



Understanding change in social-movement participation: the roles of social norms and group efficacy

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Online Appendices

Understanding change in social movement participation: the roles of social norms and group efficacy

Online Appendix S1. Unidirectional forward and reverse models, with measurement invariance tests

A series of four cross-lagged longitudinal panel models were conducted in total. The baseline model consisted only of the autoregressive relationships between constructs across each wave. The second model additionally included the hypothesised unidirectional forward paths from norms to group efficacy, and from group efficacy to social movement participation across consecutive waves. In the third model, the unidirectional reverse paths from participation in social movements to group efficacy, and from group efficacy to social norms replaced the forward paths. The final model estimated both forward and reverse paths simultaneously.

To test stationarity, which assumes stability of the relationships between constructs over time (Cole & Maxwell, 2003), paths estimated between T1 and T2, T2 and T3, and T1 and T3 are first estimated freely, and these models are then systematically compared with models in which these paths are constrained to be equal. When the CFI and RMSEA fit indices of constrained models do not differ substantially in comparison to models in which paths are estimated freely, the constrained models are retained and interpreted. Rutkowski and Svetina (2014) recommend that in samples greater than 300, path constraint should not lead to a decrease in CFI greater than .02, or an increase in RMSEA of more than .03. Although the scaled chi-square difference test (Satorra & Bentler, 2001) is traditionally used to compare constrained and freely estimated models, this test is highly sensitive when sample sizes are large, resulting in statistically significant differences when meaningful changes are

negligible (Rutkowski & Svetina, 2014; Chen, 2007). Furthermore, as standardised estimates can result in inaccurate parameter estimates and standard errors, unstandardised parameter estimates are reported throughout (Cole & Maxwell, 2003).

Autoregressive longitudinal models. In order to test the basic longitudinal model – whether constructs are predictive of themselves across time – the first model (Table S1.1, model 1a and 1b) estimated the first-order autoregressive relationships between constructs across consecutive waves, and second-order autoregressive relationships between waves one and three, for norms, group efficacy and participation. These paths were first estimated freely (1a), and then constrained to be equal over time (1b). All paths were positive and significant ($p < .05$), and this constrained model did not differ substantially in fit to the freely-estimated model ($\Delta\text{CFI} = .001$, $\Delta\text{RMSEA} = -.007$, see Table S1.1). This illustrates construct stability over time. Autoregressive paths were therefore constrained in all subsequent models.

Unidirectional forward longitudinal models. Building on the constrained autoregressive model, paths were included to estimate the hypothesised relationships between norms and group efficacy, and between group efficacy and social movement participation across consecutive waves. The indirect effect of norms on participation through group efficacy was also estimated. The hypothesised forward paths were first freely estimated (Table S1.1, model 2a), and subsequently constrained (model 2b) so that paths between norms and group efficacy, and between group efficacy and social movement participation, were equated between T1 to T2, and T2 to T3. In this constrained model, all paths were significant ($p < .05$), and the fit did not substantially decrease compared to model 2a (see Table S1.1).

In the next model, first-order direct effects were added from norms to social movement participation across consecutive waves (model 2c), in addition to the constrained

autoregressive and forward paths estimated in model 2b. The constraining of these direct paths to be equal across time (model 2d) did not substantially decrease model fit, which remained adequate (see Table S1.1). All paths were significant ($p < .05$), including the indirect effect (see Table S1.2). Therefore, this direct-indirect model 2d was retained.

These results indicate that perceiving one's close social networks as frequently participating in a valued social movement significantly influences respondents' own participation in valued social movements across subsequent years, irrespective of the influence of prior participation. These relationships operate both directly and indirectly via an increased belief in the efficacy of the movement, providing support for hypotheses one and two.

