

RUNNING HEAD: Latent Class Analyses of Life Events

Stepping Off the Hedonic Treadmill:

Latent Class Analyses of Individual Differences in Response to Major Life Events

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Abstract

Theorists have long maintained that people react to major life events but then return to a set-point of subjective well-being. Although evidence now indicates substantial inter-individual variability in these reactions, prior research has been limited by its use of average trajectories. In this study, we used latent growth mixture modeling to identify specific patterns of individual variation in response to three major life events (bereavement, divorce, and marriage). A four-class trajectory solution provided the best fit for bereavement and marriage, while a three-class solution provided the best fit for divorce. Relevant covariates predicted trajectory class membership. The modal response across events was a relatively flat trajectory (i.e., no change). However, some trajectories diverged sharply from the modal response. Despite the tendency to maintain pre-event levels of SWB, there are multiple and often divergent trajectories in response to bereavement, divorce, and marriage, underscoring the essential role of individual differences.

Stepping Off the Hedonic Treadmill:

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Brickman and Campbell (1971) first coined the term “hedonic treadmill” to describe human beings’ general propensity to return to a set-point of well-being relatively quickly after even the most aversive or auspicious life events. Since that time, several decades of research have tended to confirm this basic insight. Indeed, though we may yearn to win the lottery, make full professor, and win the heart of our beloved, or, by contrast, dread the prospect of losing a loved one, being passed over for a promotion, or being spurned in love, these events typically have relatively transient effects, either positive or negative, on our well-being (Bonanno, 2004; Brickman & Campbell, 1971; Brickman, Coates, & Janoff-Bulman, 1978; Gilbert, Pinel, Wilson, Blumberg, & Wheatley, 1998; Suh, Diener, & Fujita, 1996). But is this the whole story? Recent work has called into question a basic premise of the hedonic treadmill, namely, that the impact of events can be broadly characterized. Indeed, there appear to be marked individual differences in response to significant events, with some people experiencing enduring change and others very little change (Lucas, Clark, Georgellis, & E. Diener, 2003). However, previous research has yet to map these individual differences onto latent trajectories. In the present study, we used the emergent technique of latent class modeling to identify trajectories of response to three major life events.

Although the hedonic treadmill theory has generated a substantial body of research, evidence has increasingly suggested that it needs significant renovation (Diener, Lucas, & Scollon, 2006). For example, in a series of influential studies using a German panel dataset spanning twenty years, Lucas and colleagues (Lucas, 2005; Lucas, Clark, Georgellis, & Diener, 2003; 2004) modeled adaptation to divorce, marriage, widowhood, and unemployment in a

hierarchical linear model (HLM) framework. Although people did indeed adapt to marriage, showing initial increases in SWB and then a return to baseline, adaptation to divorce, widowhood, and unemployment was never complete. Thus, some events may have enduring effects on SWB. As important, within-person change showed marked variation, indicating substantial individual differences in adaptation. For example, people who showed more significant reductions in SWB soon after bereavement also took much longer to recover, while those persons with the strongest positive reactions to marriage saw long-term increases in their SWB. Indeed, the marked variation around the average in these studies suggests that modeling a single trajectory, even within a sophisticated random effects HLM, may not capture the full variation in the data.

A second line of evidence in favor of modeling multiple trajectories of response can be found in the stress literature. Distinct longitudinal and prospective trajectories have been identified in response to bereavement (Bonanno, Moskowitz, Papa, & Folkman, 2005; Bonanno, Rennieke, & Dekel, 2005; Bonanno et al., 2002), disaster (Bonanno, Rennieke, & Dekel, 2005), breast cancer (Deshields, Tibbs, Fan, & Taylor, 2006), and disease epidemic (Bonanno et al., 2008). Together these findings reveal a more complex set of differences than suggested by earlier approaches. For example, both a temporary disruption in functioning, suggested by the treadmill analogy, and a lasting impact of the event are evidenced but only in relatively small subsets of the sample. The majority of respondents in these studies exhibited little or no change in adjustment, which represents a resilient response (Bonanno, 2004). Additionally, however, some prospective studies have shown a surprising pattern of lasting improvement, as well as persistent distress that predated the loss (Bonanno et al., 2002).

