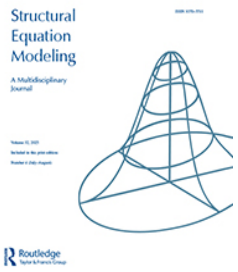

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Uncovering Asymmetric Temporal Dynamics Using Threshold Dynamics Parameters

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ABSTRACT

Statistical models to analyze longitudinal data often include parameters that capture temporal dependencies. These dynamics parameters are typically thought to operate independently of the time series value. Here, we argue that this leads to overlooking important information on psychological processes. We propose the DYNamics of ASymmetric TIme series (DYNASTI) approach, allowing dynamics parameters to differ above and below the time series mean. Through extensive simulations, we show that DYNASTI implementations of two commonly-used time series models (DSEM and RI-CLPM) adequately recover symmetric and asymmetric temporal dynamics. Importantly, we also show that assuming symmetric dynamics (as in the vast majority of the literature) when processes are in fact asymmetric leads to incorrect conclusions about these dynamics. We further illustrate how DYNASTI implementations can lead to new insights in three empirical examples. We believe asymmetric dynamics are widespread and hope, by providing open and easy-to-apply code, to aid researchers in uncovering them.

KEYWORDS

Bayesian analysis; dynamic structural equation modeling; longitudinal data; random intercept cross-lagged panel model; time series modeling

1. Introduction

A central goal in psychology is to understand how behavior and cognition evolve over time. Accordingly, researchers increasingly collect and analyze data across multiple time points (Molenaar, 2004). Such time series data are commonly referred to as "longitudinal" with a moderate number of waves and "intensive longitudinal" with many occasions. Many analysis methods exist that capture temporal dynamics in such time series data. These methods generally implicitly assume that the parameters capturing temporal dynamics are independent of the current value in the time series. In this article, we argue that this assumption often does not hold and, more importantly, that valuable information on psychological processes is overlooked when potential asymmetry in temporal dynamics is ignored. We also show through simulations that standard analysis tools do not provide warnings with respect to the presence of asymmetric dynamics. We provide examples of asymmetric dynamics, which we believe are widespread, and invite researchers to think about potential asymmetric temporal dynamics in their research field. To accommodate applied researchers, we provide openly accessible commented code and an online tutorial to run DYNASTI models enabling them to uncover such asymmetric dynamics.

A relatively straightforward way of analyzing time series data is to fit a regression model including time as a predictor. In this model, one could interpret the regression coefficient of the time effect to assess how the variable of interest increases or decreases over time. Although such a simple model allows one to investigate global temporal dynamics (increases or decreases), it does not include parameters to capture deviations or fluctuations around this global time course. That is, it assumes deviations from the average time effect are noise and therefore captures these fluctuations in the error (or residual) variance term.

However, these fluctuations may reflect meaningful temporal dynamics. That is, they may hold valuable information about the person, or process, one is modeling. For instance, mood fluctuations may serve as a risk factor for mood disorders (e.g., Bonsall et al., 2012; Hofmann & Meyer, 2006; Holmes et al., 2016; Koval & Kuppens, 2024) and fluctuations in cognitive performance can be indicative of attention problems (e.g., Aristodemou et al., 2024; Kofler et al., 2013; Kuntsi & Klein, 2012) as well as developmental leaps (Verspoor et al., 2008). To capture this information, more advanced statistical models allow us to model these fluctuations in more detail (e.g., McArdle, 2009), including Dynamic Structural Equation Models (DSEM; Asparouhov et al., 2018; Jongerling et al., 2015; McNeish & Hamaker, 2020), Random-Intercept Cross-Lagged Panel Models (RI-CLPM; Hamaker et al., 2015), STARTS models (Kenny

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& Zautra, 2001), ALT models (Bollen & Curran, 2004), latent change score models (e.g., Usami et al., 2015), ARMA models (e.g., Hamaker et al., 2002), LCM-SR models (Curran et al., 2014) and many more. Although the precise parameterization differs across models, the general characteristics are similar: parameters capture the extent to which the value of some variable at a current time point governs the rate or nature of change in the same, or another, variable at future time points.

2. Modeling (A)Symmetric Dynamics

2.1. Modeling Symmetric Dynamics Using an AR Model

As our motivating example, we will focus on arguably the simplest example of a temporal dynamics parameter, namely the autoregressive (AR) parameter. Conceptually, the AR parameter captures the extent to which the time series value at a given time point is governed by a previous value.[1] This parameter has been described by various terms, including "autoregression" (e.g., McArdle, 2009), "autocorrelation" (e.g., Bringmann et al., 2017), "self-feedback" (e.g., Estrada & Ferrer, 2019), "carry-over" (e.g., De Haan-Rietdijk et al., 2016b), and "inertia" (e.g., Hamaker & Grasman, 2015). Models including AR parameters have been successfully applied to show that, for example, affective (Kuppens et al., 2010; Wang et al., 2012) and stressed (Ekuni et al., 2022; Sperry & Kwapil, 2022) states tend to persist over longer periods of time, and that people tend to get stuck in solitude (Elmer et al., 2020).

Mathematically, a first-order autoregressive (AR1) model can be described as follows:

$$y_t = \mu + \delta_t, \tag{1}$$

in which y_t is the time series data, μ is the time series mean, and δ_t the deviation from the mean at time point t.[2] To capture fluctuations in y over time, variance in the deviations is explained by the autoregressive parameter ϕ:

$$\delta_t = \phi\delta_{t-1} + \epsilon_t, \tag{2}$$

where the residual ϵ_t indicates the deviation from the expected value after taking the autoregression into account. At the first time point ($t = 1$), this formula reduces to $\delta_1 = \epsilon_1$. Substituting Equation (2) into (1), you get

$$y_t = \mu + \phi\delta_{t-1} + \epsilon_t. \tag{3}$$

As illustrated in Figure 1, by adding an AR parameter to the regression model, fluctuations, in this example of negative affect, are captured by a parameter (ϕ), considering them valuable sources of information instead of noise. Time series with positive AR values (such as the one in Figure 1) are characterized by prolonged periods above, or below, the time series mean. The higher the AR parameter, the longer these periods are. In the example in Figure 1, this means that people with higher AR parameters report more consecutive time points above or below their average negative affect (i.e., above or below the horizontal blue line). AR values may also be negative, which implies that deviations above (or below) the mean will be followed by values closer to the mean or, in case of highly negative AR values, even below (or above) the mean.

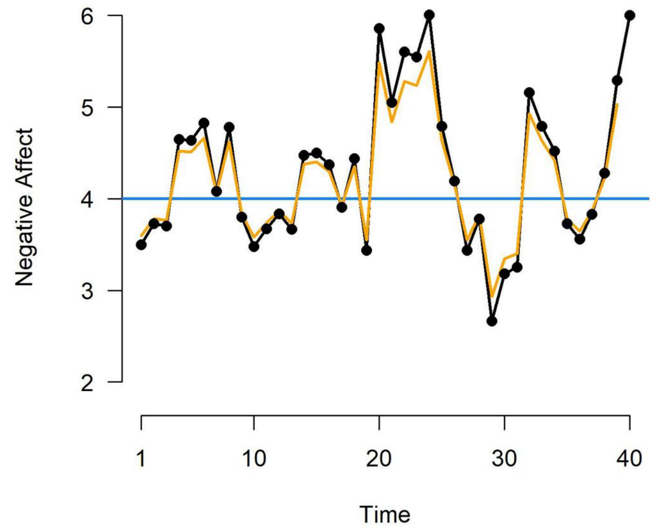

Figure 1. Example time series data (black) for negative affect values across time ($\phi = 0.8$); the horizontal blue line indicates predicted negative affect by a mean model; the orange line predicted with both mean and autoregression.

2.2. Capturing Asymmetric Dynamics Using Extended Time Series Models: The DYNASTI Approach

A problem with the AR model described in Section 2.1 is that it assumes symmetric temporal dynamics. In other words, deviations above and below a time series mean are treated as coming from the same distribution and contribute equally to the dynamics parameter. This implicit assumption is, in our view, almost never justified on substantive grounds.

Specifically, positive and negative deviations from a time series mean may hold distinct information about the psychological processes one is modeling. For instance, the mechanisms underlying emotional inertia (Koval & Kuppens, 2024; Suls et al., 1998) are likely different for positive and negative deviations from the average (De Haan-Rietdijk et al., 2016a). That is, sequences of positive and negative days likely differ in their dynamics, mechanisms and consequences: healthy individuals likely experience prolonged periods of positive days while quickly bouncing back after experiencing negative days. Also, these sequences have different consequences depending on the direction of the deviation: getting stuck in more negative mood may prompt the need for intervention whereas the same may not be needed for more positive mood. Another example of a process governed by asymmetric temporal dynamics is post-error slowing (e.g., Rabbitt & Rodgers, 1977): trials following an error (worse-than-average performance) induce a subsequent trial that is substantively slower than one's average. However, the reverse—that exceptional performance will lead to extra swift trials—is not necessarily true.

[1]We will ignore the distinction between first-order, and higher-order lag models (e.g., lag-2, etc.) without loss of generality.

[2]Note that, for simplicity and interpretability, we did not include a predictor of time and thus this model can only adequately be used to describe detrended data (see Hamaker & Dolan, 2009 for a critique).

The basic point, that temporal dynamics parameters may differ depending on the values of the variable of interest, is not new. To our knowledge, it has been made first in the form of specifying a threshold in an AR model. Specifically, Tong (1978) (extended in Tong & Lim, 1980; Tsay, 1989, and more recently applied in Bonsall et al., 2012; De Haan-Rietdijk et al., 2016a; Hamaker et al., 2009; Holmes et al., 2016) introduced the threshold autoregressive (TAR) model. In this model, the AR parameter depends on the value of the time series variable. Specifically, if the deviation from the time series mean at the previous time point (δ_{t-1}) is above a threshold (τ), one autoregressive parameter applies (ϕ^{above}), and if this deviation is below a threshold, another autoregressive parameter applies (ϕ^{below}). Replacing Equation (2), for $t = 2, \ldots, T$, we write

$$\delta_t = \begin{cases} \phi^{\text{above}}\delta_{t-1} + \epsilon_t & \text{if } \delta_{t-1} > \tau \\ \phi^{\text{below}}\delta_{t-1} + \epsilon_t & \text{if } \delta_{t-1} \leq \tau. \end{cases} \quad (4)$$

A special case of the TAR model holds when $\tau = 0$, representing the person- or unit-specific mean. In this scenario, we can distinguish the dynamics that govern the time series when a deviation is above the mean from the dynamics when the deviation is below the mean. Notably, this threshold of asymmetry will be person (or unit) specific—for instance, more sleep than average for one person may correspond to less sleep than average for another.

