Supplemental Materials for:

Are commitment profiles stable and predictable? A latent transition analysis

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(1) Confirmatory Factor Analytic Models of Mayer et al. (1995) trustworthiness scale.

Confirmatory factor analytic models based on the Mayer et al. (1995) trustworthiness scale were estimated using Mplus 6.12 (Muhtén & Muthén, 2011) and 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 (e.g., Beauducel & Herzberg, 2006; DiStephano, 2002; Dolan, 1994; Lei, 2009; Rhemtulla, Brosseau-Liard, & Savalei, 2012). Missing data were handled with Full Information Maximum Likelihood (FIML) estimation (Enders, 2001, 2010; Enders & Bandalos, 2001; Graham, 2009; Larsen, 2011; Little & Rubin, 1987; Schafer, 1997; Shin, Davidson, & Long, 2009). See the main manuscript for additional details on this procedure.

First, a longitudinal model, which includes 12 factors, was first estimated to reflect the three dimensions of trustworthiness (ability, benevolence, integrity) * two sources of trustworthiness (top management and immediate supervisor) * two measurement points. Although the use of ex-post facto correlated uniquenesses (CUs) should generally be avoided (e.g., Marsh, 2007), there are circumstances in which a priori CUs need to be included in measurement models to reflect the fact that the unique part of a specific item is likely to be shared with other items due to methodological artifacts (Jöreskog, 1979; Marsh & Hau, 1996):

(1) A common case is a self-report instrument including positively and negatively worded items. For such instruments, it is typical to find method effects associated item wording (DiStefano & Motl, 2006; Marsh, Scalas & Nagengast, 2010).
(2) Another common case is longitudinal research where correlated uniquenesses need to be posited a priori between matching indicators that are used at the different time points (Jöreskog, 1979; Marsh & Hau, 1996).
(3) Finally, when more than one construct is assessed with matching items, as is the case for the items used to measure top management versus immediate supervisor trustworthiness, correlated uniquenesses similarly need to be included between matching indicators of both constructs (Marsh & Hau, 1996).

In these cases, failure to include these correlated uniquenesses, which appropriately reflect any method artefacts present in the data, has been shown to result in positively biased estimates of stability and distorted, usually inflated, estimates of the parameters (Marsh, Martin & Debus, 2001; Marsh, Nagengast, et al., 2011; Marsh, Parada & Ayotte, 2004). For instance, failure to include longitudinal correlated uniquenessess among matching/repeated indicators will inflate test-retest correlations and estimated of the longitudinal stability of the constructs of interest. For the measures of trustworthiness, two types of correlated uniquenesses needed to be a priori incorporated to the measurement model: (a) longitudinal correlated uniquenesses among matching indicators and (b) correlated uniquenesses among matching top management and supervisor indicators.

Assessment of model fit was based on multiple indicators (Hu & Bentler, 1999; Marsh, Hau, & Grayson, 2005): the chi-square (χ^2), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), the 90% confidence interval of the RMSEA, and the standardized root mean square residual (SRMR). 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 and than .10 and .08 for the SRMR support respectively acceptable and good model fit.

The results from this model presented an adequate level of fit to the data (see Supplemental Table S1 at the end of this appendix). However, an examination of the parameters estimated from this model revealed that the within-source (e.g., for top management) within-time point (e.g., for time 1) correlations among the different facets of trustworthiness were so high as to call into question their discriminant validity and to suggest potentially serious problems of multicollinearity in subsequent analyses. For instance, the Time 1 correlations between the three facets of trustworthiness varied between .799 and .945 for the immediate supervisor and between .754 and .900 for the top management. Comparable figures for Time2 varied between .839 and .957 for the immediate supervisor and between .706 and .900 for the top management. However, when these different facets were collapsed into a single factor of trust per source and time point, the resulting 4-factor model clearly did not present an adequate level of fit to the data. Alternatively, we allowed these three facets of trustworthiness to load on a higher-order factor of trustworthiness for each source and measurement point (resulting in four higher-order factors). The resulting model (1) fit the data well, (2) showed a level of fit comparable to that of the first-order factor model differentiating the different facets of trustworthiness without specifying them as alternate indicator of a higher-order trustworthiness factor, and (3) did not suggest any problem of multicollinearity linked to the higher-order factor.

However, before saving these factor scores in order to use them as predictors in the main latent transition analyses, we wanted to compute change scores between time 1 and time 2 levels of trustworthiness in order to fully answer our research questions. However, change scores rely on strong assumptions of measurement invariance. In other words, before being able to refer to longitudinal changes in the levels of a construct of interest, one must first be able to demonstrate that the meaning (and underlying measurement model) of that construct did not switch over time. We thus conducted tests of longitudinal invariance of this higher order measurement model, following recommendations from Meredith (1993) for first order factor models, as adapted by Cheung (2008) for higher order factor models. The measurement invariance of the first-order factor model was estimated first, without a second-order latent construct (Cheung, 2008), in the following sequence: (i) configural invariance, (ii) loadings invariance (metric invariance), (iii) loadings and intercepts invariance (strong invariance), (iv) loadings, intercepts and uniquenesses invariance (strict invariance). Then, the invariance of the second-order structure was verified in the following sequence, with the baseline specified according to the conclusions of the preceding sequence: (i) baseline; (ii) second-order loadings invariance; (iii) second-order loadings and intercepts invariance; (iv) second-order loadings, intercepts and disturbances invariance. In each sequence of invariance the preceding model served as reference.

Tests of measurement invariance were evaluated by the examination of robust χ^2 difference tests[1]. However, recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). Indeed, these studies suggest that those additional indices tend to be more trustworthy than chi-square difference tests that present the same limitations as the chi square. Here, chi square differences tests are reported but changes in fit indices will be more closely inspected. A ΔCFI of .01 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. It should also be noted that for indices incorporating a penalty for lack of parsimony such as the TLI and RMSEA, it is possible for a more restrictive model to result in better fit than a less restricted model; thus changes in TLI should also be inspected (Marsh, Hau et al., 2005). Examinations of the measurement invariance results (see supplemental Table S1) showed that the higher-order measurement model of the trustworthiness scale was fully invariant across time point. In fact, none of the highly sensitive robust χ^2 difference tests are even significant. This longitudinally invariant model was used to estimate the factor scores used in the main analyses. In order to keep the result in meaningful measurement units based on a synthesis of all items forming each factor (rather than based on the units of a single referent indicator or based on standardized units) in a manner directly comparable to aggregate scale scores often used in this area of research, this model was identified using Little, Sledgers and Card (2006) effects coding method which amounts to constraining the non-standardized factor loadings to average 1 within each factors, and

[1] As this study relied on MLR, the scaling correction composite needed to be taken into account in the calculation of chi-square differences tests. These tests were computed as minus two times the difference in the log likelihood of the nested models and are interpreted as chi-square with degrees of freedom equal to the difference in free parameters between both models. The resulting difference then needs to be divided by its scaling correction composite, *cd*, where: (i) $cd = (p0 * co - p1 * c1) / (p0-p1)$; (ii) *p0* and *p1* are the number of free parameters in the nested and comparison models; and (iii) *c0* and *c1* are the scaling correction factors for the nested and comparison models (Muthén & Muthén, 2011; Satorra & Bentler, 1999). We worked from model log likelihoods for greater precision as these statistical indices are less affected by rounding in Mplus.

to constrain the item intercepts to sum to zero within each factor.

