Why do my thoughts feel so bad? Getting at the reciprocal effects of rumination and negative affect using dynamic structural equation modeling

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This is a study containing two data sets from different laboratories. We report how we determined our sample sizes, all exclusions of participants, and all measures as relevant for the research questions. There were no manipulations. Results from these datasets were previously published to test different research questions. A list of the publications pertaining to each data set is provided in the Methods section of the manuscript. The data and the items are freely available referring to Blanke, Brose, et al., 2020 (Blanke, 2019).

Abstract

Rumination means to perseveratively think about one's negative feelings and problems. It is a response to affective distress that is often referred to as maladaptive emotion regulation. According to the response styles theory and control theory, rumination may further prolong and exacerbate affective distress. This means that rumination can be viewed as both an antecedent and an outcome of negative affect (NA), and vice versa. However, at the level of short-term dynamics, state rumination and NA have previously mainly been examined as two separate outcomes. To model the reciprocal within-person effects and hence, to match theoretical assumptions, we combined the two interrelated time series in one model using dynamic structural equation modeling (DSEM). Both effects (NA on subsequent rumination and rumination on subsequent NA) were modelled simultaneously while acknowledging the autoregressive nature of both states (inert properties). We used data from two experience sampling studies ($N_{\text{Study 1}} = 200$ Belgian university students; $N_{\text{Study 2}} = 70$ German university students). Participants were paged on smartphones several times a day (Study 1: 10; Study 2: 6) for several days (Study 1: 7; Study 2: 9-12). In both studies, we found evidence for reciprocal effects of NA and rumination, and both processes showed autoregressive relationships. Aside from central findings, higher levels of rumination were also associated with higher rumination inertia, pointing towards more habitual rumination also being associated with prolonged rumination. Together, using DSEM, we found reciprocal associations between rumination and NA, while providing new insights into the dynamics between the two processes. *250/250 words*

Keywords: *negative affect, dynamic structural equation modeling, experience sampling, inertia, rumination (5/5)*

Why do my thoughts feel so bad? Getting at the reciprocal effects of rumination and negative affect using dynamic structural equation modeling

Rumination means to perseveratively think about one's negative feelings and problems (Nolen-Hoeksema et al., 2008). It is a response to affective distress, which—according to the response styles theory (Nolen-Hoeksema, 1991)—is thought to maintain and further intensify negative feelings. As such, rumination is usually categorized as a maladaptive emotion-regulation strategy (e.g., Aldao & Nolen-Hoeksema, 2010). Over time, rumination can become a habitual response to negative affect that plays a role in the emergence and maintenance of depression and other psychopathologies (e.g., Watkins & Roberts, 2020). Control theory, on the other hand, states that rumination occurs when goal progress is unsatisfactory, which likely also causes negative affect (Martin & Tesser, 1996). Rumination can then either lead to an adaptive resolving of the discrepancy or goal-disengagement, or to maladaptive perseverative thinking about the discrepancy, which can lead to (even more) negative affect. According to both theories, there should therefore be a reciprocal relation between negative affectivity and rumination.

Empirical findings support such a reciprocal link. At the trait level, negative affect and rumination are correlated (Nolen-Hoeksema et al., 2008) and predict each other over time (Calvete et al., 2015). Additionally, a growing number of studies using daily diaries or the experience-sampling method (ESM) revealed a within-person association between rumination and negative affectivity at the state level (e.g., Brans et al., 2013; Genet & Siemer, 2012; Hoorelbeke et al., 2016; Lennarz et al., 2019; Li et al., 2017; e.g., Moberly & Watkins, 2008; Pasyugina et al., 2015). Research at the state level is an important complement to research at the trait level, since trait and state measures hold different information (Robinson & Clore, 2002). Specifically, state measures capture experiential information that is only accessible in close proximity to its occurrence. In comparison, trait measures also capture beliefs about the self, informed by memory. To investigate changes in rumination and negative affect from

moment to moment (short-term dynamics), assessments and analyses at the state level are required. However, most previous studies at the state level do not seem to reflect the reciprocity of rumination and negative affectivity sufficiently. Instead, researchers commonly treated one of the states as an outcome and the other as its predictor without integrating their reciprocal effects in one model. Furthermore, previous studies did not compare the strength of the reciprocal effects to evaluate whether rumination is more of a response to negative affect, or whether rumination triggers negative affect more so than it is a reaction to it. Additionally, both negative affect and rumination were previously shown to be of lingering nature and thus to be self-predictive across time (e.g., Brans et al., 2013). While differing levels of lingering (also referred to as levels of inertia) in negative affect have received some attention as a predictor of psychopathology (e.g., Houben et al., 2015), inertia in rumination has not yet been discussed much in ESM research (Pavani et al., 2017)– despite the fact that rumination is known to be hard to stop once started (e.g.,Watkins & Roberts, 2020).

To overcome these caveats of previous research, we used a new statistical approach, dynamic structural equation modeling as implemented in Mplus (DSEM; see Asparouhov et al., 2018). This approach fits well with theoretical assumptions of the response styles theory and the control theory: it allows for examining the within-person, reciprocal dynamics between affect and rumination, considering both rumination and negative affect as predictors and outcomes simultaneously. Additionally, DSEM allows for acknowledging the lingering nature of both negative affect and rumination, and it allows comparing the size of these effects as well.

Rumination and Negative Affectivity

Rumination is a multidimensional construct, including facets that are commonly viewed as maladaptive (i.e., brooding) and facets that are viewed as more adaptive (i.e., reflection; Treynor et al., 2003). For the present study, we concentrated on the particularly maladaptive aspect of rumination, namely ruminative brooding (hereafter referred to simply

as *rumination*), including perserveratively thinking about (past) stressors and focusing on negative affective experiences (Nolen-Hoeksema, 2008). Rumination is often measured as a trait, reflecting a stable personal characteristic (e.g., Ruminative Response Scale; Treynor et al., 2003) and was shown to be a correlate of depressive symptomatology (Nolen-Hoeksema et al., 2008). Moreover, trait-level rumination and depression seem to be related across time. In a study with adolescents, who were surveyed about their stress, rumination, and depressive symptoms three times throughout a year, stressors and rumination predicted depressive symptoms, which in turn, together with stressors, worsened rumination (Calvete et al., 2015).

However, while investigating long-term associations in rumination and negative affectivity at the trait level is important, the processes as described in the response styles theory as well as in control theory likely happen on shorter time scales, such as from moment to moment, and, hence, at the level of states. Coming to a more mechanistic understanding of rumination requires a within-person approach and a focus on the process of rumination. To illustrate, rumination likely occurs within minutes or hours when one is feeling sad or feels that one's goal is blocked. Specifically, the response styles theory proposes the following mechanisms: Negative affectivity (elicited by internal or external events) leads to rumination which then exacerbates distress by activating overly pessimistic thoughts. Rumination interferes with problem solving and, in turn, prolongs negative affectivity, providing the basis for more rumination (Nolen-Hoeksema et al., 2008). Similarly, control theory proposes that states of rumination occur when one perceives that a goal is blocked (which can result in negative affect). States of rumination may then lead to or exacerbate negative affect, if no adaptive solution is obtained.

