HHS Public Access
Author manuscript
J Vocat Behav. Author manuscript; available in PMC 2020 February 01.

Published in final edited form as:
J Vocat Behav. 2019 February ; 110(Pt A): 102–116. doi:10.1016/j.jvb.2018.10.017.

Job Strain, Time Strain, and Well-Being: A Longitudinal, Person-Centered Approach in Two Industries

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Abstract

The notion of constellations is central to many occupational health theories; empirical research is nevertheless dominated by variable-centered methodologies. Guided by the job demands-resources framework, we use a person-centered longitudinal approach to identify constellations of job demands and resources (task-based and time-based) over time that predict changes in well-being. We situate our research in two dissimilar, but growing, industries in the United States—information technology (IT) and long-term care. Drawing on data collected over 18 months, we identify five patterned, stable constellations of job demands/resources using group-based multi-trajectory modeling: (1) *high strain/low hours*, (2) *high strain/low hours/shift work*, (3) *high strain/long hours*, (4) *active (high demands, high control)* and (5) *lower strain (lower demands, high control)*. IT workers are overrepresented in the lower-strain and active constellations, whereas long-term care providers are more often in high-strain constellations. Workers in the lower-strain constellation experience increased job satisfaction and decreased emotional exhaustion, work-family conflict and psychological distress over 18 months. In comparison, workers in high-strain job constellations fare worse on these outcomes, as do those in the active constellation. Industrial contexts matter, however: Compared with long-term care workers, IT workers' well-being is more at risk when working in the "high strain/long hours" constellation. As the labor market continues to experience structural changes, scholars and policy makers need to attend to redesigning the ecological contexts of work conditions to promote workers' well-being while taking into account industrial differences.

1. Introduction

Grouping people based on shared attributes is common practice, both in popular parlance and in the social sciences (Abbott & Tsay, 2000). For occupational health researchers, a major focus has been on understanding how various components of the psychosocial work environment coalesce to shape health and well-being. For instance, Karasek and Theorell's classic job strain model theorizes constellations of conditions at work, connecting well-being with a typology based on the joint effects of job demands and job control (Karasek, 1979; Karasek & Theorell, 1990). The recent job demands-resources (JD-R) model extends the job strain model by expanding the number of job demands and resources considered, even as the notion of constellations remains central to its argument (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001).

Despite these theoretical models consistent with a person-centered approach locating individuals in job constellations, empirical research continues to be dominated by variable-centered methodologies. A small and growing body of work has begun to emerge attempting to identify constellations of conditions at work, but with two exceptions (Igic et al., 2017; Mauno, Mäkikangas, & Kinnunen, 2016), most either draw on cross-sectional data or allocate respondents to predefined clusters based on cross-tabulations, limiting understanding of how working conditions coalesce empirically, as well as their stability over time.

In this research, we build on, extend, and contribute important new insights to existing evidence and the JD-R model by adopting a person-centered longitudinal approach to workers in two different industries to test 1) the interconnectedness of psychosocial job conditions, including identifiable patterns of time-based as well as task-based job demands and resources and whether certain constellations are more common in one industry than the other, 2) constellation stability over an 18-month period, and 3) whether knowing these constellations of job demands and resources predicts changes in well-being and whether these patterns differ by industry (see Figure 1 for our conceptual model).

In doing so, we contribute to the existing literature in four ways. First, we produce new knowledge about whether time-based demands and resources cooccur with other demands and resources, which is important to understand in view of the growing number of workers who are stressed because of time pressures and the new communication technologies blurring boundaries between work and non-work time (Jacobs & Gerson, 2004; Moen, Kelly, & Lam, 2013; Roxburgh, 2004). Second, given the paucity of empirical evidence, we contribute by examining whether working conditions tend to remain stable over time, a critical research gap to fill because long-term exposure to certain working environments brings about more profound effects on well-being than does short-term exposure (Tsutsumi et al., 2009; Wang et al., 2009). Stability of patterned job conditions has proved difficult to analyze methodologically because of limited longitudinal data sets and a lack of appropriate methods. To capture both complexity and potential dynamism, we use a newly developed method—group-based multi-trajectory modeling (Nagin et al., 2016) to identify a set of parsimonious "ideal-types" sufficient to capture any change or stability over time of the interrelationships among job demands and resources that are key in the job strain and time strain literatures.

