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Longitudinal Research on Resilience

Fons J. R. van de Vijver

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Pathways to Resilience III: BEYOND NATURE vs. NURTURE

JUNE 16TH – 19TH, 2015

Theme

- What can we learn about resilience by using longitudinal designs?
- Focus on recent developments in quantitative research methods to enhance the quality of our studies
  - No mixed methods studies discussed
- Challenge
  - Resilience is an interactive concept
  - Resilience influenced by
    - Personal resources
    - Contextual resources
    - Contextual challenges
    - ….

Relevance of Longitudinal Designs in Resilience Studies

- These designs can address many questions:
  - Resilience is a dynamic concept; longitudinal designs do justice to this idea
  - How does resilience develop over time?
  - Are there gender/age/ethnic differences in these patterns?
  - How important are personal and contextual (neighborhood, family) resources for the development of resilience?
  - How effective is a resilience intervention?

- More generally, longitudinal designs can address two types of questions:
- 1. **“Level questions”:** change trajectories, change in mean scores,…
- 2. **“Structure questions”:** how is change related to personal and contextual conditions?

Structure Presentation

1. Methodological perspectives on change
   – Classical dilemmas
   – Modern solutions
2. Design and analysis of some recent longitudinal studies
   – Focus in presentation on examples
   – New perspective on change
3. Conclusions

Classical Dilemmas

- 1. Can change scores be used for analysis?
  - Change scores can be unreliable
- 2. What is responsible for changes over time?
  - Concept stays the same over time
    - Changes in height, weight
  - Concept changes over time
    - Changes in intelligence in first 10 years
- 3. Is dropout selective/random in longitudinal designs?
  - Do most/least resilient children drop out?

A Bit of History

- Focus was on repeated measures of the same (in)dependent variables
- Assessment of change often considered the Achilles heel of Classical Test Theory (Lord & Novick, 1968)
- Standard statistical procedures did not work well
  - Differences could be unreliable
  - Repeated measures ANOVA could not deal with missing values
  - Models often started from the assumption that growth follows an identical pattern for all participants

Psychological Bulletin
1975, Vol. 82, No. 1, 85–86

Unreliability of Difference Scores: A Paradox for Measurement of Change

John E. Overall and J. Arthur Woodward
University of Texas Medical Branch, Galveston

Psychological Bulletin
1970, Vol. 74, No. 1, 68–80

HOW WE SHOULD MEASURE "CHANGE"—OR SHOULD WE?[1]

LEE J. CRONBACH[2] AND LITA FURBY[3]

Stanford University

Procedures previously recommended by various authors for the estimation of "change" scores, "residual" or "basefree" measures of change, and other kinds of difference scores are examined. A procedure proposed by Lord is extended to obtain more precise estimates, and an alternative to the Tucker-Damarin-Messick procedure is offered. A consideration of the purposes for which change measures have been sought in the past leads to a series of recommended procedures which solve research and personnel-decision problems *without* estimation of change scores for individuals.

Modern solutions

- Rigidity of conventional approach did not work
  - Change assessment is vital in many areas of psychology, sociology, community development, …
- In the last 30 years there has been a spectacular increase in available models and procedures for longitudinal data analysis
  - Now available for all measurement levels

- Major advances in missing value analysis and imputation (source: Wikipedia)
  - MCAR
    - Values in a data set are missing completely at random (MCAR) if the events that lead to any particular data-item being missing are independent both of observable variables and of unobservable parameters of interest, and occur entirely at random.
  - MAR
    - occurs when the missingness is related to a particular variable, but it is not related to the value of the variable that has missing data.
  - MNAR
    - data missing for a specific reason (e.g., deliberate item skipping)
- Statistical tests of MCAR available
- Dealing with missingness under MCAR and MAR
  - Imputation of missing data that are MCAR or MAR can be done
  - Procedures in Structural Equation Modeling packages available for working with missing data under MCAR and MAR

Example Longitudinal Resilience Study

- Kauai Longitudinal Study (Werner & Smith, 2001)
  - Longitudinal study from infancy to adulthood
    - identify key risk and protective factors that influence resilience outcomes
  - Outcomes were influenced by
    - (1) **individual characteristics**, such as self-esteem
    - (2) **characteristics of families**, such as maternal caregiving
    - (3) **larger social context**, especially having supportive adult role models
  - Conclusion:
    - Longitudinal study of resilience should include change at multiple levels

Part 1
Design and Analysis of Some Recent Longitudinal Studies

First Example

Size at birth and resilience to effects of poor living conditions in adult life: longitudinal study

D J P Barker, T Forsén, A Uutela, C Osmond, J G Eriksson

BMJ VOLUME 323 1 DECEMBER 2001 bmj.com

- Topic: Size at birth and resilience to effects of poor living conditions in adult life in Finland
- Sample: Participants 3676 men
  - born during 1934-1944
  - Attended child welfare clinics in Helsinki
- Setting: Helsinki, Finland
- Predictors
  - Income
  - Education
  - SES in infancy and adult life
- Outcome
  - Hospital admission for or death from coronary heart disease between 1971 and 1997

- Analyses
  - Ratio of hazard (related to probability of coronary heart disease) to non-hazard is analyzed
  - Hazard ratios predicted by background variables
- Results
  - Hazard increases as a function of each independent variable in a predictable manner

- Methodological notes
  - Different variables measured at different time points; change does not need to be modeled
  - Regression analysis (modeling hazard ratios) to predict outcomes
  - Not all members of original cohort could be followed
    - Selectivity of dropout?
      - Very often a problem; infrequently addressed

Second Example

Rand D. Conger and Katherine J. Conger
University of California—Davis

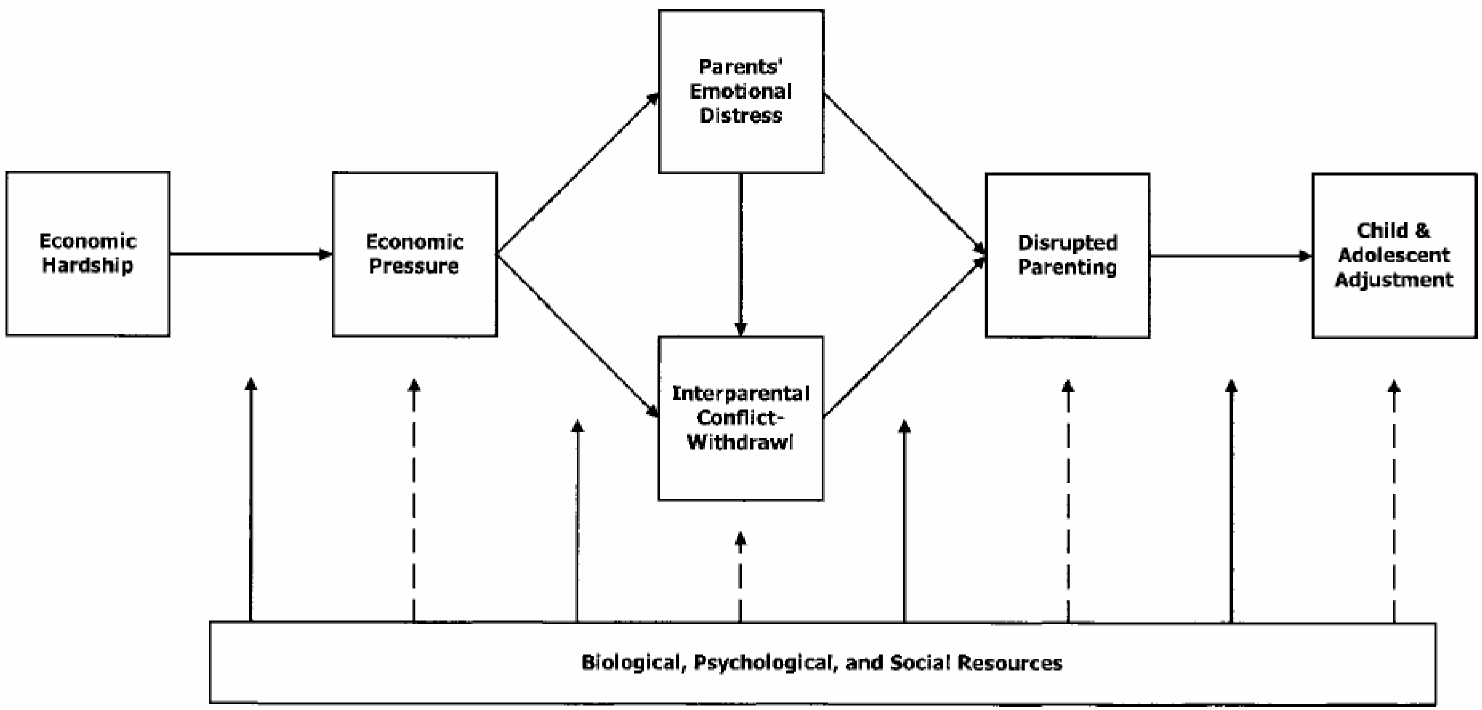
Resilience in Midwestern Families: Selected Findings from the First Decade of a Prospective, Longitudinal Study