In the last years, these short-term processes have been approached in studies using daily diary or ESM, which have greatly added to our understanding of the relation between rumination and negative affectivity. Furthermore, investigating short-term processes has also led to a refined understanding of both processes: It was shown that previous

rumination/negative affect are predictive of current rumination/negative affect (autoregressive effect, here also referred to as levels of inertia; Brans et al., 2013; Pavani et al., 2017). While inertia in rumination has not received much attention yet, higher inertia in negative affect was shown to be associated with maladaptation like depression (e.g., Houben et al., 2015; but see Dejonckheere et al., 2019 for the importance of considering mean negative affect in such analyses). Negative affect inertia and trait rumination were shown to be related, and both were associated with depressive symptoms (Brose et al., 2015; Koval et al., 2012). However, as we will point to next, research has not yet captured the full complexity of the relation between negative affect and rumination.

Previous Empirical Approaches to Associations between State Rumination and Negative Affect

Previous studies on the within-person links between rumination and affect had different theoretical foci. Some studies have mainly focused on the impact that rumination has on negative affect. In these studies, concurrent within-person associations were modelled using multilevel modeling (MLM), providing evidence for associations between rumination and affect: occasions at which individuals ruminated more were commonly those with above average levels of negative affect (see Figure 1a; e.g., Lennarz et al., 2019). A second theoretical interest of previous studies pertained to the potential moderating role of rumination for stress reactivity at the within-person level. In accordance with theoretical notions, studies revealed that above-average levels of rumination enhanced the negative effects of stressors on momentary well-being, showing that affect was more disturbed when stressors occurred in combination with rumination (see Figure 1b; e.g., Brose et al., 2011; Genet & Siemer, 2012) . These studies again used MLM and modeled within-person variation in rumination as a predictor of the within-person association between stress and negative affect. Still other studies pursued a two-model approach, investigating rumination both as an outcome and as a predictor of negative affect. These studies were mostly concerned with within-person effects

of rumination on *change* in affect and vice versa (see Figure 1c; e.g., Brans et al., 2013). The focus on change was realized here by adjusting for previous levels of the outcome variables (e.g., negative affect at the preceding occasion and rumination at the concurrent occasion predict negative affect at the concurrent occasion) in MLM. Findings were that rumination predicted increases in negative affect from one measurement occasion to the next, and that negative affect also predicted increases in rumination from one measurement occasion to the next. Relatedly, one study examined the spill-over effect of rumination on subsequent negative affect (i.e., the effect of rumination at the preceding occasion on affect at the current occasion; Moberly & Watkins, 2008).

Of these different approaches to the within-person associations of rumination and negative affect in daily life, the two-model approach comes closest to the proposed bidirectional relationship, as both states are treated as predictor and outcome. Furthermore, studies pursuing the two-model approach acknowledged that both rumination and negative affect have lingering qualities. That is, previous rumination/negative affect are predictive of current rumination/negative affect (autoregressive or lagged effect, also referred to as levels of inertia). The two-model approach thereby comes close to theoretical ideas, but it examines the two processes (effects of rumination on change in negative affect; effects of negative affect on change in rumination) in isolation. When pursuing this approach, only one of the autoregressive (lagged) effects (e.g., the effect of negative affect at time-point $t-1$ on subsequent negative affect) and one of the cross-lagged effects (e.g., the effect of rumination on subsequent negative affect) can be taken into account. This incomplete modeling of the process, split into two univariate processes, has unknown effects on the estimates—it is impossible to say from the results of these approaches whether they would replicate if the entire process as theoretically described were to be modeled. Moreover, and in relation to the proceeding: Within the two-level approach it is not possible to evaluate associations between cross-lagged and/or lagged effects. For example, this prohibits exploring whether levels of

inertia in negative affect are related to levels of inertia in rumination, which is interesting from a theoretical perspective. Finally, none of the above-mentioned studies compared effect sizes of the cross-lagged effects. Effect sizes may be relevant for interventions aimed at increasing affective well-being: If the effect of negative affect on subsequent rumination was stronger than the effect of rumination on subsequent negative affect, rumination could be viewed as a response to, rather than a trigger for, negative affect. As a response to negative affect, rumination may be sufficiently reduced by interventions targeting the decrease of negative affect, such as behavioral activation as applied in cognitive behavioral therapy (CBT). However, it has been argued that this is not the case, and that interventions are needed to directly target rumination (Watkins & Roberts, 2020).

The approach that we pursued allows for examining the two time series simultaneously (i.e., changes in both rumination and negative affect can be related to previous states of the respective predictors; see Figure 1d for illustration). We applied multivariate vector autoregressive modeling (ML VAR) as realized in DSEM. Two main approaches exist to model multivariate time series: single-subject vector autoregressive (VAR) modeling and multilevel vector autoregressive (ML VAR) modeling. In the former, time series of single subjects are analyzed. In essence, each variable is regressed on all other variables (including itself) at the previous measurement occasions here (usually $t-1$, with the covarying residuals reflecting concurrent associations between variables e.g.; Bulteel et al., 2016). The ML VAR model additionally captures quantitative differences between individuals. The ML VAR model has previously been applied to investigate multivariate associations between affect and regulatory efforts (Bringmann et al., 2013; Pavani et al., 2017).

Indeed, using a ML VAR model, Pavani et al. (2017) showed reciprocal effects between rumination and negative affect at the state level. Interestingly, in this study, the effect of negative affect on subsequent rumination was *smaller* than the other way around (when also controlling for various other regulation strategies). Furthermore, both negative affect and

rumination showed autoregressive effects, with negative affect showing higher autoregression than rumination. However, the modeling did not include random effects (i.e., differences between individuals) or their correlations (e.g., correlations between lagged or cross-lagged effects). Especially the correlation of residuals should be an important aspect of bivariate processes (i.e., if two variables are related across time, they are likely also related within a given moment). While including correlated error terms in previous ML VAR efforts was possible, it required complex modeling steps (Bringmann et al., 2013). This problem was overcome by ML VAR modeling in DSEM as implemented in Mplus. As we will show, it is a parsimonious and easily applicable approach to investigate reciprocal within-person in one model.

Approaching Reciprocal Links between Rumination and Negative Affect using DSEM

DSEM allows for exactly the type of bidirectional modelling that is needed to investigate effects that rumination and negative affect have on each other over time. DSEM has been developed in the structural equation modeling (SEM) framework and allows for modeling multilevel data, integrating time series analyses with SEM. It is set up in a Bayesian framework. Parameters are estimated with a Markov chain Monte Carlo (MCMC) procedure. In the specific case of this study, the bidirectional DSEM models two time series: negative affect and rumination, which are treated as correlated outcomes.

It is an essential advantage of DSEM that multiple outcome variables can be examined simultaneously while also allowing for modelling within-person residuals (also called innovations) and covariances among the residuals as random effects within the same model. Furthermore, DSEM as implemented in Mplus can deal with the unequal spacing of the measurement occasions (i.e., the time between measurements occasions can vary considerably). Mplus creates a time window grit in which measurement occasions can fall, automatically filling in missing values at time windows in which beeps were not answered or no measurement occasion took place (e.g., at night). That way, the data becomes

approximately evenly spaced. Although unequally spaced measurement occasions are the norm rather than the exception in ESM research, this is often ignored in data analysis. Addressing this issue is therefore a particularly valuable asset of the DSEM approach.

