Supplemental Online Appendix

Investigating the Dimensionality and Stability of Union Commitment Profiles over a 10-Year Period: A Latent Transition Analysis

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Sections

1. Preliminary Confirmatory Factor Analyses

Confirmatory factor analysis (CFA) models were estimated using Mplus 7.2 (Muthén and Muthén 2014). Because of the complexity of the measurement models underlying all constructs assessed in the present study and the relatively smaller sample size of employees who completed T2 and T3, these preliminary analyses were conducted separately for the union commitment measure, the predictors (union attitudes, union instrumentality, and union satisfaction), and the outcomes (union participation). These models were first estimated separately for each time point (T1: n = 637; T2: n = 342; T3: n = 195). These models included three factors for the union commitment measure (loyalty to the union, responsibility to the union, and willingness to work for the union); four factors for the predictors (union attitudes, union instrumentality, union satisfaction, formal aspects and quality of union–member relationships); and two factors for the outcomes (union participation: UCB-I and UCB-O). Then, complete longitudinal models were estimated across all three time waves including nine factors for the union commitment measure (three factors × three time points), 14 factors for the predictors (four factors × three time points), and four factors for the outcomes (two factors × two time points). All models were specified as congeneric, with each item allowed to load on a single factor, and all factors freely allowed to correlate within and across time points. In the union commitment model, one a priori correlated uniqueness was added to reflect the parallel wording of two items (If asked, I would serve on a committee . . . , and If asked, I would run for an elected office . . .). In the predictor model, a priori correlated uniquenesses were added to take into account the methodological artefact related to the negative wording of a subset of items. Finally, in all longitudinal models, a priori correlated uniquenesses between matching indicators of the factors utilized at the different time points were also included to ensure that these longitudinal models did not converge on biased and inflated stability estimates (Jöreskog 1973; Marsh 2007). For all models, these correlated uniquenesses reflected the fact that unique variance of these indicators was known to emerge, in part, from shared sources of influences over time (Marsh, Scalas, and Nagengast 2010; Marsh et al. 2013).

CFA models for the union commitment measure and the predictors were estimated using the robust maximum likelihood (MLR) estimator. This estimator provides standard errors and tests of fit that are robust in relation to non-normality and the use of ordered-categorical variables involving at least five response categories (Finney and DiStefano 2013). Longitudinal CFAs were conducted using the data from all respondents who completed at least one wave of data (corresponding to the T1 sample; n = 637), using Full Information MLR estimation (FIML)—rather than a listwise deletion strategy focusing only on employees having answered two or three time points—(Graham 2009; Enders 2010). FIML estimation has been found to result in unbiased parameter estimates under even a very high level of missing data (e.g., 50%), in the context of longitudinal studies with missing time points, under Missing At Random (MAR) assumptions, and even in some cases to violations of this assumption (e.g., Enders 2001, 2010; Enders and Bandalos 2001; Graham 2009; Shin, Davidson, and

Long 2009). It should be noted that preliminary tests in which scores on all variables assessed at the earlier measurement point were used to predict attrition occurring at Time 2 or Time 3 revealed a single significant predictor of attrition: Participants with an initially higher level of willingness to work for the union were slightly more likely to have dropped out of the study by Time 3 (b = –.700, s.e. = 214, $p \leq .01$). No other facet of union commitment or additional variable considered here predicted attrition. Still, this single statistically significant effect reinforces the importance of relying on missing data procedures relying on MAR assumption, and thus allowing missing values to be conditioned on earlier scores on this variable.

By contrast, because the union participation measure relies on a binary response scale, measurement models for the outcomes had to be estimated with a robust weight least square estimator using diagonal weight matrices (WLSMV), which has been found to outperform MLR estimation when response scales include four or fewer answer categories (Flora and Curran 2004; Beauducel and Herzberg 2006; Lei 2009; Rhemtulla, Brosseau-Liard, and Savalei 2012; Finney and DiStefano 2013; Bandalos 2014). A key limitation of WLSMV, when compared to MLR, has to do with the reliance on a slightly less efficient way of handling missing data (Asparouhov and Muthén 2010a). For this reason, factor scores were saved using starts value taken from the final retained WSLMV longitudinal model, but using a Bayes estimator that handles missing data in a manner comparable to FIML (Asparouhov and Muthén 2010b; Enders 2010). The reason initial measurement models and tests of measurement invariance were not directly conducted with Bayes is to be able to properly assess the adequacy of the measurement model, and its measurement invariance over time, using typical goodness-of-fit information, which are not available with Bayes.

Before saving the factor scores for our main analyses, we verified that the measurement model operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap 2011): 1) configural invariance; 2) weak invariance (loadings); 3) strong invariance (loadings and intercepts/thresholds); 4) strict invariance (loadings, intercepts/thresholds and uniquenesses); 5) invariance of the latent variance-covariance matrix (loadings, intercepts/thresholds, uniquenesses, and latent variances and covariances); 6) latent means invariance (loadings, intercepts/thresholds, uniquenesses, latent variances and covariances, and latent means). In the outcomes model relying on WLSMV estimation, thresholds replace intercepts and reflect the points at which responses change from one answer category to another. However, in models based on binary items, it is not possible to separately test the invariance of the loadings and thresholds, so steps 2 (weak) and 3 (strong) are combined into a single step of strong measurement invariance.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, and Grayson 2005), we relied on goodness-of-fit indices to describe the fit of the alternative models (Hu and Bentler 1999; Yu 2002): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi-square, chi-square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Cheung and Rensvold 2002; Chen 2007) in the context of tests of measurement invariance. A ΔCFI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the preceding one indicate that the invariance hypothesis should not be rejected. Note that with WLSMV, chi-square values are not exact, but rather adjusted or "estimated" to obtain a correct *p* value. This explains why χ^2 and CFI values can be non-monotonic with model complexity. This specificity is also important for the WLSMV χ^2 difference tests, which need to be conducted via Mplus' DIFFTEST function (MD$\Delta\chi^2$; Asparouhov and Muthén 2006).