Journal of Marriage and Family 64 (May 2002): 361-373

- Panel study 1989-1993 (yearly)
- Setting: rural Iowa; severe economic downturn in the 1980s

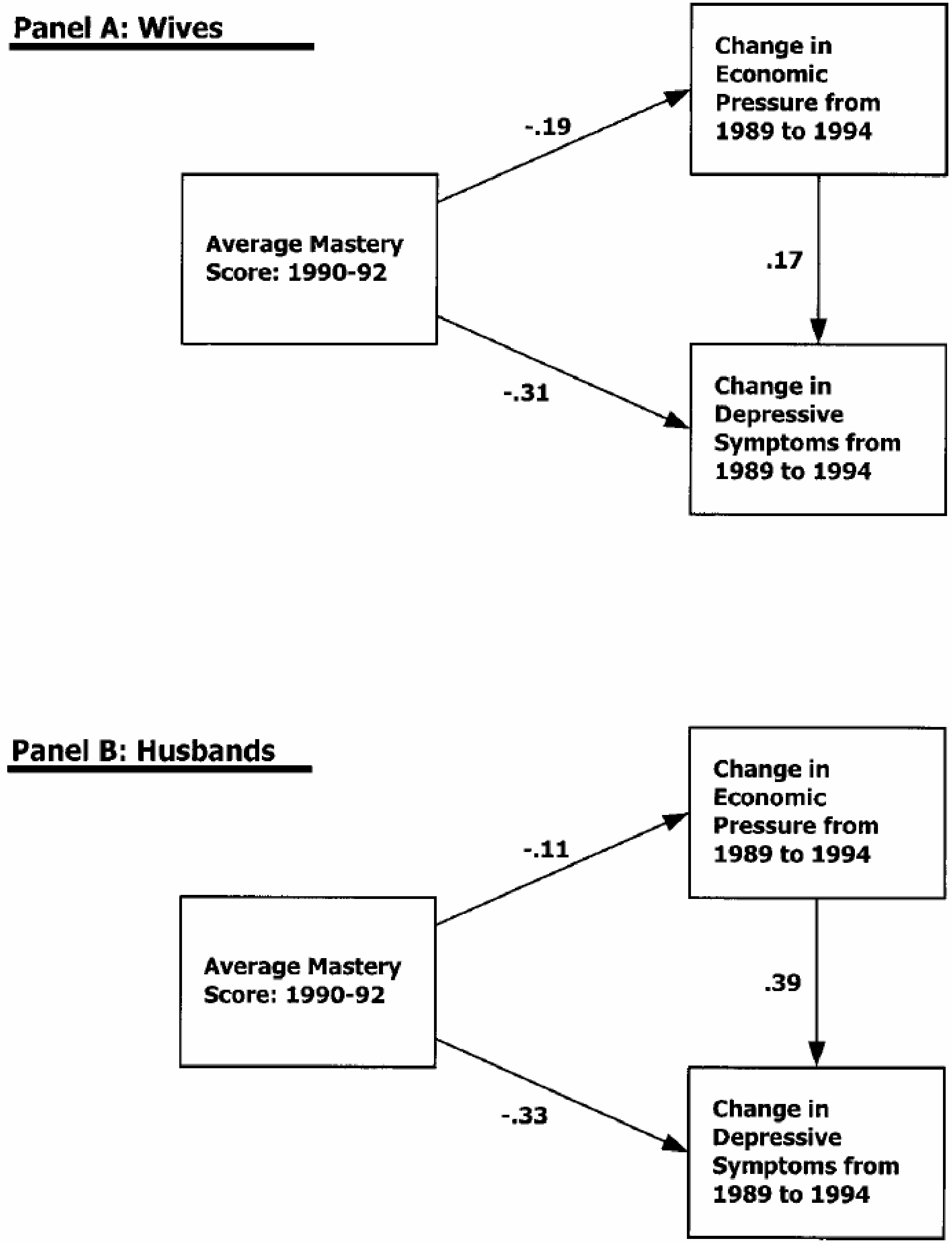
Conceptual Model

FIGURE 1. THE FAMILY STRESS MODEL OF ECONOMIC HARDSHIP INCORPORATING RESILIENCE PROMOTING SOCIAL AND PERSONAL RESOURCES



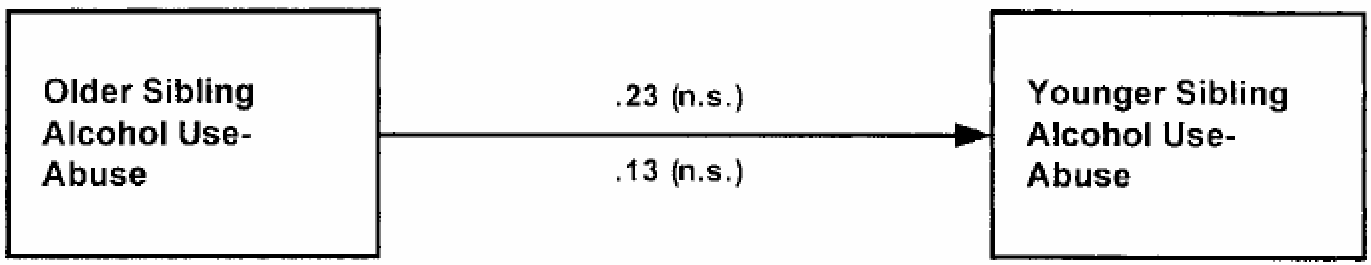
Note: Dashed arrows from resources indicate statistical main or compensatory effects and completed arrows from resources indicate statistical interaction, moderating, or buffering effects.

- Focus here on parental sense of mastery/control as a resource

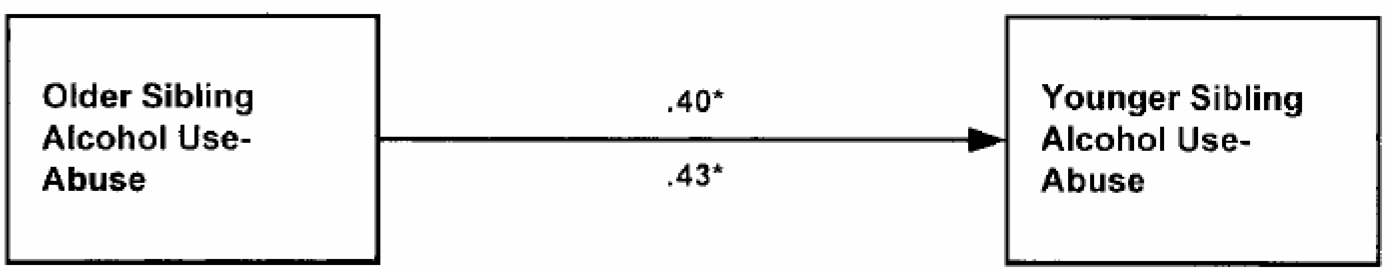

Panel A: Wives
Average Mastery Score: 1990-92
Change in Economic Pressure from 1989 to 1994
Change in Depressive Symptoms from 1989 to 1994
-.19
.17
-.31
Panel B: Husbands
Average Mastery Score: 1990-92
Change in Economic Pressure from 1989 to 1994
Change in Depressive Symptoms from 1989 to 1994
-.11
.39
-.33