Based on the above considerations, we expected that a single continuous distribution would be unlikely to fully represent individuals' responses to key life events. Instead, we hypothesized that different trajectories of response should emerge. To address this question, we used a latent growth mixture model (LGMM) framework, an approach that is uniquely suited to identifying multiple unobserved trajectories in the data. A LGMM approach has been applied to a wide variety of phenomena, including drinking among college students (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005), childhood aggression (Schaeffer et al., 2006; Schaeffer, Petras, Ialongo, Poduska, & Kellam, 2003), acclimation to retirement in late life (Pinquart & Schindler, 2007), developmental learning trajectories (Boscardin, Muthén, Francis, & Baker, 2008), and disease epidemic (Bonanno et al., 2008). In the present study we used LGMMs to identify divergent trajectories of response to marriage, divorce, and bereavement.

Method

Participants and Procedure

Participants for this study were part of the first twenty waves of the German Socioeconomic Panel Study (GSEOP: Haisken-De New & Frick, 2003) from 1984-2003, a nationally representative study of German households identified through a multistage random sampling method ($N = 16,795$). All members of the household were asked to participate in annual face-to-face interviews. Data collection addressed a variety of topics, including employment, leisure activities, life events, health, income, and educational attainment. Response rates were good (60-70%), and attrition was low (from 3-13% per year). We focused on the subset of the sample that reported widowhood, divorce, or marriage from 1985 to 2003, limiting the samples to participants at or under the age of 75 when the event occurred.

The bereaved sample had 464 participants (women, 76%), on average 60.45 years old ($SD = 11.32$), with 10.36 years of education ($SD = 1.69$) and household income of DM 3,722 ($SD = 4,171$). The divorced sample had 629 participants (women, 52.5%), on average, 40.48 years old ($SD = 11.17$), with 11.37 years of education ($SD = 2.42$) and household income of DM 7,033 ($SD = 9,790$). The married sample had 1739 participants (women, 51%), on average, 28.38 years old ($SD = 6.19$), with 12.38 years of education ($SD = 2.68$) and household income of DM 8,896.69 ($SD = 11,274.31$). We removed data for married participants after they reported being divorced and for divorced participants after remarriage, treating those waves as missing but keeping earlier data waves. We did not remove data for bereaved participants who remarried, reasoning that adaptation to loss can persist even after remarriage. For each life event, we analyzed 9 waves of data collected at yearly intervals (4 waves pre-event, 1 wave the year of the event, and 4 waves post-event). Most participants had at least 6 waves of data (bereavement, 94.8%; divorce, 73.0%; and marriage, 82.3%).

Measures

Demographics. At each wave of data collection, *age*, *gender* (1 = male, 2 = female), *educational attainment* (years of education), and *marital status* (single, separated, divorced, married, widowed), and *household income* were assessed. Household income was converted into 2003 equivalent DMs using the consumer price index (OECD, 2008). Because income data were markedly nonnormal (*skewness* = 4.98; *kurtosis* = 31.02), we log transformed these data and calculated two income variables: *Average household income* over the 9 waves of data and *change in household income* (subtracting the average household income prior to the event from the average household income post event). Higher scores thus indicated less reduction (or a larger rise) in income.

Health dysfunction was assessed using 1 item (“Does your health prevent you from completing everyday tasks like work around the house, being employed, work, studies, etc.”) ranging from 1 (not at all) to 3 (very much so). To more robustly estimate health dysfunction across time, we averaged scores for all 9 waves of data. Coefficient alpha for the 9-item longitudinal measure was very high ($\alpha = .93$).