The results from these models are reported in supplementary Table S1. These results clearly support the a priori measurement models (at each time point separately and longitudinally). For the union commitment measure, the results provided clear support for the complete longitudinal invariance of the model with none of the change in goodness-of-fit indices exceeding the recommended cut-off scores (ΔCFI ≤ .010; ΔTLI ≤ .010; ΔRMSEA ≤ .015; and overlapping RMSEA confidence intervals). To ensure that the latent profiles estimated at each time wave were based on fully comparable measures of union commitment, the factor scores used in main analyses were saved from the model of complete measurement invariance (loadings, intercepts/thresholds, uniquenesses, latent variances and covariances, and latent means). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time waves for models based on factor scores (e.g., Millsap 2011), there are advantages to saving factors scores from a model of complete measurement invariance for use in latent profile analyses. Indeed, saving factor scores based on a measurement model in which both the variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in all time waves) provides scores on profile indicators that can be readily interpreted in standardized terms as deviation from the grand mean expressed in standard deviation units. For the predictors model, however, neither the strong (ΔCFI = –.018; ΔTLI ≤ –.019), nor the strict (ΔCFI –.012; ΔTLI = –.011) measurement invariance was supported across time waves. Thus, to ensure comparability of the constructs across time waves, we pursued models of partial invariance (Byrne, Shavelson, and Muthén 1989), relaxing invariance constraints on five intercepts and three uniquenesses. In these models of partial invariance, each factor remained well-defined from a majority of invariant items. Furthermore, although the invariance of the latent means was supported by the data, it resulted in an unacceptable level of model fit according to the TLI (< .900) so that factor scores were saved from the model of invariant latent variances and covariances. Finally, for the outcomes, the results supported the configural, strong, strict, and latent variance-covariance invariance of the model, but not the invariance of the latent means (ΔCFI –.019; ΔTLI = –.018) so that factors scores were also saved from the model of invariant latent variances and covariances. For the predictors and outcomes, given that we are mainly interested in their relations with the profiles, latent mean invariance does not provide any advantage in terms of interpretation.

The parameter estimates from these models are reported in Tables S2 to S5. These parameter estimates were used to compute composite reliability coefficients associated with each of the a priori factors using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum \delta_i]}$$

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, where the factor loadings are summed and then squared, reflects the proportion of the variance in indicators that reflect true score variance, whereas the denominator reflects total amount of variance in the items including both true score variance and random measurement errors (reflects by the sum of the items uniquenesses associated with a factor). These coefficients are all satisfactory (ω = .710 to .925; *M* = .828), and reported in Tables S3 to S5.

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2. Table S1. Goodness-of-Fit Statistics of the Longitudinal Confirmatory Factor Analytic (CFA) Models

Description	$\chi^2(df)$	CFI	TLI	RMSEA	90% CI	$\Delta\chi^2$ (df)	ΔCFI	ΔTLI	ΔRMSEA
Union commitment									
Time 1	122.841*(61)	.971	.963	.040	[.030, .050]	—	—	—	—
Time 2	121.994*(61)	.923	.902	.054	[.040, .068]	—	—	—	—
Time 3	125.870*(61)	.957	.945	.074	[.056, .093]	—	—	—	—
Configural invariance	1004.110*(624)	.936	.925	.031	[.027, .034]	—	—	—	—
Weak invariance	1036.572*(644)	.934	.924	.031	[.027, .034]	32.418*(20)	–.002	–.001	.000
Strong invariance	1110.748*(664)	.925	.917	.032	[.029, .036]	80.202*(20)	–.009	–.007	+.001
Strict invariance	1206.262*(690)	.915	.908	.034	[.031, .037]	65.580*(26)	–.010	–.009	+.002
Variance-Covariance invariance	1251.901*(702)	.908	.903	.035	[.032, .038]	39.372*(12)	–.007	–.005	+.001
Latent mean invariance	1290.137*(708)	.903	.900	.036	[.033, .039]	42.752*(6)	–.005	–.003	+.001
Predictors									
Time 1	260.181*(123)	.962	.952	.042	[.035, .049]	—	—	—	—
Time 2	238.710*(123)	.948	.935	.053	[.043, .062]	—	—	—	—
Time 3	181.800*(123)	.960	.951	.050	[.033, .064]	—	—	—	—
Configural invariance	1915.836*(1239)	.928	.917	.029	[.027, .032]	—	—	—	—
Weak invariance	1946.784*(1267)	.928	.919	.029	[.026, .032]	32.047(28)	.000	+.002	.000
Strong invariance	2147.826*(1295)	.910	.900	.032	[.030, .035]	217.419*(28)	–.018	–.019	+.003
Strong partial invariance	2018.047*(1285)	.922	.913	.030	[.027, .032]	73.832*(18)	–.006	–.006	+.001
Strict invariance	2171.675*(1321)	.910	.902	.032	[.029, .034]	134.984*(36)	–.012	–.011	+.002
Strict partial invariance	2117.950*(1315)	.915	.907	.031	[.029, .033]	89.608*(30)	–.007	–.006	+.001
Variance-Covariance invariance	2182.989*(1335)	.910	.904	.032	[.029, .034]	60.915*(20)	–.005	–.003	+.001
Latent mean invariance	2268.078*(1343)	.902	.896	.033	[.031, .035]	79.064*(8)	–.008	–.008	+.001
Outcomes									
Time 2	117.710*(64)	.953	.942	.050	[.035, .064]	—	—	—	—
Time 3	88.218*(64)	.980	.976	.044	[.017-.065]	—	—	—	—
Configural invariance	343.809*(293)	.975	.973	.021	[.009, .029]	—	—	—	—
Strong invariance	365.175*(302)	.969	.967	.023	[.013, .031]	27.765**(9)	–.006	–.006	+.002
Strict invariance	372.877*(315)	.972	.971	.021	[.010, .030]	12.347(13)	+.003	+.004	–.002
Variance-Covariance invariance	380.085*(318)	.970	.969	.022	[.012, .030]	6.026(3)	–.002	–.002	+.001
Latent mean invariance	420.173*(320)	.951	.951	.028	[.020, .035]	29.716**(2)	–.019	–.018	+.006