Third, we contribute to the literature by examining job constellations and well-being in two very different, but growing, industries: an IT division of a Fortune 500 firm (knowledge work) and a group of long-term care facilities (health care work), representing the continuum between good and bad jobs (Kalleberg, 2012). Few studies have crossed industrial lines to directly compare and contrast the differential working environments that may shape well-being in distinctive ways. Our findings demonstrate that not only are job constellations distributed unevenly in the two settings, but working in certain constellations can have different well-being implications depending on industry, underscoring the need for future research and job redesign efforts to take a more contextualized view of work conditions and well-being.

Lastly, we examine change over time in a broad set of well-being outcomes spanning different domains. Two are related specifically to work. *Job satisfaction* represents workers' overall evaluation of their jobs and is strongly correlated with mental health and turnover (Karsh et al., 2005). *Emotional exhaustion* refers to feelings of being exhausted by the demands of work (Maslach & Jackson, 1986). *Work-to-family conflict* and *family-to-work conflict* capture strains and spillovers across work and home domains. *Psychological distress* is widely used to assess non-specific depressive symptoms or the absence of well-being (Kessler et al., 2003). Combined, these outcomes offer a more complete picture of the well-being impacts of job constellations.

2. Theoretical framework

2.1. The job strain and time strain models

Karasek and Theorell's job stain model (Karasek, 1979; Karasek & Theorell, 1990) has been the paradigmatic framework guiding research on occupational stress and psychological well-being. The original model distinguishes four types of jobs that workers are in: *high-strain* jobs characterized by high demands and low control, theorized as having the highest risk of health problems; *low-strain* jobs with low demands and high job control, expected to have less psychological or physical health difficulties; *active* jobs with high demands and high control, and *passive* jobs with low demands and low control, the latter two theorized as linked to average health and well-being. Empirical studies have so far largely supported direct associations between job demands, job control, and well-being, with job demands predicting lower and job control predicting greater well-being (Harvey et al., 2017; Häusser et al., 2010). Evidence for the buffering hypothesis, that high job control can moderate any deleterious well-being effects of high demands, however, is mixed (Häusser et al., 2010; van der Doef & Maes, 1999).

The recent job demands-resources (JD-R) model opens up the possibility of including other job conditions (Bakker & Demerouti, 2017), which we do by incorporating, from a time strain model, additional job characteristics that may affect workers' well-being. Time strain — consisting of high work-time demands and low control over the timing of work (Jacobs & Gerson, 2004; Kompier, 2006; Moen et al. 2013)—is examined in a number of well-being studies, although the findings are not always consistent. On the demands side, work hours are increasingly bifurcated (Jacobs & Gerson, 2004). On one end are professionals who put in long hours, often because their jobs require it, while on the other end are occupations where the number of people wanting more hours outnumbers those wanting fewer hours (Reynolds, 2003). On the control side, schedule control has become key in facilitating workers' ability to mesh work with other aspects of life (Fan et al., 2015; Kelly et al., 2014; Moen et al., 2016), even as lower-end jobs still require rigid work schedules. Given the rising time demands on the job, supervisory support for family and personal life has become more important than ever for workers (Hammer et al., 2013); its provision, nevertheless, may be uneven across organizations.

2.2. JD-R model combining job strain and time strain conditions

To incorporate both time strain and job strain, our research is guided by the job demands-resources model (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001), which classifies work conditions into two categories: job demands and job resources. The "job demands" component in JD-R includes all aspects of the job that require sustained physical or psychological effort, whereas the "job resources" component includes a broad array of resources, such as control over the timing of work as emphasized in the time strain literature. JD-R is a person-centered theoretical model from the outset, highlighting how a balance or imbalance between resources and demands shapes worker well-being, but as Bakker and Demerouti (2017: 277) acknowledge: "we usually do not specify the sign of the relationship between job demands and job resources. Although both categories of working conditions covary in the work context, whether these are positively or negatively related is basically an empirical question." Our research begins to address this question by 1) empirically assessing the nature of relationships between an array of demands and resources, and 2) examining them in two different industry contexts.

Our JD-R theoretical framing also has methodological implications, advocating for a person-centered rather than a variable-centered methodology, such as testing the effects of job schedules "net" of other conditions in the model. Additionally, it challenges the utility of interaction models as a way to link variables. Given the sheer number of variables involved, higher-order interactions are difficult to detect (McClelland & Judd, 1993), and analyses with more than two moderators are difficult to interpret. We address these issues by using group-based multi-trajectory modeling (Nagin et al., 2016) to capture workers located in complex configurations of working conditions.

