ARE COMMITMENT PROFILES STABLE AND PREDICTABLE? A LATENT TRANSITION ANALYSIS

Chester Kam
The University of Macau

Alexandre J.S. Morin
The University of Western Sydney

John P. Meyer
The University of Western Ontario

Laryssa Topolnytsky
Korn/Ferry International

This is the prepublication version of the following manuscript:

Kam, C., Morin, A.J.S., Meyer, J.P., & Topolnytsky, L. (2016). Are commitment profiles stable and predictable? A latent transition analysis. *Journal of Management*, *42* (6), 1462-1490. DOI: 10.1177/0149206313503010

Acknowledgement: The research reported in this manuscript was supported by a research grant from the Social Sciences and Humanities Research Council to John P. Meyer.

Corresponding author: John P. Meyer, Department of Psychology, Social Science Centre, The University of Western Ontario, London, Ontario, Canada, N6A 5C2
E-mail: meyer@uwo.ca

Abstract

Recent efforts have been made to identify and compare employees with profiles reflecting different combinations of affective (AC), normative (NC), and continuance (CC) organizational commitment. To date, the optimal profiles in terms of employee behavior and well-being have been found to be those in which AC, NC and CC are all strong, or those where AC, or AC and NC, dominate. The poorest outcomes are found for profiles where AC, NC and CC are all weak, or CC dominates. The primary goal of the current study was to use Latent Profile Analysis (LPA) and Latent Transition Analysis (LTA) to identify profile groups and examine changes in profile membership over an 8-month period in an organization undergoing a strategic change. We also tested hypotheses concerning the relation between perceived trustworthiness of management and employees' commitment profile within and across time. We found that commitment profiles have substantial temporal stability and that trustworthiness positively predicts memberships in more desirable commitment profiles. There was also some, albeit weak, evidence that changes in perceived trustworthiness were accompanied by corresponding shifts in the commitment profile.

INTRODUCTION

The three-component model of commitment (Meyer & Allen, 1991; Meyer & Herscovitch, 2001), defines commitment as a force that binds an individual to a target or course of action. However, this force can be characterized by three distinct mindsets – desire (affective commitment), obligation (normative commitment), and perceived cost (continuance commitment) – that can have different implications for behavior. Although Meyer and colleagues argued that the mindsets combine to influence behavior, most research has focused on their independent or additive effects. It is only recently that studies have examined the behavioral consequences of "commitment profiles" (e.g., Gellatly, Meyer, & Luchak, 2006; Wasti, 2005). These studies generated new insights into the nature and implications of commitment and served as the impetus for recent developments in commitment theory (Meyer, Becker, & Van Dick, 2006; Meyer & Maltin, 2010; Meyer & Parfyonova, 2010).

The shift in attention to commitment profiles reflects a broader trend in organizational research toward greater use of a *person-centered* approach (see Wang & Hanges, 2011). In contrast to the more common *variable-centered* approach that aims to explain relations among variables, the person-centered approach involves the identification of homogeneous subgroups of individuals within a population. The person-centered approach treats individuals in a more holistic fashion and allows for the possibility that a set of attributes (e.g., commitment mindsets) might be experienced differently, and have different implications, in combination than they do individually. Consequently, the person-centered approach affords a different perspective on a phenomenon of interest and complements the variable-centered approach (Marsh, Lüdke, Trautwein, & Morin, 2009; Meyer, Stanley, & Vandenberg, 2013).

To date, commitment profile studies have been cross-sectional and do not adequately address the important issue of profile stability. If the commitment profiles found across samples differ radically, or the profile structure within a sample is reactive to situational cues, it will be difficult to make meaningful recommendations. Therefore, our primary objective was to determine whether there is temporal stability in commitment profiles within a sample of employees. This study was conducted in an organization undergoing a large-scale change in strategy and culture, providing a strong test of within-sample stability.

Also, most of the attention in existing profile studies has been directed at their implications for behavior (Somers, 2010; Wasti, 2005) and well-being (Meyer, Stanley, & Parfyonova, 2012; Somers, 2009), with little concern for how these profiles are formed or change over time. In order to take advantage of what has been learned about the consequences of commitment profiles, we need to know more about what managers can do to foster desirable profiles and maintain them under conditions of change. Therefore, our second objective was to examine the role of one potential contributor to profile formation and change – the perceived trustworthiness of management. We focused on trustworthiness because it, and the trust it engenders, become particularly salient under conditions of change (Thomlinson & Mayer, 2009), and both have been linked to commitment in previous research (Colquitt, Scott, & Lepine, 2007; Dirks & Ferrin, 2002). Thus, there was good reason to believe that perceptions of management trustworthiness would be relevant to formation and change of commitment profiles.

Commitment Profile: Theory and Research

Meyer and Herscovitch (2001) offered a set of propositions concerning how various combinations (profiles) of the commitment mindsets – affective (AC), normative (NC), and continuance (CC) – would relate to behaviors (e.g., turnover, performance, organizational citizenship). They proposed that the optimal profiles from an outcomes perspective would be characterized by strong AC and relatively weak CC and NC (i.e., the less autonomously-motivated mindsets). The least desirable outcomes were expected for uncommitted employees (all components low) or those whose profile was dominated by strong CC. These propositions have been tested in several studies with mixed support. Although profiles characterized by strong AC were indeed found to be associated with desirable behaviors, the AC-dominant[1] profile was not necessarily optimal. Indeed, several studies reported that intention to remain, OCB and well-being were greatest among employees with AC/NC-dominant or fully-committed (high AC, NC, and CC) profiles (Gellatly et al., 2006; Wasti, 2005; Meyer, L. Stanley et al., 2012; Somers, 2009), suggesting a possible synergy of the three components (see Johnson, Groff, & Taing, 2009).

Gellatly et al. (2006) interpreted their findings as evidence that the way any component of

commitment is experienced will depend on the *context* created by the other components. For example, combined with strong AC, NC may be experienced as a *moral imperative*, whereas with weak AC and strong CC it might be experienced as *indebted obligation*. Similarly, Meyer, L. Stanley et al. (2012) suggested that, on its own, strong CC might reflect entrapment due to lack of alternatives or the economic costs of leaving. Alternatively, when combined with strong AC and NC, CC could reflect awareness of the costs associated with the loss of desirable work and/or work conditions. Thus, the implications of CC and NC will depend on their relative strength within the full commitment profile.

Considered together, the results of existing profile studies suggest that the optimal commitment profiles from an outcomes perspective are the fully-committed, AC/NC-dominant, and AC-dominant profiles. The poorest outcomes tend to be associated with the uncommitted and CC-dominant profiles. Based on these findings, one might conclude that organizations should invest effort and resources to foster the optimal profiles. However, as noted previously, recommendations such as this rest on the assumption that there is a relatively standard set of distinguishable profiles within the workforce, that there are strategies organizations can use to foster these desirable profiles, and that, once established, commitment profiles remain relatively stable over time. These assumptions remain largely untested. In the discussion to follow we focus first on the issue of stability, and then on profile development.

Stability of Commitment Profiles

The stability of commitment profiles can be addressed in several ways. First, there is the question of whether a common set of profiles emerges across samples (i.e., cross-sample stability). This question is best answered by comparing profiles across studies. Although research is still limited, Meyer, L. Stanley et al. (2012) noted that several profiles emerge quite regularly. Indeed, all of the studies they reviewed identified fully-committed, AC/NC-dominant, CC-dominant, and uncommitted profiles. Most studies identified an AC-dominant profile and two studies found a CC/NC-dominant profile. Several studies also identified profiles in which scores on all three mindsets fell in the moderate range. The only profile described by Meyer and Herscovitch (2001) that has not been found, other than through median split approaches, is the NC-dominant profile. Thus, some profiles replicate quite consistently. Although other profiles emerge occasionally, this feasible set of profiles is relatively small and easily manageable.

A second question has to do with the temporal stability of commitment profiles within a sample. That is, will the same profiles be detected for a given sample on separate occasions? Recommendations that organizations select for or promote some profiles over others (e.g., Meyer, L. Stanley et al., 2012), or use different management strategies for different types of employees (e.g., Morin, Morizot, Boudrias, & Madore, 2011), assume that profiles persist over time. However, their temporal stability has yet to be investigated. The evidence for cross-sample consistency suggests, but does not provide direct evidence for, within-sample temporal stability. Consequently, addressing this issue was one of our key objectives.

Finally, there is the question of temporal stability of individual employees' commitment profiles. The questions of within-person and within-sample temporal stability are highly related. Temporal stability at the individual level virtually assures within-sample stability. However, even if individual employees' profiles change over time, within-sample stability remains a possibility if the change involves balanced movement (i.e. switching) between existing profiles. For example, if some employees shift from a CC-dominant profile to an AC/CC-dominant profile over time, while other employees shift in the opposite direction, the profile structure of the sample should remain the same over time. Even when the switching is not fully balanced, the profile structure might still remain the same across time, although their relative sizes may differ. Only large and uniform shifts in individual employee profiles are likely to lead to within-sample instability. Thus, if a dramatic event caused a large proportion of employees with an AC/CC-dominant profile to shift to a CC-dominant profile, with no one moving in the opposite direction, the former profile might be detected before the event but not after. In addressing temporal stability, it is important to consider factors that might contribute to stability and change in individuals' profiles.

In theory, there are several reasons to expect the commitment mindsets to remain relatively stable over time. Mowday, Porter, and Steers (1982) argued that, by its very nature, (affective) commitment is a stable attitude emerging in part from a dispositional propensity to commit. Weiner (1982) proposed that NC develops largely as a function of socialization forces presumably designed

and intended to create stability. Becker (1960) suggested that (continuance) commitment develops when individuals make "side bets" (e.g., investing time to develop organization-specific skills) that make it costly to change one's course of action, potentially for a considerable period of time. Although empirical evidence for dispositional influences on commitment is sparse (Meyer et al., 2002), a few recent studies have reported correlations between personality and AC (e.g., Erdheim, Wang, & Zickar, 2006; Panaccio & Vandenberghe, 2012), as well as relations between commitment mindsets and cultural values (Clugston, Howell, & Dorfman, 2000; Fischer & Mansell, 2009; Meyer, D. Stanley et al., 2012; Wasti, 2003). Finally, Morin, Morizot et al. (2011) found evidence of a general factor underlying AC to seven distinct work-relevant foci, suggesting the existence of a general tendency to commit. Thus, to the extent that these internal factors are free to operate (i.e., without strong counter-forces in the environment), individual employees' profiles should be expected to remain stable.

There are also strong theoretical and empirical bases for expecting instability in commitment profiles over time. Indeed, in the initial formulation of the three component model, Meyer and Allen (1991, 1997) focused almost exclusively on situational factors as determinants of commitment. In contrast to research on dispositions, there has been an extensive body of research linking commitment to work conditions (or perceptions of these conditions). Meta-analyses provide strong evidence linking AC (and to a lesser extent NC) to perceived organizational support (Rhoades & Eisenberger, 2002), organizational justice (Colquitt, Conlon, Wesson, Porter, & Ng, 2001), empowerment (Seibert, Wang, & Courtright, 2011), trust (Colquitt, Scott, & Lepine, 2007), high involvement work practices (Jiang, Lepak, Hu, & Baer, 2012), and transformational leadership (Jackson, Meyer, & Wang, 2013). CC has been linked to lack of employment alternatives and non-transferability of skills and education (Meyer et al., 2002). Each of these situational factors is subject to change and, based on their relations with commitment, could contribute to changes in one or more of the commitment mindsets.

Few studies have examined relations between situational factors and commitment over time, and the findings have been mixed (see Morrow, 2011). Some of the earliest longitudinal studies involving established employees provided little evidence for time-lagged relations between work conditions and commitment (Bateman & Strasser, 1984; Curry, Wakefield, Price, & Mueller, 1986). However, Meyer and colleagues (Meyer & Allen, 1988; Meyer, Bobocel, & Allen, 1991) found significant time-lagged relations between work experiences (e.g., job challenge) and commitment among new employees. These findings suggest that situational factors may play a role in shaping commitment, but that they are most likely to do so under novel or changing conditions. Once formed, commitment might remain quite stable.

In sum, there are reasons to expect both stability and changes in commitment over time. There is no strong evidence to suggest that organizational changes such as the one experienced by employees in our study will be sufficiently strong or uniform to produce temporal instability in the profile structure of an entire sample of employees. Therefore, we predicted that we would find several of the more common profiles in our sample, and that these would remain stable over time.