Notes: χ^2 = chi-square test of exact fit; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; 90% CI = 90% confidence interval of the RMSEA; $\Delta\chi^2$ = chi-square difference test. *p < .01.

3. Table S2. Standardized Parameter Estimates from the Invariant Longitudinal Confirmatory Factor Analytic (CFA) Models

	Union commitment		Predictors		Outcomes	
	Loading (λ)	Uniqueness (δ)	λ	δ	λ	δ
Loyalty			**Union attitude**		**Participation: UCB-O**	
Item 1	.775	.302	.671	.549	.687	.528
Item 2	.729	.282	.605	.634	.758	.425
Item 3	.778	.225	.489	.761	.466	.783
Item 4	.794	.222	.709	.497	.713	.491
Item 5	.755	.422	.712	.493	.750	.465
Item 6	.753	.257			.393	.846
Item 7					.741	.451
Item 8					.899	.192
Item 9					.734	.461
Responsibility			**Union instrumentality**		**Participation: UCB-I**	
Item 1	.656	.382	.557	.690	.847	.283
Item 2	.697	.366	.625	.610	.839	.297
Item 3	.696	.320	.758	.426	.816	.333
Item 4	.603	.373	.516	.733	.731	.465
Willingness to work			**Satisfaction: Formal**			
Item 1	.757	.276	.760	.423		
Item 2	.672	.405	.806	*.350/.443/.559*		
Item 3	.645	.562	.774	.401		
Item 4			.667	*.555/.554/.682*		
			Satisfaction: Relationships			
Item 1			.812	.341		
Item 2			.734	.462		
Item 3			.764	*.417/.509/.470*		
Item 4			.838	.298		
Item 5			.808	.347		

Notes: All loadings and uniquenesses are significant ($p < .01$). *Italics:* Values for the non-invariant uniquenesses are reported sequentially for Times 1-2-3; UCBI = union citizenship behaviors: interpersonal helping; UCBO = union citizenship behaviors: union as an organization.

4. Table S3. Latent Correlations and Composite Reliability from the Invariant Longitudinal Confirmatory Factor Analytic (CFA) Model: Union Commitment Measure

	UCL1	UCR1	UCWW1	UCL2	UCR2	UCWW2	UCL3	UCR3	UCWW3
UCL1	*.925*								
UCR1	.648**	*.830*							
UCWW1	.768**	.575**	*.776*						
UCL2	.660**	.479**	.464**	*.925*					
UCR2	.388**	.593**	.331**	.648**	*.830*				
UCWW2	.483**	.392**	.618**	.768**	.575**	*.776*			
UCL3	.341**	.273**	.188*	.414**	.193**	.342**	*.925*		
UCR3	.116	.252*	.087	.154	.212*	.112	.648**	*.830*	
UCWW3	.215*	.231*	.448**	.119	.065	.459**	.768**	.575**	*.776*

Notes: UCL = union commitment: union loyalty; UCR = union commitment: responsibility to the union; UCWW = union commitment: willingness to work for the union; 1 = time 1; 2 = time 2; 3= time 3; composite reliability scores reported in the diagonal (italicized). **p* < .05; ***p* < .01.

5. Table S4. Latent Correlations and Composite Reliability from the Invariant Longitudinal Confirmatory Factor Analytic (CFA) Model: Predictors

	UA1	UI1	USF1	USR1	UA2	UI2	USF2	USR2	UA3	UI3	USF3	USR3
UA1	*.776*											
UI1	.730**	*.710*										
USF1	.537**	.723**	*.839*									
USR1	.554**	.727**	.863**	*.894*								
UA2	.584**	.540**	.346**	.345**	*.776*							
UI2	.622**	.716**	.552**	.496**	.730**	*.710*						
USF2	.352**	.431**	.576**	.501**	.537**	.723**	*.832*					
USR2	.402**	.457**	.258**	.326**	.554**	.727**	.863**	*.889*				
UA3	.438**	.385**	.153	.152	.507**	.599**	.310**	.258**	*.776*			
UI3	.226**	.447**	.371**	.314**	.379**	.548**	.392**	.326**	.730**	*.710*		
USF3	.323**	.375**	.328**	.377**	.328**	.377**	.398**	.315**	.537**	.723**	*.814*	
USR3	.214**	.330**	.314**	.464**	.314**	.464**	.303**	.335**	.554**	.727**	.863**	*.891*

Notes: UA = union attitudes; UI = union instrumentality; USF = union satisfaction: formal; USR = union satisfaction: relationships; 1 = time 1; 2 = time 2; 3= time 3; Composite reliability scores reported in the diagonal (italicized). **p* < .05; ***p* < .01.

