Journal of Adult Development (2020) 27:241–248
https://doi.org/10.1007/s10804-020-09365-x

Emotional Well-being During the First Four Months of COVID-19 in the United States

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Accepted: 15 October 2020 / Published online: 23 October 2020

Abstract

Relative to younger adults, older adults have demonstrated higher emotional well-being in the face of the threats of COVID-19 (e.g., Bruine de Bruin in J Gerontol https://doi.org/10.1093/geronb/gbaa074, 2020) and other events (Bonanno and Diminich in J Child Psychol Psychiatry 54:378–401, 2013). Thus, we predicted that levels of well-being would show minimal change in the first 4 months of COVID-19, with older adults faring better than younger adults. Adults ($N = 325$, M age = 39.7, SD = 12.3) were surveyed before the pandemic began and at four additional time points throughout the first 4 months of the COVID-19 outbreak in the United States. Participants provided demographic information and completed measures of positive and negative affect. Latent growth curves were used to analyze changes in well-being over time, with age as a covariate. There was a significant linear increase in positive affect. Older age was positively associated with initial levels, but age was not associated with the slope. There was a significant curvilinear pattern in negative affect, with an initial increase, which, although remaining elevated, exhibited slow decreases over time. Age was significantly and negatively associated with initial negative affect, but age did not influence the shape or rate of change over time. We detected changes in both positive affect and negative affect during the first 4 months of COVID-19. The magnitude of these changes suggests that the stress of COVID-19 does not lead to an immediate decrease in well-being. Moreover, although older adults showed higher positive affect and lower negative affect relative to other adults, age differences in the trajectory of change did not emerge. Delayed and long-term effects on well-being and whether those effects are age-invariant should be examined over longer periods of time.

Keywords COVID-19 · Emotional well-being · Latent growth curves · Positive affect · Negative affect

Emotional well-being is a multidimensional construct and is often defined as having high satisfaction with life, high positive affect, and low negative affect (Diener 2000, 2012). When measuring positive and negative affect, most approaches use an adjective checklist, asking respondents to indicate how frequently they have felt each emotion. Positive affect may include happiness, contentedness, and energy, whereas negative affect often includes feeling sad, worried, or depressed. Based on a large body of research in the fields of emotion and aging, there is strong evidence for a normative pattern of higher positive affect and lower negative affect in late adulthood (Cho et al. 2015). However, crises such as the COVID-19 pandemic may alter such normative patterns.

The lifespan development literature offers several examples of how the nature and timing of non-normative life events and normative history-graded events may alter the trajectory of well-being (e.g., Gerstorf et al. 2020). Indeed, examples of how the Great Depression influenced emotional development of children and adolescents are staples in most undergraduate textbooks on aging (e.g., Patrick et al. 2021). Such long-term outcomes are sometimes the continuation of early effects. Thus, examining emotional well-being in close time to the onset of an historical event may provide important information about who is most at risk for long-term negative effects.

Although some adults may experience immediate negative effects from crises (Wang et al. 2020), effects may be mitigated or delayed for others (Galea et al. 2020). For example, when examining the long-term effects of Hurricane Katrina among residents of the Greater New Orleans

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area of the United States, Adams et al. (2011) found that early in the adjustment process, older adults reported *better* coping than did those in midlife. However, over time, older adults reported that the stresses of Katrina resulted in their "aging faster than they should" (p. 12). Similarly, Lau et al. (2008) examined subjective well-being among younger and older adults in Hong Kong during the Severe Acute Respiratory Syndrome (SARS) pandemic. They found that levels of subjective well-being remained within normative ranges, even among older adults living in severely infected districts. Similar results emerged in response to the H1N1 pandemic, with only those infected by the disease showing statistically significant increases in stress and fear of death. Those who remained uninfected did not report significant psychological changes (Sahni et al. 2016). In economic crises, such as that of 2008, similar patterns of response have emerged, with the impact of the event on subjective well-being eventually decreasing in magnitude (Gonza and Burger 2017).