The lingering nature of both constructs is taken into account by lagged (autoregressive) effects of each, and the reciprocal effects from negative affect to rumination and vice versa are taken into account by cross-lagged effects. In DSEM, the data is decomposed into a within-person and a between-person component as is customary in multilevel modeling. The between-person component represents stable (or trait-like) means, whereas the within-person component represents deviations from these stable means. Recent versions of Mplus directly provide standardized results, based on a procedure proposed by Schuurman et al. (2016). This facilitates comparing the relative strength of cross-lagged effects, such as effects of rumination on change in affect and vice versa. It is a within-person standardization, meaning that the observations are standardized relative to each study participant's person specific standard-deviation.

Furthermore, in comparison to previous ML VAR models, DSEM allows for random variances of all parameters as well as their covariances, and Mplus provides the within-person standardized correlation coefficients. This enables the researcher to investigate the magnitude of the random effects as well as associations among process dynamics at the between-person level. That way, we can, for example, explore whether individuals whose negative affect is more inert are also individuals who ruminate more, or who tend to have stronger increases in negative affect after rumination, and interpret these associations on the metric of correlations and not covariances (which are dependent on the scale of the measurements). Finally, it allows including random residual variances and their covariance.

The Present Research

In two studies, we examined the likely reciprocal links between rumination and negative affect using DSEM. We also explored intercorrelations between random effects (e.g.,

correlations between lagged and cross-lagged effects) and associations of the random effects with depressive symptoms. In Study 1, we used data from the first wave of a longitudinal study (for a detailed description, see Koval et al., 2015; for other publications with this data, see Bastian et al., 2015; Blanke, Brose, et al., 2020; Brose et al., 2017; Dejonckheere et al., 2018; Erbas et al., 2018; Grosse Rueschkamp et al., 2020; Houben & Kuppens, 2020; Kalokerinos et al., 2019; Pe et al., 2015, 2016). To replicate and extend our findings, we used a second data set in Study 2. This data was also previously used to investigate other research questions (Blanke et al., 2018; Blanke, Brose, et al., 2020; Blanke, Schmidt, et al., 2019; Blanke & Brose, 2017; Grosse Rueschkamp et al., 2020). In Study 2, the assessment of negative affect and rumination differed from the assessment in Study 1, which provided us with the opportunity to explore whether our results were generalizable to these variations in measurement. Since these two data sets were collected for various purposes, there were no power analyses conducted beforehand with regard to the present research question. Sample sizes were determined by the respective principal investigators before data collection on the basis of previous experiences with experience-sampling. The data and the items are freely available (Blanke, 2019). Data1 pertains to Study 2 in the present work, and Data3 pertains to Study 1 in the present work.

Study 1

Method

Participants and Procedures. University students (bachelor students) from the University of Leuven, Belgium, were invited to fill out a Dutch translation of the Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1977). Participants for this study were selected based on their CES-D scores to maximize variation in depression (for a detailed description, see Koval et al., 2015). In accordance with previous publications, two participants

were excluded from the analyses as they answered less than 50% of the ESM beeps.[1] The final sample were 200 students (55% female) aged between 17 and 24 years (M = 18.32, SD = 0.96 years). The majority identified as European (n = 192), others identified as African (n = 3), Middle-Eastern *(*n = 3), or Asian (n = 2). The language of assessment was Dutch. In an introductory session, the final sample gave informed consent to participate and filled out questionnaires. They received smartphones (Motorola Defy Plus) programmed with custom-built software to take part in the ESM phase, which started the following day and lasted seven consecutive days with 10 beeps occurring semi-randomly each day in a 12-hr time frame (10 a.m. to 10 p.m.)[2]. On average, participants answered 61.47 beeps (SD = 6.30). Reimbursement for participation in this wave of the study was 60 Euros. The study was approved of by the ethics committee of the KU Leuven.

Measures. Depressive symptoms were assessed before the ESM phase (see Koval et al., 2015). State negative affect and rumination were measured at each beep during the ESM phase.

Depressive symptoms. Depressive symptoms were assessed using a Dutch version of the CES-D (Radloff, 1977). The CES-D consists of 20 items, which are answered on a 4-point scale ranging from *0 (rarely or none of the time, less than 1 day)* to *3 (most or all of the time, 5–7 days).* We used the mean of the scale (M = 0.63, SD = 0.39). Internal consistency was high (Cronbach's alpha = .88).

Negative affect (NA). The following items were used to measure NA: sad, depressed, anxious, and angry. The items were selected based on Russell's core affect model to represent low and high arousal NA (Russell, 2003), and they reflect the experience of three basic

[1] We are aware that excluding participants based on their compliance may create biases. We therefore reran the analyses including these two participants, which did not change the pattern of results.
[2] The 12-hr time frame was divided into 10 bins of 72 minutes each, in which the beeps could fall. In this version of the software, no minimum or maximum distance between beeps was specified otherwise.

emotions (sadness, anxiety, and anger; Ekman & Friesen, 1971). At each beep, participants were asked how much they felt these emotions *at that specific moment.* Here, participants used a slider scale ranging from *0 (not at all)* to *100 (very much)* to answer the items. The average individual mean was iM = 14.31 (SD = 8.44). The intraclass correlation (ICC) indicated that 39% of the variance was between-person variance. The within-person reliability score (according to Cranford et al., 2006) was 0.74.

Rumination. Rumination was measured with one item referring to rumination: *"Since the last beep, have you brooded about something in the past?"* The same slider scale as for NA was used ranging from *0 (not at all)* to *100 (very much).* The average individual mean for rumination was iM = 18.44 (SD = 13.59). The ICC indicated that 36% of the variance was between-person variance.

Data analysis

Data was prepared in IBM SPSS Version 25 for Windows and SAS Version 9.4. It was analyzed in Mplus Version 8.3 (Muthén & Muthén, 1998-2017).We modelled a bivariate DSEM (Hamaker et al., 2018; McNeish & Hamaker, 2019) with two related within-person time series, NA and rumination (for a commented Mplus script, see Appendix 1). When estimating parameters in DSEM, we used the *fbiter* option in Mplus[3] and gradually increased the number of iterations, checking for signs of non-convergence by using Potential Scale Reduction (PSR), and by looking at the trace plots and autocorrelation plots of the parameter estimates. The trace plots of the two chains should be overlapping, without irregularities or spikes. A small autocorrelation between the iterations of each chain is desirable to obtain relatively independent draws from the posterior distribution of the parameters. One way this is

[3] When estimating parameters using DSEM in Mplus, one needs to either specify the number of iterations (*fbiter* option in Mplus) or use the Potential Scale Reduction (PSR) as a criterion to stop the iteration process automatically (*biter* option in Mplus). However, using PSR as an automatic stopping criterion may lead to stopping at a local (unstable) maximum. The PSR should be very close to one for each parameter, meaning that there are almost no differences between the chains (i.e., the chains have converged).

typically accomplished is by using only every *k*th iteration of the estimation (a process called thinning).

