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Trajectory Classes of Job Performance: The Role of Self-Efficacy  
and Organizational Tenure

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### Abstract

*Purpose.* Previous literature has recognized the variability of job performance, calling attention to the inter-individual differences in performance change. Building on Murphy's (1989) theoretical model of performance, the study intended to verify the existence of two distinct classes of performance, reflecting stable and increasing trends, and to investigate which personal conditions prompt the inclusion of individuals in one class rather than the other.

*Design/Methodology/Approach.* Overall job performance was obtained from supervisory ratings for four consecutive years for 410 professionals of a large Italian company going through significant reorganization. Objective data were merged with employees' organizational tenure and self-efficacy. Growth mixture modeling was used.

*Findings.* Two main groups were identified: a) the first one started at higher levels of performance and showed a stable trajectory over time (stable class); b) the second group started at lower levels and reported an increasing trajectory (increasing class). Employees' with stronger efficacy beliefs and lower tenure were more likely to belong to the stable class.

*Originality/value.* Through a powerful longitudinal database, the nature, the structure and the inter-individual differences in job performance over time are clarified. The study extends Murphy's (1989) model, showing how transition stages in job performance may occur also as a result of organizational transformation. Moreover, it demonstrates the essential role of self-efficacy in maintaining high performance levels over time.

**Keywords:** Job performance; Self-efficacy; Organizational tenure; Latent Growth Mixture Modeling; Longitudinal

### Trajectory Classes of Job Performance: The Role of Self-Efficacy and Organizational Tenure

During the last two decades the debate about stability and variability of job performance animated researchers and practitioners interested in performance management. The result was the blooming of a large number of studies focused on the significance and rate of performance change, proving that employees' performance systematically varies across time (Deadrick et al., 1997; Hofmann et al., 1993; Hofmann et al., 1992; Ployhart and Hakel, 1998). Moreover, the literature reports some evidence for inter-individual variability in performance over time (Deadrick et al., 1997; Hofmann et al., 1992; 1993; Ployhart and Hakel, 1998) according to personal (Minbashian et al., 2013; Thoresen et al., 2004), situational and task characteristics (Chen and Mathieu, 2008; Day et al., 2004). A compelling theoretical model to interpret inter-individual performance change has been provided by Murphy (1989), who offers an overarching perspective on how stability and variability occur over time in different groups of employees.

In this scenario, additional research serves to achieve a more meaningful understanding of: (1) the nature and structure of job performance variability over time, since only few longitudinal studies have directly investigated the existence of diverse classes of individuals characterized by different rates of change in performance (Hofmann et al., 1992; 1993; Ployhart and Hakel, 1998); (2) the individual factors predictive of class-membership, or, loosely speaking, distinguishing groups of workers characterized by similar rates of change over time. Our study intends to verify the existence of two distinct classes of performance ratings over four consecutive years, applying Murphy's (1989) model in a

context undergoing through organizational change processes, and to examine which individual conditions prompt the inclusion of the person in one class rather than another.

### **Measuring Job Performance Over Time**

Job performance can be viewed as a set of actions or behaviors under individual control that fosters or obstructs the attainment of organizational goals (Campbell, 1990) and that produces goods or services (Rotundo and Sackett, 2002). Starting with the works of Deadrick and Madigan (1990) and Hofmann and colleagues (1992, 1993), researchers have been oriented to capture the form and nature of intra-individual performance variability, reporting systematic and significant patterns of change in different jobs and samples, including: sportive and competitive activities such as baseball, basketball or hockey players (Day et al., 2004; Hofmann et al., 1992; Rotundo et al., 2012); specialized and repetitive tasks such as sewing machine operators (Deadrick et al., 1997); variable and individual-dependent jobs such as life insurance salesmen (Hofmann et al., 1993) or security brokers (Ployhart and Hakel, 1998); and professional service employees (Minbashian et al., 2013). To be sure, these studies has focused not only on within-person variability, but they have provided evidence of significant inter-individual differences in both initial levels (i.e., the performance level at the beginning of the study) and in the rate of intra-individual change, meaning that performance varies differently across individuals over time. In particular, Hofmann et al. (1993) showed the existence of different clusters of individuals, characterized by distinct patterns of change. These pioneering results deserve extension to fully corroborate their theoretical value and to encourage the investigation and identification of systematic differences in inter-individual groupings as well as the exploration of the individual determinants of these differences.

To explain the possible performance patterns across multiple clusters of individuals, Murphy's (1989) theoretical model of job stages may be well-suited. It differentiates between transition and maintenance periods. The transition stage occurs when an employee begins a

new job or when his or her responsibilities, duties or main tasks change; since the employee is required to learn new skills, acquire new information, adapt to unfamiliar topics, his or her performance is likely to fluctuate. In contrast, the maintenance stage is characterized by stable performance, since major tasks have been learned and novelties have been reduced, making the job familiar and automatized. For the purpose of the present study, it is meaningful to emphasize that the transition stage may occur each time a structural change in the job or in the work environment happens. In fact, transition periods may be the result of an external event, which transforms work processes or adds new responsibilities and duties, and an employee may shift between the two stages over time. Thus, the model clearly recognizes the need to study the duration and frequency of each phase, not only focusing on the individual or his/her tasks, but also on the job context.

### **Antecedents of Job Performance Over Time**

The findings of inter-individual differences in performance trajectories (Deadrick et al., 1997; Hofmann et al., 1993; Thoresen et al., 2004) have generated an increasing interest into the personal variables which predict these differences. To date, the majority of research has focused on cognitive ability or job tenure (Deadrick et al., 1997; Deadrick and Gardner, 2008; Hofmann et al., 1992; 1993; Russell, 2001) and only few studies have explored more psychological factors in affecting performance trajectories, such as personality traits (Minbashian et al., 2013; Thoresen et al., 2004) or psychological capital (Peterson et al., 2011).