Bonanno (2004) proposed a set-point theory of well-being in the face of loss and trauma. He states that most individuals maintain relatively stable psychological and physical well-being in response to a potentially disruptive and/or traumatic event. Specifically, this set-point theory predicts that at the onset of an event, adults may experience slight shifts in typical functioning for several weeks, but ultimately will return to equilibrium. Such equilibrium is thought to be more common than a response that leads to the emergence of psychopathology. Even with traumatic events such as the terrorist attacks on the U. S. in September 2001, 65.1% of respondents quickly returned to pre-event levels of well-being. However, those adults who experienced high exposure to the event did show more post-traumatic stress-disorder symptoms (Bonanno et al. 2006).

Exploring this set-point approach, emerging findings suggest that many adults exhibit "minimal-impact resilience" (Bonanno and Diminich 2013; Martin 2020). That is, in the face of potentially traumatic events (PTEs), adults often display a small uptick in negative well-being, followed by a return to typical levels (Bonanno et al. 2012). Thus, people may have a normative range of well-being in which they function. Most will stay within that range, even in the face of external stressors (Cummins and Wooden 2014). There is some evidence that when age differences in the consequences of PTE are detected, it may be *younger* rather than older adults who are most at risk for negative effects on well-being (Bonanno et al. 2012).

COVID-19 and Emotional Well-being

With over 7.7 million cases and more than 214,000 deaths in the United States by mid-October 2020, COVID-19 is a source of stress for most Americans (CDC 2020b). Whether and for whom such stressors lead to a decrease in emotional well-being, however, remain empirical questions. Recent data show a variety of sources of stress, including social isolation, concern for contracting the virus, government response to COVID-19, and economic disruptions (APA 2020). Recent evidence from a nationally representative data set shows an increase in psychological distress between 2018 and April 2020, with younger adults faring much more poorly than adults ages 55+ years (McGinty et al. 2020). Similarly, Bruine de Bruin (2020) reports lower depression and anxiety among older adults in the face of the COVID-19 pandemic. Notable for relying on large, representative samples, these studies do not examine changes in well-being at the individual level. In order to understand the process of well-being, measures across multiple time points with the same individuals are necessary.

A few recent studies provide such data. In a March/April 2020 wave of a 5-year longitudinal study among older adults ages 65+ years in Sweden, Kivi et al. (2020) provide evidence that even in the face of COVID-19, older adults' life satisfaction and loneliness were consistent with previous years' reports. Financial well-being and self-reported health showed small increases. Although it is possible that Sweden's swift social interventions ameliorated potential negative effects on well-being, it is also possible that older adults were not immediately and negatively affected.

In recent examinations of age differences in emotional well-being in the context of COVID-19, a growing body of evidence demonstrates that age is an important predictor of well-being. Indeed, a lifespan approach has much to contribute to the understanding both age differences and eventual cohort effects in dealing with the pandemic (Le Couteur et al. 2020). For example, in an age-mixed sample of North American adults surveyed daily for 1 week in March and April 2020, younger adults reported lower positive affect and higher negative affect than did older adults (Klaiber et al. 2020). Similarly, after a state of emergency was declared, an age-mixed sample of adults in Serbia completed daily reports of negative affect over a 5-week period in March and April 2020 (Sadiković et al. 2020). Using a repeated measures ANOVA framework, the authors reported steady decreases in fear and worry over the 5-week period. Low and flat trends for anger and boredom emerged. Using the individual negative affect adjectives as predictors, a small but significant portion of the variance was explained in a regression equation predicting health behaviors like hand-washing frequency and social distancing. However, the team did not explicitly examine the role of age.

Thus, there is emerging evidence that older adults may fare well (e.g., Kivi et al. 2020) and may fare better than younger adults in the face of COVID-19 (e.g., Klaiber et al. 2020). Although each of these studies provides a piece of evidence about how the stresses of COVID-19 are affecting adults, a more complete picture would be provided by a study that included a wide age range of adults, more proximate pre-pandemic assessments of well-being, and a longer time frame than a single measurement or a single week. To that end, we provide data from age-mixed adults that include assessments immediately preceding pandemic status in the United States and follow these adults at multiple times during the first few months.

