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Population- and Individual-Level Changes in Life Satisfaction Surrounding Major Life Stressors

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Abstract

How do stressful life events impact well-being, and how does their impact differ from person to person? In contrast to work focusing on discrete classes of responding, the current study examines the adequacy of a model where responses to stressors are characterized by a population average and continuous variability around that average. Using decades of yearly data from a large German longitudinal study examining effects of divorce, spousal loss, and unemployment, we found that (1) in the overall population, life satisfaction was diminished for years preceding stressors and only incompletely recovered with the passage of time, and (2) there were large between-person differences around the average response, following normal and heavier-tailed continuous distributions rather than discrete classes. These findings provide a multilevel model of responses to stressors and suggest that individual differences can be understood in terms of continuous variation around what is typical for a given event and population.

Keywords

well-being, stress and coping, longitudinal methodology, quantitative models

Sooner or later, everyone is confronted with some degree of hardship, sorrow, or even tragedy. When this happens, what is a typical trajectory in well-being, and what differences in trajectory can be seen from person to person? Although more researches have examined this topic, our understanding of the many ways people can respond to aversive life experiences is still incomplete. Beyond deepening our scientific understanding of psychological resilience and vulnerability, building models of changes in well-being surrounding stressors could ultimately be used to forecast psychological outcomes for groups or individuals of interest (see Chang, Reddan, Ashar, Eisenbarth, & Wager, 2015; Russo, Murrough, Han, Charney, & Nestler, 2012).

Models of responding to stressors have often used the concept of *hedonic adaptation*—the process by which the effects of life stressors diminish over time to baseline levels (Frederick & Loewenstein, 1999; Fujita & Diener, 2005; Lykken & Tellegen, 1996). Relatedly, a large body of research has focused on psychological *resilience*—a pattern of responding to stressors that is characterized either by no measurable stressor-related change or relatively less change compared to other categories of responding (Bonanno, Westphal, & Manicini, 2011; Russo et al., 2012). Studies in this area have commonly made use of analytic techniques that classify people into a small number of distinct subpopulations that show prototypical trajectories of change in well-being over time (see Muthén, 2004; Ram & Grimm, 2009). Several reports have indicated that a resilience response is the most common trajectory—even more common than a *recovery* response (well-being is diminished surrounding a stressor but recovered to a relatively high degree over time). However, a recent investigation has shown that relaxing certain modeling assumptions results in relatively fewer people falling into a resilient class (36–48%) and more into a recovery class (52–64%; Galatzer-Levy & Bonanno, 2016; Infurna & Luthar, 2016).

Although this prior work has shed light on variability in response to stressors, it remains unclear whether different ways of responding—such as resilience, recovery, and prolonged/complicated grief—reflect distinct subpopulations of people (i.e., components of a mixture distribution) or communicative labels applied to different regions of a single continuous distribution. That is, because techniques used previously have assumed that the population of all people exposed to stressors is made up of a small number of prototypical subpopulations of different kinds of people, it is not known whether discrete

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classes of individual trajectories would emerge from a more general approach allowing for multilevel modeling of nonlinear trajectories in well-being.

We sought to address these questions by building a multilevel model of nonlinear changes in well-being surrounding stressful life events, using longitudinal data from a representative sample of German households (Wagner, Frick, & Schupp, 2007). Most common statistical models, including multilevel models that have been applied to the study of changing well-being, assume that either trends will be linear or they require the researcher to specify the nonlinearity a priori (e.g., positing quadratic or cubic functions, and/or specific points of discontinuity). For example, past studies have modeled trajectories in life satisfaction with specified piecewise combinations of polynomial terms (e.g., Burke, Shrout, & Bolger, 2007; Lucas, 2005; Lucas, Clark, Georgellis, & Diener, 2003, 2004) or with a nonlinear function having specified periods of change and stability (Anusic, Yap, & Lucas, 2014; Yap, Anusic, & Lucas, 2012). However, specifications of this kind may not be known with certainty, and if they are wrong, the resulting model estimates and inferences can be misleading. To avoid these issues, we applied the generalized additive mixed model (GAMM) approach (Wood, 2006; Zuur, Saveliev, & Ieno, 2014). In this approach, the functional form of a nonlinear trajectory is estimated in a data-driven manner, and penalties (based on an approximation to out-of-sample fit) are introduced to avoid overfitting to the sample. Moreover, the model can incorporate mixed (i.e., multilevel) effects in order to derive estimates of the trajectories apparent in the overall population and for specific individuals.

With this approach, our primary goals were (1) to estimate population- and individual-level changes in life satisfaction associated with experiencing divorce, spousal loss, and unemployment without a priori assumptions about functional form and (2) to ask whether individual differences in trajectories are well characterized by discrete classes or whether they instead follow a single continuous distribution.