In the final model, we used two MCMC chains with 500,000 iterations each (using the default Gibbs sampler), and a thinning of 100. As Mplus discards the first half of each chain as burn-in phase, our final model was thus based on 5000 saved iterations in total (per chain: 250,000 / 100 = 2,500). We used the default diffuse priors, meaning that the results are driven by the data, not by previous assumptions (see Mplus user's guide for further information, Muthén & Muthén, 1998-2017). To deal with the unequal spacing of the measurement occasions, we made use of the Mplus option *tinterval*. We set 1-hour time windows as participants were provided with 10 beeps in a 12-hour time frame. Within-person residuals were allowed to vary across individuals. Mplus uses the log of the residual variance, which ensures that all residual variances are positive. As Hamaker et al. (2018) pointed out, modeling the covariance between these residuals (i.e., unexplained portions of within-person variance in NA and rumination) is more complicated, and requires an additional latent variable that represents what the residuals have in common. We set the covariance to be positive, which is in accordance with the theoretical model (i.e., a positive covariance between negative affect and rumination; see also Hamaker et al., 2018, as to why the covariance needs to be fixed to either a positive or a negative value within the model).

To evaluate whether effects were significantly different from zero, we used the 95% credible intervals (95% CIs). When credible intervals for the effects did not contain zero, they were deemed statistically significant. To evaluate the magnitude of the cross-lagged and the lagged effects, we used the within-person standardized results provided by Mplus. If CIs of these effects were not overlapping, the effects were deemed significantly different from one another.

Results

Model Convergence

Model convergence was satisfactory. PSR values for all parameters were 1.002 or lower, trace plots suggested successful convergence for all parameters.

Reciprocal (Cross-lagged) Effects

First and foremost, we were interested in the question whether there was evidence for reciprocal (cross-lagged) effects from NA to rumination and from rumination to NA, as would be predicted by the response styles theory and control theory. This was the case (results for all fixed and random effects and their 95% CIs are presented in Table 1). The credible intervals for the cross-lagged effects did not contain zero, indicating that these effects were deemed statistically significant. That is, NA at a given moment was positively predicted by previous rumination, and rumination was positively predicted by previous NA. We further examined these effects by considering the standardized results. The standardized lagged effect from NA to rumination was 0.116 (CI = 0.095, 0.137), meaning that when NA increased by one person-specific standard deviation, rumination, on average, increased by 0.116 of a person-specific standard deviation. The standardized lagged effect from rumination to NA was 0.042 (CI = 0.021, 0.063). As the credible intervals of the standardized cross-lagged effects did not overlap, it can be concluded that NA predicted subsequent rumination more so than rumination predicted subsequent NA.

Autoregressive (Lagged) Effects

As expected based on previous research, we also found evidence for autoregressive effects, both for NA and for rumination, indicating the lingering nature of both states (see Table 1). The standardized autoregressive effect of NA was 0.361 (CI = 0.339, 0.381), whereas the standardized autoregressive effect of rumination was 0.216 (CI = 0.193, 0.238), and thus smaller. That means that previous NA predicted concurrent NA more so than previous rumination predicted concurrent rumination.

Correlations Between Random Effects

The standardized results also provide insights into the correlations between all random effects at the between-person level (see Table 2, above the diagonal). As we had no hypotheses on these associations, these correlations can be viewed as exploratory.

Average rumination and NA were strongly correlated, indicating that individuals who had high levels of NA also ruminated a lot. For individuals who had higher levels of NA, NA was more inert. In turn, more inert NA was associated with a stronger effect of NA on subsequent rumination, meaning that individuals with higher NA inertia were more likely to ruminate after experiencing NA. For individuals who ruminated more, rumination was also more inert. Levels of NA inertia and rumination inertia, however, were not related, and neither were the cross-lagged effects (rumination on NA and NA on rumination). The cross-lagged effect from NA to rumination was moderately negatively correlated with the Level-1 residual variance of NA. That means that for individuals whose NA was associated with stronger increases in rumination, there was less unexplained variance in NA. Similarly, the cross-lagged effect from rumination to NA moderately negatively correlated with the residual variance of rumination. Average levels of NA and rumination were furthermore positively correlated with the residual variances and their covariance. Residual variances and their covariance were all related to one another.

Correlations of Random Effects with Depressive Symptoms

Results are also presented in Table 2. Individuals with higher depressive symptoms had higher mean NA and higher mean rumination. Furthermore, individuals with higher depressive symptoms had higher NA inertia, higher residual variances and a stronger covariance between the residuals (all small to medium sized correlations).

Explained Variance

Overall, the average proportion of explained within-person variance for NA was 0.436 (CI = 0.408, 0.466). The average proportion of explained within-person variance for rumination was 0.249 (CI = 0.231, 0.267), and thus lower.

Discussion

According to theoretical assumptions of the response styles theory, control theory as well as previous empirical findings (using other statistical approaches), the relation between NA and rumination should be reciprocal. However, previous empirical approaches were mostly univariate, and thus did not sufficiently address this reciprocal relation. DSEM enabled us to model reciprocal associations of rumination and NA simultaneously, while also taking into account correlated residuals and unevenly spaced measurement. Furthermore, using the within-person standardized coefficients that Mplus provides allowed us to compare the sizes of the effects.

We found evidence for reciprocal effects between NA and rumination showing that higher than usual NA indeed was associated with increases in subsequent rumination, and, in turn, higher than usual rumination was associated with increases in subsequent NA. Findings from this study also seemed to indicate that NA had a stronger effect on increases in rumination than the other way around. This result may suggest that rumination is more of a response (or a regulatory strategy) that follows after experiencing negative emotion. It could be interpreted as in line with previous findings, showing that rumination was only associated with worsened mood for individuals who were already dysphoric when they received a rumination induction (Nolen-Hoeksema & Morrow, 1993). However, Pavani et al. (2017) found the *opposite* pattern, namely, rumination being potentially more of a trigger for negative affect than the other way around, when considering the whole study sample. In this previous study, only in individuals high in neuroticism, cross-lagged effects in both directions were similar. Of note, the authors applied a different methodological approach, not considering associations between negative affect and rumination at the same measurement occasion (i.e., correlation of residuals) or random effects, which may have contributed to discrepant findings in addition to differences in other study characteristics (e.g., the $N = 78$ participants in this study were aged from 13 to 80 years).

In line with previous findings, both NA and rumination showed levels of inertia in our study, with NA being more lingering than rumination. However, rumination also showed substantive levels of inertia, a fact that has received little attention thus far (see also Pavani et al., 2017). The analyses also revealed interesting associations between process dynamics and correlations between such dynamics and depressive symptoms. This became possible using DSEM, which is another major advantage of this modeling approach.

