Ten-year trajectories of stressors and resources at work

Igic, Ivana; Keller, Anita C.; Elfering, Achim; Tschan, Franziska; Kälin, Wolfgang; Semmer, Norbert K.

Published in:
Journal of Applied Psychology

DOI:
10.1037/apl0000225

Ten-year trajectories of stressors and resources at work: Cumulative and chronic effects on health and well-being

Ivana Igic
University of Bern, Switzerland

Anita C. Keller
Michigan State University

Achim Elfering
University of Bern, Switzerland

Franziska Tschan,
University of Bern, Switzerland

Wolfgang Kälin
University of Bern, Switzerland

Norbert K. Semmer
University of Bern, Switzerland

This article has been accepted for publication, but this version has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the published version. Please refer to Igic, I., Keller, A. C., Elfering, A., Tschan, F., Kälin, W., & Semmer, N. K. (2017). Ten-year trajectories of stressors and resources at work: Cumulative and chronic effects on health and well-being. Journal of Applied Psychology. Advance online publication. doi:10.1037/apl0000225

Anita C. Keller is now at the Department of Psychology, University of Groningen. Norbert K. Semmer, Achim Elfering, Wolfgang Kaelin, and Franziska Tschan are associated with the Swiss National Centre of Competence in Research on Affective Sciences, Geneva, Switzerland.

This article is based on data assessed in the research project: Work Experience and Quality of Life in Switzerland: Work, Stress and Personality Development funded by the Swiss National Science Foundation within the Swiss Priority Program: Switzerland: Towards the Future (grant 5004-047898 and 5004-058450) and was partially funded by SNF-NCCR Affective Sciences, Geneva and Swiss National Science Foundation (grant 100014_144057/1). During the review process Swiss National Science Foundation funded one of the co-authors (grant P2BEP1_158962).

Abstract

Employing five waves of measurement over a period of 10 years, we explored the effects of exposure to constellations of conditions at work on physical and psychological strain, estimating the history of exposure over time. Specifically, we first tested if the four constellations postulated by the job demand–control (JDC) model, extended to include social stressors, could be identified empirically over time through a person-centered analysis. Second, we tested two specific effects of the history of exposure on physical and psychological strain: *cumulative effects* (i.e., history of exposure predicting strain) and *chronic effects* (i.e., history of exposure being associated with reduced reversibility in strain). Data were collected from 483 respondents who were at the end of their vocational training. The results supported the hypotheses, in that not all JDC constellations could be empirically identified, the majority of participants was in rather favorable constellations, and the differences between constellations, in terms of levels of demands and control, were more subtle than suggested by theoretically predefined constellations. Since the linear and quadratic solutions were largely comparable, we decided to adopt the linear ones. The expected cumulative and chronic effects were mostly confirmed: Unfavorable JDC constellations were associated with poorer health and well-being than favorable ones, when controlling for the initial level of the respective outcome variable, demographic variables and for cumulative private stressors (cumulative effects). These differences largely remained after further adjustments for current conditions at work (chronic effects).

Keywords: trajectories; history of exposure; cumulative effects; chronic effects; job demand-control model; growth mixture modeling.

Ten-year trajectories of stressors and resources at work: Cumulative and chronic effects on health and well-being

The major theoretical models in occupational stress research (Karasek, 1979; Meijman & Mulder, 1998), along with the available empirical evidence (e.g., Belkic, Landsbergis, Schnall, & Baker, 2004; Chandola, Brunner, & Marmot, 2006), have suggested that time plays an important role in the stressor–strain relationship. Long-lasting or recurrent exposure to unfavorable conditions at work increases the risk of long-term psychological and physical harm (Frese & Zapf, 1988; Karasek, 1979; McEwen, 2004; Sonnentag & Frese, 2013). Many researchers have used the job demand–control (JDC) model (Karasek, 1979) as their theoretical background when studying the effects of work characteristics on health and well-being over time (de Lange, Taris, Kompier, Houtman, & Bongers, 2002). The JDC model emphasizes two psychosocial work characteristics: job-control, and job demands. Although Karasek (1979) originally defined demands broadly, in terms of workload demands, conflicts, or other stressors (p. 287), demands have mostly been operationalized in terms of task-related demands (i.e., workload and time pressure). The social dimension (i.e., social support) was added later in the iso-strain model (ISO- strain model; Karasek & Theorell, 1990) . However, negative conditions and events typically have stronger effects than good ones (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001). Social stressors such as tension and conflict have the potential to offend the self (Meier, Gross, Spector, & Semmer, 2013; Semmer, Jacobshagen, Meier, & Elfering, 2007), which makes them particularly stressful, and they also have repeatedly emerged as being predictive over other job stressors (Berset, Elfering, Lüthy, & Semmer, 2011; Bowling & Beehr, 2006; Spector & Jex, 1998); it therefore seems important to include social stressors in the analysis.

The JDC model, along with other theories in occupational health psychology (e.g., the effort–reward imbalance model; ERI), includes the idea of constellations of conditions at work (Siegrist, 1996). Theoretically, constellations seem important because conditions at work cannot be characterized by single variables; rather, a host of variables are important (Sonnentag & Frese, 2013), and it seems likely that the impact of a given variable depends on the level of others. The JDC model proposes four constellations of demands and control. However, the configuration of constellations over time has not been determined empirically, and some recent studies could not identify all four constellations (Keller et al., 2016; Mauno, Mäkikangas, & Kinnunen, 2016). Thus, it remains unclear to what extent the postulated combinations reflect people's actual experience.

Most studies addressing exposure to conditions at work over time have relied on two measurement waves, which limits the conclusions that can be drawn (Taris & Kompier, 2014; Zapf, Dormann, & Frese, 1996). The current study included five waves of measurement over a period of 10 years. Studies investigating the effects of exposure to conditions at work over multiple waves of measurement (e.g., Chandola et al., 2006; de Lange et al., 2002) represent a great improvement over the typical two-wave studies; nevertheless, they are not without problems. Common approaches to classifying the exposure to (un)favorable conditions over time have entailed: 1) calculating average and change scores, and 2) forming theoretically predefined constellations based on cut-off values (e.g., median). With the first approach, the problem arises that average scores cannot deal with change, whereas change scores cannot handle developments across more than two waves of measurement or constellations of several conditions simultaneously. With the second approach, theoretically proposed constellations (e.g., grounded in the JDC model) are based on rather crude classifications that employ median splits or other predefined cut-off values. Therefore, changes determined on the basis of such classifications represent rather crude categories (e.g., from high-strain to low-strain) (Chandola et al., 2006; de Lange et al., 2002; Schnall, Schwartz, Landsbergis, Warren, & Pickering, 1998). They represent inter-individual changes only (i.e., changes in the relative position of participants in the sample) and not intra-individual changes (i.e., changes that take the individual's own values as a reference, regardless of his or her relative position in the sample). Neglecting intra-individual change ignores the substantial heterogeneity in individual change (Curran & Bauer, 2011); resulting in similar patterns of development within constellations and different patterns of developments between constellations.

The aim of the current study was therefore to apply a person-centered, model-based approach (growth mixture modeling (GMM)) to determine the constellations that characterize different exposure histories. For this approach, five measurements waves over a period of 10 years were used to empirically determine constellations and to test whether the constellations proposed by the JDC model could indeed be identified. We considered initial levels as well as development over time, and included different conditions at work simultaneously. Using membership in a given constellation of trajectories over multiple waves of measurement (history of exposure) as a predictor, we analyzed the effects of constellations on health and well-being. Specifically, we tested for cumulative and chronic effects. By cumulative effects, we refer to effects of long-term exposure in general. By chronic effects, we refer to effects that have acquired a certain amount of permanence, and thus persist even if conditions at work improve. Thus, this paper offers a refinement of JDC model over time and tests the theoretical models proposing cumulative or chronic effects (Frese & Zapf, 1988; McEwen, 1998).

Theoretical Background

History of Exposure to Conditions at Work

It is clear that time is an important dimension in organizational sciences in general, and in stress research, in particular (McGrath & Tschan, 2004; Mitchell & James, 2001; Sonnentag, Pundt, & Albrecht, 2014). One-time work stressors are short exposure episodes with an identifiable onset and end. Except for traumatic experiences, such stressors are not expected to have long-term consequences (Semmer, McGrath, & Beehr, 2005). By contrast, stressors that are long-lasting or recurrent are expected to increase the risk of long-term psychological and physical harm (Frese & Zapf, 1988; Karasek, 1979; McEwen, 2004; Sonnentag & Frese, 2013). Theoretical models in work stress research have incorporated this temporal aspect. For example, the JDC model (Karasek & Theorell, 1990) , the effort-recovery model (Meijman & Mulder, 1998), and the allostatic load theory (McEwen, 2004) discuss the increased likelihood of negative effects on health and well-being if unfavorable work characteristics persist over a longer period of time. Many authors have followed this reasoning, suggesting that not only the *level* of stressors at a single assessment should be taken into account, but also the *persistence and change* in stressors over multiple assessments over longer time intervals (e.g., Ganster & Rosen, 2013; Landsbergis, Schnall, Pickering, Warren, & Schwartz, 2003; Semmer, McGrath, et al., 2005; Taris & Kompier, 2003, 2014). In this study, we use the term *history of exposure* (sometimes labeled as repeated exposure, chronic exposure, or cumulative exposure) to refer to the development of working conditions over multiple assessments over time.

Analyzing the history of exposure requires a longitudinal research design (Schalk, van der Heijden, de Lange, & van Veldhoven, 2011; Taris & Kompier, 2003; Zapf et al., 1996). There has been an increase in the number of longitudinal studies in stressor-strain research, ranging from incomplete two-wave panel designs to complex multi-wave longitudinal designs (Sonnentag & Frese, 2013; Zapf et al., 1996). Among these longitudinal designs, the two-wave design is most common but also most limited. Analyses relating to history of exposure are possible, in that one can determine whether participants belong to a given group (e.g., high-strain; low-strain) at both measurements, or whether they move from one group to another one (e.g., from high-strain to low-strain, Schnall et al., 1998). However, when exploring the cumulative effects of the history of exposure to conditions at work, this design becomes weaker as the time interval gets longer, because the time period for which there is no information becomes increasingly larger. Consequently, employing more than two waves of measurement is preferable.

There are some studies that have investigated the history of exposure over longer time intervals (Aboa-Éboulé et al., 2007; Chandola et al., 2006; de Lange, Taris, Kompier, Houtman, & Bongers, 2004). Such studies represent a methodological improvement over the typical two-wave studies when exploring the cumulative effects on strain. We found 50 such studies and analyzed the methods used for determining the history of exposure. (A table with details of these studies may be obtained from the first author.) Two approaches were the most commonly used: calculating average and change scores, and forming theoretically predefined constellations based on cut-offs values (e.g., median). A third method was applied only in three studies and involved determining groups empirically by model-based classification. In the next section, we will describe these approaches, including their advantages and disadvantages, and present a new approach that makes it possible to overcome their shortcomings when analyzing the cumulative effects of conditions at work on strain.

Calculating single scores or change scores. With this approach, authors calculate average (Johnson, Stewart, Hall, Fredlund, & Theorell, 1996; Weigl, Hornung, Petru, Glaser, & Angerer, 2012), or maximal scores (Kivimäki, Head, et al., 2006; Kivimäki, Leino-Arjas, et al., 2006) over time, or change scores between assessments (Gelsema et al., 2006; Janssen & Nijhuis, 2004; Kivimäki, Head, et al., 2006). However, in basically assuming a stable value around the mean, calculating an average score cannot account for change. Calculating change scores has been repeatedly criticized (e.g. Cronbach & Furby, 1970), although this critique has not gone undisputed (e.g., Gollwitzer, Christ, & Lemmer, 2014; Rogosa, 1995; Willett, 1997). Regardless of this debate, the problem remains that change scores are based on two scores only. Accordingly, difference scores as traditionally used (i.e., not incorporating the new possibilities offered by latent change models; Willett, 1997) are not able to accommodate developments across more than two waves or changes in several variables simultaneously.

Forming theoretically predefined groups. The second approach entails creating exposure profiles by allocating participants to theoretically predefined constellations on the basis of the characteristics of their work. Unfavorable and favorable constellations are often defined a priori on the basis of the JDC model (Karasek, 1979), its extension, the iso-strain model (Johnson et al., 1996; Karasek & Theorell, 1990), or (although less often) the effort-reward-imbalance model (ERI) (Siegrist, 1996) . Commonly, medians (de Lange et al., 2009; Gimeno et al., 2009), tertiles (Kouvonen et al., 2013; Stansfeld, Shipley, Head, & Fuhrer, 2012), or quartiles (Kivimäki et al., 2004) are used as cut-off values. Such studies then test whether exposure to stable constellations, such as high-strain or low-strain jobs (de Lange et al., 2009; de Lange et al., 2002) over time predict health outcomes (cumulative exposure hypothesis; e.g., Amick et al., 2002) and/or whether changes, such as moving from high-strain to non-high-strain jobs or vice versa (de Lange et al., 2009; de Lange et al., 2002) predict changes in outcomes (parallel change hypothesis; Chandola et al., 2006). This approach has two important advantages; first, it analyzes not only a single variable, but also *constellations of conditions*; second, it analyzes not only the effect of a one-time exposure to a particular constellation, but also the *history of stability and change* over time. The importance of considering constellations is in line with major theoretical models in occupational health research, which assume that positive employee health and well-being result from a balance between positive (e.g., resources) and negative (e.g., psychosocial stressors) conditions, and that a lack of balance may be harmful (Bakker & Demerouti, 2014; Karasek, 1979; Siegrist, 1996). Although the various models define balance in somewhat different ways, they share the idea that the effect of a single condition at work may change in the presence of other conditions, which may amplify or diminish its impact on relevant outcomes. For example, one of the most important tenets of the JDC model is that the probability of negative effects on health and well-being is highest when employees are exposed to a combination of high demands and low control (high-strain jobs) (Karasek & Theorell, 1990). However, high demands accompanied by high control is regarded as a favorable constellation (active jobs), as control is a resource that can offset the negative effects of demands.

The JDC model postulates four combinations of conditions at work, based on different combinations of job demands and job control. In terms of their proposed relationships with well-being and health, two of them are unfavorable (high-strain and passive jobs) and two are rather favorable (active and low-strain jobs). As constellations have rarely been derived empirically, the extent to which the combinations postulated reflect people's actual experience remains unclear. Indeed, two recent studies, applying a person-centered approach, (Keller et al., 2016; Mauno et al., 2016) did not find support for the two constellations referred to as passive jobs and active jobs. These studies suggest that the theoretically proposed constellations do not necessarily reflect employees' experiences at work, and that more nuanced differences in constellations may be relevant for well-being and health beyond the rather crude distinctions suggested by cut-off values. Therefore, it seems important to not rely on constellations that are defined a priori, but to estimate constellations empirically.

Another problem that arises when dealing with predefined groups concerns the number of groups. Already with two waves of measurement there are many possibilities for change between high-strain, low-strain, active, and passive jobs. With more waves of measurement, the possible combinations can quickly become prohibitively large and difficult to manage. Authors usually deal with this problem by constraining their analyses to a subset of possible combinations. For instance, Schnall and colleagues (1998) confined analyses to those exposed to high-strain jobs (high demands and low control) versus those who were not. De Lange and colleagues (2002) restricted their analyses to 10 groups that exhibited either stability or one change of groups, and omitted participants who had changed more than once. Although such solutions are necessary when assigning participants to pre-defined categories on the basis of cut-offs, they neglect more subtle changes that may well have an impact on health and well-being.

Finally, this theoretical predefinition of groups is to some extent arbitrary, implies a loss of information, has less power and lower measurement reliability, and may lead to either existing associations not being detected or to spurious associations (MacCallum, Zhang, Preacher, & Rucker, 2002; Maxwell & Delaney, 1993).

Determining trajectories empirically. The third approach of determining trajectories empirically seems to be the most promising one. More specifically, we are referring to using a person-centered model to empirically estimate constellations and changes in work conditions over time. We know of three studies that have relied on this approach (Buddeberg-Fischer, Stamm, Buddeberg, & Klaghofer, 2010; Mauno et al., 2016; Rantanen, Kinnunen, Pulkkinen, & Kokko, 2012). Buddeberg-Fischer and colleagues (2008) used cluster analysis to identify subgroups of young medical doctors exposed to (un)favorable ERI constellations of work conditions over three waves. These authors found two patterns – low effort and high rewards, and high effort and low rewards – which were differentially associated with indicators of health and well-being. Rantanen and colleagues (2012) used latent profile analysis to capture developmental heterogeneity in work–family variables. They identified four developmental patterns that were associated with different levels of well-being outcomes such as exhaustion. Lastly, Mauno and colleagues (2016) used growth mixture modeling (GMM) to empirically test the four constellations of the JDC model and their effects on exhaustion and vigor over time. Although they did find four JDC constellations that were differentially related to vigor and exhaustion – two stable (high-strain and low-strain – stable) and two changing groups (job-control increase and job-control decrease) –, these constellations only partially corresponded to the constellations proposed by the JDC model. These studies demonstrate the advantages of estimating trajectories empirically based on a person-centered approach. Using the range of information contained in the data, this approach is better able to account for the heterogeneity of individual developments than approaches employing predefined groups. Furthermore, the groups identified by this empirical approach can better reflect the actual experience of the participants; indeed, in all three studies, the groups identified did not cover the range of possibilities given by the number of combinations that would have been possible theoretically.

The first aim of our study therefore was to estimate the history of exposure to conditions at work using a person-centered approach. Since GMM, an extension of latent growth curve analysis, yields empirically determined trajectories, it seemed to be particularly suited to our purpose (B. O. Muthén, 2004; B. O. Muthén et al., 2002). By comparing those constellations of trajectories to the combinations postulated by the JDC model, extended by social stressors, we could test the extent to which those predefined combinations reflect people's actual experience. Although GMM has gained popularity in occupational health research in recent years, with the exception of the recent study by Mauno und colleagues (2016), studies have focused on well-being and person characteristics and not on estimating the history of exposure to conditions at work (Feldt, Hyvönen, Mäkikangas, Kinnunen, & Kokko, 2009; Siltaloppi, Kinnunen, Feldt, & Tolvanen, 2011; von Bonsdorff et al., 2011; Wang, 2007). Instead, such studies have identified different developmental trajectories of indicators of well-being (Mäkikangas, Hyvonen, Leskinen, Kinnunen, & Feldt, 2011; Wang, 2007), work ability (Feldt et al., 2009), or recovery after work (Siltaloppi et al., 2011).