In the remainder of this article, we show how this variant of the threshold model, in which we allow for asymmetric temporal dynamics above and below the time series mean, can be implemented in commonly-used time series models, an approach we coin the DYNamics of ASymmetric TIme series (DYNASTI) approach, and provide evidence for asymmetric dynamics in several theoretically-plausible examples. To illustrate how a DYNASTI model works, an example time series governed by asymmetric parameters above and below the mean is shown in Figure 2. The above-mean autoregression for negative affect is highly negative, which results in the negative affect value dropping below the mean after a time point on which it was above the mean. This can also be seen from the blue line segments crossing the horizontal dotted line representing average negative affect. The below-mean autoregression, on the other hand, is highly positive, resulting in multiple subsequent time points at which negative affect values are below the mean. This means that this subject quickly bounces back after experiencing high levels of negative affect (high negative above-mean autoregression) while they tend to experience prolonged periods of low levels of negative affect (high positive below-mean autoregression).

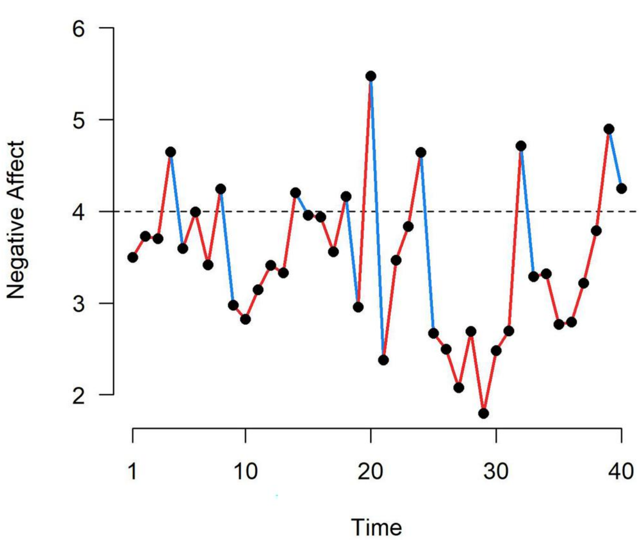

Figure 2. Example asymmetric time series of negative affect (black points) in which $\phi^{\text{above}} = -0.8$ and $\phi^{\text{below}} = 0.8$; the colored lines indicate which autoregressive parameter is used to explain deviations at the current time point: blue for ϕ^{above}, indicating the deviation at the previous time point was positive (i.e., above the mean or the horizontal black dotted line), and red for ϕ^{below}, indicating it was negative (i.e., below the mean).

The manuscript is organized as follows. Below, we briefly describe two commonly-implemented classes of models. The first, a Dynamic Structural Equation Model (DSEM), is a hierarchical extension of the standard N = 1 AR model which is mainly used for univariate intensive longitudinal data (say >50 time points). The second, a Random-Intercept Cross-Lagged Panel Model (RI-CLPM), is mostly used for multivariate longitudinal panel data (say 3–10 waves) in which one is interested in cross-lagged effects, that is, effects of one variable at the current time point on another variable at a future time point. For each model, we demonstrate how it can be extended to incorporate DYNASTI principles, how it can be implemented in open source code (Stan), and, through simulations, that the DYNASTI approach returns unbiased estimates both when data govern symmetric and asymmetric temporal dynamics. Finally, we provide three empirical examples how the DYNASTI approach can be used and will lead to new insights. These examples are accompanied by snippets of R code needed to run DYNASTI models, hopefully enticing researchers to play with the models themselves. Although we are not the first to propose neither threshold autoregressive (Tong, 1978; Tong & Lim, 1980; Tsay, 1989) nor threshold cross-lagged parameters (Hamaker et al., 2010; Haslbeck & Ryan, 2022), they have rarely been used to answer practical research questions (but see Bonsall et al., 2012; Holmes et al., 2016). Here our goal is a) to focus on asymmetry above and below the time series mean and b) to make the DYNASTI approach relatively easy to implement and extend well beyond the N = 1 time series modeling within which it was first proposed.

3. Implementing the DYNASTI Approach for Two Commonly-Used Models

3.1. Implementing DYNASTI in a Univariate Example: Asymmetric Autoregression in Time Series Models

Dynamic Structural Equation Models (DSEMs; Asparouhov et al., 2018; Jongerling et al., 2015; McNeish & Hamaker, 2020) are hierarchical extensions of the AR model. They combine strengths from time series modeling, hierarchical modeling and structural equation modeling into a single comprehensive framework. That is, DSEMs allow one to account for dependencies in the data due to repeated measurements (time series modeling) and due to clustering of subjects (hierarchical modeling), and they allow one to incorporate latent variables into the model (structural equation modeling; McNeish et al., 2021). Often, DSEMs are implemented in Mplus (Asparouhov et al., 2018; McNeish & Hamaker, 2020), but implementations also exist in other coding languages including BUGS (De Haan-Rietdijk et al., 2016a; Jongerling et al., 2015) and Stan (Snijder, 2023). For our purposes, we will use Stan (Gelman et al., 2015), a flexible framework for Bayesian estimation accessible in R (R Core Team, 2024) through the rstan package (Stan Development Team, 2023). We use Stan because it allows for flexible implementation and estimation of a wide range of models, deals well with the challenges of, for example, estimating person-specific effects, allows for model-informed imputation of missing data, and comes with frequent updates and an active community. Also it is freely available, obviating the need for expensive proprietary software and making it more widely accessible to the research community. Although comparing estimation performance of our Stan implementation to common Mplus implementations is beyond the scope of this article, we below provide extensive parameter recovery simulations that warrant interpretability of results. We also fit the DSEM to a dataset previously validated in Mplus and find comparable results (see Section 4), providing further support that our implementation performs well.

In the DYNASTI DSEM case, a time series of variable y for person i is governed by five parameters: the mean, two autoregressive parameters, the residual, and the trend. The mean indicates the average value of y; the autoregressive parameters indicate how the value of y on a given time point, above and below the time series mean, is associated with an in- or decrease at the next time point; and the residual indicates the deviation from the expected value at a given time point. The trend, indicating change over time, can either be modelled within the context of the model or removed beforehand (through detrending). For simplicity, we chose to illustrate our points for detrended data.[3]

Similar to the AR models presented in Section 2.1, a DSEM for the time series of y can be described as follows:

$$y_{it} = \mu_i + \delta_{it}, \tag{5}$$

for $i = 1, \ldots, N$ subjects and $t = 1, \ldots, T$ time points, in which y_{it} is the subject-specific time series data, μ_i is the time series mean for subject i, and δ_{it} the deviation from the mean for subject i at time point t. To model asymmetric temporal dynamics, we explain variance in the deviation with autoregressive parameter ϕ, which we estimate separately for above- and below-average values of y. We do so by setting the threshold to zero, indicating the subject-specific mean:

$$\delta_{it} = \begin{cases} \phi_i^{\text{above}} \delta_{i,t-1} + \epsilon_{it} & \text{if } \delta_{i,t-1} > 0 \\ \phi_i^{\text{below}} \delta_{i,t-1} + \epsilon_{it} & \text{if } \delta_{i,t-1} \leq 0, \end{cases} \tag{6}$$

where we introduce a residual ϵ_{it}, indicating the deviation from the expected value after taking the value-specific autoregression into account. At the first time point ($t = 1$), this formula reduces to $\delta_{i1} = \epsilon_{i1}$. For each subject, the residuals are assumed normally distributed with mean zero and variance ψ_i.

Assuming subjects are sampled from the same underlying population, we can increase statistical precision by utilizing information about that population in estimating subject-specific parameters (e.g., Efron & Morris, 1977; Katahira, 2016). That is, we explain the four (as we omit the trend) subject-specific parameters with a population-level parameter (γ) and a subject-specific deviation from the population average (u_i):

$$\mu_i = \gamma_\mu + u_{\mu i} \tag{7}$$

$$\phi_i^{\text{above}} = \gamma_{\phi^{\text{above}}} + u_{\phi^{\text{above}}i} \tag{8}$$

$$\phi_i^{\text{below}} = \gamma_{\phi^{\text{below}}} + u_{\phi^{\text{below}}i} \tag{9}$$

$$\psi_i = \text{var}(\epsilon_{it}) = \exp(\gamma_\psi + u_{\psi i}). \tag{10}$$

Note that the population-level residual variance (γ_ψ) and the subject-specific deviations ($u_{\psi i}$) are estimated on a logarithmic scale. This enables us to assume these variables are normally distributed, simplifying the estimation process. As subject-specific effects may be correlated (e.g., that subjects with a high mean display low residual variance), we model the relationship between the mean, autoregression, and residual variance. To do so, we assume that the subject-specific deviations (i.e., $u_{\mu i}$, $u_{\phi^{\text{above}}i}$, $u_{\phi^{\text{below}}i}$, and $u_{\psi i}$) are multivariate normally distributed with means zero and covariance matrix $\mathbf{\Omega}$.