Among basic individual differences, social-cognitive theory designates the set of beliefs in one's capabilities as a significant and positive predictor of performance (Bandura, 1997; Judge et al., 2007; Stajkovic and Luthans, 1998). Self-efficacy represents a fundamental component of self-regulation and plays a motivational role, which allows people to activate the cognitive resources and actions necessary to achieve targeted performance, to assure

sufficient effort and to persevere in the face of obstacles, thereby producing successful outcomes (Bandura, 1997). Cross-sectional studies in different settings have shown that self-efficacy is positively related to goal setting (Locke and Latham, 1990), control of anxiety and stress (Bandura, 1997), effective analytical strategies (Wood and Bandura, 1989), and performance (Judge et al., 2007; Stajkovic and Luthans, 1998). However, most of the studies focused on static measures of performance, rather than on its dynamic change over time, and have been conducted at the between-person level. Additionally, a recent controversial debate has been questioning the sign and direction of the relationship, suggesting that the effect of efficacy beliefs on performance may be null, or even negative, and that self-efficacy is a product of past performance, rather than the opposite (Vancouver, 2012). This negative or null influence has been documented at the within-person level of analyses (Schmidt and DeShon, 2010; Sitzmann and Yeo, 2013), while only one study (Vancouver et al., 2014) reported preliminary results at the between-person level.

Early research has disclosed a positive link between organizational tenure and performance (Quiñones et al., 1995; Schneider et al., 1995), justified by the accumulation of job-related experience and knowledge and an enhanced person-organization fit over the years. However, more recent studies (Ng and Feldman, 2010; Sturman, 2003) have shown a non-linear (i.e., inverted U-shaped) relationship, with a larger positive effect at lower levels of organizational tenure that reduces as tenure increases. This finding has been explained in light of organizational socialization processes that, supporting the acquisition of social knowledge, values, behaviors and attitudes necessary for the organizational role (Van Maanen and Schein, 1979), may enhance newcomers' performance. With the increasing of tenure and the gaining of a sufficient level of organizational knowledge, performance may depend less on learning and experience, and thus on the accumulation of years of service.

### **The Present Study**

The purpose of the study was to examine inter-individual variability in job performance, identifying homogeneous groups of employees that differ according to their level and rate of performance change, as evaluated by supervisors, across a four-year time period (from 2007 to 2010).

With respect to our research design, it is meaningful to note that the organization under study started a gradual and on-going process of reorganization in 1998, leading to major modifications in the business, part of the top management and work standards and to an expansion of the range of products and services offered, the implemented technologies, and the organizational functions. This involved a renewal of organizational values and goals, since the organization shifted from a bureaucratic culture to a goal-setting oriented culture and management, asking for major proactivity, autonomy and responsibility. Moreover, several modifications in Human Resource (HR) practices occurred. First, individuals are currently hired via assessment centers, focusing on candidates' personal characteristics and behavior, rather than via a public knowledge-based examination. Second, newly hired and graduated employees go through a structured three-year socialization program, requiring them to rotate through different job positions, functions, and geographical areas, to better familiarize with the organization. Finally, performance appraisal was introduced, founding career advancement and the reward system on performance outcomes, rather than on organizational tenure. These changes likely produced profound differences between employees with a shorter organizational tenure (i.e., hired after the reorganization process) and those with longer tenure who worked in the former organizational system and who were required to profuse greater efforts and exhibit higher motivation, engagement and responsibility to support the transformation.

In light of this scenario, we build upon Murphy's (1989) theory of job stage, fitting it in the changing work environment of the studied organization. Murphy highlighted that

transition stages do not only occur with newcomers, but they can also be the result of changes in major job demands and responsibilities or of structural modifications in the work context. Indeed, external events, as organizational restructuring, confront the individual with novelty and uncertainty and require further adjustment and learning, triggering additional transition phases relatively uniformly among all employees (Murphy, 1989). Consistently, we assumed that our sample would exhibit two major trajectories during the four-year period, namely an increasing and a stable trajectory, reflecting the transition and maintenance phases respectively. Moreover, we predicted that longer-tenured employees were more likely to show a lower but increasing trend (i.e., increasing class) in job performance, while their shorter-tenured colleagues were expected to be “situated” in the stable class, exhibiting stable but higher performance levels. More specifically, we posit that those individuals more implicated in the restructuring might start with lower mean levels of performance and increase them over time. To be clear, we refer to longer-tenured employees, who were part of the organization before the beginning of the reorganization and who found themselves directly involved into the restructuring process, forced to embrace and work for it. As they had to face new job demands, standards and HR management practices, performance may have encountered a setback, but it is supposed to gradually increase over time as the novel organizational values and culture are assimilated and the related individual abilities consolidated, in line with the changing-person model (Alvares and Hulin, 1972). Therefore, work environment modifications could have caused fluctuations in performance among longer-tenured employees, activating a transition stage.

On the contrary, the stable class is expected to capture the performance trajectory of those employees who have already learned how to perform the majority of their tasks and, especially, have “accustom” themselves to the organizational work procedures and culture. We refer to shorter-tenured workers, hired after the starting point of the reorganization, who



completed the organizational socialization program. According to the socialization theories, the socialization process supports employees' organizational familiarization, allowing them to actively learn about the desired behaviors, role expectations and organizational norms (Feldman and O'Neill, 2014; Schein, 2004). Moreover, socialization programs reduce the degree of uncertainty experienced by individuals, which may be more elevated in changing organizations, decreasing ambiguity and fostering positive attitudes and adjustment (Allen, 2006; Jones, 1986; Saks and Ashforth, 1997). As a result, employees are more likely to perform well (Bauer et al., 2007). Furthermore, short-tenured employees have not directly experienced the organizational change as a major novelty, since they joined the company when it had already started and they were guided to better fit the organizational values. Thus, they were expected to report a high and stable trend in performance, reproducing the maintenance stage.

At this point, one can wonder whether our predictions are in contrast with Murphy's theory, which states that the early tenure of a person is characterized by transition stages (and not maintenance, as in our case). However, it is important to specify that our sample did not include newcomers, so all short-tenured people had completed the socialization program, and that we intended to test whether performance transition can occur also at a later phase of the individual's employment, due to organizational modifications.