Employing GMM allowed us to represent history of exposure and empirically identify the heterogeneity that is present in trajectories over time; to detect more nuanced changes than implied by the theoretically derived classifications; and to simultaneously estimate several conditions at work over time. Such analyses may help to refine occupational health models and determine meaningful differences between work populations in terms of more subtle constellations of interest. Furthermore, they may help shed light on change process over time.

Work Conditions Used to Identify History of Exposure

Since its emergence, the JDC model has been the dominant theoretical framework (de Lange et al., 2002; Häusser, Mojzisch, Niesel, & Schulz-Hardt, 2010). Job demands have been operationalized mainly through task-related stressors such as time pressure or workload. By contrast, social stressors in terms of tension and conflict have received less attention (Dormann & Zapf, 2002; Spector & Jex, 1998), despite the fact that social stressors have repeatedly been shown to have rather strong effects on health and well-being, over and above different task-related stressors (Frese & Zapf, 1987; Keashly, Hunter, & Harvey, 1997; Sonnentag & Frese, 2013; Spector & Jex, 1998). Such effects have been found for psychosomatic complaints, depressive symptoms, and anxiety (Zapf & Frese, 1991); for rumination (Dormann & Zapf, 2002); for job-related tension, job satisfaction, job commitment, and intention to leave (Keashly et al., 1997); for changes in BMI (Berset, Semmer, Elfering, Jacobshagen, & Meier, 2011); and for death due to digestive system disease (K. A. Matthews & Gump, 2002). Other studies have demonstrated short-term effects, for instance, on angry mood (Meier et al., 2013). The harmful effects of interpersonal conflicts on health and well-being have also been demonstrated in a recent meta-analysis, in both cross-sectional and longitudinal studies (Nixon, Mazzola, Bauer, Krueger, & Spector, 2011). Finally, Keller and colleagues (2016) found social stressors to be a key variable in distinguishing favorable and less favorable constellations of conditions at work, estimated by factor mixture modeling. The strong effects of social stressors are likely to be associated with their potential to offend the self (DeWall & Bushman, 2011; Kemeny, 2009; Meier et al., 2013; Semmer et al., 2007). Specifically, social stressors signify tense relationships and are associated with the perception of a lack of fairness, with being blamed, receiving inappropriate feedback, or with being excluded. Such conditions violate a rather basic human need, the need to belong (Baumeister, 2012); implying a (perceived) lack of acceptance and appreciation, they go against the need for a positive identity, and thus offend the self (Miller, 2001; Semmer et al., 2007). Although many stressors, but also resources may have implications for the self (e.g., job control also may signal trust and acknowledgment), social stressors often contain derogative messages rather directly, in ongoing social interactions (Semmer, Meier, & Beehr, 2016). Corresponding with Baumeister and colleagues’ (2001) findings on the relative importance of negative versus positive conditions and events, social stressors appear to have a stronger impact on mental health than supportive behaviors (Vinokur & van Ryn, 1993). Therefore, in the current study, we used social stressors as a social work characteristic in addition to task-related stressors and job control. Given that they often had predictive value over and above other stressors, we did not consider social stressors as a sub-dimension of job demands, but added them as a stressor in their own right, expecting that their development would make a difference in constellations of work conditions.

What Constellations can be Expected Over Time?

On theoretical grounds and on the basis of existing evidence (Feldt et al., 2013; Mauno et al., 2016), we expect to find heterogeneity and thus be able to identify trajectories that differ in initial value and/or slope. However, it is not easy to predict how many constellations of trajectories will be found and what developments will characterize them. Although there are some bases for developing hypotheses, they are not very precise.

How many constellations of trajectories can be expected? At any point in time there are many possible constellations; furthermore, working conditions can remain stable or change over time, and the variables within a constellation may develop together, or display different patterns over time. Therefore, the number of constellations that can be derived theoretically from the JDC model is very large, especially when several waves of measurement are considered (see de Lange et al., 2002). However, as discussed earlier, these constellations may not accurately reflect participants' actual experiences. Although individual developments may be diverse, we expect the number of constellations to be reduced to a smaller number than theoretically possible as soon as one tries to identify the trajectories characterizing groups of participants. We cannot theoretically determine the exact number of constellations to expect, but the available evidence indicates a certain range. Across four large studies, Keller and colleagues (2016) found two replicable constellations; as the studies were cross-sectional, however, they could not take future developments into account. Feldt and colleagues (2013) identified five, and Mauno and colleagues (2016) four constellations over time. On this basis, it seems reasonable to expect that between three and five constellations over time will be identified by GMM.

What kind of constellations of trajectories can be expected? With three variables (task-related stressors, social stressors, and job control), there are many possibilities for developments over time, and thus which developments to expect cannot be precisely predicted. Again, however, some considerations can help to narrow down the likely developments. First, it seems likely that, overall, favorable constellations will prevail. At the outset of the study, many participants are likely to have obtained, through processes of selection and self-selection, a job that fits their aspirations and skills at least reasonably well. This expectation should hold unless people have very few skills or the economic situation is so bad that they are forced to accept unfavorable offers; neither of these cases apply to our study (see below). Second, people often deal with unsatisfying circumstances by altering them, for example by job crafting (Wrzesniewski & Dutton, 2001) or by changing employers, which often results in positive effects (Semmer, Elfering, Baillod, Berset, & Beehr, 2014). As a result, employees will often be able to avoid or mitigate strongly negative constellations, such as persistent exposure to high-strain jobs, deterioration over time. Third, participants may to some extent adapt to unfavorable conditions. For example, they may develop coping mechanisms, such as more efficient strategies to deal with their demands; due to improved personal resources, they may then perceive their conditions in a less negative way (R. A. Matthews, Wayne, & Ford, 2014; Ritter, Matthews, Ford, & Henderson, 2016). Two conclusions follow from these considerations: First, the majority of participants should be in constellations that are rather favorable, either in terms of stable favorable conditions or in terms of improvements in initially less favorable conditions; more specifically, stable favorable conditions should prevail. Second, differences between constellations should not be very drastic, as most participants should be able to avoid extremely unfavorable conditions, implying that most changes should occur within a fairly favorable range and should be more nuanced than implied by the comparatively crude constellations based on cut-off values.

Empirical findings support these conclusions, as the majority of participants typically is found to be in rather favorable constellations. For instance, in the studies by De Lange and colleagues (2002, 2009), only a small number of employees were found to be in high-strain jobs (4.5% in De Lange et al., 2002; 5.4% in De Lange et al, 2009), or to change from low-strain to high-strain jobs (0.5%; de Lange et al., 2002) or from non-high-strain to high-strain jobs (de Lange et al., 2009). Similarly, Wang and colleagues (2007) reported between 4.2% and 6.3% of participants to have very stressful jobs. Feldt and colleagues (2013; 22%), Mauno and colleagues (2016: 12.5%), and Keller and colleagues (2016; between 7% and

18%) estimated somewhat higher percentages of employees reporting unfavorable conditions; nevertheless, unfavorable constellations still constituted a clear minority.

What types of development (linear versus quadratic) can be expected? An important theoretical and empirical question is whether changes in trajectories are linear or not (Ployhart & Vandenberg, 2010). Given that people may experience all kinds of changes over time (concerning employers, types of tasks, social relations at work, etc.), one might expect quite diverse patterns. However, patterns involving many changes are likely to be rather idiosyncratic, characterizing only a few individuals but not reasonably large groups. Furthermore, our analyses refer to rather general categories, such as job control. With such categories, things may be continuous, even if one goes through several changes in specific aspects involved. Because people often try to improve unsatisfying conditions by changing employers (Semmer et al., 2014), by job crafting (Wrzesniewski & Dutton, 2001), or by developing more effective coping strategies (Ritter et al., 2016), drastic changes are likely to be dampened, thereby “linearizing” developments in the long run. In line with these considerations, neither Feldt and colleagues (2013), nor Mauno and colleagues (2016) reported deviations from linearity with respect to conditions at work. We therefore expect linear trajectories to reflect developments reasonably well. On the other hand, our time frame is 10 years, and the time lag between the last two waves is rather long (6 years; see methods section). It seems quite possible that after a few years, when participants have settled in to some degree, some developments might level off; at the same time, other developments might be accelerated (in either direction), giving rise to a quadratic trend. We therefore estimate quadratic trends as well.

Based on these considerations, we propose the following hypothesis:

Hypothesis 1: Growth mixture modeling will identify around three to five constellations of conditions at work over time, which can be distinguished in terms of their favorability (H1a). The majority of participants will be in favorable constellations, which will be characterized by high stability in the sense of no, or not very drastic, changes (H1b). Changes are expected to be more nuanced than the classic distinctions suggested by the JDC model (H1c). Linear developments will represent the changes found reasonably well (H1d).

History of Exposure and Cumulative and Chronic Effects on Health and Well-Being

Influential theoretical models in occupational stress research (Karasek, 1979; Meijman & Mulder, 1998; Siegrist, 2002) and empirical evidence (e.g., Belkic et al., 2004; Chandola et al., 2006) suggest that prolonged exposure to unfavorable conditions at work differs from short-term exposure and is more harmful to health and well-being. Continuous exposure to stressful conditions is likely to impair recovery (Geurts & Sonnentag, 2006; Meijman & Mulder, 1998), increasing the probability that strain accumulates over time. Some possible reactions to prolonged exposure to stressful conditions at work have been described by Frese and Zapf (1988). Their stress reaction model (which is equivalent to the parallel change hypothesis; Chandola et al., 2006) assumes that strain increases as long as the stressful circumstances persist, and declines thereafter. The amount of strain in this model is a function of the time for which stressful circumstances persist; in other words, strain accumulates as long as the circumstances are stressful. Accordingly, in a study by Schnall and colleagues (1998), blood pressure was reduced at time two for participants who were in a high-strain situation at time one but no longer at time two.

Things are different for Frese and Zapf’s accumulation model. This model describes strain reactions that accumulate over time but do not decline once the stressful circumstances end; rather, strain persists (or even continues to increase, as described in the dynamic variant of the accumulation model). For strain to persist beyond stressful circumstances, some more permanent changes must have occurred in the individuals involved. Allostatic load theory refers to such changes as allostatic load (or overload; e.g., McEwen, 1998). Repeated or chronic exposure to stressful conditions over a longer period of time may induce a lack of habituation to recurring stressors, a lack of adequate response to stress (i.e., the response being too weak or failing to occur), or a chronic response that is not, or not sufficiently, deactivated when the stressful period ends (McEwen, 1998). The changes induced by such long-time exposure may be associated with physical changes (McEwen, 2004), increased reactivity to stressors both physiologically (Gump & Matthews, 1999; Wirtz, Ehlert, Kottwitz, La Marca, & Semmer, 2013) and psychologically (Meier, Semmer, & Gross, 2014), and behavioral aspects, such as the formation of unhealthy habits of physical inactivity, that become increasingly hard to break (Fransson et al., 2012).

Note that such changes are not easily reversed and imply a certain degree of stability; therefore, they persist after the stressful period ends (Bakker & Costa, 2014; Rodriguez-Muñoz, Sanz-Vergel, Demerouti, & Bakker, 2012). With such changes occurring, the symptoms in question become increasingly independent of the given stressful conditions. We refer to the type of strain that is characterized by reduced reversibility as *chronic strain*, whereas we use the term *cumulative strain* in a more general sense to imply strain due to long-term exposure to stressful conditions, whether reversible or not. So far, if history of exposure is included in the analytical models, it usually is in terms of what we have labeled as cumulative strain (de Lange et al., 2009; de Lange et al., 2002). In studies including cumulative strain it remains unclear whether the symptoms of participants in unfavorable constellations in the final wave are due to the history of exposure or to the fact that the unfavorable conditions are still present.

To demonstrate chronic strain, one must additionally show that a reversal in conditions does not produce a corresponding reversal in symptoms. We are aware of three studies where this has been demonstrated to some extent. In a study by Frese and Semmer

(1986) leaving shift work upon medical advice was not associated with health symptoms (e.g., fatigue, sleep disturbances, etc.) being reduced to the level displayed by those who had never worked in shifts. As people had to pass a medical test before being allowed to work in shifts, the high level of symptoms exhibited by these former shift workers likely represent chronic effects of shift work. In a study by Schnall et al. (1998) systolic blood pressure of participants who had changed from high-strain to no-high-strain conditions was significantly reduced, indicating parallel change; however, it was still higher than the blood pressure of participants who were never in the high-strain group, suggesting that some adverse effects of having been in the high-strain group remained and had become chronic. In the third study, Landsbergis and colleagues (2003) demonstrated that the systolic blood pressure of men who had been employed for at least 25 years and exposed to high strain for at least half of their work life was higher than that of participants without past exposure; this difference was independent of current exposure, for which the authors adjusted. However, in this study, history of exposure was defined using the cut-off approach – a median split (i.e., the second approach as discussed earlier). More research on this issue is needed using more refined methodologies such as GMM.

In the current study, we explored both cumulative and chronic strain. Using empirically estimated constellations of conditions at work (i.e., history of exposure) as a predictor, and controlling for initial strain, we analyzed cumulative effects. To analyze the occurrence of chronic strain, we additionally controlled for the effects of current conditions at the last wave. High reversibility (i.e. effects as postulated by Frese & Zapf's (1998), stress-reaction, or Chandola et al.'s parallel change model (2006)) would imply that any effect of conditions at work on health would be due to current conditions, which, by definition, would "override" the effects of previous conditions. In other words, current conditions should be a significant predictor, and history of exposure should cease to predict symptoms. By contrast, if effects are chronic, history of exposure must remain a significant predictor of symptoms when adjusted for current conditions. Obviously, these models are not mutually exclusive. Current conditions may play a role without rendering history of exposure insignificant. Such a result would indicate relative, rather than absolute, chronicity, implying that symptoms would be reduced to a limited extent if conditions improved.

With regard to cumulative and chronic effects we postulate:

Hypothesis 2 (Cumulative effects): Participants with unfavorable constellations of trajectories (history of exposure) will report the most unfavorable levels on indicators of health and well-being in the last wave of measurement.

Hypothesis 3 (Chronic effects): Indicating chronic effects, the differences in health and well-being between constellations of trajectories will remain significant when controlling for current conditions at work.

Method

Participants and Design

Our analyses are based on the study "Work Experience and Quality of Life in Switzerland" (ÆQUAS) (Kälin, Keller, Tschan, Elfering, & Semmer, 2014), which contains five waves over a period of 10 years[1]. Data were collected from young employees in five occupations (salespeople, electronic technicians, bank clerks, nurses, and cooks) over their first 10 years in the labor market. Recruitment and data collection started in 1997 in vocational schools, which can be compared to a vocational – technical school in US; participants then were in the final year of their training. Vocational educational training in Switzerland typically involves spending one or two days per week at a vocational school, and three or four days working as an apprentice in a company. For the next four waves (1998,

[1] In time when the data were assessed our university needed no ethical approval for questionnaire studies, the study however followed guideline of the declaration of Helsinki and the Swiss Society of Psychology and we are aware of APA ethics policy regarding the treatment of participants and we have followed it.

1999, 2001, and 2007), questionnaires were sent by mail. In 1997, we aimed at a sample of 1,000 participants. Initial response was high, given that the questionnaires were filled out in classrooms. Thus, the initial sample was N = 1,394. However, there was a high level of drop-out over the 10 years of observation (see drop-out analyses below)[2].

For our analyses, we included those participants who had filled out the questionnaire in the first (1997 – base level) and last wave (2007) plus at least one wave in between (1998, 1999, or 2001); this resulted in a sample size of 483 employees. Data from the last wave were needed in order to predict outcomes in the last wave, and at least one interim participation was necessary for estimating development over time. Only one participant had to be excluded on the basis of this latter criterion.

In the resulting sample, 247 participants (51.1%) were female, mean age in the last wave was 30.9 years (SD = 3.5), and there were slightly more participants from the German-speaking (n = 264; 54.7%) than from the French-speaking (n = 219; 45.3%) part of Switzerland. In the last wave, the majority of participants worked at 80% or more of a full-time equivalent. In terms of occupations, 10% of participants were in sales, 17.2% were electronic technicians, 19.9% were bank clerks, 17.4% were cooks, 8.9% were nurses, and 26% had changed their occupation.

Drop-out analysis. To explore potential selection bias, the sample selected for analysis (n = 483) was compared to the excluded 911 participants who had participated in wave one but not in at least two more waves. The drop-outs differed from stayers only in one of the indicators of conditions at work, and only in one wave; they scored higher on social stressors in the first wave ($M_{\text{leavers}} = 2.13$; $M_{\text{stayers}} = 1.98$; $t = 3.62$, $p < .001$), but did not differ in private stressors or in any of the outcome variables.

[2] Some of the data were also used in other papers and book chapters. T1 to t2 data were used in two papers (Elfering, Semmer, & Kälin, 2000; Kälin et al., 2000), t3 data in one paper (Grebner et al., 2003), t1 to t4 data in one chapter (Semmer, Tschan, Elfering, Kälin, & Grebner, 2005) and one paper (Elfering, Semmer, Tschan, Kälin, & Bucher, 2007), and t1 to t5 data in a chapter (Kälin et al., 2014).

Measures

Conditions at work. *Job control* was assessed using the Instrument for Stress-Oriented Task Analysis (ISTA; Semmer, Zapf, & Dunckel, 1995). The five items measuring job control focus on the freedom to decide when (time control; two items, e.g., "To what degree are you able to decide on the amount of time you will be working on a certain task?"*)* and how (method control; three items, e.g., "Can you decide yourself which way to carry out your work?") to perform tasks at work. Items were answered on a 5-point scale. Responses ranged from 1 (*very little/not at all*) to 5 (*very much*). Cronbach's alphas across five waves ranged from α = .68 to α = .81.

We assessed five *task-related stressors* with three items each from the Instrument for Stress-Oriented Task Analysis (ISTA; Semmer et al., 1995): time pressure (e.g., "How often must you finish work later because of having too much to do?"), concentration demands (e.g., "How often must you retain information which is difficult to remember?"), work interruptions by supervisors, colleagues, or clients (e.g., "How often are you interrupted by clients during the course of your work activity?"), uncertainty about tasks (e.g., "How often do you receive contradictory instructions from different supervisors?"), and performance constraints (e.g., having to work with inadequate devices or obsolete information). We combined these five stressors into a single index representing demands from the JDC model, as has been done in other studies (Frese, 1985; Kälin et al., 2000; Meier, Semmer, Elfering, & Jacobshagen, 2008). The composite score reliability, which is appropriate for such an index (Nunnally & Bernstein, 1994), ranged from .75 to .86 across the five waves.