However, given that we were interested in changes in trustworthiness levels between time 1 and time 2 rather than in trustworthiness levels themselves, rather than directly output the latent factor scores themselves, we used the higher-order trustworthiness factors to estimate latent change scores in trustworthiness levels over time (for details on this procedure, see McArdle, 2009; for a similar procedure also see Cheung, 2009). Thus, we saved latent change scores representing initial levels (1) and change over time (2) in trustworthiness levels, separately for top management and supervisor. Apart from being better suited to model change, it should be noted that these change score models have identical covariance implications for the data, and thus identical fit statistics and degrees of freedom. It must be noted that the previously demonstrated longitudinal measurement invariance of the full factor model represents an important prerequisite to the use of latent change scores (McArdle, 2009). The input code used to estimate this final, fully invariant higher-order latent change score model and the resulting factor scores is fully reported in the section 5 of this appendix.

(2) Confirmatory Factor Analytic Models of Meyer et al. (1993) organizational commitment scale.

Using methods identical to those described in the preceding section, we used confirmatory factor analytic models on the Meyer et al. (1993) organizational commitment scale in order to verify its factor structure and longitudinal invariance. Thus, we started with a six-factor longitudinal measurement model reflecting the three components of organizational commitment (affective, normative and continuance) * two measurement points. Correlated uniquenesses were posited among negatively worded items, as well as between matching items across time points. The results from the resulting model are reported in Table S1 and confirm the adequacy of the a priori measurement model. Similarly, first order tests of measurement invariance conducted on this model confirmed to full longitudinal invariance of this measurement model. In fact, none of the highly sensitive robust χ^2 difference tests are even significant. This fully invariant model was used to estimate the factor score used in the main analyses, also using the effects coding method described in the previous section. The input code used to estimate this final, fully invariant model and the resulting factor scores is fully reported in the section 6 of this appendix.

(3) Latent Profile Analyses.

Prior to conducting the Latent Transition Analyses (LTA), we first conducted series of latent profile analyses (LPA) (Lazarfeld & Henry, 1968; Muthén, 2001) on the commitment factors based on each separate time points separately and using only the 688 and 625 participants who completed time 1 and time 2 measures, respectively. This was done in order to conduct preliminary tests of whether the latent profiles commonly reported in the literature would also be identified in the present data set, using simpler models than the more complex LTA used in the main manuscript. Also, using both time points separately allowed us to verify the extent to which the extracted latent profiles would be replicated at both time points, and also to ensure that the nature of the latent profiles extracted using only time-specific respondents would converge with the latent profiles extracted using Full Information Maximum Likelihood to handle missing data on the full longitudinal data set.

These analyses were conducted with Mplus 6.12 (Muthén & Muthén, 2011) using the default robust maximum likelihood estimator. LPA postulates that the correlations between the indicators (components of commitment represented by the factor scores obtained in the previous section of these supplemental materials) may be explained by the presence of a categorical latent variable representing qualitatively and quantitatively distinct profiles of employees. By default, Mplus constrained the variance of the indicators (factors scores) to be equal across profiles. However, following Morin, Maïano et al. (2011), we also estimated alternative models in which the variances of the indicators were freely estimated in all latent profiles in order to systematically test these implicit invariance assumptions.

Although previous research has generally yielded five to seven profiles (see Meyer et al., 2012), we examined solutions with up to eight profiles. To avoid the problem of local maxima (i.e., chance selection of a suboptimal solution), we conducted analyses for each model with 2000 random sets of start values to ensure that the best loglikelihood value was adequately replicated. We also increased the default to 100 iterations for these random starts and retained the 100 best solutions for final stage optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000). In the few cases when the best loglikelihood value was still not replicated (i.e. for solutions with 7 or 8 profiles), we increased the random sets of start values until replication could be attained. We continued to increase the number of random start values up to 5000 random sets of start values until the best logliklihood value was reliably replicated, or it was determined that convergence was unlikely.

A challenge in mixture (e.g., LPA, LTA) models is determining the number of profiles in the data. Two important criteria used in this decision are the substantive meaning and theoretical conformity of the extracted profiles (Marsh et al., 2009; Muthén, 2003) as well as the statistical adequacy of the solution (e.g. absence of negative variance estimates; Bauer & Curran, 2003). A number of statistical tests and indices are available to help in this decision process (McLachlan & Peel, 2000). Recent simulation studies indicate that four of these various tests and indicators are particularly effective in choosing the model which best recovers the sample's true parameters in mixture models (Henson et al., 2007; McLachlan & Peel, 2000; Nylund et al., 2007; Tofighi & Enders, 2007; Tolvanen, 2007; Yang, 2006): (i) the Consistent Akaïke Information Criterion (CAIC: Bozdogan, 1987), (ii) the Bayesian Information Criterion (BIC: Schwartz, 1978), (iii) the sample-size Adjusted BIC (SABIC: Sclove, 1987), and (iv) the Bootstrap Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000). Although these simulation studies showed that it had a tendency to support the over-extraction of profiles, we also report the classical Akaïke Information Criterion (AIC: Akaïke, 1987) for consistency with previous studies. A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model. The BLRT is a parametric likelihood ratio test obtained through resampling methods that compares a *k*-profiles model with a *k-1*-profiles model. A significant *p* value indicates that the *k-1*-profiles model should be rejected in favor of a *k*-profiles model. It should be noted that this test is not available for the models reported in the main manuscript. Those studies also show that, when the indicators fail to retain the optimal model, the ABIC and BLRT tend to overestimate the number of profiles, whereas the AIC, BIC and CAIC tend to underestimate it. As a complement, some (Morin, Maïano, et al., 2011; Petras & Masyn, 2010) suggest looking at the pattern of change in these information criteria to find a point where the decreases with additional profiles reach a plateau (i.e. when the decreased become less marked). Finally, the entropy indicates the precision with which the cases are classified into the various profiles. Although the entropy should not in itself be used to determine the model with the optimal number of profiles (Lubke & Muthén, 2007), it provides a useful summary of the classification accuracy. The entropy varies from 0 to 1, with values closer to 1 indicating less classification errors.