3.1.1. Simulating and Recovering Parameters from a Univariate DSEM

Now that we have specified the DYNASTI DSEM model, we can examine how it works through simulations. We performed all simulations and statistical analyses using open source software R (R Core Team, 2024). Below we provide reproducible code to perform the simulations, to fit the models using rstan (Stan Development Team, 2023), to perform model recovery, as well as empirical applications and a step-by-step tutorial (see https://osf.io/s2x3k) including how to structure data to allow the reader to conduct their own analyses. First, we examine how well our parametrization and implementation in rstan are able to recover the true model parameters, both in the standard (symmetric) as well as in the DYNASTI (asymmetric) model. More importantly, we also investigate the alternative scenarios—showing what happens if we estimate a symmetric model when the process is truly asymmetric and, conversely, what happens when we estimate a needlessly complex (asymmetric) model to data generated under a symmetric scenario. To do so, we generated data with asymmetric temporal dynamics above and below the mean (that is, two, nonequivalent autoregressive parameters), and data with symmetric dynamics (that is, a single autoregressive parameter). To both types of data, we fit the proposed DYNASTI DSEM and a standard symmetric version of the model.

In the ideal scenario, when data are governed by asymmetric dynamics, we would recover the true values under the asymmetric model, but not under the standard model, resulting in model comparison favoring the asymmetric

[3]We do provide code for modeling data with trend in our OSF repository: https://osf.io/hwmgk/.

model. When data are governed by symmetric dynamics, we would expect similar degrees of model convergence for the standard and asymmetric model, with the asymmetric model estimating two identical autoregressive parameters and with model comparison favoring the simpler, symmetric DSEM.

3.1.2. Simulation Method

To test these expectations for a univariate DSEM, we generated 500 datasets with $N = 50$ subjects across $T = 100$ time points each. As can be reproduced using the R code provided on https://osf.io/5vumh, we used a population-level mean (γ_μ) of 2 and a low residual variance ($\gamma_\psi = \log(.01)$).[4] We used a low variance to ensure relatively little noise in the simulated data (see Online Supplementary Figures 3 and 4 for results with higher noise levels), enabling us to focus on recovery of the autoregressions. In case of symmetric data, we used a population-level autoregression (γ_ϕ) of 0.5. In case of asymmetric data, we used two autoregressions with the same mean as in the symmetric case ($\gamma_{\phi^{\text{above}}} = 0.35$, and $\gamma_{\phi^{\text{below}}} = 0.65$). Subject-specific deviations (u's) for all parameters were sampled from a multivariate normal distribution with means 0, relatively small variances ($\text{var}(u_{\mu i}) = \text{var}(\log(u_{\psi i})) = 0.5$ and $\text{var}(u_{\phi i}) = \text{var}(u_{\phi^{\text{above}} i}) = \text{var}(u_{\phi^{\text{below}} i}) = 0.01$), and moderate correlations between subject-specific deviations across parameters (i.e., 0.3). In R, this is accomplished using the `mvrnorm()` function of the MASS package (Venables & Ripley, 2002). In the asymmetric case, we generated deviations for each subject for each of the four parameters (mean, two autoregressions, and residual variance) by running `u <- mvrnorm(Nsubj, rep(0,4), Omega)` in the R console, where `Nsubj` is an integer indicating the number of subjects and `Omega` is the four-by-four covariance matrix of subject-specific effects.

Subject-specific parameters were determined by adding population-level parameters and subject-specific deviations (see Equations (7)–(10)). These simulation specifics resulted in subject-specific means mostly ranging between 0.5 and 3.5, symmetric autoregressions mostly between 0.3 and 0.7, asymmetric autoregressions mostly between 0.15 and 0.55 for above-mean values and between 0.45 and 0.85 for below-mean values, and residual variances between 0.05 and 0.2. Subject-specific parameters were in turn used to generate time series data (see Equations (5) and (6)). In the asymmetric case, this is accomplished in R by running the following code.

```
# Create empty data matrix Y and predicted data matrix Y.hat (i.e., without
# noise). Nsubj indicates the number of subjects and Nobs the number of
# observations.
Y <- Y.hat <- matrix(NA, Nsubj, Nobs)
# Set the predicted value at the first time point to the subject-specific mean
Y.hat[,1] <- mu
# Sample first data point in which mu is a vector containing subject-specific
```

(*continued*)

```
# means and the rnorm() function is used to sample random error for all
Nsubj # subjects based on their subject-specific residual variance psi.
Y[,1] <- mu + rnorm(Nsubj, 0, sqrt(psi))
for (i in 1:Nsubj) {                # Loop across subjects
    for (t in 2:Nobs) {             # Loop across observations
        # Predict outcome based on mean and value-based autoregression
        Y.hat[i,t] <- mu[i] + phi_below[i] * (Y[i,(t-1)] - mu[i]) *
                ifelse(mu[i] - Y[i,(t-1)] < 0, 0, 1) +
                phi_above[i] * (Y[i,(t-1)] - mu[i]) *
                ifelse(mu[i] - Y[i,(t-1)] < 0, 1, 0)
        # Sample data point based on prediction Y.hat and the subject-specific
        # residual variance psi
        Y[i,t] <- rnorm(1, Y.hat[i,t], sqrt(psi[i]))
    }
}
```

We generated data without missing values in the simulations; see the empirical applications in Section 4 for an example including missing data. On each dataset, for the DYNASTI and symmetric model, we ran four Markov Chain Monte Carlo (MCMC) chains with 5,000 iterations of which the first half was removed as burn-in, resulting in 10,000 posterior samples per parameter. For details on the chosen true values, prior distributions, and model estimation, we refer to Online Supplementary Text 1.

We assessed model performance through parameter convergence, and model and parameter recovery. For each population-level parameter in each dataset, we determined whether our MCMC chains converged to a stable solution by assessing the R-hat statistic (Gelman & Rubin, 1992). This statistic compares the variance between MCMC chains to the variance within chains, with values above 1.1 indicating unstable parameter estimates as chains converged to different solutions. One way to obtain R-hat values in R is to print the summary of fit results by running `print(fit, pars = "gamma")`, in which `fit` is the Stan fit object and `pars` indicates for which parameters one wishes to print results. As a measure of model recovery, we performed model comparison through Bayes Factors (BF) as obtained from the bridgesampling package (Gronau et al., 2020):

```
# Obtain marginal likelihoods of the symmetric and DYNASTI model
# in which fitStandard and fitDYNASTI are the Stan fit objects for the
# standard symmetric and DYNASTI model respectively.
llStandard = bridge_sampler(fitStandard)
llDYNASTI = bridge_sampler(fitDYNASTI)
# Compute Bayes Factor
bf (llDYNASTI, llStandard)
```

Following guidelines proposed by Jeffreys (1961), we interpreted BFs > 10 as strong evidence for the DYNASTI model, between 3 and 10 as moderate evidence in that same direction, and between 1 and 3 as anecdotal evidence. In case BFs were below 1, we interpreted them as strong (<1/10), moderate (1/10 < BF < 1/3), or anecdotal (1/3 < BF < 1) evidence in favor of the standard symmetric model. To assess parameter recovery, we extracted the 95% highest density interval (HDI) of the posterior distribution (as obtained from the MCMC samples) of each parameter using the `quantile()` function from the stats package (R Core Team, 2024). We then assessed whether zero fell within the

[4]Note this residual variance was transformed to a logarithmic scale to enable us to use a multivariate normal distribution for sampling subject-specific deviations.

95% HDI and aggregated this number across the 500 datasets to obtain a percentage between 0 (indicating very poor recovery) and 100 (indicating excellent recovery). For example, in R, running `post = extract(fit)` gives you the posterior samples and `quantile(post $gamma[,1], c(0.025,0.975))` in turn gives the 95% HDI of the population-level mean.

3.1.3. Simulation Results

When data were governed by asymmetric temporal dynamics, the DYNASTI model was preferred over the standard symmetric model in almost all iterations: Bayes Factors provided strong evidence in favor of the DYNASTI model ($BF_{10} > 10$) in 488 out of 500 iterations (97.6%). Furthermore, convergence of the population-level parameters was good: R-hat values were below 1.1 in all but eight iterations (98.4%). Finally, the true values of the population-level parameters lay within the 95 % highest-density interval (HDI) in 92.2–98.4% of the iterations (see Online Supplementary Table 1 for full results). Together, these simulation results indicate that the DYNASTI implementation of a DSEM can adequately uncover asymmetric temporal dynamics. This even holds for small sample sizes (see Online Supplementary Figure 1), few time points (see Online Supplementary Figures 1 and 2), and high levels of noise (see Online Supplementary Figures 3 and 4); although estimates become more uncertain (as shown by increased variances across iterations) as a function of both smaller sample sizes and fewer time points.

When these *asymmetric* data were fit with a standard *symmetric* model, model convergence was good with R-hat values below 1.1 in all but two iterations (99.6%), suggesting this type of model misspecification need not generate telltale estimation problems. However, bias was induced in the autoregressive parameter (see Online Supplementary Table 1). As illustrated in Figure 3, the autoregressive parameter was estimated in between the two truly asymmetric ones, resulting in the true values laying outside the 95% HDI in every single iteration. Importantly, the other parameter estimates were largely unbiased (with true values laying within the 95% HDI in 93.2–96.8% of the iterations, see Online Supplementary Table 1). Together, these simulation results suggest that fitting a symmetric model to asymmetric data does not provide any signs of model misspecification, despite yielding fundamentally incorrect conclusions on the temporal dynamics. Coming back to our example in Figure 2, if we fit the symmetric model to these asymmetric negative affect data, the estimated autoregressive parameter is $\phi = 0.18$. This means we miss the seemingly healthy pattern of quickly bouncing back after experiencing higher-than-average levels of negative affect and of relatively stable periods of lower-than-average levels.