Role of Parenting

1. High nurturant - involved parenting: Mothers above, Fathers below



2. Low nurturant - involved parenting: Mothers above, Fathers below



- Methodological notes
  - Analysis of change scores in path analysis
    - Can be problematic for methodological reasons
  - Type of parenting as moderator
    - Test of similarity of regression coefficients
    - Multigroup analysis in Structural Equation Modeling

Third Example

Social Science & Medicine 68 (2009) 2190–2198

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Looking for resilience: Understanding the longitudinal trajectories of responses to stress☆

Fran H. Norris[a,*], Melissa Tracy[b], Sandro Galea[b]

[a] Dartmouth Medical School, Psychiatry/NCPTSD, VA Medical Center, 215 North Main Street, White River Junction, VT 05009, USA
[b] University of Michigan, MI, USA

- Time trajectory of coping with stress in Mexico (two sites, after floods) and in New York (after 9/11)
- Assessment: Mexico (n = 561)
- PTSD was measured by using a modified version of Module K of Version 2.1 of the Composite International Diagnostic Interview (CIDI)

- 2001 terrorist attacks in New York (n = 1267)
- National Women’s Study (NWS) posttraumatic stress module questions to assess PTSD

- Instruments in both studies ask about symptom prevalence

Hypothesized Coping Patterns

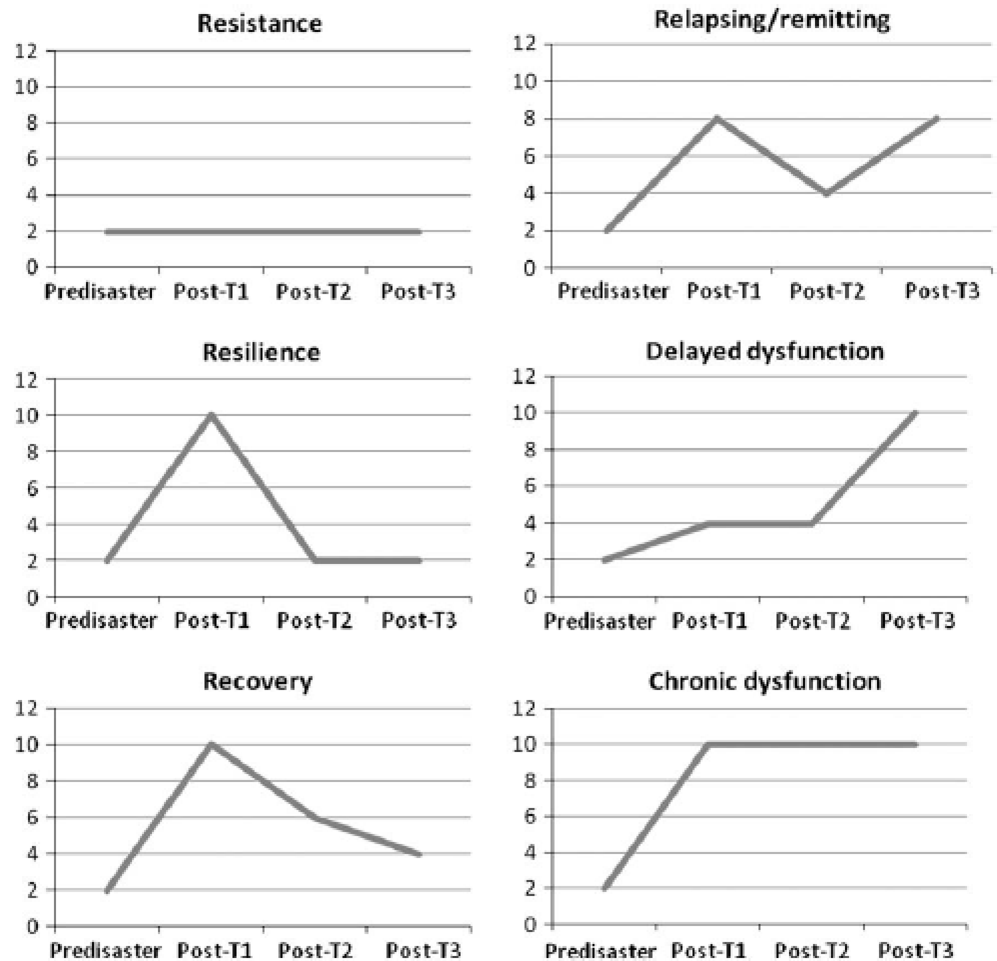


Fig. 1. Hypothesized trajectories of the course of stress responses.

- Analyses:
  - main interest in symptom trajectories
- “Manual” split in different subgroups
  - Trajectories per subgroup
- Zero inflated regression per subgroup (zero inflated to account for many people without symptoms)

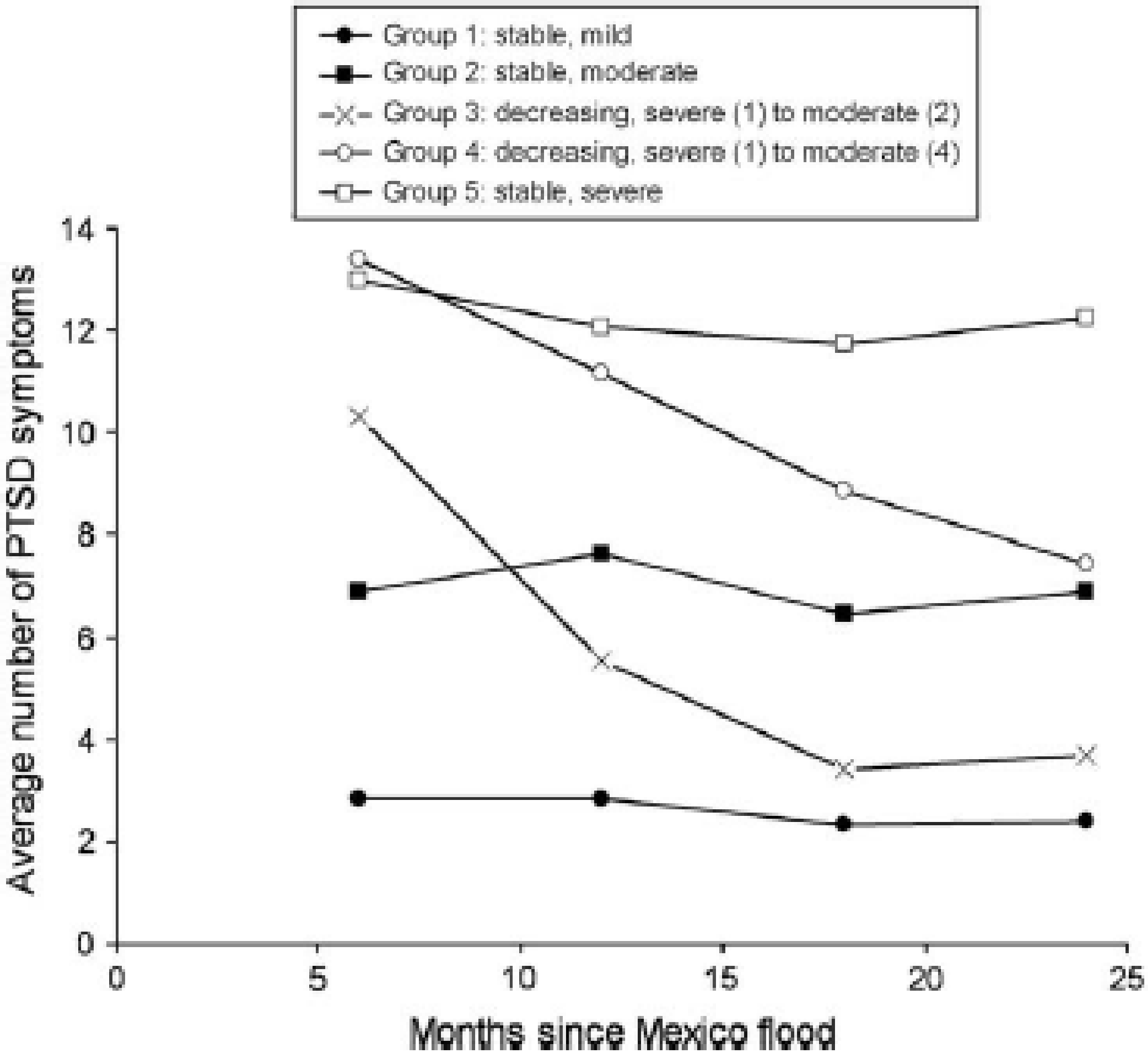


Fig. 2. Trajectories of PTSD symptoms among residents of Villahermosa and Teziutlán in Mexico ($n = 561$) after the 1999 flood. Numbers in parentheses refer to the wave of assessment.