Methods

Study Context

We began an investigation of well-being in late January 2020, when only five COVID-19 cases had been reported in the U. S. (CDC 2020a), sampling adults in the U.S. through Amazon's MTurk Prime panel (Litman et al. 2016). A total of 325 adults out of 479 MTurk panelists passed our embedded integrity and attention checks at the first time of measurement. The checks included consistency between reporting date of birth and age and correctly answering content items such as what is the day of the week today and where is the White House. We note that like most Americans, including 88% of those ages 50 to 64 years and 73% of those ages 65+ years (Pew Research Center 2019), all participants had access to the internet and completed the surveys online.

We re-contacted these adults on April 14, April 24, May 5, and May 15, providing five time points spanning the first 4 months of the pandemic in the U.S. The 325 adults whose data are used in these analyses were a little older (M age = 39.69, SD = 12.3) than those who were not re-contacted due to initial low-quality responding or who did not pass the subsequent attention checks (M age = 38.31, SD = 11.8; $t\,(400) = -2.35$, $p = 0.019$), but no significant differences were detected for gender, positive affect, or negative affect. With a mean age near 40 years, our final sample was well distributed on age, with 28.4% ages 20 to 30 years; 33.5% ages 31 to 40 years; 16.9% ages 41 to 50 years; 12.5% ages 51 to 60 years; and 8.7% ages 61 to 70 years. Approximately 53.1% were male, 46.6% female, and 1 person was non-binary. Few in our sample (6.9%) identified as Hispanic/Latinx. Most (82%) identified as White, although 9% were Black/African American, 3.7% were Asian, 1.6% reported some other racial identity, 2.7% were multiracial, and 1% did not disclose a racial identity. More than half (56.3%) were married and the average education was 15.1 years (SD = 2.2). Participants were compensated at a rate equivalent to $8.00 per hour.

Measures

We used the Philadelphia Geriatric Center Positive and Negative Affect Scales (Lawton et al. 1992) in which one uses a 5-point Likert-type scale to report the frequency of feeling different emotions. Drawing on adjectives used in many such indices of affect, positive affect includes the frequency of feeling happy, contented, warm-hearted, energetic, and interested. Negative affect incudes the frequency of feeling sad, annoyed, worried, irritated, and depressed. When appropriate (e.g., Times 3, 4, and 5), we modified the response frame from 1 month to the previous 2 weeks. Items for each subscale are summed to form scales in which higher scores represent higher levels of the underlying construct. Means, standard deviations, and Cronbach's α for the five times of measurement are presented in Table 1. Figure 1 depicts these means over time.

Analytic Plan

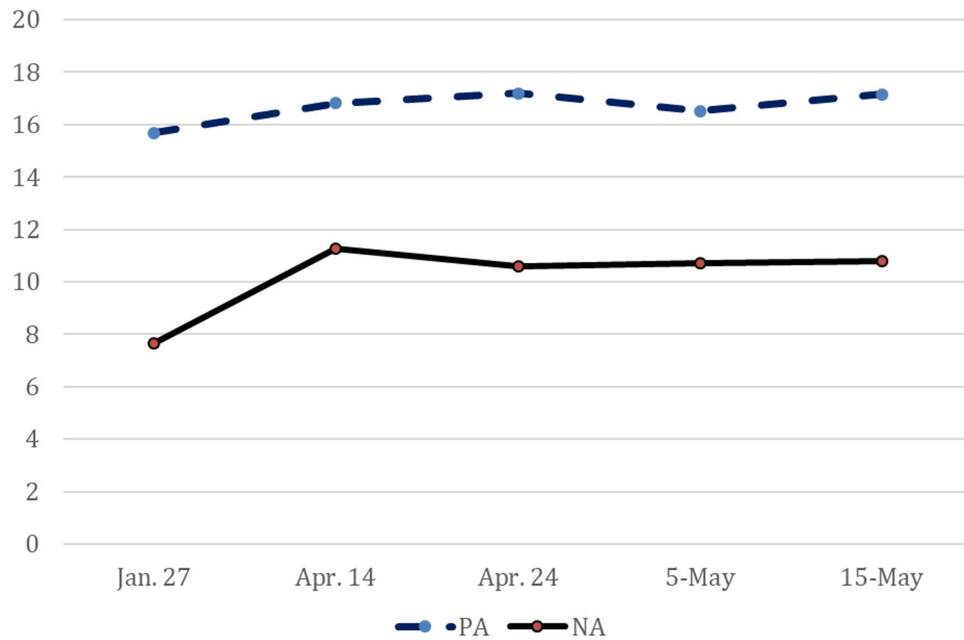
We used latent growth curves (LGC) to test whether the mean of the intercept and slope differed from zero, whether the slope and intercept were related to each other, and finally, whether age influenced these associations. LGC are robust in the presence of missing data and unequal time intervals (Preacher 2010). Because of their repeated measures design, LGC are powerful tools for detecting change as an inter-individual difference, but power estimates of the designs are often difficult. To facilitate comparisons with other studies of linear change, we used effect size indices available via the LIFESPAN program (Brandmaier et al. 2018). In addition to linear changes, LGC can be used to model non-linear curves. After examination of the means and consideration of set-point theory, we anticipated a non-linear trajectory and included an additional quadratic term to model the shape of potential change over time. We followed the recommendations and examples by of Burant (2016) and Vasantha and Venkatesan (2014) and used weights which represented time in months for the slope,