As to be expected from previous research, individuals who experienced more NA also ruminated more on average, and higher average levels of NA and rumination were both correlated with depressive symptoms (Nolen-Hoeksema et al., 2008). Levels of rumination inertia and NA inertia were both associated with their respective average levels. Individuals with higher NA inertia were also more likely to show increases in rumination after experiencing NA. Furthermore, higher levels of NA inertia were also correlated with depressive symptoms. This is in line with research showing that higher NA inertia is associated with depression and other signs of lower well-being (Houben et al., 2015). Depressive symptoms were also correlated with higher residual variance. Likely, for individuals with more depressive symptoms, there was more variance to be explained to begin with (as those individuals had higher means). Interestingly, depressive symptoms were also associated with the covariance between the residuals (representing associations between NA and rumination at the same measurement occasion), indicating that stronger correlations between NA and rumination were associated with higher depressive symptoms. However, there were no associations between cross-lagged effects and depressive symptoms. As we had no prior hypotheses for any of these associations, these results were exploratory in nature and should therefore be interpreted cautiously.

To conceptually replicate and further extend our findings, we used data from a second study. In this study, we also wanted to explore the possibility that differences in measurement of NA and rumination may have contributed to our results concerning the cross-lagged

effects. Potentially, the assessment of NA and rumination may have resulted in a stronger cross-lagged effect from NA to subsequent rumination as we assessed NA at the moment of the measurement occasion, whereas we assessed rumination referring to the time between measurement occasions. Although this is commonly done in emotion-regulation research, assessing NA this way may have weakened the lagged association between rumination and subsequent NA in our analysis, as the lag between rumination at time-point *t—1* and NA at *t* was especially long (rumination at *t—1* technically referred to the time frame *before t—1, between t—1 and t—2*; see Figure 2). In this second study, NA and rumination were measured in a comparable way, namely referring to the time frame between beeps. While this is unusual for ESM studies, we think that this may actually be a better fit for our methodological approach.

Study 2

Method

Participants and Procedures. This sample consisted of 70 university students (bachelor and master students) from various disciplines (50% female, $n = 21$ with a bachelor's or equivalent degree), recruited via posters, online advertisement, and university mailing lists in the Berlin area, Germany. Participants were between 20 and 30 years old ($M = 25.55$, $SD = 2.74$ years), and predominantly German native speakers ($n = 2$ indicated that their German language skills were equivalent to native speakers) as the language of assessment was German. There was no exclusion of participants from the present analyses. The students came to the laboratory twice, before and after the ESM phase. In the first session, they gave informed consent to participate, filled out questionnaires, and received smartphones (Huawei Ascend G330). The smartphones were programmed with an ESM technology that was developed and applied in previous studies (e.g., Riediger et al., 2009). Participants selected a fixed 12-hour time frame (e.g., 10 a.m. to 10 p.m.), during which six beeps occurred semi-

randomly each day.[4] Beeps were scheduled for nine consecutive days, but if participants missed more than one assessment per day, up to three extra days (with the same time frame and scheduling frequency) were added to the schedule so that missed beeps could be made up for. The majority of participants made use of at least one extra day (n = 47). Participants were reimbursed according to the number of beeps they had answered, and received a fixed reimbursement for the laboratory sessions. We communicated to the participants that we aimed for 54 answered beeps (9 days times 6 beeps) and they received a bonus of 10 Euros for 45 or more completed beeps. On average, participants received 65 Euros in total. Participants completed 54.41 beeps on average (SD = 3.25; range: 48–65). The ethics committee of the Humboldt-Universität zu Berlin approved of the study.

Measures. Depressive symptoms were assessed before the ESM phase in the intake session. Negative affect and rumination were measured at each beep during the ESM phase.

Depressive symptoms. As in Study 1, depressive symptoms were assessed with the CES-D (German version by Hautzinger & Bailer, 1993). Due to a programming error in the task, participants answered items on a 5-point scale ranging from *0 (never)* to *4 (always)*, instead of the usual 4-point scale. We used the mean of the scale (M = 1.44, SD = 0.61). Internal consistency was high (Cronbach's alpha = .92).

Negative affect (NA). Unlike in Study 1, NA was assessed not at the specific moment of the beep. Instead, participants were presented with the following instruction: "*How have you primarily felt since the last measurement / since waking up (for the first beep of the day): Please rate how well the following emotion adjectives describe your feelings during this time period"*. Three NA items were rated: nervous, downhearted, and distressed. The underlying model of affect was a dimensional model (Feldman Barrett & Russell, 1998). We selected

[4] The beeps were scheduled in six 2-hr bins with at least 45 minutes between the start of the beeps of adjoining bins. The 12-hr time frames could be chosen in such a way that the latest possible time to start was 12 a.m. so that the six beeps would all occur at the same day.

items that were used in previous intensive longitudinal designs, that were sufficiently variable, representing higher and lower arousal affective experiences (Brans et al., 2013; Riediger et al., 2014; Röcke et al., 2009). Participants answered the questions using a 7-point Likert scale ranging from 0 *(does not apply at all)* to 6 *(applies strongly)*. The average individual mean was iM = 1.40 (SD = 0.90). The ICC indicated that 49% of the variance was between-person variance. The within-person reliability was estimated as 0.64 (according to Cranford et al., 2006).

Rumination. Rumination was measured with two items. One item referred to rumination about feelings (adopted from Brans et al., 2013) and the other referred to rumination more broadly. Participants received the following instruction: *"How well do the following statements describe how you handled your thoughts and feelings since waking up/ since the last beep?"* The items for rumination were: *"I could not stop thinking about my feelings."* and: *"I could not stop thinking about certain things."* Items were again answered on a 7-point Likert scale ranging from 0 *(does not apply at all)* to 6 *(applies strongly)*. The average individual mean was iM = 1.80 (SD = 0.95). The ICC indicated that 39% of the variance was between-person variance. The within-person reliability was estimated as 0.67 (according to Cranford et al., 2006).

Data analysis

Data analysis was identical to that of Study 1 with the exception that we set the time window in Mplus (*tinterval* option) to two hours instead of one, as participants were asked to answer six beeps in 12 hours in this study (as compared to 10 beeps in 12 hours in Study 1). In this analysis, we also included measurement occasions at which participants only started to answer the questionnaire without finishing it (but at least answering questions on NA, which appeared before questions on rumination).

Results

Model Convergence

As in Study 1, model convergence was satisfactory. PSR values for all parameters were 1.001 or lower, trace plots suggested successful convergence for all parameters.

Reciprocal (Cross-lagged) Effects

The results for the fixed and random effects and their 95% credible intervals (CI) are presented in Table 3. As in Study 1, there was evidence for cross-lagged effects in both directions. The individually standardized results showed that the standardized cross-lagged effect from NA to rumination was 0.109 (CI = 0.066, 0.147), and the standardized cross-lagged effect from rumination to NA was 0.109 (CI = 0.073, 0.149). That is, unlike in Study 1, the effects of NA on subsequent rumination and the effect from rumination to subsequent NA were very similar (with the credible intervals almost perfectly overlapping).

Autoregressive (Lagged) Effects

As in Study 1, we also found evidence for autoregressive effects. The standardized autoregressive effect of NA was 0.314 (CI = 0.274, 0.354), whereas the average autoregressive effect of rumination was 0.250, (CI = 0.211, 0.291). In contrast to Study 1, NA and rumination showed similar levels of autoregression (see overlapping credible intervals).