Method

Participants and Design

We analyzed the data from the German Socio-Economic Panel (SOEP) study—a prospective study of life outcomes in a representative sample of German households with annual waves of survey response (Wagner et al., 2007). The SOEP study was initiated in 1984 and covers approximately 50,000 residents of West and East Germany; potential respondents were randomly selected from a set of randomly selected locations in Germany, where all family members older than 16 years of age within each household were eligible. For purposes of comparison with prior work, our participant inclusion procedures followed those used in two prior studies (Infurna & Luthar, 2016; Mancini, Bonanno, & Clark, 2011). That is, we included participants who reported experiencing spousal loss (n = 1,214; mean age at loss = 61, standard deviation [SD] = 11; 74% female), divorce (n = 1,579; mean age at divorce = 40, SD = 9; 55% female), or unemployment (n = 1,800; mean age at unemployment = 42, SD = 12; 44% female) over a 28-year span (1984–2011). As in the prior work, we included people for whom this was the first time they experienced this event during the course of the study and did not model whether they experienced more than one of any of these events. Also as in the prior work, we (1) excluded participants who were older than 75 years at the wave of reported divorce or spousal loss, (2) defined unemployment onset as the wave (year) participants reported being registered as unemployed, given that they had reported being in full-time employment for three preceding waves, and (3) included (in the unemployment data set) only participants who were aged 21–60 years at the time of their reported unemployment and who participated in the study for at minimum 4 years following their unemployment (Galatzer-Levy, Bonanno, & Mancini, 2010; Infurna & Luthar, 2016; Mancini et al., 2011). However, although we had access to data from 2,461 participants reporting unemployment, we limited our analysis to 1,800 participants randomly sampled from this group of 2,461 because of hardware/computational limitations (i.e., so estimated models would not exceed available memory). Finally, although previous studies have often only included reports for several years surrounding stressors, we modeled all available sampling waves (i.e., we did not limit our analyses to a specific window surrounding the life stressor) for our primary analyses, reasoning that including all available data improves the estimation of reliable differences from person to person as dissociable from error variation (see Bolger & Laurenceau, 2013; Gelman & Hill, 2007; for description of analyses that used data from only 10 and 20 years circa the stressor, see Online Supplemental Materials).

Measures

The outcome variable for our analyses was reported life satisfaction (0—*totally unsatisfied* to 10—*totally satisfied*), and the predictor variable was year of survey, centered on the sampling wave in which the life stressor was reported (i.e., Year 0 represents the survey in which participants indicated they had experienced one of these stressors in the past 12 months; see Cheung & Lucas, 2014; Lucas & Donnellan, 2012). Participants made an average of 23.9 annual reports of life satisfaction for spousal loss, 14.6 for divorce, and 17.4 for unemployment.

Analysis

We fit GAMMs using the *bam* function within the *mgcv* (mixed generalized additive model computation vehicle, Version 1.8.12) package in R (Wood, 2006). In the GAMM framework, an outcome variable (here, life satisfaction) varies as an unknown smooth function of a predictor variable (here, year of survey), which is represented using regression splines (i.e., piecewise polynomial fits connected by knots). Model form and smoothness are not user specified (as when selecting a linear, quadratic, or n-degree polynomial fit in regression), but rather estimated from the data via a fitting procedure in which less smooth models are penalized and an optimal smoothness is selected by penalized likelihood metrics that approximate out-of-sample predictive fit (Wood, 2006). Moreover, GAMM coefficients (i.e., intercept, linear slope, and nonlinear curve coefficients) can be estimated as varying from person to person (Gelman & Hill, 2007; Wood, 2006). That is, instead of separating a population of individual into subgroups characterized by qualitatively distinct pattern of change as in growth mixture modeling (Muthén, 2004; Ram & Grimm, 2009), this approach models a trajectory for each individual that can vary along certain parameters.

We fit models for the three categories of life stressors (divorce, spousal loss, and unemployment), fitting four different versions of each model (see Figure 1 for an illustration): (1) fixed effect of year from stressor only, with no person-specific model parameters (i.e., each person is assigned an identical curve), (2) multilevel with person-specific varying intercepts (i.e., the shape of the curve is the same for each person, but an intercept allows for different overall levels of well-being), (3) multilevel with person-specific varying intercepts and slopes (i.e., in addition to the intercept, a slope parameter allows for different linear change in well-being over time), and (4) multilevel with person-specific varying curves (the most flexible model—person-specific curves can vary in form nonlinearly, with the same smoothing parameter used for all participants). Models were estimated via restricted maximum likelihood (REML), with thin-plate splines as a smoothing basis, and setting maximum number of knots (i.e., minimum possible smoothness) to 48—one fewer than the levels of the year variable (see Wood, 2006; Wood, Goude, & Shaw, 2015). We used REML and Akaike information criterion scores to compare models on the basis of predictive fit and used deviance explained (i.e., 1 – the proportion of residual variance to null deviance) as an absolute metric of model fit (see Wood, 2006).