Table 1 Means for positive and negative affect over time

	Time 1 (1/27)		Time 2 (4/14)		Time 3 (4/24)		Time 4 (5/5)		Time 5 (5/15)	
	PA	NA	PA	NA	PA	NA	PA	NA	PA	NA
Mean	15.69	7.66	16.81	11.28	17.20	10.61	16.51	10.72	17.16	10.78
SD	4.97	3.60	4.24	4.41	4.09	4.41	4.39	4.28	4.42	4.34
α	.862	.859	.847	.880	.842	.897	.872	.875	.895	.868

PA positive affect, *NA* negative affect

Fig. 1 Means in positive and negative affect over time



squaring these values to obtain weights for the quadratic term. Thus, intercepts were coded as "1," in order to estimate means for the different months. Slopes were coded as 0, 2.5, 3.0, 3.5, and 4.0 to represent the linear (monthly) trend since the first measurement. For the quadratic term assessing non-linear change, the weights were 0, 6.25, 9.0, 12.25, and 16.0. Implemented in AMOS, in addition to the chi-square test and chi-square given degrees of freedom (CMIN/DF), we used the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and the Root Mean Square Error Approximation (RMSEA) to evaluate fit of the model to the data. We used typical cut-offs to aid in interpreting these indices, including the discrepancy CMIN/df < 5.0; CFI and TLI greater 0.90, with 0.95 preferred; and RMSEA of 0.08 or less, with values less than 0.05 preferred (Burant 2016). As noted by Preacher (2010), however, LGC models often have poor fit indices. Thus, we also verified that no unusual standardized parameter scores were present. All error variances were freely estimated, as were means and variances for the intercept and slopes. Finally, we were cognizant that if the variance of the slope was not significant, indicative that the individual growth trajectories were not different from each other, that we would not be able to predict individual differences in growth (Burant 2016). After identifying the form of the trajectory, either linear or quadratic, we examined the potential influence of age as a time-invariant covariate.

Results

Positive Affect

Fit indices for the linear model of positive affect were acceptable, with $\chi^2(14, N = 325) = 57.56$, $p < 0.001$, CMIN/DF = 4.11, CFI = 0.93, TLI = 0.93, and RMSEA = 0.10. As shown in Table 2, initial positive affect was non-zero, with the mean intercept = 15.96 ($p < 0.001$). The mean slope = 0.24 was significant ($p < 0.001$), indicating significant increases over time for the sample. With a significant covariance between intercept and slope (Estimate = -– 1.78, $p = < 0.001$), lower initial scores on positive affect related to a steeper increase over time. Lastly, the significant variance of the intercept = 20.30 ($p < 0.001$) and the slope = 0.75 ($p < 0.001$) suggest that both initial positive affect and rate of change differed between adults. Moreover, measures of effect sizes (Brandmaier et al. 2018) suggest medium to large effects, with GCR = 0.84, GRR = 0.48, ECR = 0.58, and EFF = 0.21. As depicted in Fig. 1, after an initial bump in positive affect, levels remained elevated, but relatively flat.