So what happens when we fit a DYNASTI model to symmetric data? In terms of model convergence, the DYNASTI model performed well with R-hat values below 1.1 in all but eight iterations (98.4%). Importantly, as shown in Figure 3 and Online Supplementary Table 1, the asymmetric model returned similar estimates for the two

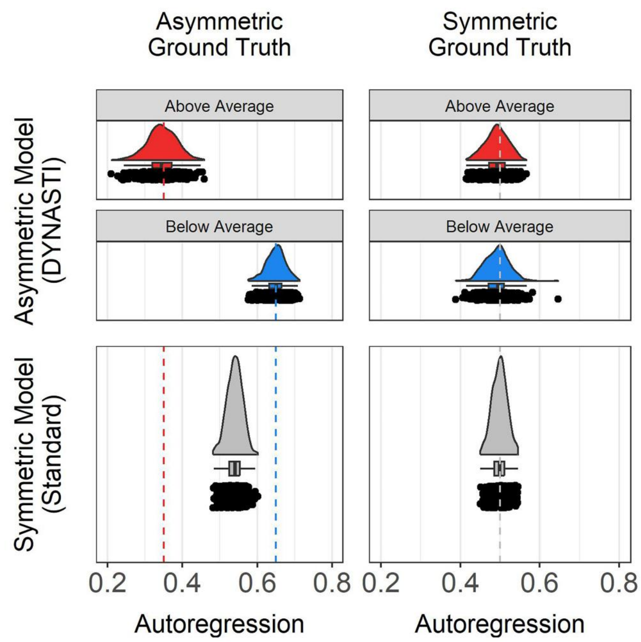

Figure 3. Recovered values of the population-level autoregressive parameters by the DYNASTI DSEM (top row) and standard DSEM (bottom row) when data govern asymmetric (left column) and symmetric (right column) temporal dynamics. Vertical dashed lines represent true values.

autoregressive parameters (as indicated by the overlapping distributions) and both contained the true symmetric autoregressive parameter in most cases (95.8–96.8%). Yet, model comparison favored the simpler, symmetric DSEM: Bayes Factors provided strong evidence in favor of the symmetric model ($BF_{10} < 1/10$) in 498 out of 500 iterations (99.6%). Based on these simulation results, we can conclude that fitting the DYNASTI model does not incur any drawbacks in terms of model convergence or parameter estimates when data are truly symmetric. Also not with small sample sizes, few time points, or high levels of noise (see Online Supplementary Figures 1–4). Next, we examine how we may extend the logic of DYNASTI DSEM to bivariate panel data.

3.2. Implementing DYNASTI in a Bivariate Example: Asymmetric Cross-Lagged Parameters in Time Series Models

The same line of reasoning regarding asymmetric dynamics can be extended to research questions involving multiple variables. In many psychological analyses, researchers hypothesize that the value of one variable at a given time point will affect the value of *another* variable on a future time point. For instance, less sleep on a given day than a person's average amount of sleep may be associated with more stress the next day (Ekuni et al., 2022). The temporal dynamics parameter that captures such dynamics between variables, called a *cross-lagged* or *coupling* parameter, may also depend on the direction of the deviation. For instance, sleep may affect one's stress levels, but only if the deviation is negative (i.e., less sleep than average).

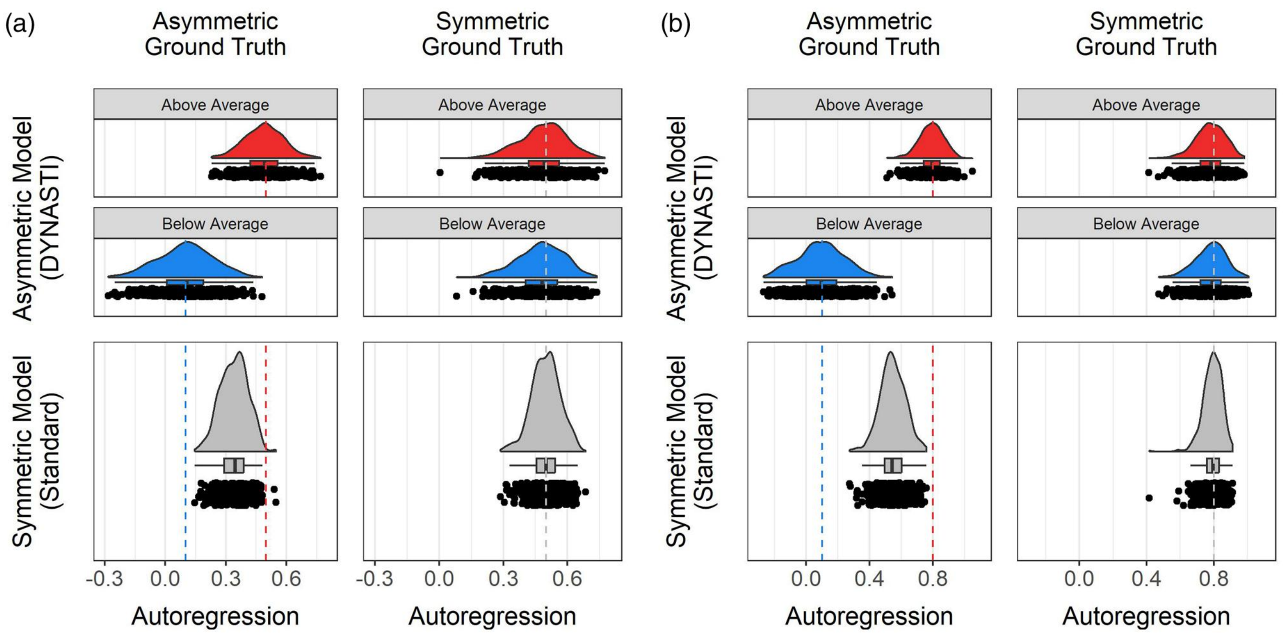

Figure 4. Recovered values of the autoregressive parameters by the asymmetric (top row) and symmetric RI-CLPM (bottom row) when data are governed by asymmetric (left column) and symmetric (right column) temporal dynamics. Vertical dashed lines represent true values. Panel (a) for variable X and panel (b) for variable Y.

As a multivariate example, we show how asymmetric temporal dynamics could be incorporated in a bivariate Random Intercept Cross-Lagged Panel Model (RI-CLPM; Hamaker et al., 2015; Mulder & Hamaker, 2021c). This structural equation model allows one to describe temporal dependencies between multiple, potentially latent, variables within subjects. The RI-CLPM is an extension of the standard Cross-Lagged Panel Model that incorporates random intercepts to separate stable between-subject differences from the within-subject dynamics. Although RI-CLPMs have been implemented in many programming languages, including Mplus (e.g., Mulder & Hamaker, 2021b) and lavaan (e.g., Mulder & Hamaker, 2021a), we again used Stan (Gelman et al., 2015) to flexibly illustrate the workings of a DYNASTI implementation of a RI-CLPM.

The time series data for two variables, x and y, can be described as

$$x_{it} = \mu_x + \eta_{xi} + \delta_{xit} \tag{11}$$

$$y_{it} = \mu_y + \eta_{yi} + \delta_{yit}, \tag{12}$$

for $i = 1, \ldots, N$ subjects and $t = 1, \ldots, T$ time points, where x_{it} and y_{it} are the time series data of both variables, μ_x and μ_y are overall means,[5] η_{xi} and η_{yi} are subject-specific deviations from the overall means, and δ_{xit} and δ_{yit} are the deviations from the expected value for subject i at time point t. The subject-specific deviations in means are assumed bivariate normally distributed with means zero and covariance matrix $\mathbf{\Sigma}$.

To allow for asymmetric temporal dynamics above and below the mean in this bivariate case, we explain variance in the deviations (δ_{xit} and δ_{yit}) by introducing asymmetric autoregressive (ϕ) and cross-lagged (β) parameters. Similar to the univariate DSEM with asymmetric dynamics (Section 3.1), we specify that when the deviation from the expected value at the previous time point ($\delta_{xi,t-1}$ and $\delta_{yi,t-1}$) is below the mean, a given set of autoregressive and cross-lagged parameters apply, and if the deviation is above the mean, another set of parameters apply.[6] We write the asymmetric dynamics as follows for δ_{xit} $(t = 2, \ldots, T)$,

$$\delta_{xit} = \begin{cases} \phi_{xx}^{\text{above}} \delta_{xi,t-1} + \beta_{xy}^{\text{above}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} > 0 \text{ and } \delta_{yi,t-1} > 0 \\ \phi_{xx}^{\text{above}} \delta_{xi,t-1} + \beta_{xy}^{\text{below}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} > 0 \text{ and } \delta_{yi,t-1} \leq 0 \\ \phi_{xx}^{\text{below}} \delta_{xi,t-1} + \beta_{xy}^{\text{above}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} \leq 0 \text{ and } \delta_{yi,t-1} > 0 \\ \phi_{xx}^{\text{below}} \delta_{xi,t-1} + \beta_{xy}^{\text{below}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} \leq 0 \text{ and } \delta_{yi,t-1} \leq 0 \end{cases} \tag{13}$$

and equivalently for δ_{yit} $(t = 2, \ldots, T)$,

$$\delta_{yit} = \begin{cases} \beta_{yx}^{\text{above}} \delta_{xi,t-1} + \phi_{yy}^{\text{above}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} > 0 \text{ and } \delta_{yi,t-1} > 0 \\ \beta_{yx}^{\text{above}} \delta_{xi,t-1} + \phi_{yy}^{\text{below}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} > 0 \text{ and } \delta_{yi,t-1} \leq 0 \\ \beta_{yx}^{\text{below}} \delta_{xi,t-1} + \phi_{yy}^{\text{above}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} \leq 0 \text{ and } \delta_{yi,t-1} > 0 \\ \beta_{yx}^{\text{below}} \delta_{xi,t-1} + \phi_{yy}^{\text{below}} \delta_{yi,t-1} + \epsilon_{xit} & \text{if } \delta_{xi,t-1} \leq 0 \text{ and } \delta_{yi,t-1} \leq 0. \end{cases} \tag{14}$$

At the first time point $(t = 1)$, we have $\delta_{xi1} = \epsilon_{xi1}$ and $\delta_{yi1} = \epsilon_{yi1}$. The subject-specific residuals (i.e., ϵ_{xit} and ϵ_{yit}) are assumed bivariate normally distributed with means zero and covariance matrix $\mathbf{\Psi}$.

[5]Note that this measurement model provides a simplified version of the RI-CLPM in which means are time-invariant (i.e., equal across time points).

