’)
- SRMR (<.10 good, <.06 better)
- Use with caution
  - SEM can disprove a model
  - It cannot prove a model

Sample Size

- Ratio 20 to 1
- Ratio 5 to 1
- 200 minimum
- Fewer if no latent variables
- Fewer with larger correlations
- Fewer for simpler models
- Power analysis

Comparing fit of nested models

- 2 times difference in LL values for two models
- LR = 2(LL2-LL1)
- df = number of parameters constrained (removed from the model)
- Statistic is distributed as chi-square

Saving factor scores

```
SAVEDATA INFORMATION

  Order and format of variables

    VERBAL1        F10.3
    VERBAL2        F10.3
    MATHS          F10.3
    ENGLISH        F10.3
    IQ             F10.3
    IQ_SE          F10.3

  Save file
    fscores.dat

  Save file format
    6F10.3

  Save file record length    5000


     Beginning Time:  14:32:35
        Ending Time:  14:32:39
       Elapsed Time:  00:00:04
```

- Descriptive
- Treat as observed in other models
- Rank people on factor
  - Percentiles
- Proxy for latent variable
- Caution – depends on fit/quality of model
- SAVE: FILE IS fscores.dat; SAVE ARE FSCORES;

Structural equation modelling steps

- Model fit=S-Σ
  - S = actual data, Σ = implied covariance matrix
- Maximum likelihood estimation
  - Given data and model, what parameter values make the observed data most likely?
- Model modification
  - Lagrange Multiplier tests
  - Wald tests (‘model trimming’)
- Regression coefficients
- Indirect effects

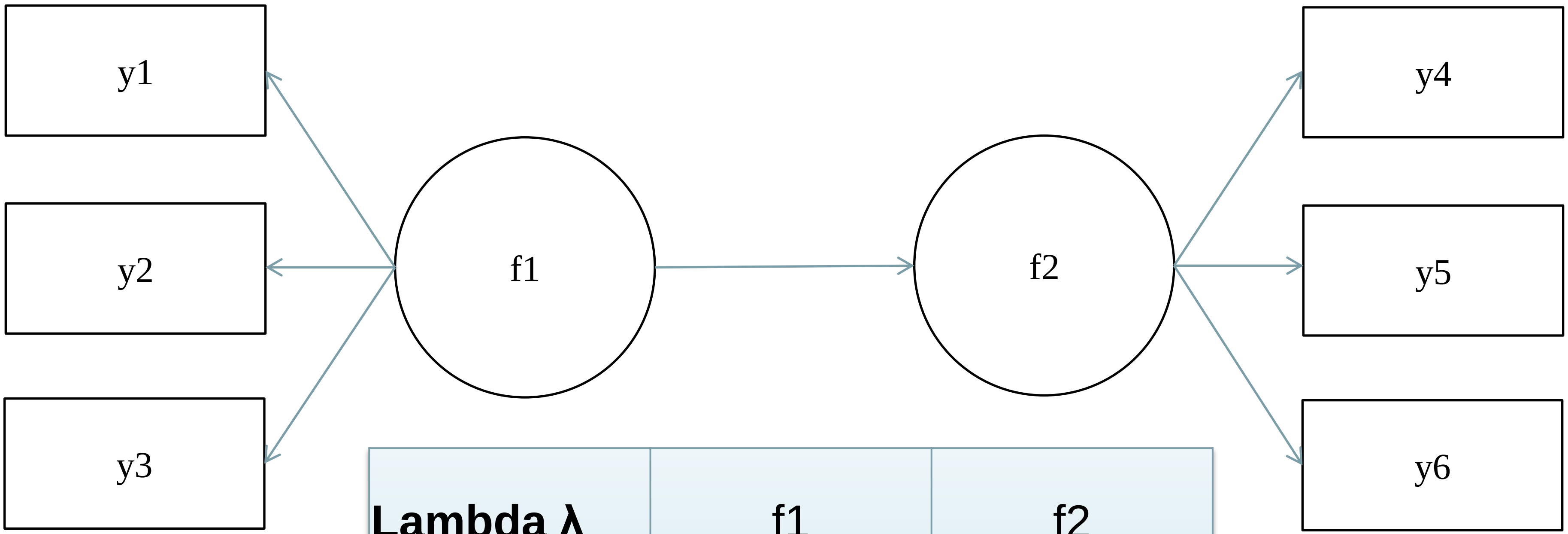
Identification

- Number of knowns = m(m+1)/2
  - m = manifest (measured) variables
- Parameters
  - Path coefficients, variances, covariances
- Identified if moments >=parameters
- Mplus gives a number to each parameter in the matrices
  - Available by asking for OUTPUT: TECH1;