Correlations Between Random Effects

The correlations between the random effects only in part replicated the findings from Study 1 (see Table 2, below the diagonal). As in Study 1, average rumination and NA were strongly correlated, indicating that individuals who had high levels of NA also ruminated a lot. Unlike in Study 1, levels of inertia in rumination and in NA were also highly correlated. Replicating findings from Study 1, higher levels of rumination were associated with higher levels of rumination inertia; however, higher levels of NA were not associated with higher NA inertia. More inert rumination was associated with a stronger effect of rumination on subsequent NA, whereas in Study 1, more inert NA was associated with a stronger effect of NA on subsequent rumination. Average levels of NA and rumination were furthermore positively correlated with the residual variances and their covariance (with the exception that

average NA was not correlated with the residual variance of rumination). Only the residual variance of rumination was correlated with the covariance of the residuals.

Correlations of Random Effects with Depressive Symptoms

Results are also presented in Table 2 (below the diagonal). Individuals with higher depressive symptoms had higher mean NA and higher mean rumination. Furthermore, individuals with higher depressive symptoms had a stronger covariation between the residuals.

Explained Variance

Overall, the average explained within-person variance was comparable to that in Study 1; for NA it was 0.573 (CI = 0.533, 0.611), whereas for rumination it was 0.381 (CI = 0.353, 0.411), and thus lower.

Discussion

As in Study 1, we found evidence for both cross-lagged and autoregressive effects in Study 2. However, in Study 1 the cross-lagged effect from NA to subsequent rumination was stronger than the other way around, whereas this was not the case in Study 2. Here, both cross-lagged effects were comparable. This may indicate that rumination was just as much a response to NA as it was a trigger for more NA in this second study. Autoregressive effects were also more similar to one another in Study 2 than in Study 1, and they were quite strongly related (unlike in Study 1 where the autoregressive effects were uncorrelated).

One plausible reason for the differences between the results from Study 1 and Study 2 may lie in the difference between the assessments of NA. In Study 1, NA was assessed at the moment of the beep, whereas in Study 2, NA was assessed relating to the time frame before the beep (between beeps). Crucially, in both studies, rumination was also assessed relating to the time frame before the beep. In Study 1, the time between rumination at time-point $t-1$ and NA at t was especially long (as the rumination item essentially referred to the time between $t-1$ and $t-2$, whereas NA referred to "right now" at t), making it less likely to find a strong

effect for this specific cross-lagged effect. However, there were other differences between the studies, such as the difference in ESM schedules (ten vs. six assessments within a 12-hour period) or in the operationalization of negative affect and rumination. As we do not know how long-lasting the effect of NA on rumination and the other way around may be, we cannot exclude that this (or other differences between the studies) may have led to the slightly different results.

As compared to Study 1, fewer significant correlations between the random effects emerged, possibly due to a smaller sample, and the pattern of correlations looked different. Replicating results from Study 1, in Study 2, higher levels of NA were associated with higher levels of rumination, and individuals with higher levels of rumination had more inert rumination. Furthermore, depressive symptoms were associated with levels of NA and rumination, and higher depressive symptoms were associated with a stronger covariation between the residuals, indicating the maladaptive nature of these same-time couplings. In contrast to results from Study 1, individuals with more inert rumination were more likely to show stronger increases in NA following rumination. This points towards rumination being problematic (in terms of higher NA) for individuals who take longer to stop ruminating once they have started it. In this study, higher NA inertia was not associated with higher depressive symptoms.

General Discussion

We used ESM data from two studies to approach the question of how negative affect and rumination impact one another within individuals across relatively short time frames (hours). We used a new methodological approach, DSEM, to test the hypothesis that the effects of negative affect and rumination across time are reciprocal. Importantly, we modeled both autoregressive and cross-lagged effects in one model, allowing for inter-individual differences in all effects, reflecting underlying theoretical assumptions about such processes in daily life. The results from both studies converged in showing reciprocal effects between

negative affect and rumination. This provides sound evidence for the propositions of the response styles theory and control theory according to which the two processes are linked—possibly because rumination hinders the engagement in problem solving strategies that may help overcoming goal-related discrepancies and negative affective affect.

The findings across studies somewhat diverged in the sense that in Study 1 the effect for negative affect on subsequent rumination was stronger than vice versa, whereas in Study 2 the effects were of similar strength. We speculate that differences between the studies in the assessment of negative affect (now vs. the last beep) may have played a role here. However, the samples also differed in other ways. Notably, in Study 1, participants were selected to maximize variance in depressive symptoms, which may have played a role as well. To our knowledge, the only other study that compared the relative strength of these effects, found that the cross-lagged effect from rumination to NA was *stronger* than the other way around (when considering the whole sample; Pavani et al., 2017). At this point, we do not think that it can be concluded that one process is stronger or more relevant than the other. Since rumination may not primarily be viewed as a response to negative affect, but also a trigger for it, our findings may be in line with the proposition that interventions targeting reductions in negative affectivity will not automatically reduce rumination to a similar degree (Watkins & Roberts, 2020). Our results suggest that targeting rumination directly may be an important ingredient in interventions that aim to improve affective well-being as well as symptoms of depression, anxiety, or other psychopathologies. Such interventions are, for example, rumination-focused CBT (Watkins, 2015), or mindfulness-based cognitive therapy (Segal et al., 2002).

In both our studies, the autocorrelation for negative affect and for rumination was significant, meaning that both processes showed some inertia. Across both studies, higher levels of average rumination were associated with higher rumination inertia – indicating that habitual rumination is also associated with rumination over extended periods of time.

Interventions may thus not only focus on decreasing the use of rumination, but also on disrupting circles of rumination.

In line with previous research at the trait level, average negative affect and average rumination were highly correlated in both studies, and higher average levels of negative affect and rumination were associated with higher depressive symptoms. Interestingly, higher levels of negative affect and rumination, as well as higher depressive symptoms were also correlated with the correlations between the residuals, representing same-time couplings between negative affect and rumination. Although we did not find associations between cross-lagged effects of negative affect and rumination with depression, this result points towards the coupling between NA and rumination being associated with higher depressive symptoms across both studies. This could also indicate that the instant coupling between rumination and NA (within minutes instead of within hours) is more characteristic of depressive symptoms than the time-lagged coupling between these two constructs.

Other correlations between process characteristics as well as between process characteristics and depressive symptoms, however, were less stable across studies, and need to be interpreted with more caution. Only in Study 1, in which participants were selected to maximize variance in depressive symptoms, did we find a correlation between higher levels of NA inertia and depressive symptoms, which is in line with previous research (e.g., Houben et al., 2015). Interestingly, in Study 1, higher levels of negative affect inertia were associated with stronger cross-lagged effects from negative affect to rumination, whereas in Study 2, higher levels of rumination inertia were associated with a stronger cross-lagged effect from rumination to negative affect. What can be concluded is that different, mutually maladaptive aspects of the process dynamics (mean levels, persistence across time, cross-over between rumination and negative affect) were intrinsically related. These are new insights into the dynamics of rumination and affect, which may help to further our understanding of how rumination may lead to psychopathology.

