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Modeling Long-Term Changes in Daily Within-Person Associations: An Application of Multilevel SEM

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Short-term within-person associations are considered to reflect unique dynamic characteristics of an individual and are frequently used to predict distal outcomes. These effects are typically examined with a 2-step statistical process. The present research demonstrates how long-term changes in short-term within-person associations can be modeled simultaneously within a multilevel structural equation modeling framework. We demonstrate the utility of this model using measurement burst data from the National Study of Daily Experiences (NSDE) embedded within the Midlife in the United States (MIDUS) longitudinal study. Two measurement bursts were separated by 9 years, with each containing daily measures of stress and affect across 8 consecutive days. Measures of life satisfaction and psychological well-being were also assessed across the 9-year period. Three-level structural equation models were fit to simultaneously model short-term within-person associations between stress and negative affect and long-term changes in these associations over the 9-year period. Individual differences in long-term changes of the short-term dynamics between stress and affect predicted well-being levels. We highlight how characterizing individuals based on the strength of their within-person associations across multiple time scales can be informative in predicting distal outcomes.

Keywords: multilevel structural equation modeling, stress reactivity, psychological well-being, measurement burst, daily diary

As research methods continue to evolve and further our understanding of developmental processes, it is becoming clear that there is a need to capture better the complex dynamic processes that operate within an individual's lived experiences. As many individual characteristics are likely to vary and develop over multiple temporal frequencies, intensive measurement designs are being deployed to better capture characteristics of the individual that represent informative aspects about their health and well-being. Indeed, recent research designs have moved beyond the traditional cross-sectional approach of measuring individuals at a single point in time and widely spaced longitudinal designs that provide multiple "snapshots" of an individual across years. While an individual's average level and rate of change is certainly informative and has been fruitful in gaining insights into the typical characteristics that are predictive of health and well-being relative to others, it is increasingly more common to consider how individuals vary, change, and respond to exposures over short intervals and how these dynamics change over longer periods of time.

Capturing Characteristics of the Individual

Developmental research into the analysis of change has taken aim at understanding how measures of short-term variability may capture characteristics of the individual not represented by measures of central tendency (e.g., Charles, Piazza, Mogle, Sliwinski, & Almeida, 2013; Hedeker, Mermelstein, Berbaum, & Campbell, 2009; Hultsch, Strauss, Hunter, & MacDonald, 2008; Hülür, Hoppmann, Ram, & Gerstorf, 2015; Piazza, Charles, Sliwinski, Mogle, & Almeida, 2013; Rast, Hofer, & Sparks, 2012; Röcke & Brose, 2013; Röcke, Li, & Smith, 2009; Sliwinski, Almeida, Smyth, & Stawski, 2009; Stawski et al., 2017). The increased prevalence of measurement burst designs in which frequent, closely spaced assessments (e.g., across hours or days) are repeated over longer intervals (e.g., months, years) enables an investigation into how short-term intraindividual variability (i.e., person-specific deviations in responses across repeated assessments)

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informs us about unique characteristics of the individual (Martin & Hofer, 2004; Nesselroade, 1991; Sliwinski, 2008). From a statistical perspective, intraindividual variability is the residual variance after conditioning on all other parameters. As this burgeoning area of research continues to develop, it is becoming clear that intraindividual variability is not merely unreliable measurement error, but rather carries systematic information about the context, the individual, and/or their interactions.

Short-term variability has been used in a variety of ways to capture unique aspects of the individual. One approach has been to measure the amount of variability an individual displays over short intervals of time (e.g., across days, hours, or trials). Though there have been numerous quantifications of intraindividual variation (see Stawski et al., 2017), the conceptual idea remains that the amount of short-term variability an individual displays can be an informative metric that furthers our understanding of that individual. Individual differences in the amount of intraindividual variability has been shown to be predictive in a number of psychological domains. For example, higher amounts of trial-to-trial variability in reaction time (RT) tasks have been predictive of cognitive performance and declines (Bielak, Hultsch, Strauss, MacDonald, & Hunter, 2010; MacDonald, Hultsch, & Dixon, 2003; MacDonald, Li, & Bäckman, 2009). Intraindividual variability in daily self-esteem has predicted depression (Gable & Nezlek, 1998). Daily variability in positive affect has been associated with daily cortisol levels (Human et al., 2015), whereas daily variability in negative affect has been associated with neuroticism and cross-sectional age differences (Röcke et al., 2009).

While the raw amount of intraindividual variability may be informative in some areas of research, it is often the contexts that coincide with the intraindividual deviations that are of primary interest. For example, day-to-day variations in negative affect (NA) can be understood in more depth if we also examine the context (e.g., amount of daily stress) that is contributing to these intraindividual deviations. The short-term covariation (i.e., coupling) of constructs within individuals further accounts for the systematic intraindividual variations. Similar to how individuals may differ in the amount of intraindividual variability they display, so too can individuals differ in the strength of their within-person (coupled) associations. This has been applied most frequently in the area of stress and affect, where individuals differ in the degree to which NA increases in response to stressful experiences (i.e., their stress reactivity). Characterizing an individual based on the strength of his or her within-person association moves beyond amount of stress or NA and toward a conceptualization of the magnitude of the contextual influence. Importantly, the magnitude of the contextual influence (i.e., the strength of the within-person association) can differ across individuals or across longer intervals of time within individuals. Hence, understanding individual differences and developmental changes in the magnitude of contextual influences could provide a unique account of how to characterize the individual.

To date numerous research studies have used individual differences in the magnitude of within-person associations as a between-person predictor variable. Hülür and colleagues (2015) found that individual differences in the within-person correlation of positive affect (PA) and NA accounted for differences in cognitive decline. People who displayed a less negative within-person correlation tended to have steeper cognitive declines than those who had a more negative within-person correlation. This finding suggests that the weaker within-person correlation of PA and NA may be indicative of poor emotional integration that is associated with declines in crystallized functioning. Research has also used individual differences in stress reactivity, the within-person association of daily stress and NA, to effectively predict a variety of physical and mental health outcomes. Greater stress reactivity has been associated with increased risk of morbidity (Piazza et al., 2013), mortality (Mroczek et al., 2015), higher levels of inflammation (Sin, Graham-Engeland, Ong, & Almeida, 2015), poorer sleep efficiency (Ong et al., 2013), and more affective disorders (Charles et al., 2013). Each of these studies has examined within-person associations from a single measurement burst. Few studies have examined whether people change over longer periods in their short-term within-person association. Sliwinski and colleagues (2009) found that there were long-term increases in the daily association of stress severity and NA. However, no study to our knowledge has examined whether long-term changes in stress reactivity is predictive of other distal outcomes.

Stress reactivity research has primarily focused on predicting physical health outcomes (e.g., inflammation, morbidity, mortality, and sleep quality). There has yet to be an examination of stress reactivity as a between-person predictor of psychological well-being (PWB) and life satisfaction. Psychological well-being reflects the breadth of wellness and includes positive evaluations of the self, a sense of meaning, personal growth, and self-determination, fulfilling relationships, and a competence to manage one's life (Ryff & Keyes, 1995). On the other hand, life satisfaction reflects an appraisal of individuals' current life domains relative to their ideal states (Diener, 2000). These domains include satisfaction with work, health, family, and life overall. Psychological well-being and life satisfaction are important indicators of positive human functioning (Diener & Ryan, 2009; Ryan & Deci, 2001; Ryff, 1989) that capture elements of living well throughout the life span (Mroczek & Spiro, 2005; Ryff, 2014). Greater insights into the factors and characteristics that account for individual differences in well-being across time will enhance our understanding of successful aging. An investigation into whether stress reactivity accounts for differing levels of well-being advances what is known about the role of stress reactivity in positive functioning distinct from physical health outcomes. Furthermore, no research has examined whether long-term changes in the short-term stress reactivity association further explains levels of PWB. Given the detrimental health effects associated with higher levels of stress reactivity, it is expected that they will also be detrimental to the experiences of PWB and life satisfaction. Increases in stress reactivity could also indicate a downward shift in life quality and an inability to manage adverse situations. Individuals undergoing such a change are expected to report lower levels of PWB and life satisfaction than those who are stable or are becoming less reactive to stressors over time.