Notation for matrices

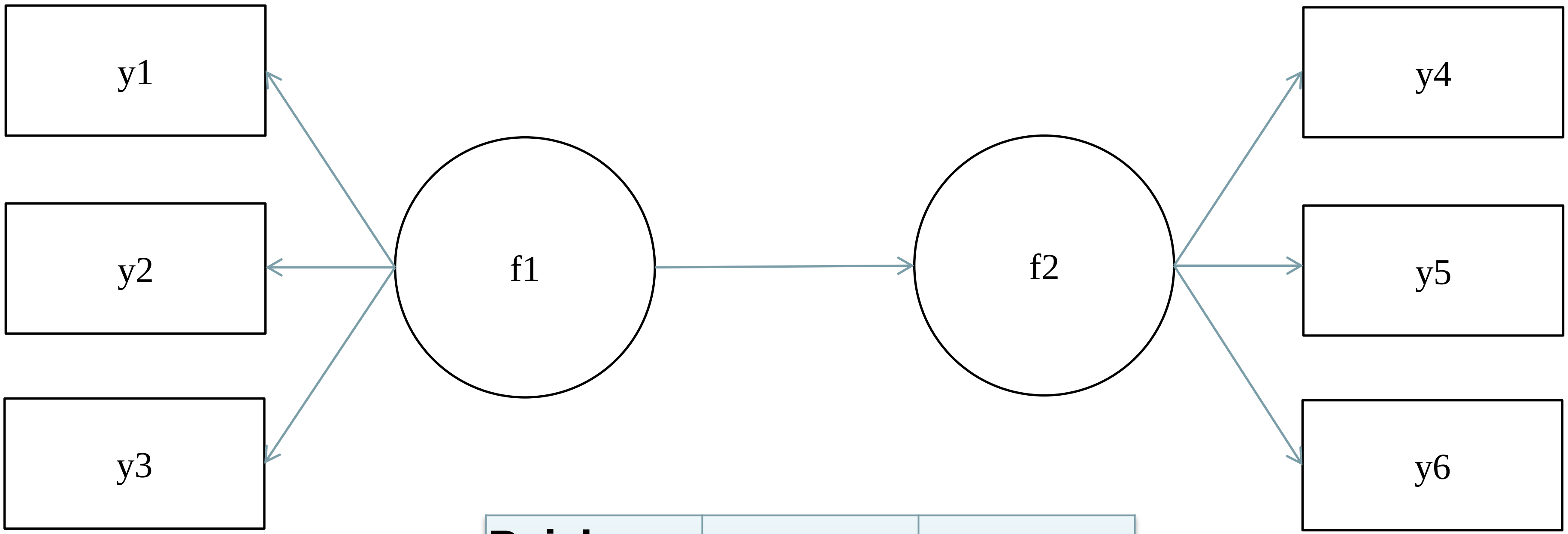
Symbol	English	
λ	Lambda	Loadings for endogenous variables
ϕ	Psi	Variances and covariances for exogenous variables
β	Beta	Causal path
θ	Theta	Measurement errors for endogenous variables

Parameters: Loadings



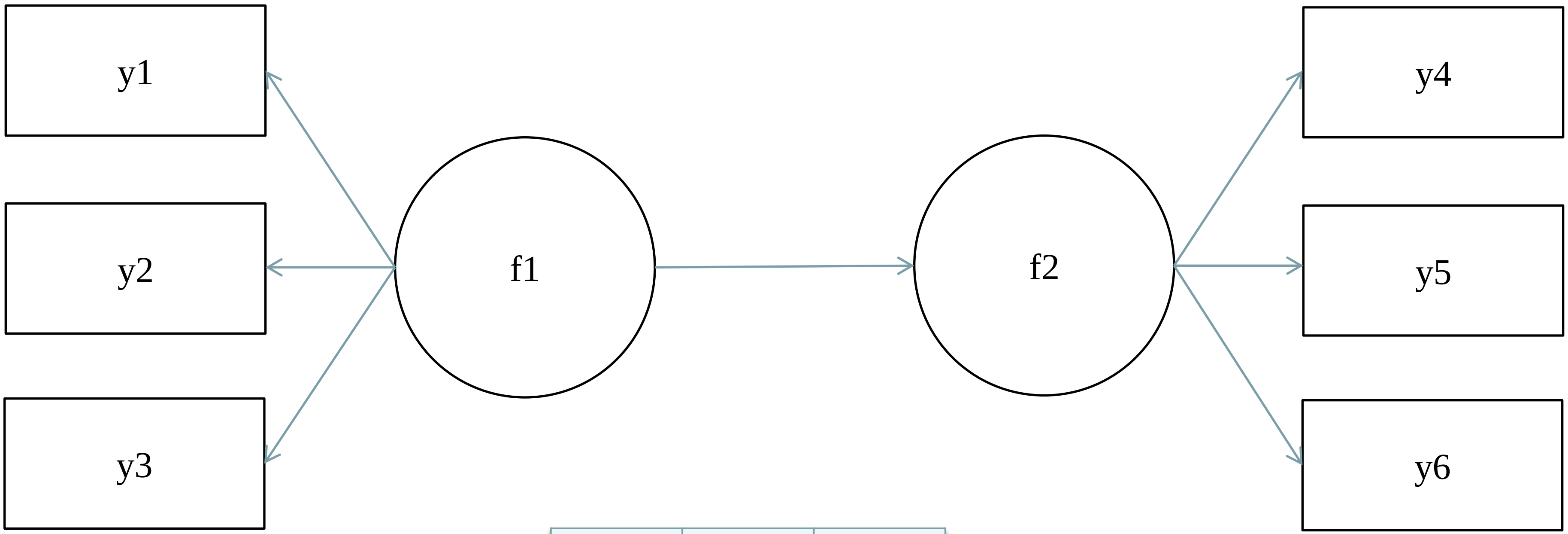
Lambda λ	f1	f2
y1	0	0
y2	7	0
y3	8	0
y4	0	0
y5	0	9
y6	0	10