Social stressors were measured with five items from the social stressors scale by Frese and Zapf (1987), referring to aspects such as conflicts, negative group climate, and social animosities (e.g., "With some colleagues there is often conflict"). Alphas ranged from α = .69 to α = .71 across the five waves.

Indicators of health and well-being. The list of potential consequences of stress in terms of health and well-being is very long and involves various physiological, affective, and behavioral strains (Sonnentag & Frese, 2013). We investigated three variables, two of which are psychological (rumination and job satisfaction) and one of which is physical (somatic complaints).

Rumination implies a sustained preoccupation with stressful conditions (Brosschot, Pieper, & Thayer, 2005) and can be regarded as opposite to psychological detachment. It impairs recovery (Sonnentag & Kruel, 2006), which is increasingly regarded as a central link between acute and chronic effects of stress (Geurts & Sonnentag, 2006). The importance of rumination as an indicator of mental health has been demonstrated in occupational stress research (Berset, Elfering, et al., 2011). Given its importance for prolonging the effects of stress, rumination (worrying) was our first psychological outcome variable; it was measured using a short version of the irritation scale by Mohr et al. (Mohr, Müller, Rigotti, Aycan, & Tschan, 2006; Mohr, Rigotti, & Müller, 2005). A sample item is "Even at home I often think of my problems at work." Responses were on a 7-point Likert-type scale (1 = *strongly disagree* to 7 = *strongly agree*). Alphas across the five waves ranged from $\alpha = .75$ to $\alpha = .84$.

Job satisfaction is probably the most frequently investigated variable in work and organizational psychology (Spector, 1997). Conditions at work have been shown to predict job satisfaction (e.g., Acker, 2004; Humphrey, Nahrgang, & Morgeson, 2007; Spector & Jex, 1998). Although little research has investigated the association between job satisfaction and constellations of conditions at work over time, Keller and Semmer (2013) showed that not only the initial level, but especially the slope of job control predicted job satisfaction over five years. De Lange (2002) and colleagues also showed that unfavorable conditions at work had negative cumulative effects on job satisfaction, both in terms of initial values and in terms of changes over time. For the current study, job satisfaction was measured using three items from a scale on general job satisfaction by Baillod and Semmer (1994): a Kunin item asking “How satisfied are you in general with your work?” (1 = *exceptionally dissatisfied* to 7 = *exceptionally satisfied*) and two items asking what people think about their work (e.g., “After a few days off I really look forward to going back to work”; 1 = *practically never* to 7 = *practically always*). Alphas across the five waves ranged between α = .75 and α = .84.

Physical symptoms, such as backache, headache, eye strain, sleep disturbance, dizziness, fatigue, appetite loss, and gastrointestinal problems, have been investigated frequently in research on occupational stress (Spector & Jex, 1998), including longitudinal studies (Frese, 1985; Nixon et al., 2011; Sonnentag & Frese, 2013), but only occasionally in terms of cumulative exposure (e.g., Godin, Kittel, Coppieters, & Siegrist, 2005). *Somatic complaints* were measured with 13 items by (Mohr, 1991), asking participants how often they had experienced complaints such as headache, eye strain, sleep disturbance, dizziness, fatigue, appetite loss, gastrointestinal problems, and musculoskeletal pain over the past 12 months. Answers were on a 5-point scale ranging from 1 = *practically never / never* to 5 = *almost daily*. Internal consistency across the waves ranged from α = .82 to α =. 84.

Control variables. In addition to the initial values of outcome variables and demographic characteristics, which are routinely controlled for in longitudinal studies (Zapf et al., 1996), we controlled for *private stressors*. As conditions at work and in private life are not independent from one another (Eby, Maher, & Butts, 2010), the effects of work-related stressors might be overestimated if private stressors are not controlled for. Private stressors were assessed using five items from a scale on stressors in free-time (Bamberg, 1991). Examples are “In my free-time, something crops up so I can’t do what I would like to do”; “My partner prefers to do something different from what I would like to do.” The response format ranged from 1 (*very little/not at all*) to 5 (*very much*). It should be noted that the underlying construct is not necessarily one-dimensional, as illustrated by the two items, which refer to things that do not necessarily go together. Consequently, we feel that the rather low Cronbach's alphas (between α = .50 and α = .60) are acceptable in this case.

Analytic Strategy

We used growth mixture modeling (B. O. Muthén, 2004; B. O. Muthén et al., 2002) to statistically identify homogeneous latent classes of individuals differing in trajectories of task-related stressors, social stressors, and job control across five waves. We then assigned individuals to one of the constellations of trajectories. GMM estimates trajectories (B. O. Muthén, 2004; B. O. Muthén et al., 2002), taking into account that there may be unobserved heterogeneity in development over time (B. O. Muthén, 2004). This approach captures information about inter-individual differences in intra-individual change over time, and allows for differences in growth parameters across unobserved subpopulations (B. O. Muthén, 2001; B. O. Muthén & Muthén, 2000). It also enables one to estimate competing models (Jung & Wickrama, 2008; B. O. Muthén, 2004; Wang & Bodner, 2007). Trajectories can differ in terms of levels, and in growth over time (slopes). When estimating more than one work characteristic simultaneously, as we did, the number of possible combinations is very large. The advantage of GMM, as compared to predefining subgroups, is that GMM estimates intercept and change over time for different work characteristics from the data, using statistical criteria to decide on the most suitable number and types of constellations.

As a first step, we tested measurement invariance over time to ensure that the same construct was measured across the observed time period. It has been argued that in practical applications full invariance frequently does not hold, and partial invariance may be tolerable. If full invariance cannot be established, one can test whether the relaxating individual constraints leads to better model fit (Byrne, Shavelson, & Muthén, 1989; Garst, Frese, & Molenaar, 2000; Steenkamp & Baumgartner, 1998; Widaman, Ferrer, & Conger, 2010). We compared the model fit of measurement models with freely estimated factor loadings (configural invariance) to measurement models with factor loadings constrained to be equal across time (metric invariance). Model fit was good for the unconstrained and constrained models, but the chi-square difference test was significant for all three constructs, implying that some of the factor constraints imposed may not have been justified. We started to test less restrictive measurement models by freeing the factor loading constraint between waves four and five (6-year time lag). For job control and social stressors, partial metric invariance was confirmed. For task-related stressors, the constraints on factor loadings between wave one and two were relaxed additionally to meet partial metric invariance. To assess general model fit, we used the comparative fit index (CFI), the root mean square error of approximation (RMSEA), and the standardized root-mean-square residual (SRMR; Byrne et al., 1989; Garst et al., 2000; Steenkamp & Baumgartner, 1998) and relied on chi-square difference tests to assess the significance of differences between measurement models over time.

We assumed that linear solutions would fit the data well, but noted that an argument could also be made for quadratic solutions. We therefore conducted step-by-step model estimation, from a 1-class model to a 6-class model, for both linear and quadratic solutions. Since we eventually decided in favor of the linear models, the quadratic models are presented in the supplemental materials. The within-class slope variance was fixed to zero, as variances were small (0.001) and not significant (Jung & Wickrama, 2008).

There has been an intensive discussion about the optimal combination of selection criteria when deciding on the number of trajectories (Hu & Bentler, 1998). The criteria currently viewed as most effective are the adjusted Lo–Mendell–Rubin likelihood ratio test (LMR) and the bootstrapped likelihood ratio test (BLRT), which both compare different solutions; a significant *p*-value ($p < .05$) indicates that the k class model has a better fit than the k-1 class model. Other important indices are the Bayesian information criterion (BIC) and the adjusted Bayesian information criterion (Nylund, Asparouhov, & Muthén, 2007); for both, the model resulting in the lowest BIC value is considered to be the best. Finally, entropy reflects the precision of the latent class categorization (Jedidi, Ramaswamy, & DeSarbo, 1993). Entropy ranges from 0 to 1.00, with higher values indicating better categorization; values around .80 or higher have been suggested as an indication of suitable classification (Greenbaum, Del Boca, Darkes, Wang, & Goldman, 2005). However, there is consensus in the literature that one must consider not only statistical criteria, but also the interpretability and usefulness of the latent classes (Jung & Wickrama, 2008).

We used the Mplus program, version 7.11 (L. K. Muthén & Muthén, 1998-2015) to analyze the data. The waves were not annual; therefore, we fixed slopes to represent years in between: time 1 (1997) to 0, time 2 (1998) to 1, time 3 (1999) to 2, time 4 (2001) to 4, and time 5 (2007) to 10. The missing data on predictor variables were modeled using full information maximum likelihood (FIML; Enders & Bandalos, 2001). After we determined the model with the best fit, latent class membership derived from this model was assigned to each participant. Multivariate analysis of covariance (MANCOVA) was used to investigate the effects of class membership (with the classes set as a fixed factor) on the outcome variables in the last wave. In these analyses, missing values in the predictors were handled by listwise deletion. We tested whether employees with unfavorable and favorable trajectories differed in the outcome variables in the last measurement, controlling for the initial level of the respective outcome, gender, and region (German-speaking vs. French-speaking) and for cumulative private stressors (mean over all waves) if significant (Hypothesis 2); and for current conditions at work (Hypothesis 3).

Results

Descriptives

Table 2 contains the means, standard deviations, and intercorrelations between the study variables.

To test Hypothesis 1, we performed a series of GMM analyses. As can be seen in Table 3, no single solution emerged as a clear favorite for the linear models; rather, there was support for solutions with four and five classes. The BIC value supported the 4-class model; entropy supported the 5-class model. LMR was somewhat ambiguous, as the value for the 4-class model was significant (supporting a 4-class solution over a 3-class solution); at the same time, the value for the 5-class model was marginally significant (p = .08), which indicated some support for a 5-class solution. However, in choosing the final model, one has to consider not only the fit indices, but also a solution`s interpretability and usefulness, taking into account aspects such as content and size of classes, and theoretical plausibility (Jung & Wickrama, 2008). Compared to the 5-class solution, the class that was missing from the 4-class solution was the Active Job & High Social Stressors – Stable class (see below). Because this class reflected a unique constellation, we decided to test its relevance and selected the 5-class model for the subsequent analyses.

The linear and quadratic solutions were almost identical for four of the five constellations, which largely supported Hypothesis 1e. In the case of a significant quadratic term, the turning point was observed between the last two measurements. Being largely identical and also more parsimonious, we decided in favor of the linear solutions. Results for the quadratic solutions can be found in the supplemental material.

Results for Hypothesis 1: Identifying History of Exposure

Our expectations regarding the constellations, their development over time, and their heterogeneity were largely supported. GMM identified five constellations, which could be distinguished in terms of favorability of conditions at work (H1a). In line with our expectations, more employees were classified in constellations with favorable conditions over time (either in terms of stable favorable conditions or in terms of improvement) than in unfavorable ones. The two unfavorable constellations together contained a rather small proportion of the whole sample (4.5%). On average, the levels of social stressors (*M* between 1.90 and 1.98) and task-related stressors (*M* between 2.87 and 2.99) were rather low, and the level of job control was rather high (*M* between 3.29 and 3.73) for the sample as a whole. The number of participants in constellations of trajectories characterized by stability (n = 354) was much larger than the number of participants in changing constellations (n = 129); thus, H1 b was confirmed. Furthermore, in constellations with changing conditions over time, the changes were, as expected, less extreme than those implied by the theoretically predefined classifications (e.g., based on the JDC model), which confirmed H1d.

Description of Constellations of Trajectories of Conditions at Work

Extending the JDC model to include social stressors at work (Karasek, 1979; Karasek & Theorell, 1990), we identified three favorable and two unfavorable constellations of trajectories (Table 4). For the most part, the extended JDC model provided criteria for considering constellations as favorable or unfavorable; difficulties arose, however, when intercept and change trends were inconsistent, as when values changed from unfavorable to favorable or vice versa. In such cases, we decided to place more weight on the change component, classifying a move to a favorable constellation as favorable and a move to an unfavorable constellation as unfavorable.

The favorable constellations were named as follows: 1) Low-Strain, 2) Improvement into Low-Strain, and 3) Active Job & Low Social Stressors – Stable. The unfavorable constellations were named: 4) Active Job & High Social Stressors – Stable and 5) Deterioration into High-Strain.

Favorable Constellations

Constellation 1: Low-Strain. The first constellation (Table 4, Figure 1) was the largest of all (*n* = 273; 56.52%) and characterized by the highest[3] level of job control (I_{jc} = 3.52), moderate task-related stressors (I_{ts} = 2.69), and a low level of social stressors (I_{ss} = 1.80) at the outset. The average growth rates (slopes) for job control (S_{jc} = .034), task-related stressors (S_{ts} = .033), and social stressors (S_{ss} = .023) were significant and positive.

Constellation 2: Improvement into Low-Strain. The second favorable constellation (*n* = 118; 24.43%; Table 4, Figure 1) represented individuals with low social (I_{ss} = 2.31) and moderate task-related stressors (I_{ts} = 2.99), but with negative growth over time for both (S_{ts} = -.03; S_{ss} = -.08). Job control had a moderate-high intercept in this group (I_{jc} = 3.17), and increased significantly over time (S_{jc} = .09). According to the JDC model, this constellation moves toward a rather favorable combination, and thus the reduction in social stressors also fits into that picture. The changes over time were rather subtle in this constellation as well.

Constellation 3: Active Job and Low Social Stressors – Stable. The third favorable constellation (*n* = 70; 14.49%¸ Table 4, Figure 1) was characterized by a moderate-high level of job control (I_{jc}, was 3.09) and task-related stressors (I_{ts} = 3.32), and a low level of social stressors (I_{ss} = 1.73). All three variables were stable over time.

Unfavorable Constellations

Constellation 4: Active Job & High Social Stressors – Stable. The first unfavorable constellation (*n* = 11; 2.28%, Table 4, Figure 2) was similar to the third favorable constellation (Active Job & Low Social Stressors – Stable) with respect to job control (I_{jc} = 3.29; S_{jc} = 0.03; *ns*.) and task-related stressors (I_{ts} = 2.99; S_{ss} = 0.02; *ns*.), but not with respect to social stressors, which were moderate-high (I_{ss} = 3.08) and stable (S_{ss} = 0.03; *ns*.); we therefore called this constellation Active Job & High Social Stressors – Stable. This was the

---

[3] Values below 2.5 were labeled as low, values between 2.5 and 3 as moderate, between 3 and 3.5 as moderate-high, and values above 3.5 were labeled as high.

only constellation for which the nonlinear solution differed from the linear one (see supplemental material).

Constellation 5. Deterioration into High-Strain. The last constellation (*n* = 11; 2.28%, Table 4, Figure 2) was characterized by moderate-high initial job control (I_{jc} = 3.14) that decreased over time (S_{ij} = -.05), a moderate initial level of task-related stressors (I_{ts} = 2.67) that increased over time (S_{ts} = .08), and a low initial level of social stressors (I_{ss} = 1.64) that displayed the highest increase over time compared to all other growth values (S_{ss} = .20); all changes were significant. This constellation represents a case in which conditions change from rather favorable to unfavorable.

Hypothesis 2: Cumulative Effects

Hypothesis 2 (*cumulative effects*) postulated that participants with unfavorable constellations would report the lowest mean levels on indicators of health and well-being in the last measurement wave. MANCOVA, adjusted for the initial value of the respective outcome variable, demographic variables and for private stressors (Tables 5–7), yielded substantial support for Hypothesis 2.

There was a significant effect of constellation on all three outcomes in wave 5 (rumination: $F(4, 471) = 11.11$, $p < .001$; job satisfaction: $F(4, 454) = 24.75$); somatic complaints: $F(4, 471) = 4.84$, $p < .001$). For all outcome variables, the two unfavorable constellations combined differed significantly from the three favorable ones combined (Tables 5–7; contrast results I and II). Furthermore, each favorable constellation (1–3) individually was significantly different from the unfavorable constellations combined (4 and 5), and each unfavorable constellation was significantly different from the favorable constellations combined 1-3).

More specific comparisons revealed that each favorable constellation differed from each unfavorable constellation for two outcome variables: job satisfaction (Table 6, contrast results I) and somatic complaints (Table 7, contrast results II). For rumination, the pattern was similar, but not as definitive as for job satisfaction and somatic complaints; specifically, the difference between Constellations 1 (Low-Strain) and 4 (Active Job & High Social Stressors – Stable) was not significant, although there was a trend ($p = .09$) (Table 5, contrast results II). However, as soon as the favorable and unfavorable constellations were combined, the differences were significant.

Within the three favorable constellations, there were only a few significant differences. Thus, Constellation 1 (Low-Strain) was the least favorable of the three favorable ones, as it showed significantly higher levels of rumination ($p < .05$) than the other two constellations, as well as lower levels of job satisfaction ($p < .001$) than Constellation 2 (Improvement into Low-Strain). Somatic complaints represented the least sensitive outcome in these analyses, as none of the tested differences were significant (Table 6). Within unfavorable constellations, Deterioration into High-Strain (Constellation 5) revealed significantly higher levels of rumination and lower levels of job satisfaction than Active Job & High Social Stressors – Stable (Constellation 4).

Hypothesis 3: Chronic Effects

Hypothesis 3 postulated the existence of chronic effects, implying that effects would become independent of the current conditions, at least to some degree. This hypothesis would be supported if the effects of the constellations of trajectories remained significant after controlling for work conditions in the last wave. Hypothesis 3 was mainly supported, as the overall effect remained significant for two outcome variables – rumination and job satisfaction – but dropped to marginal significance ($p = .09$) for somatic complaints (Table 7, contrast results II). Again, comparisons of the favorable and unfavorable constellations combined yielded significant differences for all outcome variables. Differences for each favorable constellation versus the combined unfavorable constellations were also significant, with one exception: Somatic complaints in Constellation 2 (Improvement into Low-Strain) differed from the combined unfavorable conditions only to a marginally significant extent. With regard to differences between the individual unfavorable constellations and the favorable constellations combined, Constellation 5 (Deterioration into High-Strain) remained significantly different from the favorable constellations for all outcomes; for Constellation 4 (Active Job & High Social Stressors – Stable), the difference remained significant for job satisfaction and marginally significant for somatic complaints.