We considered three parameters for each person to characterize his or her person-specific trajectory, conditional on the (GAMM) models fit: a model intercept (from Model 3, the overall level of life satisfaction), a model slope (from Model 3, the linear trend in life satisfaction over time), and a model typicality score (from Model 4, the Fisher transformed time-series correlation between his or her person-specific trajectory and the overall population trajectory—calculated only for people with at least 10 life satisfaction reports). We generated histograms of these estimated parameters in order to inspect their distributional properties (see Lange & Ryan, 1989; Pinheiro & Bates, 2000; Verbeke & Molenberghs, 2013; for a description of these distributions in terms of single component normal and *t*-distributions, see Online Supplemental Materials). To ask whether person-to-person variability could be well characterized by discrete classes, we submitted distributions of these estimated person-specific parameters to Hartigans's dip test for deviations from unimodality (*dip.test* in R package *diptest*; Hartigan & Hartigan, 1985). We also fit parametric mixture models (*normalmixEM* in R package *mixtools*) to describe the distributions as mixtures of normal components with arbitrary mean and variance (i.e., the normal distributions were not assumed to have equal variances), using a bootstrapping approach to select between 1 and 10 component mixtures (i.e., we ran 500 instances of the likelihood ratio test for the null hypothesis of a k-component fit versus the alternative hypothesis of a $k + 1$ component fit).

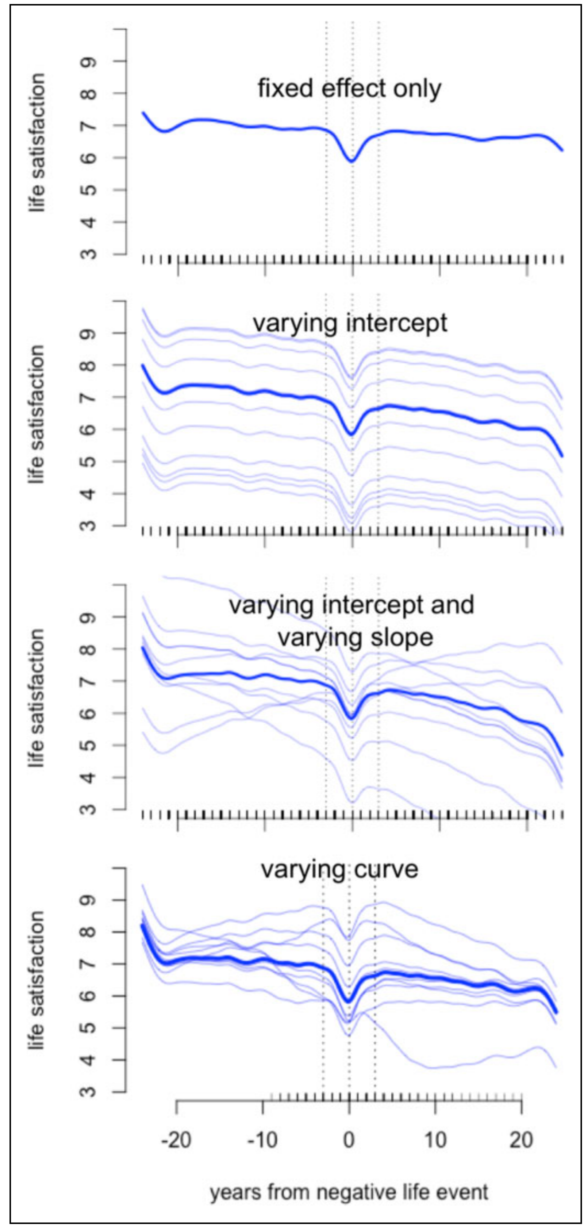

Figure 1. Illustration of models that differ in their varying coefficient structures. For a *fixed effect-only* model, every person in the data set is pooled into a single curve. For a *varying intercept* model, a single intercept parameter adjusts the height of the model from person to person. For a *varying intercept and varying slope* model, an intercept and a slope parameter adjust the height and the temporal trend of the model from person to person. For a *varying curve* model, the functional form of the curve can vary nonlinearly from person to person. Graphs show the overall population-level model (thick blue line) and person-specific models for 10 randomly selected subjects (thin blue lines) for the spousal loss data set.

Table 1. Sample Size, Effective Degrees of Freedom, *F* Score for the Smooth Effect of Year, Pseudo-R^2, Optimized REML Selection Criterion, and AIC for (1) Fixed Effect-Only Models, (2) Varying Intercept Models, (3) Varying Intercept, Varying Slope Models, and (4) Varying Curve Models of Trajectories in Life Satisfaction Surrounding Divorce, Spousal Loss, and Unemployment.

Divorce (n = 1,214)	Effective *df*	*F* (Year)	Pseudo-R^2	REML	AIC
Fixed effect only	16.2	15.8***	1.2	48,841	97,648
Varying intercept	1,391.8	28.5***	42.3	44,948	87,702
Varying intercept and slope	2,054.9	19.0***	48.9	44,523	86,156
Varying curve	3,133.5	14.4***	56.4	44,163	84,650
Spousal loss (n = 1,579)					
Fixed effect only	25.8	17.2***	2.6	40,156	80,251
Varying intercept	1,100.4	30.7***	44.9	36,690	71,487
Varying intercept and slope	1,686.8	24.2***	52.2	36,247	69,892
Varying curve	2,564.5	20.4***	59.6	36,076	68,954
Unemployment (n = 1,800)					
Fixed effect only	27.5	30.3***	2.9	63,734	127,405
Varying intercept	1,657.1	38.1***	43.6	58,330	113,816
Varying intercept and slope	2,673.7	22.2***	51.8	57,516	111,002
Varying curve	4,136.5	19.4***	57.9	57,003	108,864

Note. Pseudo-R^2 indicates proportion of deviance explained by the model. Lower REML/AIC scores indicate better predictive fit. REML = restricted maximum likelihood; AIC = Akaike information criterion.
***$p < 10^{-16}$.

