

Stepping Off the Hedonic Treadmill

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 eventually return to a setpoint of subjective well-being. Yet prior research is inconclusive regarding the extent of interindividual variability. Recent theoretical models suggest that there should be heterogeneity in long-term stress responding (Bonanno, 2004; Muthén & Muthén, 2000). To test this idea, 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). Nevertheless, some trajectories diverged sharply from the modal response. Despite the tendency to maintain preevent levels of SWB, there are multiple and often divergent trajectories in response to bereavement, divorce, and marriage, underscoring the essential role of individual differences.

Keywords: bereavement, divorce, marriage, individual differences, latent growth mixture modeling

Introduction

Brickman and Campbell (1971) first coined the term “hedonic treadmill” to describe the general propensity of human beings 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, or 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 only 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. In fact, there appear to be marked individual differences in response to significant events, with some people experiencing enduring change and others very little (Lucas, Clark, Georgellis, & 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 growth mixture modeling to identify trajectories of response to three major life events.

Although the hedonic treadmill theory has generated a substantial body of research, evidence increasingly sug-

gests that it needs significant renovation (Diener, Lucas, & Scollon, 2006). In a series of influential studies using a German panel dataset spanning 20 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 more enduring effects on SWB. Just 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, Renniecke, & Dekel, 2005; Bonanno et al., 2002), disaster (Bonanno, Renniecke et al., 2005), breast cancer (Deshields, Tibbs, Fan, & Taylor, 2006; Lam et al., 2010), unemployment (Galatzer-

Levy, Bonanno, & Mancini, in press), 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).

However, most prior research relied on simple mathematical algorithms to identify trajectories, an approach with important limitations (Bonanno, Westphal, & Mancini, in press). The first is that they rely on a single mean and standard deviation to classify individuals (e.g., Bonanno et al., 2002), which implies a homogeneous distribution. Because different pathways may possess different degrees of variance, a single estimate of functioning does not permit this source of variability to influence trajectory designation. As a result, prior investigations were essentially relying on a fixed effects model to define trajectories when a random effects approach is more appropriate because it allows for within-person variability. A second critical limitation prior trajectory research is that a priori cut-points are inherently arbitrary and make it impossible to know whether naturally occurring distinctions are being identified.

By contrast, an emergent set of statistical techniques derived from structural equation modeling explicitly identifies different subpopulations using empirical criteria. Essentially, this approach seeks to assess heterogeneous groupings or subpopulations based on the distributional properties of the data themselves. Moreover, these subpopulations are not premised on a priori assumptions, which could simply confirm preconceived ideas, but on empirical criteria and interpretability (Muthén & Muthén, 2000). This approach, called latent growth mixture modeling (LGMM), is likely the most powerful method for estimating population heterogeneity (Muthén, 2003) and is ideally suited to addressing the question of whether multiple pathways characterize responses to stressful events. LGMM does this by simultaneously modeling both continuous latent variables (e.g., intercept and slope) and categorical latent variables (trajectory class). Moreover, in contrast to the related technique of latent class analysis and other semi-parametric approaches (Nagin, 1999), LGMM can model variances within each subpopulation, allowing each grouping different degrees of variability. This allows for a more nuanced and accurate estimation of population heterogeneity.

The 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 expected to find divergent trajectories of response to marriage, divorce, and bereavement that are uniquely associated with relevant covariates.

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 to 2003, a nationally representative study of German households identified through multistage random sampling ($N = 16,795$). 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 below the age of 75 when the event occurred.