6. Table S5. Latent Correlations and Composite Reliability from the Invariant Longitudinal Confirmatory Factor Analytic (CFA) Model: Outcomes

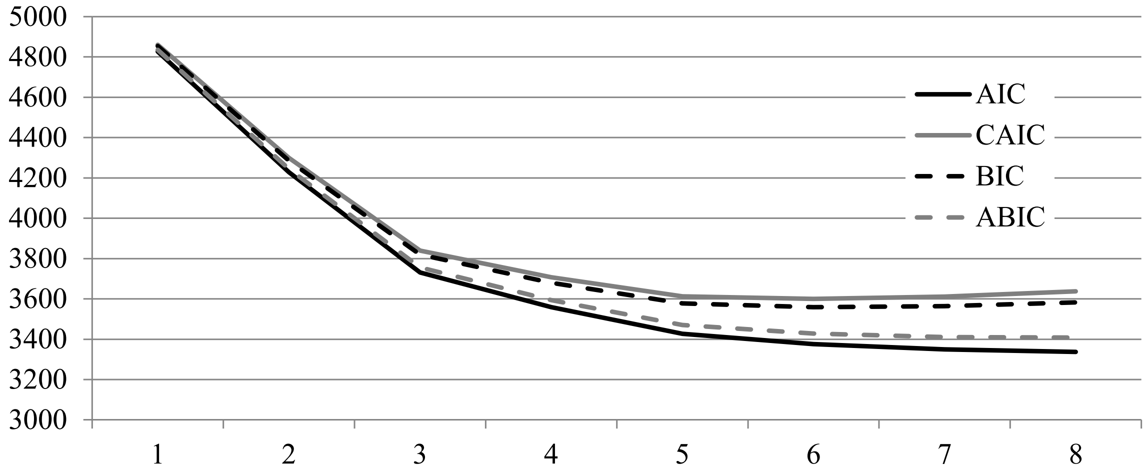
	UCBI2	UCBO2	UCBI3	UCBO3
UCBI2	*.884*			
UCBO2	.887**	*.890*		
UCBI3	.359**	.359**	*.884*	
UCBO3	.331*	.594**	.887**	*.890*

Notes: UCBI = union citizenship behaviors: interpersonal helping; UCBO = union citizenship behaviors: union as an organization; 2 = time 2; 3= time 3; Composite reliability scores reported in the diagonal (italicized). *$p < .05$; **$p < .01$.

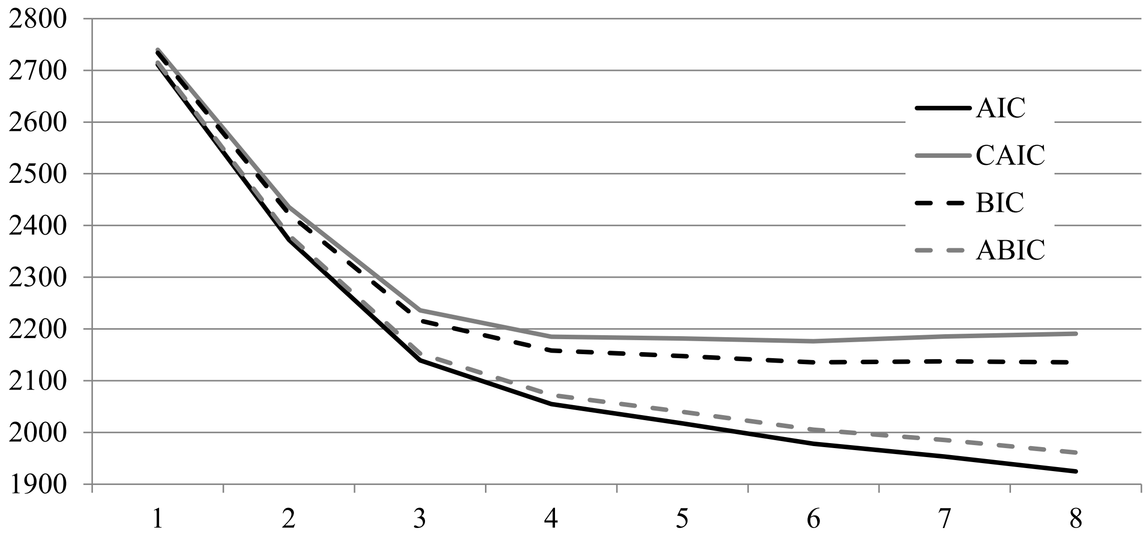
7. Table S6. Results from the Latent Profile Analysis Models Estimated Separately at Each Time Wave