Statistical Approaches to Modeling Within-Person Variability

Intraindividual variability, when treated as an individual difference predictor variable, has most commonly been examined through a two-step procedure. The first step utilizes a multilevel model to produce estimates of person-specific deviations in either the amount of intraindividual variability or random effects in the strength of the within-person covariation between two time-varying variables (e.g., NA and stress). In this current application we focus on these random effect variances, which can be reframed as person-specific deviations from the fixed effect. The estimates can be extracted for each individual and, as a second step, entered as a time-invariant individual difference predictor into a separate statistical model to predict some other outcome (e.g., cognitive performance, mental health, or mortality). Though this approach is frequently applied throughout the literature, it is unclear what impact the additional step has on the variance components of the final model. By extracting individual slopes and entering them into a subsequent model, the two-step approach treats each individual slope equally regardless of data points contributed and fails to account for variance across levels of analysis. Analogous to the concerns of the slopes-as-outcomes model (see Hoffman, 2015; Singer & Willett, 2003), the two-step approach may result in biased parameter estimates as the dependence of within-person variability from individual means is not explicitly modeled (cf. Mestdagh et al., 2018; Verbeke & Davidian, 2009).

An alternative approach is to model all effects simultaneously within a single statistical model using a multilevel structural equation modeling (MSEM) framework (Muthén & Asparouhov, 2009; Preacher, Zyphur, & Zhang, 2010; Rush, Ong, Hofer, & Horn, 2017). MSEM combines features of multilevel modeling and structural equation modeling. It handles hierarchically structured data and time-varying effects (that are present in measurement burst designs) while permitting a multivariate examination of time-varying relationships across levels of analysis. An important feature of the MSEM approach is that random effects at each level can be modeled as either exogenous or endogenous variables at subsequent levels of analysis. That is, the latent random slopes can be specified to represent individual differences in the within-person associations, and these individual differences can be included as predictors of concurrent or distal outcomes. Furthermore, measurement burst designs that assess individuals across multiple time-scales can now be modeled in a manner that permits random effects from lower levels of analysis to also be specified as random effects at subsequent levels. An example of this would be specifying short-term intraindividual associations as a random slope that may also change within individuals over longer intervals of time. The long-term change in the random short-term association can further be specified as a random slope, permitting individual differences in the magnitude of change. This model could also provide an evaluation of whether individual differences in this change in within-person dynamics are predictive of other outcomes. The flexibility of the MSEM framework in concert with measurement burst designs permit numerous innovative questions about the utility of short-term variability and within-person associations to characterize an individual during a given period, as well as the long-term changes in these within-person dynamics.

Present Study

The present study utilized data from the Midlife in the United States (MIDUS) project that embeds intensive measurement burst data within a longitudinal panel design. Through this form of study design, it was possible to examine how short-term (i.e., daily) within-person associations changed over longer intervals of time (i.e., 9 years). Furthermore, individual differences in the degree of change was then used to account for between-person differences in levels of psychological well-being and life satisfaction. MSEMs were used to simultaneously model these effects across multiple time-scales and levels of analysis. The present study extends previous research in several important ways. First, the study examined long-term changes across 9 years in the daily within-person association of stress and NA (i.e., long-term change in stress reactivity). Second, to test the hypothesis that increases in stress reactivity reduce well-being, individual differences in the within-person association of daily stress and affect, and long-term changes in this within-person association, were used to predict between-person differences in levels of well-being at Wave 2, after adjusting for well-being at Wave 1. Finally, research to date has primarily used a two-step approach to examine individual differences and patterns of change among short-term within-person associations. The present study models individual differences in both the within-person association, as well as individual differences in the degree to which the within-person association changes over time, simultaneously as random slopes within an MSEM framework. This approach permits the random effects of within-person associations to be modeled as latent slopes that can then act as either exogenous or endogenous variables across levels of analysis. By modeling these effects simultaneously within a single statistical model, the variability within and across levels of analysis can be accounted for more appropriately (see Lüdtke et al., 2008; Marsh et al., 2009 for a full discussion).

Method

Participants and Procedure

Participants were from the MIDUS project, a publicly available data set that consists of multiple subprojects aimed at collecting a large representative sample of Americans assessed during midlife (age 24–74 at baseline). Figure 1 displays the study design for the variables used in the present research. The MIDUS project incorporates a large-scale longitudinal panel design, where participants complete a comprehensive survey on many aspects of their health and well-being at 9-year intervals. In addition, a random subset of participants were invited to participate in the National Study on Daily Experiences (NSDE) subproject. Individuals who agreed to participate responded to end-of-day telephone interviews for eight consecutive days that assessed daily levels of stress and affect. The NSDE data collection burst was repeated approximately 9 years later, providing two measurement bursts of the daily diary data (see Almeida, 2005; Almeida, McGonagle, & King, 2009 for detailed description of data collection). The present study made use of the first two waves of the MIDUS survey (MIDUS I and II), as well as the two bursts of the NSDE data collection (NSDE I and II; see Figure 1). The NSDE data collection burst followed the MIDUS survey data collection by an average of 1.29 and 1.73 years for Waves 1 and 2, respectively. Daily diary data was collected on a total 23,592 days out of 28,168 possible days (completion rate of 84%). The current research made use of all available data from respondents who participated in the NSDE I or II and MIDUS I and II survey studies (N = 2485; number daily assessments = 23,592). Previous studies have demonstrated that participants who completed both of the NSDE bursts did not significantly differ from those who only complete Burst 1 in terms of age, sex, and education (see Charles et al., 2013). Descriptive statistics for all study variables are included in Table 1. Correlations among study variables are included in Table 2.

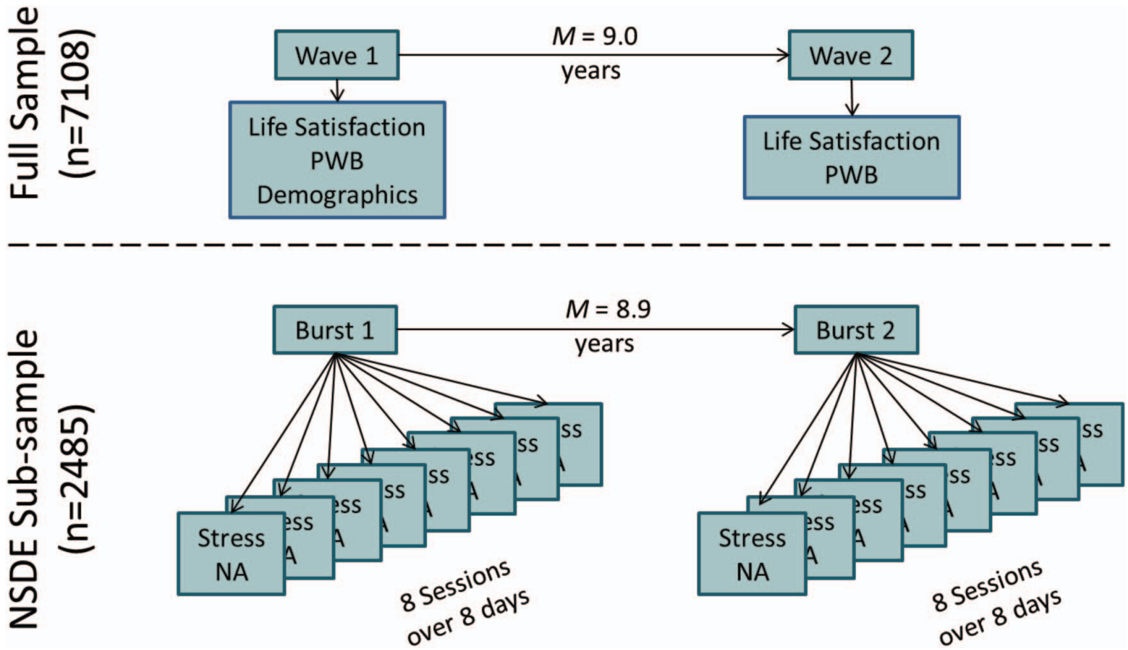

Figure 1. Midlife in the United States (MIDUS) study design. All participants completed Wave 1. A subsample completed the National Study of Daily Experiences (NSDE) daily assessments (2,485 participants completed either Burst 1 or Burst 2). PWB = psychological well-being scales; NA = negative affect. See the online article for the color version of this figure.