Within the three favorable constellations, Constellation 1 (Low-Strain) remained the least favorable, but only for job satisfaction ($p < .001$) when compared to Constellation 2 (Improvement into Low-Strain). Within the unfavorable constellations, Deterioration into High-Strain was less favorable than Active Job & High Social Stressors – Stable, but only for rumination ($p < .05$). Overall, while the results did not demonstrate complete irreversibility, they did demonstrate reduced reversibility and thus confirmed Hypothesis 3 to a considerable extent.

Discussion

This paper sought to address three questions. First, it sought to identify empirically favorable and unfavorable constellations in terms of the history of exposure to work conditions, as specified by the JDC model extended to include social stressors; second, it aimed to test the cumulative effects of exposure to trajectories of conditions at work over a considerable time span; and third, to test whether such effects become chronic in terms of reduced reversibility.

Hypothesis 1: Identifying History of Exposure

As expected (H1b), the number of constellations of trajectories identified was rather small, especially compared to the many possibilities implied by theoretically predefined constellations (see De Lange et al., 2002; 2009). As empirically derived constellations are more likely to reflect participants' actual experiences, this deviation from theoretically derived constellations is important, as it suggests that theories need to be revised and refined in order to better account for these experiences. Specifically with regard to the JDC theory, the empirically derived constellations were to some extent consistent with the JDC model, in that we identified elements of active jobs (Constellation 3), low-strain jobs (Constellations 1 and 2), and high-strain jobs (Constellation 5) when looking at task-related stressors and job control. The only JDC constellation that we did not identify was the passive job constellation characterized by low levels of both task stressors and job control. Other recent studies using a person-centered approach have also failed to identify the passive job constellation (Keller et al., 2016; Mauno et al., 2016). These findings imply that passive jobs do not seem to comprise a frequent constellation; it seems likely that, in the face of economic competition, employers would either eliminate such jobs or increase demands (Paškvan, Kubicek, Prem, & Korunka, 2016; Ulferts, Korunka, & Kubicek, 2013), and employees might try to actively craft such jobs, for example, by increasing their challenges (see below). It is possible that the passive job constellation only emerges with low skilled jobs, which neither our study nor the other studies cited have included.

In terms of social stressors, our results do support their inclusion in theoretical models on work stress as a stressor in its own right. As discussed below, social stressors are an essential characteristic of both unfavorable constellations. High and stable social stressors constitute the critical characteristic of Constellation 4 (Active Job and High Social Stressors – Stable) when compared to the favorable Constellation 3 (Active Job & Low Social Stressors – Stable), and increasing social stressors, which reach the highest value of all constellations, characterized Constellation 5 (Deterioration into High-Strain).

Furthermore, as expected (H1a), the majority of participants (95.44%) were classified into one of the three favorable constellations. A small, but still substantial, proportion

(4.56%) was classified into one of the two unfavorable constellations. Note, however, that terms such as “high-strain” are relative, and the values in the high-strain constellation were still fairly moderate.

Our results are consistent with previous findings from both variable-centered (de Lange et al., 2002) and person-centered approaches (Wang, 2007). With respect to stability and change, conditions were rather stable for about 73.29% of participants; most of these stable conditions were favorable (71.01%), 2.28% were unfavorable. For one quarter (24.43%), conditions improved over time (Constellation 2: Improvement into Low-Strain); conditions deteriorated only for a small number of participants (2.28%); Constellation 5: Deterioration into High-Strain). These results are in line with the assumptions that many people manage to find jobs that fit their qualifications and needs reasonably well (Ployhart & Schneider, 2012), and that discrepancies that occur can be solved or attenuated, for example by job crafting (Wrzesniewski & Dutton, 2001), changing jobs (Semmer et al., 2014), or adapting, which may lead to a more positive appraisal of a job because of improved personal resources due to training or better coping skills (R. A. Matthews et al., 2014; Ritter et al., 2016). Eventually, such processes are likely to result in an at least a reasonable fit between the person and the job (Semmer & Schallberger, 1996). Such processes of improving person–environment fit may also be responsible for the (expected) finding that changes were less extreme than those suggested by predefined JDC or iso-strain groups (de Lange et al., 2009; Schnall et al., 1998).

It should be noted, however, that such processes did not seem to operate for the minority of participants in the two negative constellations. For Constellation 4 (Active Job and High Social Stressors – Stable), conditions did not develop into a favorable constellation, and in Constellation 5 (Deterioration into High-Strain), social stressors even increased by two scale points. This was quite a strong increase, given that the standard deviation for social stressors was between .65 and .71 (see Table 2). It is difficult to determine the reasons for these exceptions to the rather positive stable or improving conditions found in general. Our analyses yielded no indication that these exceptions were related to specific personality traits of the participants found in the less favorable conditions (see supplemental material). The most likely explanation is that sometimes people are forced or induced to accept unfavorable conditions. For instance, they might want to change employers, but the job market may not offer adequate opportunities. They may also accept unfavorable conditions for strategic reasons, expecting to be rewarded (e.g., promoted) for their loyalty later on (Fried, Grant, Levi, Hadani, & Slowik, 2007; Siegrist, 1996). In a similar vein, people may accept negative conditions because of other positive aspects or benefits of their job (e.g., high social stressors but adequate demands and control; good fringe benefits; short travel distance), or because they have personal reasons to stay in their job (e.g., their partner has a good job in the vicinity, or they have obligations preventing them from moving away, such as caring for relatives). All of these factors may induce a dominant continuance commitment, inducing them to stay in unfavorable circumstances at the expense of their well-being (Meyer, Stanley, & Parfyonova, 2012). It is also conceivable that some people have unsuccessfully tried to improve their conditions at work and so do not evaluate their chances for improvement positively. Finally, challenge stressors may take their toll in some instances: Challenge stressors, such as time pressure, may be perceived as “rewarding work experiences well worth the discomfort that was involved” (Cavanaugh, Boswell, Roehling, & Boudreau, 2000, p. 66); this may well imply that people might accept or ignore that challenge stress “also has costs with respect to personal well-being” (LePine, LePine, & Jackson, 2004, p. 889). Whereas the positive effects of challenge stressors are often rather immediate, the negative effects may take quite some time to develop; this may encourage individuals to overuse their resources, the negative effect of which may appear only after extended exposure to such conditions (Widmer, Semmer, Kälin, Jacobshagen, & Meier, 2012). Future research should explore these processes.

These considerations concerning successful and less successful developments have important theoretical and empirical implications. Specifically, although there has been a major advancement in studies investigating the development of conditions at work over time, such studies still cannot provide a comprehensive picture of the specific reasons for the developments found and the mechanisms involved.

Eventually, stress-related theories will have to be combined with career- and life-span-related theory and research (Fried et al., 2007; Keller, Samuel, Bergman, & Semmer, 2014; Leong, Hartung, & Pearce, 2014; Scheibe & Zacher, 2013). We see three avenues as especially promising for research aiming at such integration. First, increasing age and different career stages come with different working conditions. For example, advancing in one's career tends to be accompanied by increases in control (Keller & Semmer, 2013; Scheibe & Zacher, 2013), but also with less heterogeneity in stressors, with this reflected in how many domains' stressors are present (Brose, Scheibe, & Schmiedek, 2013).

Second, depending on career stage or age, stressors may be interpreted differently. For example, certain conditions may be perceived as transitory or even necessary for being able to move to another position (Fried et al., 2007) conversely, they may be seen as a sign of entrenchment (Zacher, Ambiel, & Noronha, 2015) or of reaching a plateau (Jiang, 2016). For example, feeling pressured to achieve a certain position (Biemann, Zacher, & Feldman, 2012) may have an accentuating effect on stressors like workload or conflicts with the supervisor, because employees are not only confronted with the immediate stressors at work, but see themselves threatened by more severe consequences for their career if they cannot adequately cope with the acute stressor. Furthermore, according to socioemotional selectivity theory (Löckenhoff & Carstensen, 2004) employees are likely to change their focus from achievement goals to emotional goals as they get older, which may also change the meaning and impact of stressors and resources

Finally, future research should take the active role of individuals in selecting and shaping their work environment more into account (Bakker & Demerouti, 2014). The concept of career construction, which is part of career theory (Savickas, 2002) includes constructs such as adaptability, with sub- constructs that are also relevant for stress theory, such as control and confidence (Hirschi, Herrmann, & Keller, 2015) (in addition to concern and curiosity. Results from lifespan psychology showing that secondary control strategies, such as disengagement, may foster adaptation, but only if opportunities are low and barriers high, have implications for coping (Tomasik, Silbereisen, & Heckhausen, 2010).

At the same time, it should be noted that our sample, like many samples in occupational health psychology, was fairly well educated. Our participants had a professional certificate through vocational training, which can be roughly compared to attending a vocational-technical school in the United States, but is completed by about 60% of a birth cohort in Switzerland (for further information see Kälin et al., 2000). Including unskilled participants would most likely have resulted in higher percentages in unfavorable trajectories.

Hypothesis 2: Cumulative Effects

We postulated that participants exposed to favorable versus unfavorable constellations of JDC conditions, extended to include social stressors over time, would differ in terms of indicators of physical (somatic complaints) and psychological strain (rumination, job satisfaction) after 10 years. The hypothesized relationships were largely supported and could be attributed neither to the initial values of the outcome variables nor to average private stressors over time.

Comparisons within the favorable constellations were in line with the JDC model, in that, the Active Job and Low Social Stressors – Stable constellation was more favorable than both Low-Strain constellations. This finding underscores that job demands should not simply be reduced to very low levels. Rather, if the activity required by the demands is not too high, and combined with job control and low social stressors, demands seem to be beneficial. A further noteworthy finding was that the Improvement into Low-Strain constellation was more favorable than the stable low-strain constellations over time; on the less favorable side, there was a corresponding result with regard to Constellation 5, which was characterized by a rather steep increase in social stressors. Such results imply that change may be more powerful than stability. It has been well established that not only reaching goals, but also moving toward (or away from) goals is associated with affective reactions (Plemmons & Weiss, 2013) and it may well be that the perception of moving toward more favorable conditions maintains or induces optimism, whereas the perception of moving toward more unfavorable conditions induces pessimism. To the extent that this is true, it has important implications for stress theory. It will have to consider that situations may sometimes be seen as favorable, or at least acceptable, only as long as one expects improvement over time (possibly related to advances in tenure and career, as discussed above). Findings that the slope of conditions at work over time predicts well-being, often more so than levels, would be in line with such reasoning. For example Keller and Semmer (2013) found that the lack of change in job control predicted a drop in job satisfaction over time.

Hypothesis 3: Chronic Effects

We argued that chronic effects would be indicated by trajectories remaining significant when controlling for current conditions, and this was the case for all outcome variables except somatic complaints, for which effects were marginally significant. The most important difference – favorable versus unfavorable groups – remained significant for all outcomes. In contrast to the parallel change hypothesis (e.g., Chandola et al., 2006) and its equivalent, the stress-reaction model (Frese & Zapf, 1988), our data therefore suggest a chronification for job satisfaction, and partially for rumination and somatic complaints. Given that such results have often been postulated but rarely investigated, we consider these analyses to constitute a core contribution of this study.

Our approach to test reduced reversibility represents a new development, and we encourage researchers to conduct similar analyses. However, our results raise new questions as well. Our data indicated reduced reversibility after 10 years, and the effects were not equally strong for each outcome. However, we do not know why chronic effects were different for the various outcomes, nor do we know whether these differences would disappear or be accentuated over periods longer than 10 years. When confronted by sparse knowledge on these issues, authors are typically rather vague when referring to “long-term consequences” (Sonnentag & Frese, 2013); we feel that more refined theories are needed to determine the time frame necessary to produce reduced reversibility. Theories such as JDC focus on the issue of which stressors and resources are relevant. With regard to the question of which conditions are likely to predict chronic effects in which types of outcomes over which time periods, however, these theories are silent, and new theories will have to be developed. We feel that such developments will only be possible on the basis of more empirical data and a constant interplay between empirical results and theory.

Another approach to chronic effects that could be pursued refers to reactivity to acute stressors. Being exposed to unfavorable conditions over a long time may not only impair health in general, it may also induce unusually high (or low) reactivity to acute stressors (McEwen, 2004). Such effects have been suggested by research on background stressors (Gump & Matthews, 1999). For instance, Wirtz and colleagues (2013) showed that people exposed to background stressors exhibited a stronger physiological reaction to the Trier Social Stress Test. Research on reactions to acute stressors should include assessments of both current and previous conditions at work as potential moderators (see Landsbergis, Schnall, Pickering, & Schwartz, 2002).

Methodological Implications.

We argued that people might well experience many changes that could yield a quadratic picture in the short term, but that they would tend to react to unfavorable conditions by trying to alter or leave them. As a result, developments might be straightened out in the long run for many participants, and we therefore expected linear solutions to fit the data reasonably well. Indeed, in all but one case, quadratic solutions were extremely similar to the linear ones (see supplemental materials). It is noteworthy, however, that the changes in slopes that did occur in the nonlinear solutions peaked at time four, implying that developments between waves 1 to 4 were rather similar, but some, albeit slight, changes in direction occurred after that, possibly connected with the long time interval between waves 4 and 5.

Our test for measurement invariance showed that job control, task-related stressors, and social stressors were not re-conceptualized by the participants over the study period of 10 years (i.e., confirmation of configural invariance demonstrated lack of gamma change). However, we were not able to confirm full metric invariance, which may imply that some individual calibration took place after the first few years (i.e., beta change; Schaubroeck & Green, 1989), implying a shift in the relative importance of some indicators. For example, performance constraints became slightly more, concentration demands slightly less important in the last wave compared to the previous ones. This may reflect habituation to certain conditions, as participants' interpretation of their working conditions changed with increased experience. Thus, our findings may reflect the fact that participants were gaining their first experiences as employees during the first years of the study (Elfering et al., 2007), and that a meaningful new stage began after that. Such stages would correspond with the "emerging adults” (ages 18–24) and “settling in” (25–39) stages suggested by the adapted life-span perspective of James, McKechniee, and Swanberg (2011).

This study also showed that GMM can be successfully applied to time-related research questions, and extend our descriptive and explanatory knowledge of processes over time. In most cases, a linear trajectory seemed to capture the development as accurately as a quadratic trajectory in terms of the characteristics of the developmental trend and the prediction of outcomes.

Lastly, GMM offers some advantages for dealing with research design limitations. As suggested by Ployhart and Vandenberg (2010), it might be beneficial for researchers to design studies with unequal spacing between measurements in order to gain a better understanding of evolving processes over time. GMM is suitable even if measurement assessments are not equally spaced over time. Nevertheless, our results suggest that a 6-year time lag may be too long to capture fine-grained, nonlinear developments. Researchers investigating if, and under what conditions, these processes level off may need to design projects with a greater number of measurements.

Overall Implications for Theory and Research

Chronic Effects. The notion that the effects of conditions at work may become chronic (in the sense of reduced reversibility) if they persist over an extended period of time is not new (see, for instance, Meijman and Mulder (1998), McEwen (2004). Our results are in line with this theoretical assumption, albeit in a very general sense; they imply that spending 10 years in comparatively unfavorable conditions renders effects on some outcomes at least partly irreversible. We do not know, however, exactly how long it takes for which kind of health indicator to develop reduced reversibility, and to our knowledge, no theory exists that can specify such aspects in detail. Nevertheless, our results are among the few to corroborate the general notion of reduced reversibility, thus implying that it is a worthwhile task to investigate such processes. Theoretical refinement of the general notion of reduced reversibility is needed, but this should be done through the continuous process of empirical research feeding theory and theory feeding research. Given the sparse knowledge on chronic effects, the one recommendation we want to offer is that researchers try to have longitudinal data over as long a timeframe as possible, with as frequent measures as are feasible. As very frequent measurements are likely to lead to high dropout rates, effort will be needed for developing short measures (Fisher, Matthews, & Gibbons, 2016) and for gaining access to data that are collected routinely anyway (e.g. yearly surveys or medical check-ups in organizations). Eventually, such a process should result in theories that incorporate the notion of time in a much more explicit manner.

Constellations. The notion of constellations is central to many theories in occupational health psychology (Bakker & Demerouti, 2014; Karasek & Theorell, 1990; Siegrist, 2002). Given that the effect of the negative is typically stronger than that of the positive (Baumeister et al., 2001), and given the potential of social stressors to offend the self (Semmer et al., 2007), we argued for including social stressors, rather than social support, as a separate predictor (see our arguments in the introduction). Our results showed, indeed, that social stressors are potent enough to change the nature of an otherwise relatively favorable constellation into an unfavorable one. Thus, Constellation 4 is very similar to Constellation 3 for two of the three variables in terms of task-related stressors and control, but social stressors are strikingly different Thus, it is the social stressors that are responsible for Constellation 3 being favorable but Constellation 4 being unfavorable, underscoring their impact; that this impact refers to chronic effects is in line with results that show (albeit in short-term studies) that stressors containing social-evaluative threat is associated not only with increased physiological reactivity but also with delayed recovery (Kemeny, 2009). As our results also confirmed the importance of control, in line with many theoretical approaches and empirical findings (Spector, 2002), they support a variant of the JDC model that is extended to include social stressors. At the same time, many other combinations of stressors and resources are conceivable (Bakker & Demerouti, 2014), yet a comprehensive theory of which stressors and resources are important under what conditions, and how they may be combined into constellations, is lacking. What has become apparent, however, is that the number of empirically distinguishable constellations is relatively limited. Research employing methods that can identify constellations empirically, and can incorporate both initial values and developments over time, such as GMM, should support theory-building in this area.

Predominance of favorable conditions. A third aspect of general theoretical importance relates to the fact that the number of participants in the unfavorable constellations was rather small. We have already discussed several mechanisms that could contribute to a comparatively favorable situation for most participants. These include improving personal resources (e.g., through training, developing effective coping skills, and habituation), which may change the (perceived) conditions at work, and lead to adaptation (Ritter et al., 2016); they also include (self-) selection, change of jobs, and job crafting, which support participants in eventually achieving a reasonably good fit (Semmer & Schallberger, 1996). It would be relevant for theory building to investigate to what extent such processes occur in a temporal sequence (e.g., first trying to develop better coping skills; if unsuccessful, trying to change the working conditions; if unsuccessful, taking more drastic measures, such as changing employers or occupations). Also, it would be interesting to investigate if such a sequence occurs frequently, if such a systematic way of proceeding increases the chances of success, and to what extent these processes depend on the situation and the time of exposure.