Parameters: Variances and covariances



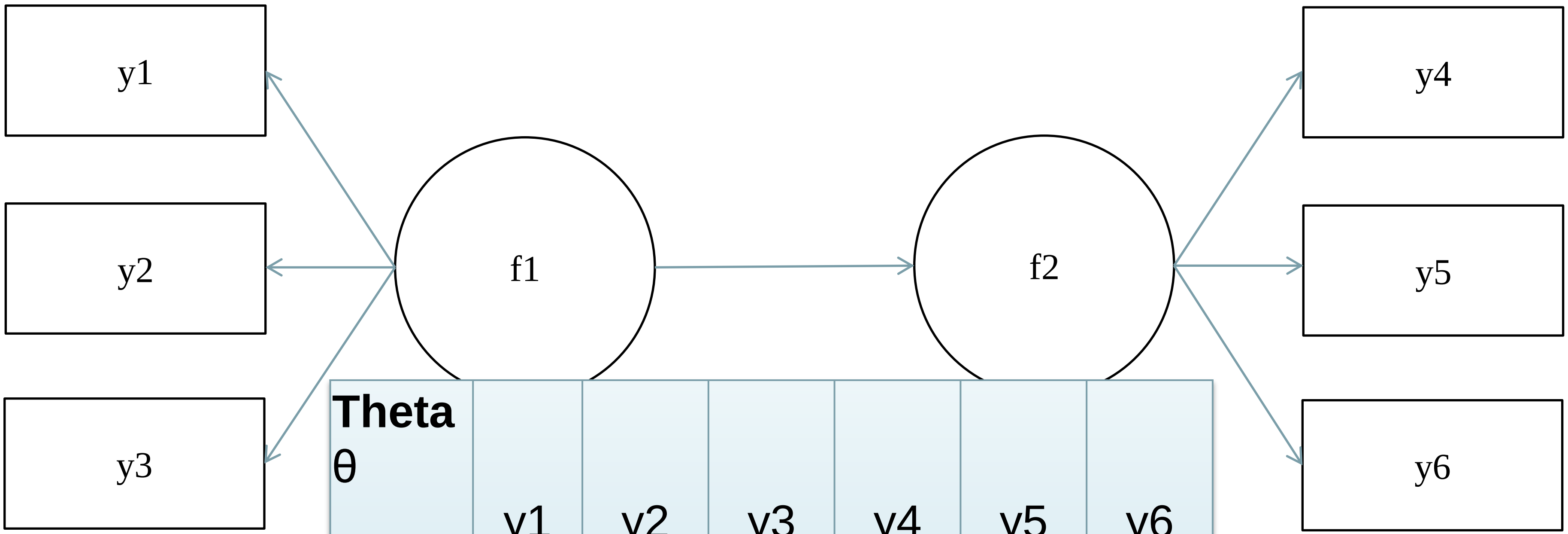
Psi ϕ	f1	f2
f1	18	
f2	0	19

Parameters: Causal paths (regressions)



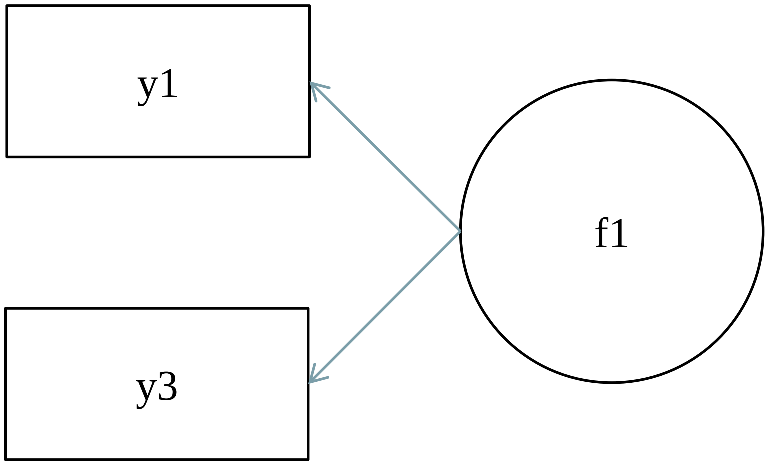
Beta β	f1	f2
f1	0	0
f2	17	0

Parameters: Measurement errors



Theta θ	y1	y2	y3	y4	y5	y6
y1	11					
y2	0	12				
y3	0	0	13			
y4	0	0	0	14		
y5	0	0	0	0	15	
y6	0	0	0	0	0	16