Hypothesis 1: Our sample will be heterogeneous with regard to commitment profile and should include the following: fully committed, AC/NC-dominant, AC-dominant, CC-dominant, uncommitted. Other possible profiles include CC/NC-dominant and all-mid profiles.

Hypothesis 2: The same profiles will exist prior to and following the change.

Perceived Management Trustworthiness and Commitment

As noted earlier, there has been little research to identify factors involved in the formation of, or change in, commitment profiles (see Gellatly, Hunter, Currie & Irving [2009] for an exception). Therefore, our second objective was to investigate the roles of perceived management trustworthiness, and change in perceived trustworthiness, respectively, in the formation and changes in commitment profiles. Trust is commonly conceptualized as a willingness to make oneself vulnerable to the decisions or actions of others, whereas trustworthiness is a quality of the trustee (Mayer, Davis, & Schoorman, 1995; Colquitt et al., 2007). According to Mayer et al. (1995), judgments of trustworthiness reflect an assessment of three characteristics: benevolence (concern for the trustor's well-being), ability (situation-relevant competence), and integrity (adherence to acceptable moral and ethical principles). Trust and trustworthiness are inextricably intertwined. Indeed, many measures of trust make direct reference to two or more of the facets of trustworthiness (Salamon & Robinson, 2008). We focused on trustworthiness rather than trust per se because the findings are likely to be

more directly actionable.

A basic theoretical underpinning of organizational commitment is social exchange (Meyer & Allen, 1991). At the heart of high quality exchanges is the belief that the other party will fulfill its obligations (Blau, 1964; Cropanzano & Mitchell, 2005). Trust is therefore important at any stage of a relationship, but becomes central under conditions of uncertainty such as a large-scale organizational change (Mayer et al., 1995). In these contexts, employees are likely to be guided by their perceptions of managements' trustworthiness. Indeed, there is considerable empirical evidence linking commitment, particularly AC, to trust (Dirks & Ferrin, 2002) and trustworthiness (Colquitt et al., 2007). In their meta-analysis, Dirks and Ferrin found that AC correlated positively with trust in top management and immediate supervisor, but that the former relation was stronger. They argued that the difference might be because top management plays a greater role in developing strategy and policy. Thus, when it comes to their willingness to commit to the organization, employees may pay particular attention to whether they trust top management to steer the organization in the proper direction.

In contrast to its positive relation with AC, trust in management has generally been found to have a negative (Albrecht & Travaglione, 2003; Laschinger et al., 2000) or non-significant (Hopkins & Weathington, 2006; Ozag, 2006) relation with CC. Although these studies did not address the issue of causality, to the extent that a negative relation exists, we expect it may be because employees with strong CC find it difficult to leave the situation despite concerns about management's trustworthiness. It is unlikely that lack of trust contributes directly to the perceived cost of leaving. To our knowledge, only two studies have examined the relation between trust and NC. Ozag (2006) found a positive correlation with a combined measure of trust in supervisor and the organization. Colquitt et al. (2012) found positive correlations with both affect- and cognition-based measures of trust in supervisor. However, when the cognition-based measure of trust (conceptually similar to our trustworthiness measure) was included in a structural equation modeling analysis, the relation with NC disappeared. Thus, the findings pertaining to both CC and NC are somewhat inconsistent. It is important to note, however, that research is limited and has not considered CC or NC as they might be experienced within a commitment profile.

Based on the foregoing theory and research, we developed hypotheses pertaining to profile formation. First, we expected that employees who perceived management to be trustworthy would be more likely to have a profile characterized by strong AC. Employees who see management as untrustworthy may have little reason to commit to the organization, and might therefore be uncommitted (waiting for an opportunity to leave) or CC-dominant (seeing no alternative but to stay). Finally, employees who perceive management as trustworthy might also develop a felt obligation to remain (NC-dominant) as a means of reciprocation, or a sense of indebtedness due to expectation from other individuals (e.g., CC/NC dominant), although both NC- and CC/NC-profiles were rare in past research. A trusting environment is likely to be perceived positively, in which case NC might combine with AC to form an AC/NC-dominant or fully-committed profile.

> Hypothesis 3: Employees' perceptions of management trustworthiness will relate positively to their likelihood of having a fully-committed, AC/NC-dominant, or AC-dominant profile, and negatively to the likelihood of having an uncommitted or CC-dominant profile.

Although some studies have examined the relations between trust and commitment under conditions of change (Albrecht & Travaglione, 2003; Laschinger et al., 2000), we are unaware of any studies that investigated how changes in perceptions of management trustworthiness related to changes in commitment mindsets over time. Consequently, our hypotheses were guided by the broader literature on commitment and change (see Meyer, 2009). Moreover, to be consistent with Hypothesis 2 regarding the temporal stability at the sample level, we focused our attention on the role that changes in perceptions of management trustworthiness might have on individual employees' transitions between profiles over time.

Morrow's (2011) review of longitudinal studies revealed that commitment can increase or decrease as a consequence of organizational change. Although she did not address the role of trust per se, it is interesting to note that the strongest and most consistent evidence for a decrease in AC was obtained in the case of downsizing (e.g., Armstrong-Stassen, 1998). Changes such as this can lead employees to engage in a process of sense-making (Tomlinson & Mayer, 2009) with implications for the nature and strength of their commitment (Meyer, Allen, & Topolnytsky, 1998). For example, employees may see the change as unjust (Caldwell, Liu, Fedor, & Herold, 2009) or a violation of its

psychological contract (Korsgaard, Sapienza, & Schweiger, 2002), thereby reducing perceptions of trustworthiness. However, large-scale organizational changes can also provide an opportunity for management to build trust by using fair procedures and/or communicating the need to "rewrite" the psychological contract in a mutually satisfactory manner (Meyer, 2009). Therefore, how employees react to management's actions may depend on how they interpret the situation, and this could vary from employee to employee. This may have implications for temporal movement of profiles at the individual level:

> Hypothesis 4: An increase (decline) in perceptions of management trustworthiness will relate positively (negatively) to the likelihood of an employee transitioning from a less-favorable to a more favorable profile, and will relate negatively (positively) with the likelihood of transitioning from a more favorable to a less favorable profile.

Other Methodological Considerations

Before moving on, three additional methodological issues warrant consideration. First, there is disagreement concerning the dimensionality of trustworthiness. For example, Mayer and Davis (1999) found evidence for three factors, whereas Searle et al. (2011) found two (benevolence and integrity combined). Some investigators (e.g., Salamon & Robinson, 2008) combine the three subscales, whereas others treat them individually (e.g., Colquitt & Rodell, 2011). For purposes of hypothesis development, we focused on global trustworthiness. However, as described later, we conducted preliminary analyses to determine how to best represent the trustworthiness construct in tests of these hypotheses.

Second, recall that Dirks and Ferrin (2002) found that AC correlated positively with trust in top management and the immediate supervisor, but that the former correlation was stronger. In this study we measured perceptions of the trustworthiness of both levels of management. This allowed us to determine whether Dirks and Ferrins' findings would replicate in analyses of commitment profiles. Additionally, it provided a partial control for concerns about the effects of common method bias. That is, such concerns should be reduced if the strength of relations differs across foci of trustworthiness.

Finally, because ours is the first study to examine relations between perceived trustworthiness and commitment profiles, the generalizability of our findings is a potential concern. Therefore, we also examined relations between profile membership and turnover intent for comparison with previous research (e.g., Somers, 2009, 2010; Wasti, 2005). If our results are similar, we can have greater confidence that our sample is not unique and the findings regarding trustworthiness will generalize.

METHOD

Research Setting and Change Context

The research site was a large energy company undergoing a planned structural and cultural transformation. The company itself was fairly new – a by-product of a recent and significant re-organization by its parent company. Due to deregulation in the Canadian energy sector, and in an attempt to remain competitive, the parent company split the business into three separate companies, one of which was a shared services provider. The latter company, which served as the research site, provided services (e.g., HR, IT) to the other companies within the umbrella organization.

The shared service provider had its own revenue and earnings targets, strategies for success, and business plans. According to senior management, the company's goal was to become a profitable and significant player in its market niche. To achieve this objective, it had to be profit-oriented and adaptable to changes in the energy and shared services industries. This philosophy was dramatically different from the one that had existed under regulation. The regulator had required the utility to meet strict guidelines and placed limits on profits. Among the most immediate and visible events affecting employees after the reorganization were the layoff of approximately 20 percent of permanent employees, the hiring of a slightly greater number of contract workers, minor changes in the senior management team, and a variety of initiatives undertaken by senior management to promote the changes in strategy and culture (e.g., "town hall" meetings, site visits, and management training).

Participants, Data Collection, and Missing Data Procedures

The data reported in this manuscript were collected as part of a much larger project on organizational change.[2] The first survey was administered one month prior to the official announcement of the planned change. The entire workforce (N = 1041) was asked to participate and 699 (67%) responded. The second survey was administered eight months later. Again, the entire workforce (N = 1075) was invited to participate and 637 (59%) responded. Surveys were distributed

via interoffice mail. Participation in the survey was voluntary and anonymous. Employees were given two weeks to return the surveys. Reminders were e-mailed and posted on bulletin boards a few days before the deadline for return. We were able to match Time 1 and Time 2 surveys by having employees use a unique code number. All of the measures described below were included on both administrations of the survey. The demographic information, descriptive statistics, reliabilities and correlations for all of the studies variables are reported in Table 1.

Insert Table 1 about here

For present purposes, data obtained from those involved in planning and overseeing the change initiative (i.e., senior management) were not included in the analyses. Within-time analyses were conducted on data from all of the remaining respondents (Time 1: N = 688; Time 2: N = 625). Longitudinal analyses were conducted using the data from all respondents, using Full Information Maximum Likelihood estimation (FIML)—rather than a listwise deletion strategy focusing only on employees having answered both time points—to handle missing data (Enders, 2010; Little & Rubin, 1987; Schafer, 1997). FIML estimation, especially when used in conjunction with robust maximum likelihood estimation (MLR), 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 & Bandalos, 2001; Graham, 2009; Larsen, 2011; Shin, Davidson, & Long, 2009). FIML is recognized to perform better than most alternative missing data strategies (listwise deletion, pairwise deletion, mean-substitution) – especially in the context of longitudinal studies, and has been shown to perform equivalently (or even better in some cases, e.g. Larsen, 2011), than more computationally intensive multiple imputation procedures (e.g. Enders, 2010; Graham, 2009). Contrary to popular beliefs, FIML does not replace the missing values (i.e., is not an imputation method). Rather, FIML estimates model parameters (versus specific missing values on specific variables) based on all of the available information in the variance-covariance matrix.

An important advantage of using FIML, specific to this study, is that it allowed us to maximize sample size, which was important given that latent transition analysis is clearly a large sample strategy, at least in order to converge on proper, replicated, solutions and to achieve reasonable generalizability (recall that the total sample size is divided into profiles so that the ability to extract stable small, yet meaningful profiles is a direct function of the total sample size). Furthermore, to ensure that the results from the main longitudinal models were unbiased by this decision, latent profiles analyses were also conducted on the time-specific subsamples (see the online supplemental materials) and the results regarding the nature of the profiles were found to replicate across time points, and converged with those from the latent transition analyses reported here.

Measures

Trustworthiness. We assessed the perceived trustworthiness of both top management and the immediate supervisor using slightly modified (i.e., shortened) versions of the measures of ability, benevolence, and integrity developed by Mayer et al. (1995). Ability was measured with four items (e.g., Top management [My supervisor] is very capable of performing its [his/her] job), benevolence with four items (e.g., Top management [My supervisor] is very concerned about my welfare), and integrity with five items (e.g., Top management [My supervisor] has a strong sense of justice). Responses were made on a 5-point Likert-type scale (1 = *strongly disagree* and 5 = *strongly agree*). Preliminary confirmatory factor analyses were conducted on this instrument and are fully reported in the online supplemental materials accompanying this manuscript. The results from these analyses showed that, although the a priori measurement model fitted the data well, the three a priori facets of trustworthiness where so highly correlated as to detract from their discriminant validity. Indeed, an alternate factor model in which these three facets were used to define a higher-order factor of trustworthiness for each source (i.e. supervisor, top management) and measurement point (resulting in four higher-order factors) provided an equivalent fit to the data while providing a much more parsimonious representation of the data.[3] This model also proved perfectly invariant (i.e., equivalent) across time points (Meredith, 1993), suggesting that comparisons of trustworthiness levels over time were justified. Given that we had no specific predictions about the implications of specific facets of trustworthiness, for purposes of hypothesis testing, we used the higher-order trustworthiness factors to

estimate the latent factor scores for (1) initial levels of perceived trustworthiness at Time 1 and (2) change over time (between Time 1 and Time 2) in trustworthiness levels (e.g., McArdle, 2009). These factor scores were estimated separately for top management and supervisor, and saved in an external data file to use in the main analyses reported in this manuscript. It should be noted that, when we conducted exploratory analyses to examine predictive models including single facet of trustworthiness at a time (see Table S4 on the online supplements), the pattern and size of effects were roughly the same across facets, and in line with those based on the higher-order factor. This further supports the interpretation that these effects largely reflect variance shared among the facets.