Consistently, we set the following hypotheses:

*Hypothesis 1:* There are multiple developmental trajectories of job performance that differ in terms of mean levels and changes in mean levels and that characterize two distinct classes of individuals. It is expected that one class will show lower mean levels and an increasing trajectory (i.e., increasing class) in performance and another class will report higher mean performance levels and a stable trajectory (i.e., stable class) over the study period.

*Hypothesis 2:* Organizational tenure will be (a) positively associated to the probability of belonging to the increasing class and (b) negatively to the stable class.

Finally, to uncover the role of efficacy beliefs in explaining trajectory membership, we relied on the social-cognitive perspective (Bandura, 1997), which considers self-efficacy as one of the strongest predictor of work success (Bono and Judge, 2003; Stajkovic and Luthans, 1998; Wood and Bandura, 1989). Especially in challenging situations as a changing environment, self-efficacious employees are expected to better handle novelties and job responsibilities, effectively cooperate with colleagues, and activate major effort and persistence. The anticipatory and self-regulatory capabilities underling efficacy beliefs allow them to effectively read and understand the changing context, to anticipate future and positive scenarios, to regulate and adjust their actions, to persevere in front of difficulties, supporting changes (Bandura, 1997). By encouraging effort, resilience and engagement, self-efficacy secures higher performances (Bandura, 1997). Hence, we assumed that highly self-efficacious employees demonstrate elevated levels of performance, which are able to maintain over time. However, role ambiguity may threaten the beneficial effects of efficacy beliefs on job achievement, since employees need to clearly visualize how much effort put in to attain the expected outcomes (Schmidt and DeSchon, 2010; Vancouver, 2012). Therefore, a robust association may be expected between self-efficacy and performance among shorter-tenured individuals, who went trough the organizational socialization program, which likely reduced uncertainty and ambiguity (Allen, 2006; Jones, 1986).

Consistently, we predicted that:

*Hypothesis 3:* Self-efficacy will be (a) positively associated to the probability of belonging to the stable class and (b) negatively to the increasing class.

## **Method**

### *Sample*

The participants were part of an on-going longitudinal project investigating the main determinants of success in one of the largest service organizations in Italy. Individuals were white-collar workers from line functions in the headquarters of the company, followed for four years (2007-2010). At every yearly Wave, additional workers agreed to participate; consequently, the sample size increased from 375 (Wave 1) to 420 individuals at Wave 4 (approximately 60% female individuals were added to this final sample).

We included all participants in the analyses, since the pattern of missingness generated by the delayed inclusion of subjects satisfied criteria of “missing by design” observations, and thus we used Full Information Maximum Likelihood (FIML), which draws on all available data to estimate model parameters without imputing missing values (Arbuckle, 1996).

Table 1 gives an overview of the demographic characteristics for the six separate waves. In sum, our sample was composed by more males (57%) than females, with a mean age of 46.30 years ( $SD = 8.1$ ) and an average organizational tenure of 16.54 years ( $SD = 10.1$ ). Their years of education ranged from 8 to 18; 55% earned a University degree, 44% completed high school, and 1% completed junior high school. The data were hierarchical in nature, with individuals nested within 102 different offices, with a mean team sample size of 4 ( $SD = 4.28$ ).

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Insert Table 1 about here  
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### *Procedure*

Data on supervisor-rated job performance were obtained for all individuals by the HR department at the end of each year. Data on psychological measures were obtained in the spring of the first Wave (2007). Socio-demographic variables were gathered when individuals entered the study. Participation in the study was voluntary, and confidential data processing

was guaranteed through the use of a code.

*Attrition.* No participants dropped out of the study. However, some missing data were observed for a few subjects, since three individuals retired over the years, and seven individuals moved to another job. No significant differences were detected in paired T-test between attrited participants and the rest of the sample with regard to the major study variables and socio-demographic characteristics, except for a higher chronological age for retired participants and a higher proportion of males among individuals who resigned.

### *Measures*

*Self-efficacy* (alpha = .73). Consistent with Bandura's (2006) recommendations for construct specificity, perceived work self-efficacy was measured by a customized 7-point Likert-type scale (from 1 = "Cannot do" to 7 = "Highly certain can do"), specifically related to work domains of our sample. Six statements were framed as beliefs of being able to handle job responsibilities, challenging situations and coordination with colleagues (e.g., "In my work I am confident I can overcome all frustrations related to my failures"). The observed scale mean was 5.33 (SD = .72).

*Job performance* (alpha = .92). Supervisors rated their employees' performance through the company's performance appraisal tool which comprised five behavioral domains measured on a 10-point scale (from 1 = "Inadequate" to 10 = "Beyond expectations"): "Customer focus" (e.g., "Anticipates clients' needs"); "Communication" (e.g., "Adjusts his/her communication style to different people"); "Network management" (e.g., "Builds constructive relationships to achieve common results"); "Problem solving" (e.g., "Identifies problems correctly and finds appropriate solutions"), and "Change management" (e.g., "Explores new opportunities that contribute to the on-going change process"). Alphas were .92 from Wave 1 to Wave 5, and .95 at Wave 6. Average job performance scores were: 7.57 (SD = 1.27), 7.59 (SD = 1.39), 7.71 (SD = 1.31), and 7.89 (SD = 1.09) at Waves 1, 2, 3, and 4

respectively.

*Demographics.* Gender was coded 0 = females and 1 = males, age and organizational tenure were expressed in years.