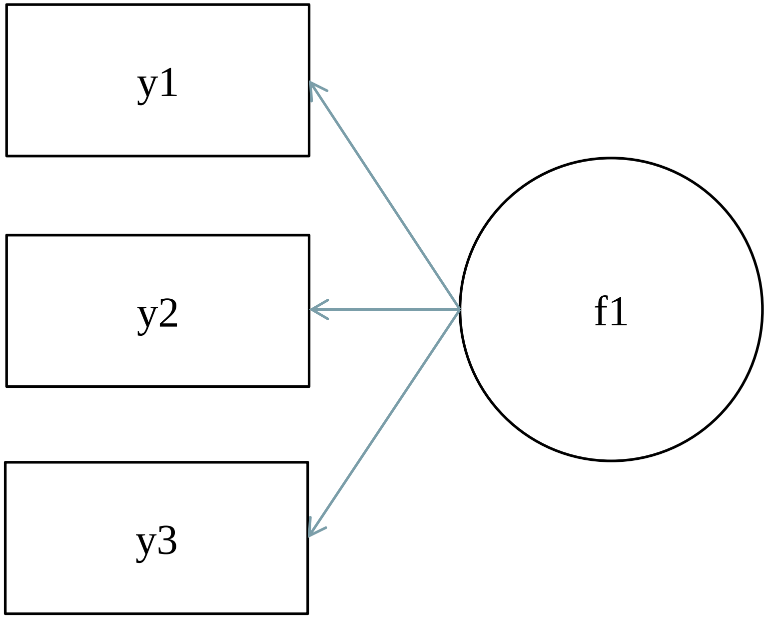
Not identified



- This model has 4 parameters
- 2(2+1)/2 = 3 knowns

#	Matrix	
1	Lambda	Loadings for endogenous variables
1	Psi	Variances and covariances for endogenous variables
0	Beta	Causal paths
2	Theta	Measurement errors for endogenous variables

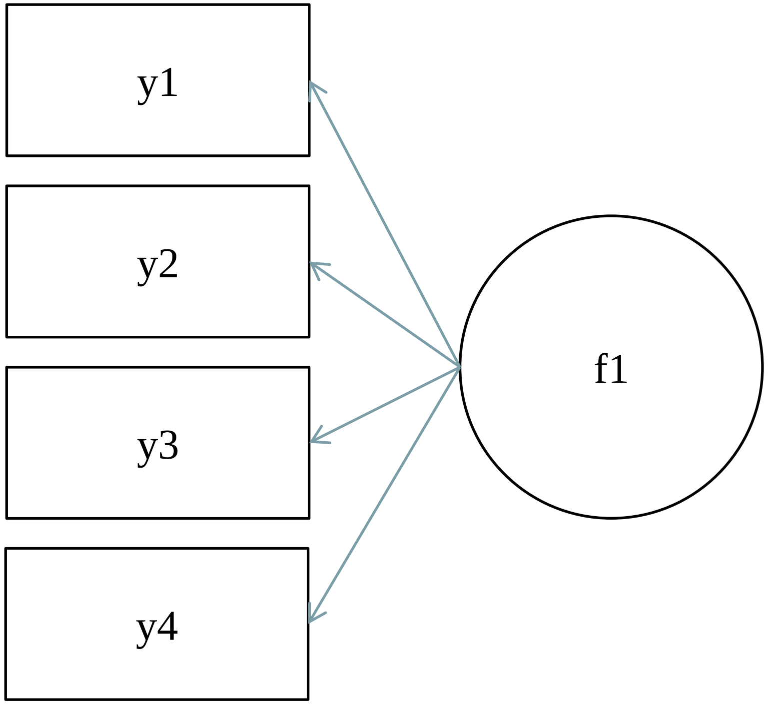
Just identified



- This model has 6 parameters
- 3(3+1)/2 = 6 knowns
- Fit cannot be tested

#	Matrix	
1	Lambda	Loadings for endogenous variables
1	Psi	Variances and covariances for endogenous variables
0	Beta	Causal paths
2	Theta	Measurement errors for endogenous variables

Over identified



- This model has 8 parameters
- 4(4+1)/2 = 10 knowns
- Fit can be tested

#	Matrix	
1	Lambda	Loadings for endogenous variables
1	Psi	Variances and covariances for endogenous variables
0	Beta	Causal paths
2	Theta	Measurement errors for endogenous variables

Model modification

- Parsimony
  - Remove non-significant pathways
  - Starting with the lowest t value
  - MODEL TEST: p1=1; !provides Wald test
- Better fit
  - Add additional pathways
  - MODINDICES provide Lagrange Multiplier Tests
- Describe your modifications transparently

Problems with model modification

- Capitalize on chance
- Rarely reported as happened
- Using p values to make decisions unwise
- Hypothesized model has now changed
- Equivalently well-fitting but different models

Lothian Birth Cohort Study (1936)

- Do childhood risk factors influence cardiovascular disease risk (inflammation) in old age?
  - Father's social class
  - Intelligence at age 11