At the same time, these processes are rather context-specific, in that we are dealing with a highly skilled sample in a highly developed and very affluent country; such conditions are likely to make it comparatively easy to achieve a fairly good fit (Semmer & Schallberger, 1996). However, the effects of (un)favorable conditions depend on other factors as well, notably social comparison and perceptions of fairness (Oishi, Kesebir, & Diener, 2011).

Strengths and Limitations

As is true for any study, the present one is not without its limitations. First, the study was based on survey data, raising the issue of self-report bias (Luthans, Avolio, Avey, & Norman, 2007). Note, however, that controlling for initial values of outcome variables also controls for stable sources of self-report bias. Second, the two unfavorable groups of conditions at work were small in size. Although this result seems plausible in light of existing studies and the characteristics of our sample, further studies are needed on this issue; these should try to focus on unskilled employees to a greater extent. A third limitation refers to the high level of drop-out. Fortunately, pertinent analyses did not yield sufficient differences between drop-outs and remaining participants to seriously put our results into question; however, drop-out could have contributed to the small size of unfavorable classes, as employees with higher levels of social stressors dropped out more. Fourth, the time lag between the last two waves was rather long. From a career stage and socialization perspective, changes in working conditions are more likely to occur during the first few years in the labor market and may stabilize after an establishment phase. However, we cannot exclude the possibility that meaningful changes occurred between waves 4 and 5 for some participants (e.g., increase and subsequent decrease in job control or stressors). Fifth, our results are specific to our sample, and the extent to which they can be generalized to other samples, notably older employees, is unclear. It is reasonable to assume that similar developmental patterns might be found among older employees (i.e., in mid- or late-career stages) and in other occupations. However, there may be additional trajectories, although we would not expect those to appear in large numbers. Differences may be found with regard to the distribution of the patterns (e.g., higher percentages of employees in some subgroups), and cumulative effects as well as chronic effects can be expected to be stronger in older samples. Lastly, the reduced reversibility implied by our results refers only to the timeframe we studied, and it remains open what happens afterwards, calling for research over even longer time-lags (e.g., 20 years). We assume that for longer time lags, chronic effects would become more likely and stronger for persistent unfavorable conditions or moves toward unfavorable constellations.

At the same time our study also has a number of strengths. First, we estimated trajectories of different conditions at work simultaneously, over a period of 10 years, and used them as predictors of health and well-being. Second, we incorporated five waves of measurement over a period of 10 years, which is rare in this kind of research. Third, our statistical approach, growth curve modeling for multiple groups, captures stability and change in conditions at work over a long period of time. This kind of person-centered approach enabled us to explore in a more elaborate way the development of the exposure to different conditions at work and their relationship with outcomes in terms of health and well-being. Fourth, we showed that constellations of trajectories of different conditions at work were associated with health and well-being outcomes even after controlling for the level of current conditions at work. In addition to analyzing constellations, this demonstration of chronic effects makes a strong contribution to the literature.

Practical Implications

The importance of constellations of work conditions has often been postulated (Karasek, 1979). However, when investigated using statistical interaction terms, such constellations have often not been confirmed (Podsakoff, MacKenzie, & Podsakoff, 2012). Furthermore, when using cut-offs on an a priori basis to create constellations, they may reflect people’s actual experience of work only in an approximate way. Our results confirm the importance of constellations and provide some guidance as to which aspects can be expected. More specifically, our results suggest focusing on: a) task stressors (e.g., by providing tasks that can be carried out within the given time frame and resources), b) job control (e.g., by granting employees a say in deciding how and when they work on which task), and c) inclusion of social stressors (e.g., by taking the consideration aspect of leadership seriously). Importantly, our results suggest that strong increases in social stressors can dominate the constellation to a large degree, turning otherwise favorable, or at least neutral, conditions into unfavorable ones.

Furthermore, our results are in line with the assumption that many unfavorable constellations may be sustainable for quite some time, yet may induce a lasting effect on health in the long run. Such deteriorations are likely to be gradual, and thus run the risk of being detected rather late, possibly only after they have become chronic.

Finally, our results contain some good news for organizations as well as for employees. At least in Switzerland, but possibly in many Western countries, the percentage of employees exposed to unfavorable conditions for a long period of time is likely to be rather low. Being sensitive to signs of deteriorating health among those (few) who are confronted with unfavorable conditions may, however, be well worth the time and effort. Multiple, repeated assessments of conditions at work, as well as health indicators, should therefore become standard in organizations.

Concluding Remarks

Determining typical constellations on the basis of statistical criteria seems to be a promising approach, enabling researchers to model groups based on both initial values as well as on change over time. We feel that finding differences between such groups in terms of well-being and health after many years of exposure speaks to the usefulness of this approach. In addition, we feel that the issue of chronicity, which is of great theoretical and practical importance, deserves more attention in future research. Given the sparse knowledge about long term processes, we had to start with rather general hypotheses, and more theoretical and empirical work will be needed to refine such an approach. But we see great potential in our approach for advancing theory, as it allows modeling and testing assumptions about constellations, their stability and instability over time, and the relevance of constellations and temporal trajectories on outcomes over time.

References

Aboa-Éboulé, C., Brisson, C., Maunsell, E., Mâsse, B., Bourbonnais, R., Vézina, M., . . . Dagenais, G. R. (2007). Job strain and risk of acute recurrent coronary heart disease events. *JAMA, 298*(14), 1652–1660. doi:10.1001/jama.298.14.1652

Acker, G. M. (2004). The effect of organizational conditions (role conflict, role ambiguity, opportunities for professional development, and social support) on job satisfaction and intention to leave among social workers in mental health care. *Community Mental Health Journal, 40*(1), 65-73. doi:10.1023/B:COMH.0000015218.12111.26

Amick, B. C. I., McDonough, P., Chang, H., Rogers, W. H., Pieper, C. F., & Duncan, G. (2002). Relationship between all-cause mortality and cumulative working life course: Psychosocial and physical exposures in the United States labor market from 1968 to 1992. *Psychosomatic Medicine, 64*(3), 370-381. doi:10.1097/00006842-200205000-00002

Baillod, J., & Semmer, N. K. (1994). Fluktuation und Berufsverläufe bei Computerfachleuten. [Turnover and career paths of computer specialists]. *Zeitschrift für Arbeits-und Organisationspsychologie, 38*(4), 152-163.

Bakker, A. B., & Costa, P. L. (2014). Chronic job burnout and daily functioning: A theoretical analysis. *Burnout Research, 1*(3), 112-119. doi:10.1016/j.burn.2014.04.003

Bakker, A. B., & Demerouti, E. (2014). Job demands–resources theory. In P. Y. Chen & C. L. Cooper (Eds.), *Wellbeing: A complete reference guide, work and wellbeing* (Vol. 3, pp. 37-64). Chichester, UK: Wiley.

Bamberg, E. (1991). Arbeit, Freizeit und Familie. In S. Greif, E. Bamberg, & N. K. Semmer (Eds.), *Psychischer Stress am Arbeitsplatz* (pp. 201-221). Göttingen, Germany: Hogrefe.

Baumeister, R. F. (2012). Need-to-belong theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (Vol. 2, pp. 121-140). Thousand Oaks, CA: Sage Publishing Company.

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology, 5*(4), 323-370. doi:10.1037//1089-2680.5.4.323

Belkic, K. L., Landsbergis, P. A., Schnall, P. L., & Baker, D. (2004). Is job strain a major source of cardiovascular disease risk? *Scandinavian Journal of Work, Environment and Health, 30*(2), 85-128. doi:10.5271/sjweh.769

Berset, M., Elfering, A., Lüthy, S., & Semmer, N. K. (2011). Work stressors and impaired sleep: Rumination as a mediator. *Stress and Health, 27*(2), e71-e82. doi:10.1002/Smi.1337

Berset, M., Semmer, N. K., Elfering, A., Jacobshagen, N., & Meier, L. L. (2011). Does stress at work make you gain weight? A two-year longitudinal study. *Scandinavian Journal of Work Environment and Health, 37*(1), 45-53. doi:10.5271/sjweh.3089

Biemann, T., Zacher, H., & Feldman, D. C. (2012). Career patterns: A twenty-year panel study. *Journal of Vocational Behavior, 81*(2), 159-170.

Bowling, N. A., & Beehr, T. A. (2006). Workplace harassment from the victim's perspective: A theoretical model and meta-analysis. *Journal of Applied Psychology, 91*(5), 998. doi:10.1037/0021-9010.91.5.998

Brose, A., Scheibe, S., & Schmiedek, F. (2013). Life contexts make a difference: Emotional stability in younger and older adults. *Psychology and Aging, 28*(1), 148.

Brosschot, J. F., Pieper, S., & Thayer, J. F. (2005). Expanding stress theory: Prolonged activation and perseverative cognition. *Psychoneuroendocrinology, 30*(10), 1043-1049. doi:10.1016/j.psyneuen.2005.04.008

Buddeberg-Fischer, B., Stamm, M., Buddeberg, C., Bauer, G., Hammig, O., & Klaghofer, R. (2008). Arbeitsstress, Gesundheit und Lebenszufriedenheit junger Arztinnen und Arzte. Ergebnisse einer Schweizer Longitudinalstudie. [Work stress, health and satisfaction of life in young doctors. Results of a longitudinal study in Switzerland]. *Deutsche medizinische Wochenschrift (1946), 133*(47), 2441-2447. doi:10.1055/s-0028-1100936

Buddeberg-Fischer, B., Stamm, M., Buddeberg, C., & Klaghofer, R. (2010). Chronic stress experience in young physicians: Impact of person- and workplace-related factors. *International Archives of Occupational and Environmental Health, 83*(4), 373-379. doi:10.1007/s00420-009-0467-9

Byrne, B. M., Shavelson, R. J., & Muthén, B. O. (1989). Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement invariance. *Psychological Bulletin, 105*(3), 456-466. doi:10.1037/0033-2909.105.3.456

Cavanaugh, M. A., Boswell, W. R., Roehling, M. V., & Boudreau, J. W. (2000). An empirical examination of self-reported work stress among U.S. managers. *Journal of Applied Psychology, 85*(1), 65-74. doi:10.1037/0021-9010.85.1.65

Chandola, T., Brunner, E., & Marmot, M. G. (2006). Chronic stress at work and the metabolic syndrome: Prospective study. *British Medical Journal, 332*, 521-525. doi:10.1136/bmj.38693.435301.80

Cronbach, L. J., & Furby, L. (1970). How we should measure "change": Or should we? *Psychological Bulletin, 74*(1), 68-80. doi:10.1037/h0029382

Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology, 62*, 583-619. doi:10.1146/annurev.psych.093008.100356

de Lange, A. H., Kompier, M. A. J., Taris, T. W., Geurts, S. A. E., Beckers, D. G. J., Houtman, I. L. D., & Bongers, P. M. (2009). A hard day's night: A longitudinal study on the relationships among job demands and job control, sleep quality and fatigue. *Journal of Sleep Research, 18*(3), 374-383. doi:10.1111/j.1365-2869.2009.00735.x

de Lange, A. H., Taris, T. W., Kompier, M. A. J., Houtman, I. L., & Bongers, P. M. (2002). Effects of stable and changing demand-control histories on worker health. *Scandinavian Journal of Work, Environment and Health, , 2*(28), 94-108. doi:10.5271/sjweh.653

de Lange, A. H., Taris, T. W., Kompier, M. A. J., Houtman, I. L. D., & Bongers, P. M. (2004). The relationships between work characteristics and mental health: Examining normal, reversed and reciprocal relationships in a 4-wave study. *Work & Stress, 18*(2), 149-166. doi:10.1080/02678370412331270860

DeWall, C. N., & Bushman, B. J. (2011). Social acceptance and rejection the sweet and the bitter. *Current Directions in Psychological Science, 20*(4), 256-260.

Dormann, C., & Zapf, D. (2002). Social stressors at work, irritation, and depressive symptoms: Accounting for unmeasured third variables in a multi-wave study. *Journal of Occupational and Organizational Psychology, 75*, 33-58. doi:10.1348/096317902167630

Eby, L. T., Maher, C. P., & Butts, M. M. (2010). The intersection of work and family life: The role of affect. *Annual Review of Psychology, 61*, 599-622. doi:10.1146/annurev.psych.093008.100422

Elfering, A., Semmer, N. K., & Kälin, W. (2000). Stability and change in job satisfaction at the transition from vocational training into "Real Work". *Swiss Journal of Psychology, 59*(4), 256-271.

Elfering, A., Semmer, N. K., Tschan, F., Kälin, W., & Bucher, A. (2007). First years in job: A three-wave analysis of work experiences. *Journal of Vocational Behavior, 70*(1), 97-115. doi:10.1016/j.jvb.2006.07.001

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*(3), 430-457. doi:10.1207/S15328007SEM0803_5

Feldt, T., Huhtala, M., Kinnunen, U., Hyvönena, K., Mäkikangas, A., & Sonnentag, S. (2013). Long-term patterns of effort-reward imbalance and over-commitment: Investigating occupational well-being and recovery experiences as outcomes. *Work & Stress, 27*(1), 64-87. doi:10.1080/02678373.2013.765670

Feldt, T., Hyvönen, K., Mäkikangas, A., Kinnunen, U., & Kokko, K. (2009). Development trajectories of Finnish managers' work ability over a 10-year follow-up period. *Scandinavian Journal of Work Environment and Health, 35*, 37-47. doi:10.5271/sjweh.1301

Fisher, G. G., Matthews, R. A., & Gibbons, A. M. (2016). Developing and investigating the use of single-item measures in organizational research. *Journal of Occupational Health Psychology, 21*(1), 3.

Fransson, E. I., Heikkilä, K., Nyberg, S. T., Zins, M., Westerlund, H., Westerholm, P., . . . Kivimäki, M. (2012). Job strain as a risk factor for leisure-time physical inactivity: An individual-participant meta-analysis of up to 170,000 men and women: The IPD-Work Consortium. *American Journal of Epidemiology, 176*, 1078-1089. doi:10.1093/aje/kws336

Frese, M. (1985). Stress at work and psychosomatic complaints: A causal interpretation. *Journal of Applied Psychology, 70*(2), 314. doi:10.1037/0021-9010.70.2.314

Frese, M., & Semmer, N. K. (1986). Shiftwork, stress, and psychosomatic complaints: A comparison between workers in different shiftwork schedules, non-shiftworkers, and former shiftworkers. *Ergonomics, 29*(1), 99-114. doi:10.1080/00140138608968244

Frese, M., & Zapf, D. (1987). Eine Skala zur Erfassung von Sozialen Stressoren am Arbeitsplatz. [A scale for assessing social stressors at the workplace]. *Zeitschrift für Arbeitswissenschaft, 41*(3), 134-141.

Frese, M., & Zapf, D. (1988). Methodological issues in the study of work stress: Objective vs. subjective measurement and the question of longitudinal studies. In C. L. Cooper & R. Payne (Eds.), *Causes, coping, and consequences of stress at work* (pp. 375-411). Chichester, UK: Wiley.

Fried, Y., Grant, A. M., Levi, A. S., Hadani, M., & Slowik, L. H. (2007). Job design in temporal context: A career dynamics perspective. *Journal of Organizational Behavior, 28*(7), 911-927. doi:10.1002/job.486

Ganster, D. C., & Rosen, C. C. (2013). Work stress and employee health: A multidisciplinary review. *Journal of Management, 39*, 1085-1122. doi:doi:10.1177/0149206313475815

Garst, H., Frese, M., & Molenaar, P. C. M. (2000). The temporal factor of change in stressor-strain relationships: A growth curve model on a longitudinal study in East Germany. *Journal of Applied Psychology, 85*(3), 417-438. doi:10.1037/0021-9010.85.3.417

Gelsema, T. I., van der Doef, M., Maes, S., Janssen, M., Akerboom, S., & Verhoeven, C. (2006). A longitudinal study of job stress in the nursing profession: Causes and consequences. *Journal of Nursing Management, 14*(4), 289-299. doi:10.1111/j.1365-2934.2006.00635.x

Geurts, S. A. E., & Sonnentag, S. (2006). Recovery as an explanatory mechanism in the relation between acute stress reactions and chronic health impairment. *Scandinavian Journal of Work, Environment and Health 32*(6), 482-492. doi:10.5271/sjweh.1053

Gimeno, D., Elovainio, M., Jokela, M., De Vogli, R., Marmot, M. G., & Kivimäki, M. (2009). Association between passive jobs and low levels of leisure-time physical activity: The Whitehall II cohort study. *Occupational and Environmental Medicine, 66*(11), 772-776. doi:10.1136/oem.2008.045104

Godin, I., Kittel, F., Coppieters, Y., & Siegrist, J. (2005). A prospective study of cumulative job stress in relation to mental health. *BMC Public Health, 5,* 67-76. doi:6710.1186/1471-2458-5-67

Gollwitzer, M., Christ, O., & Lemmer, G. (2014). Individual differences make a difference: On the use and the psychometric properties of difference scores in social psychology. *European Journal of Social Psychology, 44*(7), 673-682. doi:10.1002/ejsp.2042

Grebner, S., Semmer, N., K., Faso, L. L., Gut, S., Kälin, W., & Elfering, A. (2003). Working conditions, well-being and job-related attitudes among call centre agents. *European Journal of Work and Organizational Psychology, 12*(4), 341-365.

Greenbaum, P. E., Del Boca, F. K., Darkes, J., Wang, C.-P., & Goldman, M. S. (2005). Variation in the drinking trajectories of freshmen college students. *Journal of Consulting and Clinical Psychology, 73*(2), 229-238. doi:10.1037/0022-006X.73.2.229

Gump, B. B., & Matthews, K. A. (1999). Do background stressors influence reactivity to and recovery rrom acute stressors? *Journal of Applied Social Psychology, 29*(3), 469-494. doi:10.1111/j.1559-1816.1999.tb01397.x

Häusser, J. A., Mojzisch, A., Niesel, M., & Schulz-Hardt, S. (2010). Ten years on: A review of recent research on the Job Demand–Control (-Support) model and psychological well-being. *Work & Stress, 24*(1), 1-35. doi:10.1080/02678371003683747

Hirschi, A., Herrmann, A., & Keller, A. C. (2015). Career adaptivity, adaptability, and adapting: A conceptual and empirical investigation. *Journal of Vocational Behavior, 87*, 1-10.