### *Statistical Analyses*

To investigate the presence of distinct trajectories in performance, we implemented a Second Order Growth Mixture Model (SOGMM; Grimm and Ram, 2011), which allows for the identification of homogenous subgroups within a heterogeneous sample characterized by the same longitudinal trend. A SOGMM takes the benefits of multivariate measurement models (Hancock et al., 2001; McArdle, 1988), such as the increased statistical power and higher reliability of indicators (Hertzog et al., 2006) and combines them with the Growth Mixture Model (GMM). The availability of a measurement model is particularly relevant in longitudinal research where it is important to establish that the same construct has been measured at each occasion in the same metric, or, in other words, that measurement invariance holds (Meredith, 1993). A SOGMM can be built in four steps (Grimm and Ram, 2011). First, a longitudinal common factor model is specified and its fit is tested against the data. Second, measurement invariance constraints are imposed on parameter estimates and their tenability investigated, to assure that performance has been measured in the same metric at each occasion. Following Meredith (1993), we verified: a) the *configural invariance*, which hypothesizes the equality of the overall structure (i.e., same factor and same patterns of fixed and freed parameters) over time; b) the *weak factor invariance*, which tests the equality of the factor loadings across time; c) the *strong factorial invariance* which verifies the equality of the intercepts of the measured variables over time; d) and the *strict factorial invariance*, which hypothesizes the equality of variables' uniqueness across time. Third, a second order growth curve can be identified from multiple indicators, that is, the four repeated performance measures. The second-order nature of the model means that intercept and slope are built as

higher order exogenous factors on the first layer given by the first-order longitudinal factor model, and not on observed variables (as frequently done). Consistent with Bollen and Curran (2006), we fit a series of nested and non-nested growth models (i.e., intercept only, linear, quadratic) to individuate the best fitting model for describing the longitudinal performance trajectory. Finally, in the fourth step, the Growth Mixture Model (GMM) is specified (Muthén, 2004) to model heterogeneity in the performance trajectories. GMM allows for latent classes of growth trajectories to be specified. In particular, between-class variation in the trajectory is allowed (i.e., the average intercept and slope may differ across classes), and within-class variation (i.e., the intercept variance and slope variance within class) can be estimated. Two-, and three-class models were examined, and their fit compared to select the best fitting solution.

#### *Model Evaluation*

The data gathered in this study had a hierarchical structure with employees nested within their respective offices. To determine the extent of between-unit variance in all variables, we computed the Muthén's (1994) Intra-Class Correlation (ICC) and, to better understand the bias introduced by the nested structure of the data on parameter estimates, we calculated the Design Effect Index (DEF; Muthén and Satorra, 1995). For self-efficacy, the items' mean ICC was .01 (SD = .01) and the items' mean DEF was 1.04 (SD = .02). For performance, the mean ICC and DEFs ranged from .09 to .13 and from 1.27 to 1.42, respectively (Table 3). Overall, the ICC values ranged from negligible (self-efficacy) to moderate (job performance), indicating a moderate low grouping effect (Hox, 2002); this was further corroborated by the DEF indices, all below the critical level of 2, that signals a potential effect of clustering on parameter estimates. In performing all subsequent analysis, the dependence of employees data within offices was taken into account, employing an estimation procedure that “includes a Taylor series-like function to provide a normal theory

covariance matrix for analysis” (Stapleton, 2006, p. 352) and produces correct parameter estimates, standard errors, and test statistics. To estimate all the models and handle missing data, we used Full Information Maximum Likelihood with robust standard errors (i.e., "Complex") as implemented in Mplus 7.0 (Muthén and Muthén, 2012). For measurement models, measurement invariance models and latent growth models, model fit was assessed according to the following criteria:  $\chi^2$  likelihood ratio statistic, Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA). The critical value of chi-square is sensitive to large sample sizes and easily produces a statistically significant result (Kline, 2008). We accepted CFI values greater than .90 and RMSEA values lower than .08.

To determine the appropriate number of classes in the SOGMM, models were compared using (1) the Bayesian Information Criterion (BIC) with smaller values indicating better fit (Boscardin et al., 2008), and (2) likelihood ratio tests, such as the adjusted Lo–Mendell–Rubin likelihood-ratio test (A-LRT; Lo et al., 2001). A-LRT tests whether adding an additional class to the null model (i.e., the model with  $k - 1$  classes) results in a statistically significant better fit (i.e., significant values indicate a better fit for the model with the additional class). Following standard procedures the highest-class model with a significant A-LRT ( $p < .05$ ) was selected. We also took into account indices of the separability of latent classes, such as the *average latent class probabilities*, indicating the most likely individuals’ latent class membership, and the overall percentage of participants categorized into each class.

To compare the fit of the nested models in the longitudinal invariance sequence and to compare GMM models with increasingly restricted structures, we used the Satorra–Bentler scaled chi-square difference tests (Satorra, 2000;  $SB\Delta\chi^2$ ). In the longitudinal invariance routine, we also considered differences in comparative fit index (symbolically,  $\Delta CFI$ ): a

difference larger than .01 indicates a meaningful change in model fit (Cheung and Rensvold, 2002).

## Results

### *Preliminary Analyses*

Factor analyses were used to investigate the fit of the measurement model of the self-efficacy scale. The theoretical one-factor model fit the data very well (Table 2) with high and significant loadings, ranging from .49 to .82 ( $M = .60$ ,  $SD = .12$ ). We also computed zero order correlations among sex [1] (codified as 0 = females, 1 = males), tenure and self-efficacy. None of these correlations reached the conventional level of significance (i.e.,  $p < .05$ ), and were quite small in magnitude ( $< |.07|$ ). We then calculated the correlations between the above variables and the average individual score on job performance (as resulting from the arithmetic mean of the items) within each wave. Overall, sex was almost statistically unrelated to job performance ( $r_m = .04$ ), but job tenure and self-efficacy revealed moderate ( $r_m = -.25$ ) and small ( $r_m = .15$ ) statistically significant correlations with job performance.

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### *Step 1: Longitudinal Measurement Model*

The one factor model for performance fit the data very well at each time point. However, at Wave 4, including a covariance between indicator 4 and indicator 5 was necessary to achieve a good data fit. This is likely due to the conceptual overlap of the two competencies “problem solving” and “change management”, both of them evaluating the abilities needed to cope with unusual and unexpected problems and to successfully adapt to swift contextual changes. Thus, we re-estimated all models by including this covariance within each wave, resulting in very good data fit at each wave (Table 2). All residual



correlation coefficients were significant ( $M = .30$ ,  $SD = .07$ ). Loadings ranged from .80 (“Problem solving”, Wave 3) to .91 (“Change management”, Wave1), with a mean of .85 ( $SD = .03$ ). Then we fit the longitudinal measurement invariance model. The longitudinal measurement model fit the data very well (Table 2). Latent factors representing job performance at different waves were strongly correlated between adjacent time points (mean = .81, Table 3), attesting a high degree of rank order stability.