NSDE Daily Diary Measures (Burst 1 and 2)

Negative Affect. Daily NA was assessed during Bursts 1 and 2 of the NSDE data collections. Participants were presented with a list of six emotions (fidgety, nervous, worthless, so sad that nothing could cheer you up, everything was an effort, and hopeless; Mroczek & Kolarz, 1998) and asked to indicate how frequently they felt each emotion in the past 24 h. Responses ranged from 0 (*none of the time*) to 4 (*all of the time*). Daily NA scores were computed by averaging across the items. Multilevel ω was used to estimate within- and between-person reliability (see Geldhof, Preacher, & Zyphur, 2014). Within-person reliability provides an estimate of the covariance among the items at each specific occasion, pooled across occasions and individuals, and represents the ratio of within-person true score variance to total within-person variance. Between-person reliability provides an estimate of the covariance in individual levels of the items aggregated across time (i.e., person-mean level). Between-person reliability estimates are typically higher in repeated measurement designs (Rush & Hofer, 2017). Within-person reliability estimates were .60 and .58 for Bursts 1 and 2, respectively. Between-person reliability was .81 and .82 for Bursts 1 and 2, respectively.

Table 1
Means and SDs of Study Variables

Variable	Wave 1/Burst 1 (*N* = 1,499) *M*	*SD*	Range	Wave 2/Burst 2 (*N* = 2,022) *M*	*SD*	Range
Demographics						
Age	47.02	12.60	24–74	56.15	12.31	34–84
Female	.55[a]	.50	0–1	—	—	—
Education	2.94	.94	1–4	—	—	—
Well-being						
Life satisfaction	7.78	1.23	2–10	7.82	1.20	2.12–10
PWB	5.54	.79	1.75–7	5.55	.80	2.06–7
Burst-level variables						
Daily NA	.19[b]	.29	0–4	.21[b]	.28	0–4
Daily stressor	.40[c]	.26	0–1	.40[c]	.27	0–1

Note. PWB = psychological well-being; NA = negative affect.
[a] Proportion of female participants. [b] Aggregated across daily assessments. [c] Proportion of stress days. *N* = 793 participants completed both Bursts 1 and 2.

Daily stressors. Daily stressors were assessed using the Daily Inventory of Stressful Events (DISE; Almeida, Wethington, & Kessler, 2002). The inventory consisted of six questions inquiring whether certain types of stressors had been experienced in the last 24 h (e.g., "In the past 24 hours, did you have an argument or disagreement with anyone?"). A dichotomous variable was used to characterize days as either stress days (at least one stressor was reported) or nonstress days (no stressor reported). A daily stressor was reported on 40% of days during both Bursts 1 and 2, respectively.

MIDUS Longitudinal Panel Measures (Waves 1 and 2)

Life satisfaction. Participants rated their satisfaction across four life domains (work, health, family, and overall) on a scale from 0 (*worst possible*) to 10 (*best possible*). The scores for satisfaction with family were based on two items (relationship with partner and relationship with children) that were averaged to create

Table 2
Correlations Among Study Variables

Variable	LS1	PWB1	Daily NA1[b]	Daily stressor1[c]	LS2	PWB2	Daily NA2[b]	Daily stressor2[c]	Age	Female
LS1	*.67*									
PWB1	**.51**	*.81*								
Daily NA1[b]	**−.31**	**−.36**	*.60[a]/.81*							
Daily Stressor1[c]	**−.17**	−.02	**.31**	—						
LS2	**.52**	**.40**	**−.28**	**−.14**	*.65*					
PWB2	**.38**	**.62**	**−.28**	−.00	**.55**	*.83*				
Daily NA2[b]	**−.27**	**−.25**	**.42**	**.21**	**−.36**	**−.31**	*.58[a]/.82*			
Daily Stressor2[c]	**−.18**	**−.06**	**.26**	**.50**	**−.19**	**−.09**	**.44**	—		
Age	**.19**	.03	**−.10**	**−.21**	**.18**	**.07**	**−.15**	**−.24**	—	
Female	.00	−.02	.03	**.07**	.01	.00	**.06**	**.09**	.00	—
Education	.01	**.19**	**−.16**	**.19**	**.07**	**.17**	.00	**.19**	**−.09**	**−.11**

Note. LS = life satisfaction; PWB = psychological well-being; NA = negative affect; 1 = measured at Wave/Burst 1; 2 = measured at Wave/Burst 2. Reliability estimates displayed in italics along the diagonal. Bold values are statistically significant correlations, $p < .01$.
[a] Within-person reliability. [b] Aggregated across daily assessments. [c] Proportion of stress days.

a single item. This item was averaged with the remaining items to create an overall mean score (Prenda & Lachman, 2001).

Psychological well-being. The 18-item Ryff Scales of Psychological Well-Being were measured at Waves 1 and 2. The scale captures elements of psychological well-being, which include autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance (Ryff & Keyes, 1995). Participants responded to each item on a scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). An overall mean score was computed by averaging across the 18 items with higher scores representing higher levels of PWB (range = 1.75 to 7).

Covariates. Participant age at Wave 1, sex, and education were included as covariates to adjust for sample heterogeneity. Age at Wave 1 was centered at the grand mean in all statistical models. Sex was coded with males as the reference category. Education was measured on a 4 point scale (1 = *less than high school*, 2 = *high school degree*, 3 = *some college*, 4 = *graduated college*) and was centered on the median response of 3.

Data Analytic Strategy

MSEM analyses were used to permit a multivariate examination of stress reactivity and well-being across time-scales and levels of analysis. These models handle the hierarchical structure of the data and allow random slope coefficients to be simultaneously modeled as either exogenous predictor variables or endogenous outcome variables across levels of analysis. Daily measurement occasions were nested within measurement bursts and measurement bursts were nested within people, resulting in three-levels of analysis. Model specification for each level of analysis is described next and the full model is depicted in Figure 2.

Level 1 (daily measurements within burst). At the within-burst level, daily stress exposure$_{ijk}$ was included as a predictor of daily levels of NA$_{ijk}$. The subscript *ijk* in Figure 2 indicates that both stress exposure and NA could vary across days (*k*), measurement bursts (*j*), and individuals (*i*). Stress reactivity was modeled as the daily within-person association between stress exposure and NA. Because stress exposure was a dichotomous variable, stress reactivity can be defined as the difference in NA on stress days compared with nonstress days. This daily within-person association between stress exposure and NA (i.e., stress reactivity) was modeled as a random slope and was permitted to vary across bursts and individuals. That is, the strength of the daily stress-NA association could differ across bursts within an individual, as well as across individuals. Each of the days within the burst were treated as interchangeable and, thus, autocorrelations were not modeled in the results reported.[1] This approach is commonly used in research examining stress reactivity, where the primary effect of interest is the coupled association between stress and NA on the same day (see Charles et al., 2013; Mroczek et al., 2015; Sliwinski et al., 2009).