The fit indices for the 1 to 8 profiles solutions across the two alternative parameterizations are reported in supplementary Table S2 (at the end of these supplemental materials). First, these results show that, for both time points, the model where the variances are freely estimated in all profiles provide a much better degree of fit to the data as shown by lower AIC, BIC, CAIC, and SABIC for models including the same number of profiles, but differing in whether the variances of the indicators are freely estimated or not in all profiles. Second, these results show that the fit indices (AIC, BIC, CAIC, SABIC) keep on increasing with the addition of profiles, at least up to seven profiles and that the BLRT indicator is not helpful in choosing the optimal number of profiles in the data, which is common in these types of models (e.g., Marsh et al., 2009; Morin, Maïano et al., 2011; Petras & Masyn, 2010). However, examination of the values of the various information criteria, and particularly the BIC and CAIC, shows that decreased in values seemed to reach a plateau at around 5 profiles. Examination of the 5-profile solution, and bordering 4 and 6 profiles solutions shows that the five profiles solution had the greatest level of theoretical conformity, and also results in perfectly replicated solutions at both time points, as shown in Supplementary Table 3 at the end of these supplemental materials. It is also interesting to note that this solution is also perfectly replicated in the LTA models results reported in the main manuscript.

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(5) Mplus input code to estimate the fully invariant higher-order latent change score model for the trustworthiness scales and to save the resulting change scores.

```
TITLE:     Trustworthiness CFA model ;
DATA:      FILE = data.dat;
VARIABLE:
! This section lists the variables in the data file, the variables used in the analysis, the ID variable, and the
! missing data codes.
NAMES =  ID
! time 1 trust in top management items
toc1 toc2 toc3 toc4 toc5 toc6 toc7 toc8 toc9 toc10 toc11 toc12 toc13 toc14 toc15
! time 1 trust in supervisor items
ts1      ts2 ts3 ts4 ts5 ts6 ts7 ts8 ts9 ts10 ts11 ts12 ts13 ts14 ts15
! time 2 trust in top management items
toc1t2 toc2t2 toc3t2 toc4t2 toc5t2 toc6t2  toc7t2 toc8t2 toc9t2 toc10t2 toc11t2 toc12t2 toc13t2
toc14t2 toc15t2
! time 2 trust in supervisor items
ts1t2 ts2t2 ts3t2 ts4t2 ts5t2 ts6t2 ts7t2 ts8t2 ts9t2 ts10t2 ts11t2 ts12t2 ts13t2 ts14t2 ts15t2 ;
USEV =
toc1 toc2 toc3 toc4 toc5 toc6 toc7 toc8 toc9 toc10 toc11 toc12 toc13 toc14 toc15 ts1 ts2 ts3 ts4
ts5 ts6 ts7 ts8 ts9 ts10 ts11 ts12 ts13 ts14 ts15 toc1t2 toc2t2 toc3t2 toc4t2 toc5t2 toc6t2  toc7t2
toc8t2 toc9t2 toc10t2 toc11t2 toc12t2 toc13t2 toc14t2 toc15t2 ts1t2 ts2t2 ts3t2 ts4t2 ts5t2 ts6t2
ts7t2 ts8t2 ts9t2 ts10t2 ts11t2 ts12t2 ts13t2 ts14t2 ts15t2 ;
MISSING = ALL (-999);
IDVAR = ID;

ANALYSIS: ! this section indicates the use of the robust maximum likelihood estimator.
ESTIMATOR = MLR;

MODEL: ! This section presents the model
! parameters with the same code in parentheses are invariant. Please refer to the Mplus manual for
! additional details on CFA model specifications.
!top management
! Time 1 (3 factors at time 1 = ocabi_1, ocben_1, and ocint_1)
ocabi_1 by toc1* (b1)
toc4 toc7 toc9 (b2-b4);
ocben_1 by toc2*  (b5)
toc5 toc10 toc12 (b6-b8);
ocint_1 by toc3*  (b9)
toc6 toc8 toc11 toc13 (b10-b13);
! First order variances = second order disturbances, to be constrained in tests of second order invariances.
ocabi_1* (b300);
ocben_1* (b301);
ocint_1* (b302);
! Time 2
ocabi_2 by toc1t2*  (b1)
toc4t2 toc7t2 toc9t2 (b2-b4);
ocben_2 by toc2t2* (b5)
toc5t2 toc10t2 toc12t2 (b6-b8);
ocint_2 by toc3t2* (b9)
toc6t2 toc8t2 toc11t2 toc13t2 (b10-b13);
```

```
ocabi_2* (b300);
ocben_2* (b301);
ocint_2* (b302);
! Mean structure (means, intercepts) denoted by []
[toc1*] (b20);
[toc4 toc7 toc9] (b21-b23);
[toc2*] (b24);
[toc5 toc10 toc12] (b25-b27);
[toc3*] (b28);
[toc6 toc8 toc11 toc13] (b29-b32);
[ocabi_1*] (b200);
[ocben_1*] (b201);
[ocint_1*] (b202);
[toc1t2*] (b20);
[ toc4t2 toc7t2 toc9t2](b21-b23);
[toc2t2*] (b24);
[toc5t2 toc10t2 toc12t2](b25-b27);
[toc3t2*] (b28);
[toc6t2 toc8t2 toc11t2 toc13t2](b29-b32);
[ocabi_2*] (b200);
[ocben_2*] (b201);
[ocint_2*] (b202);
! First-order uniquenesses
toc1 toc2 toc3 toc4 toc5 (b41-b45);
toc6 toc7 toc8 toc9 toc10 (b46-b50);
toc11 toc12 toc13 (b51-b53);
toc1t2 toc2t2 toc3t2 toc4t2 toc5t2 (b41-b45);
toc6t2 toc7t2 toc8t2 toc9t2 toc10t2 (b46-b50);
toc11t2 toc12t2 toc13t2  (b51-b53);
! Higher order factors at time 1 and time 2
OCTHO1 BY  ocint_1*    (b100)
ocben_1 ocabi_1 (b101-b102);
OCTHO2 BY  ocint_2* (b100)
ocben_2  ocabi_2 (b101-b102);

!Same thing for supervisor
sabi_1 by ts1* (a1)
ts4 ts7 ts9 (a2-a4);
sben_1 by ts2* (a5)
ts5 ts10 ts12 (a6-a8);
sint_1 by ts3* (a9)
ts6 ts8 ts11 ts13 (a10-a13);
sabi_1* (a300);
sben_1* (a301);
sint_1* (a302);
sabi_2 by ts1t2* (a1)
ts4t2 ts7t2 ts9t2 (a2-a4);
sben_2 by ts2t2* (a5)
ts5t2 ts10t2 ts12t2 (a6-a8);
sint_2 by ts3t2* (a9)
ts6t2 ts8t2 ts11t2 ts13t2 (a10-a13);
```

```
sabi_2* (a300);
sben_2* (a301);
sint_2* (a302);
[ts1] (a20);
[ts4 ts7 ts9] (a21-a23);
[ts2] (a24);
[ts5 ts10 ts12](a25-a27);
[ts3] (a28);
[ts6 ts8 ts11 ts13](a29-a32);
[sabi_1*] (a200);
[sben_1*] (a201);
[sint_1*] (a202);
[ts1t2*] (a20);
[ts4t2 ts7t2 ts9t2](a21-a23);
[ts2t2*] (a24);
[ts5t2 ts10t2 ts12t2](a25-a27);
[ts3t2*] (a28);
[ts6t2 ts8t2 ts11t2 ts13t2](a29-a32);
[sabi_2*] (a200);
[sben_2*] (a201);
[sint_2*]  (a202);
ts1 ts2 ts3 ts4 ts5 (a41-a45);
ts6 ts7 ts8 ts9 ts10  (a46-a50);
ts11 ts12 ts13  (a51-a53);
ts1t2 ts2t2 ts3t2 ts4t2 ts5t2 (a41-a45);
ts6t2 ts7t2 ts8t2 ts9t2 ts10t2 (a46-a50);
ts11t2 ts12t2 ts13t2 (a51-a53);
SHO1 BY  sint_1* (a100)
sben_1 sabi_1   (a101-a102);
SHO2 BY   sint_2* (a100)
sben_2 sabi_2 (a101-a102);
! Correlated uniquenesses between matching supervisor + top management items.
toc1 toc2 toc3 toc4 toc5 PWITH ts1 ts2 ts3 ts4 ts5;
toc6 toc7 toc8 toc9 toc10 PWITH ts6 ts7 ts8 ts9 ts10;
toc11 toc12 toc13 PWITH ts11 ts12 ts13 ;
toc1t2 toc2t2 toc3t2 toc4t2 toc5t2 PWITH ts1t2 ts2t2 ts3t2 ts4t2 ts5t2       ;
toc6t2 toc7t2 toc8t2 toc9t2 toc10t2 PWITH ts6t2      ts7t2 ts8t2 ts9t2 ts10t2;
toc11t2 toc12t2 toc13t2 PWITH ts11t2 ts12t2 ts13t2 ;
ocabi_1 ocben_1 ocint_1 PWITH sabi_1 sben_1 sint_1;
ocabi_2 ocben_2 ocint_2 PWITH sabi_2 sben_2 sint_2;
! Longitudinal correlated uniquenesses among matching items.
toc1 toc2 toc3 toc4 toc5 PWITH toc1t2 toc2t2 toc3t2 toc4t2 toc5t2;
toc6 toc7 toc8 toc9  PWITH toc6t2 toc7t2 toc8t2 toc9t2;
toc10 WITH toc10t2;
toc11 toc12 toc13 PWITH toc11t2 toc12t2 toc13t2;
ts1 ts2 ts3 ts4 ts5 PWITH ts1t2 ts2t2 ts3t2 ts4t2 ts5t2;
ts6 ts7 ts8 ts9 ts10 PWITH ts6t2 ts7t2 ts8t2 ts9t2 ts10t2;
ts11 ts12 ts13 PWITH ts11t2 ts12t2 ts13t2;
ocabi_1 ocben_1 ocint_1 PWITH ocabi_2 ocben_2 ocint_2;
sabi_1 sben_1 sint_1 PWITH sabi_2 sben_2 sint_2;
! Latent change score component. See McArdle et al. (2009) for more details.
```

```
MAN1 BY OCTHO1@1;
CHMAN2 BY OCTHO2@1;
OCTHO1@0;
OCTHO2@0;
OCTHO2 ON OCTHO1@1;
MAN1 WITH CHMAN2;
[OCTHO1@0];
[OCTHO2@0];
[MAN1 CHMAN2];
SUP1 BY SHO1@1;
CHSUP2 BY SHO2@1;
SHO1@0;
SHO2@0;
SHO2 ON SHO1@1;
SUP1 WITH CHSUP2;
[SHO1@0];
[SHO2@0];
[SUP1 CHSUP2];
MODEL CONSTRAINT:
! This part used to constrain the loadings to average 1.
b1 = 4 - b2 - b3 - b4;
b5 = 4 - b6 - b7 - b8;
b9 = 5 - b10 - b11 - b12 - b13;
b100 = 3 - b101 - b102;
! This part used to constrain the intercepts to sum to 0.
0 = b20 + b21 + b22 + b23;
0 = b24 + b25 + b26 + b27;
0 = b28 + b29 + b30 + b31 + b32;
0 = b200 + b201 + b202;
! and so on
a1 = 4 - a2 - a3 - a4;
a5 = 4 - a6 - a7 - a8;
a9 = 5 - a10 - a11 - a12 - a13;
a100 = 3 - a101 - a102;
0 = a20 + a21 + a22 + a23;
0 = a24 + a25 + a26 + a27;
0 = a28 + a29 + a30 + a31 + a32;
0 = a200 + a201 + a202;
! Request for some specific output sections.
OUTPUT:    STDYX TECH1  SAMPSTAT SVALUES;
! Request for saving the factor scores in an external file
SAVEDATA:
FILE IS trustfscores.dat;
SAVE = Fscores;
```

