

# Trajectory modeling of developmental theories of depression

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**17<sup>th</sup> May 2017**

**RAINE Study Biostatistics Special Interest Group**

# What do we know about the course of depression?

- There is a small and clinically significant subgroup with child-onset depression ([Birmaher et al., 2004](#))
- **Most** (?) children under 12 years of age have very low levels of depressive symptoms [Toumbourou et al., 2011](#).
- the first clinically significant episode is generally between the ages of 12 and 15 years.
- The incidence of new cases of depression increases markedly around the time of puberty
- maintaining high prevalence across adulthood ([Kim-Cohen et al., 2003](#)) and impacts on females at a ratio of at least 2:1 (in western samples)

# So why trajectories?...

- child psychopathology research typically assumes a variable-oriented model that suggests that development is in every dimension a homogenous process.
- assumes development unfolds at a universal rate and all individuals develop in the same way over time.
- In contrast, Person-centred models take the individual rather than the measured variable as the unit of analysis (ideographic approach to psychological research) (Bergman, 1997; von Eye 2003)
- As applied to psychopathology, discerning common patterns of symptom severity (trajectories) over time empirically is more subtle than determining group membership simply based on clinical cut points or diagnostic measures (and assuming disorder/'illness' as an absolute reference).
- Trajectories test if there is meaningful **continuity and patterns** in symptom development (Rutter, Kim-Cohen, Maughan, 2006)

von Eye A, Bergman LR. Research strategies in developmental psychopathology: Dimensional identity and the person-oriented approach. *Development and psychopathology*. 2003;15(03):553-580.

Bergman LR, Magnusson D. A person-oriented approach in research on developmental psychopathology. *Development and psychopathology*. 1997;9(2):291-319.

Muthén, B., & Muthén, L. K. (2000). Integrating person-centered and variable-centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research*, 24, 882–891.

*Development and Psychopathology* 22 (2010), 239–254  
© Cambridge University Press, 2010  
doi:10.1017/S0954579410000015

*Special Section*  
*Match Between Person-Oriented Methods and Theory*

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#### KEYNOTE ARTICLE

Matching method with theory in person-oriented developmental psychopathology research

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# What are trajectories.

- Definition:
  - Mixture models are measurement models that use observed variables as indicators of one or more nominal latent variables (i.e. categorical variables).
  - Attempt to identify subsets or "classes" of observations within the observed data.
  - The latent variable (classes) is categorical, but the indicators may be either categorical or continuous.
- Main data analytic approaches used:
  - latent class analysis (Mplus)
  - Growth mixture models (GMM) (Mplus)
  - semi-parametric group based methods (SAS)
- Relatively new application to depression: Approx 2005 first papers emerged using the above methods to identify child and adolescent depression symptom trajectories

## Example 1:

Latent class analysis of trajectories of depressive symptoms (from Longitudinal Study of Australian Children n=~3500), Lewis and Rowland (in prep)