Unidirectional reverse longitudinal models. To examine the veracity of the reverse causal relationships, the forward paths in models 2a-d were replaced with reverse paths. First, building on the constrained autoregressive paths, relationships were estimated from participation in social movements to group efficacy, and from group efficacy to social norms across consecutive waves. Additionally, the indirect effect from participation to norms through efficacy was estimated. Reverse paths were first estimated freely (model 3a) and subsequently constrained to be equal across time (model 3b). Constraining these paths did not result in a substantially lower model fit (see Table S1.1). In both unconstrained and constrained models, paths from group efficacy to norms were not significant from either T1 to T2 or T2 to T3. In the unconstrained model, the path between participation in social movements and group efficacy from T2 to T3 was additionally not significant. The indirect relationship between participation and norms through group efficacy was not significant in either model (see Table S1.2). Direct reverse paths were next added from social movement participation to norms across consecutive waves. Again, these paths were first estimated freely (model 3c) and then equality constraints were imposed (model 3d). The direct paths

were significant in both models, and constraining these paths did not substantially decrease model fit. Both models showed good fit (see Table S1.1). The addition of constrained direct paths did, however, significantly increase the CFI index of model fit in comparison to model 3b ($\Delta\text{CFI} = -.023$, $\Delta\text{RMSEA} = .010$). The best unidirectional forward model 2d and the best unidirectional reverse model 3d did not substantially differ with respect to their model fit ($\Delta\text{CFI} = -.001$, $\Delta\text{RMSEA} = .001$). Therefore, both models are retained, and a bidirectional model is next estimated.

Bidirectional longitudinal models. The unidirectional forward and reverse models were combined in order to test whether the relationship between norms and social movement participation, and the indirect effect through group efficacy can be best considered recursive or unidirectional. First, in addition to the constrained autoregressive paths, forward and reverse paths were included and estimated freely (model 4a). Indirect effects were also estimated. The constraint of the forward and reverse paths to be equal across time (model 4b) did not substantially decrease model fit. This model was a good fit to the data, and indicated significance of the autoregressive paths, forward paths and forward indirect effect ($p < .05$). The reverse paths were not significant, nor was the reverse indirect effect ($p > .05$). Next, direct forward and reverse paths were included and freely estimated (model 4c). The model fit did not substantially decrease when these direct paths were constrained (model 4d). Thus, this fully constrained model was maintained (see Figure 1). This final model demonstrated good fit (see Table S1.1). In addition to significant autoregressive paths, all forward paths were significant (see Table 2). Of the reverse paths, only the direct reverse paths were significant ($p < .05$). The forward indirect effect was additionally significant ($p = .039$, see Table S1.2). The fully constrained bidirectional model 4d did not significantly improve or worsen the fit of the model compared with either the fully constrained forward or reverse models 2d or 3d (see Table S1.1).