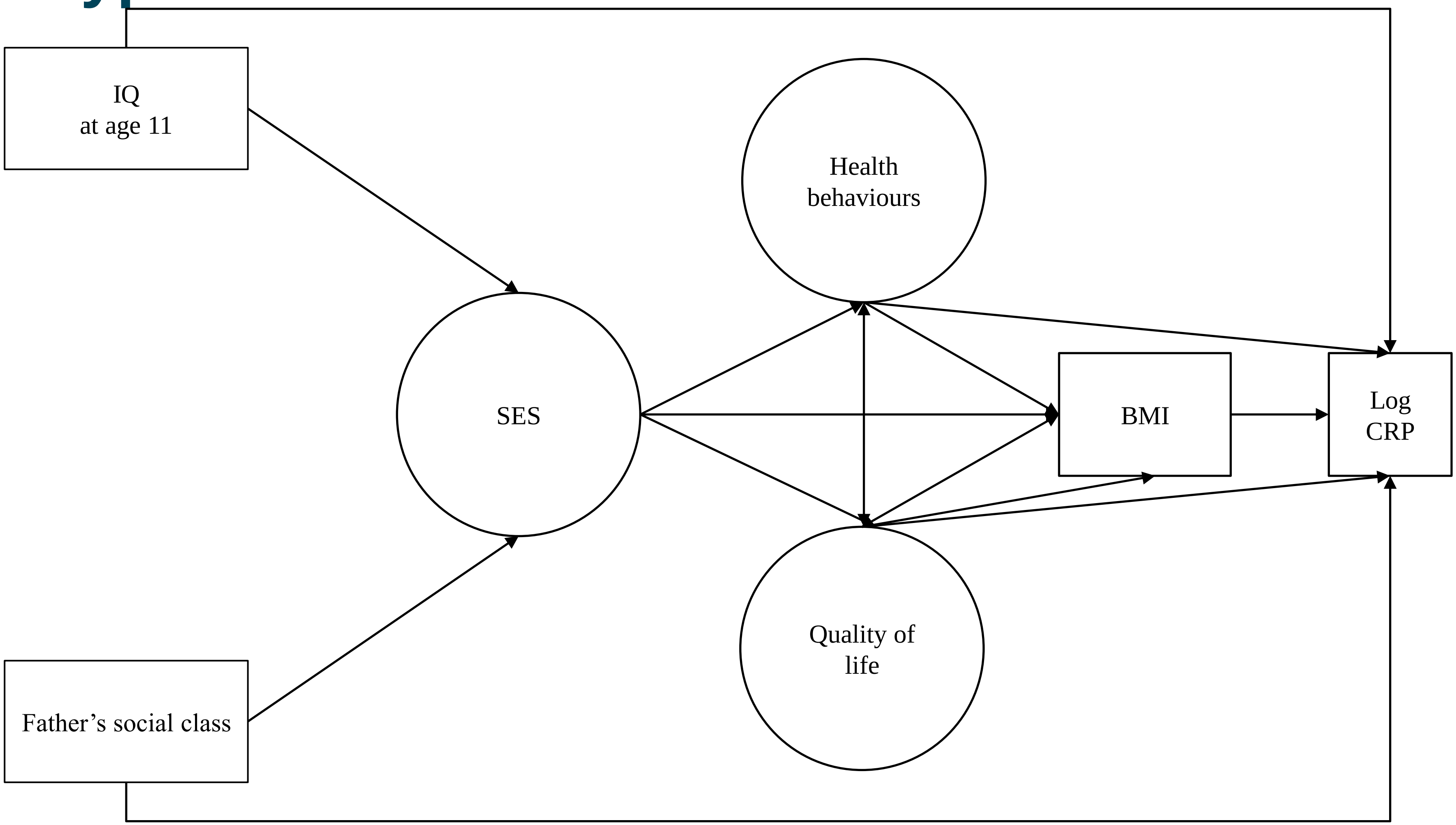
Participants

- Lothian Birth Cohort (1936)
- Survivors from Scottish Mental Survey 1947
- Located and recruited 2004-2007
- N=1091 (548 men), age 68 to 71

C-reactive protein

- Distal causes
  - SES in childhood (father's social class)
  - Intelligence at age 11
- Proximal causes
  - Health behaviours, quality of life, own SES
  - Pathophysiological causes
  - Body mass index
- Own SES