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 Insert Table 3 about here  
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### *Step 2: Measurement Invariance Analyses*

As reported in Table 2, the  $\Delta\chi^2$  and  $\Delta CFI$  tests supported configural and weak invariance, and  $\Delta CFI$  supported strong invariance, accordingly constructs were comparable over time. Standardized factor loadings (Table 3) were all high and significant ( $M = .87$ ,  $SD = .04$ ). Finally, latent means suggested a slight increase from Wave1 to Wave 4 ( $d = .19$ ).

### *Step 3. Second-Order Latent Growth Models*

We fit three second-order latent growth models to establish the best baseline model for comparison with the SOGMMs. As stated above, we tested: (1) a second-order intercept only model,  $\chi^2(180) = 367.99$ ,  $p < .01$ ,  $CFI = .968$ ,  $TLI = .966$ ,  $RMSEA = .050$  (95%CI = .043 - .057), (2) a second-order linear model  $\chi^2(177) = 275.68$ ,  $p < .01$ ,  $CFI = .983$ ,  $TLI = .982$ ,  $RMSEA = .036$  (95%CI = .028 - .045), and (3) a second-order quadratic model  $\chi^2(177) = 263.81$ ,  $p < .01$ ,  $CFI = .986$ ,  $TLI = .984$ ,  $RMSEA = .034$  (95%CI = .025 - .043). We found the linear growth model to be the best fitting, as compared to the intercept only  $\Delta\chi^2(7) = 72.56$ ,  $p < .01$ , as well as to the quadratic model  $\Delta\chi^2(4) = 9.18$ ,  $p = .06$ . The linear model had a significant intercept ( $\kappa_1 = 7.85$ ,  $p < .01$ ) and a significant slope mean ( $\kappa_1 = .09$ ,  $p < .01$ ), suggesting an increasing trajectory. There were significant between-individual differences in

the intercept ( $\varphi_{1,1} = .98, p < .01$ ) and slope ( $\varphi_{2,2} = .07, p < .01$ ).

*Step 4. Second-Order Growth Mixture Models*

The 2-class model was considered the best GMM model for job performance (see Table 4). The 3-class model was not considered suitable. Although the sample-size adjusted BICs and entropy values were slightly better in the 3-class relative to the 2-class models, the A-LRT suggested that the 3-class model was not significantly better. Furthermore, the 3-class model resulted highly unbalanced in terms of individuals' distribution within classes, with one class counting only two individuals that was difficult to interpret. Thus, based on parsimony and practical consideration we selected the 2-class model, which also met the theoretical expectations and made conceptual sense.

To ensure that the 2-class model reproduces accurately within-class mean and covariance structures (see Enders and Tofighi, 2008), we compared models with an increasingly restricted structure. Following the sequence of steps in Table 4 and employing Satorra–Bentler scaled chi-square difference tests, we selected the unconstrained 2-class model, which did not impose any constraint on intercept and slope variances or covariances, suggesting that variability in both the initial level and the rate of change, as well as variability in the intercept-slope covariance, are group specific. This model is illustrated in Figure 1.

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Insert Table 4 and Figure 1 about here  
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One class ( $n = 334$ ) contained the vast majority of individuals and it was characterized by high levels of performance at Wave 1 (intercept mean = 8.20,  $p < .05$ ) and a flat trajectory (slope mean = .02,  $p = .55$ ) over time. We named this class the *stable class* and its average trajectory is represented by the black line in Figure 2. The variance components of the model indicated that, within-class, there was significant between-person variance in the intercept

( $\phi_{11} = .50, p < .01$ ), and in the rate of change ( $\phi_{22} = .02, p < .05$ ). However, there was no association between individuals' performance levels at Wave 1 and the observed rate of change over time ( $\phi_{12} = .05, p = .09$ ). The second class included 20% of the sample ( $n = 86$ ). We named this group the *increasing class* since individuals were characterized by lower levels of performance at Wave 1 (intercept mean = 6.46,  $p < .01$ ), and an increasing trajectory over time (slope mean = .20,  $p < .05$ ) (see the dotted line in Figure 2). For this model, within-class, there was significant between-person variance in the intercept ( $\phi_{11} = .59, p < .01$ ), and in the rate of change ( $\phi_{22} = .20, p < .01$ ). Employees' performance at Wave 1 was significantly and negatively associated with observed rate of change ( $\phi_{12} = -.70, p < .01$ ), meaning that the lower the initial performance level, the higher the rate.

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 Insert Figure 2 about here  
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#### *Scrutinizing the Nature of the Two Latent Classes*

To characterize the nature of the two latent classes and clarify the characteristics of their individuals, organizational tenure and self-efficacy were included as covariates in the model. Sex was included as a control. After the inclusion of the covariates, the model with three classes had convergence problems, likely signaling an over extraction of classes and further suggesting the goodness of the chosen two-class model.

The conditional model maintains the same characteristics of the unconditional model, entailing the same two classes. The first one was still characterized by high levels of job performance at Wave 1 (intercept mean = 7.54,  $p < .01$ ) and longitudinal stability (slope mean = .34,  $p = .08$ ). Within class, we observed a significant residual variability for the intercept ( $\psi_{11} = .26, p < .01$ ), but not for the slope ( $\psi_{22} = .01, p = .56$ ), and slope and intercept were uncorrelated ( $\psi_{12} = -.05, p = .82$ ). The second class was characterized by a low starting

(intercept mean = 6.00,  $p < .01$ ) but steadily increasing trajectory (slope mean = .46,  $p < .01$ ), in line with the above increasing class. We found significant residual variability in both intercept ( $\psi_{11} = .81$ ,  $p < .01$ ) and slope ( $\psi_{22} = .17$ ,  $p < .01$ ), and a significant negative correlation between intercept and slope ( $\psi_{12} = -.25$ ,  $p < .01$ ). In this model, 275 (65%) individuals belonged to the stable class, and 145 (35%) to the increasing class. Classification quality was adequate, as noted by the entropy value (.64) and the classification probabilities (class 1 = .91, class 2 = .88). This model also fit better in terms of the BIC than the previous best fitting unconditional model (19493.24). The minor discrepancies between the present model and the unconditional model were fully expected, since adding important covariates to the model has the potential to alter the number and composition of latent classes (Grimm and Ram, 2009).