Subjective Well-Being (SWB). We assessed SWB based on responses to the question, “How satisfied are you nowadays with your life as a whole?” Respondents rated this question on a scale of 0 (completely dissatisfied) to 10 (completely satisfied).

Statistical Analysis

We employed LGMMs to analyze each of the life events (Muthén & Muthén, 2000). LGMM extends conventional latent trajectory approaches (Curran & Hussong, 2003) by estimating growth parameters within groups or classes of individuals that represent distinct multivariate normal distributions. In effect, LGMM tests whether the population under study is composed of a mixture of discrete classes of individuals with differing profiles of growth, with class membership determined by these different growth parameters.

We used Mplus 5.1 to identify latent classes of event response. Mplus employs a robust full-information maximum-likelihood (FIML) estimation procedure for handling missing data. FIML assumes missing data are unrelated to the outcome variable (missing at random). The appropriateness of FIML is widely endorsed (Enders, 2001; Graham, in press).

Our analyses for each life event consisted of three steps. First, we identified a univariate single-class growth model without covariates to facilitate model specification for the LGMM. Second, we compared one- to five-class unconditional LGMMs (no covariates), assessing relative fit with conventional indices, including the Bayesian, (BIC), sample-size adjusted

Bayesian (SSBIC), and Aikaike (AIC) information criterion indices, entropy values, the Lo-Mendell-Rubin likelihood test (LRT: Lo, Mendell, & Rubin, 2001), and the bootstrap likelihood ratio test (BLRT: Nylund, Asparouhov, & Muthén, 2007). We sought a model with lower values for the criterion indices, higher entropy values, and significant p values for both the LRT and the BLRT. We also used theory regarding prototypical loss trajectories to inform our model selection (e.g., Bonanno, 2004).

Consistent with recommendations for correct model specification (e.g., Muthén, 20003), a third step was to extend the LGMM to include covariate predictors of class membership. We selected covariates that would be likely to improve class assignment but that were also of substantive interest. However, we were mindful that too many covariates, especially with weak associations to SWB, would impair model convergence.

Results

Specifying Growth Parameters for LGMMs

For each life event, we first estimated a univariate model designed to capture a single growth trajectory of SWB for each life event. Using the likelihood ratio chi-square test to determine fit, we examined models with linear-only, linear and quadratic, and freely-estimated parameters (first wave set to 0 and last wave set to 1 and the remaining freely estimated). Based on these preliminary analyses, we retained the freely-estimated model for LGMM analyses of divorce and bereavement and a linear and quadratic model for marriage. In initial model testing for each analysis, we constrained the growth parameters and their covariances to be equivalent across classes. However, because we assumed inter-class heterogeneity, we sought to relax these constraints, using log-likelihood ratio chi squares to adjudicate fit. In the final models for bereavement and divorce, the slope variance was fixed at zero, while the intercept variance was

allowed to differ across classes. For the marriage analysis, the quadratic parameter was fixed at zero but the intercept and slope and their covariance was allowed to be estimated across classes.

LGMMs: Bereavement

Unconditional Model. Table 1 summarizes the fit statistics for the one- to five-class solutions for bereavement. Both the two- and three-class solutions provided successive improvements according to the AIC, SSBIC, and the BLRT. When moving to four-classes, the AIC, SSBIC, entropy value, and the BLRT ($p < .001$, $p_{\text{rep}} > .99$) indicated better fit, whereas the LRT and the BIC indicated slightly poorer fit. Inspection of the graphed trajectories of the three- and four-class solutions indicated that the difference between the models was the introduction of a small fourth class with a dramatically divergent trajectory of sharp improvement in SWB at the time of loss. This trajectory has previously been reported in the literature (Bonanno et al., 2002) and has been elaborated in theoretical arguments (Mancini, Pressman, & Bonanno, 2006). Although the five-class solution showed some improvement in fit, entropy declined and the BIC increased. Following recommendations that the best solution to a LGMM combines fit with theoretical justification and interpretability (Muthén, 2003), we selected the four-class solution as optimal.

