Online Supplement S-6

Description of the Procedures to Determine Simulation Parameters and their Results

We obtained discrete time parameter estimates for our simulation, with a stationary (i.e., constrained) and non-stationary (i.e., unconstrained) SEM, using lavaan (Rossel, 2012). The results are presented in Table S-6 below. In brief, this yielded the expected parameters (shown in Table 5 of the manuscript as *'M(expected)'*), which were compared with the empirical results of the Monte Carlo simulations.

The stationary discrete time SEM was fitted in order to obtain a single set of estimates for autoregressive effects, cross-lagged effects, and error (co-)variances. In the stationary model, the two autoregressive effects of work pressure Time 0 on work pressure Time 1 and of work pressure Time 1 on work pressure Time 2 were constrained to be equal. The same applied to the autoregressive effects of exhaustion. Further, the effects of work pressure Time 0 on exhaustion Time 1 and of work pressure Time 1 on exhaustion Time 2 were constrained to be equal. The same applied for the two reversed effects of exhaustion on work pressure. Both the stationary and non-stationary model were first-order autoregressive models like those in Figure 1 (i.e., effects of Time 0 on Time 2 variables were excluded).

Table S-6 Resulting Parameter Estimates, their Ranges, and their 1-week Re-Scaled Counterparts in Stationary and Non-Stationary Cross-Lagged Structural Equation Models of the Data Reported by Demerouti, Bakker, and Bulters (2004)

#	Lag	Parameters						
		X0 -> X1	X0 -> Y1	Y0 -> X1	Y0 -> Y1	var(err(X1))	covar(err(X1Y1))	var(err(X1))
		Parameter Estimates from Stationary Model						
1	6	.55	.08	.13	.67	.63	.14	.50
2	1	.90	.02	.03	.93	.16	.02	.11
		Range of Parameter Estimates from Non-Stationary Model						
3	6	[.48, .62]	[.07, .10]	[.09, .16]	[.64, .69]	[.56, .69]	[.07, .20]	[.48, .53]
		Extended Range of Parameter Estimates from Non-Stationary Model						
4	6	[.38, .71]	[-.02, .18]	[-.00, .26]	[.56, .78]	[.47, .79]	[.02, .27]	[.40, .61]
		Example of Parameter Set for a Single Lag of a Single Non-Stationary Primary Study						
5	6	.39	.07	.09	.73	-	-	-
6	1	.85	.02	.03	.95	.25[c]	.03[c]	.09[c]

Note: The superscript c indicates parameters that were computed rather than sampled. Computation was based on the respective set of cross-lagged and autoregressive effects in order to keep the variance of the variables at 1.0 and their covariance at .38 (as at T0) across all waves. This allows interpretation of effect sizes as standardized effects.

The parameter estimates are shown in Table S-6. The stationary model yielded the discrete time parameter estimates shown in the row #1 of Table S-6, where the number 6 in the second column indicated that this effect occurred across six weeks. We then used the procedures outlined earlier in this article to re-scale the coefficients into 1-week lagged effects because we aimed at generating data across 52 adjacent weeks. The rescaled coefficients are shown in row #2 of Table S-6.

The values shown in row #2 are the actual modeling parameters we used in the Monte Carlo simulation of stationary models. These were also the expected values for the simulated stationary and non-stationary CoTiMAs across a 1-week lag (for the categorization-based MASEM the expected values were re-scaled as explained later). Since these parameters were based on correlations, the variance of the two variables across the simulated waves were kept constant at 1.0, on average. This allows interpreting coefficients as standardized effect size estimates.

For the non-stationary model, selection of model parameters was more complex because parameters varied from lag to lag and from study to study. The non-stationary SEM of the Demerouti et al. (2004) data yielded two estimates (for the two lags) of each model parameter. Their respective lowest and highest values are shown in row #3 of Table S-6. Since the naturally occurring variation could be even larger, we estimated the lower limit of each of the coefficients as the lowest of the respective two values minus two times its standard error (e.g., for the autoregressive effect of X0 -> X1 this was .48 – 2 × .05= .38) and the upper limits as the larger of the two values plus two times its standard error. This yielded the extended range of parameters used in simulating non-stationary models, which is shown in row #4 of Table S-6. Note that the non-stationary model fitted the data significantly better than the stationary model ($\Delta\chi 2 = 14.62, \Delta\text{df} = 7, p < .042$).

To simulate non-stationary models, for each simulated primary study the cross-lagged effects and the autoregressive effects were allowed to randomly vary across the simulated waves within the ranges shown in row #4 of Table S-6. The variances of the error terms were fixed at values that kept the variance of X and Y invariant at 1.00 over time and their covariance at .38 (as at T0). This enables interpreting effect sizes as standardized effects.

After the set of autoregressive and cross-lagged parameters was randomly chosen and the set of error variances were computed, they were again time-scaled to obtain parameters across a 1-week lag.

Note that there is no single set of parameter values because all autoregressive and cross-lagged parameters varied independently from each other across all primary studies and all waves. An example for one sample of 6-week discrete effects (row #5), their corresponding 1-week effects (row #6), and the 1-week error (co-)variances (also row #6) is shown in Table S-6. Obviously, the effects of this *single primary study* (rows #5 and #6) are different from those shown in rows #1 and #2. However, expected values (i.e., mean values *across a sample of primary studies)*, were identical to those shown in row #2 of

Table S-6, because the values for primary studies were randomly sampled from the symmetrical interval around these values. Thus, the values shown in row #2 of Table S-6 were the expected values for both the stationary as well as the non-stationary meta-analyses across a 1-week lag.

Categorizations for categorization-based MASEM. For each set of k = 9, 24, or 42 simulated primary studies, we calculated the 33rd and 66th percentile of the sampled time lags and used these to divide the k studies into three categories with “short”, “medium”, and “long” time lags.

For each category, random-effect correlations were computed using the approach of Borenstein et al. (2009), which we used in Study 1. The resulting sets of six correlations were then analyzed using lavaan (Rossel, 2012) to estimate the MASEM autoregressive and cross-lagged parameters.