[6]Again, note that this structural model provides a simplified version of the RI-CLPM in which the regression coefficients (i.e., the four ϕs and four βs) are time-invariant (i.e., equal across time points). It could be useful to use time-dependent coefficients, for example, when time intervals are unequal (Hamaker et al., 2015) ; however, this also increases the number of regression parameters from 8 to $8 \times T$.

3.2.1. Simulating and Recovering Parameters from a Bivariate RI-CLPM

We again performed simulations for two data generating scenarios: data governed by asymmetric temporal dynamics and data governed by symmetric dynamics. We tested whether (1) the DYNASTI implementation of the RI-CLPM adequately captures asymmetric temporal dynamics, whether (2) fitting a standard symmetric RI-CLPM on asymmetric data results in biased parameter estimates, and whether (3) fitting a DYNASTI RI-CLPM on symmetric data incurs any drawbacks in terms of model convergence and parameter estimation. To do so, we generated 500 datasets for $N = 50$ subjects across $T = 8$ time points on two variables X and Y. As can be reproduced using the R code on https://osf.io/wjvxg, we used a mean of zero for both variables ($\mu_x = \mu_y = 0$). In the symmetric case, we generated data with autoregressive effects of $\phi_{xx} = 0.5$ and $\phi_{yy} = 0.8$, and cross-lagged effects of $\beta_{yx} = 0.1$ and $\beta_{xy} = -0.2$. In the asymmetric case, we changed the autoregressive effects of x to $\phi_{xx}^{\text{above}} = 0.5$ for above-mean values and to $\phi_{xx}^{\text{below}} = 0.1$ for below-mean values; for y we changed autoregressive effects to $\phi_{yy}^{\text{above}} = 0.8$ and $\phi_{yy}^{\text{below}} = 0.1$ for above- and below-mean values respectively. We arbitrarily changed cross-lagged effects of x on y ($\beta_{xy}^{\text{above}} = -0.2$ and $\beta_{xy}^{\text{below}} = 0$), but not y on x ($\beta_{yx}^{\text{above}} = \beta_{yx}^{\text{below}} = 0.1$). In our R code, this is accomplished by first specifying whether to simulate following the standard symmetric or DYNASTI model (`mod = "standard"` or `mod = "DYNASTI"`) and then using so-called if-else statements (e.g., `phi_xx_below <- ifelse(mod == "standard", .5, .1)` for the below-average autoregressive effect of x). Subject-specific deviations in means were sampled from a bivariate normal distribution with means zero, variances of 1, and a small covariance (i.e., 0.3). Residuals were similarly generated from a bivariate normal distribution with means 0, variances of 1, and a small covariance (i.e., 0.1). In R both were accomplished using the `rmvnorm()` function from the SimDesign package (Genz & Bretz, 2009): `eta <- rmvnorm(N, mean = rep(0,2), sigma = Sigma)` for the `N` subject-specific means in which `Sigma` is the two-by-two covariance matrix of means and `epsilon <- rmvnorm(N * T, mean = rep(0,2), sigma = Psi)` for the `N * T` subject- and time point-specific residuals in which `Psi` is the two-by-two residual covariance matrix.

Time series data were then generated following Equations (11)–(14). That is, the deviations (`delta`) on each time point for each subject were determined by the autoregressive effect (`phi`), the cross-lagged effect (`beta`) and the residual (`epsilon`):

```
for(i in 2:nrow(data)) {          # Loop across observations
    # Deviations for dependent variable X
    delta_x[[i]] <- phi_xx * delta_x_lag + beta_yx * delta_y_lag
                         + epsilon_x[[i]]
    # Deviations for dependent variable Y
    delta_y[[i]] <- phi_yy * delta_y_lag + beta_xy * delta_x_lag
                         + epsilon_y[[i]]
}
```

We generated data without missing values in the simulations. We ran eight MCMC chains with 5,000 iterations for each of the two models with the first 2,500 discarded as burn-in, resulting in 20,000 samples per parameter. We used the same procedure to assess model performance as described for the DSEM in Section 3.1.2. For details on the chosen true values, prior distributions, and model estimation, we refer to Online Supplementary Text 1.

3.2.2. Simulation Results

As shown in Figures 4 and 5, when data are governed by *asymmetric* temporal dynamics, the DYNASTI implementation of the RI-CLPM adequately recovers these dynamics. The figure shows that the posterior means are centered around the true values, and that the autoregressive parameters as well as cross-lagged parameters are returned unbiased. This is corroborated by the 95% HDIs containing the true value in 92.2–97.8% of iterations (see Online Supplementary Table 2). Convergence was perfect with R-hat values below 1.1 in all iterations. Model comparison mostly favored the DYNASTI model over the symmetric model (BF_{10}'s > 1 in 350 out of 500 iterations, 70%). This evidence was strong ($BF_{10} > 10$) in 256 iterations (51.2%), moderate ($3 < BF_{10} < 10$) in 52 iterations (10.4%) and anecdotal ($1 < BF_{10} < 3$) in 42 iterations (4.8%). These simulation results thus indicate that our DYNASTI implementation of a panel model is able to capture asymmetric temporal dynamics, even in cohort style data with as few as eight waves.

When these *asymmetric* data are fit with a standard *symmetric* RI-CLPM, parameter estimates become biased and interpretations of the person- or process-specific dynamics one is modeling are compromised. Specifically, the symmetric RI-CLPM yields autoregressive and cross-lagged estimates lying in between the truly asymmetric parameters above- and below the time series mean (see Figures 4 and 5). For the autoregressive parameters, this resulted in poor coverage (see Online Supplementary Table 2). Yet, for the cross-lagged parameters, coverage was sufficient, at least for β_{xy}. This is, however, unsurprising as the chosen values of β_{xy} were symmetric (i.e., both 0.1) and those of β_{yx} relatively similar (i.e., 0 and -0.2). Moreover, coverage was sufficient for most other parameters. The means, however, were slightly overestimated, resulting in the 95% HDIs containing the true value in only 72.6% of iterations (see Online Supplementary Table 2). Convergence was excellent with R-hat values of all population parameters below 1.1. Together, these simulation results suggest that fitting the standard symmetric RI-CLPM when data is governed by asymmetric temporal dynamics results in biased autoregressive and cross-lagged estimates, especially when this asymmetry is large, resulting in incorrect conclusions about temporal dynamics within and between variables.

Finally, when data are governed by symmetric temporal dynamics, both models can recover these dynamics. That is, all population-level parameters reached convergence (all R-hat values below 1.1) and the true value lay within the 95% HDI in 92.2–97.0% of the iterations for the DYNASTI model and in 93.0–95.8% of the iterations for the symmetric model

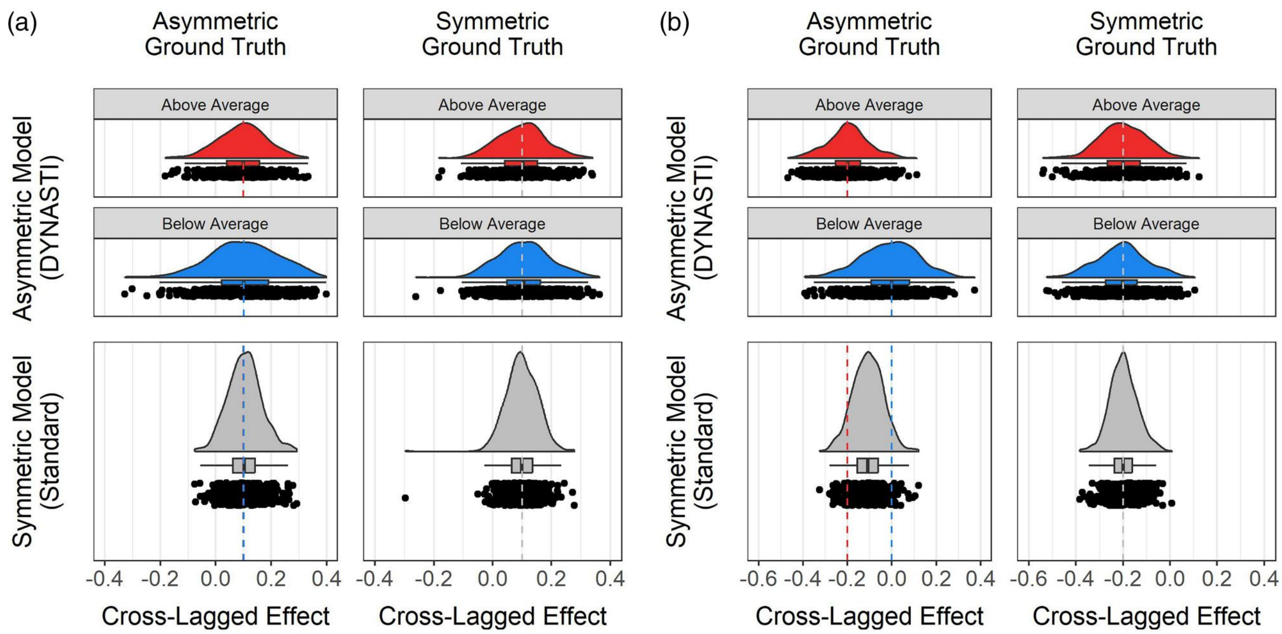

Figure 5. Recovered values of the cross-lagged parameters by the asymmetric (top row) and symmetric RI-CLPM (bottom row) when data are governed by asymmetric (left column) and symmetric (right column) temporal dynamics. Vertical dashed lines represent true values. Panel (a) for variable X and panel (b) for variable Y.

(see Online Supplementary Table 2). Also, the DYNASTI RI-CLPM returned overlapping posterior distributions for the autoregressive and cross-lagged parameters above and below the time series mean (see Figures 4 and 5). Yet, model comparison adequately suggested that the dynamics were symmetric: Bayes Factors consistently favored the symmetric model over the DYNASTI model ($BF_{10} < 1/10$ in 499 out of 500 iterations, 99.8%). These simulation results indicate that one can safely fit the DYNASTI RI-CLPM to symmetric bivariate panel data with at least eight waves.