Conditional Model. Age, health dysfunction, and change in income were the only covariates that significantly improved model fit, $\chi^2(9, N = 455) = 100.88$, $p_{\text{rep}} > .99$. Table 2 shows growth parameter estimates and confidence intervals for the freely-estimated model. Note that the slope growth factor is interpreted as the estimate of total change from 4 years pre- to 4 years post-loss. The trajectory patterns in the conditional model were essentially identical to those in the unconditional model and the percentages of participants assigned to each class were similar. Figure 1 shows that the majority of participants (58.7%) were assigned to a class with

relatively stable levels of SWB across assessment points. We labeled this class *resilient*. The second largest class (21.3%) was composed of participants with high levels of pre-loss SWB who experienced a sharp dip and a gradual improvement toward pre-loss levels. We labeled this class *acute-recovery*. The third largest class (14.6%) differed from the second class in having low pre-loss SWB but also showed a dip in SWB following the loss and a gradual return to pre-loss levels of SWB. We labeled this class *chronic low*. A fourth class (5.4%) presented a markedly different growth profile, with sharply increasing SWB at the time point of the loss and then a gradual decline. This anomalous group has previously been identified in the literature. We labeled this class *improved*.

Covariate Prediction of Class Membership. To assess the role of covariates in the LGMM, we designated the resilient category as the reference group. The resilient group was significantly older than the chronic low ($B = -.10, SE = .03, p_{\text{rep}} = .98$), acute-recovery ($B = -.04, SE = .02, p_{\text{rep}} = .96$), and the improved groups ($B = -.05, SE = .03, p_{\text{rep}} = .88$). The resilient group also reported substantially less health dysfunction than the chronic low ($B = 3.39, SE = .61, p_{\text{rep}} > .99$) and the improved groups ($B = 1.81, SE = .57, p_{\text{rep}} > .99$). Finally, the resilient group saw less of a reduction in income than the chronic low ($B = -1.13, SE = .53, p_{\text{rep}} = .93$) and the acute-recovery groups ($B = -2.55, SE = .96, p_{\text{rep}} = .92$), but the improved group saw an increase in income when compared to the resilient group ($B = 2.71, SE = .84, p_{\text{rep}} > .99$).

LGMMs: Divorce

Unconditional Model. Table 3 shows the fit indices for the one- to five-class models. Substantial improvements in fit were apparent when moving from the one- to the two-class solutions, as well as when moving from the two- to the three-class solution. A four-class solution introduced a very small fourth class (< 1.0%), with a flat trajectory of very low SWB. This class

had no basis in theory and the overall model showed only marginal improvements in fit, whereas the five-class solution split the largest class based on intercept values, a distinction that seemed uninformative. By contrast, the three-class solution consisted of trajectories readily distinguished by both intercept and slope values. Based on interpretability and fit, we selected the three-class solution as optimal.

Conditional Model. Health dysfunction and years of education were the only covariates that significantly improved model fit compared to the unconditional model $\chi^2(4, N = 625) = 51.76, p_{\text{rep}} > .99$. Table 4 shows growth parameter estimates and confidence intervals for the freely-estimated model. The slope growth factor is interpreted as the estimate of total change from 4 years pre- to 4 years post-loss. As shown in Figure 2, by far the largest class (71.8%) consisted of participants with relatively high SWB and a flat profile of growth, indicating no change over time. We labeled this class *resilient*. Participants in the next largest class (19.1%) showed moderate levels of SWB well before the divorce and then a considerable decline over time. We labeled this class *moderate-decreasing*. The smallest class (9.1%) consisted of participants with low pre-divorce SWB who saw sharp increases in SWB over time. We labeled this class *low-increasing*.