Because the fit indices were equivocal and because set-point approaches (e.g., Bonanno 2004) would suggest

Table 2 Latent growth curve analyses: positive affect ($N = 325$)

	Estimate	S.E	Critical ratio (CR)	p-value
Positive affect (linear trajectory)				
Intercept	15.96	.269	59.23	***
Slope	0.242	.071	3.39	***
Intercept ↔ Linear Slope	− 1.78	.386	− 5.11	***
Variance intercept	20.30	1.853	10.96	***
Variance slope	0.75	.117	6.36	***
χ^2 (DF = 14) = 57.56, $p < .001$; CMIN/DF = 4.11; CFI = .93; TLI = .93; RMSEA = .10				
Positive affect (quadratic trajectory)				
Intercept	15.95	.274	58.26	***
Slope-Linear	0.39	.193	2.01	.044
Slope-Quadratic	− 0.04	.044	− 0.97	.332
Intercept ↔ Linear Slope	− 4.96	1.038	− 4.78	***
Intercept ↔ Quad. Slope	0.82	.229	3.57	***
Linear ↔ Quadratic	− 0.21	.196	− 1.07	.286
Variance intercept	20.89	1.918	10.89	***
Variance linear slope	2.39	.890	2.69	.007
Variance quadratic slope	− 0.01	.046	− 0.31	.758
χ^2 (DF = 10) = 26.70, $p < .003$; CMIN/DF = 2.67; CFI = .98; TLI = .96; RMSEA = .07				

**Represents significant estimates at the 0.01 level

***Represents significant estimates at the 0.001 level

a curvilinear trajectory, we tested a second model of positive affect, in which a quadratic term was included. Results of these analyses are presented in the lower portion of Table 2. The model fit was adequate overall, $\chi^2(10, N = 325) = 26.70$, $p < 0.003$, CMIN/DF = 2.67, CFI = 0.98, TLI = 0.96, and RMSEA = 0.07. The intercept ($b = 15.95$, $p < 0.001$) and the linear slope ($b = 0.39$, $p < 0.05$) retained their significance, but the quadratic term was not significant ($b = -0.04$, $p = 0.33$). Moreover, the variance for the quadratic term ($b = -0.01$, $p = 0.76$) was not significant. Thus, the most parsimonious model favored the linear slope. We conducted post hoc exploratory analyses (available upon request) using a piece-wise approach (see Curran et al. 2010), which also suggested that despite an initial bump between Time 1 and Time 2, the data were best characterized by a linear trend.

Having identified a linear trend in positive affect, we examined age as a time-invariant covariate. The model had adequate fit, with $\chi^2(17, N = 325) = 58.73$, $p < 0.001$, CMIN/DF = 3.46, CFI = 0.94, TLI = 0.92, and RMSEA = 0.09. Age was associated with higher initial levels of positive affect ($\beta = 0.12$, $p = 0.046$), but was not associated significantly with the slope ($\beta = 0.11$, $p = 0.20$). Moreover, the addition of age into the equation altered the mean slope such that in the presence of age, the linear slope was not significantly different from zero (mean = − 0.08, SE = 0.24, CR = − 0.32, $p = 0.80$).

Negative Affect

Fit indices for the linear model of negative affect were poor, $\chi^2(14, N = 325) = 80.27$, $p = 0.001$, CMIN/DF = 5.73, CFI = 0.835, TLI = 0.88, and RMSEA = 0.12. As shown in Table 3, initial negative affect was significantly non-zero (intercept $b = 7.74$, $p < 0.01$). The slope ($b = 3.69$, $p < 0.001$) showed significant increases over time. The covariance of intercept and slope was not significant ($b = -0.15$, $p = 0.88$); thus, one's rate of change was not associated with their initial level of negative affect. Lastly, the significant variance for the intercept ($b = 10.07$, $p < 0.001$) and slope ($b = 7.74$, $p < 0.001$) shows that both the initial levels and the rate of change over time for negative affect differed between participants. Effect size estimates (Brandmaier et al. 2018) suggested moderate to large effects, with GCR = 0.67, GRR = 0.51, ECR = 0.53, and EFF = 0.40.