Table 1
Parameter estimates, prevalence, and mean posterior probability of assignment for each PTSD symptoms trajectory group among residents of Villahermosa and Teziutlán in Mexico ($n = 561$) after the 1999 flood.

Group	Symptom trajectory[a]	Parameter	Estimate (SE)[b]	p-Value	Prevalence	Mean posterior probability (SD)[c]
1	Stable, mild	Intercept	2.308 (0.161)	<0.001	34.5%	0.926 (0.133)
2	Stable, moderate	Intercept	6.881 (0.699)	<0.001	12.0%	0.702 (0.163)
3	Decreasing, severe (1) to moderate (2)	Intercept	17.686 (0.991)	<0.001	32.0%	0.821 (0.180)
		Linear	−1.453 (0.130)	<0.001	–	–
		Quadratic	0.036 (0.004)	<0.001	–	–
4	Decreasing, severe (1) to moderate (4)	Intercept	15.377 (1.355)	<0.001	11.4%	0.818 (0.146)
		Linear	−0.343 (0.079)	<0.001	–	–
5	Stable, severe	Intercept	12.343 (0.393)	<0.001	10.0%	0.827 (0.161)

[a] Mild: 0–3 symptoms; moderate: 4–8 symptoms; severe: ≥9 symptoms; numbers in parentheses indicate survey wave.
[b] Standard error.
[c] Standard deviation.

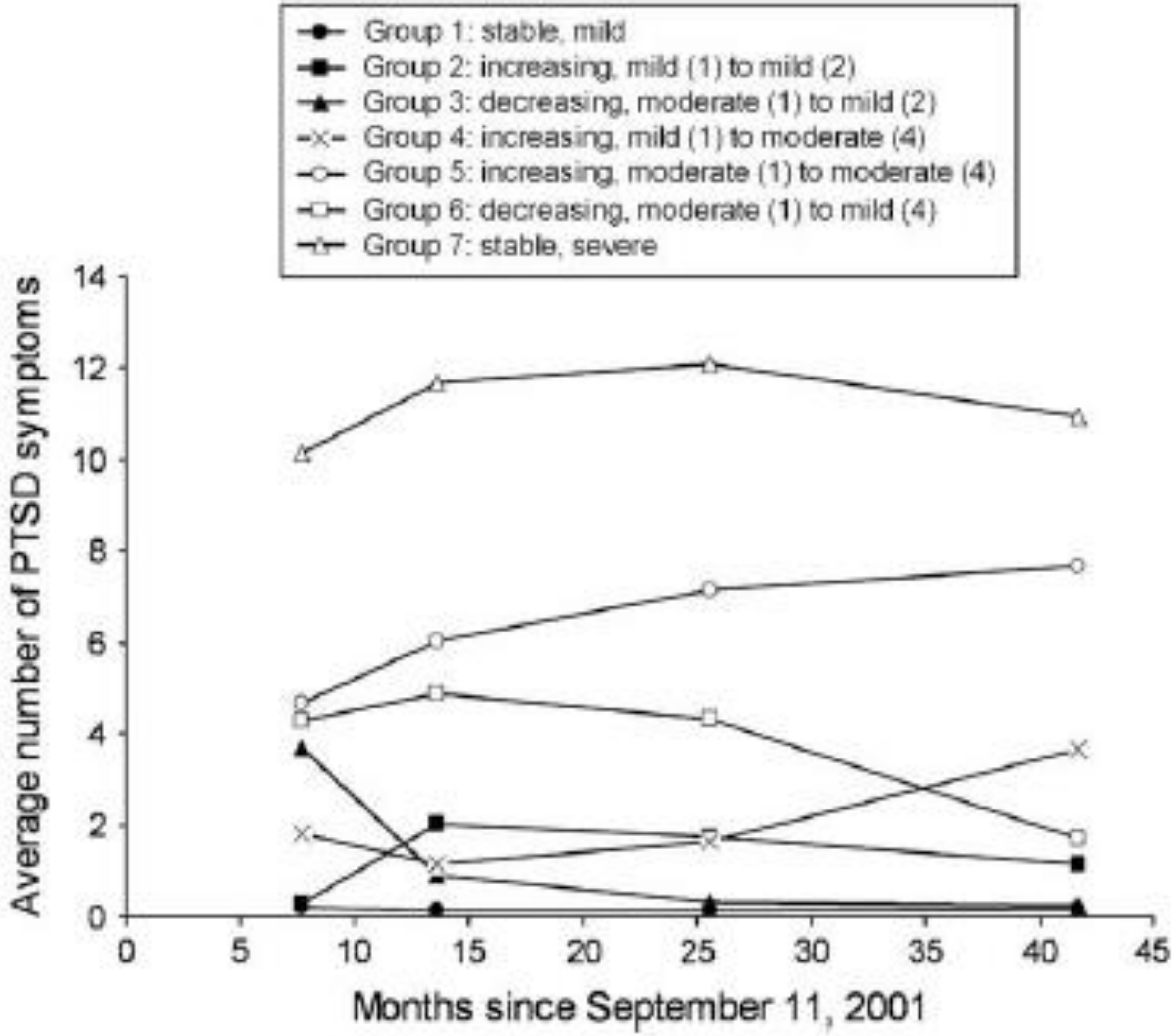


Fig. 3. Trajectories of PTSD symptoms among residents of the New York City metropolitan area ($n = 1{,}267$) after the September 11, 2001 attacks. Numbers in parentheses refer to the wave of assessment.

Table 2
Parameter estimates, prevalence, and mean posterior probability of assignment for each PTSD symptoms trajectory group among residents of the New York City metropolitan area ($n = 1{,}267$) after the September 11, 2001 attacks.

Group	Symptom trajectory[a]	Parameter	Estimate (SE)[b]	p-Value	Prevalence	Mean posterior probability (SD)[c]
1	Stable, mild	Intercept	−1.847 (0.174)	<0.001	40.1%	0.921 (0.135)
2	Increasing, mild (1) to mild (2)	Intercept	−7.617 (3.239)	0.019	13.3%	0.806 (0.179)
		Linear	1.108 (0.433)	0.011	–	–
		Quadratic	−0.044 (0.016)	0.006	–	–
		Cubic	0.001 (0.0002)	0.003	–	–
3	Decreasing, moderate (1) to mild (2)	Intercept	3.210 (0.573)	<0.001	10.1%	0.834 (0.175)
		Linear	−0.291 (0.066)	<0.001	–	–
		Quadratic	0.004 (0.001)	<0.001	–	–
4	Increasing, mild (1) to moderate (4)	Intercept	2.360 (0.812)	0.004	14.3%	0.829 (0.175)
		Linear	−0.335 (0.133)	0.011	–	–
		Quadratic	0.015 (0.006)	0.015	–	–
		Cubic	−0.0002 (0.00008)	0.029	–	–
5	Increasing, moderate (1) to moderate (4)	Intercept	0.320 (0.504)	0.525	9.9%	0.878 (0.139)
		Linear	0.195 (0.056)	0.001	–	–
		Quadratic	−0.007 (0.002)	0.001	–	–
		Cubic	0.00009 (0.00003)	0.001	–	–
6	Decreasing, moderate (1) to mild (4)	Intercept	0.885 (0.305)	0.004	9.3%	0.862 (0.152)
		Linear	0.079 (0.025)	0.001	–	–
		Quadratic	−0.002 (0.001)	<0.001	–	–
7	Stable, severe	Intercept	2.049 (0.215)	<0.001	3.1%	0.937 (0.104)
		Linear	0.039 (0.015)	0.008	–	–
		Quadratic	−0.001 (0.0002)	0.002	–	–

[a] Mild: 0–3 symptoms; moderate: 4–8 symptoms; severe: ≥ 9 symptoms; numbers in parentheses indicate survey wave.
[b] Standard error.
[c] Standard deviation.