Table S1.1. *Fit indices of longitudinal cross-lagged models*

Model	Model Fit	Model Comparison	CFI & RMSEA Change
1a	$\chi^2(18)=132.177, p<.001$; CFI=.946; RMSEA=.044; SRMR=.067		
1b	$\chi^2(24)=136.265, p<.001$; CFI=.947; RMSEA=.037; SRMR=.069	1b vs. 1a	$\Delta CFI = .001$; $\Delta RMSEA = -.007$
2a	$\chi^2(20)=106.520, p<.001$; CFI=.959; RMSEA=.036; SRMR=.056		
2b	$\chi^2(22)=109.532, p<.001$; CFI=.959; RMSEA=.035; SRMR=.056	2b vs. 2a	$\Delta CFI = .000$; $\Delta RMSEA = -.001$
2c	$\chi^2(20)=80.772, p<.001$; CFI=.971; RMSEA=.030; SRMR=.038		
2d	$\chi^2(21)=81.301, p<.001$; CFI=.972; RMSEA=.029; SRMR=.038	2d vs. 2c	$\Delta CFI = .001$; $\Delta RMSEA = -.001$
		2d vs. 2b	$\Delta CFI = -.013$; $\Delta RMSEA = .006$
		2d vs 1b	$\Delta CFI = -.025$; $\Delta RMSEA = .008$
3a	$\chi^2(20)=126.378, p<.001$; CFI=.950; RMSEA=.040; SRMR=.063		
3b	$\chi^2(22)=128.184, p<.001$; CFI=.950; RMSEA=.038; SRMR=.063	3b vs. 3a	$\Delta CFI = .000$; $\Delta RMSEA = -.002$
3c	$\chi^2(20)=78.364, p<.001$; CFI=.973; RMSEA=.030; SRMR=.040		
3d	$\chi^2(21)=77.759, p<.001$; CFI=.973; RMSEA=.028; SRMR=.040	3d vs. 3c	$\Delta CFI = .000$; $\Delta RMSEA = -.002$
		3d vs. 3b	$\Delta CFI = -.023$; $\Delta RMSEA = .010$
		3d vs 2d	$\Delta CFI = -.001$; $\Delta RMSEA = .001$
		3d vs 1b	$\Delta CFI = -.026$; $\Delta RMSEA = .009$
4a	$\chi^2(16)=100.667, p<.001$; CFI=.960; RMSEA=.040; SRMR=.054		
4b	$\chi^2(20)=105.843, p<.001$; CFI=.960; RMSEA=.036; SRMR=.055	4b vs. 4a	$\Delta CFI = .000$; $\Delta RMSEA = -.004$
4c	$\chi^2(16)=34.024, p=.005$; CFI=.992; RMSEA=.018; SRMR=.018		
4d	$\chi^2(18)=41.504, p=.001$; CFI=.989; RMSEA=.020; SRMR=.021	4d vs. 4c	$\Delta CFI = -.003$; $\Delta RMSEA = .002$
		4d vs. 4b	$\Delta CFI = -.029$; $\Delta RMSEA = .016$
		4d vs 3d	$\Delta CFI = -.016$; $\Delta RMSEA = .008$
		4d vs 2d	$\Delta CFI = -.017$; $\Delta RMSEA = .009$
		4d vs 1b	$\Delta CFI = -.042$; $\Delta RMSEA = .017$

Note. CFI = comparative fit index; RMSEA = root-mean-square error of approximation; SRMR = standardized root-mean-square residual; 1a = autoregressive model (freely estimated parameters); 1b = autoregressive model (within construct path equivalence); 2a = unidirectional forward model: predictor → mediator → outcome (freely estimated parameters); 2b = unidirectional forward model (within construct path equivalence); 2c = unidirectional forward model (within construct path equivalence) and freely estimated first order direct paths; predictor → outcome; 2d = unidirectional forward model and

first order direct paths (all within construct path equivalence); 3a = unidirectional backward model: outcome → mediator → predictor (freely estimated parameters); 3b = unidirectional backward model (within construct path equivalence); 3c = unidirectional backward model (within construct path equivalence) and freely estimated first order direct paths; outcome → predictor; 3d = unidirectional backward model and first order direct paths (all within construct path equivalence); 4a bidirectional model (paths freely estimated); 4b bidirectional model (within construct path equivalence for new paths); 4c = bidirectional model with freely estimated first-order direct paths; 4d = bidirectional model with first-order direct paths (all within construct path equivalence).

Table S1.2. *Significance of the mediation effects*

						95% Confidence interval	
	T1	T2	T3	Indirect Effect (b)	p	Lower limit	Upper limit
Forward Model (2d)							
Total effect	Norms		Participation in social movements	0.061	<.001	0.039	0.084
Total indirect effect	Norms		Participation in social movements	0.061	<.001	0.039	0.084
Specific indirect effect	Norms	Group efficacy	Participation in social movements	0.005	.017	0.001	0.009
Backward Model (3d)							
Total effect	Participation in social movements		Norms	0.065	<.001	0.044	0.086
Total indirect effect	Participation in social movements		Norms	0.065	<.001	0.044	0.086
Specific indirect effect	Participation in social movements	Group efficacy	Norms	-0.001	.403	-0.004	0.001
Bidirectional Model (4d)							
Total effect	Norms		Participation in social movements	0.050	<.001	0.029	0.070
Total indirect effect	Norms		Participation in social movements	0.050	<.001	0.029	0.070
Specific indirect effect	Norms	Group efficacy	Participation in social movements	0.005	.039	0.000	0.011
Total effect	Participation in social movements		Norms	0.057	<.001	0.037	0.077
Total indirect effect	Participation in social movements		Norms	0.057	<.001	0.037	0.077
Specific indirect effect	Participation in social movements	Group efficacy	Norms	0.000	.695	-0.001	0.001

Note. Unstandardized coefficients.