Results

Models With Person-Specific Curves Were Highest in Model Fit

In an initial model-building procedure, we asked for each type of stressor (divorce, spousal loss, and unemployment) whether the data were better described by (1) a *fixed effect-only* model, (2) a *varying intercept model*, (3) a *varying intercept, varying slope model*, or (4) a *varying curve* model. For all three types of life stressors, a varying curve model fits the data best (see Table 1). This result indicates that individual differences in life satisfaction trajectories surrounding stressors are not adequately described with a "one-shape-fits-all" curve nor a curve that varies from person to person only by intercept (reflecting differences in baseline life satisfaction) and slope (reflecting differences in whether life satisfaction curve generally trended upward or downward over time) but are better described with a varying curve model allowing different people to show a wide variety of different trajectories in life satisfaction surrounding a life stressor. In the GAMM framework, the variance accounted for by a model can be represented with the deviance explained statistic. The fixed effect of time models (with no person-specific parameters) accounted for less than 3% of the variance in life satisfaction reports; the varying intercept models accounted for about 44%; the varying intercept and varying slope models accounted for about 51%; and the varying curve models accounted for about 58% (see Table 1).

Life Satisfaction Was Diminished Surrounding Stressors and Only Incompletely Recovered Over Time

Next, we inspected estimated smooth curves for changes in life satisfaction over time in the overall population, with 95% credible intervals reflecting the form that these curves could plausibly take in light of the observed data. (These curves and intervals provide a data-driven estimate of the overall trajectory, including where periods of relative change versus stability emerge for each of the stressors.) Four key findings emerged. First, the smooth effect of time was highly significant in every model (i.e., zero effect of time was excluded as a plausible value; see Table 1 and Figure 2). Second, there was a substantial drop in life satisfaction surrounding the sampling wave in which the stressful event was reported, indicating that life satisfaction began to decline before the event and was slow to recover afterward (i.e., life satisfaction was diminished up to 3 years before and after reporting a stressor). Third, recovery was not only slow but also incomplete (defining "recovery" as a return to the stable baseline apparent in the years before the

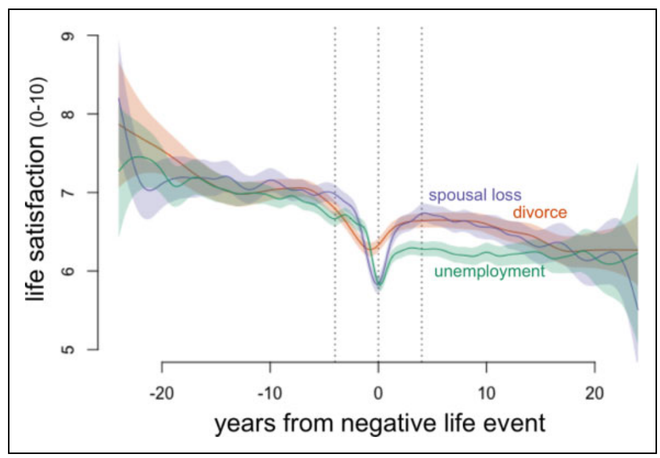

Figure 2. Estimated population-level trajectories of life satisfaction surrounding divorce, spousal loss, and unemployment (from varying curve models). Dotted vertical lines provide reference to –4, 0, and +4 years from reporting the stressor (see online version for full color figure.).

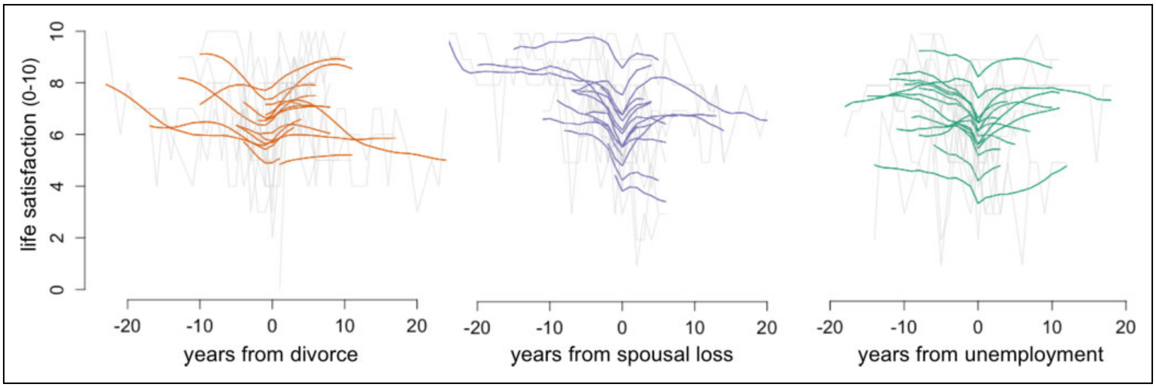

Figure 3. Raw life satisfaction reports and model estimated individual-level smooth trajectories for randomly selected participants. Raw reports of life satisfaction are shown in thin gray lines, and model-estimated trajectories are shown in thicker lines (see online version for full color figure.).