Organizational Commitment. We measured commitment to the organization using slightly reworded versions of Meyer, Allen and Smith's (1993) 6-item affective (e.g., [The company] has a great deal of personal meaning for me.), 6-item normative (e.g., I would feel guilty if I left [the company] now), and 6-item continuance (e.g., I have no choice but to work for [the company]) commitment scales. Responses were made on a 5-point Likert-type scale (1 = *strongly disagree* and 5 = *strongly agree*). Preliminary confirmatory factor analyses were also conducted on this instrument and used to estimate factor scores on the commitment factors to use as inputs for the main analyses. These results are fully reported in the online supplements accompanying this manuscript and fully supported the a priori factor model, as well as its complete longitudinal measurement invariance.

Turnover Intention. We measured turnover intention with one item: "How likely is it that you will voluntarily leave [the company] within the next 2 years?" Responses could vary from 1 (*very unlikely*) to 5 (*very likely*). High scores reflected greater likelihood of leaving.

Data Analysis

The Latent Transition Analyses (LTA) models (Collins & Lanza, 2009; Nylund, Asparouhov, & Muthén, 2007) used in this study were estimated using the robust maximum likelihood estimator in Mplus 6.12 (Muthén, & Muthén, 2011). Although previous research has generally yielded five to seven profiles (see Meyer, L. Stanley, 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). By default, Mplus constrains the variance of the indicators (factors scores) to be equal across profiles. However, following Morin, Maïano et al. (2011), we estimated alternative models in which the variances of the indicators were freely estimated in all profiles. Annotated Mplus code used to estimate all models in this present study are reproduced in the online supplements to this article.

In all cases, to determine the final solution we first examined several fit statistics, including the Akaike Information Criterion (AIC), the Bayesian information criterion (BIC), the Consistent Akaïke Information Criterion (CAIC) and the sample-adjusted Bayesian information criterion (SABIC). A lower value on the AIC, CAIC, BIC and SABIC suggests a better-fitting model. Simulation studies showed that inspection of the BIC, CAIC, and SABIC, but not the AIC, were particularly efficient in selecting the optimal model (see the online supplements for additional details on the relative efficacy of these indicators). Finally, because relying on only empirical fit indices for model selection can lead to over-interpretation of the empirical results (Lubke & Muthén, 2005; Marsh et al., 2009; Muthén, 2003), we also used theory and previous commitment profile studies (see Meyer, L. Stanley et al., 2012) to guide our selection of the optimal profile solution.

Although LTA does not require the estimation of a common set of profiles at each time period, it is often useful to systematically test whether the nature of the profile has switched over time. Therefore, we used the final retained LTA solution to systematically test for the equality of the estimated profiles by including longitudinal invariance constraints on the component means and variances within each of the profiles across the two time periods. This analysis permitted a finer-grain assessment of the nature of sample-level changes in commitment profiles over time.

Multinomial logistic regression analyses were conducted to verify whether the demographic predictors, initial levels of perceived management trustworthiness, and changes in trustworthiness over time were indeed predictive of the likelihood of membership into the various profiles from this final, time-invariant, LTA model. Results from multinomial logistic regressions differ from those provided by standard linear or logistic regressions. First, each predictor has k-1 (with k being the number of profiles in the data) different complementary effects for comparison of one profile to a referent profile.

Second, the regression coefficients represent the effects of the predictors on the log odds of the outcome (i.e., the probability of membership in one profile versus another in a pairwise comparison) that can be expected for a one-unit increase predictor. Since these coefficients are expressed in log-odds units, they are complex to interpret. We therefore provide easy-to-interpret odds ratios (OR), which reflect the change in likelihood of membership in the target profile versus the comparison profile for each unit increase in the predictor. ORs allow the size of the different effects to be compared more directly. For instance, an OR of 2 indicates that for each unit increase in the predictor, participants are twice as likely to be member of the target profile versus the comparison profile. ORs under 1, related to negative logistic regression coefficients, indicate that the likelihood of membership in the target profile is reduced. Thus, an OR of .5 shows that the likelihood of membership in the target profile versus the comparison profile is reduced by 50% per unit increase in the predictor.

It should be noted that the direct inclusion of covariates (predictors and outcomes) into the model that is used here takes into account the model-estimated posterior probabilities (the estimated probability that each individual has of belonging to each profile). Contrasting with the traditional methods of assigning individuals based on their most-likely profile-membership to a single profile, the present method avoids the biases associated with the dichotomization of continuous variables (MacCallum, Zhang, Preacher, & Rucker, 2002) and systematically reduces biases in the estimation of the model parameters (Bolck et al., 2004; Clark & Muthén, 2009).

Finally, in order to verify whether turnover intention was affected by membership into the various latent profiles, participants' turnover intent at both time points were added to the final unconditional model as additional indicators of the profiles at their respective time points (i.e. turnover intent at time 1 was included as an indicator of the profiles estimated at time 1, and turnover intent at time 2 was included as an indicator of the profiles estimated at time 2). In order to test for mean level differences between the profiles, we used the MODEL TEST command of Mplus which provides an omnibus Wald chi square test of mean differences across the profiles (Muthén, & Muthén, 2011) and the Mplus MODEL CONSTRAINT function to systematically test mean-level differences across all specific pairs of profiles (using the multivariate delta method, e.g., Raykov & Marcoulides, 2004).

RESULTS

Unconditional Latent Transition Analysis

The fit indices for the 2- to 8-profiles solutions at each time point are reported in Table 2. We report fit for two alternative parameterizations for each model – one where variances are constrained to equality across profiles and one where they are freely estimated. As can be seen, fit is improved when variances are freely estimated. The values for AIC, CIC, CAIS, and SABIC continued to decrease with the addition of profiles, at least up to six or seven profiles, which is common in these types of models (e.g., Marsh et al., 2009; Morin, Maïano et al., 2011; Petras & Masyn, 2010). However, the decrease tended to plateau at around five profiles, which is consistent with the time-specific results reported in the online supplements.

Insert Table 2 about here

As a further aid in identification of the optimal solution, we examined the means for AC, NC and CC for the bordering (4-profile and 6-profile) solutions. This inspection revealed that the 5-profile solution conformed most closely to theory and the findings of previous profile studies. Moreover, the five profiles were the same at both time points and were identical to the solutions obtained in the preliminary latent profile analyses conducted with the Time 1 and Time 2 data (see online supplementary materials). In contrast, profiles in the 4-profile solution differed primarily in the level of the three mindsets, with little evidence of differentiation in terms of profile shape. The 6-profile solution differed from the 5-profile solution primarily by splitting one profile based on a slight difference in commitment levels. Therefore, for the sake of parsimony, and because the added-value of person-centered analyses is greater in the presence of qualitative (shape) differences across profiles (see Marsh et al., 2009; Meyer et al., 2013), we retained the 5- profile model as our final solution.

Examination of the most likely assignment of each participant into the various combinations of profiles also reveals the impressive stability of membership into these profiles. In fact, only 2.76% of the cases switch classes over time, corresponding to 27 participants out of the 978 included in the sample. Also, the very high entropy indicator (.92) associated with this final model reveals that

classifications where quite accurate for most participants. Interestingly, when we further examined the probability of membership into the various profiles for the participants who changed profile over time, we noted that at least half of them had an unclear dominant profile membership at Time 1 (with only 45%-65% likelihood of being member of their Time 1 profile, but also an elevated likelihood of being member of the profile they joined at Time 2). In other words, half of the very few employees who changed profile over time were already "border" cases (i.e. participants with an unclear dominant profile) at the beginning of the study so their "changing" of profile may only reflect classification imprecision (e.g., similar to measurement error in classical factor analyses) rather than a real modification of their commitment profiles over time. This reinforces the fact that commitment profiles are highly stable and that very few employees change profile over time, even when exposed to important organizational changes.

To aid in the interpretation of the five commitment profiles, we plotted the means for AC, NC and CC (see Figure 1). Consistent with most previous research, we first plotted the raw means to illustrate absolute and relative differences in the three mindsets across profiles. However, we also plotted the normed-means to take into account deviations from population levels of commitments in the interpretation of the profiles (see Figure 2). To this end, we use normative data reported by Meyer, D. Stanley et al. (2012) for the English Canadian studies included in their meta-analysis.

Insert Figures 1 and 2 about here

Looking first at the raw mean plots at the top of Figure 1, it can be seen that Profile 1 is characterized by comparatively high scores on AC and NC. Indeed, AC and NC are higher in this profile than in any other profile and, while both are above the scale midpoint (3), CC scores fall below the midpoint. Therefore, we labeled this profile *AC/NC-dominant*. This profile describes close to 22% of the employees. In Profile 2, which describes approximately 21% of the employees, only the AC mean is above the scale midpoint, thus we used the label *AC-dominant*. The shape of Profile 3 is similar to that of Profile 2, but the levels of all three mindsets are lower and all fall below the midpoint of the scale. We labeled this profile *all mid with AC-dominant* to reflect the fact that, despite AC being somewhat elevated, the overall level of commitment was only moderate. This profile describes approximately 18% of the employees. Profiles 4 and 5 were somewhat similar in shape in that the mean for CC is considerably stronger than the means for AC and NC. However, all three means were higher in Profile 4 than in Profile 5. Given that the means for Profile 4 were in the moderate range, we labeled this profile *all mid with CC-dominant*. Because the AC and NC means for Profile 5 were very low, we labeled this profile *CC-dominant*. Whereas Profile 4 describes approximately 22% of the employees, the least favorable Profile 5 describes closer to 17% of them.

The plot of the norm-standardized means at the bottom of Figure 2 appears similar, particularly in shape, to that for the raw means. However, looking at the norm-standardized means, it is clear that the majority of the means fall below those for Canadian employees in general (i.e., above zero). Indeed, only the AC and NC means in Profiles 1 and the AC mean in Profile 2 are above average. The other most notable difference between the two sets of plots is in the relative strength of NC within each profile. This is perhaps most obvious in the AC/NC-dominant profile where the means for the standardized AC and NC scores are more similar than the means for the raw scores. This reflects the fact that for Canadian employees, the mean is generally lower for NC than for AC.

These profiles depicted in Figure 1 and 2 are similar to those commonly found in previous research. Perhaps the most notable exclusions are the fully-committed and uncommitted profiles. Thus, our findings provide partial support for Hypothesis 1. The fact that the same profiles were identified at both time points, prior to and following the change, provides strong support for Hypothesis 2. Considering this, and the fact that very few individuals shifted between profiles over time, it is not surprising that the size of the profile groups reflected in Figure 1 are also very similar. It is also noteworthy that the different profiles are so similar in size, suggesting that they are all meaningful subgroups with the participating organization.

Predicting Profile Membership from Demographic Characteristics.

To explore the implications of demographic differences on commitment profiles, we included demographic variables in the LTA model as predictors of the Time 1 profiles. The CC-dominant profile was selected as the reference profile because, based on previous research, it is the least

favorable of the profiles identified in this study. The multinomial regression statistics compared the likelihood of belonging to a particular profile (for example, AC/NC-dominant profile) as compared to the reference profile (the CC-dominant profile in this case). The results of these analyses are reported in Table 3. Recall that the odds ratios (OR) reflect the change in likelihood of membership in the target profile versus the comparison profile for each unit increase in the predictor. An OR above 1 means that as the value of a predictor increases, the likelihood of being classified in a target profile (e.g., AC/NC-dominant group) is higher than the likelihood of being classified in a reference profile (i.e., CC-dominant group). Conversely, an OR below 1 means that, as the value of a predictor increases, the likelihood of being classified in a target profile is reduced, as compared to the likelihood of being classified in a reference profile (i.e., CC-dominant group).