- Methodological notes
  - Unclear why latent class analysis was not applied; now possible to combine latent class and regression analysis

Fourth Example

Child Development, July / August 2002, Volume 73, Number 4, Pages 1220–1237

Family Adversity, Positive Peer Relationships, and Children's Externalizing Behavior: A Longitudinal Perspective on Risk and Resilience

Michael M. Criss, Gregory S. Pettit, John E. Bates, Kenneth A. Dodge, and Amie L. Lapp

- Site: Families with children entering kindergarten were recruited from two cohorts in 1987 and 1988 from three sites: Knoxville and Nashville, Tennessee and Bloomington, Indiana
- Data collected in two consecutive years
- Risk factors were assessed in interviews
  - three measures of family adversity: ecological disadvantage (e.g., low SES), violent marital conflict, and harsh discipline

- Moderators:
  - Peer ratings of acceptance (liked and disliked peers)
  - Ethnicity
  - Gender
  - Temperament (rating by mother)
- Outcome measured after one year
  - child's teacher completed the 112-item Child Behavior Checklist-Teacher Report Form (CBCL-TRF; Achenbach, 1991) → externalizing behavior

- Analysis
  - Stepwise regression, with moderators entered as interactions
  - E.g., can positive peer relations help to overcome ecological hardship?
  - Tw-step regression
    - Step 1: positive peer relations and ecological hardship
    - Step 2: interaction (multiplication of centered independent variables) added
      - Moderation if interaction is significant

Table 3 Regressions Examining Positive Peer Relationships as Moderators in the Link between Family Adversity and Children's Externalizing Behavior

		Moderators			
		Peer Acceptance		Friendships	
Step	Predictor	Standardized β	ΔR^2	Standardized β	ΔR^2
1	Ecological Disadvantage	.22***	.22***	.28***	.13***
	Positive Peer Relationship	−.37***		−.19***	
2	Ecological Disadvantage × Peer Relationship	−.12**	.01**	.05	.00
1	Violent Marital Conflict	.14**	.16***	.17***	.07***
	Positive Peer Relationship	−.36***		−.19***	
2	Marital Conflict × Peer Relationship	−.17***	.02***	−.05	.00
1	Harsh Discipline	.09*	.18***	.17***	.07***
	Positive Peer Relationship	−.40***		−.21***	
2	Harsh Discipline × Peer Relationship	−.08*	.01*	−.09*	.01*

Note: *N*s = 449 to 517.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Detailed Analysis of Interaction

Table 4 Regression Slopes Depicting the Association between Family Adversity and Children's Externalizing Behavior at Different Levels of Positive Peer Relationship

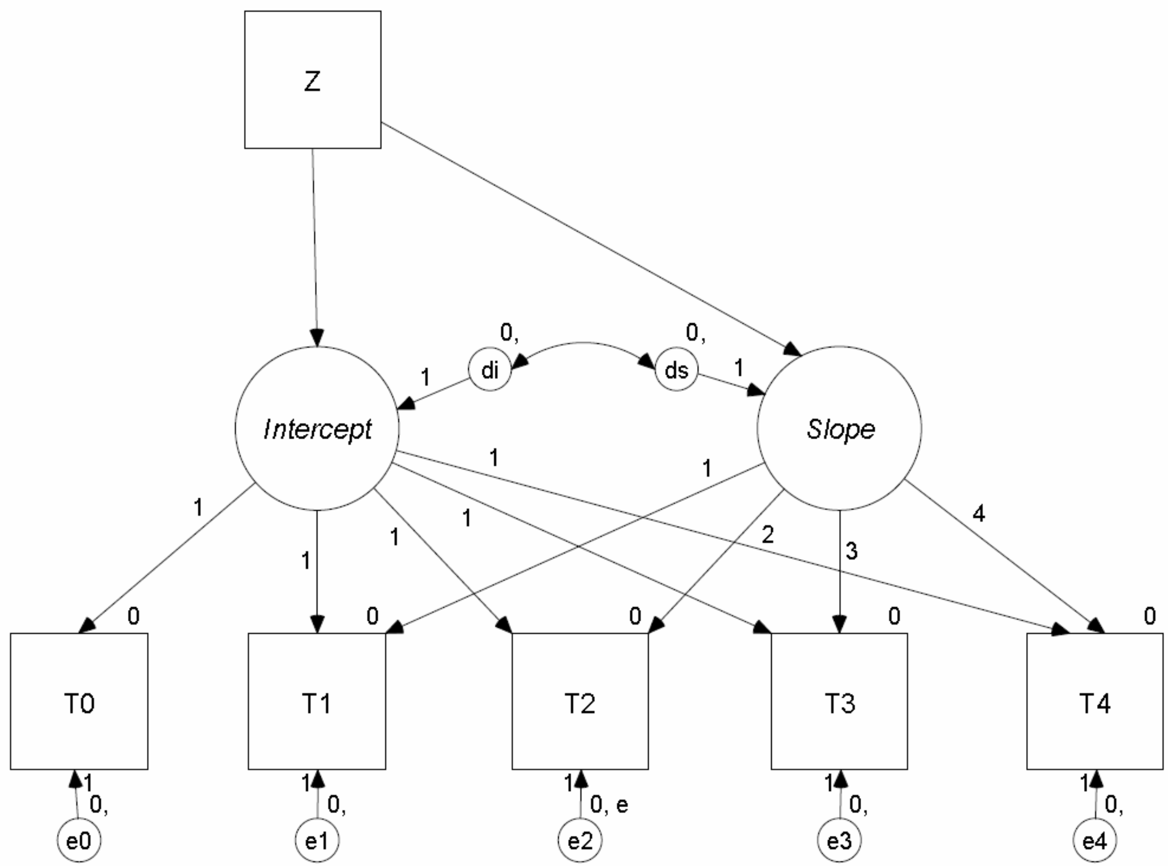
		Levels of Positive Peer Relationship		
Predictor	Moderator	High	Medium	Low
Ecological disadv.	Peer acceptance	.92	2.27***	3.62***
Violent marital conflict	Peer acceptance	−1.30	.86	3.03***
Harsh discipline	Peer acceptance	.10	1.10*	2.10**
Harsh discipline	Friendships	.99	1.97***	2.94***

* $p < .05$; ** $p < .01$; *** $p < .001$.