Hu, L., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods, 3*(4), 424-453. doi:10.1037/1082-989X.3.4.424

Humphrey, S. E., Nahrgang, J. D., & Morgeson, F. P. (2007). Integrating motivational, social, and contextual work design features: A meta-analytic summary and theoretical extension of the work design literature. *Journal of Applied Psychology, 92*(5), 1332-1356. doi:10.1037/0021-9010.92.5.1332

James, J. B., McKechnie, S., & Swanberg, J. (2011). Predicting employee engagement in an age-diverse retail workforce. *Journal of Organizational Behavior, 32*(2), 173-196. doi:10.1002/job.681

Janssen, N., & Nijhuis, F. J. N. (2004). Associations between positive changes in perceived work characteristics and changes in fatigue. *Journal of Occupational and Environmental Medicine, 46*(8), 866-875.

Jedidi, K., Ramaswamy, V., & DeSarbo, W. S. (1993). A maximum likelihood method for latent class regression involving a censored dependent variable. *Psychometrika, 58*(3), 375-394. doi:10.1007/BF02294647

Jiang, Z. (2016). The relationship between career adaptability and job content plateau: The mediating roles of fit perceptions. *Journal of Vocational Behavior, 95*, 1-10.

Johnson, J. V., Stewart, W., Hall, E. M., Fredlund, P., & Theorell, T. (1996). Long-term psychosocial work environment and cardiovascular mortality among Swedish men. *American Journal of Public Health, 86*(3), 324-331. doi:10.2105/AJPH.86.3.324

Jung, T. A., & Wickrama, K. A. S. (2008). An introduction to latent class growth analysis and growth mixture modeling. *Social and Personality Psychology Compass, 2*(1), 302-317. doi:10.1111/j.1751-9004.2007.00054.x

Kälin, W., Keller, A. C., Tschan, F., Elfering, A., & Semmer, N. K. (2014). Work experiences and well-being in the first years of professional work in Switzerland: A ten-year follow-up study. In A. C. Keller, R. Samuel, M. M. Bergman, & N. K. Semmer (Eds.), *Psychological,* *educational, and sociological perspectives on success and well-being in career development.* (pp. 151-170). Dordrecht, Netherlands: Springer.

Kälin, W., Semmer, N. K., Elfering, A., Tschan, F., Dauwalder, J. P., Heunert, S., & von Roten, F. C. (2000). Work characteristics and well-being of Swiss apprentices entering the labor market. *Swiss Journal of Psychology, 59*(4), 272-290. doi:10.1024//1421-0185.59.4.272

Karasek, R. A. (1979). Job demands, job decision latitude, and mental strain: Implications for job redesign. *Administrative Science Quarterly, 24*(2), 285-308. doi:10.2307/2392498

Karasek, R. A., & Theorell, T. (1990). *Healthy work: Stress, productivity, and the reconstruction of working life*. New York, NY: Basic Books.

Keashly, L., Hunter, S., & Harvey, S. (1997). Abusive interaction and role state stressors: Relative impact on student residence assistant stress and work attitudes. *Work & Stress, 11*(2), 175-185. doi:10.1080/02678379708256833

Keller, A. C., Igic, I., Meier, L. L., Semmer, N. K., Schaubroeck, J. M., Brunner, B., & Elfering, A. (2016). Testing job typologies and identifying at-risk subpopulations using factor mixture models. *Journal of Occupational Health Psychology*, Advance online publication. doi:10.1037/ocp0000038

Keller, A. C., Samuel, R., Bergman, M. M., & Semmer, N. K. (2014). *Psychological, educational, and sociological perspectives on success and well-being in career development*. Dordrecht, Netherlands: Springer Netherlands.

Keller, A. C., & Semmer, N. K. (2013). Changes in situational and dispositional factors as predictors of job satisfaction. *Journal of Vocational Behavior, 83*(1), 88-98.

Kemeny, M. E. (2009). Psychobiological responses to social threat: Evolution of a psychological model in psychoneuroimmunology. *Brain Behavior and Immunity*(23), 1-9.

Kivimäki, M., Ferrie, J. E., Head, J., Shipley, M. J., Vahtera, J., & Marmot, M. G. (2004). Organisational justice and change in justice as predictors of employee health: The Whitehall II study. *Journal of Epidemiology and Community Health, 58*(11), 931-937. doi:10.1136/jech.2003.019026

Kivimäki, M., Head, J., Ferrie, J. E., Shipley, M. J., Brunner, E., Vahtera, J., & Marmot, M. G. (2006). Work stress, weight gain and weight loss: Evidence for bidirectional effects of job strain on body mass index in the Whitehall II study. *International Journal of Obesity, 30*(6), 982-987. doi:10.1038/sj.ijo.0803229

Kivimäki, M., Leino-Arjas, P., Kaila-Kangas, L., Luukkonen, R., Vahtera, J., Elovainio, M., . . . Kirjonen, J. (2006). Is incomplete recovery from work a risk marker of cardiovascular death? Prospective evidence from industrial employees. *Psychosomatic Medicine, 68*(3), 402-407. doi:10.1097/01.psy.0000221285.50314.d3

Kouvonen, A., Vahtera, J., Oksanen, T., Pentti, J., Väänänen, A. K. P., Heponiemi, T., . . . Kivimäki, M. (2013). Chronic workplace stress and insufficient physical activity: A cohort study. *Occupational and Environmental Medicine, 70*(1), 3-8. doi:10.1136/oemed-2012-100808

Landsbergis, P. A., Schnall, P. L., Pickering, T. G., Warren, K., & Schwartz, J. (2003). Life-course exposure to job strain and ambulatory blood pressure in men. *American Journal of Epidemiology, 11*(157), 998-1006. doi:10.1093/aje/kwg095

Leong, F. T. L., Hartung, P. J., & Pearce, M. (2014). Work and career development: Theory and research. In F. T. L. Leong, L. Comas-Díaz, G. C. Nagayama Hall, V. C. McLoyd, & J. E. Trimble (Eds.), *APA handbook of multicultural psychology, Vol. 1: Theory and research* (Vol. 1, pp. 451-469). Washington, DC: American Psychological Association.

LePine, J. A., LePine, M. A., & Jackson, C. L. (2004). Challenge and hindrance stress: relationships with exhaustion, motivation to learn, and learning performance. *Journal of Applied Psychology, 89*(5), 883-891. doi:10.1037/0021-9010.89.5.883

Löckenhoff, C. E., & Carstensen, L. L. (2004). Socioemotional selectivity theory, aging, and health: The increasingly delicate balance between regulating emotions and making tough choices. *Journal of Personality, 72*(6), 1395-1424.

Luthans, F., Avolio, B. J., Avey, J. B., & Norman, S. M. (2007). Positive psychological capital: Measurement and relationship with performance and satisfaction. *Personnel Psychology, 60*(3), 541-572. doi:10.1111/j.1744-6570.2007.00083.x

MacCallum, R. C., Zhang, S., Preacher, K. J., & Rucker, D. D. (2002). On the practice of dichotomization of quantitative variables. *Psychological Methods, 7*(1), 19-40. doi:10.1037//1082-989X.7.1.19

Mäkikangas, A., Hyvonen, K., Leskinen, E., Kinnunen, U., & Feldt, T. (2011). A person-centred approach to investigate the development trajectories of job-related affective well-being: A 10-year follow-up study. *Journal of Occupational and Organizational Psychology, 84*(2), 327-346. doi:10.1111/j.2044-8325.2011.02025.x

Matthews, K. A., & Gump, B. B. (2002). Chronic work stress and marital dissolution increase risk of posttrial mortality in men from the Multiple Risk Factor Intervention Trial. *Archives of Internal Medicine, 162*(3), 309-315. doi:10.1001/archinte.162.3.309

Matthews, R. A., Wayne, J. H., & Ford, M. T. (2014). A work–family conflict/subjective well-being process model: A test of competing theories of longitudinal effects. *Journal of Applied Psychology, 99*(6), 1173-1187. doi:10.1037/a0036674

Mauno, S., Mäkikangas, A., & Kinnunen, U. (2016). A longitudinal person-centred approach to the job demands-control model. *European Journal of Work and Organizational Psychology*(25), 914-927. doi:10.1080/1359432X.2016.1187135

Maxwell, S. E., & Delaney, H. D. (1993). Bivariate median splits and spurious statistical significance. *Psychological Bulletin, 113*(1), 181-190. doi:10.1037/0033-2909.113.1.181

McEwen, B. S. (1998). Protective and damaging effects of stress mediators. *New England Journal of Medicine, 338*(3), 171-179. doi:10.1056/NEJM199801153380307

McEwen, B. S. (2004). Protection and damage from acute and chronic stress: Allostasis and allostatic overload and relevance to the pathophysiology of psychiatric disorders. *Annals of the New York Academy of Sciences 1032*, 1-7. doi:10.1196/annals.1314.001

McGrath, J. E., & Tschan, F. (2004). *Temporal matters in social psychology: Examining the role of time in the lives of groups and individuals*. Washington, DC: American Psychological Association.

Meier, L. L., Gross, S., Spector, P. E., & Semmer, N. K. (2013). Relationship and task conflict at work: Interactive short-term effects on angry mood and somatic complaints. *Journal of Occupational Health Psychology, 18*(2), 144-156. doi:10.1037/a0032090

Meier, L. L., Semmer, N. K., Elfering, A., & Jacobshagen, N. (2008). The double meaning of control: Three-way interactions between internal resources, job control, and stressors at work. *Journal of Occupational Health Psychology, 13*(3), 244-258. doi:10.1037/1076-8998.13.3.244

Meier, L. L., Semmer, N. K., & Gross, S. (2014). The effect of conflict at work on well-being: Depressive symptoms as a vulnerability factor. *Work & Stress, 28*(1), 31- 48. doi:10.1080/02678373.2013.876691

Meijman, T. F., & Mulder, G. (1998). Psychological aspects of workload. In P. J. D. Drenth, H. Thierry, & C. J. d. Wolff (Eds.), *Handbook of work and organizational psychology* (2nd ed., Vol. 2, pp. 5-33). Hove, UK: Psychology Press.

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), 1-16. doi:10.1016/j.jvb.2011.07.002

Miller, D. T. (2001). Disrespect and the experience of injustice. *Annual Review of Psychology, 52*(1), 527-553.

Mitchell, T. R., & James, L. R. (2001). Building better theory: Time and the specification of when things happen. *Academy of Management Review, 26*(4), 530-547. doi:10.5465/AMR.2001.5393889

Mohr, G. (1991). Fünf Subkonstrukte psychischen Befindensbeeinträchtigungen bei Industriearbeitern: Auswahl und Entwicklung. In S. Greif, E. Bamberg, & N. K. Semmer (Eds.), *Psychischer Stress am Arbeitsplatz* (pp. 91-119). Göttingen: Hogrefe.

Mohr, G., Müller, A., Rigotti, T., Aycan, Z., & Tschan, F. (2006). The assessment of psychological strain in work contexts: Concerning the structural equivalency of nine language adaptations of the irritation scale. *European Journal of Psychological Assessment, 22*(3), 198-206. doi:10.1027/1015-5759.22.3.198

Mohr, G., Rigotti, T., & Müller, A. (2005). Irritation-ein Instrument zur Erfassung psychischer Beanspruchung im Arbeitskontext. Skalen-und Itemparameter aus 15 Studien. [Irritation – an instrument for assessing mental strain in working contexts. Scale and item parameters from 15 studies]. *Zeitschrift für Arbeits-und Organisationspsychologie, 49*(1), 44-48. doi:10.1026/0932-4089.49.1.44

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

Muthén, B. O. (2004). Latent variable analysis: Growth mixture modeling and related techniques for longitudinal data. In D. Kaplan (Ed.), *The Sage handbook of quantitative methodology for the social sciences* (pp. 345-368). Thousand Oaks, CA: Sage.

Muthén, B. O., Brown, C. H., Masyn, K., Jo, B., Khoo, S. T., Yang, C. C., . . . Liao, J. (2002). General growth mixture modeling for randomized preventive interventions. *Biostatistics, 3*(4), 459-475. doi:10.1093/biostatistics/3.4.459

Muthén, B. O., & Muthén, L. K. (2000). Integrating person‐ centered and variable‐ centered analyses: Growth mixture modeling with latent trajectory classes. *Alcoholism: Clinical and Experimental Research, 24*(6), 882-891. doi:10.1111/j.1530-0277.2000.tb02070.x

Muthén, L. K., & Muthén, B. O. (1998-2015). *Mplus user's guide: Statistical analysis with latent variables* (7 ed.). Los Angeles, CA: Muthén & Muthén.

Nixon, A. E., Mazzola, J. J., Bauer, J., Krueger, J. R., & Spector, P. E. (2011). Can work make you sick? A meta-analysis of the relationships between job stressors and physical symptoms. *Work & Stress, 25*(1), 1-22. doi:10.1080/02678373.2011.569175

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). New York: McGraw-Hill.

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*(4), 535-569. doi:10.1080/10705510701575396

Oishi, S., Kesebir, S., & Diener, E. (2011). Income inequality and happiness. *Psychological Science, 22*(9), 1095-1100. doi:10.1177/0956797611417262

Paškvan, M., Kubicek, B., Prem, R., & Korunka, C. (2016). Cognitive appraisal of work intensification. *International Journal of Stress Management, 23*(2), 124-146. doi:10.1037/a0039689

Plemmons, S. A., & Weiss, H. M. (2013). Goals and affect. In E. A. Locke & G. P. Latham (Eds.), *New developments in goal setting and task performance* (pp. 117-132). New York: NY: Routledge.

Ployhart, R. E., & Schneider, B. (2012). The social and organizational context of personnel selection. In N. Schmitt (Ed.), *The Oxford handbook of personnel assessment and selection* (pp. 48-67). New York: Oxford University Press.

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*(1), 94-120. doi:10.1177/0149206309352110

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63,* 539-569. doi:10.1146/annurev-psych-120710-100452

Rantanen, J., Kinnunen, U., Pulkkinen, L., & Kokko, K. (2012). Developmental trajectories of work–family conflict for Finnish workers in midlife. *Journal of Occupational Health Psychology, 17*(3), 290-303. doi:10.1037/a0028153

Ritter, K.-J., Matthews, R. A., Ford, M. T., & Henderson, A. A. (2016). Understanding role stressors and job satisfaction over time using adaptation theory. *Journal of Applied Psychology*, Advance online publication. doi:10.1037/apl0000152

Rodriguez-Muñoz, A., Sanz-Vergel, A. I., Demerouti, E., & Bakker, A. B. (2012). Reciprocal relationships between job demands, job resources, and recovery opportunities. *Journal of Personnel Psychology, 11*(2), 86-94. doi:10.1027/1866-5888/a000049

Rogosa, D. (1995). Myths and methods: "Myths about longitudinal research" plus supplemental questions. In J. M. Gottman (Ed.), *The analysis of change* (pp. 3-66). Mahwah, NJ: Erlbaum.

Savickas, M. L. (2002). Career construction: A developmental theory of vocational behavior. In S.D. Brown (Ed.), *Career choice and development* (4 ed., pp. 149-205). Hoboken, NJ: Wiley.

Schalk, R., van der Heijden, B., de Lange, H. A., & van Veldhoven, M. (2011). Long-term developments in individual work behaviour: Patterns of stability and change. *Journal of Occupational and Organizational Psychology, 84*(2), 215-227. doi:10.1111/j.2044-8325.2011.02031.x

Schaubroeck, J., & Green, S. G. (1989). Confirmatory factor analytic procedures for assessing change during organizational entry. *Journal of Applied Psychology, 74*(6), 892-900. doi:10.1037/0021-9010.74.6.892

Scheibe, S., & Zacher, H. (2013). A lifespan perspective on emotion regulation, stress, and well-being in the workplace *The role of emotion and emotion regulation in job stress and well being* (Vol. 11, pp. 163-193). Bingley, UK: Emerald Group Publishing Limited.

Schnall, P. L., Schwartz, J. E., Landsbergis, P. A., Warren, K., & Pickering, T. G. (1998). A longitudinal study of job strain and ambulatory blood pressure: Results from a three-year follow-up. *Psychosomatic Medicine, 60*(6), 697-706. doi:10.1097/00006842-199811000-00007

Semmer, N. K., Elfering, A., Baillod, J., Berset, M., & Beehr, T. A. (2014). Push and pull motivations for quitting: A three-wave ingestigation of predictors and consequences of turnover. *Zeitschrift für Arbeits-und Organisationspsychologie, 58*, 173-185. doi:10.1026/0932-4089/a000167

Semmer, N. K., Jacobshagen, N., Meier, L. L., & Elfering, A. (2007). Occupational stress research: The "stress-as-offense-to-self" perspective. In J. Houdmont & S. McIntyre (Eds.), *Occupational health psychology: European perspectives on research, education and practice* (Vol. 2, pp. 43-60). Castelo da Maia, Portugal: ISMAI Publishing.

Semmer, N. K., McGrath, J. E., & Beehr, T. A. (2005). Conceptual issues in research on stress and health. In C. L. Cooper (Ed.), *Handbook of stress and health* (2nd ed., pp. 1-43). Boca Raton, FL: CRC Press.

Semmer, N. K., Meier, L. L., & Beehr, T. A. (2016). Social aspects of work: Direct and indirect social messages conveying respect or disrespect. In A. M. Rossi, J. A. Meurs, & P. L. Perrewé (Eds.), *Stress and Quality of Working Life: Interpersonal and occupation-based stress* (pp. 13-32). Charlotte, NC: Information Age Publishing.

Semmer, N. K., & Schallberger, U. (1996). Selection, socialisation, and mutual adaptation: Resolving discrepancies between people and work. *Applied Psychology: An Internatonal Review, 45*(3), 263-288. doi:10.1111/j.1464-0597.1996.tb00768.x

Semmer, N. K., Tschan, F., Elfering, A., Kälin, W., & Grebner, S. (2005). Young adults entering the workforce in Switzerland: Working conditions and well-being. In P. Kriesi, M. Farago, M. Kohli, & M. Zarin-Nejadan (Eds.), *Contemporary Switzerland: Revisiting the Special Case* (pp. 163-189). Houndmills, UK: Palgrave Macmillan.