(6) Mplus input code to estimate the fully invariant factor model for the commitment scales and to save the resulting change scores.

```
! Previous sections (e.g. variable description) as in the precedent model. See the precedent model for
! input annotations (as the model is similar).
ANALYSIS:
ESTIMATOR = MLR;
MODEL:
!Time 1
ACt1 by oc1* (a1)
oc4 oc7 oc10 roc13 roc16 (a2-a6);
CCt1 by oc2* (a7)
oc5 oc8 oc11 oc14 oc17 (a8-a12);
NCt1 by oc3* (a13)
oc6 oc9 oc12 oc15 oc18 (a14-a18);
ACt1*;
NCt1*;
CCt1*;
[oc1 oc4 oc7 oc10 roc13 roc16] (b1-b6);
[oc2 oc5 oc8 oc11 oc14 oc17] (c1-c6);
[oc3 oc6 oc9 oc12 oc15 oc18] (d1-d6);
[ACt1*];
[NCt1*];
[CCt1*];
oc1 oc4 oc7 oc10 roc13 roc16 (e1-e6);
oc2 oc5 oc8 oc11 oc14 oc17 (f1-f6);
oc3 oc6 oc9 oc12 oc15 oc18 (g1-g6);
!Time 2
ACt2 by oc1t2* (a1)
oc4t2 oc7t2 oc10t2 roc13t2 roc16t2 (a2-a6);
CCt2 by oc2t2* (a7)
oc5t2 oc8t2 oc11t2 oc14t2 oc17t2 (a8-a12);
NCt2 by oc3t2* (a13)
oc6t2 oc9t2 oc12t2 oc15t2 oc18t2 (a14-a18);
ACt2*;
NCt2*;
CCt2*;
[oc1t2 oc4t2 oc7t2 oc10t2 roc13t2 roc16t2](b1-b6);
[oc2t2 oc5t2 oc8t2 oc11t2 oc14t2 oc17t2](c1-c6);
[oc3t2 oc6t2 oc9t2 oc12t2 oc15t2 oc18t2](d1-d6);
[ACt2*];
[NCt2*];
[CCt2*];
oc1t2 oc4t2 oc7t2 oc10t2 roc13t2 roc16t2 (e1-e6);
oc2t2 oc5t2 oc8t2 oc11t2 oc14t2 oc17t2 (f1-f6);
```

```
oc3t2 oc6t2 oc9t2 oc12t2 oc15t2 oc18t2 (g1-g6);
! CUs
roc13 WITH roc16;
roc13t2 WITH roc16t2;
roc13 WITH roc16t2;
roc16 WITH roc13t2 ;
oc1 oc4 oc7  PWITH oc1t2 oc4t2 oc7t2 ;
oc10 roc13 roc16  PWITH oc10t2 roc13t2 roc16t2;
oc2 oc5 oc8 oc11 PWITH oc2t2 oc5t2 oc8t2 oc11t2 ;
oc14 oc17 PWITH oc14t2 oc17t2;
oc3 oc6 oc9 oc12  PWITH oc3t2 oc6t2 oc9t2 oc12t2 ;
 oc15 oc18 PWITH  oc15t2 oc18t2;
MODEL CONSTRAINT:
a1 = 6 - a2 - a3 - a4 - a5 - a6;
a7 = 6 - a8 - a9 - a10 - a11 - a12;
a13 = 6 - a14 - a15 - a16 - a17 - a18;
0 = b1 + b2 + b3 + b4 + b5 + b6;
0 = c1 + c2 + c3 + c4 + c5 + c6;
0 = d1 + d2 + d3 + d4 + d5 + d6;
OUTPUT:    STDYX TECH1  SAMPSTAT SVALUES;
SAVEDATA:
FILE IS Comitfscores.dat;
SAVE = FSCORES;
```