stressor was reported). Life satisfaction did not recover to prestressor baseline for any of divorce ($b_{-6\text{ years}} = 6.91$, 95% confidence interval (CI) [6.81, 7.00]; $b_{+4\text{years}} = 6.65$, 95% CI [6.54, 6.76]), spousal loss ($b_{-4\text{years}} = 6.98$, 95% CI [6.86, 7.10]; $b_{+4\text{years}} = 6.62$, 95% CI [6.50, 6.74]), or unemployment ($b_{-4\text{years}} = 6.67$, 95% CI [6.58, 6.75]; $b_{+4\text{years}} = 6.28$, 95% CI [6.19, 6.37]). Fourth, there were important differences between different kinds of stressors. For example, recovery in life satisfaction was especially incomplete for unemployment: Estimated life satisfaction dropped about .82 points, 95% CI [.70, .94] on the 1–10 scale (from 4 years before reporting the stressor to the year of reporting the stressor), and only about half of this drop was recovered after 4 years (.44 points, 95% CI [.32, .56]). Strikingly, the 95% credibility intervals for the postunemployment trajectory were consistently lower and did not overlap with the divorce or spousal loss trajectories until more than 10 years poststressor. Other notable differences were as follows: (1) Spousal loss was associated with a large drop in life satisfaction (1.14 points, 95% CI [0.99, 1.30]), but a relatively high degree of recovery (0.88 points, 95% CI [0.73, 1.03]), and (2) divorce was associated with the lowest magnitude and earliest anticipatory drop in life satisfaction such that life satisfaction dropped to a local minimum of 6.27, 95% CI [6.19, 6.35] at approximately 9 months before divorce was reported.

Individual Differences in Life Satisfaction Trajectories Followed Continuous Probability Distributions

These overall trajectories provide information about what is plausible to expect in a population experiencing these unfortunate life events, but they are not informative about the nature and extent of person-to-person variability. To address this issue, we inspected estimated trajectories for individual people. Notably, there was substantial person-to-person variability in the smooth effect of time for all three types of major life stressors, such that a wide range of different trajectories in life satisfaction were apparent in this data set (see Figure 3 and Online Supplemental Figures S2a, S2b, and S2c). In order to quantify this variability, we computed three values for each person: (1) his or her model intercept (i.e., each person's overall life satisfaction, from very low to very high), (2) his or her model slope (i.e., each person's change in life satisfaction over time, from dramatic downward, to relatively stable, to dramatic upward trajectory), and (3) a model typicality score representing the similarity (Fisher-transformed time-series correlation) of his or her person-specific curve with the estimated overall group curve (i.e., how closely each person's trajectory in life satisfaction corresponded with the overall group curve; for a visualization of example trajectories low vs. high in model typicality, see Supplemental Figure S1). For each of divorce, spousal loss, and unemployment, these intercept, slope, and similarity values were generally uncorrelated with each other (less than 2% shared variance), except for slopes and typicality scores for unemployment, which were moderately negatively correlated ($\sim$19% shared variance). As shown in Figure 4, estimated person-specific intercepts formed continuous distributions with left skew (skewness = –.41 to –.65), suggesting a ceiling effect in average life satisfaction. Estimated person-specific slopes formed continuous distributions high in kurtosis (i.e., more heavy tailed than a normal distribution), suggesting more people with extreme upward and extreme downward change in life satisfaction over time than expected under normality ($k = 4.20$–4.81). Model typicality scores (i.e., Fisher-transformed time-series correlation coefficients) formed roughly normal distributions with an average correlation of $r = .60$ to .73 ($z' = .70$ to .98) and standard deviations (*SD*s) of .71 to .90. This suggests that people's estimated individual trajectories were strongly correlated with the group trajectory on average, but there was substantial variability, such that many people showed trajectories that were essentially uncorrelated with or even opposite to the trajectory of the overall group.

One of our primary questions was whether individual differences in trajectories were well characterized by discrete classes. To address this, we considered distributions of person-specific intercepts (reflecting overall levels of life satisfaction), person-specific slopes (reflecting the degree of change