Only a few studies to date identity job constellations using a person-centered approach. One line of research constructs clusters based on cross-tabulations, such as de Lange and colleagues (2002), who classified workers into clusters based on predefined cutoff values (high/low for job demands and job control at four waves). But 44% of respondents had to be removed from the analysis because their "demand-control histories included more than a single transition" (p. 99). In addition to this loss of information, defining constellations *a priori* rather than estimating them empirically forces respondents into pre-conceived groupings rather than allowing categories to reflect the ways working conditions in fact intersect.

Two recent studies by Igic et al. (2017) and Mauno et al. (2016) use more sophisticated analytic techniques and, as described below, offer insightful guidance for our research. Still, a few limitations remain. Loss-to-follow-up, for example, is a severe issue: Only 43% and 34% participants respectively were retained in Mauno et al.'s (2016) and Igic et al.'s (2017) analyses. Additionally, neither study made a conceptual distinction between task- and time-related job demands and resources, which is critical given the number of contemporary workers who are stressed due to time pressures limiting their ability to combine work and private life (Jacobs & Gerson, 2004; Moen et al., 2016) and the possibility that these two types of demands/resources are decoupled within individuals' work environments. Also, these two studies did not compare patterns across industry, a research gap we begin to fill.

3. Research questions and research sites

Our first research question is, are there identifiable groups of workers with similar patterns of job demands and resources? The job strain model provides a useful starting point by conceiving job conditions as occurring in four categories based on their psychological job demands (high/low) and job control (high/low). A similar four categories can be proposed based on more broadly defined job demands and job resources. However, given previous studies and our sample, we do not expect to find a "passive" type (low demands/low resources). Neither of the two recent studies examining work constellations over time (Igic et al., 2017; Mauno et al., 2016) found support for a passive job constellation, and the IT and long-term care workers in our sample are unlikely to hold jobs characterized by both low demands and low resources. Further, we expect most of the constellations identified to be stable because individual job characteristics are shown to be stable over time (Seppälä et al., 2014). Using data collected from two Finnish universities, for example, Mauno et al. (2016) identified four subgroups based on workload and job control measured over two years: "stable high strain," "stable low strain," "increasing control," and "decreasing control," with the two stable groups constituting 92% of the respondents. Similarly, drawing on employees' perceived job stressors and resources over their first 10 years in the labor market, Igic et al. (2017) identified five job constellations: "low-strain," "improvement into low-strain," "active job and low social stressors—stable," "active job and high social stressors—stable," and "deterioration into high-strain," with 73% of participants falling into stable categories. Accordingly, we hypothesize that:

H1a.

Group-based multi-trajectory modeling techniques should produce at least three job constellations which will be stable over time: one with more demands than resources (high strain), one with more resources than demands (low strain), and one with high resources and high demands (active).

As described, we compare workers in two growing industries: economically advantaged IT knowledge workers and relatively disadvantaged long-term health care workers. Our second research question therefore asks, are certain job constellations more prevalent in the IT or long-term care setting? The underlying assumption is that certain industries tend to adopt specific work arrangements, given social stratification across jobs and workplaces. IT workers in occupations with high status, for example, are more likely, compared to long-term care workers, to be equipped with resources at their disposal such as high control and supervisory support, even as some may have high-pressure jobs characterized by high demands and long work hours. Therefore:

H1b.

We anticipate workers in IT to more likely be in constellations with high resources (active or low strain) and those in long-term care environments to be more likely in low resource constellations (high strain).

Once we have identified patterned job clusters, we then examine whether those working under different constellations experience variable changes in well-being over an 18-month period. The existing literature typically investigates whether a particular type of job demand or resource predicts well-being, net of other job characteristics. This variable-centered approach has produced mounting, but not always consistent, evidence. For example, working long hours contributes to work-to-home conflict (Adkins & Premeaux, 2012; Mennino et al., 2005; Schieman et al., 2009) but also predicts energy and mastery (de Lange et al., 2003; Moen et al., 2013). Decision latitude has been shown to be strongly related to job satisfaction (Karsh et al., 2005) but also to work-to-home conflict (Butler et al., 2005; Mennino et al., 2005; Schieman et al., 2009). Schedule control predicts job satisfaction (Karsh et al., 2005; Krausz et al., 2000), less emotional exhaustion (Fenwick & Tausig, 2001; Moen et al., 2016), and work-nonwork balance (Nijp et al., 2012). However, flexibility may permeate into personal life to create more conflicts (Schieman et al., 2009). Results for having a supportive supervisor are more consistent, associated with greater job satisfaction (Chou & Robert, 2008) and lower work-to-family conflict (Allen et al., 2008).