Hypothesized model

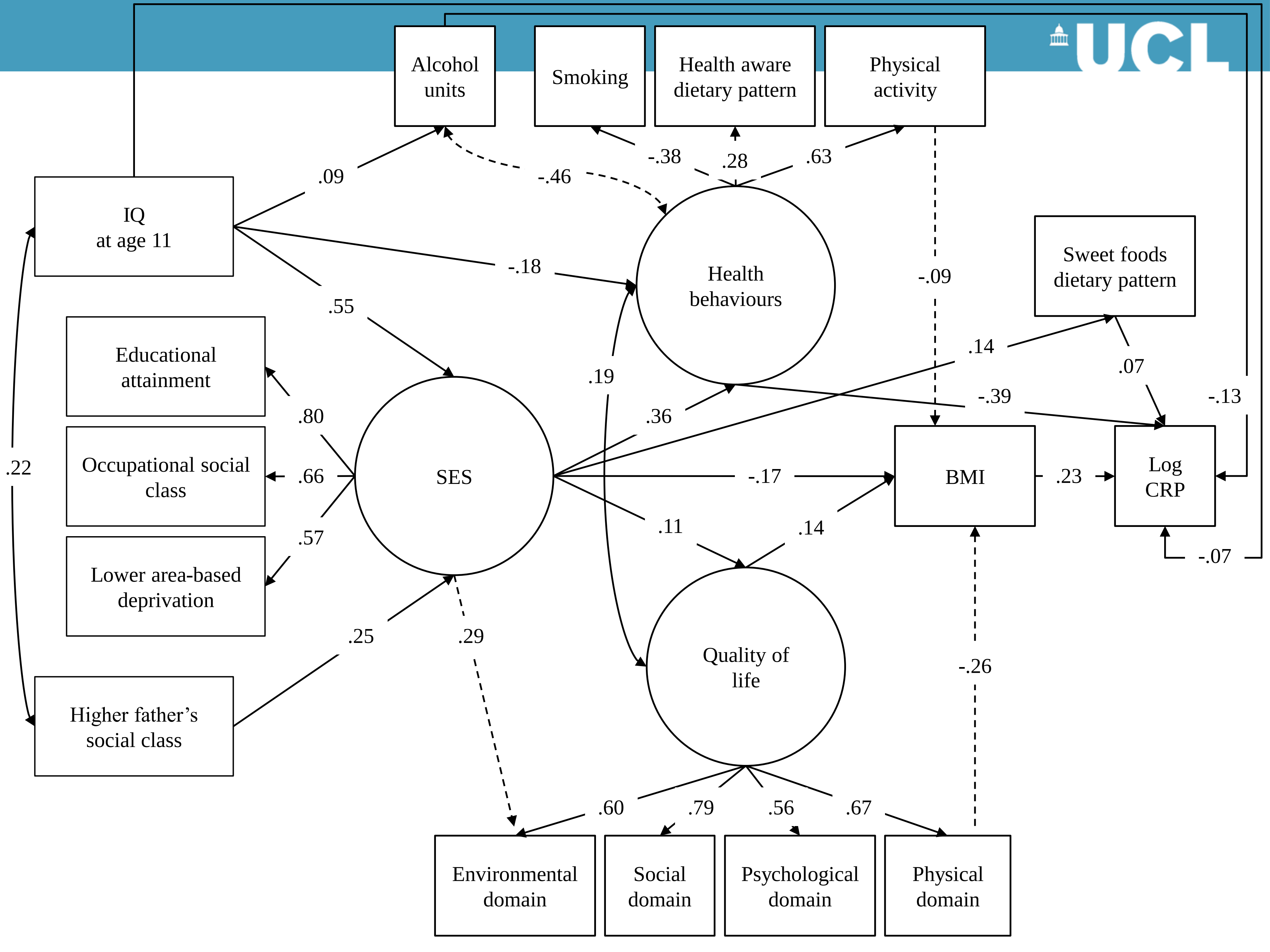


Mplus input file, new additions

- DEFINE: lncrprot1=ln(crprot1); units=unitwk1/10;
- MODEL:
- ses BY highered* higherclass lowerdep WHOQOL4; ses@1; !WHOQOL4 added
- hb BY smokcat1* phyactiv f2 units; hb@1;
- who BY WHOQOL1* WHOQOL2-WHOQOL4; who@1; WHOQOL3 WITH WHOQOL2;

Indirect pathways

- MODEL INDIRECT:
- lncrprot1 IND bmi1 ses AGE11IQ;
- lncrprot1 IND hb ses AGE11IQ;
- lncrprot1 IND hb AGE11IQ;
- lncrprot1 IND BMI1 who;
- lncrprot1 IND f4 ses AGE11IQ;
- lncrprot1 IND bmi1 ses hfclass;
- lncrprot1 IND hb ses hfclass;
- lncrprot1 IND hb hfclass;
- lncrprot1 IND BMI1 who;
- lncrprot1 IND f4 ses hfclass;



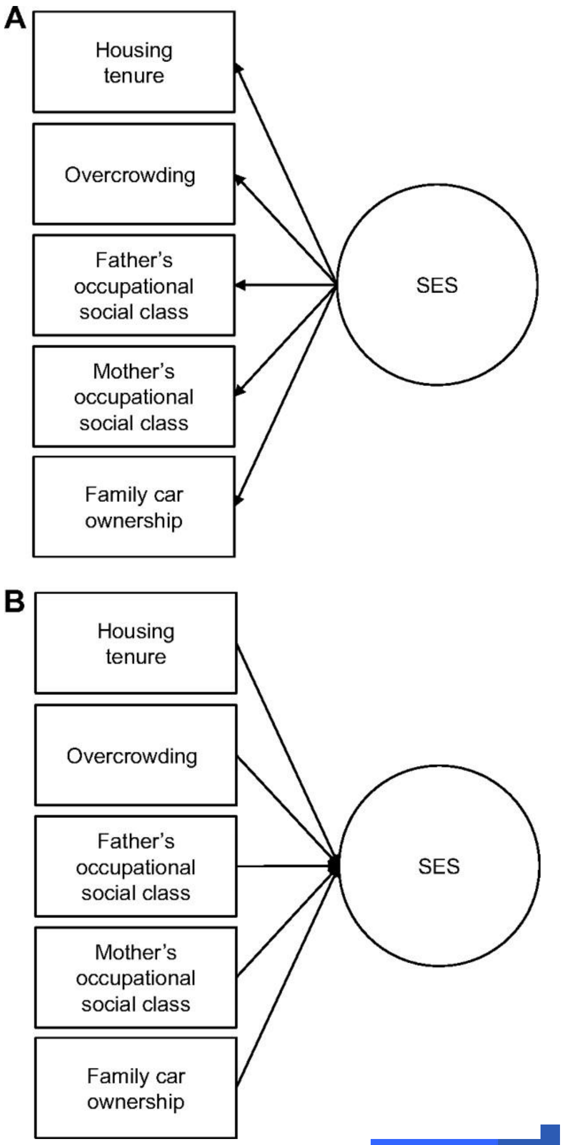
Alcohol units
Smoking
Health aware dietary pattern
Physical activity
IQ at age 11
.09
-.46
-.38
.28
.63
-.18
Health behaviours
-.09
Sweet foods dietary pattern
.55
Educational attainment
.80
.19
.14
.07
-.39
-.13
.36
Occupational social class
.66
SES
-.17
BMI
.23
Log CRP
.22
.57
.11
.14
-.07
Lower area-based deprivation
.25
.29
Quality of life
-.26
Higher father's social class
.60
.79
.56
.67
Environmental domain
Social domain
Psychological domain
Physical domain