The bereaved sample had 464 participants (76% women), on average 60.45 years old ($SD = 11.32$), with 10.36 years of education ($SD = 1.69$) and a household income of DM 3,722 ($SD = 4,171$). The divorced sample had 629 participants (52.5% women), on average 40.48 years old ($SD = 11.17$), with 11.37 years of education ($SD = 2.42$) and a household income of DM 7,033 ($SD = 9,790$). The married sample had 1,739 participants (51% women), on average 28.38 years old ($SD = 6.19$), with 12.38 years of education ($SD = 2.68$) and a household income of DM 8,896.69 ($SD = 11,274.31$). We removed data for married participants if 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 nine waves of data collected at yearly intervals (four waves preevent, one wave the year of the event, and four waves postevent). Most participants had at least six waves of data (bereavement, 94.8%; divorce, 73.0%; and marriage, 82.3%).

Measures

Demographics

At each wave of data collection, age, sex (1 = male, 2 = female), educational level (years of education), 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 nine 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 working around the house, being employed, working, studying, etc.") with answers ranging from 1 (*not at all*) to 3 (*very much so*). To more robustly estimate health dysfunction across time, we averaged scores for all nine waves of data. Coefficient α for the 9-item longitudinal measure was very high ($\alpha = .93$).

Subjective Well-Being (SWB)

We measured 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 Akaike (AIC) information criterion indices, entropy values, the Lo-Mendell-Rubin likelihood test (LRT: Lo, Mendell, & Rubin, 2001), and the bootstrap likelihood ratio test (BLRT: Ny-

lund, 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, 2003), a third step extended the LGMM to include covariate predictors of class membership in a conditional model. 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. Because the conditional and unconditional models are nested, we could use log likelihood ratio χ^2 tests to assess fit. Only those covariates that significantly improved model fit were retained in the final solution for the conditional model.

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 χ^2 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 LGMM analyses of 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 interclass 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.

Determining Trajectory Class Solutions for Each Life Event

We next compared one- to five-class unconditional models (i.e., no covariates) for each life event. To determine the appropriate number of trajectory classes, we examined fit indices, inspected the functional form of the trajectories, and also considered theoretical justification and interpretability (Muthén, 2003). Based on these analyses (available from first author), we selected four-, three-, and four-class

Table 1. 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)

Notes. Est. = Estimate. CI = confidence interval. Model includes covariates (age, health dysfunction, and change in income).

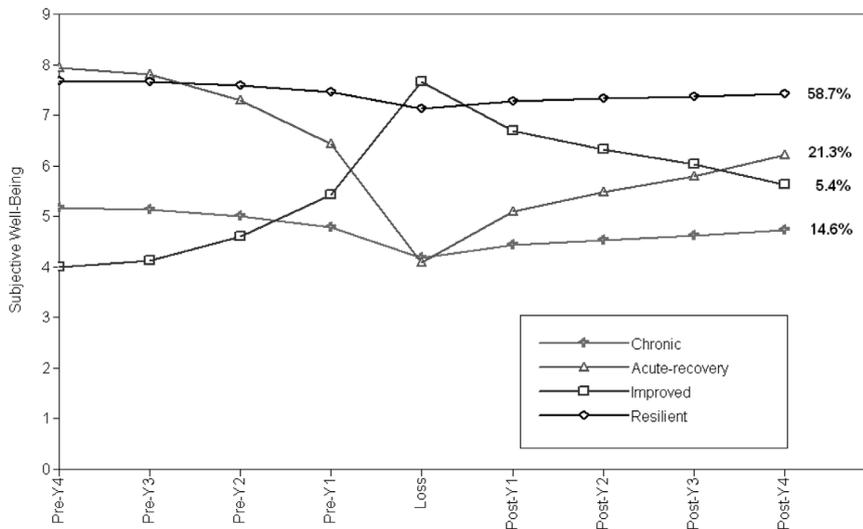


Figure 1. Bereavement trajectory classes for the conditional model (with covariates).

solutions as optimal for bereavement, divorce, and marriage, respectively. Having determined the optimal trajectory class solution for each event, we then included covariate predictors for our final models, which we describe below.