3.2.3. Simulation Summary

To summarize, the simulation results for both univariate and bivariate cases indicate that it does not hurt to fit a DYNASTI implementation of the time series model: when temporal dynamics are truly asymmetric, the model will adequately recover this asymmetry; when dynamics are truly symmetric, the results will imply symmetric dynamics, both by returning overlapping posterior distributions of above- and below-mean autoregressive and cross-lagged parameters and through model selection. Fitting a symmetric model to asymmetric data, on the other hand, produces incorrect results, with parameters differing in degree (bias), kind (sign flips) or presence/absence, depending on the underlying nature of the true data generating mechanism. Importantly, this leads to incorrect conclusions about the dynamics of psychological processes. These simulation results even hold with small sample sizes (see Online Supplementary Figure 1), few time points (see Online Supplementary Figures 1 and 2), and high levels of noise (see Online Supplementary Figures 3 and 4). We thus find evidence in favor of a "keep it maximal" modeling strategy (Barr et al., 2013) over the traditional symmetric default when asymmetric temporal dynamics are theoretically plausible. In the next section, we examine whether asymmetric dynamics are present in several empirical examples.

4. Empirical Examples of DYNASTI

To demonstrate how DYNASTI models work in practice, we next present three empirical examples. In the first, we show how a univariate DYNASTI DSEM gives different results on the dynamics of negative affect as compared to a standard symmetric DSEM. In the second, we show that the DYNASTI DSEM returns symmetric temporal dynamics in a classic example on smoking urges. And in the third, we show how the bivariate DYNASTI RI-CLPM indicates asymmetric effects of anxiety on subsequent sleep problems but not the opposite effect. All three examples are illustrated using snippets of R code. As we realize many researchers may be unfamiliar with R and/or Stan, we first guide researchers through the installation and data preprocessing process in R.

4.1. Getting Started with rstan

Stan (Stan Development Team, 2023) is an open-source statistical modeling and computing platform which can be accessed through all popular data analysis languages. We here access it through R (R Core Team, 2024). To do so, one first needs to install R and, optionally but recommended, a user-friendly interface for R called RStudio. Both programs can be installed on the following website: https://posit.co/download/rstudio-desktop/. Once installed, one needs to install the rstan package to enable R to use the computing platform. This is accomplished by running `install.packages("rstan")` and subsequently `library (rstan)` in the R console (see also https://github.com/stan-dev/rstan/wiki/rstan-Getting-Started).

4.2. Univariate Dynamics Using DYNASTI: The Dynamics of Negative Affect Differ for Above- and Below-Average Values

As an intuitive example, we first fit the symmetric and DYNASTI DSEMs to an openly available dataset on a wide range of emotions and behaviors in people with personality disorders (Wright & Simms, 2016). Following Arizmendi et al. (2021), we here focus on a subset of the data on negative affect in $N = 94$ subjects across $T = 102$ time points. Figure 6 shows the negative affect data averaged across subjects (black line).

4.2.1. Data Loading and Preprocessing in R

First, one needs to download the data from the OSF page (https://osf.io/g3xd2) and save them. Then direct R to this folder, `setwd("Insert-path-here")`, and load the data into the environment, `dat <- read.csv("weather-padded.csv")`. To get a feel for the data, one may run `head(dat)`, which returns the first six rows of the dataset.

id	negaff	posaff	domin	love	avgtemp	day
1	2.6	1.00	−7.12	−7.95	41	1
1	2.8	1.60	−6.41	−3.66	32	2
1	2.8	1.80	−7.71	−5.95	32	3
1	2.4	1.25	−9.24	−2.41	32	4
1	2.2	1.80	−6.83	−1.83	30	5
1	2.2	1.20	−10.95	−0.12	24	6

This preview shows that the dataset is in long format, that is, it has one row per day per participant. As we create objects in R to give to Stan, it does not matter which format the data are in, as long as the created objects are in a certain format, which we will get to below. The dataset contains a column with user ids (`id`), columns with negative (`negaff`) and positive (`posaff`) affect scores, a column with dominance scores (`domin`), one with love scores (`love`), one with the average temperature on a given day (`avgtemp`), and a column with a day counter (`day`). We here only use the `id`, `negaff`, and `day` columns. Specifically, we create an object indicating the number of subjects, based on the `id` column, `Nsubj <- length(unique(dat$id))`, and an object indicating the number of days, based on the `day` column, `Ndays <- max(dat$day)`.

We then create an object for the time series data (`negAff`) based on the `negaff` column. It can be a matrix, array, or data frame as long as it has the dimensions `Nsubj` rows by `Ndays` columns. For example, `negAff <- matrix(dat$negaff, Nsubj, Ndays, byrow= TRUE)`. If the data contain missing values, these values need to be recoded to an arbitrary number for Stan to handle them. Our data contained 11.4% missing data points on average, ranging from 1.0 to 42.2% per subject. We chose to code these missing values as −999, `negAff[is.na(negAff)] <- -999`. As a final data preprocessing step, we create objects containing the number of missing values (`Nmiss`), and the row and column numbers of these values (`coordinates`).

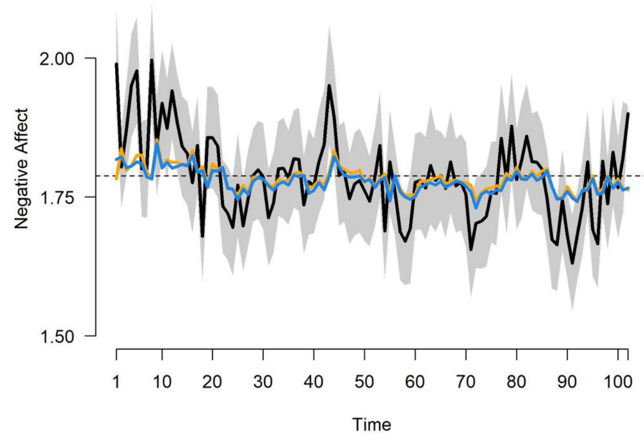

Figure 6. Negative affect data (Arizmendi et al., 2021) for $N = 94$ subjects across $T = 102$ consecutive time points; the colored band represents one standard error of the mean. The orange and blue lines represent predicted values by the standard symmetric and DYNASTI DSEM respectively.

```
# Function to compute number of misses
computeMisses <- function(x) {length(which(x == −999))}
Nmiss <- computeMisses(Y)
# Object containing the coordinates of the missing values
coordinates <- numeric()
for (it in 1:nrow(Y)) {
    if (length(which(Y[it,] == −999)) > 0) {
        coordinates = rbind(coordinates, cbind(it,which(Y[it,] == −999)))
    }
}
```

We then combine all these objects in a list (`datNeg`) to give to Stan. The list contains the number of subjects (`N`), the number of time points (`T`), the time series data (`Y`), the number of missing values (`N_miss`), the row and column numbers of these missing values (`ii_miss`), and the mean (`y_mean`) and standard deviation (`y_sd`) of the observed data to use for data imputation (see below).

```
# Data list to give to Stan
datNeg <- list(N = Nsubj,                                    # Number of subjects
               T = Ndays,                                    # Number of days
               Y = negAff,                                   # Time series data
               N_miss = Nmiss,                               # Number of misses
               ii_miss = coordinates,                        # Coordinates of misses
               y_mean = mean(negAff[negAff != −999]),        # Mean observed data
               y_sd = sd(negAff[negAff != −999]))            # Sd observed data
```

Without going into the details of our DSEM implementation in Stan, it is important to understand how we handle missing data. We imputed missing data based on all parameters within the model by implementing them as parameters in the model. In this way, missing data points are estimated in a model-informed way. Our approach is thus similar to full information multiple imputation in that values are randomly drawn multiple times based on the available time series data and the dynamics therein. To estimate missing data points, one needs to specify a prior distribution in Stan, which we did based on the mean and standard deviation of the observed data.

4.2.2. Fitting the Symmetric DSEM Using rstan

Now that we have created a data list in R to give to Stan (`datNeg`), we can actually fit the model. One first needs to download the Stan implementation of the symmetric DSEM from OSF (https://osf.io/8smqt) and save it in the same folder where the data are stored. Then, to run the model and thus to estimate the parameters, one needs to run the `stan()` function in R. This function takes the arguments `file`, a character string with the name of the model file, `data`, the name of the data list you created, `iter`, the number of iterations, optionally `seed`, a random seed to make results reproducible, and `pars`, the parameters you wish to save. Beware that Stan uses Bayesian estimation which means it may take a while. The more iterations you run, the more reliable your parameter estimates become, but also the longer it takes. Moreover, the more iterations you run, the larger the fit object becomes. It is thus wise to only save the posterior samples of the parameters you really need.

```
fitNegSym <- stan(file     = "Standard-DSEM-withimputation.stan",
                  data     = datNeg,
                  iter     = 4000,
                  seed     = 9845,
                  pars     = "gamma")
```

Once computing is finished, one can obtain an overview of the results using the `print()` function. For example, when interested in a summary of the population-level parameters (gammas), one may run `print(fitNegSym, pars = "gamma", probs=c(0.025, 0.975), digits=2)`. This will give you the means, standard errors, standard deviations, 95% credible intervals, and several convergence statistics of the parameters specified in the `pars` argument. Plots of the posterior distributions of parameters can also easily be obtained by running `stan_dens(fitNegSym, pars = "gamma")`. For other plotting options and many excellent examples, we refer to the Stan documentation (https://mc-stan.org/docs/).

4.2.3. Results from Fitting the Symmetric DSEM to Negative Affect Data

Results from fitting the symmetric DSEM to the negative affect data showed that negative affect carries over from one time point to the next ($\gamma_\phi = 0.27$, $95\%\ HDI = [0.24, 0.31]$; see Online Supplementary Table 3 for full results). As illustrated in Figure 6, this means that negative affect values tended to persist over time.