The MSEM framework combines a measurement model with structural models across each level of analysis (Muthén & Asparouhov, 2009; Preacher et al., 2010, 2011). The measurement model permits the observed NA$_{ijk}$ to be linked to latent variables that decompose NA into within-burst, between-burst, and between-person parts, adjusting for sampling unreliability (Lüdtke et al., 2008). A reduced form of the measurement model can be represented by the following equation (see Preacher, 2011):

$$\mathrm{Y}_{ijk} = \lambda\eta_{ijk} \tag{1}$$

where Y_{ijk} is the observed NA for individual *i* during burst *j* on day *k*; λ is a 1×3 matrix of factor loadings; η_{ijk} is a 3×1 vector of latent variables (i.e., $\eta_{\mathrm{NA}ijk}$, $\eta_{\mathrm{NA}ij}$, and $\eta_{\mathrm{NA}i}$). Each of the factor loadings in λ have been constrained to 1 to link the observed NA variable to its latent counterpart across the three levels of analysis (see Lüdtke et al., 2008; Preacher, 2011 for detailed discussion). The Level 1 structural model can be represented by the following equation:

$$\eta_{ijk} = \alpha_{ij} + \mathrm{B}_{ij}\mathrm{Stress}_{ijk} + \zeta_{ijk} \tag{2}$$

where η_{ijk} is the latent NA value that varies across individuals, bursts, and days; α_{ij} is the NA intercept that is permitted to vary across individuals and bursts; B_{ij} is the within-burst regression coefficient (i.e., stress reactivity) for individual *i* during burst *j* that is also permitted to vary across individuals and bursts; and ζ_{ijk} is a vector of Level 1 residuals, which are assumed to have a

[1] To ensure that the autocorrelation did not impact the reported results we also examined an autoregressive, AR(1) model and found that the structure of the model outcome was practically unaltered.

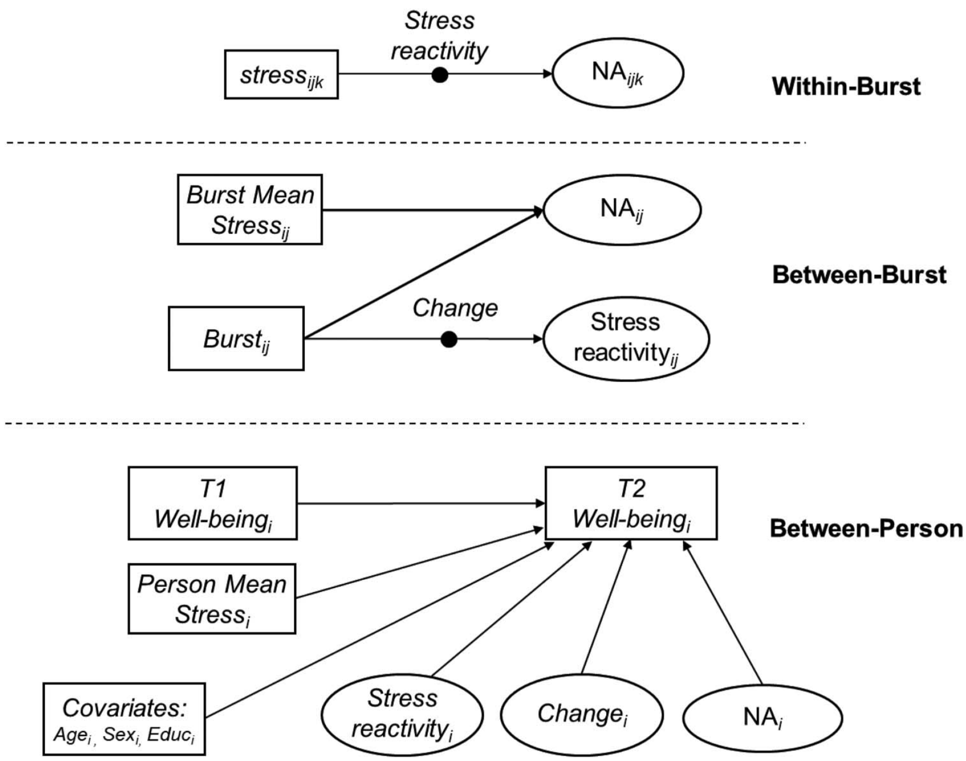

Figure 2. Three-level structural equation model. Daily assessments are nested within-bursts and bursts of measurements are nested within people. Ovals indicate variables were estimated within the model. Black dots indicate that pathway was modeled as a random slope. NA = negative affect; stress = stress day; Educ = highest education level obtained.

multivariate normal distribution with mean of zero and covariance matrix θ.

Level 2 (within-person, between-bursts). At the second level of analysis, the random stress reactivity$_{ij}$ slope was modeled as a latent endogenous variable that varies across bursts and individuals. Burst-level NA$_{ij}$ was also modeled as a latent endogenous variable that represents the mean NA for person *i* during burst *j*. A dichotomous Burst$_{ij}$ variable (0 = Burst 1; 1 = Burst 2) was included as a predictor of both burst-level NA$_{ij}$ and stress reactivity$_{ij}$ to examine whether there was a within-person change from Burst 1 to Burst 2 in the level of NA or the strength of the daily stress-NA association, respectively. The change in stress reactivity from Burst 1 to Burst 2 was modeled as a random slope, permitting individual differences in the magnitude of change in the daily within-person association of stress and NA across bursts. That is, modeling whether some individuals differed in the extent to which their stress reactivity changed from Burst 1 to Burst 2. Burst mean stress, which is the proportion of burst-specific stress days for individual *i* during burst *j*, was also included as a predictor of burst-level NA$_{ij}$ to adjust for differences in burst-level stress exposure. The Level 2 structural portion of the model can be represented by the following equation:

$$\eta_{ij} = \alpha_i + \beta_i X_{ij} + \zeta_{ij} \quad (3)$$

where η_{ij} is a vector consisting of the random intercept and slope of NA$_{ij}$ and stress reactivity$_{ij}$, respectively, that vary across individuals and bursts; α_i is a vector of intercepts; β_i is a matrix of regression coefficients for individual *i* (i.e., between-burst fixed effects); X_{ij} is a vector of observed Level 2 predictor variables (i.e., Burst$_{ij}$ and Burst-mean Stress$_{ij}$); and ζ_{ij} is a vector of Level 2 residuals (i.e., between-burst random effects), which are assumed to have a multivariate normal distribution with mean of zero and covariance matrix ψ. The between-burst random effects of stress reactivity$_{ij}$ and NA$_{ij}$ estimate the amount of between-burst variation within each individual.