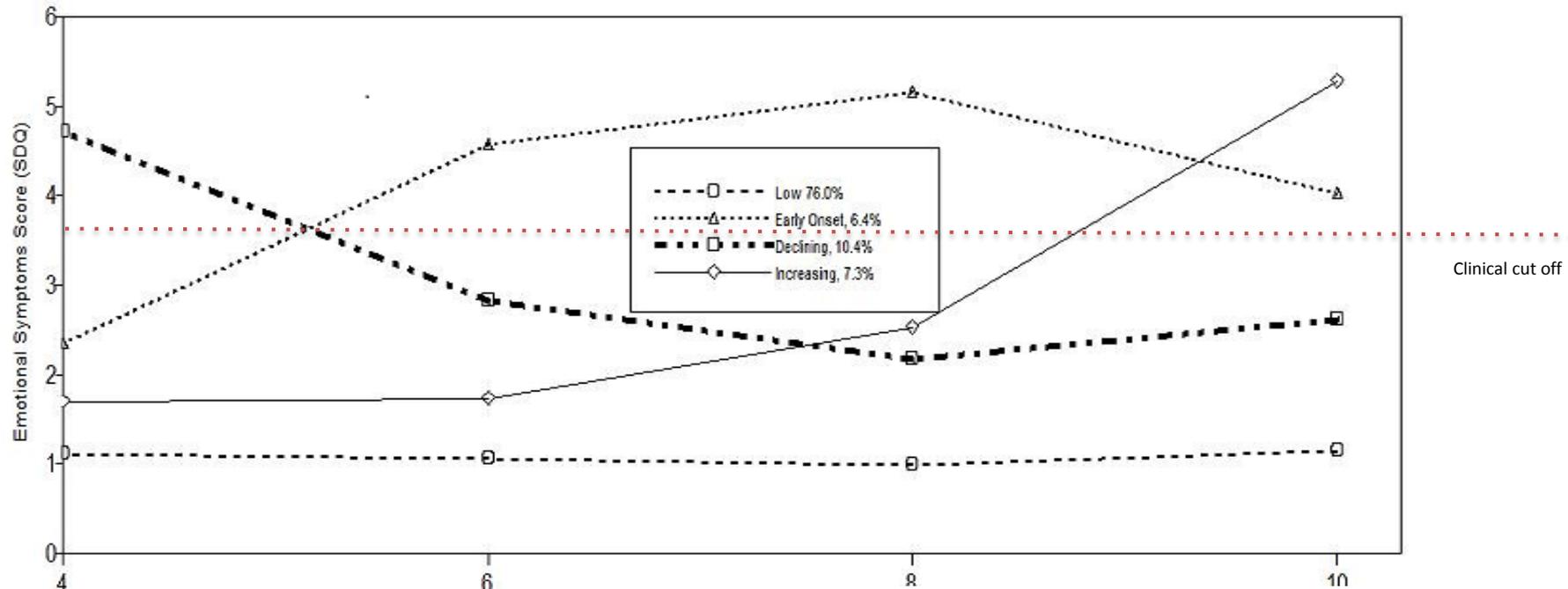


Table X Model Fit for linear and quadratic models for child emotional symptoms

	ll	AIC	aBIC	Entropy	Lo	p	Model description
Model 1	-31966.89	63959.77	64003.13	na	na	na	1 Class Quadratic
Model 2	-31514.94	63063.89	63120.59	0.822	878.10	0.000	2 Class Quadratic
Model 3	-31180.62	62403.24	62473.28	0.834	649.57	0.000	3 Class Quadratic
Model 4	-31011.13	<b>62072.26</b>	<b>62155.64</b>	<b>0.809</b>	<b>329.31</b>	<b>0.002</b>	<b>4 Class Quadratic</b>
Model 5	-30856.16	61770.33	61867.05	0.804	301.09	0.379	5 Class Quadratic
Model 6	-30716.21	61498.42	61608.49	0.798	271.92	0.029	6 Class Quadratic
Model 7	-32041.15	64100.30	64130.32	na	na	na	1 Class linear
Model 8	-31606.96	63237.92	63277.94	0.800	835.66	0.000	2 Class linear
Model 9	-31376.03	62782.05	62832.08	0.814	444.46	0.000	3 Class linear
Model 10	-31210.10	62456.20	62516.24	0.798	319.35	0.070	4 Class linear
Model 11	-31115.50	62273.00	62343.04	0.788	182.08	0.718	5 Class linear
Model 12	-31040.53	62129.06	62209.10	0.792	144.29	0.015	6 Class linear

ll= Loglikelihood, aBIC= Sample-Size Adjusted Bayesian Information Criteria, AIC= Akaike Information Criteria  
Lo= Lo-Mendell-Rubin Adjusted LRT Test, p= significance value for Lo, **Bold**= selected model.

# Predictors of Trajectory Class Membership for Child Depressive Symptoms

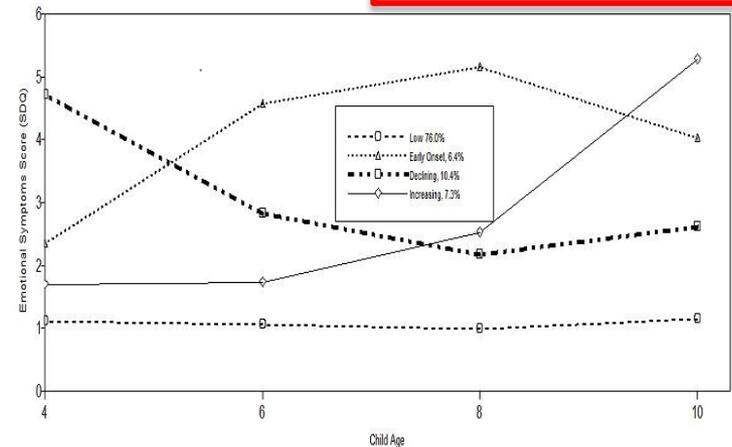
Table X  
Covariate Predictors of Trajectory Class Membership for Child Depressive Symptoms