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Time 1 (*n* = 637)										
1 Profile	–2407.584	6	1.068	4827.169	4859.909	4853.909	4834.860	Na	Na	Na
2 Profiles	–2101.009	13	1.602	4228.018	4298.956	4285.956	4244.682	.760	.022	≤.001
3 Profiles	–1845.235	20	1.278	3730.470	3839.606	3819.606	3756.107	.835	≤.001	≤.001
4 Profiles	–1752.716	27	1.452	3559.432	3706.765	3679.765	3594.042	.842	.226	≤.001
5 Profiles	–1679.283	34	1.121	3426.566	3612.096	3578.096	3470.149	.838	≤.001	≤.001
6 Profiles	–1646.935	41	1.187	3375.869	3599.597	3558.597	3428.425	.851	.191	≤.001
7 Profiles	–1626.790	48	1.267	3349.581	3611.506	3563.506	3411.109	.825	.527	.020
8 Profiles	–1613.636	55	1.066	3337.272	3637.394	3582.394	3407.773	.827	.008	.040
Time 2 (*n* = 342)										
1 Profile	–1349.447	6	1.310	2710.894	2739.903	2733.903	2714.869	Na	Na	Na
2 Profiles	–1173.355	13	1.446	2372.711	2435.563	2422.563	2381.325	.828	.004	≤.001
3 Profiles	–1049.680	20	1.280	2139.361	2236.057	2216.057	2152.612	.862	≤.001	≤.001
4 Profiles	–1000.311	27	1.264	2054.623	2185.162	2158.162	2072.512	.842	.010	≤.001
5 Profiles	–974.704	34	1.141	2017.408	2181.791	2147.791	2039.936	.848	.037	≤.001
6 Profiles	–948.024	41	1.100	1978.047	2176.274	2135.274	2005.213	.835	.008	≤.001
7 Profiles	–928.725	48	1.004	1953.451	2185.521	2137.521	1985.255	.852	.064	≤.001
8 Profiles	–907.347	55	0.933	1924.695	2190.609	2135.609	1961.137	.862	.008	.126
Time 3 (*n* = 195)										
1 Profile	–876.815	6	1.152	1765.631	1791.269	1785.269	1766.262	Na	Na	Na
2 Profiles	–749.991	13	1.101	1525.983	1581.532	1568.532	1527.350	.828	≤.001	≤.001
3 Profiles	–659.728	20	1.132	1359.456	1444.916	1424.916	1361.559	.898	.002	≤.001
4 Profiles	–607.336	27	1.100	1268.672	1384.043	1357.043	1271.511	.926	.082	≤.001
5 Profiles	–584.936	34	1.133	1237.873	1383.155	1349.155	1241.448	.877	.181	.010
6 Profiles	–563.455	41	.986	1208.909	1384.102	1343.102	1213.221	.885	.050	≤.001
7 Profiles	–547.276	48	.983	1190.552	1395.656	1347.656	1195.599	.899	.190	≤.001
8 Profiles	–532.372	55	.965	1174.744	1409.759	1354.759	1180.527	.905	.201	.051

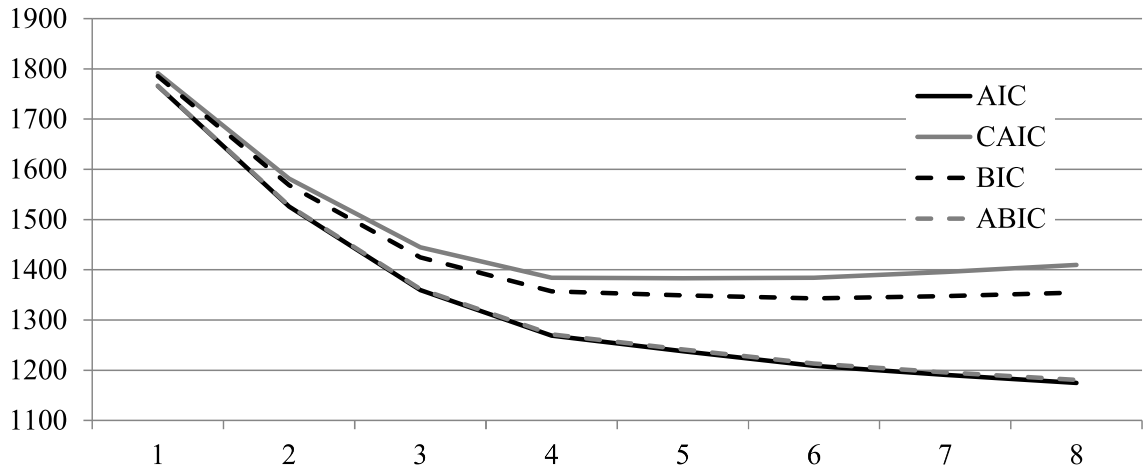
Notes: Na = not applicable; LL = model loglikelihood; #fp = number of free parameters; scaling = scaling correction factor associated with robust maximum likelihood estimates; AIC = Akaïke information criteria; CAIC = constant AIC; BIC = Bayesian information criteria; ABIC = sample size adjusted BIC; aLMR = adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.



8. **Figure S1.** Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 1)



9. **Figure S2.** Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 2)



10. **Figure S3.** Elbow Plot of the Information Criteria for the Latent Profile Analyses (Time 3)