Covariate Prediction of Class Membership. We designated the resilient group as the referent. Health dysfunction distinguished the *low-increasing* ($B = 1.75, SE = .42, p_{\text{rep}} > .99$) and the *moderate-decreasing* ($B = 1.86, SE = .36, p_{\text{rep}} > .99$) groups from the *resilient* group, with both groups reporting more health dysfunction than the resilient group. In addition, years of education were marginally higher in the *resilient* group when compared to the *moderate-decreasing* group ($B = -.20, SE = .12, p_{\text{rep}} = .88$).

LGMMs: Marriage

Unconditional Model. Table 5 shows the fit indices for the one- to five-class models. The two- and three-class solutions provided successive improvements in fit according to the AIC, BIC, and SSBIC, though entropy declined somewhat going from two to three class (.87 to .83). Further improvement in fit was obtained when going to the four- and to the five-class solutions. The four- and five-class models each replicated four primary trajectories, but the five-class model introduced a very small fifth class (0.9%), with a sharply declining trajectory of progressively lower SWB. Classes under 1% are usually anomalous (Jung & Wickrama, 2008) and thus the four-class solution was optimal.

Conditional Model. Income and health dysfunction were the only covariates to significantly improved fit when compared to the unconditional model $\chi^2(6, N = 1733) = 97.75$, $p_{\text{rep}} > .99$. Table 5 shows growth parameter estimates and confidence intervals for the linear and quadratic model. Note that because we used a linear and quadratic model of change, growth parameter estimates are interpreted as average change per year. As show in Figure 2, by far the most prevalent class (79.6%) again described a profile of high SWB and flat growth, indicating no change over time. This class, which we labeled *high-stable*, evidenced the same trajectory pattern as the resilient group in the two previous samples. Participants in the next largest class (9.1%) showed decreasing SWB leading up to marriage and then a gradual increase after the marriage. We labeled this class *decreasing-increasing*. The two remaining classes showed contrasting profiles. One class (6.0%) evidenced sharply decreasing SWB after marriage, while the other class (5.2%) evidenced sharply increasing SWB leading up to and then sustained after marriage. We labeled these classes *decreasing* and *increasing*, respectively.

Covariate Prediction of Class Membership. With the largest class, the *high-stable* group, serving as the referent, these analyses showed that health dysfunction distinguished each of the

classes, with the *increasing* group ($B = 1.72, SE = .37, p_{rep} > .99$), the *decreasing-increasing* group ($B = 1.91, SE = .30, p_{rep} > .99$), and the *decreasing* group ($B = 2.09, SE = .34, p_{rep} > .99$), and the each reporting significantly more health dysfunction than the *high-stable* group. Lower income also distinguished the *increasing* group ($B = -2.27, SE = .68, p_{rep} > .99$) and the *decreasing-increasing* group ($B = -1.87, SE = .61, p_{rep} = .98$) from the *high-stable* group.

Discussion

In this study, we sought to model divergent trajectories of response to significant life events among a large representative sample of Germans followed from 1984 to 2003. Consistent with previous work (Lucas, 2005; Lucas et al., 2003), findings revealed marked individual differences in response to three signal life events (widowhood, divorce, and marriage). Importantly, however, the present findings extended previous research by explicitly modeling multiple trajectories of response to each life event. In support of the validity of the analyses, covariates predicted these trajectories in expectable ways (Muthén, 2003). Moreover, the findings demonstrated that the most robust response to each life event was a stable and high level of SWB that was fundamentally unperturbed by the life event.

Although there has now been considerable evidence of individual differences in response to critical life events (e.g., Bonanno, 2004; Lucas et al., 2003), the current study is one of the first to model adaptation to such events using the emergent technique of LGMMs, an approach specifically designed to capture divergent trajectories empirically. Unlike conventional growth model approaches, such as a random effects HLM, which assume that individuals can be adequately described using a single estimate of growth parameters, the LGMM approach estimates multiple latent trajectories that more fully capture the heterogeneity of responses. It is noteworthy that in the current study the trajectories were, in a number of cases, markedly

divergent from one another. It is a distinct virtue of LGMMs that divergent trajectories can be teased apart from the average. Indeed, the average response to these life events across time can be misleading. An average trajectory, for example, carries no information about the specific patterns of variation across time, as were observed in the present study.