(7) Mplus input code to estimate the latent profile analysis model with indicators' variances invariant across profiles.

```
DATA:     FILE = datfin.dat;
VARIABLE:
NAMES = TIME1 ID sex wktime LEVEL union tenure turnt1 turnt2
MAN1 CHMAN2 SUP1 CHSUP2 FACT1 FCCT1 FNCT1 FACT2 FCCT2 FNCT2;
USEV = FACT1 FNCT1 FCCT1  FACT2 FNCT2 FCCT2;
MISSING = ALL (-999);   IDVAR = ID;
! Use the following section to label the latent categorical variables (profiles)
! C1 refers to the profiles at Time 1 and the model estimates 5 profiles.
CLASSES = c1 (5);
! To select only participants who completed time 1 questionnaires.
USEOBSERVATION = TIME1 EQ 1;
! In the analyses section a mixture (latent transition analysis) model is request, with 2000
! random starts, 200 retained for final optimization and an increase in the defaults iterations.
ANALYSIS:
TYPE = MIXTURE;
STARTS = 2000 200;
STITERATIONS = 100;
PROCESS = 3;
MODEL:
%OVERALL%
! This describes the overall (not profile-specific) part of the model. Here: nothing to include.
! the next section are class specific, and "[FACT1 FNCT1 FCCT1 ]" request the free estimation of
! commitments means in each profile "%c#1%" to "%c#5%".
%c#1%
[FACT1 FNCT1 FCCT1 ];
%c#2%
[FACT1 FNCT1 FCCT1];
%c#3%
[FACT1 FNCT1 FCCT1];
%c#4%
[FACT1 FNCT1 FCCT1];
%c#5%
[FACT1 FNCT1 FCCT1 ];
! to request specific sections of output, TECH14 provides the BLRT.
OUTPUT:   STDYX SAMPSTAT CINTERVAL MODINDICES (10) SVALUES
RESIDUAL TECH1 TECH7 TECH11 TECH13 TECH14;
```

(8) Mplus input code to estimate the latent profile analysis model with indicators' variances freely estimated across profiles.

```
! Compared to the previous model, the model section is changed for the following, to request a free
! estimation of commitment variances in each profile:
MODEL:
%OVERALL%
%c#1%
[FACT1 FNCT1 FCCT1 ];
FACT1 FNCT1 FCCT1 ;
%c#2%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1 ;
%c#3%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1 ;
%c#4%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1 ;
%c#5%
[FACT1 FNCT1 FCCT1 ];
FACT1 FNCT1 FCCT1 ;
```

(9) Mplus input code to estimate the latent transition analysis model with indicators' variances invariant across profiles.

```
DATA:     FILE = datfin.dat;
VARIABLE:
NAMES = ID sex wktime LEVEL union tenure turnt1 turnt2
MAN1 CHMAN2 SUP1 CHSUP2 FACT1 FCCT1 FNCT1 FACT2 FCCT2 FNCT2;
USEV = FACT1 FNCT1 FCCT1  FACT2 FNCT2 FCCT2;
MISSING = ALL (-999);   IDVAR = ID;
! Use the following section to label the latent categorical variables (profiles)
! C1 refers to the profiles at Time 1, and C2 at time 2, and the model estimates 5 profiles.
CLASSES = c1 (5) C2 (5);
ANALYSIS:
! In the analyses section a mixture (latent transition analysis) model is request, with 2000
! random starts, 200 retained for final optimization and an increase in the defaults iterations.
TYPE = MIXTURE;
STARTS = 2000 200;  STITERATIONS = 100;
! [ NEXT INPUTS EXAMPLES WILL START FROM HERE]
MODEL:
%OVERALL%
! This describes the overall (not profile-specific) part of the model
! The next statement indicates latent transition analyses whereby C2 is predicted by C1.
c2 on c1;
MODEL C1:
! This describes statements specific to C1 (Time 1 profiles) and the next sections map
! characteristics specific to each profile.
%c1#1%
! This indicates that the means of the time 1 commitment variable are freely estimated in each profile.
[FACT1 FNCT1 FCCT1 ];
%c1#2%
[FACT1 FNCT1 FCCT1];
%c1#3%
[FACT1 FNCT1 FCCT1];
%c1#4%
[FACT1 FNCT1 FCCT1];
%c1#5%
[FACT1 FNCT1 FCCT1 ];
MODEL C2:
! And the same specifications are given to Time 2 profiles.
%c2#1%
[FACT2 FNCT2 FCCT2];
%c2#2%
[FACT2 FNCT2 FCCT2];
%c2#3%
[FACT2 FNCT2 FCCT2];
%c2#4%
[FACT2 FNCT2 FCCT2];
%c2#5%
[FACT2 FNCT2 FCCT2 ];
! Specific sections of the output are requested here (part excluded from the next examples).
OUTPUT:  STDYX SAMPSTAT CINTERVAL MODINDICES SVALUES RESIDUAL TECH1;
```

(10) Mplus input code to estimate the latent transition analysis model with indicators' variances freely estimated across profiles.