11. Table S7. Detailed Results from the Final Latent Transition Solution (Partial Dispersion Similarity)

		Profile 1		Profile 2		Profile 3		Profile 4	
	Waves	Mean	CI	Mean	CI	Mean	CI	Mean	CI
Loyalty to the union	Similar	1.031	0.915; 1.146	0.231	0.149; 0.314	–0.327	–0.446; -0.209	–1.365	–1.577; –1.152
Responsibility to the union	Similar	0.853	0.739; 0.967	0.106	0.056; 0.156	–0.178	–0.242; -0.114	–1.088	–1.275; –0.902
Willingness to work for the union	Similar	0.931	0.799; 1.062	0.199	0.087; 0.312	–0.312	–0.422; -0.202	–1.187	–1.353; –1.021
		Variance	CI	Variance	CI	Variance	CI	Variance	CI
Loyalty to the union	Wave 1 & 2	0.158	0.116; 0.201	0.068	0.044; 0.092	0.139	0.109; 0.169	0.377	0.264; 0.491
	Wave 3	0.277	0.167; 0.386	0.046	0.032; 0.059	0.085	0.063; 0.108	0.860	0.514; 1.205
Responsibility to the union	Wave 1 & 2	0.311	0.213; 0.410	0.116	0.057; 0.174	0.288	0.192; 0.383	0.623	0.456; 0.790
	Wave 3	0.343	0.254; 0.431	0.024	0.018; 0.03	0.045	0.029; 0.061	1.135	0.630; 1.640
Willingness to work for the union	Wave 1 & 2	0.372	0.241; 0.502	0.099	0.073; 0.125	0.129	0.074; 0.184	0.263	0.183; 0.343
	Wave 3	0.539	0.361; 0.718	0.130	0.098; 0.162	0.168	0.117; 0.218	0.689	0.325; 1.053

Notes: CI = 95% confidence interval.

12. Mplus Input to Estimate a 4-Class Latent Profile Analysis (Time 1)

```
! In all input files, statements preceded by ! are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled Unionprofile.dat.
DATA:
FILE IS Unionprofile.dat;
! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevariable command identifies the variables used in the analysis.
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1 UCW1;
! The following identifies the unique identifier for participants
IDVARIABLE = ID;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
! The following set up is to estimate the model using 3 processors, 3000 starts values, 100 final stage
optimizations, and 100 iterations.
process = 3;
STARTS = 3000 100;
STITERATIONS = 100;
! In this input, the overall model statement defines sections that are common across profiles.
! Here, there is no need to include anything in this section.
! The %c#1% to %c#5% sections are class-specific statement to specify which part of the
! model is freely estimated in each profile.
! For a simple latent profile model, include the means of the indicators (using []) in all profiles.
! To also freely estimate all variances, add the following in each class-specific statement:
! UCL1 UCR1 UCW1;
MODEL:
%OVERALL%
%c#1%
[UCL1 UCR1 UCW1];
UCL1 UCR1 UCW1;
%c#2%
[UCL1 UCR1 UCW1];
UCL1 UCR1 UCW1;
%c#3%
[UCL1 UCR1 UCW1];
UCL1 UCR1 UCW1;
%c#4%
[UCL1 UCR1 UCW1];
UCL1 UCR1 UCW1;
! Specific sections of output are requested. TECH11 estimates LMR, and TECH14 estimates BLRT.
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

13. Mplus Input to Estimate a Configural Similarity Model for a Longitudinal Latent Profile Analysis

```
! Annotations only focus on functions not previously defined.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3;
IDVARIABLE = ID;
! The following identifies the number of latent profiles (4) requested in the analysis
! One latent profile variable (c1, c2, c3) is required for each specific time wave.
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ; ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
! In this input, the statements included in the overall model statement indicates that employees can
! make a transition from one profile to the other across adjacent time points.
! Then, subsections corresponding to the various latent profile variables (one per time waves;
! MODEL C1 to C3).
! The labels in parentheses are used to impose equality constraints on parameters (parameters
! with the same labels are constrained to equality). Here, no equality constraint is added.
Model:
%OVERALL%
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](mb1-mb3); UCL2 UCR2 UCW2(vb1-vb3);
%c2#2%
[UCL2 UCR2 UCW2](mb4-mb6); UCL2 UCR2 UCW2(vb4-vb6);
%c2#3%
[UCL2 UCR2 UCW2](mb7-mb9); UCL2 UCR2 UCW2(vb7-vb9);
%c2#4%
[UCL2 UCR2 UCW2](mb10-mb12); UCL2 UCR2 UCW2(vb10-vb12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](mc1-mc3); UCL3 UCR3 UCW3 (vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](mc4-mc6); UCL3 UCR3 UCW3 (vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](mc7-mc9); UCL3 UCR3 UCW3 (vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW4](mc10-mc12); UCL4 UCR4 UCW4(vc10-vc12);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

14. Mplus Input to Estimate a Structural Similarity Model for a Longitudinal Latent Profile Analysis

! Annotations only focus on functions not previously defined.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
! Labels in bold indicate newly imposed equality constraints on means across time waves.
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](**ma1-ma3**); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](**ma4-ma6**); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](**ma7-ma9**); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](**ma10-ma12**); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](**ma1-ma3**); UCL2 UCR2 UCW2(vb1-vb3);
%c2#2%
[UCL2 UCR2 UCW2](**ma4-ma6**); UCL2 UCR2 UCW2(vb4-vb6);
%c2#3%
[UCL2 UCR2 UCW2](**ma7-ma9**); UCL2 UCR2 UCW2(vb7-vb9);
%c2#4%
[UCL2 UCR2 UCW2](**ma10-ma12**); UCL2 UCR2 UCW2(vb10-vb12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](**ma1-ma3**); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](**ma4-ma6**); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](**ma7-ma9**); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](**ma10-ma12**); UCL3 UCR3 UCW3(vc10-vc12);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

15. Mplus Input to Estimate a Dispersion Similarity Model for a Longitudinal Latent Profile Analysis

! Annotations only focus on functions not previously defined.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
! Labels in bold indicate newly imposed equality constraints on variances across time waves.
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(**va1-va3**);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(**va4-va6**);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(**va7-va9**);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(**va10-va12**);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(**va1-va3**);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(**va4-va6**);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(**va7-va9**);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(**va10-va12**);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(**va1-va3**);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(**va4-va6)**;
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(**va7-va9**);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