Online Appendix S2. Bidirectional cross-lagged panel model excluding ‘refreshed’ sample

The fully constrained bidirectional model was conducted again, excluding the 1,519 participants in the ‘refreshed’ sample. As in the original model, the hypothesised forward paths, and the direct reverse paths were significant (see Table S2.1). The indirect path from social norms to participation through group efficacy did not reach significance, however ($b = .004$, $p = .059$, 95% CI [.00, .01]). Again, there was no significant reverse indirect effect ($p > .05$). This model displayed good fit ($\chi^2(18) = 40.477$, $p = .002$; CFI = .987; RMSEA = .023; SRMR = .021).

Table S2.1. *Estimated paths and significance values for the model excluding ‘refreshed’ sample*

Equated paths		95% Confidence interval			
Predictor	Outcome	b	p	Lower limit	Upper limit
Norms	Norms	0.190	<.001	0.154	0.225
Group Efficacy	Group Efficacy	0.113	<.001	0.074	0.153
Participation in social movements	Participation in social movements	0.230	<.001	0.196	0.265
Norms	Group Efficacy	0.076	.002	0.028	0.124
Norms	Participation in social movements	0.100	<.001	0.053	0.148
Group Efficacy	Participation in social movements	0.059	.017	0.011	0.108
Group Efficacy	Norms	0.010	.702	-0.039	0.059
Participation in social movements	Norms	0.128	<.001	0.082	0.174
Participation in social movements	Group Efficacy	0.005	.831	-0.040	0.050

Note: Unstandardised estimates. As paths from T_1 to T_2 and T_2 to T_3 are equated, unstandardised coefficients, p -values and confidence intervals are equal across time.
N = 2,437

Online Appendix S3. Bidirectional cross-lagged panel model with age and education as covariates

The bidirectional model was additionally conducted with the inclusion of covariance between age and educational attainment and the model variables at Time 1. Again, the hypothesised forward paths, and the direct reverse paths were significant (see Table S3.1). The forward indirect path through group efficacy was also significant ($b = .005$, $p = .040$, 95% CI [.00, .01]). Furthermore, there was no significant reverse indirect effect ($p > .05$). The fit of this model, however, was poor in comparison to the original model ($\chi^2(31) = 453.292$, $p < .001$; CFI = .849; RMSEA = .060; SRMR = .066).

Table S3.1. *Estimated paths and significance values for model including age and education as covariates*

Equated paths		95% Confidence interval			
Predictor	Outcome	b	p	Lower limit	Upper limit
Norms	Norms	0.193	<.001	0.159	0.227
Group Efficacy	Group Efficacy	0.119	<.001	0.079	0.159
Participation in social movements	Participation in social movements	0.237	<.001	0.204	0.271
Norms	Group Efficacy	0.084	.001	0.035	0.133
Norms	Participation in social movements	0.108	<.001	0.062	0.154
Group Efficacy	Participation in social movements	0.065	.010	0.016	0.115
Group Efficacy	Norms	0.014	.579	-0.035	0.063
Participation in social movements	Norms	0.135	<.001	0.090	0.180
Participation in social movements	Group Efficacy	0.013	.568	-0.032	0.059

Note: Unstandardised estimates. As paths from T_1 to T_2 and T_2 to T_3 are equated, unstandardised coefficients, p -values and confidence intervals are equal across time. Parameters are estimated when controlling for covariance with age and educational attainment at T_1