- Methodological notes
  - Focus on individual-level moderators
  - Stepwise regression used to examine the role of moderators
    - SPSS + specific routines available to estimate significance
  - Alternative
    - Structural equation modeling
      - Split up in groups with different levels of moderator and test invariance of model
      - Suitable in particular for nominal moderators such as gender and ethnicity
  - Caveat
    - Estimate proportion of variance accounted for by moderator (significance may not imply salience)

New Perspective on Change

Latent Growth Analysis

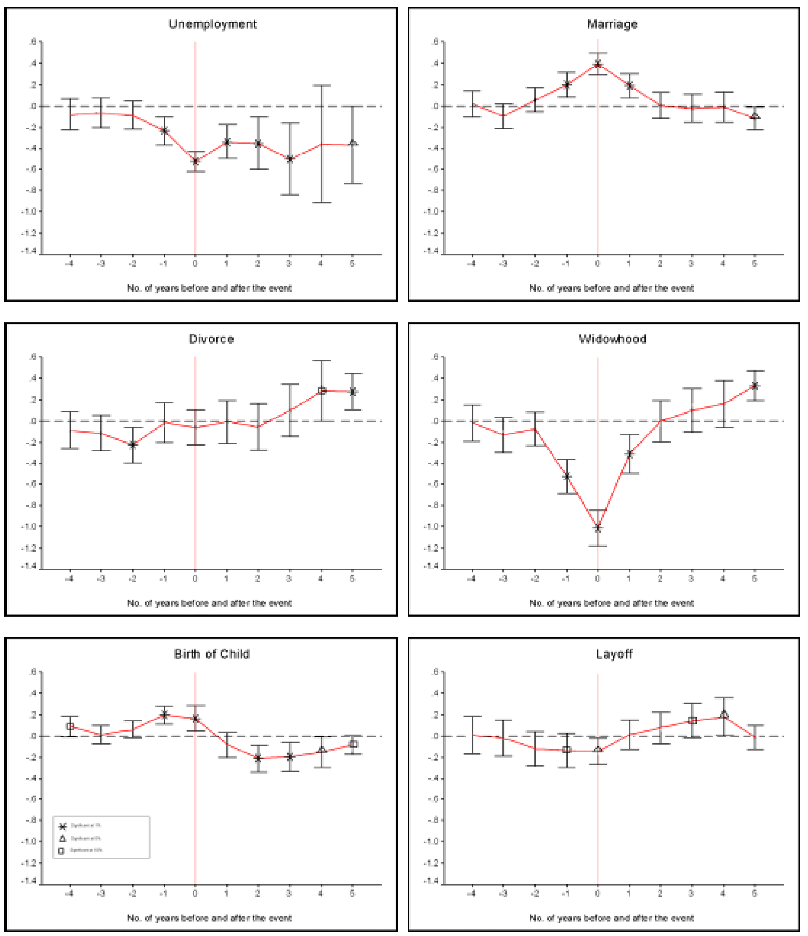


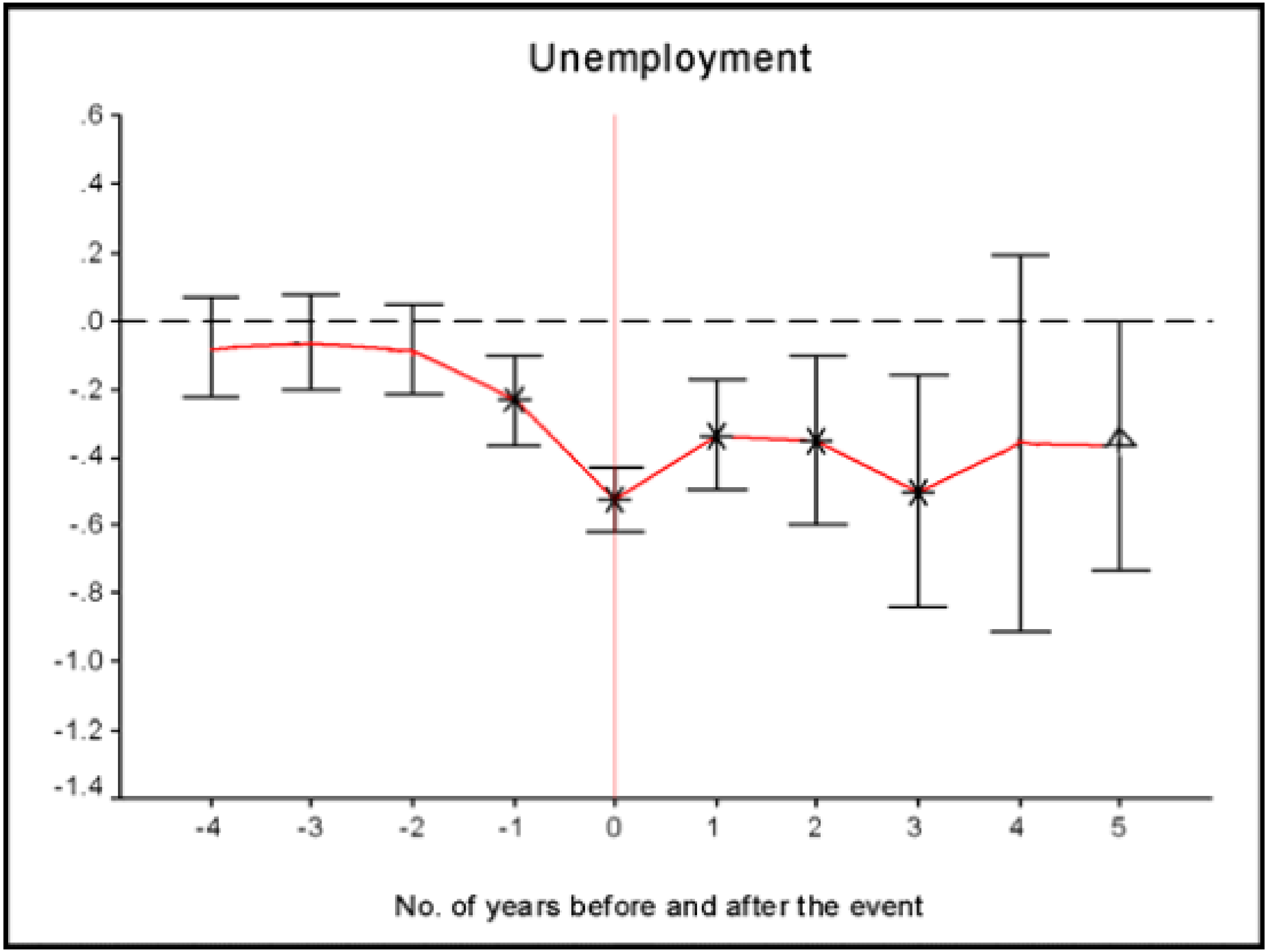
(Hox, 2000)

Example

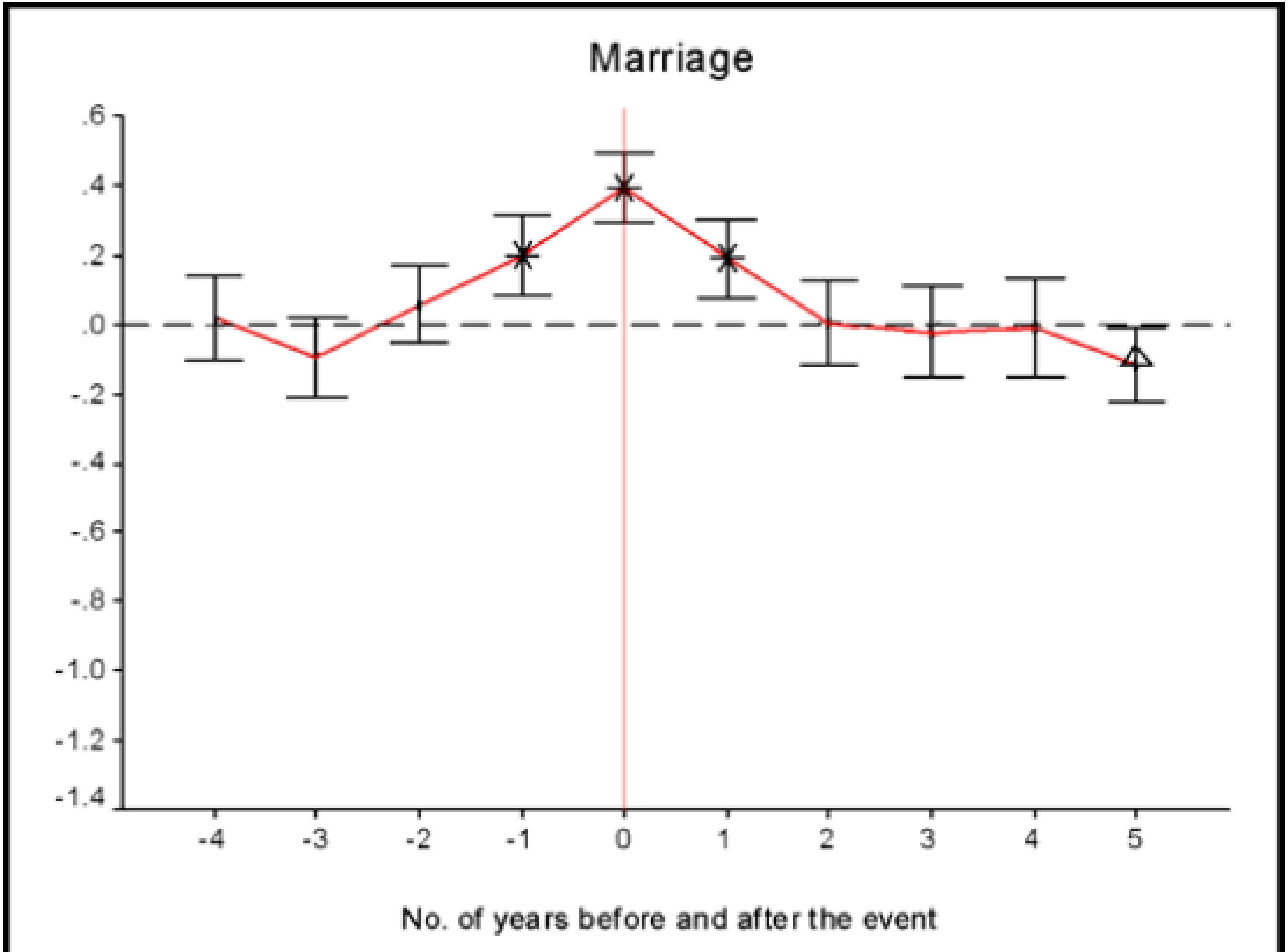
- Clark, Diener et al. (2008), *The Economic Journal*
- German Panel Data (1984-2003), N = 16,795
- Life satisfaction after
  - unemployment
  - layoff
  - marriage
  - divorce
  - death of spouse
  - birth of child