PRACTICAL SESSION

Appendices

MODEL EXTENSIONS

Formative indicators

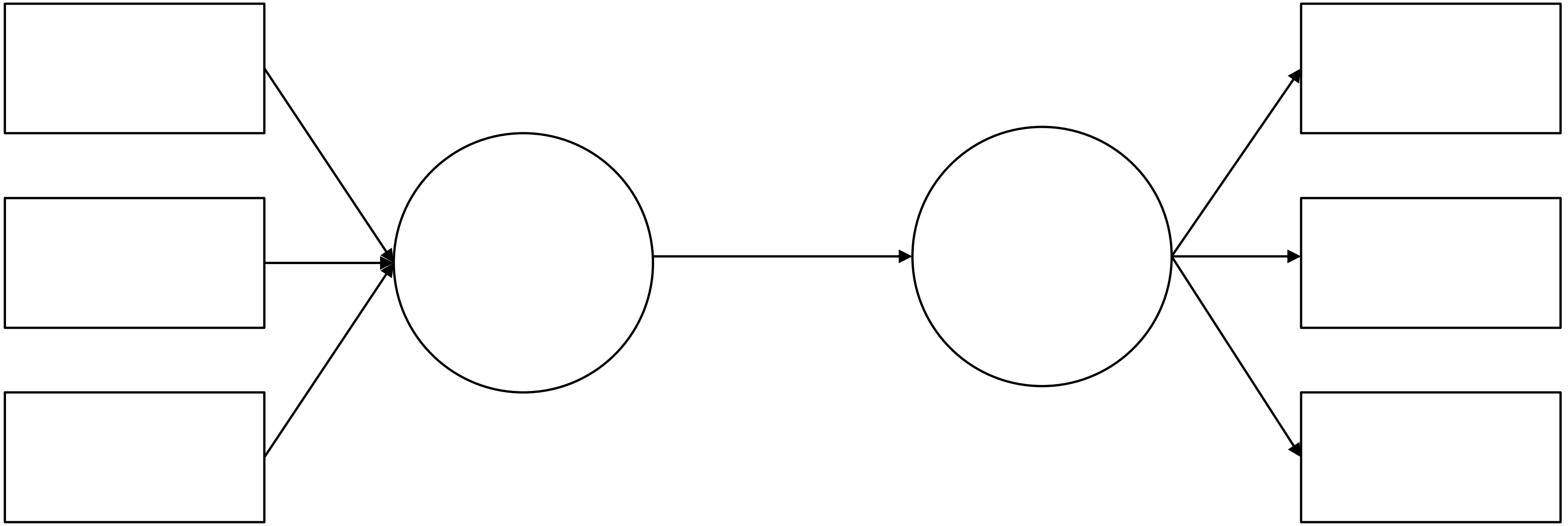


- Latent variables with reflective indicators
  - Construct causes the variables
- Latent variables with formative indicators
  - Indicators cause the construct
- SES a good example
  - Which model is more believable?

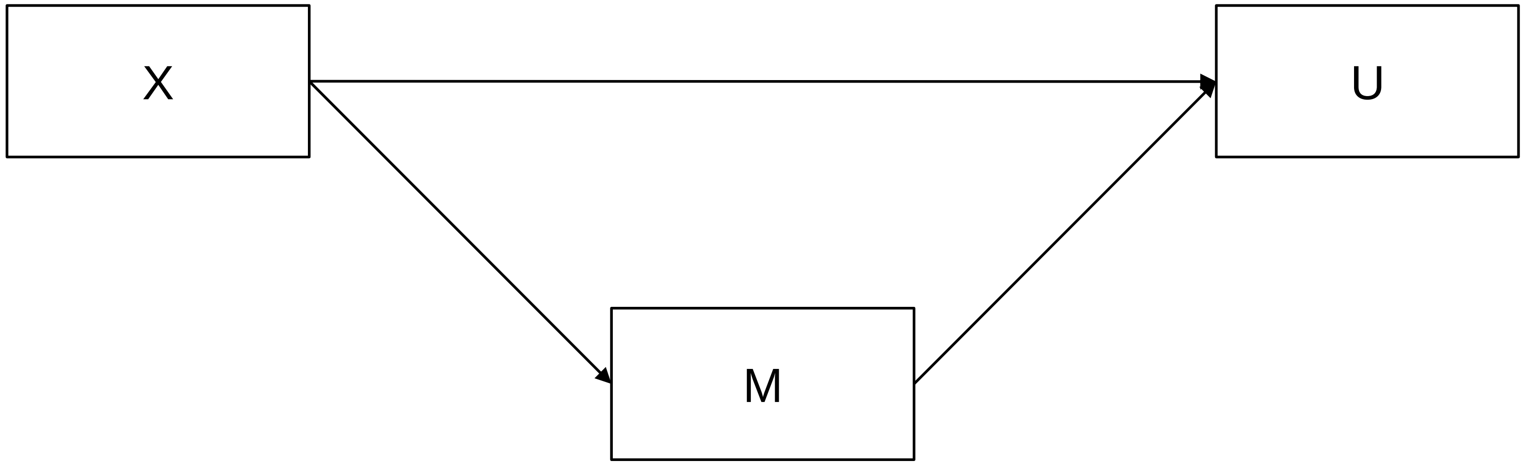
Hagger-Johnson G et al. J Epidemiol Community Health
doi:10.1136/jech.2010.127696