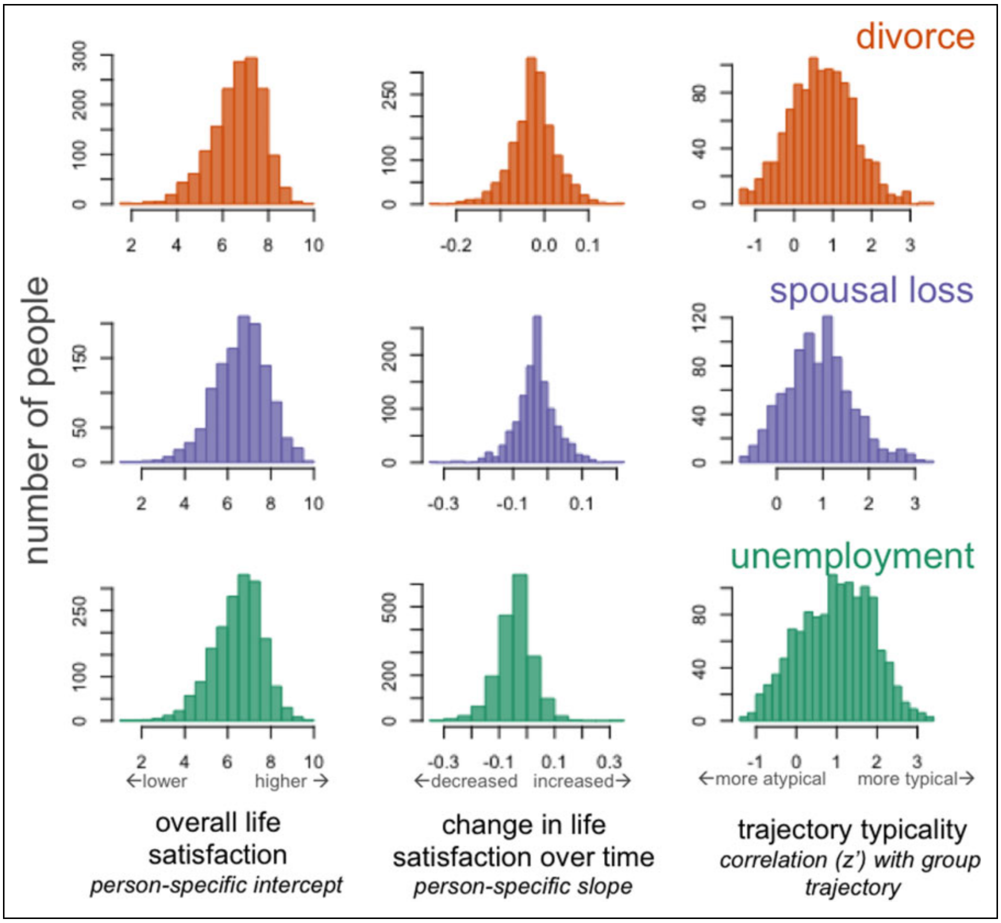

Figure 4. Distributions of estimated person-specific *model intercepts*, representing individual differences in overall life satisfaction, ranging from very low to very high; estimated person-specific *model slopes*, representing individual differences in change in life satisfaction over time, ranging from dramatic downward (more negative) to relatively stable (around zero) and to dramatic upward (more positive) trajectories; and estimated person-specific *model typicality scores* (Fisher-transformed time-series correlation between the person-specific trajectory and the overall group trajectory), ranging from highly atypical (negatively correlated) to highly typical (positively correlated).

in life satisfaction over time, surrounding the life stressor), and person-specific model typicality scores (reflecting how similar each person's trajectory was to the overall group trajectory), reasoning that discrete classes of responding could in theory be apparent on any or all of these dimensions. Distributions of estimated person-specific intercepts, slopes, and typicality scores showed no evidence for multimodality by Hartigans's dip test (*d*'s of .005 to .009, *p*'s of .81 to 1.00) suggesting no clear evidence for multimodality or discrete classes of trajectory types. However, even distributions that are continuous and unimodal can be characterized as mixtures of normal components—to test this, we fit mixture models to these distributions, using bootstrapping to select an optimal number of normal mixture components of arbitrary mean and variance. Considering person-specific intercepts, for each of divorce, spousal loss, and unemployment, a two-component solution (i.e., a model of these individual differences as reflecting two underlying normal distributions) described the data better than higher dimensional mixture models (see Figure 5). Similarly, for person-specific slopes in change over time, two-component solutions described the data better than higher dimensional mixtures. Notably, for the varying slope distributions, the fitted component normals had means that were approximately centered at the mean of the overall distribution (see Figure 5). Considering person-specific typicality scores, a one-component solution (for divorce typicality scores) and two-component solutions (for spousal loss and unemployment typicality scores) described the data better than higher dimensional mixture models (see Figure 5). These results suggest that these person-specific parameters are well characterized as one- or two-dimensional mixtures of normal components but not as higher dimensional mixtures representing discrete classes of responding.

Discussion

We sought to better understand how well-being changes when people experience major life stressors like divorce, spousal loss, and unemployment. We used nonlinear multilevel models (1) to identify how life satisfaction typically changes surrounding these stressful life events and (2) to characterize the nature and extent of individual differences in these life satisfaction