Individuals in the two classes differed significantly in organizational tenure and self-efficacy beliefs. Indeed, tenure and self-efficacy were significantly related to latent class membership while gender was not. The log odds of belonging to the stable class versus the increasing class were  $-.12$  ( $p < .01$ ) higher for individuals with high organizational tenure and  $.10$  ( $p = .048$ ) higher for individuals with high self-efficacy beliefs. Finally, we found no prediction of variations in the latent growth factors in the two latent classes by gender, organizational tenure or self-efficacy.

### Discussion

The purpose of the study was two-fold. First, drawing upon Murphy's (1989) maintenance and transition model, it described the inter-individual variability in job performance, identifying classes of employees with different levels and rates of change in performance over a four-year period. Second, it intended to investigate the role of organizational tenure and self-efficacy in predicting membership to the classes.

Our findings support and extend the predictions drawn from Murphy's (1989) model, revealing the existence of two distinct longitudinal trajectories: one is composed by individuals with stable high scores on performance; the other includes individuals starting with lower performance ratings and progressively increasing over time, respectively. Thus, the two different classes seem to reflect the maintenance and transition stages. More interestingly, our study provides some insights regarding the occurrence of these different stages, proving how structural changes in the work context may trigger additional transitional phases across a group of those interested by the process. In other words, job performance may not only vary for newcomers but also for workers who have gone through organizational restructuring, such as our longer-tenured employees. Indeed, the increasing class was characterized by longer years of tenure, including those employees who found themselves directly implicated in the organizational restructuring course and who were required to adapt to the novel procedures and HR practices, to fit in with the new organizational culture. Therefore, their increasing performance trend over time has likely been generated by the need to acquire new skills and values, resulting in a transition stage (Deadrick and Madigan, 1990; Murphy, 1989). Conversely, employees with shorter organizational tenure reported high and stable performance levels across time, reflecting the maintenance phase of job performance (Murphy, 1989), likely because they had completed the organizational socialization program, which allowed them to effectively learn their job role and the organization (Feldman and O'Neill, 2014).

Consistent with our hypotheses, individuals in the two classes differed significantly not only with regard to organizational tenure but also to their efficacy beliefs: higher self-efficacious employees were more likely to belong to the stable class whereas the increasing class was characterized by lower self-efficacious individuals. Therefore, self-efficacy was positively related to elevated and stable levels of performance over time. This finding

corroborates that efficacy beliefs are associated to higher performance (Bandura, 1997; Judge et al., 2007; Stajkovic and Luthans, 1998) at the between-level of analyses, and it also demonstrates that it contributes to the maintenance of success across years.

Finally, the study stresses the relevance of using different perspectives and methodologies to investigate variability in job performance over time. The results are very different when observed from a LGM perspective, which privileges the synthesis of the developmental trends in data, in comparison to a more refined SOGMM perspective, which instead, allows the breakdown of different developmental trends in data. Indeed, for the entire sample, the LGM suggests a linear and increasing trajectory in performance over the four-year period. However, when we look for heterogeneity in the performance trajectory using SOGMM, we find the presence of two distinct trajectories, characterized by different trends.

With regard to study's limitations, employees' performance was obtained from supervisor ratings, which are subjective in nature. However, supervisor evaluations reflect typical performance and are able to capture a broader range of behaviors (Rotundo and Sackett, 2002) than objective measure of performance, being more appropriate to investigate the fluctuating nature of performance (Sturman, 2003). Moreover, although we had no direct access to data on the association between each employee and his or her supervisor, most individuals in the present sample belong to the same work unit during the study period and, thus, were coordinated by the same supervisor.

A second limitation pertains to the fact that self-efficacy was assessed cross-sectionally at Wave 1; hence, we were not able to analyze whether and how it changed during the four years, together with any changes in performance. Moreover, we found a small, albeit significant, effect for the association between self-efficacy and the two trajectory classes. Additional research is required to further test this relationship, to investigate how efficacy

beliefs develop across time especially for employees who start with lower performance levels, which then increase over time (i.e., the increasing class).

Third, the present research did not explicitly include a measure of work context features related to the organizational restructuring. Nevertheless, we based our hypotheses and conclusions on the analysis of organizational change via several meetings with the HR Department management, helping us to understand the main modifications in HR practices relevant for the study, as described above.

Finally, the study was conducted within an organization going throughout a restructuring process. Thus, on the one hand, our results draw attention to the relevance of the organizational context in determining and interpreting different trajectory classes, on the other hand, some caution must be taken in generalizing the findings to organizations that have not experienced such profound changes. Further studies should extend the present approach and methodology to the study of longitudinal performance changes in different contexts and jobs. Furthermore, researchers should consider investigating other individual differences (e.g., personality traits or self-esteem) that may help to explain group membership of individuals with different patterns of change in job performance.

From a practical perspective, the detection of two trajectory classes suggests that HR training and developmental actions should focus on the specific needs of the individuals included in the increasing or stable groups. Especially, since the study proved that organizational modifications can trigger transition stages in longer-tenured employees, organizations may want to not limit their trainings to organizational socialization practices for newcomers, but to set up specific interventions to guide through the transformational process those individuals with medium and long length of service, more involved in the organizational change. In other words, management should focus not only on the acknowledgement and support of newcomers, but it should also address communication and training needs of their

longer-tenured colleagues to facilitate the transition to the new job requirements and organizational culture. This is also likely to reduce the gap between recently hired and longer-tenured employees, enhancing overall job performance and preventing possible subsequent withdrawal behaviors, as absenteeism.