4.2.4. Fitting the DYNASTI DSEM Using rstan

As we were specifically interested in whether the temporal dynamics (i.e., autoregressive effects) differed for above- and below-average levels of negative affect, we also fitted a DYNASTI DSEM to the negative affect data. To do so oneself, first download the DYNASTI model file (https://osf.io/v58qn) and save it in the same folder as the data (and symmetric model file). Fitting the model and inspecting the fit results is done in the same way as for the symmetric DSEM, but with a different file name (and a different seed for reproducibility):

```
fitNegAsym <- stan(file     = "DYNASTI-DSEM-withimputation.stan",
                   data     = datNeg,
                   iter     = 4000,
                   seed     = 12,
                   pars     = "gamma")

print(fitNegAsym, pars = "gamma", probs = c(0.025, 0.975), digits = 2)
```

4.2.5. Results from Fitting the DYNASTI DSEM to Negative Affect Data

When fitting the DYNASTI model, there is a substantial separation of γ_ϕ ($M = 0.27$, $95\%\ HDI = [0.24, 0.31]$) into $\gamma_{\phi^{above}}$ ($M = 0.20$, $95\%\ HDI = [0.14, 0.26]$) and $\gamma_{\phi^{below}}$ ($M = 0.35$, $95\%\ HDI = [0.28, 0.43]$), where the 95% HDIs for the two autoregressive parameters do not overlap. This means that levels of negative affect above the mean carry over less to the next time point than levels below the mean. Important for specificity, the estimates of the *other* parameters barely changed (see Online Supplementary Table 3). Together, these results illustrate how assuming symmetric temporal dynamics can lead to incorrect conclusions about these dynamics. If one would do so, one would miss the seeming healthy pattern of low levels of negative affect being more sticky than high levels.

4.3. Univariate Dynamics Using DYNASTI: Similar Dynamics for Above- and Below-Average Smoking Urges

To benchmark the DYNASTI DSEM, we also fit the symmetric and DYNASTI models to an openly available dataset used as a standard example in the DSEM literature. For this example, we also provide an online tutorial (available at https://osf.io/fjtx5) guiding one through all of the steps. The dataset (McNeish & Hamaker, 2020) contains $T = 50$ measurements of the urge to smoke and depressive symptoms for $N = 100$ subjects. Raw urges data are displayed in black in Figure 7; the data contain no missing values. To load these data into the R environment, first download the data from https://osf.io/mwujr/ and save them in a folder. Then, direct R to this folder, `setwd("Insert-path-here")`, and load the data, `twolevel <- read.csv("Two-Level-Data.csv")`.

As these data do not contain missing data, preparing the data for Stan is simpler than in the negative affect example. We define the number of subjects (`Nsubj <- length(unique(twolevel$id))`), the number of observations (`Nobs <- max(twolevel$t)`), and the time series data for smoking urges (`urges <- matrix(twolevel$Urge, Nsubj, Nobs, byrow=T)`) and for depressive symptoms (`dep <- matrix(twolevel$Dep, Nsubj, Nobs, byrow= TRUE)`). Then, we combine these objects in a list to transfer from R to Stan (`datUrge <- list(N=Nsubj, T=Nobs, Y=urges, X=dep)`).

Then, download the symmetric (https://osf.io/t82rn) and DYNASTI DSEM (https://osf.io/9dngj) files without imputation of missing data (as there are no) from OSF. The Stan code implemented in these files is similar to the models described in the previous section, although without the missing values part.

Then fit the symmetric and DYNASTI models to the urges data and print a summary of the main results (see https://osf.io/fjtx5 for the step-by-step R code used for model fitting) to test how the urge to smoke at time t for subject i relates to prior urge to smoke $(t-1)$ and concurrent depression (t) of that subject:

```
# Fit standard symmetric model to urges data
fitUrgeSym <- stan(file          = "Standard-DSEM.stan",
                   data          = datUrge,
                   iter          = 5000,
                   seed          = 42)
# and print population-level results
print(fitUrgeSym, "gamma", probs = c(0.025, 0.975), digits = 2)

# Fit DYNASTI model to urges data
fitUrgeAsym <- stan(file          = "DYNASTI-DSEM.stan",
                    data          = datUrge,
                    iter          = 5000,
                    seed          = 23432)
# and print population-level results
print(fitUrgeAsym, "gamma", probs = c(0.025, 0.975), digits = 2)
```

Detailed fit results of the symmetric DSEM can be seen in Online Supplementary Table 4. We essentially replicated the previous DSEM analysis with this dataset (McNeish & Hamaker, 2020), further validating our rstan implementation. We then proceeded to fit the asymmetric model to the urges data, estimating separate autoregressive parameters for above- and below-average smoking urges.

When fitting this asymmetric model, we see relatively little separation of γ_ϕ $(M = 0.20,\ 95\%\ HDI = [0.16, 0.23])$ into $\gamma_{\phi^{\text{below}}}$ $(M = 0.20,\ 95\%\ HDI = [0.15, 0.26])$ and $\gamma_{\phi^{\text{above}}}$ $(M = 0.18,\ 95\%\ HDI = [0.13, 0.23]$; see Online Supplementary Table 4 for full details). Importantly for specificity, however, we also see very little difference in the *other* parameters within the model when we adopt the DYNASTI model. This suggests that even when the results point to only one autoregressive parameter being necessary, fitting a DYNASTI version of the same model (with "unnecessary" additional parameters) does not adversely affect our ability to estimate other features of the model.

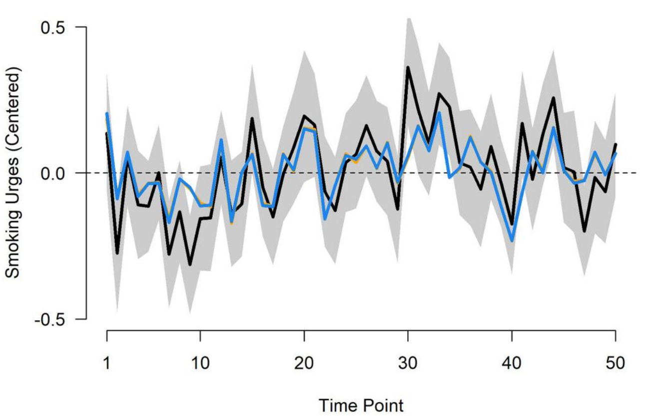

Figure 7. Raw data (McNeish & Hamaker, 2020) showing average smoking urges for $N = 100$ participants across $T = 50$ time points (black); the grey band represents one standard error of the mean. The orange and blue lines represent predicted values by the standard symmetric and DYNASTI DSEM respectively; note that they largely overlap, indicating similar model fit.

4.4. Bivariate Dynamics Using DYNASTI: Reciprocal Relationships between Sleep Problems and Anxiety in Adolescence

For the final empirical illustration, we investigate (a)symmetric cross-lagged parameters using the DYNASTI RI-CLPM. Here we used data derived from a longitudinal study of adolescent sleep problems and anxiety (Mulder & Hamaker, 2021d; Narmandakh et al., 2020). Data were collected from 2,056 adolescents every 2–3 years across $T = 5$ waves. We here analyze data from the $N = 1,189$ adolescents that completed all waves; the data thus do not contain missing data. Across adolescence, sleep problems were scored on a three-point Likert scale, with higher values indicating more sleep problems; in adulthood, this changed to two answer options (i.e., yes/no). Scores were averaged across items to obtain a continuous measure of sleep problems. Anxiety was scored on multiple items using a three-point Likert scale with higher values indicating higher anxiety. Mean scores were used as continuous proxy of anxiety.

The original paper (Narmandakh et al., 2020) fitted a symmetric RI-CLPM and found evidence for only the cross-lagged effect of sleep problems on anxiety across two adjacent time points, but no effects in the reverse direction. Here we consider both symmetric and DYNASTI (consistent with Equations (13) and (14)) models. Note that we estimate dynamics parameters equality constrained across waves, rather than individual cross-wave effects.

4.4.1. Data Loading and Preprocessing in R

To assess whether or not temporal dynamics within and between sleep problems and anxiety are asymmetric, one first downloads the data from https://osf.io/m5pg6 and saves them in a folder on your computer. The data are in wide format, that is, they contain five columns for each of the two dependent variables. It is easier to work with them in long format so while opening the data in R, one may also restructure them to long format and add subject ids:

```
# Set working directory to folder where you saved the downloaded data
setwd("Insert-path-here")

dat <- read.table("RICLPM.dat",
                  # Specify column names
                  col.names = c("x1", "x2", "x3", "x4", "x5",
                                "y1", "y2", "y3", "y4", "y5"))| >
                  # Add subject ids
                  dplyr::mutate(id = dplyr::row_number())| >
                  # Restructure to long format
                  tidyr::pivot_longer(cols = starts_with(c("x","y")),
                  names_to = c(".value","wave"),
                  names_pattern = "(.)(.)")
```

Also define the number of subjects (`Nsubj <- length(unique(dat$id))`), the number of time points (`Nobs <- 5`), and the two dependent variables (`sleep <- matrix(dat$x, Nsubj, Nobs, byrow= TRUE)` and `anx <- matrix(dat$y, Nsubj, Nobs, byrow = TRUE)`). These variables then need to be combined in a list (`datSleepAnx <- list(N=Nsubj, T=Nobs, X=sleep, Y=anx)`) to give to Stan.

4.4.2. Fitting the Symmetric RI-CLPM Using rstan

Now that we have created a data list to give to Stan, download the symmetric RI-CLPM (without missing values as there are none in this dataset) from OSF (https://osf.io/42ckw), fit the model to the data, and print the fit results as in the previous empirical examples:

```
fitSleepAnxSym <- stan(file      = "Standard-RICLPM.stan",
                       data      = datSleepAnx,
                       iter      = 5000,
                       seed      = 38284)

print(fitSleepAnxSym, pars = c("mu","phi","beta"), probs = c(0.025,
0.975), digits = 3)
```

4.4.3. Results from Fitting the Symmetric RI-CLPM to Anxiety and Sleep Data

When considering the symmetric RI-CLPM, we find similar results to those reported previously. Both autoregressive effects were comparatively large and positive (ϕ_{xx}: $M = 0.28$, 95% $\text{HDI} = [0.24, 0.32]$; ϕ_{yy}: $M = 0.27$, 95% $\text{HDI} = [0.23, 0.32]$; Online Supplementary Table 5). Also consistent with the original article, we find a modest positive effect for the cross-lagged effect of sleep problems (β_{xy}) such that greater sleep problems (x) prospectively predict greater anxiety (y) at the subsequent time point ($M = 0.09$, 95% $\text{HDI} = [0.04, 0.14]$) but no cross-lagged effect of anxiety on sleep problems β_{yx} ($M = 0.001$, 95% $\text{HDI} = [-0.02, 0.03]$).