Due to theory and the pattern of the means, which suggested a non-linear change in negative affect, we re-examined the negative affect model using a quadratic term. As shown in the lower portion of Table 3, the fit indices for this model were somewhat better than the linear-only model: $\chi^2(10, N = 325) = 33.65$, $p = 0.001$, CMIN/DF = 3.37, CFI = 0.958, TLI = 0.96, and RMSEA = 0.09. The intercept ($b = 7.74$, $p < 0.001$) and linear slope ($b = 2.59$, $p < 0.001$) continued to be non-zero. In addition, the quadratic slope term ($b = -0.47$, $p < 0.001$) was significant. Post hoc

Table 3 Latent growth curve analyses: negative affect ($N = 325$)

	Estimate	S.E	Critical ratio (CR)	p-value
Negative affect (linear trajectory)				
Intercept	7.80	.208	37.59	***
Slope	3.69	.262	14.11	***
Intercept ↔ Linear Slope	− 0.15	1.047	− 0.15	.883
Variance intercept	10.07	1.127	8.94	***
Variance slope	7.74	1.506	5.14	***
χ^2 (DF = 14) = 80.27, $p < .001$; CMIN/DF = 5.73; CFI = .89; TLI = .88; RMSEA = .12				
Negative affect (quadratic trajectory)				
Intercept	7.74	.208	37.28	***
Slope-Linear	2.59	.232	11.18	***
Slope-Quadratic	− 0.47	.058	− 8.05	***
Intercept ↔ Linear Slope	− 0.03	.887	− 0.04	.970
Intercept ↔ Quad. Slope	− 0.08	.217	− 0.36	.716
Linear ↔ Quadratic	− 0.81	.272	− 2.99	**
Variance intercept	10.72	1.127	9.51	***
Variance linear slope	4.32	1.140	3.79	***
Variance quadratic slope	0.16	.068	2.41	.016
χ^2 (DF = 10) = 33.65, $p < .001$; CMIN/DF = 3.37; CFI = .96; TLI = .94; RMSEA = .09				

**Represents significant estimates at the 0.01 level

***Represents significant estimates at the 0.001 level

piece-wise exploratory analyses (available upon request) confirmed that negative affect increased after the onset of the COVID-19 outbreak and remained elevated from pre-pandemic levels across the 4 months. Negative affect decreased from Time 2 to Time 3, after which it remained elevated relative to Time 1, but stable through Times 4 and 5 with a slope equal to zero from Time 3 through Time 5. Additional post hoc analyses showed that age continued to be associated with the slope at Time 3, 4, and 5.

Having identified a curvilinear trend for negative affect, we tested the influence of age as a time-invariant covariate. The model fit the data well, $\chi^2(12, N = 325) = 37.43$, $p = 0.001$, CMIN/DF = 3.12, TLI = 0.96, and RMSEA = 0.08. Younger age was associated with higher initial negative affect (intercept $b = -0.04$, $p < 0.02$). Age was not associated significantly with either the linear ($b = -0.01$, $p = 0.71$) or quadratic ($b = 0.00$, $p = 0.41$) slope. All other model elements were similar in magnitude, direction, and significance to the model which excluded age.

Discussion

Much of the current attention related to COVID-19 has focused on the negative aspects of the pandemic for older adults (Le Couteur et al. 2020). Although older age has been identified with risk for contracting the virus (CDC 2020a, b), it is not necessarily a risk factor for experiencing negative emotional effects (APA 2020). That much of the public and scientific discourse has focused on protecting vulnerable older adults suggests that lessons learned from previous historical events have not been applied to the issues surrounding the COVID-19 pandemic. Lifespan approaches to the long-term effects of normative history-graded events (e.g., Gerstorf et al. 2020) suggest that the nature and timing of stressors may be important factors to examine. Rather than assuming that an event will exert similar effects on all adults, it is critical to actually measure such changes.