Insert Table 3 about here

Inspection of Table 3 reveals a few statistically significant associations between the demographic variables and the likelihood of membership into a profile. For example, managerial level significantly predicted the relative likelihood of membership in the two AC-dominant profiles (i.e., all mid with AC-dominant profile and AC-dominant profile). Interestingly it did not predict likelihood of membership into the arguably most desirable AC/NC-dominant profile. Similarly, tenure negatively predicted the relative likelihood of membership in the two AC-dominant profiles, but not in the AC/NC-dominant profile. Gender negatively predicted the relative likelihood of membership in the profile characterized by mid-levels of commitments with AC-dominant, suggesting that men are more likely to be members of this profile than women. No other profiles were predicted by gender. Finally, union membership negatively predicted the relative likelihood of membership in the AC/NC-dominant profile. Overall, despite some significant associations, the demographic variables were generally not strong predictors of profile membership.

Predicting Profile Membership from Perceived Management Trustworthiness

A final set of models were estimated in which initial levels of perceived top management and supervisor trustworthiness were included as predictors of profile membership at Time 1. In these same models, changes in trustworthiness ratings from Time 1 and Time 2 were included as predictors of profile membership at Time 2. The latter analysis was conducted to determine whether changes in levels of perceived trustworthiness would contribute to the prediction of profile membership at Time 2 above and beyond the prediction afforded by Time 1 profile membership (i.e., longitudinal stability). Thus, this corresponds to an estimation of whether changes in levels of perceived trustworthiness could contribute to the prediction of change in profile membership over time. To ease the interpretation of the odds ratio produced by these multinomial logistic regressions, the predictors (i.e., Time 1 trustworthiness and change in trustworthiness) were converted to *z* scores before the analyses. Thus, a *z* score of 1 on the initial levels of Time 1 trustworthiness reflects a perception of the trustworthiness of the target that is higher than the average perception by 1 *SD*. For the change scores, 1 reflects a level of change that is greater than the average level of change by 1 *SD*. It should be noted that the observed levels of changes where in fact so low so as to create problems in the estimation of the coefficients when not converted to z scores. This is because OR coefficients reflect changes in the outcomes as a function of 1 unit in the predictor which, in the case of the raw change scores, reflects an extreme level of change. Thus, the average levels and standard deviations of the raw latent change scores for top management and immediate supervisor trustworthiness have, respectively, means of 0.11 and -0.01, with SD of 0.41 and 0.56. So, that means that a change of 1 in raw score units corresponds to a change of approximately 2 *SD*s over the mean, which is enormous.

Top management trustworthiness at Time 1 positively predicted the likelihood of being a member of all four profiles relative to the reference (CC-dominant) profile. Inspection of the odds ratios reveals that top management trustworthiness predicts likelihood of membership in the profiles more strongly as the favorability of the profiles is increased. Specifically, the odds ratios for membership in the two all mid profiles (i.e., all mid with CC-dominant or with AC-dominant) were similar (2.51 and 2.34 respectively), but were twice as high when predicting membership into the AC-dominant profile (5.92) and five times as high when predicting membership into the AC/NC-dominant profile (11.78). Therefore, an increase in perceptions of management trustworthiness substantially enhances the chance of an employee corresponding to a more favorable profile.

Although the pattern of findings was similar for analyses involving the trustworthiness of immediate supervisor, including the increase in odds ratio with profile favorability, the size of the odds ratio was considerably smaller. Specifically, the odds ratios for immediate supervisor trustworthiness ranged from 1.30 to 1.82 compared to the 2.34 to 11.78 range for top management trustworthiness. Together, these findings support Hypothesis 3 regarding the implications of perceived management trustworthiness for commitment profiles. They were also in line with Dirks and Ferrins' (2002) results, demonstrating that top management trustworthiness is more important than immediate supervisor trustworthiness in predicting commitment profiles.

Perhaps not surprisingly, given the great stability of the profiles noted above, changes in perception of management trustworthiness did not generally predict the likelihood of membership in the Time 2 profiles beyond the prediction afforded by the Time 1 profile membership. Indeed, only one significant effect was observed – increases in the perceived trustworthiness of top management positively predicted increases in the relative likelihood of switching from the reference profile (CC-dominant profile) at Time 1 to an all mid with CC-dominant profile at Time 2. In addition, no significant effects were found for changes in immediate supervisor trustworthiness. The fact that the only significant prediction was found for change in perceptions of top management trustworthiness provides weak support for Hypothesis 4. Again, it must be emphasized that these findings are attributable to the fact that the profiles were highly stable over time and that classification of employees into these profiles was highly accurate (as illustrated with the .92 entropy indicator) and stable. Recall that less than three percent of the sample were deemed to have switched profiles from Time 1 to Time 2. This explains the relatively high standard errors associated with the multinomial logistic regression coefficients for the changes scores. The largest transition involved 10 individuals who moved from the CC-dominant profile at Time 1 to the all mid with CC-dominant profile at Time 2. This helps to explain why this was the only transition predicted by changes in top management trustworthiness.

Within-time Comparisons of the Profile Groups on Turnover Intention

The results from the next set of analyses in which turnover intention was included as an additional profile indicator are reported in Table 4. For both time points, the omnibus test of mean differences was highly significant. Also noteworthy is the fact that the means and variances of turnover intention within each profile are very similar across time points, again reinforcing the stability of the profiles. In fact, an additional omnibus test of mean differences across time points confirmed that they did not differ significantly from one another ($\chi^2 = 3.87$, $df = 5$, $p = .57$). A detailed examination of mean differences shows significant differences between most of the profiles, with only the all mid with CC-dominant profile and the AC-dominant profile not significantly different from one another. Although turnover intentions are similar for employees with these two profiles, the motives (desire *vs.* perceived cost) are different. Perhaps the most surprising finding is that employees with an all mid with AC-dominant profile were more likely to intend to leave than those with an all mid with CC-dominant profile. This might suggest that at moderate levels, CC provides a stronger tie to the organization than does AC. Perhaps least surprisingly, and consistent with previous research, turnover intentions were lowest among employees with an AC/NC-dominant profile. Overall, the pattern of means is largely consistent with that from previous research (e.g., Somers, 2009, 2010).

Insert Table 4 about here

DISCUSSION

Our study extends earlier commitment profile research in several important ways. First, we provide further evidence for the heterogeneity of the workforce with regard to commitment mindset profiles, demonstrate the cross-sample generalizability of several such profiles, and provide the first evidence for within-sample temporal stability of the profile structure. Second, we provide some of the first evidence that the likelihood of having a particular profile, and of changing profiles over time, can be predicted. Specifically, we demonstrated that, in an organization undergoing change, perceptions of management trustworthiness were associated with formation and change in commitment profiles.

Commitment Profiles and Profile Stability over Time

Our findings regarding profile structure and stability help to address two potential concerns about the utility of the profile approach: first that the number of potential profiles is too great to be of

practical value, and second that these profiles might fluctuate in unpredictable ways across and/or within samples. Our analyses revealed five commitment profiles, all of which were similar to profiles identified in previous research - AC/NC-dominant, AC-dominant, CC-dominant and two mid-level profiles (one with AC-dominant, and one with CC-dominant). Thus, the number of potential profiles appears to be quite small – between five and nine (cf. Meyer, L. Stanley et al., 2012). Moreover, these profiles can arguably be grouped into smaller subsets with similar outcomes, including: (1) the fully-committed and AC/NC-dominant profiles, (2) the AC-dominant and AC/CC-dominant profiles, (3) the mid-level profiles, (4) the CC-dominant and CC/NC-dominant profiles, and (5) the uncommitted profile. This limited set of profiles is certainly manageable and emerging evidence concerning their implications for organizations and employees suggest the distinctions are worth making.

With regard to stability, we not only found that the profiles in our sample were similar to those in other studies, but also that these profiles were relatively stable within a sample (at least for a period of 8 months), even under conditions of organizational change. Indeed, we even found considerable stability in individual employees' profiles as they were exposed to the change. As we note below, the change being experienced by these employees may not have been as dramatic or turbulent as might occur in other organizations. Still, the fact that profiles remained relatively constant under these conditions should allay fears that commitment profiles are too ephemeral and responsive to day-to-day fluctuations in working conditions to be of practical value. Of course, this stability does not mean that profiles are insensitive to management interventions. As we discuss below, profile formation and change appears to be somewhat sensitive to perceptions of management trustworthiness.

Perceived Management Trustworthiness and Commitment Profiles

With the odd exception (e.g., Gellatly et al., 2009), little attention has been paid to date to the formation of commitment profiles, and we are unaware of any studies that have examined change in profile over time. Although we conducted exploratory analyses with several demographic variables (e.g., age, gender), we found little in the way of systematic relations with profile membership. Given the exploratory nature of these analyses and the lack of consistency in the observed effects, the findings are difficult to interpret with confidence. Therefore, we focus attention on the antecedent of primary interest in this study – the perceived trustworthiness of management.

Due to existing disagreement concerning the dimensionality of Mayer and colleagues' (1995) trustworthiness measure, we first conducted analyses to determine how the facets (ability, benevolence, integrity) should best be treated in testing our hypotheses: as individual factors, as a unidimensional construct, or as latent indicators of a higher-order construct. These analyses provided strong evidence for the existence of a higher-order construct, and therefore we conducted our primary analyses using this construct as our predictor. As expected, we found that perceptions of the overall trustworthiness of top management and the immediate supervisor related positively to the relative odds of membership in the more favorable profiles. The strength of these relations increased directly with profile favorability. Interestingly, this pattern mirrors that found in previous research involving outcomes (e.g., retention, job performance, OCB, well-being). Thus, those profiles associated with the highest levels of perceived management trustworthiness are also the most desirable from an outcomes perspective.

Our focus on global trustworthiness is not to suggest that employees never make distinctions, or that organizations should not use the three-facet model as a guide in shaping employee perceptions (e.g., focusing on demonstrating ability when it is likely to be a major concern for employees). To the contrary, we argue below that this is precisely what organizations should do. However, based on recent findings in other domains, more research may be needed to determine exactly how employees' form and utilize perceptions of trustworthiness. For example, it has been demonstrated that employees form global perceptions of organizational justice (e.g., Ambrose & Schminke, 2009) and develop general attitudes (Harrison, Newman, & Roth, 2006), and that these global variables mediate the influence of individual facets of justice (e.g., distributive, procedural, interactional) or specific attitudes (e.g., job satisfaction, job involvement, attitudinal commitment) on their behavior. The same might apply to trustworthiness, where global assessments reflecting the higher-order factor may mediate the impact of the facets. Therefore, it would be interesting to determine whether, and when, employees form inconsistent perceptions of the three facets. If they do make distinctions, are these reconciled in the formation of a global assessment of trustworthiness, or do employees react differentially to the pattern of facet scores?

We also found some support for Dirks and Ferrin's (2002) observation that employees' organizational commitment is more sensitive to the trustworthiness of top management than of their immediate supervisor. Although the pattern of results was generally similar for the two foci, the effects were clearly stronger for top management. This is to be expected given that top management is generally seen as responsible for organization-level events, including the implementation of change initiatives such as that experienced by employees in the current study. Of course, if correspondence between the target of the perception and commitment is indeed the explanation (cf. Lewin, 1951), then the reverse might be expected in studies involving other foci of commitment. For example, in a study of commitment to a work team or project, trust in immediate supervisor may play a substantially greater role.

Finally, our ability to test our hypothesis regarding the prediction of profile change was limited by the fact that we found very little evidence of change. Interestingly, the largest shift was from the CC-dominant profile at Time 1 to the all mid with CC-dominant profile at Time 2, and this movement was predicted by increases in the level of perceived trustworthiness of top management. These findings, combined with the fact that perceptions of trustworthiness of both top management and immediate supervisor increased over time (see Table 1), suggest that, rather than undermining commitment, organizational change might provide opportunities for management to demonstrate their trustworthiness and foster more desirable commitment profiles (see Meyer, 2009).

We can only speculate on why we did not find stronger evidence for individual profile change in our sample. It is also possible that the turbulence created by the change under investigation was not as great as initially expected, or that it was managed particularly well. Although, it has been argued that radical changes can undermine trust (Gillespie & Dietz, 2009) and commitment (Meyer, 2009), it might do so only under some conditions. For example, Tomlinson and Mayer (2009) argued that the implications for managerial actions on perceptions of their trustworthiness will depend on the consequences for employees and, importantly, the attributions they make for these actions. The greatest damage to perceptions of trustworthiness can be expected when employees attribute negative outcomes to stable, internal, and controllable factors (e.g., managers' persistent tendency to make decisions that favor themselves or shareholders rather than employees). Viewed with this lens, the change faced by the organization in this case was stimulated by deregulation of the industry (an external factor). Thus, senior managers may have been seen as taking appropriate action to keep the company competitive in the newly deregulated industry – a change that would benefit the majority of employees as well as other stakeholders. Indeed, it may have been managements' response to this external "threat" that contributed to some employees' increasing their perceptions of trustworthiness and the accompanying shift to a more desirable profile. This leaves open the possibility that more negative perceptions of management might be observed in other change contexts with an accompanying shift to less desirable commitment profiles.