!Here and in the following inputs, the parts already shown in the previous examples will be in greyscale.

```
MODEL:
%OVERALL%
c2 on c1;
MODEL C1:
%c1#1%
[FACT1 FNCT1 FCCT1 ];
! From the previous model, here this part is added to each profile to indicate that the variances
! are freely estimated in all profiles.
FACT1 FNCT1 FCCT1          ;
%c1#2%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1;
%c1#3%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1;
%c1#4%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1;
%c1#5%
[FACT1 FNCT1 FCCT1];
FACT1 FNCT1 FCCT1;
MODEL C2:
%c2#1%
[FACT2 FNCT2 FCCT2];
FACT2 FNCT2 FCCT2;
%c2#2%
[FACT2 FNCT2 FCCT2];
FACT2 FNCT2 FCCT2;
%c2#3%
[FACT2 FNCT2 FCCT2];
FACT2 FNCT2 FCCT2;
%c2#4%
[FACT2 FNCT2 FCCT2];
FACT2 FNCT2 FCCT2;
%c2#5%
[FACT2 FNCT2 FCCT2 ];
FACT2 FNCT2 FCCT2;
```

(11) Mplus input code to estimate the invariant latent transition analysis model.

```
MODEL:
%OVERALL%
c2 on c1;
MODEL C1:
%c1#1%
! Numbers and letters numbers in parentheses are used to label the parameter estimates.
! All parameters with the same labels are estimated to be equal to one another.
[FACT1 FNCT1 FCCT1] (1-3);
! Here, the label (1-3) is in fact a list saying the first parameter [FACT1] is labeled 1, the
! second [FNCT1]  labeled 2, and the last [FCCT1] labeled 3.
FACT1 FNCT1 FCCT1          (a1-a3);
%c1#2%
[FACT1 FNCT1 FCCT1] (4-6);
FACT1 FNCT1 FCCT1          (a4-a6);
%c1#3%
[FACT1 FNCT1 FCCT1] (7-9);
FACT1 FNCT1 FCCT1          (a7-a9);
%c1#4%
[FACT1 FNCT1 FCCT1] (10-12);
FACT1 FNCT1 FCCT1          (a10-a12);
%c1#5%
[FACT1 FNCT1 FCCT1 ] (13-15);
FACT1 FNCT1 FCCT1          (a13-a15);
MODEL C2:
%c2#1%
[FACT2 FNCT2 FCCT2](1-3);
FACT2 FNCT2 FCCT2 (a1-a3);
%c2#2%
[FACT2 FNCT2 FCCT2](4-6);
FACT2 FNCT2 FCCT2 (a4-a6);
%c2#3%
[FACT2 FNCT2 FCCT2](7-9);
FACT2 FNCT2 FCCT2 (a7-a9);
%c2#4%
[FACT2 FNCT2 FCCT2](10-12);
FACT2 FNCT2 FCCT2 (a10-a12);
%c2#5%
[FACT2 FNCT2 FCCT2] (13-15);
FACT2 FNCT2 FCCT2 (a13-a15);
```

(12) Mplus input code to add predictors to the model.

To add predictors to the preceding models, only the following commands need to be added to the %OVERALL% section of the preceding model.

```
C1 ON sex wktime LEVEL union tenure; ! To include demographics predicting C1
C1 ON MAN1 SUP1; ! To include initial trust levels predicting C1
C2 ON CHMAN2 CHSUP2; ! To include changes in trust levels predicting C2
```

(13) Mplus input code to estimate the associations of the outcome with the latent transition model.