16. Mplus Input to Estimate a Partial Dispersion Similarity Model for a Longitudinal Latent Profile Analysis

! Annotations only focus on functions not previously defined.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3 BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3 SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
! Labels in bold indicate that equality constraints on Wave 3 variances have been taken out.
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(**vc1-vc3**);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(**vc4-vc6)**;
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(**vc7-vc9**);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

17. Mplus Input to Estimate a Distribution Similarity Model for a Longitudinal Latent Profile Analysis

! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1 UCW1 UCL2 UCR2 UCW2 UCL3 UCR3 UCW3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
! The additions in bold (in %Overall%) constrain class sizes to be equivalent across time waves.
! c1, c2, c3 refer to the various latent profile variables (for each time waves), whereas #1, #2, #3
! refer to the specific profile in this model. One less statement than the number of profiles is needed.
MODEL:
%OVERALL%
[c1#1] (p1); [c1#2] (p2); [c1#3] (p3);
[c2#1] (p1); [c2#2] (p2); [c2#3] (p3);
[c3#1] (p1); [c3#2] (p2); [c3#3] (p3);
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT: STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;

18. Mplus Input to Convert the Final Partial Dispersion Similarity Model to the Latent Transition Analysis Context

```
! Annotations only focus on functions not previously defined.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
! The line of code below is sufficient to request a complete LTA model, with profile
! membership at Time t allowed to predict profile membership at Time t+1.
! The situation would be more complex if the model of distributional similarity had
! was retained. For a detailed presentation of the approach to adopt in this specific
! circumstance, see Morin and Litalien (2017: http://smslabstats.weebly.com/webnotes.html)
c2 on c1; c3 on c2;
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

19. Mplus Input to Estimate a Latent Transition Analysis with Predictors Freely Estimated across Time Waves and Profiles

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
! To ensure stability, starts values from the previously most similar solution should be used.
DATA: FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 SFA1 SQUMR1 BIGL2 UNINST2 SFA2 SQUMR2
BIGL3 UNINST3 SFA3 SQUMR3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE; ESTIMATOR = MLR; process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c2 on c1; c3 on c2;
! The following statements indicate that class membership at each specific time wave is predicted by
! the predictors. The prediction of C2 and C3 is also allowed to be profile specific.
C1 ON BIGL1 UNINST1 SFA1 SQUMR1;
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
MODEL C3:
%c3#1%
```

```
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

20. Mplus Input to Estimate a Latent Transition Analysis with Predictors Freely Estimated across Time Waves

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
! To ensure stability, starts values from the previously most similar solution should be used.
DATA: FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 SFA1 SQUMR1 BIGL2 UNINST2 SFA2 SQUMR2
BIGL3 UNINST3 SFA3 SQUMR3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ; ESTIMATOR = MLR; process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c2 on c1; c3 on c2;
! The following statements indicate that class membership at each specific time wave is predicted by
! the predictors.
C1 ON BIGL1 UNINST1 SFA1 SQUMR1;
C2 on BIGL2 UNINST2 SFA2 SQUMR2;
C3 on BIGL3 UNINST3 SFA3 SQUMR3;
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

21. Mplus Input to Estimate a Predictive Similarity Latent Transition Analysis

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
! To ensure stability, starts values from the previously most similar solution should be used.
DATA: FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 SFA1 SQUMR1 BIGL2 UNINST2 SFA2 SQUMR2
BIGL3 UNINST3 SFA3 SQUMR3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ; ESTIMATOR = MLR; process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
MODEL:
%OVERALL%
c2 on c1; c3 on c2;
! The following statements constrain the predictions to be equal across time waves (one less label
! than profiles)
C1 ON BIGL1(bi1-bi3);
C1 on UNINST1(un1-un3);
C1 on SFA1(sf1-sf3);
C1 on SQUMR1(sq1-sq3);
C2 ON BIGL2(bi1-bi3);
C2 on UNINST2(un1-un3);
C2 on SFA2(sf1-sf3);
C2 on SQUMR2(sq1-sq3);
C3 ON BIGL3(bi1-bi3);
C3 on UNINST3(un1-un3);
C3 on SFA3(sf1-sf3);
C3 on SQUMR3(sq1-sq3);
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
MODEL C3:
%c3#1%
```

```
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

22. Mplus Input to Estimate a Latent Transition Analysis with Outcomes Levels Freely Estimated across Time Waves

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
! To ensure stability, starts values from the previously most similar solution should be used.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
UCBI2 UCBO2 UCBI2 UCBO3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
! The additions in bold request the free estimation of the outcomes means in each profile
! Remember that outcomes are only assessed at Waves 2 and 3.
MODEL:
%OVERALL%
c2 on c1; c3 on c2;
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
   [UCBI2](aa1); [UCBO2](ab1);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
   [UCBI2](aa2); [UCBO2](ab2);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
   [UCBI2](aa3); [UCBO2](ab3);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
   [UCBI2](aa4); [UCBO2](ab4);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
   [UCBI3](ba1); [UCBO3](bb1);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
   [UCBI3](ba2); [UCBO3](bb2);
```

```
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
    [UCBI3](ba3); [UCBO3](bb3);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
    [UCBI3](ba4); [UCBO3](bb4);
! The model constraint function uses the labels used with the outcomes to request mean level
comparisons on the outcomes across profiles.
MODEL CONSTRAINT:
NEW (yaa12); yaa12 = aa1-aa2;
NEW (yaa13); yaa13 = aa1-aa3;
NEW (yaa14); yaa14 = aa1-aa4;
NEW (yaa23); yaa23 = aa2-aa3;
NEW (yaa24); yaa24 = aa2-aa4;
NEW (yaa34); yaa34 = aa3-aa4;
NEW (yab12); yab12 = ab1-ab2;
NEW (yab13); yab13 = ab1-ab3;
NEW (yab14); yab14 = ab1-ab4;
NEW (yab23); yab23 = ab2-ab3;
NEW (yab24); yab24 = ab2-ab4;
NEW (yab34); yab34 = ab3-ab4;
NEW (yba12); yba12 = ba1-ba2;
NEW (yba13); yba13 = ba1-ba3;
NEW (yba14); yba14 = ba1-ba4;
NEW (yba23); yba23 = ba2-ba3;
NEW (yba24); yba24 = ba2-ba4;
NEW (yba34); yba34 = ba3-ba4;
NEW (ybb12); ybb12 = bb1-bb2;
NEW (ybb13); ybb13 = bb1-bb3;
NEW (ybb14); ybb14 = bb1-bb4;
NEW (ybb23); ybb23 = bb2-bb3;
NEW (ybb24); ybb24 = bb2-bb4;
NEW (ybb34); ybb34 = bb3-bb4;
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

23. Mplus Input to Estimate an Explanatory Similarity Latent Transition Analysis