Limitations and Future Directions

As is true of any study, it is unclear whether our findings generalize beyond the current sample and context. The fact that we found many of the same profiles as previous research (c.f. Meyer, L. Stanley et al., 2012), and that these profiles related similarly to turnover intention, suggests that our sample was not particularly unique. Thus, our findings help to bolster confidence in the notion that the workforce consists of heterogeneous subgroups with distinct commitment profiles. We also have confidence in the generalizability of our findings regarding within-time relations between perceived trustworthiness and profile membership. However, as noted above, the context surrounding the organizational change in our study might not have been conducive to the kinds of attributions needed to undermine perceptions of top management trustworthiness (Tomlinson & Mayer, 2009). A useful strategy to investigate this issue in the future would be to assess employees' attributions for the organizational change (or any other precipitating event) to use as a moderator in within-study analyses or cross-study comparisons. The same applies to other potential contextual factors such as implications for job security, workload, or compensation.

Our investigation of profile formation and change was admittedly limited. There are likely to be many factors other than management trustworthiness involved in shaping commitment profiles. It would be particularly useful to identify factors that can help to differentiate more clearly between specific profiles. For example, our findings suggest that when employees perceive management as trustworthy, the odds of having one of the more desirable profiles increases, and that the odds increase

as a function of the level of desirability. However, if it is actually the case that an AC/NC-dominant profile is qualitatively distinct from an AC-dominant profile, it would be useful to know what specific initiatives, or combination of initiatives, is likely to foster the former as opposed to the latter. That is, what does it take to foster a moral imperative mindset (Gellatly et al., 2006) rather than merely an affective bond or desire to remain.

Finally, two commonly expressed concerns with studies such as ours involve the use of a non-experimental design and the potential for common method bias. The nature of the constructs makes it difficult to use direct manipulation. Nevertheless, future studies might take advantages of situations that involve the natural manipulation of conditions likely to affect perceptions of trustworthiness and to test for mediating effects of the latter on profile formation or change. Similarly, it would have been difficult to measure our key constructs without using self-report. However, there are two reasons why we believe our finding reflect more than method bias. First, profile analyses detected different patterns of high and low scores on the commitment mindsets within the sample. Second, we found that relations between trustworthiness perceptions and commitment profiles varied depending on focus (top management or supervisor). Strong method bias would have worked against our finding both of these patterns in our data.

Implications

Our findings have implications for both commitment theory and practice. With regard to theory, they provide further support for the notion that several organizational commitment profiles (e.g., AC/NC-dominant; AC-dominant; mid-level; CC-dominant) are common among the workforce. Perhaps more importantly, these profiles demonstrate remarkable temporal stability at both the individual and sample levels. Thus, in conjunction with previous studies, our findings help to alleviate concerns that profiles might be too complex and unstable to be of heuristic value.

An important next step in profile research is to address explanations for, and limits to, stability. As we noted earlier, existing theory and research provides arguments for both stability and instability. Most situations will likely involve a mix of forces for and against change. Indeed, as is often the case in psychological and organizational research, complex questions are rarely answered in an either-or manner, suggesting that it might be worthwhile to test models that include state and trait components (cf. Cole, Martin, & Steiger, 2005; Morin, Maïano et al., 2011). Such models would allow for greater precision in disentangling stable trait and unstable state aspects of commitment and in studying the determinants and outcomes of these components. For example, based on repeated measures of commitment, such models would allow for the separate consideration of trait-commitment (i.e., trajectories of commitment over time showing some form of longitudinal consistency) from state-commitment (i.e. time-specific fluctuations that deviate from the estimated smoothed individual trajectory), and to consider predictors and outcomes of both components.

Also of relevance to commitment theory are our findings regarding the AC/NC-dominant profile. This profile has commonly been found to associate more strongly with retention, job performance, and OCB than the AC-dominant profile (e.g., Somers, 2009, 2010; Wasti, 2005). Its clearest rival is the fully committed profile that also includes strong AC and NC. We also found that turnover intention was lowest for employees in the AC/NC-dominant profile. In addition, this profile had a strong association with perceived management trustworthiness. The AC/NC-dominant, or moral-imperative profile (Gellatly et al., 2006), is only beginning to garner attention, and research is shedding new light on the relevance of NC more generally (cf. Meyer & Parfyonova, 2010). It is possible that the combination of obligation (NC) with desire (AC) provides an optimal mix of self- and collective-interest where employees are willing to exert effort for the benefit of both when possible, and to make personal sacrifices for the collective when the situation demands it. This AC/NC combination might be what theorists are referring to when they describe commitment as an outcome of transformational leadership (e.g. Bass, 1999), perceived organizational support (e.g. Eisenberger, Fasolo, & Davis-LaMastro, 1990), organizational justice (e.g., Sweeney & McFarlin, 1993), and relational psychological contracts (e.g., Rousseau, 1995). However, research to date has focused almost exclusively on AC. The accumulating evidence suggests that it might be time to look beyond AC alone. The same might be true for managers.

From a practical perspective, our findings regarding profile stability combined with evidence linking commitment to personality (Erdheim et al., 2006; Panaccio & Vandenberghe, 2012) and values (Clugston et al., 2000; Wasti, 2003) suggest that organizations might begin to establish desired forms

of commitment in the selection process. Some personality characteristics (e.g., conscientiousness) and values (e.g., collectivism) might contribute directly to development of an AC/NC-dominant profile. Other personality characteristics and values may need to be targeted differentially to achieve fit with the organization's goals, values, and mission (see Kristof-Brown, Zimmerman, & Johnson, 2005).

Regardless of how predisposed employees might be to developing specific commitment profiles, their experiences at work will play an important role in shaping or changing their commitment. Early experiences and those that stimulate sense-making (Morrison & Robinson, 1997; Tomlinson & Mayer, 2009) are likely to have the strongest influence. Although it is too early to provide clear prescriptions for how to manage these experiences, our study suggests that behaving in a way that establishes perceptions of trustworthiness may be important. Employees who perceived top management as trustworthy going into the change tended to have more desirable commitment profiles than those who did not. Although we did not detect much change in commitment profiles over time, we found evidence that positive changes in perceptions of trustworthiness were associated with a positive shift in profile. This finding is consistent with the idea that organizational change affords an opportunity to build trust (Meyer, 2009). In the present case, despite the fact that there were layoffs and some permanent positions were replaced by contract positions, the senior management team took a number of steps (e.g., town hall meetings) to communicate the rationale for the change and listen to concerns, which may have helped to maintain perceptions of trustworthiness, and perhaps even enhance it in the eyes of some employees.

There are many things that organizations can do prior to and during a change to maintain or enhance perceptions of trustworthiness. To illustrate, consider the facets of trustworthiness identified by Mayer et al. (1995) – ability, benevolence, and integrity – as key considerations. Management must instill confidence in their ability to manage the change effectively. A track record of success will help but, in its absence, evidence of a clear and rational vision for the future could help, as might evidence of "small wins" (Kotter & Cohen, 2002) in the early stages of change. Consultation with employees at the various stages of change, where appropriate, will help to foster perceptions of both benevolence and integrity. Even when change has detrimental consequences for some employees, benevolence and integrity can be fostered by efforts to acknowledge and compensate those affected. An important key to all three facets is continuous, open and honest communication (Gopinath & Becker, 2000; Schweiger & DeNisi, 1991). These and other strategies designed to foster perceptions of trustworthiness are likely to pay off in terms of building, maintaining, or enhancing desirable commitment profiles among employees during the change. Although it is beyond the scope of the present discussion, authors of a recent special topic forum in the *Academy of Management Review* provide numerous suggestions for ways that organizations can rebuild trust once it has been damaged (see Dirks, Lewicki, Zaheer, 2009).

Conclusion

Our findings provide preliminary evidence for the temporal stability of commitment profiles and, by implication, offer some justification for targeting profile development as a strategy for achieving a healthier and more productive workforce. Efforts to foster perceptions of trustworthiness in the eyes of employees may be one key to fostering more desirable profiles. More research is needed to identify other important drivers, perhaps beginning with other variables (e.g., perceived organizational support; transformational leadership) that have been studied largely in relation to individual mindsets.

REFERENCES

Albrecht, S., & Travaglione, A. 2003. Trust in public-sector senior management. *International Journal of Human Resource Management*, 14: 76-92.

Ambrose, M. L., & Schminke, M. 2009. The role of overall justice judgments in organizational justice research: A test of mediation. *Journal of Applied Psychology*, 94: 491-500.

Armstrong-Stassen, M. 1998. The effect of gender and organizational level on how survivors appraise and cope with organizational downsizing. *Journal of Applied Behavioral Science*, 34: 125-142.

Bass, B.M. (1999) Current developments in transformational leadership. *The Psychologist-Manager Journal*, 3: 5-21.

Bateman, T. S., & Strasser, S. 1984. A longitudinal analysis of the antecedents of organizational commitment. *Academy of Management Journal*, 27: 95-112.

Becker, H. S. 1960. Notes on the concept of commitment. *American Journal of Sociology*, 66: 32-42.

Blau, P. 1964. *Exchange and power in social life*. New York: Wiley.

Bolck, A., Croon, M., & Hagenaars, J. 2004. Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis*, 12: 3-27.

Caldwell, S., Liu, Y., Fedor, D., & Herold, D. 2009. Why are perceptions of change in the "eye of the beholder"? The role of age, sex, and tenure in procedural justice judgments. *Journal of Applied Behavioral Science*, 45: 437-459.

Clark, S. L., & Muthén, B. O. 2009. Relating latent class analysis results to variables not included in the analysis. Manuscript submitted for publication and downloaded (23-07-2009) from http://www.statmodel.com/download/relatinglca.pdf

Clugston, M.,, Howell, J. P., & Dorfman, P. W. 2000. Does cultural socialization predict multiple bases and foci of commitment? *Journal of Management*, 26: 5-30.

Cole, D.A., Martin, N.C., & Steiger, J.H. 2005. Empirical and conceptual problems with longitudinal trait-state models: Introducing a trait-state-occasion model. *Psychological Methods*, 10: 3-20.

Collins, L. M., & Lanza, S. T. 2009. *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences*. New York: John Wiley & Sons.

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O. L. H., & Ng, K. L. 2001. Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology*, 86: 425-445.

Colquitt, J. A., LePine, J. A., Piccolo, R. F., Zapata, C. P., & Rich, R. L. 2012. Explaining the justice-performance relationship: Trust as exchange deepener or trust as uncertainty reducer? *Journal of Applied Psychology*, 97: 1-15.

Colquitt, J. A., & Rodell, J. B. 2011. Justice, trust, and trustworthiness: A longitudinal analysis integrating three theoretical perspectives. *Academy of Management Journal*, 54: 1183-1206.

Colquitt, J. A., Scott, B. A., & LePine, J. A. 2007. Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. *Journal of Applied Psychology*, 92: 909-927.

Cropanzano, R. and Mitchell, M.S. 2005. Social exchange theory: an interdisciplinary review. *Journal of Management*, 31, 874-900.

Curry, J. P., Wakefield, D. S., Price, J. L., & Mueller, C. W. 1986. On the causal ordering of job satisfaction and organizational commitment. *Academy of Management Journal*, 29: 847-858.

Dirks, K. T., & Ferrin, D. L. 2002. Trust in leadership: Meta-analytic findings and implications for research and practice. *Journal of Applied Psychology*, 87: 611-628.

Dirks, K. T., Lewicki, R. J., & Zaheer, A. 2009. Repairing relationships within and between organizations: Building a conceptual foundation. *Academy of Management Review*, 34: 68-84.

Eisenberger, R., Fasolo, P., & Davis-LaMastro, V. 1990. Perceived organizational support and employee diligence, commitment, and innovation. *Journal of Applied Psychology*, 75: 51–59.

Enders, C. K. 2001. The impact of nonnormality on full information maximum-likelihood estimation for structural equation models with missing data. *Psychological Methods*, 6: 352-370.

Enders, C. K. 2010. *Applied missing data analysis*. New York, NY: Guilford.