In this model, we used starts values from the preceding model (obtained with Mplus SVALUES function) and turned off the random start function of the analysis section (STARTS = 0) to ensure that the analysis would converge on the same Latent Transition Analysis model as previously estimated. Indeed, we want to estimates the association between our final retained model and predictors/outcomes, not use the predictors/outcomes to impact the nature of the model (for related discussions, see Marsh et al., 2009; Morin et al., 2011). For the outcomes, we could not use the Auxilliary (e) function (as illustrated in Morin et al., 2011) to obtain similar results. However this function is not available in models including more than one latent categorical variable.

```
MODEL:
   %OVERALL%
! All parameters from the models are given starts values with *. In fact, this full input (at least the
! greyscale part of it), was directly cut-and-pasted from the SVALUE section of the output of the
! previous model.
  MODEL C1:
   %C1#1%
! In each class, we add class specific statements to request that the means (and variances) of
! the turnover intent variable be freely estimated in all classes. The means are labeled. These
! labels will be used later in the MODEL CONSTRAINT and MODEL TEST sections.
[turnt1] (y1);
turnt1;
   [ fact1*2.715 ] (1);
   [ fnct1*2.107 ] (2);
   [ fcct1*3.189 ] (3);
   fact1*0.117 (a1);
   fnct1*0.099 (a2);
   fcct1*0.179 (a3);
   %C1#2%
[turnt1] (y2);
turnt1;
   [ fact1*2.886 ] (7);
   [ fnct1*1.854 ] (8);
   [ fcct1*2.002 ] (9);
   fact1*0.208 (a4);
   fnct1*0.087 (a5);
   fcct1*0.124 (a6);
   %C1#3%
[turnt1] (y3);
turnt1;
   [ fact1*3.766 ] (13);
   [ fnct1*3.002 ] (14);
   [ fcct1*2.720 ] (15);
   fact1*0.166 (a7);
   fnct1*0.207 (a8);
   fcct1*0.406 (a9);
   %C1#4%
[turnt1] (y4);
turnt1;
   [ fact1*3.294 ] (19);
```

```
    [ fnct1*2.401 ] (20);
    [ fcct1*2.424 ] (21);
    fact1*0.082 (a10);
    fnct1*0.060 (a11);
    fcct1*0.057 (a12);
    %C1#5%
[turnt1] (y5);
turnt1;
    [ fact1*1.959 ] (25);
    [ fnct1*1.433 ] (26);
    [ fcct1*2.950 ] (27);
    fact1*0.118 (a13);
    fnct1*0.062 (a14);
    fcct1*0.608 (a15);
  MODEL C2:
    %C2#1%
[turnt2] (z1);
turnt2;
    [ fact2*2.715 ] (1);
    [ fnct2*2.107 ] (2);
    [ fcct2*3.189 ] (3);
    fact2*0.117 (a1);
    fnct2*0.099 (a2);
    fcct2*0.179 (a3);
    %C2#2%
[turnt2] (z2);
turnt2;
    [ fact2*2.886 ] (7);
    [ fnct2*1.854 ] (8);
    [ fcct2*2.002 ] (9);
    fact2*0.208 (a4);
    fnct2*0.087 (a5);
    fcct2*0.124 (a6);
    %C2#3%
[turnt2] (z3);
turnt2;
    [ fact2*3.766 ] (13);
    [ fnct2*3.002 ] (14);
    [ fcct2*2.720 ] (15);
    fact2*0.166 (a7);
    fnct2*0.207 (a8);
    fcct2*0.406 (a9);
    %C2#4%
[turnt2] (z4);
turnt2;
    [ fact2*3.294 ] (19);
    [ fnct2*2.401 ] (20);
    [ fcct2*2.424 ] (21);
    fact2*0.082 (a10);
    fnct2*0.060 (a11);
    fcct2*0.057 (a12);
```

```
    %C2#5%
[turnt2] (z5);
turnt2;
    [ fact2*1.959 ] (25);
    [ fnct2*1.433 ] (26);
    [ fcct2*2.950 ] (27);
    fact2*0.118 (a13);
    fnct2*0.062 (a14);
    fcct2*0.608 (a15);

MODEL CONSTRAINT:
! New parameters are created using this function and reflect pairwise mean differences between
! profiles. So the first of those (y12) reflect the differences between the means of profiles 1 and
! 2 at time 1. This will be included in the outputs as new parameters reflecting the significance of
! the differences between the means, without those parameters having an impact on the model.
NEW (y12);
y12 = y1-y2;
NEW (y13);
y13 = y1-y3;
NEW (y14);
y14 = y1-y4;
NEW (y15);
y15 = y1-y5;
NEW (y23);
y23 = y2-y3;
NEW (y24);
y24 = y2-y4;
NEW (y25);
y25 = y2-y5;
NEW (y34);
y34 = y3-y4;
NEW (y35);
y35 = y3-y5;
NEW (y45);
y45 = y4-y5;
! Same thing at time 2
NEW (z12);
z12 = z1-z2;
NEW (z13);
z13 = z1-z3;
NEW (z14);
z14 = z1-z4;
NEW (z15);
z15 = z1-z5;
NEW (z23);
z23 = z2-z3;
NEW (z24);
z24 = z2-z4;
NEW (z25);
z25 = z2-z5;
NEW (z34);
```

```
z34 = z3-z4;
NEW (z35);
z35 = z3-z5;
NEW (z45);
z45 = z4-z5;
MODEL TEST:
! With the following specifications, MODEL TEST will conduct an omnibus tests that the means
! of the turnover variables are equal across classes at Time 1.
y12 = 0;
y23 = 0;
y34 = 0;
y45 = 0;
! To conduct the same test at time 2, the previous sections will need to be replaced by the
! following greyscale section and the model estimated anew.
MODEL TEST:
z12 = 0;
z23 = 0;
z34 = 0;
z45 = 0;
! Finally, to test whether the means are equal across time points, the previous section can be replaced by:
MODEL TEST:
y1 = z1 ;
y2 = z2 ;
y3 = z3;
y4 = z4;
y5 = z5;
```

Supplementary Table S1

Goodness-of-Fit Statistics of the Longitudinal Confirmatory Factor Analytic (CFA) Models

Model	Description	$R\chi^2(df)$	CFI	TLI	RMSEA	90% CI	SRMR	$\Delta R\chi^2$ (df)	ΔCFI	ΔTLI	ΔRMSEA
Trustworthiness	T1. 4-factor model	3909.971 (1216)*	.897	.887	.048	.046-.049	.045	–	–	–	–
Main models	T2. 12-factor model	1812.415 (1156)*	.975	.971	.024	.022-.026	.033	–	–	–	–
	T3. 12-factor model with 4 higher order factors	1886.471 (1192)*	.973	.970	.024	.022-.026	.041	–	–	–	–
Trustworthiness	T2-1. Configural invariance	1812.415 (1156)*	.975	.971	.024	.022-.026	.033	–	–	–	–
Invariance of the	T2-2. λ invariant	1830.790 (1176)*	.975	.972	.024	.022-.026	.034	17.698 (20)	.000	+.001	.000
3 first-order	T2-3. λ, τs invariant	1857.494 (1196)*	.975	.972	.024	.022-.026	.034	26.184 (20)	.000	.000	.000
factors	T2-4. λ, τs, δs invariant	1869.538 (1222)*	.975	.973	.023	.021-.025	.035	21.817 (26)	.000	+.001	-.001
Trustworthiness	T3.1. λ, τs, δs invariant	1942.890 (1258)*	.974	.972	.024	.022-.026	.042	–	–	–	–
Invariance of the	T3.2. λ, τs, δs, γs invariant	1950.987 (1262)*	.974	.972	.024	.022-.026	.043	8.411 (4)	.000	.000	.000
higher-order	T3.3. λ, τs, δs, γs, η invariant	1957.533 (1266)*	.974	.972	.024	.022-.026	.044	6.597 (4)	.000	.000	.000
factor	T3.4. λ, τs, δs, γs, η, ζs invariant	1967.476 (1272)*	.973	.972	.024	.022-.026	.043	9.813 (6)	-.001	.000	.000
Commitment	C1. 2-factor model	3757.485 (571)*	.639	.602	.076	.073-.078	.142	–	–	–	–
Main models	C2. 6-factor model	1254.386 (557)*	.921	.911	.036	.033-.038	.074	–	–	–	–
Commitment	C2-1. Configural invariance	1254.386 (557)*	.921	.911	.036	.033-.038	.074	–	–	–	–
Invariance of the	C2-2. λ invariant	1264.327 (572)*	.921	.914	.035	.033-.038	.075	9.510 (15)	.000	+.003	-.001
3 first-order	C2-3. λ, τs invariant	1284.098 (587)*	.921	.915	.035	.032-.037	.075	17.555 (15)	.000	+.001	.000
factors	C2-4. λ, τs, δs invariant	1293.875 (605)*	.921	.919	.034	.032-.037	.075	15.763 (18)	.000	+.004	-.001

Note. $*p < .01$; $R\chi^2$: Robust chi-square; *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; SRMR: Standardized root mean square error of approximation; λ: Loading; τ: Items intercepts; δ: Uniqueness; γ: Structural relations among the latent constructs (i.e. second-order factor loadings; ζ: Factor error terms; η: Factor intercepts; $\Delta R\chi^2$: Robust chi-square difference tests (calculated from loglikelihoods for greater precision); Δ: Change from previous model.

Supplementary Table S2.