	Early Onset Class			Declining Class			Increasing Class		
	Est	SE	p	Est	SE	p	Est	SE	p
Warm Parenting (age 4)	0.35	0.29	0.23	0.28	0.21	0.19	0.42	0.34	0.22
Warm Parenting (age 6)	-0.34	0.27	0.20	<b>-0.75</b>	<b>0.19</b>	<b>0.00</b>	0.14	0.34	0.69
Maternal Dep (age 4)	<b>0.39</b>	<b>0.19</b>	<b>0.04</b>	<b>0.65</b>	<b>0.14</b>	<b>0.00</b>	<b>0.92</b>	<b>0.18</b>	<b>0.00</b>
Maternal Dep (age 6)	<b>0.61</b>	<b>0.17</b>	<b>0.00</b>	<b>0.32</b>	<b>0.16</b>	<b>0.04</b>	0.07	0.20	0.72
Sociable Temperament (age 4)	0.00	0.12	0.99	-0.14	0.11	0.21	0.13	0.12	0.26
Persistent Temperament (age 4)	-0.02	0.15	0.87	-0.10	0.11	0.37	-0.20	0.14	0.17
Reactive Temperament (age 4)	0.08	0.13	0.54	<b>0.32</b>	<b>0.12</b>	<b>0.01</b>	0.09	0.17	0.60
Persistent Temperament (age 6)	-0.31	0.17	0.07	-0.04	0.11	0.71	-0.14	0.14	0.30
Reactive Temperament (age 6)	<b>0.33</b>	<b>0.17</b>	<b>0.05</b>	0.05	0.11	0.67	0.18	0.16	0.26
Sociable Temperament (age 6)	<b>-0.28</b>	<b>0.14</b>	<b>0.05</b>	-0.21	0.12	0.08	<b>-0.42</b>	<b>0.12</b>	<b>0.00</b>

Note. Low Symptom class served as the referent group.

Est= Probit Estimate, SE= Standard Error, p = two tailed alpha value

Bold= predictors at or below p=.05



# Example 2: Avon Longitudinal Study of Parents and Children (ALSPAC)

Background literature: A meta-analysis by Beck (1998) (9 studies from 1978-1995) reviewed the effects of post natal Dep on cognitive development and suggested an effect of  $d=.30$  ( more pronounced for boys)-  
more recent review by Grace et al. (2003) found an additional 8 studies: Murray has published 5 studies of *post partum dep* concerning child cognitive development using the same cohort showing an impact at 18 months which dissipates by 5 yrs. See also: (Kurstjens and Wolke, 2001) (Hay and Kumar, 1995; Sharp et al., 1995), (Brennan et al. 2000)

## ■ Objectives

- What timing and level of maternal depression over pregnancy and post-natally influences child cognitive development?
- Use first 8 waves of ALSPAC data
- Mat dep measured using the EPDS- 8 measurement points
- Child Cog measured using the WISC-III at 8 yrs.
- Wide range of possibly confounding variables, eg SES, BF, parental Ed, etc.