Enders, C.K., & Bandalos, D.L. 2001. The relative performance of Full Information Maximum-Likelihood estimation for missing data in structural equation models. *Structural Equation Modeling*, 8: 430-457.

Erdheim, J., Wang, M., & Zickar, M. J. 2006. Linking the Big Five personality constructs to

organizational commitment. *Personality and Individual Differences*, 41: 959-970.
Fischer, R., & Mansell, A. 2009. Commitment across cultures: A meta-analytic approach. *Journal of International Business Studies,* 40: 1339-1358.
Gellatly, I. R., Hunter, K. H., Currie, L. G., & Irving, P. G. 2009. HRM practices and organizational commitment profiles. *The International Journal of Human Resource Management,* 20: 869-884.
Gellatly, I. R., Meyer, J. P., & Luchak, A. A. 2006. Combined effects of the three commitment components on focal and discretionary behaviors: A test of Meyer and Herscovitch's propositions. *Journal of Vocational Behavior,* 69: 331-345.
Gillespie, N., & Dietz, G. 2009. Trust repair after an organization-level failure. *Academy of Management Review,* 34: 127-145.
Gopinath, C., & Becker, T. E. 2000. Communication, procedural justice, and employee attitudes: Relationships under conditions of divestiture. *Journal of Management,* 26: 63-83.
Graham, J. W. 2009. Missing data analysis: Making it work in the real world. *Annual Review of Psychology*, 60: 549-576.
Harrison, D. A., Newman, D. A., & Roth, P. L. 2006. How important are job attitudes? Meta-analytic comparisons of integrative behavioral outcomes and time sequences. *Academy of Management Journal*, 49: 305-325.
Hipp, J. R., & Bauer, D. J. 2006. Local solutions in the estimation of growth mixture models. *Psychological Methods*, 11: 36-53.
Hopkins, S. M., & Weathington, B. L. 2006. The relationships between justice perceptions, trust, and employee attitudes in a downsized organization. *The Journal of Psychology: Interdisciplinary and Applied*, 140: 477-486.
Jackson, T., Meyer, J. P., & Wang, F. 2013. Leadership, commitment, and culture: a meta-analysis. *Journal of Leadership and Organizational Studies, 20*: 84-106.
Jiang, K., Lepak, D., Hu, J., & Baer, J. 2012. How does human resource management influence organizational outcomes? A meta-analytic investigation of mediating mechanisms. *Academy of Management Journal*, 55: 1264-1294.
Johnson, R. E., Groff, K. W., & Taing, M. U. 2009. Nature of the interactions among organizational commitments: Complementary, competitive or synergistic? *British Journal of Management,* 20: 431-447.
Korsgaard, M., Sapienza, H., & Schweiger, D. 2002. Beaten before begun: The role of procedural justice in planning change. *Journal of Management,* 28: 497-516.
Kotter, J. P., & Cohen, D. S. 2002. The heart of change: Real-life stories of how people change their organizations. Boston: Harvard University Press.
Kristof-Brown, A. L., Zimmerman, R. D., & Johnson, E. C. 2005. Consequences of individuals' fit at work: A meta-analysis of person-job, person-organization, person-group, and person-supervisor fit. *Personnel Psychology*, 58: 281-342.
Larsen, R. 2011. Missing data imputation versus full information maximum likelihood with second level dependencies. *Structural Equation Modeling*, 18: 649-662.
Lashinger, H. K. S., Finegan, J., Shamian, J., & Casier, S. 2000. Organizational trust and empowerment in restructured healthcare settings: Effects on staff nurse commitment. *Journal of Nursing Administration,* 30: 413-425.
Lewin, K. 1951. *Field Theory in Social Science*. New York: Harper and Brothers.
Little, R. J. A., & Rubin, D. B. 1987. Statistical analysis with missing data. New York: Wiley.
Lubke, G. H., & Muthén, B. 2005. Investigating population heterogeneity with factor mixture models. *Psychological Methods,* 10: 21-39.
MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. 2002. On the practice of dichotomization of quantitative variables. *Psychological Methods*, 7: 19-40.
Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. 2009. Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling,* 16: 191-225.
Mayer, R. C., & Davis, J. H. 1999. The effect of the performance appraisal system on trust for management: A field quasi-experiment. *Journal of Applied Psychology*, 84: 126-136.
Mayer, R. C., Davis, J. H., & Schoorman, F. D. 1995. An integrative model of organizational trust. *Academy of Management Review,* 20: 709-734.

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. 2009. Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling,* 16: 191-225.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. 1995. An integrative model of organizational trust. *Academy of Management Review,* 20: 709-734.

McArdle, J. J. 2009. Latent variable modeling of differences and change with longitudinal data. *Annual Review of Psychology,* 60: 577-605.

McLachlan, G., & Peel, D. 2000. *Finite mixture models*. New York: John Wiley.

Meredith, W. 1993. Measurement invariance, factor analysis and factorial invariance. *Psychometrika,* 58: 525-543.

Meyer, J. P. 2009. Commitment in a changing world of work. In H. J. Klein, T. E. Becker, & J. P. Meyer (Eds.), *Commitment in organizations: Accumulated wisdom and new directions*: 383−416. Florence, KY: Routledge/Taylor and Francis Group.

Meyer, J. P., & Allen, N. J. 1988. Links between work experiences and organizational commitment during the first year of employment: A longitudinal analysis. *Journal of Occupational Psychology,* 61: 195-209.

Meyer, J. P., & Allen, N. J. 1991. A three-component conceptualization of organizational commitment. *Human Resource Management Review,* 1: 61-89.

Meyer, J. P., & Allen, N. J. 1997. *Commitment in the workplace: Theory, research, and application*. Thousand Oaks, CA: Sage.

Meyer, J. P., Allen, N. J., & Smith, C. A. 1993. Commitment to organizations and occupations: Extension and test of a three-component conceptualization. *Journal of Applied Psychology,* 78: 538-551.

Meyer, J. P., Allen, N. J., & Topolnytsky, L. 1998. Commitment in a changing world of work. *Canadian Psychology,* 39: 83-93.

Meyer, J. P., Becker, T.E., & Van Dick, R. 2006. Social identities and commitments at work: Toward an integrative model. *Journal of Organizational Behavior,* 27: 665-683.

Meyer, J. P., Bobocel, D. R., & Allen, N. J. 1991. Development of organizational commitment during the first year of employment: A longitudinal study of pre- and post-entry influences. *Journal of Management,* 17: 717-733.

Meyer, J. P., Hecht, T. D., Gill, H., & Topolonytsky, L. 2010. Person-organization (culture) fit and employee commitment under conditions of organizational change: A longitudinal study. *Journal of Vocational Behavior,* 76: 458-473.

Meyer, J. P., & Herscovitch, L. 2001. Commitment in the workplace: Toward the general model. *Human Resource Management Review,* 11: 299-326.

Meyer, J. P., & Maltin, E. R. 2010. Employee commitment and well-being: A critical review, theoretical framework and research agenda. *Journal of Vocational Behavior,* 77: 323-337.

Meyer, J. P., & Parfyonova, N. M. 2010. Normative commitment in the workplace: A theoretical analysis and re-conceptualization. *Human Resource Management Review,* 20: 283−294.

Meyer, J. P., Srinivas, E. S., Lai, J. B., & Topolnytsky, L. 2007. Employee commitment and support for an organizational change: Test of the three-component model in two cultures. *Journal of Occupational and Organizational Psychology,* 80: 185-211.

Meyer, J. P., Stanley, D. J., Herscovitch, L., & Topolnytsky, L. 2002. Affective, continuance and normative commitment to the organization: A meta-analysis of antecedents, correlates and consequences. *Journal of Vocational Behavior,* 61: 20-52.

Meyer, J. P., Stanley, D. J., Jackson, T. A., McInnis, K. J., Maltin, E. R., & Sheppard, L. 2012. Affective, normative, and continuance commitment levels across cultures: A meta-analysis. *Journal of Vocational Behavior,* 80, 225-245.

Meyer, J. P., Stanley, L. J., & Parfyonova, N. M. 2012. Employee commitment in context: The nature and implication of commitment profiles. *Journal of Vocational Behavior,* 80: 1-6.

Meyer, J. P., Stanley, L. J., & Vandenberg, R. M. 2013. A person-centered approach to the study of commitment. *Human Resource Management Review,* 23: 190-202.

Morin, A. J. S., Maïano, C., Marsh, H. W., Janosz, M., & Nagengast, B. 2011. The longitudinal interplay of adolescents' self-esteem and body image: A conditional autoregressive latent trajectory analysis. *Multivariate Behavioral Research,* 46: 157-201.

Morin, A. J. S., Morizot, J., Boudrias, J.-S., & Madore, I. 2011. A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture analysis. *Organizational Research Methods*, 14: 58-90.

Morrison, E. W., & Robinson, S. L. 1997. When employees feel betrayed: A model of how psychological contract violation develops. *Academy of Management Review*, 22: 226-256.

Morrow, P. C. 2011. Managing organizational commitment: Insights from longitudinal research. *Journal of Vocational Behavior*, 79: 18-35.

Mowday, R. T., Porter, L. W., & Steers, R. M. 1982. *Employee-organization linkages: The psychology of commitment, absenteeism, and turnover*. New York: Academic Press.

Muthén, B. 2003. Statistical and substantive checking in growth mixture modeling: Comment on Bauer and Curran (2003). *Psychological Methods*, 8: 369-377.

Muthén, L.K., & Muthén, B.O. 2011. *Mplus user's guide*. Los Angeles, CA: Muthén & Muthén.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. 2007. Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling*, 14: 535-569.

Ozag, D. 2006. The relationship between the trust, hope, and normative and continuance commitment of merger survivors. *Journal of Management Development*, 25: 870-883.

Panaccio, A., & Vandenberghe, C. 2012. Five-factor model of personality and organizational commitment The mediating role of positive and negative affective states. *Journal of Vocational Behavior*, 80: 647-658.

Petras, H., & Masyn, K. 2010. General growth mixture analysis with antecedents and consequences of change. *Handbook of quantitative criminology*: 69-100. New York: Springer.

Raykov, T., & Marcoulides, G. A. 2004. Using the delta method for approximate interval estimation of parameter functions in SEM. *Structural Equation Modeling*, 11: 621-637.

Rhoades, L., & Eisenberger, R. 2002. Perceived organizational support: A review of the literature. *Journal of Applied Psychology*, 87: 698-714.

Rousseau, D. 1995. *Psychological contracts in organizations*. Thousand Oaks, CA: Sage.

Salamon, S.D., & Robinson, S.L. 2008. Trust that binds: The impact of collective felt trust on organizational performance. *Journal of Applied Psychology*, 93, 593-601.

Schafer, J. L. 1997. *Analysis of incomplete multivariate data*. London: Chapman & Hall.

Schoorman, F. D., Mayer, R. C., & Davis, J. H. 2007. An integrative model of organizational trust: Past, present, and future. *Academy of Management Review*, 32: 344-354.

Schweiger, D. M., & DeNisi, A. S. 1991. Communication with employees following a merger: A longitudinal field experiment. *Academy of Management Journal*, 34: 110-135.

Searle, R., Den Hartog, D. N., Weibel, A., Gillespie, N., Six, F., Hatzakis, T., et al. 2011. Trust in the employer: The role of high-involvement work practices and procedural justice in European organizations. *The International Journal of Human Resource Management*, 22: 1069-1092.

Seibert, S. E., Wang, G., & Courtright, S. H. 2011. Antecedents and consequences of psychological and team empowerment in organizations: A meta-analytic review. *Journal of Applied Psychology*, 96: 981-1003.

Shin, T., Davidson, M. L., & Long, J. D. 2009. Effects of missing data methods in structural equations modeling with nonnormal data. *Structural Equation Modeling*, 16: 70-98.

Somers M. J. 2009. The combined influence of affective, continuance and normative commitment on employee withdraw. *Journal of Vocational Behavior*, 74: 75-81.

Somers, M. J. 2010. Patterns of attachment to organizations: Commitment profiles and work outcomes. *Journal of Occupational and Organizational Psychology*, 83: 443-453.

Stanley, D. J., Meyer, J. P., & Topolnytsky, L. 2005. Employee cynicism and resistance to organizational change. *Journal of Business and Psychology*, 19: 429-459.