Limitations and Future Directions

Our study has several limitations. First, although efforts were made to diversify the sample in Study 1 in terms of depressive symptoms, both samples were still relatively healthy student samples, and it is possible that rumination is not as problematic in such a population as it would be in a subclinical or clinical sample. Second, we focused on the more maladaptive brooding component of rumination. However, even brooding may not always be maladaptive. According to recent theory, emotion-regulation strategies may not be adaptive or maladaptive per se, but their effect may be context-dependent (e.g., Aldao et al., 2015; Blanke, Brose, et al., 2020). Thus, occasionally, even brooding could be helpful. Third, there are a number of unresolved issues with the DSEM approach (Hamaker et al., 2018). To briefly mention some of those here, missing values were not random (e.g., at night), possible time trends were not considered, and time was treated as discrete. Forth, since the two studies reported in the present work differed not only in the approach to assess negative affect (right now vs. since the last beep), but in several other characteristics (e.g., sample composition, time between assessments), we cannot conclude that the observed differences between the studies are due to the assessment time frame.

As in all non-experimental studies, the closest that we can get to a causal relationship with the ML VAR model is Granger causality. Granger causality in a time series is obtained when previous states of a time series have effects on subsequent changes in another time series, with the causing time series holding unique information about the series being caused (Eichler, 2013). We found evidence for two granger-causal mechanisms, negative affect predicting rumination, and rumination predicting negative affect. A more rigorous test of causality would be the use of a within-person encouragement design, in which, in essence, states of a time series are manipulated (Schmiedek & Neubauer, 2020). For example, participants could be encouraged to disengage from rumination at some randomly selected occasions (and not receive such encouragements at other occasions). Assuming that the effect

of such disengagement on negative affect is fully mediated via rumination would allow for estimating the causal effect of rumination on negative affect via an instrumental variable approach (see Schmiedek & Neubauer, 2020, for details).

Moving forward, we think that it is important to also further our understanding of how different emotion-regulation strategies work. Rumination is only one of the many ways that individuals regulate their affect, and DSEM may be useful in uncovering dynamics for other strategies (and other facets of affect) as well. In the case of rumination, there is strong theoretical and empirical evidence to believe that a reciprocal relationship between negative affect and rumination does exist. For other strategies, there might be less theoretical rationale as to why the relationship should be reciprocal. For example, positive reappraisal is conceptualized as a reaction towards some event (that an individual then tries to see in a different light) and may repair affect after such an event. Yet, there are no theoretical grounds on which to expect that experiencing positive affect leads to using more reappraisal following this experience (if there is nothing to reappraise). Thus, theoretical expectations on the links between affect and emotion regulation strategies need to be thoroughly formulated for each strategy. Another avenue for future research could be to formulate and test assumptions about the relation between various strategies and affect in the long term. That is, future research may couple short-term associations with longer-term developments to show how such short-term dynamics and regulatory efforts may lead to longer term changes (Hollenstein et al., 2013).

Conclusion

Using a new modeling approach, DSEM, we confirmed theoretical notions that the relationship between negative affect and rumination should be reciprocal within persons over time. We conclude that rumination seems to be both a response to and a trigger for negative affect. This implies that interventions aimed at reducing rumination need to target rumination directly, not relying on the assumption that rumination will sufficiently be impacted by

interventions targeting negative affect. Furthermore, both processes showed lingering qualities (inert properties) that need to be taken into account. Specifically, higher levels of rumination were consistently associated with higher levels of rumination inertia, suggesting that rumination might be hard to disrupt for individuals who use it regularly. Both studies implied that higher inertia of either negative affect or rumination were associated with stronger cross-öagged effects, highlighting the role that process dynamics may play for the vicious circle between rumination and negative affect. While depressive symptoms were not associated with the cross-lagged effects, there was an association with the correlations of the residuals, which represent same-time associations between rumination and negative affect, indicating the maladaptive nature of this coupling. In sum, the present findings may help us gaining a better understanding of how rumination may eventually lead to a downward spiral into psychopathology.

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Table 1

Study 1: Unstandardized fixed and random effects from the bivariate DSEM

	Fixed effects (means)			Random effects (variances)		
	estimate	95% CI		estimate	95% CI	
Parameters		lower	upper		lower	upper
NA intercept	13.998	12.880	15.125	62.077	49.394	79.542
RUM intercept	17.971	16.183	19.785	161.426	127.798	204.622
Autoregressive effects						
$NA_{t-1} \rightarrow NA_t$	0.361	0.324	0.396	0.044	0.033	0.058
$RUM_{t-1} \rightarrow RUM_t$	0.216	0.177	0.255	0.049	0.036	0.065
Cross-lagged effects						
$RUM_{t-1} \rightarrow NA_t$	0.034	0.017	0.053	0.004	0.002	0.007
$NA_{t-1} \rightarrow RUM_t$	0.205	0.150	0.261	0.074	0.046	0.114
Log residuals						
Variance NA	3.649	3.483	3.810	1.041	0.810	1.370
Variance RUM	4.995	4.809	5.185	1.744	1.421	2.187
Covariance	2.460	2.122	2.757	2.445	1.799	3.466

Note. CI = credible intervals, NA = Negative affect, RUM = Rumination, CES-D = Depressive symptoms.

Table 2

Studies 1 and 2: Between-person correlations among random effects from the bivariate DSEM

Parameters	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. NA intercept	-	.744*	.271*	.164	.017	-.112	.582*	.429*	.518*	.417*
2. RUM intercept	.659*	-	.131	.301*	-.162	.077	.324*	.660*	.510*	.370*
3. $NA_{t-1} \rightarrow NA_t$	-.082	-.072	-	.077	.045	.424*	.049	-.001	-.018	.217*
4. $RUM_{t-1} \rightarrow RUM_t$	.275	.376*	.568*	-	.230	-.132	.128	.096	-.099	.075
5. $RUM_{t-1} \rightarrow NA_t$	.179	.213	-.126	.478*	-	-.010	-.029	-.438*	.106	.101
6. $NA_{t-1} \rightarrow RUM_t$	-.197	-.230	.174	-.122	-.154	-	-.398*	.149	.122	-.098
7. Log residual variance NA	.467*	.363*	-.155	.136	.289	-.423	-	.359*	.245*	.272*
8. Log residual variance RUM	.076	.409*	.252	.129	-.113	.264	.011	-	.514*	.292*
9. Log residual covariance	.356*	.457*	.032	.197	.229	.073	.236	.456*	-	.192*
10. CES-D	.583*	.431*	-.144	.038	-.025	.062	.049	.093	.359*	-

Note. * = credible interval does not include zero, NA = Negative affect, RUM = Rumination, CES-D = Depressive symptoms. Study 1 results are depicted above the diagonal, Study 2 results are depicted below the diagonal.