```
! Annotations only focus on functions not previously defined.
! This model builds from the model of partial dispersion similarity
! To ensure stability, starts values from the previously most similar solution should be used.
DATA:
FILE IS Unionprofile.dat;
VARIABLE:
NAMES = ID UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
BIGL1 UNINST1 BIGL2 UNINST2 BIGL3 UNINST3 SFA1 SQUMR1 SFA2 SQUMR2 SFA3
SQUMR3 UCBI2 UCBO2 UCBI3 UCBO3;
USEVARIABLES = UCL1 UCR1  UCW1 UCL2  UCR2 UCW2 UCL3  UCR3 UCW3
UCBI2 UCBO2 UCBI2 UCBO3;
IDVARIABLE = ID;
CLASSES = c1 (4) c2 (4) c3 (4);
Analysis:
TYPE = MIXTURE ;
ESTIMATOR = MLR;
process = 3;
STARTS = 10000 500; STITERATIONS = 1000;
! The additions in bold constrain outcome levels to be equivalent across time waves.
MODEL:
%OVERALL%
c2 on c1; c3 on c2;
MODEL C1:
%c1#1%
[UCL1 UCR1 UCW1](ma1-ma3); UCL1 UCR1 UCW1(va1-va3);
%c1#2%
[UCL1 UCR1 UCW1](ma4-ma6); UCL1 UCR1 UCW1(va4-va6);
%c1#3%
[UCL1 UCR1 UCW1](ma7-ma9); UCL1 UCR1 UCW1(va7-va9);
%c1#4%
[UCL1 UCR1 UCW1](ma10-ma12); UCL1 UCR1 UCW1(va10-va12);
MODEL C2:
%c2#1%
[UCL2 UCR2 UCW2](ma1-ma3); UCL2 UCR2 UCW2(va1-va3);
    [UCBI2](aa1); [UCBO2](ab1);
%c2#2%
[UCL2 UCR2 UCW2](ma4-ma6); UCL2 UCR2 UCW2(va4-va6);
   [UCBI2](aa2); [UCBO2](ab2);
%c2#3%
[UCL2 UCR2 UCW2](ma7-ma9); UCL2 UCR2 UCW2(va7-va9);
    [UCBI2](aa3); [UCBO2](ab3);
%c2#4%
[UCL2 UCR2 UCW2](ma10-ma12); UCL2 UCR2 UCW2(va10-va12);
    [UCBI2](aa4); [UCBO2](ab4);
MODEL C3:
%c3#1%
[UCL3 UCR3 UCW3](ma1-ma3); UCL3 UCR3 UCW3(vc1-vc3);
    [UCBI3](aa1); [UCBO3](ab1);
%c3#2%
[UCL3 UCR3 UCW3](ma4-ma6); UCL3 UCR3 UCW3(vc4-vc6);
    [UCBI3](aa2); [UCBO3](ab2);
%c3#3%
[UCL3 UCR3 UCW3](ma7-ma9); UCL3 UCR3 UCW3(vc7-vc9);
```

```
    [UCBI3](aa3); [UCBO3](ab3);
%c3#4%
[UCL3 UCR3 UCW3](ma10-ma12); UCL3 UCR3 UCW3(va10-va12);
    [UCBI3](aa4); [UCBO3](ab4);
! The model constraint function uses the labels used with the outcomes to request mean level
comparisons on the outcomes across profiles.
MODEL CONSTRAINT:
NEW (yaa12); yaa12 = aa1-aa2;
NEW (yaa13); yaa13 = aa1-aa3;
NEW (yaa14); yaa14 = aa1-aa4;
NEW (yaa23); yaa23 = aa2-aa3;
NEW (yaa24); yaa24 = aa2-aa4;
NEW (yaa34); yaa34 = aa3-aa4;
NEW (yab12); yab12 = ab1-ab2;
NEW (yab13); yab13 = ab1-ab3;
NEW (yab14); yab14 = ab1-ab4;
NEW (yab23); yab23 = ab2-ab3;
NEW (yab24); yab24 = ab2-ab4;
NEW (yab34); yab34 = ab3-ab4;
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```