Sweeney, P. D., & McFarlin, D. B. 1993. Workers' evaluations of the "ends" and the "means": An examination of four models of distributive and procedural justice. *Organizational Behavior and Human Decision Processes*, 55: 23-40

Tomlinson, E. C., & Mayer, R. C. 2009. The role of causal attribution dimensions in trust repair. *Academy of Management Review*, 34: 85-104.

Wang, M., & Hanges, P. J. 2011. Latent class procedures: Applications to organizational research. *Organizational Research Methods*, 14: 24-31.

Wasti, S. 2003. Organizational commitment, turnover intentions and the influence of cultural values. *Journal of Occupational and Organizational Psychology*, 76: 303-321.

Wasti, S. 2005. Commitment profiles: Combinations of organizational commitment forms and job outcomes. *Journal of Vocational Behavior*, 67: 290–308.

Weiner, Y. 1982. Commitment in organizations: A normative view. *Academy of Management Review*, 7: 418-428.

FOOTNOTES

[1] We use the term "dominant" to identify the commitment mindset that has the highest score and therefore dominate the profile.

[2] Data pertaining to some of the variables in the present study were analyzed for other purposes in previous published work (Meyer, Hecht, Gill, & Topolnystsky, 2010; Meyer, Sriniva, Lal & Topolntysky, 2007; Stanley, Meyer, & Topolnytsky, 2005).

[3] In contrast to its treatment as a single factor, proposing the existence of a second-order factor helps to account for the strong correlations among the facets yet acknowledging the existence of a common core construct. This approach is also more consistent with the theoretical underpinnings of the construct (e.g., Mayer & Davis, 1999; Colquitt et al., 2012) as being inherently multidimensional.

TABLES

Table 1

Descriptive Statistics, Correlations and Reliabilities

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Gender (0 = male; 1 = female)	-																
2. Full-time (0 = part-time; 1 = full-time)	-.23	-															
3. Level (0 = frontline; 1 = manager)	-.27	.35	-														
4. Union membership (0 = no; 1 = yes)	-.16	.23	-.53	-													
5. Tenure	-.06	.25	.16	.01	-												
6. Turnover Intention t1	-.13	.04	.11	.00	-.10	-											
7. Turnover Intention t2	-.13	.00	.02	.04	-.11	.72	-										
8. Management Trustworthiness t1 (fs)	-.07	-.07	.14	-.20	-.04	-.31	-.21	**.94**									
9. Management Trustworthiness t2 (fs)	-.11	-.06	.16	-.24	-.08	-.26	-.26	.78	**.94**								
10. Supervisor Trustworthiness t1 (fs)	.02	-.09	.06	-.14	-.06	-.15	-.16	-.33	.17	**.97**							
11. Supervisor Trustworthiness t2 (fs)	-.04	-.07	.07	-.15	-.07	-.13	-.22	-.27	.31	.71	**.97**						
12. Affective Commitment t1 (fs)	-.05	.01	.11	-.14	.02	-.55	-.44	-.60	.47	.32	.28	**.85**					
13. Normative Commitment t1 (fs)	-.08	.04	.03	-.08	.03	-.43	-.34	-.49	.36	.25	.22	.79	**.85**				
14. Continuance Commitment t1 (fs)	-.15	-.08	-.28	.16	.21	-.08	-.04	-.11	-.17	-.11	-.11	-.21	.05	**.83**			
15. Affective Commitment t2 (fs)	-.08	.04	.16	-.18	-.03	-.46	-.52	-.50	.58	.25	.35	.85	.66	-.31	**.86**		
16. Normative Commitment t2 (fs)	-.08	.05	.07	-.10	-.01	-.38	-.42	-.42	.45	.21	.29	.71	.83	-.04	.79	**.86**	
17. Continuance Commitment t2 (fs)	-.17	.06	-.27	.15	.22	-.08	-.09	-.11	-.16	-.09	-.06	-.18	.03	.93	-.26	.04	**.83**
M	-	-	-	-	-	2.91	2.80	2.64	2.74	3.59	3.58	2.94	2.19	2.67	3.00	2.22	2.68
SD	-	-	-	-	-	1.14	1.12	0.61	0.59	0.74	0.74	0.72	0.62	0.68	0.68	0.60	0.64

Note. t1 = time 1; t2 = time 2; fs = factor scores. All correlation coefficients above .05 are statistically significant at $p < .05$; correlations above .07 are significant at $p < .01$; correlations above .10 are significant at $p < .001$. Cronbach's alphas are reported on the diagonal and have been bolded.

Table 2
Latent Transition Analyses

k	LL	SCF	#fp	AIC	BIC	CAIC	SABIC	Entropy
Equal variances across profiles								
2	-4906.43	1.19	21	9854.85	9957.45	9978.45	9890.75	0.91
3	-4460.36	1.23	32	8984.73	9141.07	9173.07	9039.43	0.92
4	-4208.31	1.18	45	8506.63	8726.48	8771.48	8583.55	0.92
5	-4027.70	1.13	60	8175.40	8468.53	8528.53	8277.97	0.92
6	-3840.50	0.96	77	7835.00	8211.19	8288.19	7966.63	0.93
7	-3698.82	1.00	96	7589.64	8058.65	8154.65	7753.76	0.93
8	-3580.25	1.19	117	7394.49	7966.09	8083.09	7594.50	0.93
Variances free in all profiles								
2	-4834.28	1.11	27	9722.56	9854.47	9881.47	9768.72	0.91
3	-4378.91	1.21	44	8845.82	9060.78	9104.78	8921.04	0.91
4	-4109.80	1.26	63	8345.59	8653.38	8716.38	8453.29	0.92
5	-3851.90	1.34	84	7871.80	8282.18	8366.18	8015.39	0.93
6	-3642.77	1.05	107	7499.54	8022.29	8129.29	7682.46	0.93
7	-3549.85	0.97	132	7363.71	8008.60	8140.60	7589.36	0.93
8	-3544.87	0.91	159	7407.73	8184.53	8343.53	7679.54	0.92
Final model invariant across time point (free variances)								
5	-3876.97	1.90	54	7861.34	8125.76	8179.76	7954.25	0.92

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; BIC = Bayesian information criterion; CAIC = Consistent AIC; SABIC = Sample-size adjusted BIC.

Table 3
Demographics and Management Trustworthiness Predicting in Latent Transition Analyses

	All mid with CC-dominant (profile 4)		All mid with AC-dominant (profile 3)		AC-dominant (profile 2)		AC/NC-dominant (profile 1)	
	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*	Coefficient (*SE*)	*OR*
Effects of the demographic predictors on membership into Time 1 profiles								
Gender	-0.14 (0.30)	0.87	-0.71 (0.33)*	0.49	-0.38 (0.36)	0.68	-0.50 (0.29)	0.61
Full-time	0.32 (0.40)	1.37	0.33 (0.65)	1.39	0.18 (0.40)	1.19	0.50 (0.42)	1.64
Level	0.28 (0.45)	1.32	2.17 (0.71)**	8.79	1.35 (0.42)**	3.85	0.32 (0.51)	1.38
Union	-0.16 (0.33)	0.85	0.05 (0.55)	1.05	-0.45 (0.36)	0.64	-0.86 (0.37)*	0.43
Tenure	0.01 (0.02)	1.01	-0.07 (0.02)**	0.94	-0.04 (0.02)*	0.96	-0.01 (0.02)	1.00
Effects of the initial trustworthiness levels on membership into Time 1 profiles								
Top management	0.92 (0.18)**	2.51	0.85 (0.20)**	2.34	1.78 (0.27)**	5.92	2.47 (0.26)**	11.78
Immediate supervisor	0.26 (0.13)*	1.30	0.45 (0.19)*	1.56	0.47 (0.15)**	1.61	0.60 (0.17)**	1.82
Effects of changes in trustworthiness levels on membership into Time 2 profiles								
Top management	1.17 (0.51)*	3.21	4.62 (4.63)	101.77	2.26 (2.54)	9.60	5.94 (5.22)	380.18
Immediate supervisor	0.32 (0.40)	1.38	-0.29 (0.57)	0.75	2.36 (2.17)	10.63	3.17 (2.57)	23.89

Note. The CC-dominant profile was selected as the reference profile. *OR* = Odds Ratio. Gender is coded as 0 (male) or 1 (female). Full-time is coded as 0 (part-time) or 1 (full-time). Level is coded as 0 (frontline) or 1 (manager). Union membership is coded as 0 (no) or 1 (yes).
* $p < .05$; ** $p < .01$

Table 4
Within-time Comparisons of Commitment Profiles on Turnover Intention

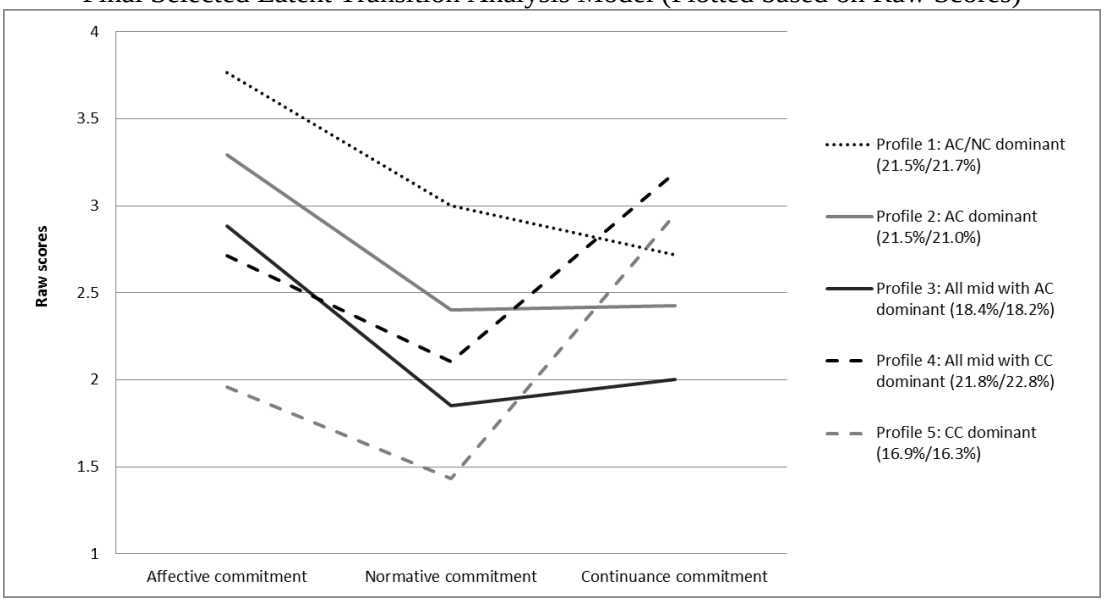
	CC-dominant	All mid with CC-dominant	All mid with AC-dominant	AC-dominant	AC/NC-dominant	Omnibus test
	M (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	χ^2 (*df*)
Time 1	3.85 (1.33)	2.82 (1.36)[a]	3.31 (1.23)	2.69 (1.04)[a]	1.84 (0.87)	110.43 (4)*
Time 2	3.92 (1.50)	2.66 (1.44)[a]	3.29 (1.20)	2.50 (0.93)[a]	1.85 (0.94)	152.15 (4)*

NOTE: Means with similar labels within each time points are not significantly different from one another, all of the other means are significantly different from one another (* $p \leq .01$).

FIGURES

Figure 1

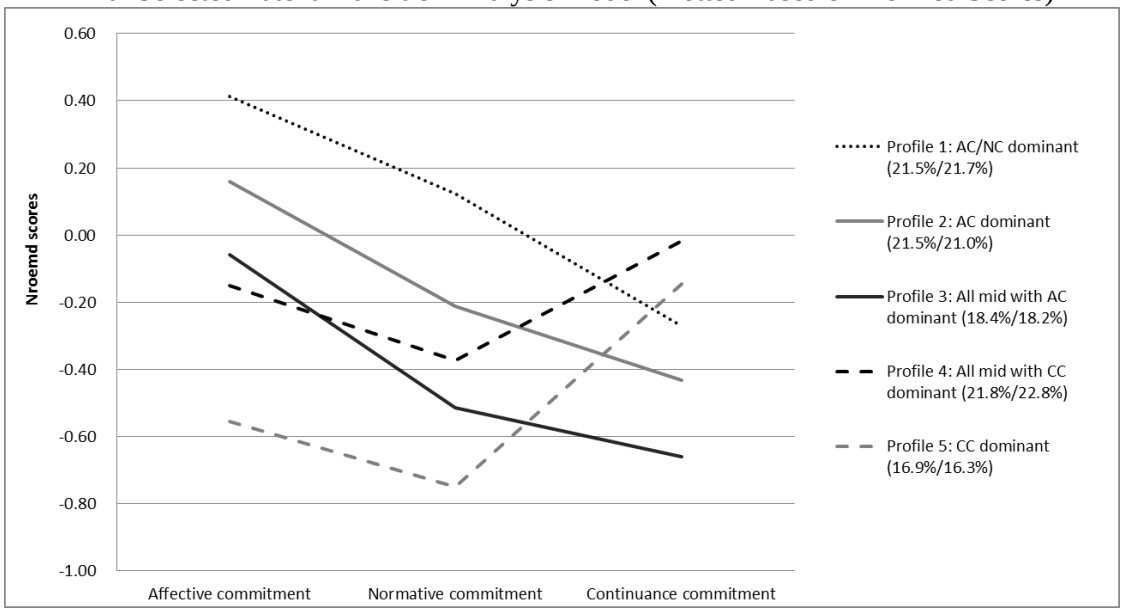
Final Selected Latent Transition Analysis Model (Plotted based on Raw Scores)



Note. The figure is plotted based on raw scores of commitment taken from the present study. Percentages in the legend represent the proportion of individuals classified to the respective profile at Time 1/Time 2.