Data from other pandemics, such as SARS (Lau et al. 2008) and the H1N1 flu (Sahni et al. 2016), show that older adults often fare well in the face of history-graded events. Similarly, older adults evacuated during Hurricane Katrina showed minimal immediate changes, although there may have been delayed effects (Adams et al. 2011). The idea that some events may exert longer-term effects that are not identifiable in the immediate period following the event has been discussed in the literature (e.g., Gerstorf et al. 2020), but few have studied it directly. An exception are data from the September 11, 2001 terrorist attacks in the U.S. These data provide the foundation for set-point theory (Bonanno, 2004). Those data showed that a majority of adults returned quickly to pre-attack levels of well-being. Thus, people may have a normative range of well-being, within which they typically function (Bonanno et al. 2012; Cummins and Wooden 2014).

A variety of repeated measures well-being data related to COVID-19 were collected after the pandemic began. Collectively, these studies show that negative affect tends to be higher than positive affect, especially for younger adults (Klaiber et al. 2020) and that negative affect tends to decrease over time (Sadiković et al. 2020). Without the pre-pandemic time point, however, it is difficult to draw conclusions about how the pandemic has influenced well-being.

Our data, which have that pre-pandemic time point, are consistent with a set-point approach. We sampled emotional well-being in 2-week intervals, allowing us to model changes over time. We included a direct examination of whether and in what ways age alters the pattern of changes over time. Finally, our study adds to the literature by examining the immediate effects of the COVID-19 pandemic in the United States on well-being, using sophisticated growth curve modeling techniques. Most previous work has examined effects of the pandemic and/or major stressors via retrospective reports, while the present study examined coping and affect during the COVID-19 outbreak (from onset through several months). Consistent with our predictions, small increases in both positive and negative affect over 2-week intervals were detected. Mean age differences were observed, but the trajectory of change did not differ by age. Thus, immediate responses to COVID-19 may be age-invariant. Of course, it is possible, and even likely, that effects on well-being are not immediate, but that they may emerge over a longer course of time (Adams et al. 2011; Gerstorf et al. 2020). Moreover, the changes in well-being reported by younger adults may be the result of different types and numbers of stressors related to the pandemic, including childcare and employment disruptions (APA 2020).

It is noteworthy that although both positive affect and negative affect increased early in the pandemic, negative affect increased more rapidly, whereas the absolute levels of positive affect were higher. Moreover, after the onset of the COVID-19 outbreak, increases in negative affect slowly decelerated over time. Neither initial levels of negative affect nor rate of change were associated with age. Change in positive affect was linear with older age being associated with higher initial levels of positive affect, but age was not associated with the rate in which positive affect increased. This suggests a complex process that warrants continued investigation, but we are aware that relatively stable levels of well-being may be the norm (Bonanno et al. 2012). Another explanation for this seeming stability relates directly to the propositions of set-point theory. Specifically, it is possible that our data have captured a resetting of one's set-point, whereby the influence of COVID-19 and all its accompanying economic and social limitations has raised people's set-point to a "new normal" (Bonanno et al. 2012).

Assumptions that all adults will fare poorly may harm individuals. At least two important implications of this emerge. First, treating older adults as an homogenous group of "high-risk" adults may cause harm to the older adults who are faring well and may divert resources from the younger adults who are vulnerable to negative effects on well-being. Second, as Gerstorf et al. (2020) argue, it is important to identify the needs of older adults now and into the future. It is possible, and indeed likely, that as adults continue to face restrictions in daily living due to the pandemic, additional emotional effects may be observed. We must remain vigilant to such changes, but we must do so without the implicit assumption that older adults are especially at risk for negative well-being outcomes.

Funding Not applicable.

Data Availability Upon request.

Compliance with Ethical Standards

Conflict of interest No conflicts of interest to disclose.

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