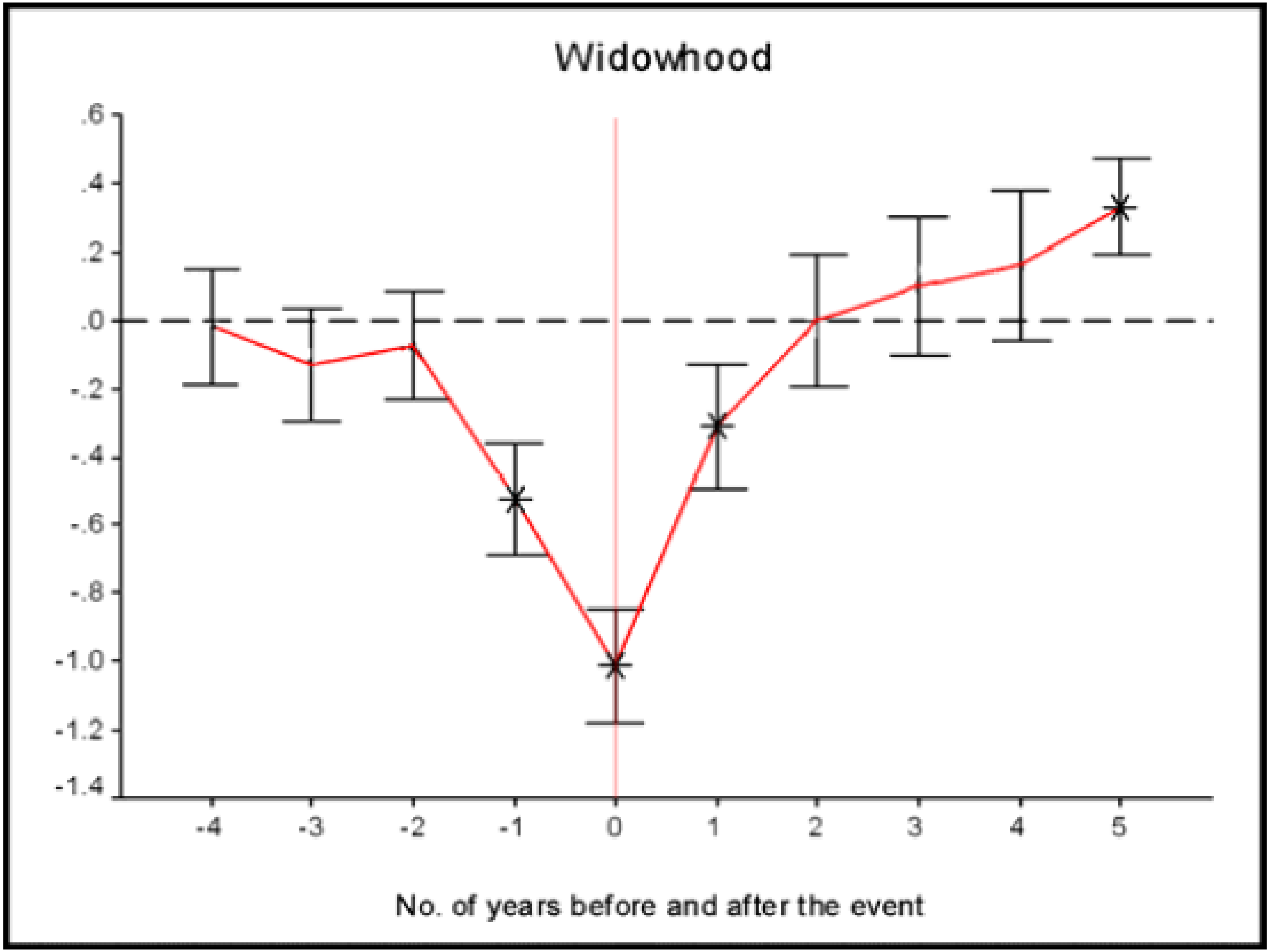
Figure 2. The Dynamic Effect of Life and Labour Market Events on Life Satisfaction (Females)





Unemployment
.6
.4
.2
.0
-.2
-.4
-.6
-.8
-1.0
-1.2
-1.4
-4
-3
-2
-1
0
1
2
3
4
5
No. of years before and after the event


Marriage
.6
.4
.2
.0
-.2
-.4
-.6
-.8
-1.0
-1.2
-1.4
-4
-3
-2
-1
0
1
2
3
4
5
No. of years before and after the event


Widowhood
.6
.4
.2
.0
-.2
-.4
-.6
-.8
-1.0
-1.2
-1.4
-4
-3
-2
-1
0
1
2
3
4
5
No. of years before and after the event

Rehabilitation Psychology
2010, Vol. 55, No. 1, 1–11

0090-5550/10/$12.00 DOI: 10.1037/a0018601

Psychopathology and Resilience Following Traumatic Injury: A Latent Growth Mixture Model Analysis

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Anthony D. Mancini
Pace University

Mark D. Rusch
Medical College of Wisconsin

George A. Bonanno
Columbia University

- A longitudinal study of 330 injured trauma survivors (mostly car accidents)
- Assessed during hospitalization, and at 1, 3, and 6 months follow-up.
- Instruments
  - Acute Stress Disorder Interview (ASD-I)
  - Post-Traumatic Stress Diagnostic Scale (PDS)
  - Center for Epidemiologic Studies Depression Scale (CESDS).