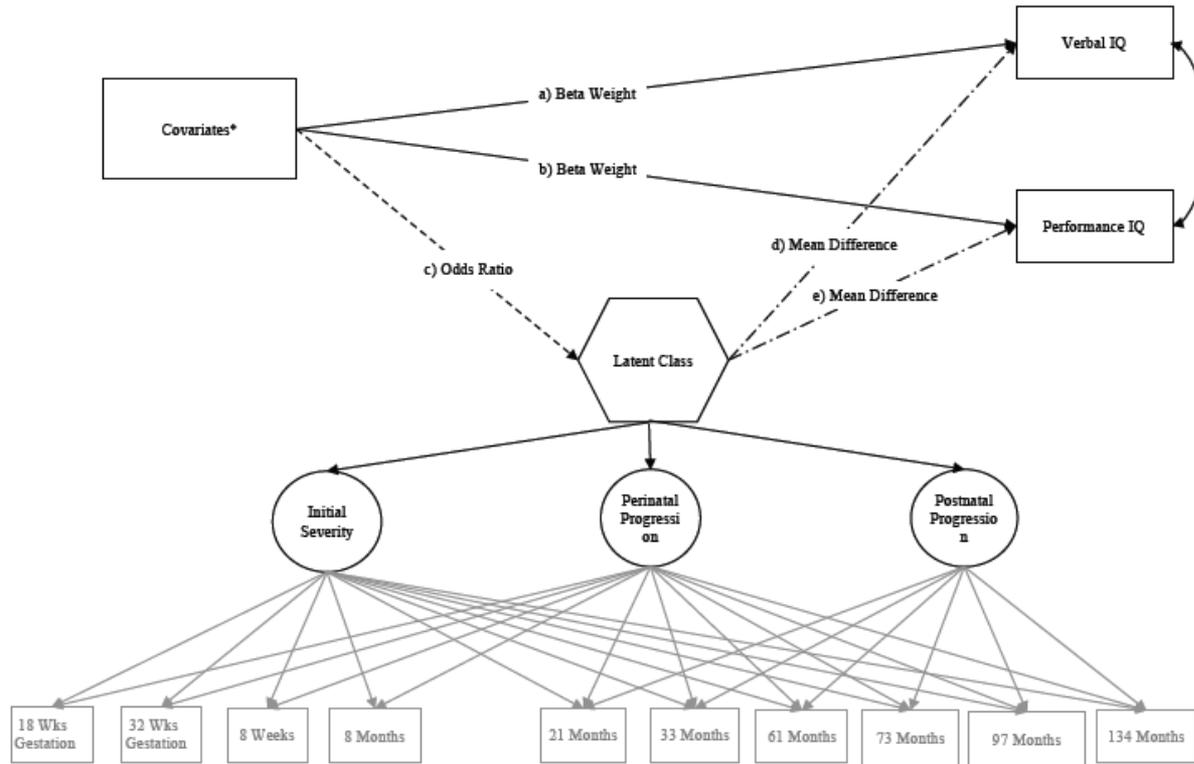
# Approach

- Three steps using Mplus 7.4
- **Latent Growth Modelling**
  - ( ie what is the best fitting curve for the depression data)
- **Mixture modelling**
  - ( ie how many trajectories are there and what do they look like)
- **Predictors and outcome**
  - how do the categories of mat dep predict child IQ ( before and after considering covariates)

# Growth Mixture Model

Figure 1

Final Growth Mixture Model (GMM) with Covariate predictors of Intelligence Quotient (IQ) at 8 years of age.



\*Covariates: Marriage Status, Home Ownership, Maternal Education Level, Maternal Age, Maternal Ethnicity, Nicotine Exposure, Alcohol Exposure, THC Exposure, Gestational Age at Birth, Infant Gender, Weight at Birth, and Breastfeeding

# Factor Loadings for rate of change in tested Latent Growth Models

	8 Wks Gestation	32 Wks Gestation	8 Weeks	8 Months	21 Months	33 Months	61 Months	73 Months	97 Months	134 Months
Time Since Birth (Months)	-5.5	-2	2	8	21	33	61	73	97	134
Rescaled Time	-0.55	-0.2	0.2	0.8	2.1	3.3	6.1	7.3	9.7	13.4
Intercept	1	1	1	1	1	1	1	1	1	1
Linear Slope	-0.55	-0.2	0.2	0.8	2.1	3.3	6.1	7.3	9.7	13.4
Quadratic Slope (Linear <sup>2</sup> )	0.3025	0.04	0.04	0.64	4.41	10.89	37.21	53.29	94.09	179.56
Cubic Slope ([Linear/10] <sup>3</sup> ) *	-0.00017	-8 x 10 <sup>-6</sup>	8 x 10 <sup>-6</sup>	0.00051	0.00926	0.03594	0.22698	0.38902	0.91267	2.4061
<b>Piecewise</b>										
<b>- Antenatal Slope</b>	<b>-0.55</b>	<b>-0.2</b>	<b>0.2</b>	<b>0.8</b>						
<b>- Postnatal Slope</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>1.3</b>	<b>2.5</b>	<b>5.3</b>	<b>6.5</b>	<b>8.9</b>	<b>12.6</b>

MODEL:

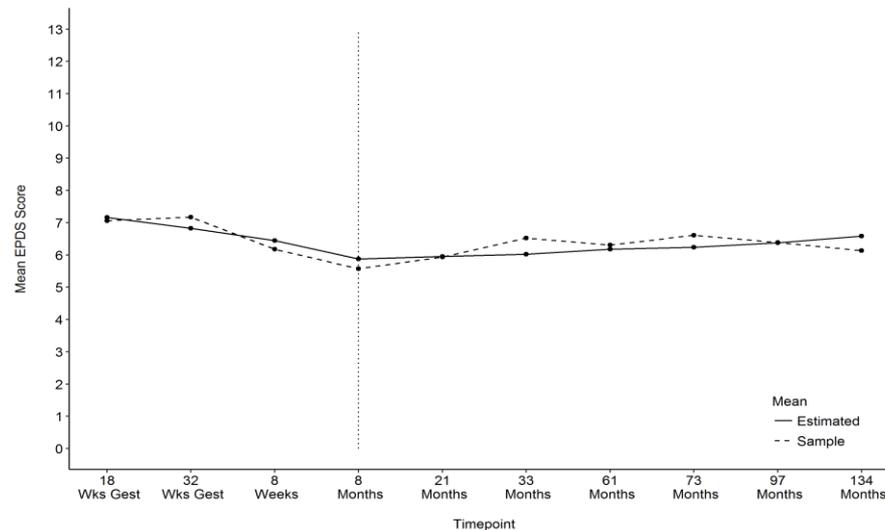
%OVERALL%

i ante | E\_18wg@-0.55 E\_32wg@-0.2 E\_8w@0.2 E\_8m@0.8 [E\\_21m@0.8](#) E\_33m@0.8 E\_61m@0.8 E\_73m@0.8 E\_97m@0.8 E\_134m@0.8;

i post | E\_18wg@0 E\_32wg@0 E\_8w@0 E\_8m@0 E\_21m@1.3 [E\\_33m@2.5](#) E\_61m@5.3 E\_73m@6.5 E\_97m@8.9 E\_134m@12.6;