LGMMs: Bereavement

Table 1 shows growth parameter estimates and confidence intervals for the freely-estimated four-class conditional model for bereavement. This model included age, health dysfunction, and change in income as covariate predictors of class membership. Only these covariates resulted in significantly improved model fit for the conditional model when compared to the unconditional model, $\chi^2(9, N = 455) = 100.88, p > .001$. Figure 1 shows that the majority of the 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 preloss SWB who experienced a sharp dip and a gradual improvement toward preloss levels; we labeled this class *acute-recovery*. The third largest class (14.6%) differed from the second class in having low preloss SWB but also showed a dip in SWB following the loss and a gradual return to preloss 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*.

To assess the role of covariates, we designated the resilient category as the reference group. The resilient group was significantly older than the chronic low ($B = -.10, SE = .03, p < .01$), acute-recovery ($B = -.04, SE = .02, p < .01$), and the improved groups ($B = -.05, SE = .03, p < .10$). The resilient group also reported substantially less health dysfunction than the chronic low ($B = 3.39, SE = .61, p > .001$) and the improved groups ($B = 1.81, SE = .57, p > .001$). Finally, the resilient group saw less of a reduction in income than the chronic low ($B = -1.13, SE = .53, p < .05$) and the acute-recovery groups ($B = -2.55, SE = .96, p < .05$), but the improved group saw an increase in income compared to the resilient group ($B = 2.71, SE = .84, p > .001$).

LGMMs: Divorce

Table 2 shows growth parameter estimates and confidence intervals for the freely-estimated three-class model for divorce. This model included health dysfunction and years of education as covariate predictors of class membership.

Table 2. 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)

Notes. Est. = Estimate. CI = confidence interval. Model includes covariates (health dysfunction and years of education).

Table 3. 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	-6.94	(-.17, -.09)

Notes. Est. = Estimate. CI = confidence interval. Model includes covariates (health dysfunction and income).

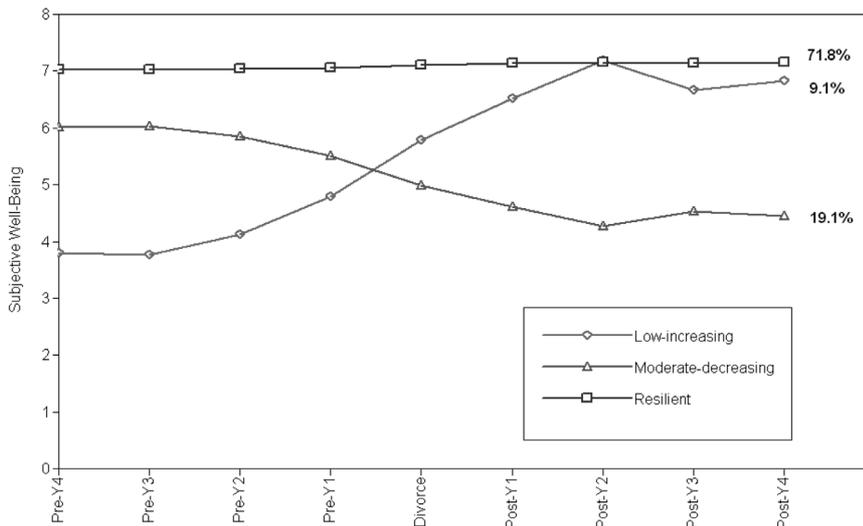


Figure 2. Divorce trajectory classes for the conditional model (with covariates).

Only these covariates resulted in significantly improved model fit for the conditional model when compared to the unconditional model, $\chi^2(4, N = 625) = 51.76, p > .001$. 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 predivorce SWB who saw sharp increases in SWB over time; we labeled this class *low-increasing*.

To assess the role of covariates, we designated the resilient group as the referent. Health dysfunction distinguished the low-increasing ($B = 1.75, SE = .42, p > .001$) and the moderate-decreasing ($B = 1.86, SE = .36, p > .001$) 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 ($B = -.20, SE = .12, p = .10$).