Moreover, our findings uncovered the role of self-efficacy in contributing to the prediction of multiple performance stages and to enhance high and stable levels of job performance. Therefore, consistent with the social cognitive theory (Bandura, 1997) and with the malleability and development potential of self-efficacy, organizations may want to direct HR interventions at improving employees' beliefs in their capabilities to master job assignments and the work context. These kinds of HR interventions may be included in the organizational socialization programs for lower-tenured employees (Feldman, 1981; Gruman et al., 2006) and, more importantly, in coaching actions for their longer-tenured counterpart. The training can focus on the main source of self-efficacy (Bandura, 1997) and it could be oriented toward self-management to strengthen the self-regulation, self-reflection and anticipation capabilities underlying efficacy beliefs (Latham and Frayne, 1989). As a result, employees should be able to improve their problem solving skills as well as their abilities to keep calm in stressful situations, recover quickly after intense activity periods, and anticipate future scenarios to effectively adjust their behaviors, all central aspects to deal with transforming work environments. The training should include strategies aimed at developing the principal sources of self-efficacy based on enacting mastery and vicarious experiences, promoting verbal persuasion and controlling somatic and affective states (Bandura, 1997). A coaching program may provide the occasion to test one's own capabilities and to experience practical success in a safe and nonthreatening context, under the guide of the coach who, through support, encouragements and detailed feedbacks, may show the link between behaviors and positive outcomes, persuading the coachee of his or her abilities. Furthermore,



peer-coaching sessions could be useful to encourage social modeling (Sue-Chan and Latham, 2004) and self-management interventions may help in boosting beliefs in one's own capabilities by promoting strategies to monitor and module physiological and emotional states as well as stress (Richardson and Rothstein, 2008), likely stemming from feelings of uncertainty related to novelty and change.

Finally, along with other personal characteristics (e.g., personality traits), organizations might consider to take individual efficacy beliefs into account when selecting employees, especially in transitional job situations, in light of the role of self-efficacy as a key determinant of stable patterns of successful performance over time.

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Footnote

[1] All correlations involving sex have been computed using the polyserial correlation coefficient.

Table 1

*Demographic Characteristics of the Sample*

	<i>N</i>	Males (proportion)	Age Mean (SD)	Age range	Job tenure Mean (SD)	Job tenure range
Wave 1 (2007)	375	.57	47.26 (8.1)	31 - 61	17.32 (10.22)	3 - 38
Wave 2 (2008)	397	.58	46.34 (8.2)	30 - 61	16.58 (10.22)	3 - 38
Wave 3 (2009)	420	.57	45.78 (8.0)	30 - 61	16.11 (10.21)	3 - 38
Wave 4 (2010)	419	.57	45.80 (8.3)	30 - 61	16.14 (10.00)	4 - 38

*Note.* Age and job tenure are reported in years

Table 2

*Fit Indices for the Models and Results of the Invariance Routine*

	$\chi^2$	<i>df</i>	CFI	TLI	RMSEA	CI95%			
Self-efficacy	6.69	5	.994	.989	.028	.00 - .08	-	-	-
W1 - Job Performance	9.845*	4	.994	.984	.062	.01 - .11	-	-	-
W2 - Job Performance	12.67*	4	.987	.975	.071	.05 - .13	-	-	-
W3 - Job Performance	9.42	4	.995	.987	.057	.00 - .11	-	-	-
W4 - Job Performance	1.51*	4	.992	.98	.062	.02 - .11	-	-	-
	$\chi^2$	<i>df</i>	CFI	TLI	RMSEA	CI95%	Ctm	<i>SB</i> $\Delta\chi^2$	$\Delta$ CFI
Model 1. Configural	194.67	130	.989	.984	.034	.024 - .44	-	-	-
Model 2. Weak	207.95	142	.989	.985	.033	.023 - .043	1	13,40 (12)	.000
Model 3. Strong	226.97	154	.988	.985	.034	.024 - .43	2	19,270 (12)	-.001
Model 4. Strict	279.34	176	.982	.981	.037	.029 -.045	3	42,93* (22)	-.004

*Note.* CFI = Comparative Fit Index; TLI = Tucker Lewis fit Index; RMSEA = Root Mean Square Error of Approximation; Ctm = compared to model.

\* $p < .05$

Table 3

*Results from Longitudinal Measurement Invariance Analysis*

	Job performance					
	$\lambda$ (uns)	$\lambda$ (std) <sup>b</sup>	$\tau$	$\varepsilon$	ICC <sub>mean</sub> (SD)	DEF <sub>mean</sub> (SD)
1. Customer focus	.96	.80	.42	.50	.09 (.06)	1.30 (.19)
2. Communication	1.11	.90	-.91	.39	.11 (.04)	1.34 (.13)
3. Network management	1.00	.88	.00	.46	.13 (.09)	1.42 (.31)
4. Problem solving	1.23	.89	-.49	.42	.09 (.08)	1.27 (.25)
5. Change management	1.07	.87	-.91	.48	.10 (.06)	1.32 (.20)

	Latent correlations				Latent Means (SE)
	(1)	(2)	(3)	(4)	
1. Job perf. Wave1	1				Wave1 7.84 (.07)
2. Job perf. Wave2	.76	1			Wave2 7.94 (.07)
3. Job perf. Wave3	.62	.80	1		Wave3 8.01 (.07)
4. Job perf. Wave4	.57	.70	.86	1	Wave4 8.11 (.07)

*Note.*  $\lambda$ (uns) = unstandardized loadings (on which invariance constraints were posited);  $\lambda$  (std) = Standardized loadings;  $\tau$  = intercepts;  $\varepsilon$  = error terms. All parameters (loadings, intercepts, error terms, covariances, and latent means) were significant. ICC<sub>mean</sub> (SD) = ICC averaged across the six waves for each indicator separately (with standard deviation); DEF<sub>mean</sub> (SD) = DEF averaged across the six waves for each indicator separately (with standard deviation). SE = Standard errors of Latent means. <sup>b</sup> The standardized coefficients were averaged across time intervals using Fisher's Z-to-r transformations. Although the coefficients,  $\lambda$  (std), were constrained to be equal across time intervals, the constraints were imposed on unstandardized coefficients (as typically recommended), which led to slight variation in the resulting standardized coefficients.