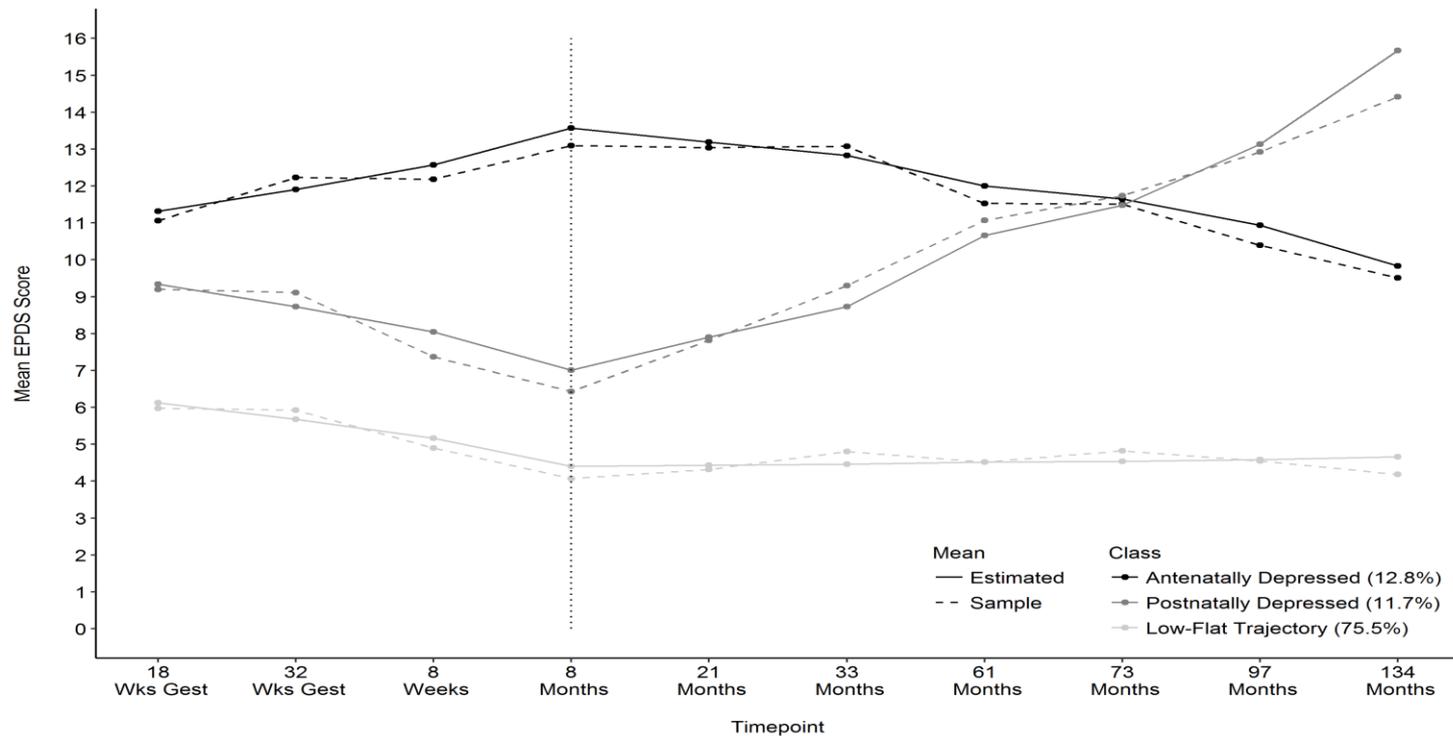
# Fit statistics and model

Model	$\chi^2$ (df)	BIC	CFI	TLI	RMSEA [90%CI]
Intercept	43998.750 (53)**	545416.326	.866	.886	.079 [.077, .081]
Linear	3101.693 (50)**	543769.466	.906	.916	.068 [.066, .070]
Quadratic	2438.325 (46)**	542964.271	.926	.928	.063 [.060, .065]
Cubic	1604.264 (41)**	541927.030	.952	.947	.054 [.051, .056]
Linear Piecewise	1324.177 (46)**	541519.370	.961	.962	.046 [.044, .048]



# Step 2= Growth Mixture modeling

GMM	Log-Likelihood	BIC	Entropy	VLMRT	BLRT
1 Class	-270669.497	541519.370	-	-	-
2 Class	-269908.782	540035.915	0.741	1482.392**	1521.430**
3 Class	-269566.604	539389.531	0.703	666.800**	684.357**