LGMMs: Marriage

Table 3 shows growth parameter estimates and confidence intervals for the four-class linear and quadratic model for marriage. This model included income and health dysfunction as covariate predictors of class membership. Only these covariates significantly improved model fit for the four-class conditional model when compared to the unconditional model, $\chi^2(6, N = 1733) = 97.75, p > .001$. As shown in Figure 3, 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-*

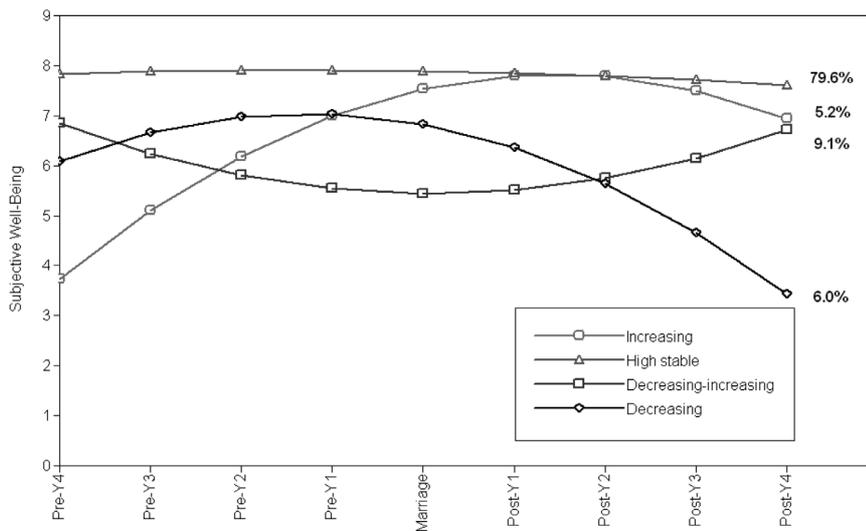


Figure 3. Marriage trajectory classes for the conditional model (with covariates).

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 sharply 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.

To assess the role of covariates, we designated the high-stable group as the referent. These analyses showed that health dysfunction distinguished each of the classes, with the increasing group ($B = 1.72$, $SE = .37$, $p > .001$), the decreasing-increasing group ($B = 1.91$, $SE = .30$, $p > .001$), and the decreasing group ($B = 2.09$, $SE = .34$, $p > .001$), each reporting significantly more health dysfunction than the high-stable group. Lower income also distinguished the increasing group ($B = -2.27$, $SE = .68$, $p > .001$) and the decreasing-increasing group ($B = -1.87$, $SE = .61$, $p < .01$) 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), the 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 fundamentally unperturbed by the life event.

Although there is 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 a number of cases in the current study, the trajectories were 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 in 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 mar-

riage, even higher proportions of the sample evidenced a stable pre- and posttrajectory. Moreover, in these samples, the mean for the stable trajectory was for all intents and purposes flat. Finally, as documented elsewhere (Diener et al., 2006; 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). However, the present results extended previous work in three critical ways: First, by relaxing the assumption of a single homogeneous distribution, the trajectories in the present study were derived empirically using distributional information contained in the data themselves. By contrast, most prior work on trajectories has relied on a priori conceptualizations and arbitrary cutpoints to identify patterns of response. Second, because subjects were assessed up to 4 years before the marker event, we had a more robust estimate of preevent functioning and could therefore obtain a more accurate gauge of the reaction to the marker event in comparison to baseline functioning. A third contribution of the present study is the large population-based sample in which subjects were not recruited following the marker event, but instead enrolled in an ongoing study of longitudinal functioning and adjustment. Because this recruitment approach mitigates the potential for selection bias, a particular concern in bereavement research, the present findings are more likely to generalize to the broader population.