4.4.4. Fitting the DYNASTI RI-CLPM Using rstan

In order to estimate separate autoregressive and cross-lagged parameters above and below the mean, one needs a different model file from OSF, that is, the one obtained from https://osf.io/w6fpz. Download this file, save it in the folder with the saved data, and fit the DYNASTI model through the `stan()` function:

```
fitSleepAnxAsym <- stan(file      = "DYNASTI-RICLPM.stan",
                        data      = datSleepAnx,
                        iter      = 5000,
                        seed      = 57812)

print(fitSleepAnxAsym, pars = c("mu","phi","beta"), probs = c(0.025, 0.975),
digits = 2)
```

4.4.5. Results from Fitting the DYNASTI RI-CLPM to Anxiety and Sleep Data

When fitting the DYNASTI model, we can see different patterns of effects depending on the focal parameter. For the autoregressive effect for sleep problems, the asymmetric effects are directionally consistent, but when adolescents are below their average in sleep problems, the carry-over effect is much greater than for when they are above their average ($\phi_{xx}^{\text{above}} = 0.09$ compared to $\phi_{xx}^{\text{below}} = 0.45$). Similarly, the autoregressive effect of anxiety shows substantial differentiation. Although both autoregressive effects for above- and below-average levels of anxiety are positive, the effect for above-average levels is higher (ϕ_{yy}^{above}: $M = 0.35$, 95% $\text{HDI} = [0.28, 0.41]$) than for below-average levels (ϕ_{yy}^{above}: $M = 0.21$, 95% $\text{HDI} = [0.14, 0.27]$).

The cross-lagged effect of sleep problems on anxiety, on the other hand, shows relatively little separation where the parameters above and below the mean remain similar in magnitude and sign ($\beta_{xy}^{\text{above}}$: $M = 0.08$, 95% $\text{HDI} = [-0.01, 0.17]$; β_{xy}^{below}: $M = 0.09$, 95% $\text{HDI} = [0.02, 0.17]$; see Online Supplementary Table 5 for full results). In contrast, the cross-lagged effect of anxiety on subsequent sleep problems shows a greater differentiation. When individuals were above average in their anxiety symptoms, greater anxiety predicted reductions in subsequent sleep problems (β_{yx}^{above}: $M = -0.10$, 95% $\text{HDI} = [-0.14, -0.06]$). In contrast, when they were below average in their anxiety, this relationship was positive (β_{yx}^{below}: $M = 0.10$, 95% $\text{HDI} = [0.06, 0.14]$). This heterogeneous effect—with similar magnitudes but opposite signs—cancels out in the symmetric model, resulting in the near-zero estimate.

5. Discussion

We here proposed DYNASTI implementations of longitudinal or time series models in which temporal dynamics are allowed to vary above and below the time series mean. In simulations, we showed that asymmetric temporal dynamics are adequately recovered by DYNASTI implementations and that fitting a DYNASTI model to symmetric data does not incur drawbacks in terms of model convergence or parameter estimation. The opposite scenario, modeling symmetric temporal dynamics when data are truly governed by asymmetric dynamics, leads to incorrect parameter estimates, resulting in conclusions that can be, and in empirical examples are, incorrect in magnitude (bias), kind (positive/negative) and presence (zero/non-zero).

Therefore, in line with the "keep it maximal" proposition in linear mixed modeling (Barr et al., 2013), we believe the DYNASTI approach should be preferred over the standard symmetric default in time series modeling. We do so due to the combination of considerable a priori plausibility of asymmetric dynamics in many research fields in combination with negligible estimation costs. As we showed in two of the empirical applications, DYNASTI implementations produce substantially different results regarding temporal dynamics, a well-recoverable pattern in our simulations. Specifically, we observed that low levels of negative affect are more sticky (positive autoregression) than high levels (lower positive autoregression). Besides, we observed that when individuals experienced above-average anxiety symptoms on a given time point, greater anxiety predicted reduced subsequent sleep problems (negative cross-lagged effect). Yet, when they experienced below-average symptoms, greater anxiety predicted increased subsequent sleep problems (positive cross-lagged effect). These applications demonstrate that the DYNASTI approach may yield novel empirical findings with different translational implications. However, we should note that even when the DYNASTI model can be estimated with only modest additional computational costs and demands on the data, this does not negate the general principle that more parsimonious models should be preferred unless the inferential or generalization benefits of a more complex model are justified (Pitt & Myung, 2002). Moreover, even if fitting a DYNASTI model shows good explanatory power, and superior fit to the non-DYNASTI equivalent, this does not ensure that this is the true generating process or mechanism. The problem of model equivalence (that for any observed data pattern there exist many models with equivalent explanatory power), should always be kept in mind (Raykov & Marcoulides, 2001).

We emphasize that the DYNASTI approach is general and thus not limited to the time series and panel models we used as examples. The DYNASTI logic can readily be applied to other models, including (but not limited to) STARTS models (Kenny & Zautra, 2001), ALT models (Bollen & Curran, 2004), latent change score models (e.g., Usami et al., 2015), ARMA models (e.g., Hamaker et al., 2002), and LCM-SR models (Curran et al., 2014). To enable researchers to create DYNASTI versions of their preferred time series models, we implemented the models in a fully open source code base. We purposely used Stan (Gelman et al., 2015) to obviate the need for expensive proprietary software and to allow greater flexibility and modifiability.

For simplicity, we focused on population-level effects in the manuscript. However, the current DYNASTI implementations of the DSEM (Equations (7)–(10)) and RI-CLPM (Equations (11)–(14)) contain subject-specific effects. Such subject-specific effects could prove useful, for example, when identifying risk factors or when personalizing treatment. For instance, an influential body of findings has demonstrated that higher emotional inertia is a risk factor for depression (e.g., Kuppens et al., 2010). Using a DYNASTI approach would allow researchers to tease apart such emotional inertia for days that are "better" than average versus days that are "worse" than average (De Haan-Rietdijk et al., 2016a) and to specifically target emotional inertia for more negative mood. Moreover, the DYNASTI approach may provide tools to treat, for example, individuals suffering from bipolar disorder (Bonsall et al., 2012; Hofmann & Meyer, 2006; Holmes et al., 2016) as it will show whether individuals are more prone to getting stuck in positive or negative mood. Another benefit coming with these subject-specific effects is that one could incorporate covariates which *predict* individual differences in the autoregressive asymmetry. For instance, they allow one to assess which personal or environmental factors cause one person to suffer more from a short night of sleep than another. However, our current DYNASTI DSEM implementation is unable to recover subject-specific effects adequately. This means that even if individual differences in asymmetric temporal dynamics exist, we would not be able to identify them. Preliminary simulations suggest that over 300 time points are needed to recover subject-specific effects. Therefore, future studies are advised to examine exactly how many time points are needed to draw individualized conclusions.

Further extensions are also evident. For conceptual reasons, we focused on asymmetry above and below the time series mean. To do so, we set the threshold to zero. This threshold could also be set to a clinically-relevant value (e.g., a threshold above which an individual is considered clinically depressed) or estimated. For example, it could be that the negative effect of sleep on mood only occurs when sleep deviations are of a certain severity, say two hours less than average. This could easily be implemented in the open source code by specifying the autoregressive parameters based on an estimated threshold (instead of the mean). Moreover, both univariate and multivariate DYNASTI implementations can be extended with latent variables explaining multiple observed variables at each time point (see e.g., Molenaar, 1985). By doing so, temporal dynamics within and between latent, instead of observed, variables can be investigated.

We must note that DYNASTI implementations are not the only (non)linear extensions of AR models proposed in the literature. We here focused on a psychologically plausible extension in which dynamics depend on the time series value. Yet, depending on the research question, it may be more suitable to fit models that allow dynamics parameters to vary across time points. Examples of such models are change point models (Cabrieto et al., 2017; Ma et al., 2020) with which changes in temporal dynamics can be detected, time-varying effects models (TVEM; Hastie & Tibshirani, 1993; Hoover et al., 1998; Tan et al., 2012) or time-varying autoregressive models (TVAR; Bringmann et al., 2017, 2018; Haslbeck et al., 2021; Haslbeck & Ryan, 2022) that allow temporal dynamics parameters to differ across time points, and nonstationary state-space models (Molenaar et al., 2009) that allow for time-varying dynamics parameters in combination with latent variables. These models are thus more flexible in allowing differing dynamics over time and could be combined with DYNASTI implementations in future studies. In this way, one may not only answer how dynamics differ above and below the mean, but also how these asymmetric dynamics develop over time.

To conclude, we propose DYNASTI implementations of time series models as we suspect asymmetric temporal dynamics to be more of a rule than an exception in psychological processes. By providing openly available R and Stan code, we hope to aid applied researchers and invite them to use DYNASTI versions of their preferred time series models to uncover asymmetric temporal dynamics.

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Author Contributions

JVS: Conceptualization, Methodology, Software, Validation, Formal Analysis, Data Curation, Writing—Original Draft, Writing—Review & Editing, Visualization; ØS: Conceptualization, Methodology, Software, Validation, Formal Analysis, Resources, Data Curation, Writing—Review & Editing, Supervision; EMM: Conceptualization, Methodology, Software, Formal Analysis, Data Curation, Writing—Review & Editing; MA: Software, Data Curation, Writing—Review & Editing; RAK: Conceptualization, Methodology, Writing—Original Draft, Writing—Review & Editing, Supervision, Funding Acquisition.

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The authors report there are no competing interests to declare.

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Data Availability Statement

Code for model fitting and simulation code are openly available at the Open Science Framework https://osf.io/hwmgk/. Here you will also find data and code to reproduce the empirical examples, and a step-by-step tutorial.

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