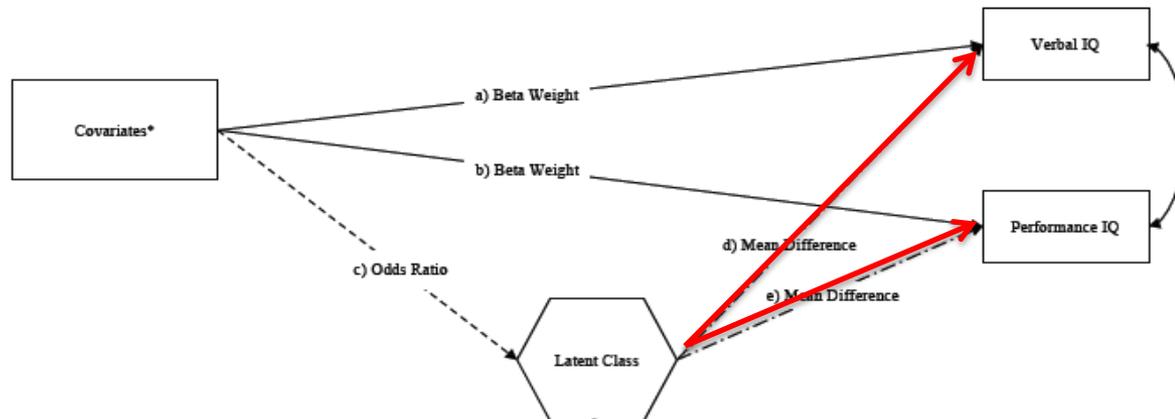


# Step 3: Means, Standard Errors, and Effect Sizes for Differences in IQ from Ante/Postnatally Depressed Groups vs. 'Low-Flat' Group

		Adjusted Mean (SD)	Mean Difference from Low-Flat	Standard Error	Cohen's <i>d</i>
Antenatally Depressed vs low					
<b>Verbal (d)*</b>		<b>92.072 (15.696)</b>	<b>-2.624, <i>p</i> = .031</b>	<b>1.214</b>	<b>.169</b>
Performance (e)*		85.026 (16.872)	-2.030, <i>p</i> = .126	1.327	.123
Postnatally Depressed vs low					
Verbal (d)*		92.941 (15.184)	-1.755, <i>p</i> = .089	1.032	.115
Performance (e)*		85.935 (16.796)	-1.121, <i>p</i> = .322	1.131	.068

Figure 1

Final Growth Mixture Model (GMM) with Covariate predictors of Intelligence Quotient (IQ) at 8 years of age.



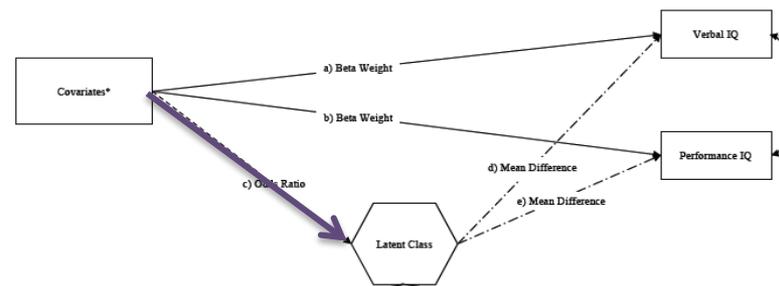
### Step 3 (con't)

## Odds Ratios for Effects of Covariates on the Probability of Belonging to Ante/Postnatally Depressed Groups vs. 'Low-Flat' Group

	Antenatally Depressed vs. Low-Flat (c)*	Postnatally Depressed vs. Low-Flat (c)*
Infant Gender (male=1, female=0)	1.089, $p = .449$	.998, $p = .985$
Married (yes=1/no=0)	<b>.637, <math>p = .001</math></b>	1.159, $p = .363$
Home ownership (yes=1/no=0)	<b>.564, <math>p &lt; .001</math></b>	.873, $p = .376$
Gestational Age (weeks)	<b>.909, <math>p = .006</math></b>	1.051, $p = .208$
Education (O level vrs less)	.883, $p = .393$	.947, $p = .671$
Breastfeeding	<b>.915, <math>p = .020</math></b>	1.002, $p = .954$
Maternal Age (yrs)	<b>1.060, <math>p &lt; .001</math></b>	1.001, $p = .935$
Smoking in preg (yes=1/no=0)	<b>1.742, <math>p &lt; .001</math></b>	<b>1.627, <math>p &lt; .001</math></b>
Marijuana in preg (yes=1/no=0)	1.224, $p = .573$	1.576, $p = .207$
Alcohol in preg (yes=1/no=0)	<b>1.172, <math>p = .034</math></b>	1.014, $p = .851$
Ethnicity (White vs Other)	.748, $p = .279$	.668, $p = .140$
Weight at Birth (gms)	1.076, $p = .567$	.962, $p = .747$

Figure 1

Final Growth Mixture Model (GMM) with Covariate predictors of Intelligence Quotient (IQ) at 8 years of age.