Fit Indices from Alternative Latent Profile Analyses Estimated Separately at Both Time Points.

	k	LL	SCF	#fp	AIC	BIC	CAIC	SABIC	Entropy	BLRT
TIME 1. Equal variances across profiles										
	2	-2069.18	1.16	10	4158.36	4203.68	4213.68	4171.93	0.72	< .001
	3	-1964.20	1.25	14	3956.41	4019.86	4033.86	3975.41	0.77	< .001
	4	-1911.02	1.11	18	3858.04	3939.62	3957.62	3882.47	0.79	< .001
	5	-1888.09	1.21	22	3820.18	3919.89	3941.89	3850.03	0.77	< .001
	6	-1871.24	1.22	26	3794.48	3912.32	3938.32	3829.77	0.74	< .001
	7	-1854.86	1.43	30	3769.71	3905.68	3935.68	3810.43	0.76	< .001
	8	-1829.04	1.16	34	3726.07	3880.17	3914.17	3772.21	0.78	< .001
TIME 1. Variances free in all profiles										
	2	-2043.52	0.99	13	4113.03	4171.95	4184.95	4130.67	0.72	< .001
	3	-1936.54	1.27	20	3913.07	4003.72	4023.72	3940.22	0.79	< .001
	4	-1873.87	1.04	27	3801.75	3924.12	3951.12	3838.39	0.8	< .001
	5	-1842.37	1.06	34	3752.74	3906.84	3940.84	3798.89	0.79	< .001
	6	-1814.97	1.12	41	3711.94	3897.76	3938.76	3767.58	0.79	< .001
	7	-1789.20	1.15	48	3674.39	3891.94	3939.94	3739.53	0.79	< .001
	8	-1766.43	1.12	55	3642.85	3892.13	3947.13	3717.50	0.78	< .001
TIME 2. Equal variances across profiles										
	2	-1828.03	1.13	10	3676.07	3720.44	3730.44	3688.70	0.72	< .001
	3	-1728.71	1.24	14	3485.41	3547.54	3561.54	3503.09	0.78	< .001
	4	-1682.14	1.20	18	3400.27	3480.15	3498.15	3423.00	0.78	< .001
	5	-1660.68	1.11	22	3365.37	3462.00	3484.00	3393.15	0.78	< .001
	6	-1629.20	1.23	26	3310.39	3425.77	3451.77	3343.23	0.78	< .001
	7	-1606.70	1.12	30	3273.39	3406.52	3436.52	3311.28	0.81	< .001
	8	-1589.28	1.09	34	3246.55	3397.44	3431.44	3289.49	0.82	< .001
TIME 2. Variances free in all profiles										
	2	-1803.90	0.99	13	3633.80	3691.49	3704.49	3650.21	0.73	< .001
	3	-1704.58	2.37	20	3449.17	3537.92	3557.92	3474.42	0.78	< .001
	4	-1650.69	1.17	27	3355.40	3475.20	3502.20	3389.48	0.77	< .001
	5	-1617.15	1.07	34	3302.30	3453.19	3487.19	3345.24	0.79	< .001
	6	-1587.37	1.04	41	3256.74	3438.69	3479.69	3308.52	0.81	< .001
	7	-1561.73	1.04	48	3219.46	3432.47	3480.47	3280.09	0.83	< .001
	8	-1536.77	1.03	55	3183.53	3427.61	3482.61	3252.99	0.84	<.001

Note. k = number of latent profiles in the model; LL = Model loglikelihood; #fp = Number of free parameters; SCF: Scaling correction factor of the robust maximum likelihood estimator; AIC = Akaïke information criterion; CAIC = Consistent AIC; BIC = Bayesian information criterion; SABIC = Sample-size adjusted BIC; BLRT = Bootstrap likelihood ratio test.

Supplementary Table S3.

Mean levels of commitment for the final retained latent profile solution.

	Time 1			Time 2		
	Affective commitment	Normative commitment	Continuance commitment	Affective commitment	Normative commitment	Continuance commitment
Profile 1	2.757	1.844	2.225	3.096	1.741	1.685
Profile 2	1.696	1.177	2.654	1.752	1.237	2.782
Profile 3	3.340	2.535	2.706	3.351	2.342	2.404
Profile 4	4.079	3.386	2.735	3.777	3.057	2.789
Profile 5	2.289	1.816	3.511	2.584	1.970	3.028

Supplementary Table S4.

Complementary results from the prediction of latent transition profiles by single constructs of management trustworthiness

	All mid with CC-dominant (profile 1)		All mid with AC-dominant (profile 2)		AC-dominant (profile 4)		AC/NC-dominant (profile 3)	
	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*
Effects of the initial ability levels on membership into Time 1 profiles								
Top management	0.92 (1.69)	2.50	0.80 (1.57)	2.23	1.63 (2.40)	5.11	2.45 (3.90)	11.55
Immediate supervisor	0.32 (0.12)**	1.37	0.77 (0.25)**	2.17	0.69 (0.14)**	1.99	0.94 (0.13)**	2.57
Effects of changes in ability levels on membership into Time 2 profiles								
Top management	0.52 (1.44)	1.68	4.78 (181.70)	118.54	13.44 (312.60)	IE	6.29 (191.86)	539.61
Immediate supervisor	0.11 (0.43)	1.12	0.75 (0.66)	2.11	1.96 (0.45)**	7.13	2.21 (0.66)**	9.08
Effects of the initial benevolence levels on membership into Time 1 profiles								
Top management	1.33 (0.21)**	3.80	1.18 (0.20)**	3.25	2.28 (0.27)**	9.81	3.05 (0.26)**	21.10
Immediate supervisor	0.43(0.15)**	1.53	0.70 (0.25)**	2.01	0.77 (0.20)**	2.17	1.11 (0.18)**	3.04
Effects of changes in benevolence levels on membership into Time 2 profiles								
Top management	1.14 (0.58)*	3.12	1.70 (0.95)	5.50	91.05 (0.56)**	IE	3.04 (0.72)**	21.00
Immediate supervisor	0.03 (0.39)	1.03	0.61 (1.44)	1.83	2.29 (0.90))*	9.90	2.46 (1.19)*	11.66
Effects of the initial integrity levels on membership into Time 1 profiles								
Top management	1.05 (0.20)**	2.85	0.99 (0.16)**	2.68	2.23(0.27)**	9.26	3.03 (0.25)**	20.73
Immediate supervisor	0.39 (0.16)*	1.48	0.70 (0.38)	2.02	0.75 (0.16)**	2.11	1.03 (0.20)**	2.80
Effects of changes in integrity levels on membership into Time 2 profiles								
Top management	2.37 (0.89)**	10.72	1.69 (0.75)*	5.41	117.04 (124.76)	IE	3.90 (0.91)**	49.50
Immediate supervisor	0.07 (0.40)	1.08	0.95 (0.55)	2.59	1.79 (0.40)**	6.00	2.92 (1.00)**	18.54

Note. The CC-dominant profile was selected as the reference profile. *OR* = Odds Ratio. IE = the model resulted in an improper parameter estimate and the odds ratio could not be computed; * $p < .05$; ** $p < .01$