Level 3 (between-person). Individual differences in stress reactivity$_i$ and the magnitude of changes in stress reactivity (i.e., change$_i$) were modeled as latent slopes, indicating that they are estimated from the model and reflect strength of the daily stress reactivity association and amount of change in stress reactivity, respectively, for individual *i*. NA$_i$ was modeled as a latent mean that reflects average levels of NA for individual *i* across days and bursts. Individual differences in (a) stress reactivity, (b) the magnitude of changes in stress reactivity, and (c) mean levels of NA were used to predict individual differences in well-being (PWB and life satisfaction) measured at Wave 2. A set of observed covariates were included to adjust for the effects of Wave 1 age (centered at the grand mean), sex, education, corresponding Wave 1 well-being, and person mean stress (i.e., the proportion of days where at least one stressor was reported across days and bursts, calculated from the data) on Wave 2 well-being. By adjusting for the effects of Wave 1 well-being on Wave 2 well-being, the model examines predictors of residual change in well-being levels. The

Level 3 structural portion of the model can be represented by the following equation:

$$\mathrm{WB}_i = \mu + \Gamma\eta_i + \gamma \mathrm{X}_i + \zeta_i \tag{4}$$

where WB_i is the Wave 2 well-being outcome for individual i; μ is a vector of Level 3 coefficient means; η_i is a vector of between-person latent variables (i.e., NA_i, change_i, and stress $\mathrm{reactivity}_i$); Γ is a matrix of Level 3 regression coefficients that regress WB_i on latent variables; X_i is a vector of observed covariates (i.e., age, sex, education, and well-being at Wave 1, as well as person-mean stress); γ represents a matrix of Level 3 regression slopes; and ζ_i is a vector of Level 3 residuals (i.e., between-person random effects), which are assumed to have a multivariate normal distribution with mean of zero and covariance matrix Ψ. The between-person random effects estimate the amount of individual differences (between-person variation) in NA_i, change_i, and stress $\mathrm{reactivity}_i$. All effects were estimated simultaneously using full information maximum likelihood with robust standard errors (MLR), which makes use of all available data and adjusts for nonnormality. Mplus Version 8 software (Muthén & Muthén, 2017) was used to fit all models.

Results

An empty three-level model revealed that 47% of total variation in NA was within-burst, 21% was between-burst, and 32% was between-person. Between-burst and between-person intraclass correlation coefficients (ICCs) were .21 and .32, respectively. Table 3 presents the findings from the full MSEMs. Each of the Wave 2 well-being outcomes (i.e., life satisfaction and PWB) were examined in separate models.

Daily Within-Person Associations Over Time

The daily within-person associations over time (i.e., the within-burst and between-burst effects, see Table 3) were consistent across all of the models, regardless of the well-being outcome. Presented below are the estimates from the model where life satisfaction was the well-being outcome. Stressor exposure was associated with NA within-bursts. On days when individuals were exposed to a stressor their NA was higher than on days when they did not report a stressor. This effect was significant during both Burst 1 (*estimate* $= 0.13$, *SE* $= .008$ $p < .001$, 95% confidence interval, CI [0.12, 0.15]) and Burst 2 (*estimate* $= 0.17$, *SE* $= .006$, $p < .001$, 95% CI [0.16, 0.18][2]). Furthermore, there was evidence of burst-specific and person-specific variations in the strength of the daily association between stress and NA as indicated by the amount of variability around the burst-level and person-level fixed effects of stress reactivity (see Between-burst and Between-person random effects estimates of Stress Reactivity from Table 3[3]). Based on the model estimates, the expected plausible values of individual's stress reactivity estimates at Burst 1 ranged from -0.15 to 0.42. Figure 3 depicts the individual differences in strength of the daily association.[4] The solid black line represents the average within-person effect (i.e., the fixed effect), while the dotted colored lines demonstrate the person-specific deviations in this effect for five individuals (i.e., the random effects). Some individuals are more emotionally reactive to stressors and others are less reactive. Furthermore, these individual deviations are present in both Bursts 1 and 2.

Stress reactivity changed from Burst 1 to Burst 2. From Table 3, the fixed effect of stress reactivity change between bursts indicates that individuals displayed higher levels of stress reactivity during Burst 2 than Burst 1. That is, the strength of the daily association between stress and NA was significantly stronger during Burst 2 than it was during Burst 1, indicating that on average individuals were more reactive to daily stressors over time. In addition, there was also evidence of individual differences in the degree of change in stress reactivity across bursts as indicated by the between-person random effects estimate of stress reactivity change in Table 3. Based on model estimates, the expected plausible values for each individual's change in stress reactivity ranged from -0.03 to 0.10. Figure 4 displays the average (fixed) change in stress reactivity (solid black line), as well as individual deviations in the degree of stress reactivity change (colored dotted lines) for five individuals. Figure 4 also highlights the multiple levels of random slopes, wherein there are individual deviations in stress reactivity during both bursts of measurement (depicted in the balloons) as well as individual deviations in the degree of stress reactivity change across bursts.

Predicting Wave 2 Well-Being

The primary effect of interest was whether individual differences in change in stress reactivity was predictive of well-being at Wave 2 (see Table 3; Between-person Stress Reactivity Change predicting Wave 2 Well-being). Results revealed that change in stress reactivity significantly accounted for individual differences in life satisfaction at Wave 2. Individuals who became more reactive to stressors over time relative to others had lower levels of life satisfaction at Wave 2. That is, for one unit increase in stress reactivity change, life satisfaction was 23.67 units lower. Therefore, an individual who had a mean stress reactivity change score of 0.04 would be expected to rate their life satisfaction 0.95 units lower (on a scale from 0 to 10) than an individual who was stable in their stress reactivity (i.e., their stress reactivity change score was zero; $[-23.67] \times 0.04 = -0.95$). This result was present after adjusting for age, sex, average stress reactivity, average levels of NA, amount of stress exposure, and Wave 1 life satisfaction. Furthermore, higher average levels of NA and a greater proportion of stress day exposure was reliably related to lower levels of life satisfaction (see Person-mean NA and Person-mean Stress estimates, respectively). Figure 5 displays the unstandardized estimates from the three-level SEM predicting life satisfaction and PWB.

[2] To obtain confidence intervals for Burst 2 stress reactivity, a separate model was run that only examined data from Burst 2.

[3] Mplus produces a test of statistical significance for variances that is based on a two-tailed Wald test. This is a conservative test that should be interpreted with caution when used to examine variances that can only be one-tailed (i.e., they cannot be negative).

[4] To produce the figure, stress reactivity estimates for each individual were extracted at both Bursts 1 and 2. These values were plotted in a random subsample of 100 participants with complete data to display the change in stress reactivity. Upon visual inspection, five participants were selected to highlight the range in variability.

Table 3
Three-Level Structural Equation Modeling Analyses of the Effects of Daily Stress Reactivity on Well-Being

Variable	Life satisfaction		Psychological well-being	
	Estimate (*SE*)	95% CI	Estimate (*SE*)	95% CI
Fixed effects				
Within-burst variables				
NA intercept	.053 (.007)***	[.039, .068]	.053 (.007)***	[.039, .069]
Wave 1 stress reactivity	.132 (.008)***	[.117, .148]	.133 (.008)***	[.117, .149]
Between-burst variables				
NA change	.001 (.006)	[−.011, .012]	.001 (.006)	[−.011, .012]
Burst-mean stress	.178 (.018)***	[.143, .213]	.179 (.018)***	[.143, .214]
Stress reactivity change	.037 (.009)***	[.019, .054]	.036 (.009)***	[.018, .053]
Between-person variables predicting Wave 2 well-being				
Intercept	5.539 (.339)***	[4.874, 6.204]	2.922 (.175)***	[2.580, 3.265]
Female	.114 (.044)*	[.027, .201]	.050 (.029)†	[−.007, .106]
Education	.103 (.025)***	[.055, .151]	.055 (.017)**	[.022, .089]
Wave 1 age	.007 (.002)**	[.003, .010]	.002 (.001)	[−.001, .004]
Wave 1 well-being	.439 (.024)***	[.392, .486]	.586 (.020)***	[.546, .626]
Person-mean NA	−2.496 (.693)***	[−3.855, −1.137]	−1.408 (.394)***	[−2.181, −.636]
Person-mean Stress	−.443 (.102)***	[−.643, −.243]	−.118 (.060)*	[−.237, .000]
Stress reactivity	−.325 (.583)	[−1.469, .818]	.025 (.313)	[−.588, .638]
Stress reactivity change	−23.674 (7.674)**	[−38.714, −8.633]	−14.774 (2.700)***	[−20.066, −9.481]
Random effects				
Within-burst NA	.047 (.002)***	[.043, .051]	.047 (.002)***	[.043, .051]
Between-burst				
NA intercept	.013 (.003)***	[.007, .020]	.013 (.003)***	[.007, .020]
Stress reactivity	.023 (.005)***	[.013, .033]	.022 (.005)***	[.012, .033]
Between-person				
NA intercept	.016 (.004)***	[.008, .025]	.016 (.004)***	[.008, .025]
Stress reactivity	.020 (.006)**	[.007, .032]	.020 (.006)**	[.008, .033]
Stress reactivity change	.001 (.000)†	[.000, .002]	.001 (.000)**	[.000, .002]
Residual variance				
Wave 2 well-being	.507 (.429)	[−.334, 1.349]	.139 (.146)	[−.148, .426]
AIC/BIC	8469.87/8639.38		6627.22/6796.70	