Figure 2

Final Selected Latent Transition Analysis Model (Plotted Based on Normed Scores)



Note. The raw means of commitment components from Figure 1 were standardized based on normative means in the Canadian (English-speaking) population. The norm for the Canadian population can be found in Meyer, Stanley, et al. (2012). Percentages in the legend represent the proportion of individuals classified to the respective profile at Time 1/Time 2.

Supplemental Materials for:

Are commitment profiles stable and predictable? A latent transition analysis

Sections

(1) Confirmatory factor analytic models of Mayer et al. (1995) trustworthiness scale.
(2) Confirmatory factor analytic models of Meyer et al. (1993) organizational commitment scale.
(3) Latent profile analyses.
(4) References used in these supplemental materials.
(5) Mplus input code to estimate the fully invariant higher-order latent change score model for the trustworthiness scales.
(6) Mplus input code to estimate the fully invariant factor model for the commitment scales and to save the resulting change scores.
(7) Mplus input code to estimate the latent profile analysis model with indicators' variances invariant across profiles.
(8) Mplus input code to estimate the latent profile analysis model with indicators' variances freely estimated across profiles.
(9) Mplus input code to estimate the latent transition analysis model with indicators' variances invariant across profiles.
(10) Mplus input code to estimate the latent transition analysis model with indicators' variances freely estimated across profiles.
(11) Mplus input code to estimate the invariant latent transition analysis model.
(12) Mplus input code to add predictors to the model.
(13) Mplus input code to estimate the associations of the outcome with the latent transition model.
(14) Supplementary Table S1. Goodness-of-Fit Statistics of the Longitudinal Confirmatory Factor Analytic (CFA) Models
(15) Supplementary Table S2. Fit Indices from Alternative Latent Profile Analyses Estimated Separately at Both Time Points.
(16) Supplementary Table S3. Mean levels of commitment for the final retained latent profile solution.
(17) Supplementary Table S4. Complementary results from the prediction of latent transition profiles by single constructs of management trustworthiness.

(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

[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.

which amounts to constraining the non-standardized factor loadings to average 1 within each factors, and 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.

(4) References Used in these Supplemental Materials.

Akaike, H. (1987). Factor analysis and AIC. *Psychometrika, 52,* 317-332.

Beauducel, A., & Herzberg, P. Y. (2006). On the Performance of Maximum Likelihood Versus Means and Variance Adjusted Weighted Least Squares Estimation in CFA. *Structural Equation Modeling, 13,* 186–203.

Bauer, D.J. & Curran, P.J. (2003). Distributional assumptions of growth mixture models over-extraction of latent trajectory classes. *Psychological Methods*, *8*, 338-363.

Bozdogman, H. (1987). Model Selection and Akaike's information criterion (AIC): The general theory and its analytical extensions. *Psychometrika, 52,* 345-370.

Chen, F.F. (2007). Sensitivity of goodness of fit indexes to lack of measurement. *Structural Equation Modeling*, *14*, 464–504.

Cheung, G.W. (2008). Testing equivalence in the structure, means, and variances of higher-order constructs with structural equation modeling. *Organizational Research Methods*, *11*, 593-613.

Cheung, G. W. (2009). Introducing the latent congruence model for improving the assessment of similarity, agreement, and fit in organizational research. Organizational Research Methods, 12(1), 6-33.

Cheung, G.W., & Rensvold, R.B. (2002). Evaluating goodness-of fit indexes for testing measurement invariance. *Structural Equation Modeling*, *9*, 233–255.

DiStefano, C. (2002). The impact of categorization with confirmatory factor analysis. *Structural Equation Modeling*, *9*, 327–346.

DiStefano, C., & Motl, R. W. (2006). Further investigating method effects associated with negatively worded items on self-report surveys. Structural Equation Modeling, 13, 440-464.

Dolan, C. V. (1994). Factor analysis of variables with 2, 3, 5 and 7 response categories: A comparison of categorical variable estimators using simulated data. *British Journal of Mathematical and Statistical Psychology*, *47*, 309–326.

Enders, C. K. (2001). The impact of nonnormality on full information maximum-likelihood estimation for structural equation models with missing data. *Psychological Methods*, *6*, 352-370.

Enders, C. K. (2010). *Applied missing data analysis*. New York: Guilford.

Enders, C. K., & Bandalos, D. L. (2001). The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Structural Equation Modeling*, *8*, 430-457.

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review of Psychology*, *60*, 549-576.

Henson, J. M., Reise, S. P. & Kim, K. H. (2007).. Detecting mixtures from structural model differences using latent variable mixture modeling: a comparison of relative model fit statistics. *Structural Equation Modeling*, *14*, 202-226.

Hipp, J.R., & Bauer, D.J. (2006). Local solutions in the estimation of growth mixture models. *Psychological Methods*, *11*, 36-53.

Hu, L.-T., & Bentler, P.M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6,* 1–55.

Jöreskog, K.G. (1979). Statistical models and methods for the analysis of longitudinal data. In K.G. Jöreskog & D. Sörbom (Eds.), *Advances in Factor Analysis and Structural Equation Models*. Cambridge, MA: Abt Books.

Larsen, R. (2011). Missing data imputation versus full information maximum likelihood with second level dependencies. *Structural Equation Modeling*, *18*, 649-662.

Lazarfeld, P. F. & Henry, N. W. (1968) *Latent structure analysis*. Boston: Houghton Mifflin.

Lei, P.-W. (2009). Evaluating estimation methods for ordinal data in structural equation modeling. *Quality & Quantity*, *43*, 495-507.

Little, R. J. A. & Rubin, D. B. (1987). *Statistical analysis with missing data*. New York: Wiley.

Little, T.D., Sledgers, D.W., & Card, N.A. (2006). A non-arbitrary method of identifying and scaling latent variables in SEM and MACS models. *Structural Equation Modeling, 13*, 59-72.

Lubke, G. & Muthén, B. (2007). Performance of factor mixture models as a function of model size, criterion measure effects, and class-specific parameters. *Structural Equation Modeling, 14*, 26–47.

Marsh, H. W. (2007). Application of confirmatory factor analysis and structural equation modeling in sport and exercise psychology. In G. Tenenbaum & R. C. Eklund. (Eds), *Handbook of sport psychology, 3rd edition* (pp. 774–798). Hoboken, NJ: Wiley.

Marsh, H. W., & Hau, K-T. (1996). Assessing goodness of fit: Is parsimony always desirable? *Journal of Experimental Education, 64*, 364–390.

Marsh, H. W., Hau, K., & Grayson, D. (2005). Goodness of Fit in Structural Equation Models. In Maydeu-Olivares, Albert (Ed); McArdle, John J. (Ed), *Contemporary psychometrics: A festschrift for Roderick P. McDonald.* (pp. 275-340). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling,* 16: 191-225.

Marsh, H. W., Martin, A., & Debus, R. (2001). Individual differences in verbal and math self-perceptions: One factor, two factors, or does it depend on the construct? In R. Riding & S. Rayner (Eds.). *Self perception. International Perspectives on Individual Differences,* (pp. 149-170). Westport, CT, US: Ablex Publishing.

Marsh, H. W., Nagengast, B., Morin, A. J. S., Parada, R. H., Craven, R. G., & Hamilton, L. R. (2011). Construct validity of the multidimensional structure of bullying and victimization: An application of exploratory structural equation modeling. Journal of Educational Psychology, 103(3), 701-732.

Marsh, H. W., Parada, R. H. & Ayotte, V. (2004). A multidimensional perspective of relations between self-concept (Self-Description Questionnaire II) and adolescent mental health (Youth Self Report). *Psychological Assessment, 16, 27-41*.

Marsh, H. W., Scalas, L. F. & Nagengast, B. (2010). Longitudinal tests of competing factor structures for the Rosenberg self-esteem scale: Traits, ephemeral artefacts, and stable response styles. *Psychological Assessment,22, 366-381*.

McArdle, J.J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology, 60*, 577-605.

McLachlan, G., & Peel, D. (2000). *Finite Mixture Models.* New York: Wiley.

Meredith, W. (1993). Measurement invariance, factor analysis and factorial invariance. *Psychometrika, 58*, 525–543.

Meyer, J.P., Stanley, L.J., & Vandenberg, R.M. (in press). A person-centered approach to the study of commitment. *Human Resource Management Review*.

Morin, A.J.S., Maïano, C., Nagengast, B., Marsh, H.W., Morizot, J., & Janosz, M. (2011). General growth mixture analysis of adolescents' developmental trajectories of anxiety: The impact of untested invariance assumptions on interpretations. *Structural Equation Modeling, 18*, 613-648.

Morin, A.J.S., Morizot, J., Boudrias, J.-S., & Madore, I. (2011). A multifoci person-centered perspective on workplace affective commitment: A latent profile/factor mixture Analysis. *Organizational Research Methods, 14*, 58-90.

Muthén, B. O. (2001). Latent variable mixture modeling. In G. Marcoulides & R. Schumacker (Eds.), *New developments and techniques in structural equation modeling*: 1–33. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Muthén, B.O. (2003). Statistical and Substantive Checking in Growth Mixture Modeling: Comment on Bauer and Curran (2003). *Psychological Methods, 8*, 369-377.

Muthén, L. K., & Muthén, B. O. (2011). *Mplus user's guide*. Los Angeles, CA: Muthén & Muthén.

Nylund, K.L., Asparouhov, T., & Muthén, B. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling. A Monte Carlo simulation study. *Structural Equation*

Modeling, *14*, 535-569.

Petras, H., & Masyn, K. (2010). General growth mixture analysis with antecedents and consequences of change. In A.R. Piquero, & D. Weisburd (Eds.), *Handbook of Quantitative Criminology* (pp. 69-100). New York, NY: Springer.

Satorra, A., & Bentler, P. (1999). *A Scaled Difference Chi-square Test Statistic for Moment Structure Analysis*. Technical Report, University of California, Los Angeles.

Schafer, J. L. (1997). *Analysis of incomplete multivariate data*. Boca Raton, FL: Chapman & Hall.

Schwartz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6,* 461-464.

Sclove, L. (1987). Application of model-selection criteria to some problems in multivariate analysis. *Psychometrika, 52*, 333-343.

Shin, T., Davidson, M. L., & Long, J. D. (2009). Effects of missing data methods in structural equations modeling with nonnormal data. *Structural Equation Modeling*, *16*, 70-98.

Rhemtulla, M., Brosseau-Liard, P.É., & Savalei, V. (2012). When can categorical variables be treated as continuous? A comparison of robust continuous and categorical SEM estimation methods under suboptimal conditions. *Psychological Methods, 17*, 354-373.

Tofighi, D., & Enders, C. (2008). Identifying the correct number of classes in growth mixture models. In G. R. Hancock & K. M. Samuelsen (Eds.), Advances in latent variable mixture models (pp. 317-341). Charlotte, NC: Information Age Publishing.

Tolvanen, A. (2007). *Latent growth mixture modeling: A simulation study*. Doctoral dissertation, Department of Mathematics, University of Jyvaskyla, Finland.

Vandenberg, R.J., & Lance, C.E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*, 4-70.

Yang, C. (2006). Evaluating latent class analyses in qualitative phenotype identification. *Computational Statistics & Data Analysis, 50*, 1090–1104.

(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; * $p < .05$; ** $p < .01$