The covariates in our models offered support for our trajectory solutions. As Muthén (2003) has discussed, a key feature of LGMMs is their ability to incorporate auxiliary information from covariates into the formation of the trajectory classes. Indeed, in order for an LGMM analysis to be interpretable, there should be significant and theoretically relevant relationships between covariates and trajectory classes. In the present analyses, we found the expected relationships from prior research and theory. For example, among the covariate predictors for the improved trajectory there 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 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. Finally,

health dysfunction was a robust predictor of the trajectory of stable SWB in comparison with other trajectories across bereavement and divorce. 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).

One critical strength of the present results is the inclusion of preevent (or prospective) data, which are exceedingly rare in research on life events. Prospective data allow one to disentangle a person's response to the event and their typical level of functioning. In the absence of such data, it is impossible to know, for example, whether significant dysfunction in response to bereavement actually reflects chronic psychopathology or a reaction to the loss itself (Bonanno et al., 2002). In the present results, we found just such a bereavement trajectory of marked low functioning across time. Without preloss data, it might appear that this trajectory represents a particularly severe response to loss when in fact it primarily represents the continuation of a chronic low SWB. Thus, the prospective nature of these data greatly increases our confidence that these trajectories are veridical representations of reactions to life events and not just reflections of preexisting conditions.

The present findings confirm that people are generally able to cope well with bereavement and divorce. Following each life stressor, most people showed a flat trajectory of stable SWB in response to these life experiences (bereavement, 58.7%, divorce, 71.8%). In the case of bereavement, these findings strongly suggest that treatment interventions should only be offered to people who show persistent difficulties (Mancini, Bonanno, & Pressman, 2006). This conclusion is consistent with a recent meta-analysis of grief therapies implicating the failure to target grievers with high distress as the principal explanation for the surprisingly lack of efficaciousness of these treatments (Currier, Neimeyer, & Berman, 2008). In the case of divorce, a surprisingly large minority (9.1%) showed improved SWB following divorce. This finding is at odds with previous suggestions that divorce should be understood as having fundamentally detrimental effects (Lucas, 2005). It also suggests that divorce is an appropriate and desirable alternative for a subset of persons. We would hasten to add that this improvement represents an increase from low levels of SWB before the divorce, suggesting that the marriage was an unhappy one.

Limitations of this study should be borne in mind. Perhaps most important, we relied on a 1-item measure of subjective well-being. Although 1-item measures are commonly used in research on subjective well-being, they obviously cannot account for a multidimensional conceptualization of subjective well-being. However, 1-item measures typically show high correlations with longer measures and are generally deemed adequate assessments of subjective well-being (Andrews & Withey, 1976; Diener, 1984). Another limitation is the absence of an outcome measure of psychopathology. This is of primary concern in

the analyses of bereavement, which is reliably associated, in the short term, with depressive, grief, and PTSD symptoms (Bonanno et al., 2007). However, as noted above, the trajectories identified in the bereavement analyses bore a clear resemblance to those identified in previous studies using less sophisticated methods (Bonanno et al., 2002). An advantage therefore of using subjective well-being as an outcome measure in the present study is that it provides evidence of convergent validity for trajectories previously found.

An additional limitation is that participants were recruited entirely from Germany. It is possible that different results would obtain using different samples, and we would recommend that researchers conduct similar analyses using panel datasets from other countries. We also hasten to emphasize that life satisfaction was measured annually and was thus potentially less sensitive to change than would be ideal. This length of time between measurement points may explain why we did not identify a purely defined recovery trajectory (or a return to baseline within a year of the loss).

Finally, in some cases LGMM analyses may identify nonnormality rather than true mixture distributions. Although we used the best practices to ensure that our model selection reflected a true mixture distribution, we cannot rule out our merely having diagnosed nonnormality. However, we consider this possibility unlikely, given the large representative sample, the degree to which the trajectory patterns conformed to prior theory, and the coherent patterns of covariate prediction for each of the trajectories.

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. Despite 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 setpoint. Although in some ways this is 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 largely 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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