Note. Results are based on 23,592 daily assessments ($N = 2{,}485$). NA = negative affect; CI = confidence interval; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria. Estimates of fixed effects are reported as unstandardized regression coefficients. Estimates of random effects are reported as variances.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Similar patterns were found for psychological well-being. Individuals who became more reactive over time relative to others had lower levels of PWB at Wave 2. That is, individual differences in changes in stress reactivity was a significant predictor of PWB. Therefore, an individual who had a mean stress reactivity change score of 0.04 would be expected to rate their PWB 0.59 units lower (on a scale from 1 to 7) than an individual who was stable in their stress reactivity (i.e., their stress reactivity change score was zero; $[-14.77] \times 0.04 = -0.59$). Individuals with higher average levels of NA also had reliably lower levels of PWB (Person-mean NA estimate). Greater proportion of stress day exposure was related to lower levels of PWB (Person-mean Stress estimate). Average levels of stress reactivity across bursts (Table 3; Between-person Stress Reactivity) was not predictive of well-being at Wave 2 after adjusting for the effects of other variables of interest.

Discussion

The present study examined the potential to characterize individuals through short-term (daily) within-person associations. Longitudinal changes in the short-term within-person associations of daily stress and NA were modeled across time. Individual differences in longitudinal changes of these within-person associations were further examined to predict levels of PWB and life satisfaction. All effects were modeled simultaneously through an innovative MSEM framework, rather than the two-step approach that is most prevalent in the literature.

Consistent with previous findings, on average, individuals were emotionally reactive to daily stressors across both measurement bursts. That is, the tendency was to report higher levels of NA on days when they were exposed to a stressor relative to nonstress days. However, despite a significant average within-person association between daily stress and NA, there was considerable person-specific variability in the strength of the association both within and across bursts (see Figure 3). These individual differences in stress reactivity within and across bursts highlight the importance of considering multivariate dynamics to capture individual processes.

Extending previous research that has examined the role of stress reactivity during a single measurement burst, the current research demonstrated that on average individuals tend to change in their level of stress reactivity over longer periods of time. The strength of the daily association increased over time as individuals became more emotionally reactive to daily stressors. It is unclear why there was a tendency for individuals to become more reactive at the

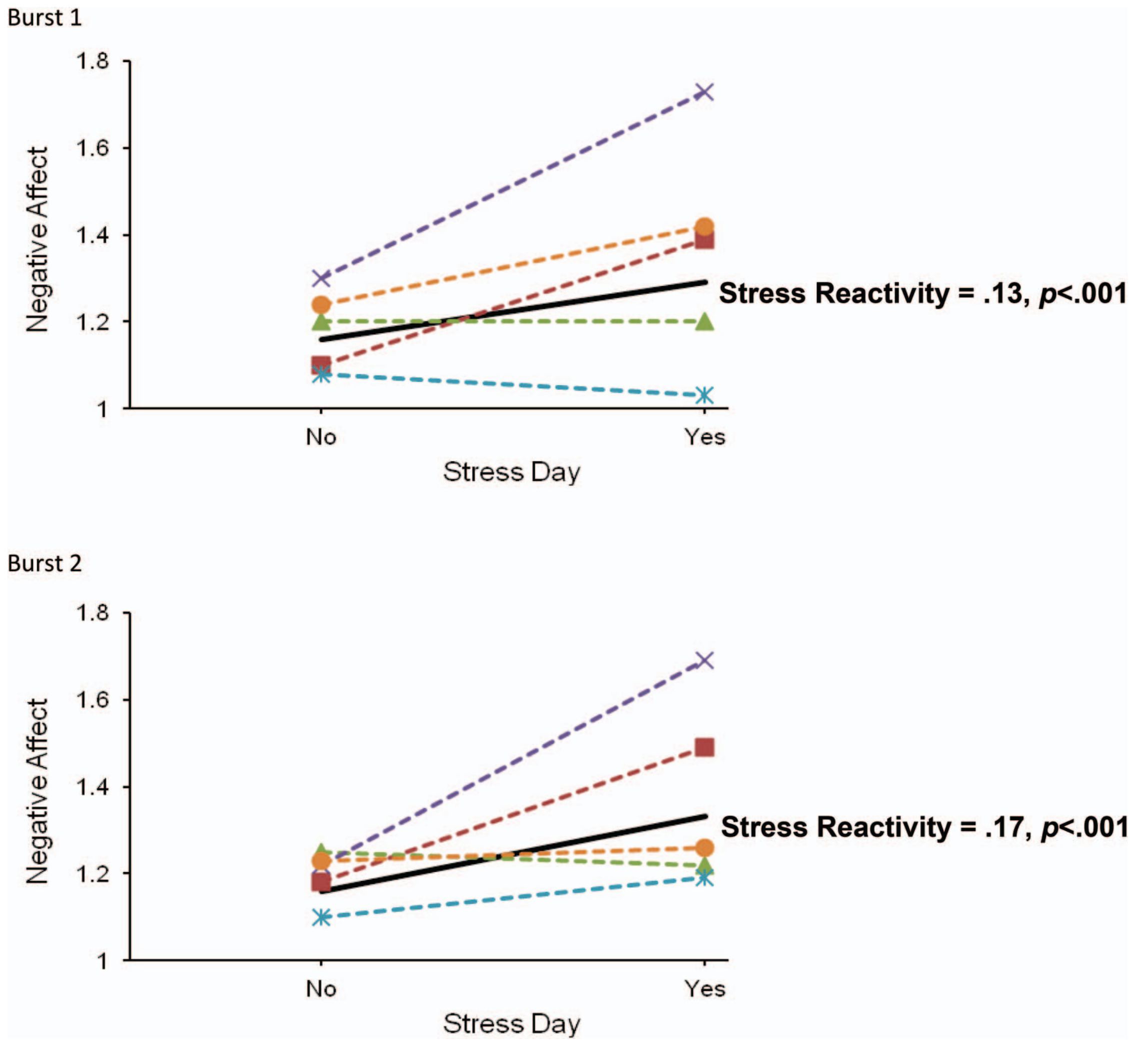

Figure 3. Individual differences in within-person association of stress and negative affect (NA). Top panel represents the within-person association between stress and NA (i.e., stress reactivity) at Burst 1 (stress reactivity = .13, $p < .001$). Bottom panel represents within-person association between stress and NA (i.e., stress reactivity) at Burst 2 (stress reactivity = .17, $p < .001$). Solid black line represents average within-person association between stress and NA. Colored dotted lines represent individual participants with varying strengths of within-person association within each measurement burst. Lines of the same color (geometric marker) represent same individual across bursts. Individuals were selected to illustrate the range in variability within and across bursts. See the online article for the color version of this figure.