Table 4

*Model Fit of Second-Order Growth Mixture Models of Job Performance*

*Note.* Scr = Scaling correction factor;  $SB\Delta\chi^2$  = Satorra-Bentler difference Chi-square;  $\Delta df$  = model differences in terms of degrees of freedom;

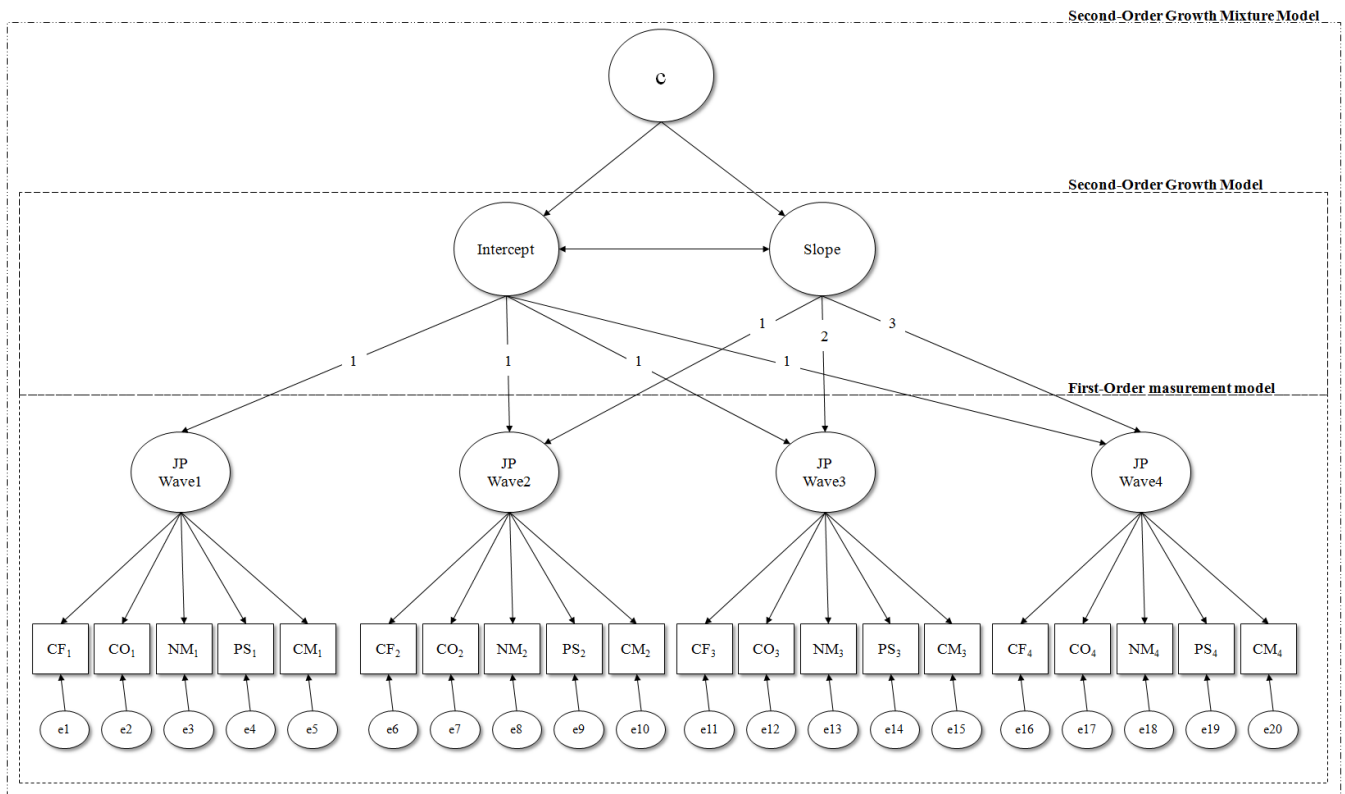
Model	Number of classes	Log likelihood	Parameters	BIC	A-LRT	Entropy	Estimated	Posterior
							Class Count	Probabilities
1	2	-9.690.24	58	19.731	85,45**	.58	(333 vs 87)	(20 vs 80)
2	3	-9.698.24	63	19.506	25.00	.77	(303 vs 2 vs 115)	(72 vs .01 vs 27)
Log								
Restricted models			likelihood	Parameters	Scr	$SB\Delta\chi^2$	$\Delta df$	<i>p</i>
1	$\phi_{11}, \phi_{22}, \phi_{12}$ : Unrestricted		-9.699	58		0	0	-
2	$\phi_{22}, \phi_{12}$ : Unrestricted; $\phi_{11}$ : restricted to be equal across classes		-9.708	57	2	9	1	.01
3	$\phi_{22}, \phi_{12}$ : Unrestricted; $\phi_{22}$ : restricted to be equal across classes		-9.712	57	2	12	1	.001
4	$\phi_{11}, \phi_{22}$ : Unrestricted; $\phi_{12}$ : restricted to be equal across classes		-9.699	57	2	5	1	.03

$\phi_{11}$  = Intercept variance;  $\phi_{22}$  = Slope variance;  $\phi_{12}$  = Intercept-slope covariance.

\*\*p < .01

Figure 1

Path Diagram of the Second-order Growth Mixture Model



Note. JP = Job Performance. CF = Customer Focus; CO = Communication; NM = Network Management; PS = Problem Solving; CM = Change Management. Indicators are indexed by Wave (1-4). Errors terms are indexed progressively.

Figure 2

Predicted Job Performance Class Trajectories for the Two-class Model