Semmer, N. K., Zapf, D., & Dunckel, H. (1995). Assessing stress at work: A framework and an instrument. In O. Svane & C. Johansen (Eds.), *Work and health: Scientific basis of progress in the working environment* (pp. 105-113). Luxembourg: Office for Official Publications of the European Communities.

Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. *Journal of Occupational Health Psychology, 1*(1), 27-41. doi:10.1037/1076-8998.1.1.27

Siegrist, J. (2002). Effort-reward imbalance at work and health. In P. L. Perrewé & D. C. Ganster (Eds.), *Research in occupational stress and well being* (Vol. 2, pp. 261-291). Amsterdam, Netherlands: JAI.

Siltaloppi, M., Kinnunen, U., Feldt, T., & Tolvanen, A. (2011). Identifying patterns of recovery experiences and their links to psychological outcomes across one year. *International Archives of Occupational and Environmental Health, 84*(8), 877-888. doi:10.1007/s00420-011-0672-1

Sonnentag, S., & Frese, M. (2013). Stress in organizations. In N. W. Schmitt & S. Highhouse (Eds.), *Handbook of psychology* (2 ed., Vol. 12, pp. 560-592). Hoboken, NJ: Wiley.

Sonnentag, S., & Kruel, U. (2006). Psychological detachment from work during off-job time: The role of job stressors, job involvement, and recovery-related self-efficacy. *European Journal of Work and Organizational Psychology, 15*(2), 197-217. doi:10.1080/13594320500513939

Sonnentag, S., Pundt, A., & Albrecht, A.-G. (2014). Temporal perspectives on job stress. In A. J. Shipp & Y. Fried (Eds.), *Time and work: How time impacts individuals* (Vol. 1, pp. 111-140). London, UK: Psychology Press.

Spector, P. E. (1997). *Job satisfaction: Application, assessment, causes, and consequences* (Vol. 3). Thousand Oaks, CA: Sage.

Spector, P. E. (2002). Employee control and occupational stress. *Current Directions in Psychological Science, 11*(4), 133-136. doi:10.1111/1467-8721.00185

Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: Interpersonal Conflict at Work Scale, Organizational Constraints Scale, Quantitative Workload Inventory, and Physical Symptoms Inventory. *Journal of Occupational Health Psychology, 3*(4), 356-367. doi:10.1037/1076-8998.3.4.356

Stansfeld, S. A., Shipley, M. J., Head, J., & Fuhrer, R. (2012). Repeated job strain and the risk of depression: Longitudinal analyses from the Whitehall II study. *American Journal of Public Health, 102*(12), 2360-2366. doi:10.2105/Ajph.2011.300589

Steenkamp, J. B. E. M., & Baumgartner, H. (1998). Assessing measurement invariance in cross-national consumer research. *Journal of Consumer Research, 25*(1), 78-90. doi:10.1086/209528

Taris, T. W., & Kompier, M. A. J. (2003). Challenges in longitudinal designs in occupational health psychology. *Scandinavian Journal of Work Environment and Health, 29*(1), 1-4. doi:10.5271/sjweh.697

Taris, T. W., & Kompier, M. A. J. (2014). Cause and effect: Optimizing the designs of longitudinal studies in occupational health psychology. *Work & Stress, 28*(1), 1-8. doi:10.1080/02678373.2014.878494

Tomasik, M. J., Silbereisen, R. K., & Heckhausen, J. (2010). Is it adaptive to disengage from demands of social change? Adjustment to developmental barriers in opportunity-deprived regions. *Motivation and Emotion, 34*(4), 384-398.

Ulferts, H., Korunka, C., & Kubicek, B. (2013). Acceleration in working life: An empirical test of a sociological framework. *Time & Society, 22*(2), 161-185. doi:10.1177/0961463X12471006

Vinokur, A. D., & van Ryn, M. (1993). Social support and undermining in close relationships: Their independent effects on the mental health of unemployed persons. *Journal of Personality and Social Psychology, 65*(2), 350-359. doi:10.1037/0022-3514.65.2.350

von Bonsdorff, M. E., Kokko, K., Seitsamo, J., von Bonsdorff, M. B., Nygård, C. H., Ilmarinen, J., & Rantanen, T. (2011). Work strain in midlife and 28-year work ability trajectories. *Scandinavian Journal of Work Environment and Health, 37*(6), 455-463. doi:10.5271/sjweh.3177

Wang, M. (2007). Profiling retirees in the retirement transition and adjustment process: Examining the longitudinal change patterns of retirees' psychological well-being. *Journal of Applied Psychology 92*(2), 455-474. doi:10.1037/0021-9010.92.2.455

Wang, M., & Bodner, T. E. (2007). Growth mixture modeling: Identifying and predicting unobserved subpopulations with longitudinal data. *Organizational Research Methods, 10*(4), 635-656. doi:10.1177/1094428106289397

Weigl, M., Hornung, S., Petru, R., Glaser, J., & Angerer, P. (2012). Depressive symptoms in junior doctors: a follow-up study on work-related determinants. *International Archives of Occupational and Environmental Health, 85*(5), 559-570. doi:10.1007/s00420-011-0706-8

Widaman, K. F., Ferrer, E., & Conger, R. D. (2010). Factorial invariance within longitudinal structural equation models: Measuring the same construct across time. *Child Development Perspectives, 4*(1), 10-18. doi:10.1111/j.1750-8606.2009.00110.x

Widmer, P. S., Semmer, N. K., Kälin, W., Jacobshagen, N., & Meier, L. L. (2012). The ambivalence of challenge stressors: Time pressure associated with both negative and positive well-being. *Journal of Vocational Behavior, 80*(2), 422-433. doi:10.1016/j.jvb.2011.09.006

Willett, J. B. (1997). Measuring change: What individual growth modeling buys you. In E. Amsel & K. A. Renninger (Eds.), *Change and development: Issues of theory, method, and application* (Vol. 213-243, pp. 243). Mahwah, NJ: Lawrence Erlbaum.

Wirtz, P. H., Ehlert, U., Kottwitz, M. U., La Marca, R., & Semmer, N. K. (2013). Occupational role stress is associated with higher cortisol reactivity to acute stress. *Journal of Occupational Health Psychology, 18*(2), 121-131. doi:10.1037/a0031802

Wrzesniewski, A., & Dutton, J. E. (2001). Crafting a job: Revisioning employees as active crafters of their work. *Academy of Management Review, 26*(2), 179-201. doi:10.2307/259118

Zacher, H., Ambiel, R. A., & Noronha, A. P. P. (2015). Career adaptability and career entrenchment. *Journal of Vocational Behavior, 88*, 164-173.

Zapf, D., Dormann, C., & Frese, M. (1996). Longitudinal studies in organizational stress research: A review of the literature with reference to methodological issues. *Journal of Occupational Health Psychology, 1*(2), 145-169. doi:10.1037/1076-8998.1.2.145

Zapf, D., & Frese, M. (1991). Soziale Stressoren am Arbeitsplatz. In E. Bamberg & N. K. Semmer (Eds.), *Psychischer Stress am Arbeitsplatz* (pp. 168-184). Göttingen, Germany: Hogrefe.

Table 1

Measurement Invariance Over Time for Indicators of Growth Mixture Models

	Measurement models	Chi-square	*df*	*p*	CFI	RMSEA	SRMR	Model comparison	ΔChi-square	Δ*df*	*p*
Job control											
1a	Configural invariance	354.7	215	< .001	.97	.04	.05				
1b	Metric invariance	430.5	231	< .001	.95	.04	.06	1a vs. 1b	75.8	16	< .001
1c	Partial metric invariance	373.1	227	< .001	.96	.04	.05	1a vs. 1c	18.4	12	ns
Task-related stressors											
2a	Configural invariance	531.6	215	< .001	.92	.06	.06				
2b	Metric invariance	566.7	231	< .001	.92	.06	.07	2a vs. 2b	35.1	6	< .001
2c	Partial metric invariance	539.9	223	< .001	.92	.05	.06	2a vs. 2c	8.3	8	ns
Social stressors											
3a	Configural invariance	458.6	335	< .001	.96	.03	.05				
3b	Metric invariance	517.4	355	< .001	.95	.03	.05	3a vs. 3b	58.8	20	< .001
3c	Partial metric invariance	287.0	227	< .001	.98	.02	.05	3a vs. 3c	14.5	12	ns

Note. CFI=comparative fit index, RMSEA=root mean square error of approximation, SRMR=standardized root-mean-square residual.

Table 2

Means, Standard Deviations, and Bivariate Correlations for Study Variables

Variables	M	SD	N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1. t1 Task-related stressors	2.88	0.50	482																											
2. t2 Task-related stressors	2.87	0.55	427	.56**																										
3. t3 Task-related stressors	2.92	0.56	405	.52**	.61**																									
4. t4 Task-related stressors	2.91	0.54	386	.41**	.50**	.54**																								
5. t5 Task-related stressors	2.99	0.50	469	.35**	.41**	.45**	.52**																							
6. t1 Social stressors	1.98	0.67	482	.37**	.09	.07	-.03	-.02																						
7. t2 Social stressors	1.91	0.71	427	.16**	.38**	.10	.10	.11*	.28**																					
8. t3 Social stressors	1.94	0.70	405	.22**	.24**	.42**	.18**	.19**	.23**	.42**																				
9. t4 Social stressors	1.90	0.65	388	.14**	.15**	.17**	.38**	.20**	.19**	.26**	.31**																			
10. t5 Social stressors	1.92	0.67	470	.11*	.12*	.08	.19**	.40**	.14**	.24**	.23**	.34**																		
11. t1 Job control	3.29	0.71	483	-.03	-.04	.02	.04	.04	-.16**	-.16**	-.11*	-.01	.02																	
12. t2 Job control	3.40	0.78	429	-.11*	-.12*	.01	-.05	-.11*	-.05	-.27	-.09	.00	-.08	.42**																
13. t3 Job control	3.43	0.78	406	-.11*	-.09	-.10	.01	-.13**	-.09	-.06	-.14**	.08	-.06	.36**	.50**															
14. t4 Job control	3.59	0.73	388	-.17**	-.16**	-.13*	-.09	-.17**	-.01	-.06	-.04	-.09	-.04	.30**	.41**	.46**														
15. t5 Job control	3.73	0.82	477	-.07	-.08	-.02	-.09	-.10*	.06	.05	.02	-.05	-.19**	.21**	.27**	.25**	.44**													
16. t1 Private stressors	2.38	0.66	480	.38**	.26**	.28**	.19**	.16**	.17**	.05	.17**	.16**	.06	-.06	.00	-.05	-.12*	-.01												
17. t2 Private stressors	2.43	0.67	428	.27**	.33**	.18**	.23**	20**	.07	.22**	.15**	.19**	.14**	-.08	-.09	-.02	-.05	-.08	.44**											
18. t3 Private stressors	2.50	0.67	405	.26**	.29**	.37**	.25**	.25**	.08	.05	.32**	.11*	.08	-.11*	-.07	-.08	-.09	-.04	.35**	.46**										
19. t4 Private stressors	2.60	0.60	388	.19**	.20**	.14*	.29**	.17**	.04	.001	.07	.31**	.04	-.04	.00	.001	-.04	.01	.37**	.37**	.39**									
20. t5 Private stressors	2.85	0.58	481	.12**	.16**	.13**	.16**	.16**	-.01	-.02	.04	.11*	.10*	-.04	-.03	-.11*	-.04	-.06	.33**	.30**	.25**	.35**								
21. t1 Rumination	3.26	1.38	481	.35**	.17**	.15**	.12*	.13**	.26**	.10*	.13*	.10*	.12**	-.20**	-.12*	-.07	-.13**	-.08	.26**	.20**	.14**	.18**	.10*							
22. t5 Rumination	3.23	1.35	480	.08	.07	.04	.16**	.35**	.09	.18**	.15**	.17**	.32**	-.05	-.04	-.02	.04	.04	.09	.21**	.14**	.21**	.25**	.18**						
23. t1 Somatic complaints	2.09	0.64	478	.25**	.12*	.16**	.11*	.05	.22**	.12*	.21**	.16**	.06	-.06	-.04	.001	-.12*	-.01	.31**	.24**	.21**	.20**	.07	.33**	.09*					
24.T5 Somatic complaints	1.93	0.57	483	.14**	.11*	.06	.11*	.22**	.12**	.15**	.19**	.13*	.22**	-.04	-.10*	-.04	-.03	-.06	.20**	.26**	.21**	.22**	.27**	.23**	.40**	.49**				
25. t1 Job satisfaction	4.14	1.14	474	-.04	-.02	.03	.11*	.10*	-.38**	-.09	-.10*	-.09	.01	.17**	.12*	.07	-.05	-.05	-.02	-.03	-.08	-.06	.03	-.02	.02	-.16**	-.09*			
26. t5 Job satisfaction	4.40	1.18	469	.05	.01	.01	-.11*	-.25**	.001	-.07	-.05	-.16**	-.47**	.01	.06	.04	.06	.27**	.06	.02	-.01	.05	.001	-.02	-.21**	-.03	-.19**	.17**		
27. t1 Gender	0.49	0.50	483	-.14**	-.11*	-.12*	-.10	-.03	.07	.06	-.04	.02	.01	.02	-.02	.001	.10	.12*	-.20**	-.15**	-.12*	-.12*	-.16**	-.16**	.05	-.28**	-.18**	-.07	.03	
28. t1 Region	0.55	0.50	483	.05	.04	.11*	.01	.001	.12**	.001	.04	.03	.07	.31**	.20**	.21**	.14**	.16**	-.01	-.15**	-.06	-.11*	-.13**	-.16**	-.13**	.11*	-.02	-.03	.03	-.09*

Note. Gender was coded as 0 = female and 1= male, Region was coded as 0 = French-speaking part 1 =German-speaking part. * $p < .05$; ** $p < .01$

Table 3

Fit Indices for the Long-Term Growth Mixture Models of Job Control, Task-Related Stressors, and Social Stressors – Linear Model

No. of classes	BIC	Adj. BIC	Entropy	LMR	BLRT (*p*)	Individuals per class (n)							
						1	2	3	4	5	6	7	8
1	11775.94												
2	11681.55		0.529	134.54**	**	292	191						
3	11663.14	11573.64	0.728	60.28***	**	330	143	10					
4	**11652.2**	11533.01	0.711	61.25***	**	281	119	73	10				
5	11661.99	11499.85	**0.748**	**56.20**$^{+}$	**	**273**	**118**	**70**	**11**	**11**			
6	11673.16	11487.42	0.742	38.95	**	237	137	72	17	11	9		
7	11688.73	11476.38	0.714	20.87	**	189	149	73	38	16	11	7	

Note. BIC = Bayesian information criterion; adj. BIC = Adjusted Bayesian information criterion; LMR = Lo-Mendell-Rubin test; BLRT = Bootstrapped likelihood ratio test $^{+}p \leq .10$; * $p \leq .05$¸** $p \leq .01$. Best fit per indicator printed in bold.

Table 4

Parameter Estimates of the Five-Class Linear Growth Mixture Models

Classes	Mean of growth factor Intercept Factor		Mean of growth factor Slope Factor		Variance of growth factor Intercept Factor	
	Estimate	SE	Estimate	SE	Estimate	SE
FAVORABLE CONSTELLATIONS						
1. LOW-STRAIN – (n=273)						
Social stressors	1.80**	0.03	0.02**	0.01	0.09**	0.02
Task-related stressors	2.69**	0.04	0.03**	0.01	0.10**	0.01
Job control	3.52**	0.05	0.03**	0.01	0.17**	0.02
2. IMPROVEMENT INTO LOW-STRAIN – (n=118)						
Social stressors	2.31**	0.13	-0.08**	0.01	0.09**	0.02
Task-related stressors	2.99**	0.08	-0.03**	0.01	0.10**	0.01
Job control	3.17**	0.09	0.09**	0.01	0.17**	0.02
3. ACTIVE JOB & LOW SOCIAL STRESSORS – STABLE – (n=70)						
Social stressors	1.73**	0.07	-0.001	0.01	0.09**	0.02
Task-related stressors	3.32**	0.08	-0.003	0.01	0.10**	0.01
Job control	3.09**	0.10	0.002	0.01	0.17**	0.02

UNFAVORABLE CONSTELLATIONS

	Mean of growth factor Intercept Factor		Mean of growth factor Slope Factor		Variance of growth factor Intercept Factor	
	Estimate	SE	Estimate	SE	Estimate	SE
4. ACTIVE JOB & HIGH SOCIAL STRESSORS – STABLE – (n=11)						
Social stressors	3.08**	0.18	0.004	0.03	0.09**	0.02
Task-related stressors	2.99**	0.26	0.01	0.02	0.10**	0.01
Job control	3.29**	0.24	0.05	0.03	0.17**	0.02
5. DETERIORATION INTO HIGH-STRAIN – (n=11)						
Social stressors	1.64**	0.13	0.20**	0.02	0.09**	0.02
Task-related stressors	2.67**	0.14	0.08**	0.02	0.10**	0.01
Job control	3.14**	0.26	-0.05	0.03	0.17**	0.02

Table 5

Prediction of Rumination at T5 by Class Membership

	LINEAR 1–5 Classes	n	Unadjusted	+Adj. for initial rumination	Contrast Results I	+Adj. for cumulative private stressors	Contrast Results II	+ Adj. for work stressors and resources in t5	Contrast Results III
		n	F = 8.564** η^2 = .067 *M* (SE)	F = 9.194** η^2 = .072 *M* (SE)	__4,5 > 1, 2, 3 **__	F = 11.106** η^2 = .086 *M* (SE)	__4,5 > 1, 2, 3 **__	F = 4.356** η^2 = .037 *M* (SE)	__4,5 > 1, 2, 3__ **
Favorable	1) LOW-STRAIN	270	3.23 (.08)	3.30 (.08)	1 < 4 __1 < 5 **__ __1 < 4, 5 **__ 1 > 2 1 > 3	3.33 (.08)	1 < 4 (*p* = .091) __1 < 5 **__ __1 < 4, 5 **__ __1 > 2*__ __1 > 3*__	3.25 (.074)	1 < 4 __1 < 5__ ** __1 < 4, 5__ * 1 > 2 1 > 3
Favorable	2) IMPROVEMENT INTO LOW-STRAIN	116	3.03 (.12)	2.96 (.12)	__2 < 4 *__ __2 < 5 **__ __2 < 4, 5 **__ 2 > 3	2.96 (.12)	2 < 4 (*p* = .010) __2 < 5 **__ __2 < 4, 5 **__ 2 > 3	3.21 (.13)	2 < 4 __2 < 5*__ __2 < 4, 5__ * 2 > 3
Favorable	3) ACTIVE JOB & LOW SOCIAL STRESSORS – STABLE	70	3.12 (.16)	3.03 (.15)	__3 < 4 *__ __3 < 5 **__ __3 < 4, 5 **__	2.92 (.15)	__3 < 4 *__ __3 < 5 **__ __3 < 4, 5 **__	2.94 (.16)	3 < 4 __3 < 5__ ** __3 < 4, 5__ **
Unfavorable	4) ACTIVE JOB & HIGH SOCIAL STRESSORS – STABLE	11	4.03 (.39)	3.92 (.39)	__4 > 1, 2, 3 *__ __4 < 5*__	3.98 (.38)	__4 > 1, 2, 3 *__ __4 < 5*__	3.62 (.37)	4 > 1, 2, 3 __4 < 5*__
Unfavorable	5) DETERIORATION INTO HIGH-STRAIN	11	5.27 (.39)	5.20 (.39)	__5 > 1, 2, 3 **__	5.26 (.36)	__5 > 1, 2, 3 **__	4.79 (.41)	__5 > 1, 2, 3__ **

Note. Gender and region as covariates were not significant; ***p* < .001 * *p* < .05; Sidak correction for overall F; significant effects are printed in bold; *p* values for current conditions: cumulative private stressors: *p* < .001; job control: *p* = .004; social stressors: *p* = .075; task-related stressors: *p* < .001.