9-year follow-up compared with the values obtained from the initial measurement. Given that the study sample follows individuals through midlife, it is plausible that the demands and strains of midlife (e.g., changes in health, occupational responsibilities, family strain, etc.; Lachman, 2004) elicit a stronger emotional response than the types of stressors experienced at a younger age, which may be contributing to increases in the level of stress reactivity. In a sample of older adults from the Cognition, Health, and Aging Project, Sliwinski and colleagues (2009) found that individuals on average became more reactive to stressors as they aged. This finding appears to be at odds with Carstensen and colleagues' (1999) theory of socioemotional selectivity, which posits that older adults tend to become more accepting of life and their emotional experience improves and becomes more stable as they age. Research examining longitudinal changes in momentary levels of affect across three measurement bursts found that average levels of affect did improve over a 10-year period (Carstensen et al., 2011). Furthermore, Röcke and colleagues (2009, 2013) have found evidence that older adults are less variable in NA than are younger adults. Of note is that these results are based on average levels and raw amount of affect and they do not consider how individuals are impacted by contextual influences (e.g., daily stressors). Along these lines, Charles' (2010) strength and vulnerability integration (SAVI) theory proposes that as individuals age they are better able to maintain higher levels of emotional well-being by relying on aging-related strengths (e.g., experience, emotional

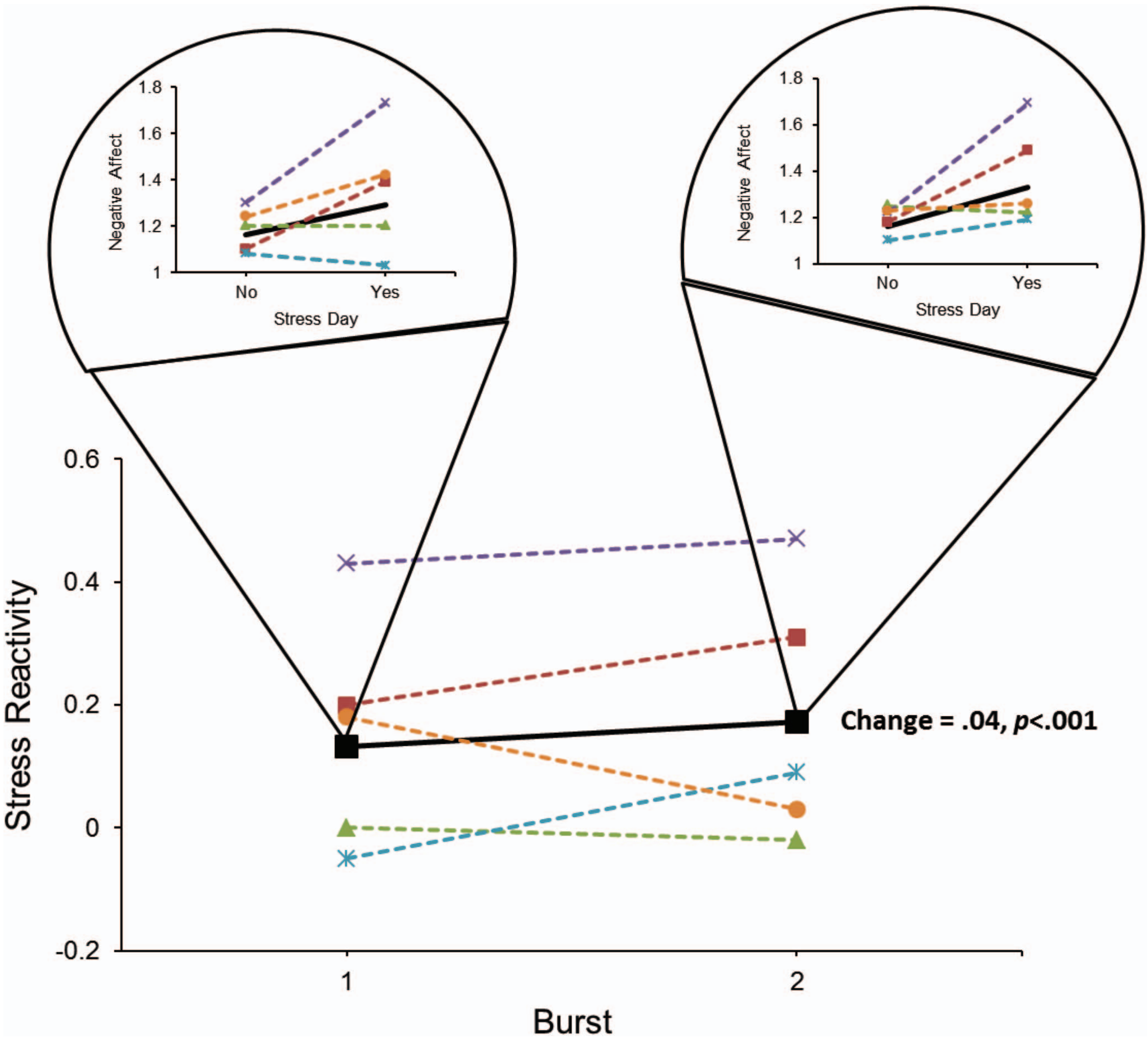

Figure 4. Change in within-person association between stress and negative affect (NA; i.e., stress reactivity) across bursts. Black square (solid line) represents average within-person association between stress and NA and change in average within-person association across bursts (Δstress reactivity $= .04$, $p < .001$). Colored dotted lines represent individual participants with varying strengths of within-person association within and across bursts. Lines of the same color (geometric marker) represent same individual across bursts. See the online article for the color version of this figure.

dampening) to reduce or avoid negative situations. However, when faced with negative events (i.e., stressors) age-related strengths are attenuated and their age-related vulnerabilities (e.g., difficulties regulating sustained physiological arousal—elevated blood pressure, cortisol) are magnified, resulting in a more adverse response. The SAVI model is consistent with the results of the current research. On average, cross-sectional differences in age were related to higher levels of well-being. However, there was a tendency over time for individuals to become more reactive to daily stressors, demonstrating a reduced ability to regulate their negative emotions in response to the stressor.

Importantly, not all individuals increased in their stress reactivity over the 9-year period. Individual differences in changes in stress reactivity emerged (see Figure 4), where some individuals became more reactive to daily stressors and others remained stable or became less reactive. Person-specific variation in changes in stress reactivity is also consistent with the SAVI model, as individuals are expected to vary in the balance of strengths and