- Identified four latent classes
  - chronic distress
  - delayed distress
  - recovered
  - Resilience (low stress)

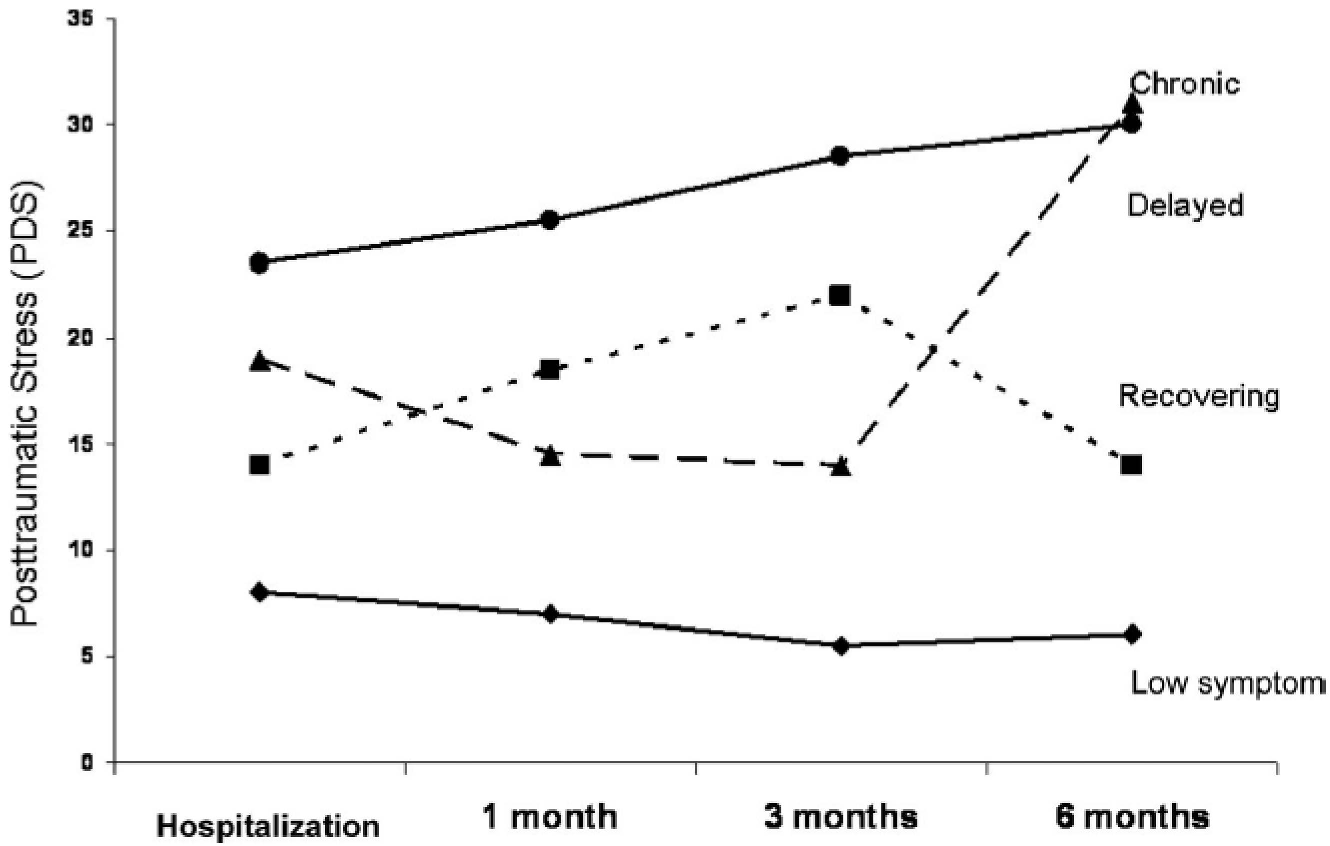

Figure 1. Four-class solution for PTSD symptoms (includes covariates).

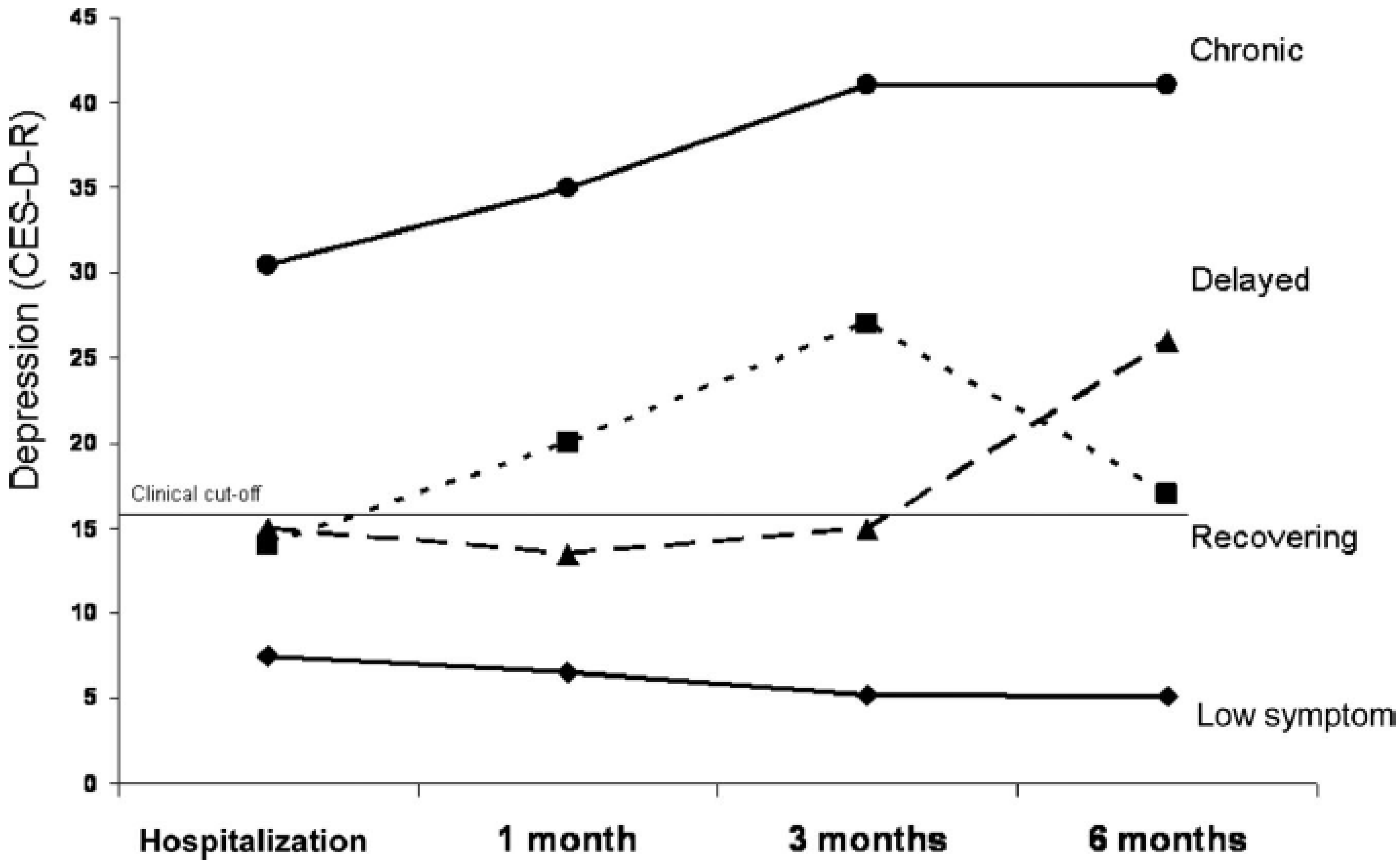

Figure 2. Four-class solution for depression symptoms (includes covariates).

Table 6

Covariate Prediction of Trajectory Class Membership: Depression

Variable	Delayed		Recovering		Chronic	
	OR	95% CI	OR	95% CI	OR	95% CI
Human intention$_a$	2.06†	.40–12.56	5.59	.59–53.01	6.42*	1.43–28.74
Education	.83†	.66–1.03	.81	.56–.1.17	.80†	.62–1.04
Self-efficacy T1	1.04	.74–1.45	.68	.40–1.14	.62*	.43–.90
Anger T1	1.16*	1.03–1.32	1.15†	.98–1.35	1.22*	1.04–1.42

Note. Low symptom class served as the referent. OR = odds ratio; CI = confidence interval; T1 = baseline.
$_a$ 1 = human intention; 0 = accident.
† = $p < .10$. * = $p < .05$.

- Study combines analysis of
  - Mean changes across time
  - Latent classes
  - Predictors of change

Part 3
Conclusions

- Many procedures developed in the last decades, both level- and structure-oriented
- Procedures often do not use change scores but model change as a function of original scores
- What is the best procedure will vary across studies

Future

- No models yet of systemic change at multiple levels (interrelated changes in child, family, community)
- Change from relatively few time points to multiple time points (collecting "big data" using modern technology)
  - Following an intervention program using Facebook, Twitter, local media, dedicated apps, ...