# 3<sup>rd</sup> example

## Review: Longitudinal trajectories of child and adolescent depressive symptoms and their predictors – a systematic review and meta-analysis

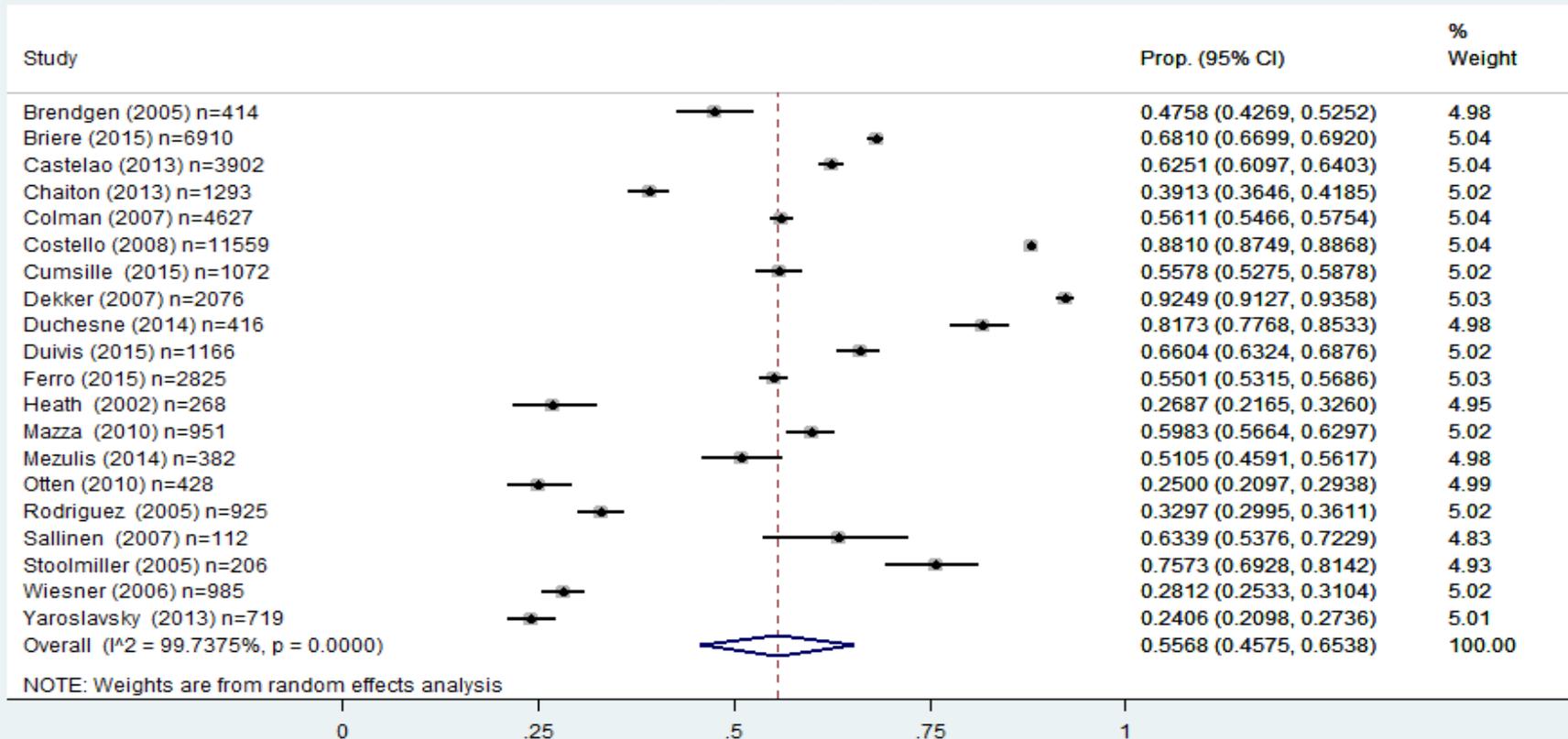
Lori Shore<sup>1</sup> , John W. Toumbourou<sup>1</sup>, Andrew J. Lewis<sup>2</sup> & Peter Kremer<sup>3</sup>

- Twenty studies published between 2002 and 2015 were included sampling N = 41,236.
- Participants were 4 through to 17 (average age 12.34) and followed longitudinally for an average of 7.45 years.
- Between three and eleven trajectory subgroups were identified.
- A random pooled effect estimate identified weighted prevalence estimates were:

Trajectory	Prevalence	Range
<i>No or low</i>	67%	24 – 93%
<i>Moderate</i>	17%	0 - 76%
<i>High</i>	3%	0 – 25%
<i>Increasing</i>	4%	0 - 22%
<i>Decreasing</i>	8%	0 - 23%

# using metaprop in STATA

## Low trajectory groups



**Table 2.** Details of 20 depressive symptom trajectory studies included in the review

Studies	Measure	Methodology	Follow-up period (years)	No of waves	No of trajectories
Brendgen et al. (2005)	Children's Depression Inventory (CDI; Kovacs, 1992)	Semiparametric Group Based Method (SPGBM; Nagin, 2005)	3	4	4
Briere, Janosz, Fallu, and Morizot (2015)	Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977)	General Growth Mixture Models (GMMM; Muthen & Muthen, 2000)	4	5	5
Castelao and Kroner-Herwig (2013)	Youth Self Report Depression Scale (YSR; Achenbach, 1991)	GMMM	4	4	4 (4f and 3m)
Chaiton et al. (2013)	Global Negative Self-Evaluation Scale (GSE; Kandel & Davies, 1986)	SPGBM	4	20	3 (3f and 3m)
Colman et al. (2007)	B2 Questionnaire (Rutter, 1967)	Latent class modeling	40	5	6
Costello, Swendsen, Rose, and Dierker (2008)	CES-D (3 items)	SPGBM	5.75	3	4
Cumsille, Martinez, Rodriguez, and Darling (2015)	6 items stated to be similar to CES-D	GMMM	3	4	4
Dekker et al. (2007)	Child Behavior Checklist (CBCL; Achenbach & Rescorla, 2001)	SPGBM	14	5	11 (6f and 6m, 2 equivalent)
Duchesne and Ratelle (2014)	CDI	SPGBM	5	6	4
Duvis et al. (2015)	YSR	Latent class modeling	5.3	3	5
Ferro, Gorter, and Boyle (2015)	CES-D	Latent class growth analysis	13	8	3
Heath and Camerarena (2002)	CDI	Manual classification	2	6	6
Mazza et al. (2010)	Seattle Personality Questionnaire (SPQ; Greenberg & Kusche', 1990)	SPGBM	6	6	5
Mezulis, Salk, Hyde, Priess-Groben, and Simonson (2014)	CDI	GMMM	7	4	3
Otten, Barker, Maughan, Arseneault, and Engels (2010)	GSE	GMMM	4	5	3
Rodriguez, Moss, and Audrain-McGovern (2005)	CES-D	GMMM	3	5	3
Sallinen et al. (2007)	Recent Mood and Feelings Questionnaire (Angold et al., 1995)	SPGBM and Analysis of Covariance	2	3	4
Stoolmiller, Kim, and Capaldi (2005)	CES-D	GMMM	8	7	4
Wiesner and Kim (2006)	CES-D	Dual Trajectory Analysis	2	3	4
Yaroslavsky, Pettit, Lewinsohn, Seeley, and Roberts (2013)	CES-D	GMMM	14	4	3

*m*, males; *f*, females; CDI, Children's Depression Inventory; CES-D, Center for Epidemiologic Studies Depression Scale; YSR, Youth Self Report depression scale; GSE, Global Negative Self-Evaluation Scale; CBCL, Child Behavior Checklist; SPGBM, Semiparametric Group Based Method; GMMM, General Growth Mixture Models.

# Predictors of class membership

- *'High'* or *'Increasing'* trajectories were predominantly predicted by:
  - female gender,
  - low socio-economic status,
  - higher stress reactivity;
  - conduct issues;
  - substance misuse
  - Problems with peers
  - Poor relationships with parents

# So...what does trajectory modeling tell us about the development of depression?

- There are consistent and meaningful subgroups which show distinct developmental pathways- (typically 3-5 subgroups)
- 60-70% of children are NOT at risk- so universal prevention may be a questionable practice (selected is preferable).
- Females consistently over represented in the High and increasing trajectory
- Stressful life events and high stress reactivity are similarly predictive.

# Some comments/issues.

- Sample size
- How many traj are clinically relevant
- Large samples are needed, but measurement quality declines in larger studies -
- How to handle multiple informants (eg parent report, teacher report and then youth report)

# References

Mplus User's Manual available at [www.statmodel.com](http://www.statmodel.com)

Tony Jung and K. A. S. Wickrama (2008) An Introduction to Latent Class Growth Analysis and Growth Mixture Modeling, *Social and Personality Psychology Compass* 2/1 : 302–317, 10.1111/j.1751-9004.2007.00054.x