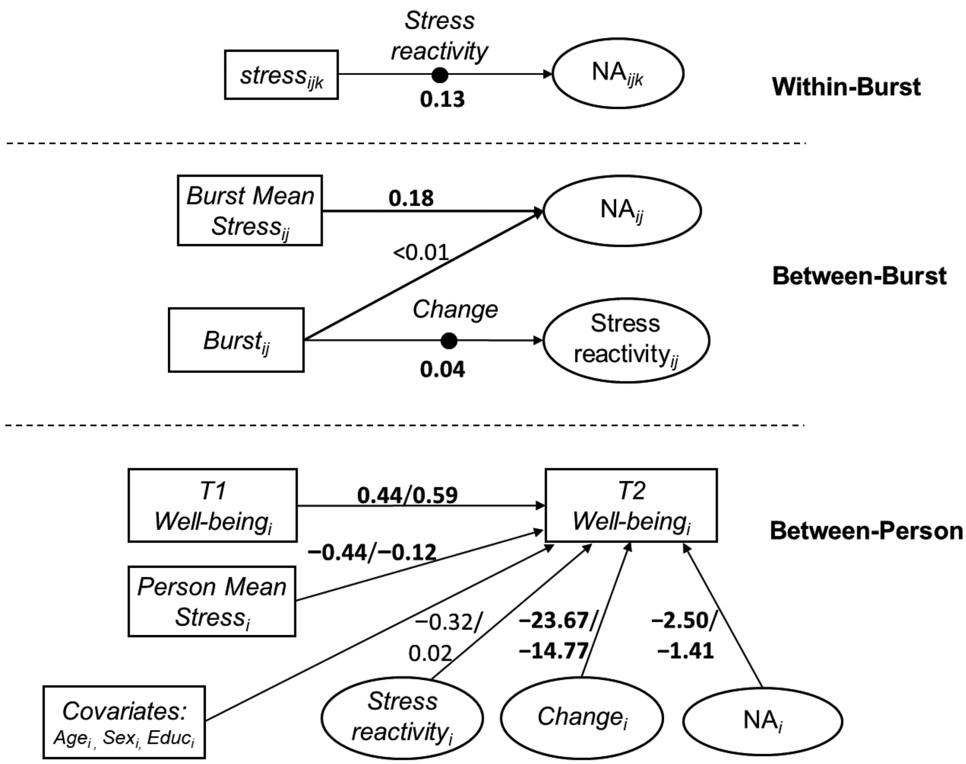

Figure 5. Estimated three-level structural equation model predicting between-person differences in well-being. *Note:* Values are unstandardized coefficients. Bold values are statistically significant, $p < .05$. Ovals indicate variables were estimated within the model. Black dots indicate that pathway was modeled as a random slope. Between-person estimates are from model predicting life satisfaction/psychological well-being, respectively. NA = negative affect; stress = stress day; Educ = education.

vulnerabilities they possess in dealing with stressful experiences (Charles, 2010). Furthermore, these individual differences in changes in stress reactivity were reliable predictors of levels of well-being. Individuals who demonstrated greater increases in their stress reactivity from Burst 1 to Burst 2 had lower levels of well-being than individuals who did not change as much in their stress reactivity. This pattern was consistent across measures of both life satisfaction and PWB.

Greater levels of stress reactivity have consistently been shown to relate to a number of detrimental outcomes, including chronic health conditions (Charles et al., 2013), mental disorders (Piazza et al., 2013), mortality (Mroczek et al., 2015), inflammation (Sin et al., 2015), and sleep quality (Ong et al., 2013). Each of these previous studies examined daily stress reactivity during a single measurement burst. This study adds to this literature by demonstrating that stress reactivity changes over long intervals (i.e., 9 years) and that individual differences in the degree of change accounts for between-person differences in levels of PWB and life satisfaction. It is clear that greater NA levels in response to daily stressors represent an adverse characteristic of the individual that is associated with poorer health and well-being across a number of life domains. The current results reveal that not only levels of stressor reactivity, but also changes in stress reactivity over time are particularly concerning. That changes in stress reactivity was uniquely predictive of well-being over and above the effects of average levels of NA, stress exposure, and Wave 1 well-being, further demonstrates that the within-person association of stress and NA is capturing an element of the individual that is not captured by NA or stress exposure on their own.

The current approach to model each of the effects simultaneously across levels of analysis and time-scales provides an important methodological extension to previous research in the area of intraindividual variability and covariation. Nearly all research examining individual differences in within-person associations as a predictor variable have used a two-step approach. Within-person estimates from multilevel models are first exported then subsequently entered into regression models (or univariate growth models) to predict outcomes (e.g., Charles et al., 2013; Hülür et al., 2015; Mroczek et al., 2015; Piazza et al., 2013; Sin et al., 2015; Stawski et al., 2017). In contrast, the current research utilized an MSEM framework, where the variance components are decomposed within a single model that adjusts for variance across levels of analysis and permits random slopes to be integrated as both exogenous predictor variables and endogenous outcome variables. This extension opens a number of possibilities in how we conceptualize the complex developmental relationships across time-scales. By permitting the random slopes of within-person associations to be either predictor or outcome variables, pathways that link short-term and long-term processes can be specified to enable a thorough investigation of developmental changes in the impact of contextual influences. Furthermore, moderator variables can be included to evaluate changes in within-person dynamics relative to life events (e.g., child birth) and developmental periods (e.g., midlife, retirement). These extensions will have important ramifications for how we characterize the individual and how we attempt to capture the slower and more rapidly developing influences at each stage of the life span.

Limitations and Future Directions

The MIDUS study design consisting of multiple daily measurement bursts within a longitudinal panel design on a large representative national sample provides unique opportunities to examine and statistically model the complex relationships across multiple time-scales that were under investigation. Despite these clear strengths, there are still a number of limitations that should be addressed with future research. First, further investigation is needed into the number and spacing of short-term measurement occasions necessary to reliably estimate within-person associations as a stable individual difference variable. It is unknown how many measurement occasions (e.g., daily assessments) are needed for the within-person association to be an accurate and valid characterization of the individual. Because the estimates are a measure of variance based on random effects, they are likely to be more volatile than measures of central tendency. Some research has suggested that within-person associations based on fewer than seven measurement occasions have low reliability (Estabrook, Grimm, & Bowles, 2012; Mejía, Hooker, Ram, Pham, & Metoyer, 2014; Wang & Grimm, 2012). However, this is likely to depend on the quality and temporal spacing of the measures in addition to the number of occasions. The within-person associations of the current study are based on measurement bursts of eight daily assessments, which have been used frequently throughout the literature. Nevertheless, a thorough empirical investigation into this issue is warranted to establish best practices that will optimize study designs and analyses. Second, the current statistical models are computationally demanding and often require large sample sizes to converge. The strengths of the MIDUS data collection permitted these models to converge. In addition to understanding the measurement design requirements to appropriately model person-specific variations in within-person associations, it will be important for future research to understand the person-level sample size requirements to permit stable estimates and model convergence. Third, it is important to note that these models represent a pattern of relationships from which we cannot infer a causal direction. Though the pattern is consistent with both previous research and a coherent theoretical direction, it is still plausible that the direction of results operates in a different ordering. In the absence of true experimental designs, the direction of the causal relationship will remain unclear.

Finally, the 9-year interval between measurement bursts makes it difficult to interpret what the change in the strength of the within-person stress reactivity association truly represents. It is impossible to determine the processes that are unfolding during this period that are contributing to the changes in stress reactivity. Furthermore, it is unknown whether the change is occurring linearly or is in response to more slowly occurring contextual factors. In the same way that NA varies daily based on contextual factors (e.g., stressful experiences), so too could stress reactivity change be dependent on slower occurring contextual processes (e.g., life transitions—parenthood, occupational commitments, and family strain) that are accounting for why some individuals are becoming more reactive to daily stressors than others over longer intervals of time. It is also plausible that changes in stress reactivity reflect a retest effect, where individuals are more willing to report greater NA in response to stressful events. More frequent measurement bursts assessed at shorter intervals (e.g., annually) would permit a better understanding of the nature of change in stress reactivity within each individual.

The MIDUS project is ongoing and additional measurement waves and bursts continue to be collected. The MSEM framework outlined in the current study provides opportunities to examine additional complex questions of change and development across time-scales. The current study examined individual differences in measures of well-being assessed at Wave 2. Future research could also investigate how long-term changes in daily relationships coincide with long-term changes in well-being to understand how these processes unfold together.

Conclusions

The current study presents a novel approach for simultaneously modeling short-term within-person relationships and long-term changes in these short-term relationships. We further demonstrated how the strength of individual within-person relationships across multiple time scales, parameterized as changes in random effects, can serve as important predictors of distal outcomes. Individuals who became more reactive to daily stressors over a 9-year period consistently reported lower levels of well-being relative to those who did not become more reactive. These effects were present over and above the effects of person-mean levels of NA and stress exposure. This approach provides new opportunities to capture the informative characteristics of the individual across various periods of the life span and to better understand how the impact of contextual influences change and moderate concurrent and future individual states.

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