Table 6

Prediction of Job Satisfaction at T5 by Class Membership

	LINEAR 1–5 Classes		Unadjusted	Adj. for initial job satisfaction	Contrast Results I	+ Adj. for conditions at work in t5	Contrast Results II
			F = 18.284 ** η^2 = .136	F = 24.750** η^2 = .179		F = 2.847** η^2 = .024	
		n	*M* (SE)	*M* (SE)	4,5 < 1, 2, 3 **	*M* (SE)	4,5 < 1, 2, 3 **
Favorable	1) LOW-STRAIN	262	4.29 (1.12)	4.26 (.07)	1 > 4 ** 1 > 5 ** 1 > 4,5 ** 1 < 2 ** 1 < 3	4.30 (.06)	1 > 4 ** 1 > 5 ** 1 > 4, 5 * 1 < 2 * 1 < 3
	2) IMPROVEMENT INTO LOW-STRAIN	110	4.88 (1.02)	5.03 (.10)	2 > 4 ** 2 > 5 ** 2 > 4, 5 ** 2 > 3**	4.64 (.11)	2 > 4 ** 2 > 5 ** 2 > 4, 5* 2 > 3
	3) ACTIVE JOB & LOW SOCIAL STRESSORS – STABLE	67	4.47 (1.17)	4.36 (.13)	3 > 4 ** 3 > 5 ** 3 > 4, 5 **	4.46 (.14)	3 > 4 ** 3 > 5 ** 3 > 4, 5 *
Unfavorable	4) ACTIVE JOB & HIGH SOCIAL STRESSORS – STABLE	11	3.09 (.99)	3.18 (.32)	4 < 1, 2, 3 ** 4 > 5*	3.78 (.32)	4 < 1, 2, 3 ** 4 > 5
	5) DETERIORATION INTO HIGH-STRAIN	11	2.45 (1.18)	2.22 (.32)	5 < 1, 2, 3 **	3.62 (.35)	5 < 1, 2, 3 **

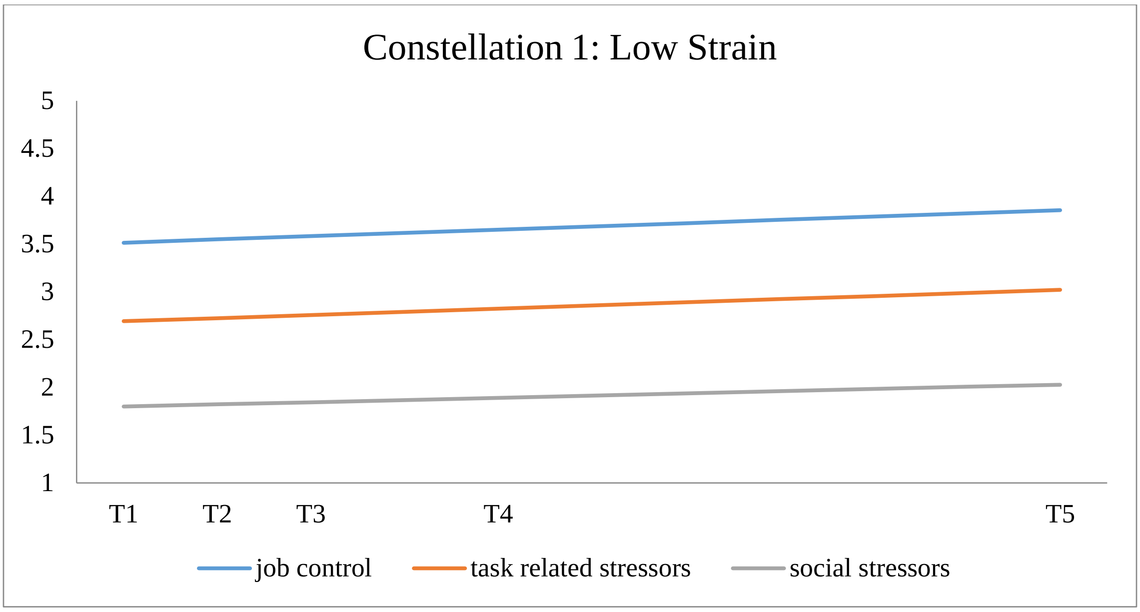
Note. Gender and region as covariates were not significant; cumulative private stressors also were not significant (therefore no Contrast II); $^{**}p < .001$ $^{*}p < .05$, Sidak correction for overall F; significant effects are printed in bold; *p* values for current conditions: job control: $p < .001$; social stressors: $p < .001$; task-related stressors: $p = .048$.

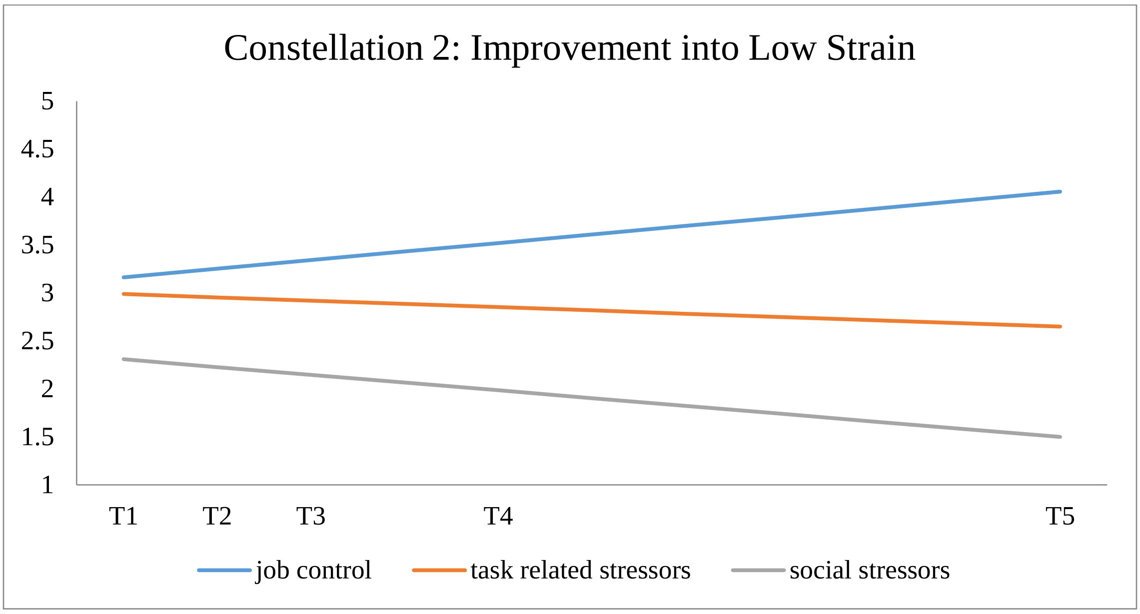
Table 7

Prediction of Somatic Complaints at T5 by Class Membership

	LINEAR 1–5 Classes	n	Unadjusted	Adj. for initial somatic complaints	Contrast Results I	+ Adj. for the cumulative private stressors	Contrast Results II	+ Adj. for work stressors and resources in T5	Contrast Results III
		n	F = 3.839** η^2 = .031 *M* (SE)	F = 3.856** η^2 = .032 *M* (SE)	**4,5 > 1, 2, 3 ****	F = 4.841** η^2 = .039 *M* (SE)	**4,5 > 1, 2, 3 ****	F = 2.003 (p = .093) η^2 = .021 *M* (SE)	**4,5 > 1, 2, 3 ***
Favorable	1) LOW-STRAIN	273	1.89 (.03)	1.93 (.03)	**1 < 4 *** **1 < 5 *** **1 > 4, 5 **** 1 < 2 1 < 3	1.94 (.03)	**1< 4 *** **1< 5 *** **1< 4, 5 **** 1 < 2 1 < 3	1.90 (.03)	1 < 4 **1 < 5 *** **1 < 4, 5 *** 1 < 2 1 < 3
	2) IMPROVEMENT INTO LOW-STRAIN	118	1.96 (.05)	1.89 (.05)	**2 < 4 *** **2 < 5 *** **2 > 4, 5 **** 2 > 3	1.89 (.05)	**2 < 4 *** **2 < 5 *** **2 < 4, 5 **** 2 > 3	1.91 (.06)	2 < 4 2 < 5 (*p* = .085) 2 < 4, 5 (*p* = .082) 2 > 3
	3) ACTIVE JOB & LOW SOCIAL STRESSORS – STABLE	70	1.92 (.07)	1.89 (.06)	**3 < 4 *** **3 < 5 *** **3 < 4, 5 ****	1.85 (.06)	**3 < 4 *** **3 < 5 *** **3 < 4, 5 ****	1.79 (.07)	**3 < 4 *** **3 < 5 *** **3 < 4, 5 ***
Unfavorable	4) ACTIVE JOB & HIGH SOCIAL STRESSORS – STABLE	11	2.41 (.17)	2.29 (.15)	**4 > 1, 2, 3 *** 4 > 5	2.32 (.15)	**4 > 1, 2, 3 *** 4 > 5	2.16 (.16)	4 > 1, 2, 3 (*p* = .076) 4 > 5
	5) DETERIORATION INTO HIGH-STRAIN	11	2.34 (.17)	2.36 (.15)	**4 > 1, 2, 3 ***	2.37 (.15)	**5 > 1, 2, 3 ***	2.24 (.17)	**5 > 1, 2, 3 ***

Note. Gender and region as covariates were not significant; ***p* < .001* *p* < .05; Sidak correction for overall F; significant effects are printed in bold; *p* values for current conditions: cum. private stressors: *p* < .001; job control: *p* = .321; social stressors: *p* = .255; task-related stressors: *p* = .007.


Constellation 1: Low Strain
5
4.5
4
3.5
3
2.5
2
1.5
1
T1
T2
T3
T4
T5
job control
task related stressors
social stressors


Constellation 2: Improvement into Low Strain
5
4.5
4
3.5
3
2.5
2
1.5
1
T1
T2
T3
T4
T5
job control
task related stressors
social stressors

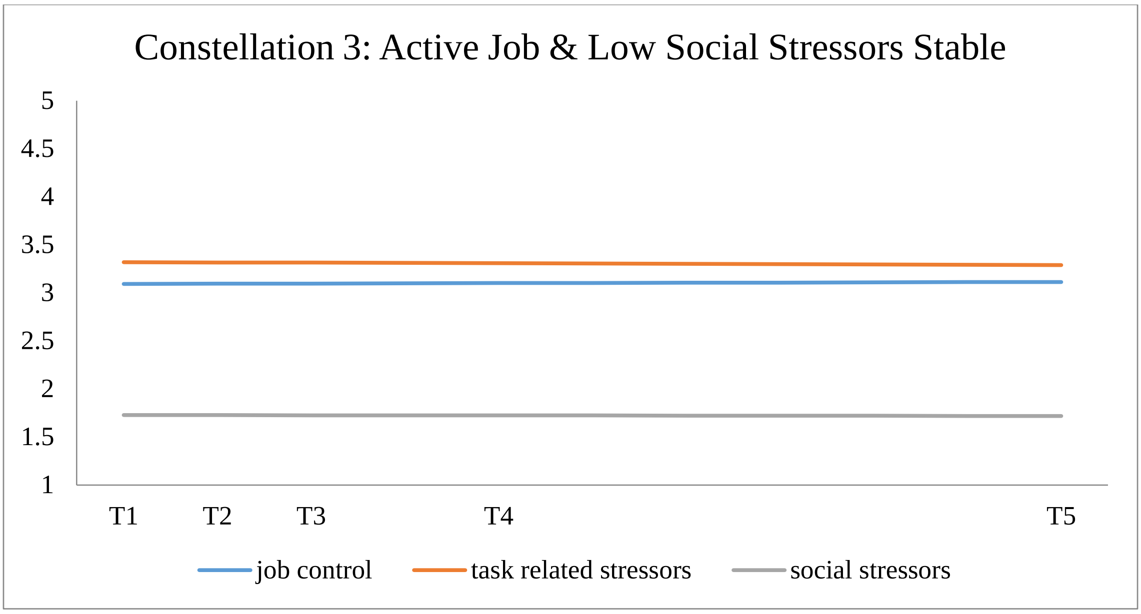
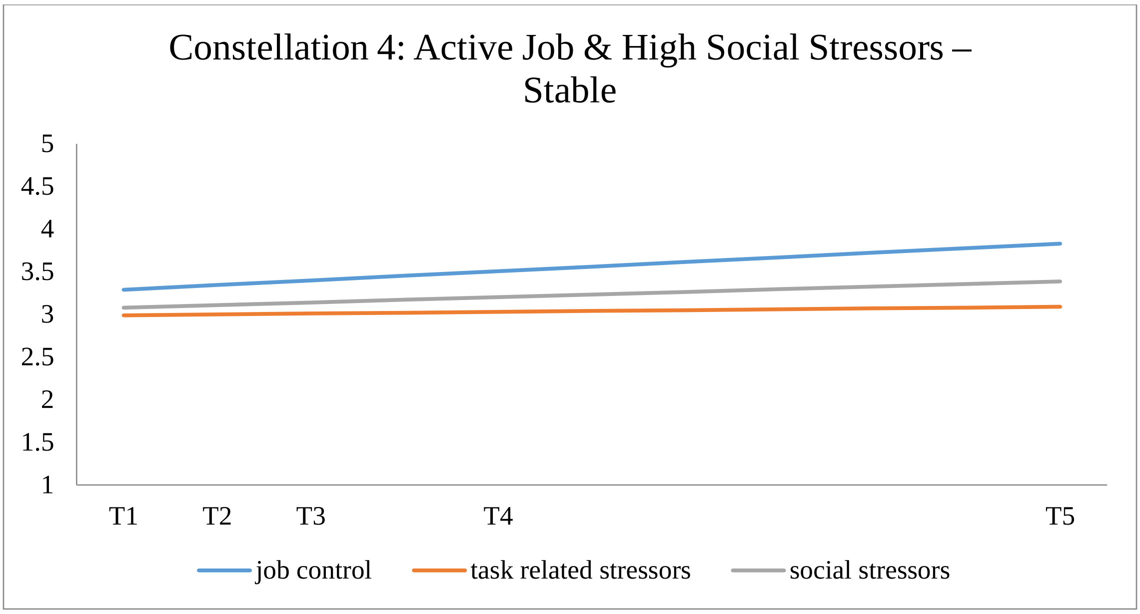


Figure 1. Favorable classes of conditions at work: 1) Low-Strain, 2) Improvement into Low-Strain, 3a) Active Job & Low Social Stressors – Stable.



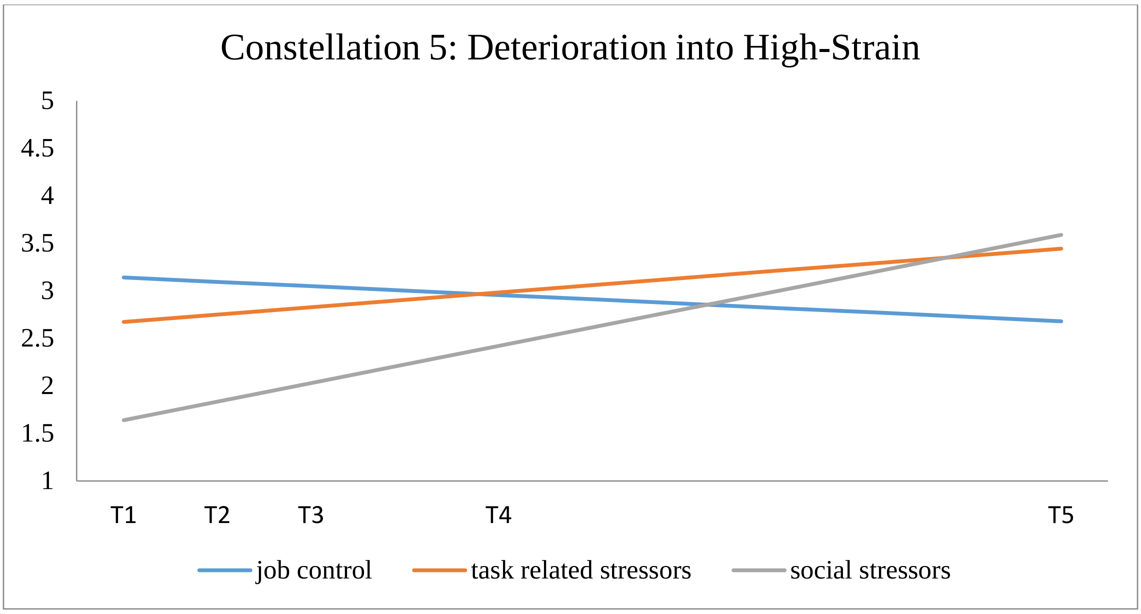


Figure 2. Unfavorable classes of conditions at work: 4a) Active Job & High Social Stressors – Stable; 5) Deterioration into High-Strain.