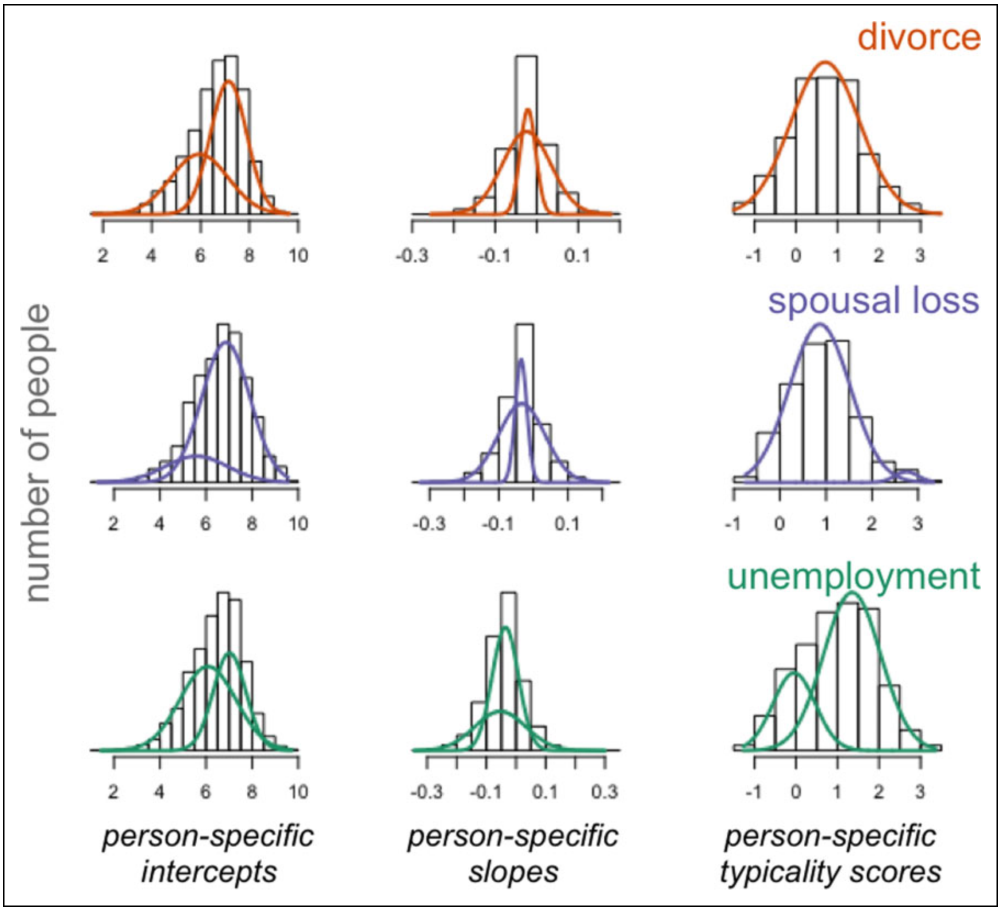

Figure 5. Optimal mixture models (of 1 through 10 component solutions) fit to distributions of person-specific intercepts, slopes, and trajectory typicality scores, for divorce, spousal loss, and unemployment.

trajectories. In contrast to previous work, the approach we applied estimated trajectories of changing life satisfaction from data (rather than prespecifying them) and was not aimed at classifying individual trajectories into a small set of discrete classes of responding.

In terms of the typical population response, life stressors were preceded by an anticipatory decline in life satisfaction that preceded the stressor by several years, reached a minimum around when the stressor was reported and was only incompletely recovered with the passage of time (cf. Carnelley, Wortman, Bolger, & Burke, 2006; Lucas, 2007; Luhmann, Hofmann, Eid, & Lucas, 2012). That is, we did not see that people—on average—showed full recovery to stable levels of life satisfaction that were apparent before experiencing divorce, spousal loss, and unemployment. There were also clear differences between different kinds of stressors. For example, recovery of life satisfaction was especially incomplete for unemployment but was relatively high for losing a spouse (i.e., although life satisfaction dropped dramatically for spousal loss, it showed near complete recovery within 4 years). In terms of person-specific trajectories, we saw large individual differences around these modal responses, and these individual differences formed continuous distributions rather than discrete classes. The individual difference distributions indicated that there were more people with extreme (positive or negative) changes in life satisfaction surrounding life stressors than expected under a normal distribution (i.e., high kurtosis). They also indicated that individual trajectories were (on average) moderately correlated with the overall population trajectory, but with high variability such that many people showed close correspondence with the population trajectory (i.e., they showed highly typical trajectories), whereas others showed essentially no correspondence (i.e., showed highly atypical trajectories).

Resilience Is Relative to What Is Typical for a Given Stressor and Population

These findings expand psychological models of coping with stressors in several important ways. First, they provide a counterpoint to previous work suggesting that resilience and full recovery of prestressor well-being are typical outcomes to major life stressors, instead indicating diminished life satisfaction and incomplete recovery as the typical population response. Importantly, reduced life satisfaction preceded the report of the stressful event, indicating that life satisfaction began to decline well before spousal loss, divorce, and unemployment were experienced (cf. Clark, Diener, Georgellis, &

Lucas, 2008). We also saw that the population trajectory returned to relative stability within 2–4 years, at levels of life satisfaction lower than prestressor baseline.

Second, although previous theories have posited that concepts such as resilience, recovery, and complicated grief represent qualitatively distinct classes, we didn't find evidence for discrete subpopulations of responding—rather, individual differences were well characterized by continuous distributions. More generally, it is not clear from the prior literature if resilience to a stressor is characterized by an absence of negative life outcomes or by relatively low-magnitude negative outcomes that are relatively quickly recovered. At the other extreme, it is not clear if complicated grief is characterized by an absolute lack of recovery or relatively high-magnitude negative outcomes that are relatively slowly recovered (see Bonanno et al., 2011; Infurna & Luthar, 2016; Luthar, Cicchetti, & Becker, 2000; Russo et al., 2012).