Formative indicators

- MODEL:
  f2 BY verbal1 verbal2 maths english;
  ses BY f2*;
  ses@0;
  ses ON occupation@1 education income;

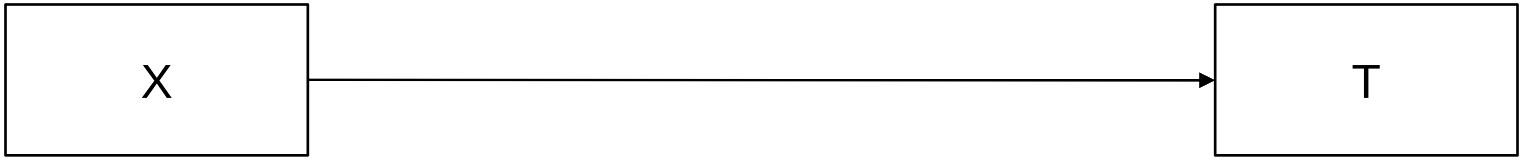


Categorical outcomes



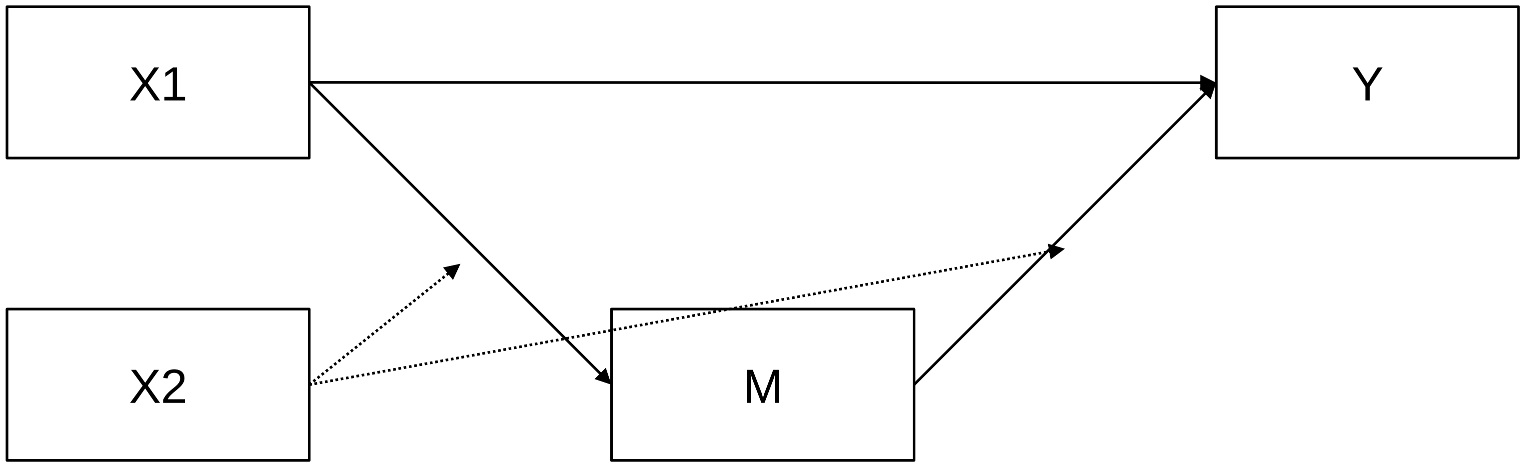
- CATEGORICAL ARE smoker84;

Time to event data (survival analysis)



- SURVIVAL = t_all;
- TIMECENSORED = eventall (1 = NOT 0 = RIGHT);
- ANALYSIS: BASEHAZARD = OFF;
- TYPE=RANDOM;
- MODEL:
- t_all ON agyrs sex smoker84 n84;

Moderated mediation



Example of suppression

- Simple regression shows a positive association between *BP* and birth weight: the regression coefficient for birth weight is 1.861 mmHg/Kg (95% CI: 0.770, 2.953).
- Simple regression also reveals a positive association between *BP* and current weight: the regression coefficient for current weight is 0.382 (95% CI = 0.341, 0.423) mmHg/Kg.
- *BP* is regressed on birth weight and current weight simultaneously and the partial regression coefficients for birth weight and current weight are -3.708 (95% CI = -4.794, -2.622) and 0.465 (95% CI = 0.418, 0.512) mmHg/Kg respectively, and both are highly statistically significant
- Adjusting for a mediator? birth weight → BP

Nine scenarios

		Population value of direct effect		
		0	Positive	Negative
Population value of third variable effect	0	*	*	*
	Positive	Fully mediated or confounded *	Partly mediated or confounded *	Suppression
	Negative	Fully mediated or confounded *	Suppression *	Partly mediated or confounded *

*Possible by chance
Suppression is also called ‘inconsistent mediation’ or ‘negative confounding’.
Mediation or confounding may also be called mediation or ‘positive confounding’.

Other terms used

Zhao et al. (2010) terms	
Complementary mediation	Mediated effect ab and direct effect c exist and in same direction
Competitive mediation	Mediated effect ab and direct effect c exist and in opposite directions
Indirect-only mediation	Mediated effect ab exists No direct effect c
Direct-only non-mediation	Direct effect c exists, no significant ab
No-effect non-mediation	Neither direct nor indirect exists

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