In addition to demonstrating individual differences in response to life events, the findings offered strong confirmation for the notion that most people are unperturbed by highly aversive events such as divorce and widowhood. Elsewhere, this pattern has been referred to as resilience (Bonanno, 2004). The modal response to marriage was also a stable pattern of unperturbed high SWB. Although this trajectory would obviously not be described as resilience, it nevertheless testifies to the homeostatic quality of SWB across both positive and negative events.

How do we reconcile these findings with the hedonic treadmill metaphor? A treadmill-like pattern of change followed by recovery toward baseline was in fact observed in each sample, but only by a minority of participants. For most participants, the treadmill metaphor did not apply. In the bereaved sample, most respondents evidenced little or no change in SWB after loss. In the case of divorce and marriage, even higher proportions of the sample evidenced a stable pre- and post-trajectory. Moreover, in these samples, the mean for the stable trajectory was for all intents and purposes flat. Finally, as has been documented elsewhere (Lucas, 2005; Lucas et al., 2003), there were also classes of participants in each sample who evidenced lasting changes in SWB.

These findings have additional substantive implications. In the case of the most pointed stressor, bereavement, the trajectories were strikingly similar to those mapped previously in response to other types of extreme stressors (Bonanno et al., 2002; Burke, ShROUT, & Bolger, 2007; Deshields et al., 2006). As in previous studies, which used a variety of methods, not only

was resilience the most common response, we also replicated a pattern of improvement after the loss (Bonanno et al., 2002; Schulz et al., 2001). Among the covariate predictors for the improved trajectory was an increase in income. In the context of Hobfoll's conservation of resources model of coping (Hobfoll, 1989), this finding suggests that increased income may have offered significant aid to the person's coping and boosted, albeit temporarily, their SWB. Other covariate findings supported our class solutions as well. For example, age was a positive predictor of the resilient bereaved group, which is consistent with findings that grief reactions are typically less pronounced in old age (Lichtenstein, Gatz, Pedersen, Berg, & et al., 1996).

In the case of divorce, less education predicted the *moderate-decreasing* trajectory, suggesting that lack of education may complicate one's ability to adapt to divorce. Lower levels of income also were also more likely among people for whom marriage appeared to be a stressor (the *decreasing* group) and for people whose SWB had been decreasing prior to marriage and then gradually increased after marriage (*decreasing-increasing*). Finally, health dysfunction was a robust predictor of the trajectory of stable SWB in comparison with other trajectories across bereavement, divorce, and marriage. Gender did not significantly predict trajectory assignment for any of the life events. However, a more robust test of gender's influence would be obtained using a multiple group approach within a LGMM framework (e.g., Schaeffer et al., 2006).

The LGMM approach offers a palliative to the broad strokes characterization of the impact of life events. Indeed, it appears that people respond in surprisingly diverse ways to life events. In spite of this diversity, however, the impact of these events, for most people, is largely negligible. Most people in fact maintained a stable level of SWB in the face of both positive and negative events. In other words, they never varied from the set point. Although this is in some ways compatible with a hedonic treadmill, a critical point is that some people responded

positively to ostensibly negative events (bereavement and divorce), while others responded negatively to an ostensibly positive event (marriage). The findings thus underscore that the impact of life events may depend to a great degree on individual differences and on life circumstances. Rather than attempting to characterize these events in monotonic terms, research should seek to refine our understanding of the factors that contribute to these diverse outcomes.

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Table 1.

*Fit Indices for One- to Five-Class Growth Mixture Models for **Bereavement** (Unconditional)*

Fit Indices	Growth Mixture Model				
	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
AIC	14204.28	14131.95	14093.79	14080.95	14071.86
BIC	14282.94	14223.03	14197.29	14196.87	14200.19
SSBIC	14222.64	14153.20	14117.94	14108.01	14101.81
Entropy	--	.50	.68	.68	.64
LRT <i>p</i> value	--	.04	.53	.49	.10
BLRT <i>p</i> value	--	<.001	<.001	<.001	<.001

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.