In light of our results, we propose an alternative way of understanding these kinds of individual differences. In a multilevel model, people who show trajectories that are more positive on some parameter than an estimated population response (e.g., a less dramatic drop in well-being or a faster recovery to prestressor levels) can be understood as relatively more resilient or showing a relatively high degree of adaptation. People who show more negative trajectories than an estimated population response (e.g., a more dramatic drop in well-being, or a slower recovery) can be understood as relatively less resilient or showing a relatively low degree of adaptation (see Bonanno et al., 2011; Yap et al., 2012). Such an approach comes naturally out of a multilevel framework, grounding use of the labels resilience and adaptation in reference to what is typical for a given event and population. In addition, although our analyses did not give evidence for discrete classes of responding, an overarching framework in which resilience is understood relative to a reference trajectory does not preclude the existence of classes as causal entities or as useful communicative labels.

Relatedly, understanding resilience as relative highlights that not all life stressors are created equal. For example, we found that recovery was especially incomplete for unemployment, where life satisfaction was diminished for up to 10 years relative to divorce or spousal loss (cf. Clark et al., 2008; Lucas et al., 2004). On the other hand, divorce was associated with an early (up to 6 years prior to the divorce) and less dramatic decline compared to the more sudden declines seen for spousal loss and unemployment. These findings make it clear that stressor-to-stressor differences should be incorporated in models of change in well-being—for example, a resilient trajectory for unemployment may look very different from a resilient trajectory for divorce or spousal loss.

Finally, our results shed new light on how individual differences in responding to stressors are distributed in the population. In the growth mixture modeling framework, the existence of a small set of homogenous classes (i.e., 1 to k, where k is much smaller than the total number of participants) within a larger population is taken as a default model of individual differences (Muthén, 2004; Ram & Grimm, 2009). In many other contexts, the normal distribution is taken as a default model of individual differences (see Bolger & Laurenceau, 2013; Gelman & Hill, 2007). However, statistical defaults (whether discrete classes or normality) reflect modeling assumptions that can and should be updated in light of new data. In our analyses, we found that individual differences in model slopes followed heavy-tailed probability distributions, suggesting more people with extreme (positive or negative) change in life satisfaction over time than expected under normality. Alternatively, rather than a single heavy-tailed distribution, these model slopes (i.e., change in well-being over time surrounding a life stressor) could also be described as consisting of two intermixed normal distributions with similar mean levels (i.e., a small decrease in life satisfaction over time) but one with lower variance and one with higher variance (i.e., one "class" showed little variability around this mean, whereas the other class showed high variability, including people with radical drops in life satisfaction and radical increases). Future research in this area could extend our work by asking whether heavy-tailed probability distributions (e.g., *t*-, Cauchy, or Laplace distributions) describe variability in overall trajectories of well-being surrounding other difficult life circumstances and by developing and applying analytic methods that can directly compare the fit of multilevel models of changing well-being that differ only in their specified random effects distributions (Ghidey, Lesaffre, & Verbeke, 2010; McCulloch & Neuhaus, 2011; Verbeke & Molenberghs, 2013).

Limitations and Future Directions: Identifying Sources of Resilience and Adaptation

Limitations of this study are worth noting, in part because they may provide direction for future work. First, our data were limited to three specific categories of stressor (divorce, spousal loss, and job loss), and our results indicate important differences between these three. On this basis, we suggest caution when attempting to generalize across the population of life stressors that can be experienced, just as when generalizing across populations of people. Relatedly, we focused on better understanding how life stressors change reports of a single global assessment of well-being—life satisfaction. Future studies could follow-up on our work by using additive modeling to simultaneously estimate trajectories across multiple channels of responding (see Infurna & Luthar, 2017). On another point, our models predicted a gradually decreasing trend in life satisfaction for both divorce and spousal loss many years after the acute impact of these stressors (i.e., about 10–24 years after), but we did not aim to explain this change. However, such a trajectory may be attributable to age-related change in well-being late in the life span. Future work could investigate this issue by applying matching methods designed for causal inference from observational data (see Anusic et al., 2014; Gelman & Hill, 2007). Finally, although we have estimated individual differences in trajectories of well-being, we have not sought to identify biological, cognitive, or social sources of these differences.

It may be that relatively resilient responding is related to specific emotion regulation skills or interpersonal support processes (Bonanno et al., 2011; Infurna et al., 2017) or to personality (see Yap et al., 2012). At the biological level, it may also be that relatively resilient trajectories are associated with specific patterns of physiological reactivity or structural and functional brain connectivity (Russo et al., 2012). In general, future research that attempts to connect long-term trajectories in psychological outcomes with genetic, environmental, and neural underpinnings may help us understand where resilience to stressors comes from and how to optimize it.

Conclusion

Although everyone experiences life stressors, how we respond to these stressors can vary tremendously. Prior work has highlighted methods for categorizing responses into a small number of discrete classes, but our understanding of the ways that stressors can impact well-being is largely incomplete. Here, we show that divorce, unemployment, and spousal loss are associated with decreased well-being that is subsequently only incompletely recovered and that individual differences around this typical response form a continuous distribution rather than discrete classes. We hope that future work will extend this research by seeking to further identify the conditions and mechanisms that underlie adaptive responding in the face of potential trauma.

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Supplemental Material

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