Table 3

Study 2: Unstandardized fixed and random effects from the bivariate DSEM

	Fixed effects (means)			Random effects (variances)		
	estimate	95% CI		estimate	95% CI	
Parameters		lower	upper		lower	upper
NA intercept	1.397	1.143	1.664	1.148	0.785	1.772
RUM intercept	1.801	1.530	2.093	1.304	0.884	1.997
Autoregressive effects						
$NA_{t-1} \rightarrow NA_t$	0.314	0.237	0.387	0.065	0.039	0.111
$RUM_{t-1} \rightarrow RUM_t$	0.250	0.181	0.315	0.051	0.029	0.090
Cross-lagged effects						
$RUM_{t-1} \rightarrow NA_t$	0.089	0.046	0.134	0.013	0.005	0.030
$NA_{t-1} \rightarrow RUM_t$	0.156	0.082	0.234	0.038	0.016	0.080
Log residuals						
Variance NA	-1.496	-1.830	-1.204	1.238	0.733	2.205
Variance RUM	-0.454	-0.688	-0.221	0.907	0.596	1.421
Covariance	-1.655	-2.051	-1.291	2.014	1.246	3.320

Note. CI = credible intervals, NA = Negative affect, RUM = Rumination, CES-D = Depressive symptoms.

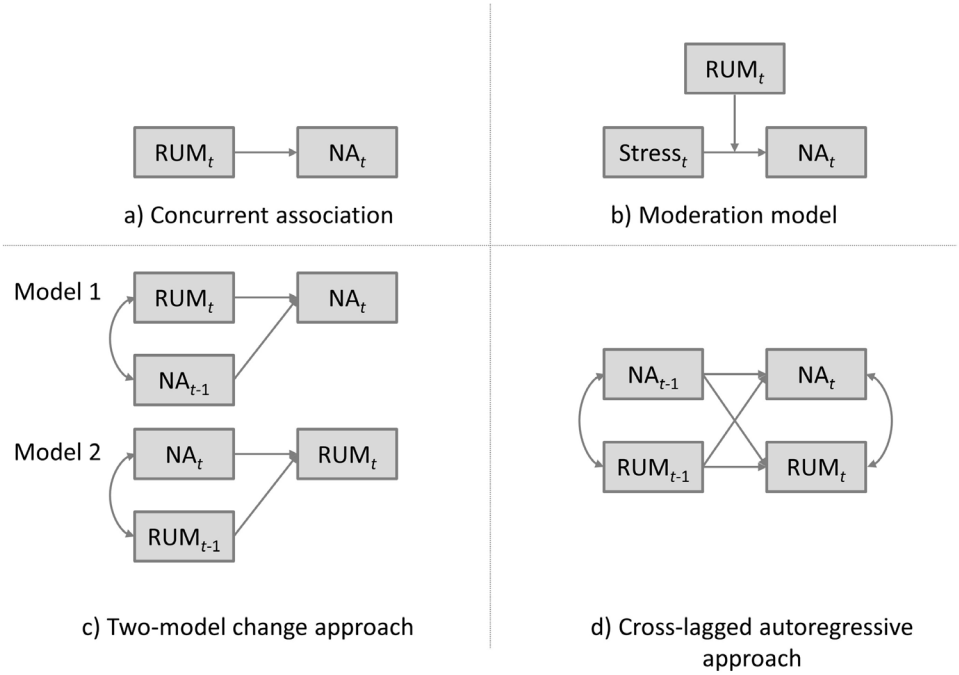

Figure 1. Schematic illustration of different theoretical model types underlying investigations of the association between rumination (RUM), negative affect (NA) and stress (Stress).

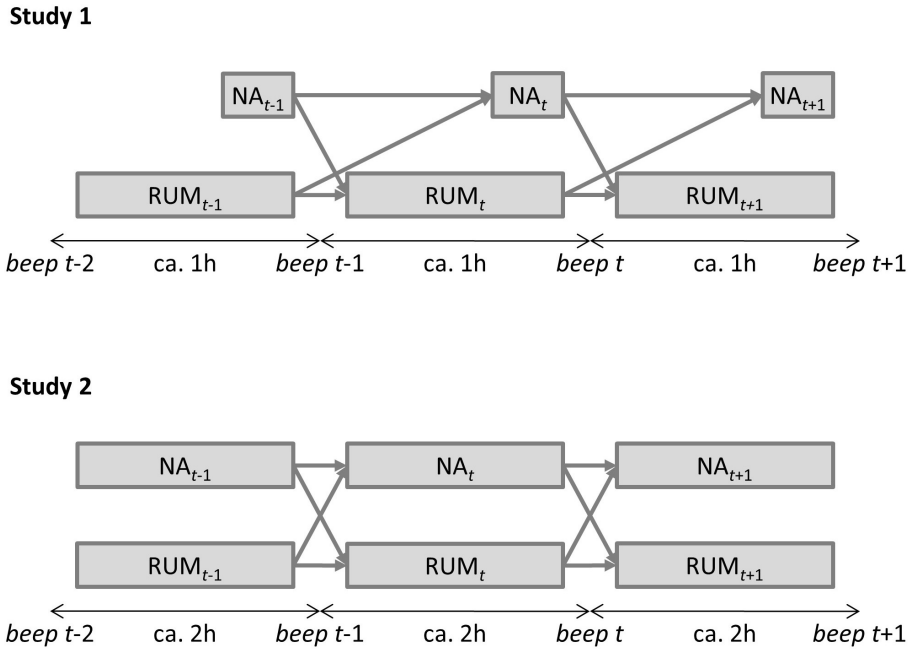

Figure 2. Schematic illustration of different measurement schemes of rumination (RUM) and negative affect (NA) in Studies 1 and 2.

Appendix A

Mplus Input Bivariate DSEM Study 1

DATA:
FILE IS "*path\file*";
FORMAT IS free;

VARIABLE:
names = A_ID a_tis_h RUM NA CESD; *! A_ID = ID, a_tis_h = hours since start of study, RUM = rumination, NA = negative affect, CESD = depressive symptoms*
cluster = A_ID;
usevar = NA RUM CESD;
between = CESD;
lagged = NA(1) RUM(1); *! lagged variables are created, referred to below as NA&1/RUM&1*
tinterval = a_tis_h(1); *! 1-hr time window in which measurements can fall, otherwise missings are added for the time window*
missing = all (9999); *! missing value definition*

ANALYSIS:
type is twolevel random;
estimator = bayes;
proc = 2; *! two chains*
fbiter = 5000; *! 5000 iterations per chain*
bseed = 45; *! random starting number for chain one to make the results replicable*
thin = 100; *! only the results of every 100th iteration is saved to reduce autoregression of draws*

MODEL:
%WITHIN%
NA_NA | NA ON NA&1; *! autoregressive effect NA*
RUM_RUM | RUM ON RUM&1; *! autoregressive effect RUM*
NA_RUM | NA on RUM&1; *! cross-lagged effect, lagged RUM predicting NA*
RUM_NA | RUM on NA&1; *! cross-lagged effect, lagged NA predicting RUM*
NAv | NA; *! random variance of residuals for NA*
RUMv | RUM; *! random variance of residuals for RUM*
eta by NA@1 RUM@1; *! new factor, positive covariance between residuals*
logpsi | eta; *! random covariance between residuals*
%BETWEEN%
NA_NA RUM_RUM NA_RUM RUM_NA NA RUM NAv RUMv logpsi CESD WITH
NA_NA RUM_RUM NA_RUM RUM_NA NA RUM NAv RUMv logpsi CESD; *! covariation among all effects*

OUTPUT:
standardized; *! standardized results, refer to STDYX*
tech8; *! tech8 provides output for PSR value*

PLOT:
TYPE = PLOT2; *! creates trace plots and autocorrelation plots*