Table 2

Growth Factor Parameter Estimates for 4-Class Conditional Model: Bereavement

Class	Intercept			Slope		
	Est.	Z score	95% CI	Est.	Z score	95% CI
Chronic Low	5.16	13.53	(4.41, 5.91)	-.44	-1.76	(-.93, .05)
Acute-Recovery	7.94	30.97	(7.43, 8.44)	-1.73	-3.83	(-2.61, -.08)
Improved	3.99	3.48	(1.74, 6.23)	1.64	1.81	(-.13, 3.41)
Resilient	7.67	48.21	(7.36, 7.98)	-.24	-1.93	(-.49, .004)

Note. Est. = Estimate. CI = confidence interval.

Table 3.

Fit Indices for One- to Five-Class Growth Mixture Models for Divorce (Unconditional)

Fit Indices	Growth Mixture Model				
	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
AIC	16963.960	16880.50	16818.69	16805.28	16800.50
BIC	17048.398	16978.27	16929.79	16929.72	16938.272
SSBIC	16988.075	16908.42	16850.42	16840.82	16839.851
Entropy	--	.64	.72	.70	.71
LRT p value	--	.50	.21	.82	.37
BLRT p value	--	>.001	>.001	>.001	.13

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.

Table 4

Growth Factor Parameter Estimates for 3-Class Conditional Model: Divorce

Class	Intercept			Slope		
	Est.	Z score	95% CI	Est.	Z score	95% CI
Low-increasing	3.80	7.13	(2.75, 4.84)	3.03	5.73	(2.00, 4.07)
Moderate-decreasing	6.02	14.83	(5.22, 6.81)	-1.57	-3.70	(-2.40, -.74)
Resilient	7.02	47.68	(6.73, 7.31)	.12	.87	(-.15, .41)

Note. Est. = Estimate. CI = confidence interval.

Table 5.

*Fit Indices for One- to Five-Class Growth Mixture Models for **Marriage** (Unconditional)*

Fit Indices	Growth Mixture Model				
	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
AIC	43335.65	43188.15	43031.17	42899.85	42857.85
BIC	43417.56	43291.91	43156.77	43047.30	43027.14
SSBIC	43369.91	43231.550	43083.70	42961.52	42928.66
Entropy	--	.87	.83	.81	.82
LRT p value	--	.08	.22	<.001	.26
BLRT p value	--	<.001	<.001	<.001	<.001

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSBIC = sample size adjusted Bayesian information criterion; LRT = Lo-Mendell-Rubin test; BLRT = bootstrap likelihood ratio test.

Table 6

Growth Factor Parameter Estimates for 4-Class Conditional Model: Marriage

Class	Intercept			Slope			Quadratic		
	Est.	Z score	95% CI	Est.	Z score	95% CI	Est.	Z score	95% CI
Increasing	3.74	8.88	(2.91, 4.56)	1.50	7.09	(1.08, 1.91)	-0.14	-6.12	(-.18, -.09)
High-Stable	7.84	128.74	(7.71, 7.96)	0.05	2.18	(.006, .11)	-0.01	-3.90	(-.02, -.005)
Decreasing-Increasing	6.84	16.69	(6.03, 7.64)	-0.69	-4.53	(-.98, -.38)	0.08	5.85	(.06, .11)
Decreasing	6.09	13.41	(5.20, 6.99)	0.70	3.85	(.34, 1.06)	-0.13	-6.941	(-.17, -.09)

Note. Est. = Estimate. CI = confidence interval.

Figure Captions

Figure 1. Bereavement trajectory classes for the conditional model (with covariates).

Figure 2. Divorce trajectory classes for the conditional model (with covariates).

Figure 3. Marriage trajectory classes for the conditional model (with covariates).