These mixed findings may have to do with failure to consider the interrelatedness of various job demands and resources. As suggested by the JD-R model, high job demands decrease well-being due to depletion of personal resources such as time and energy, but job resources can buffer the impact of job demands on strain (Bakker & Demerouti, 2007, 2017). Therefore, high-strain job holders, with high job demands but low job resources, are expected to fare worst in terms of changes in their well-being, whereas low-strain job holders (low demands/high resources) are expected to fare best. Indeed, using a person-centered approach, Mauno et al. (2016) report that workers holding high-strain jobs have the highest exhaustion whereas those with low-strain jobs have the lowest exhaustion. Similarly, Igic et al. (2017) show that the “deterioration into high-strain” constellation is associated with the lowest job satisfaction and highest somatic complaints, whereas the “low-strain” and “improvement into low-strain” job constellations are associated with the best well-being. The well-being implications of active relative to low-strain jobs, however, are unclear. On the one hand, low-strain work might not be sufficiently challenging compared with active jobs, given the low demands, thereby providing a poorer basis for motivation or personal development (which may affect job satisfaction in particular). On the other hand, empirical research does tend to support the well-being benefits of low-strain jobs versus active jobs. Indeed, Butler et al. (2005) find that active—rather than high-strain—job holders have the highest work-to-family conflict. In view of these ambiguities and the dependency of this research question on the types of job constellations to be identified, our next hypothesis is tentative.

H2a.

Respondents in job constellations with more resources—especially when coupled with low demands—will report greater increases in well-being over the 18-month study period than those in constellations with fewer resources and high demands.

Our final question asks, does being in the same working condition constellation but in different working environments (IT and long-term care) exacerbate or temper its effects on changes in well-being? This might be the case given distinctive institutional logics and types of work across industries. For example, subjective interpretations of demands and resources may differ across the two environments we study. Many workers in low-wage, high pressure jobs may experience requirements for more self-direction as yet more demands rather than job enhancements (Gruss et al., 2004). Similarly, long work hours may be considered “normal” by professionals and therefore less stressful. Additionally, the material benefits provided by professional jobs may compensate for their high stress levels, making it possible to outsource non-work demands of housework, child care, and adult care. Therefore:

H2b.

Compared with long-term care workers, IT workers experience less adverse well-being consequences associated with job constellations with fewer resources and high demands, and more well-being benefits associated with job constellations with more resources.

4. Methods

4.1. Data and procedure

We draw on data from the Work, Family, and Health Network Study, an interdisciplinary study designed to examine the impact of workplace practices and policies on work, family life, and health (King et al., 2012). Data were collected from two U.S. industries: an information technology (IT) division of a Fortune 500 company and a chain of long-term care facilities (LTC hereafter) (King et al., 2012). This study was approved by appropriate Institutional Review Boards. Eligible participants provided informed written consent and received $20 to complete a computer-assisted personal interview (CAPI). At baseline, 1,044 (73%) IT workers and 1,708 (86%) LTC workers invited completed CAPI. Following baseline, three additional waves of data were collected, each six months apart. The retention rates among IT workers surveyed at baseline were 87% at Wave 2, 85% at Wave 3, and 80% at Wave 4; corresponding rates in the LTC setting were 84%, 72%, and 67%. Our analytic sample consists of those who completed all four waves over the 18 months (692 IT workers and 918 LTC workers for a pooled sample of 1,610). We found those lost to follow-up were more likely to be women, younger, single, less educated, and non-supervisory employees. At baseline they had lower job satisfaction, greater emotional exhaustion, and higher psychological distress; they also worked slightly fewer hours and had lower decision authority, schedule control, and family-related supervisor support. Characteristics that were similar regardless of attrition status included: race, nativity, parental status, adult care responsibilities, work-family conflict and psychological job demands. Given these differences, our analysis may not capture the job constellations of those with unfavorable job conditions.

4.2. Sample

Included in our IT sample are employees who develop software, test applications, and work with clients to plan how applications can meet their needs. As shown in Table 1, this is a relatively older workforce, with a mean age of 46. As is typical of the IT industry, the majority (62%) are men; about one in four were born outside the United States (typically in India). The average tenure with the organization is 13 years. These IT workers have high socioeconomic status: four in five have a college degree, and the average income in 2010 was $96,574. The long-term care providers include licensed workers such as registered nurses (RNs) and unlicensed workers such as certified nursing assistants (CNAs). Consistent with the national profile, they are overwhelmingly women (93% vs. 38% for IT workers, $p < .001$), with an average age of 40, and one in four was born outside the United States. Given the high turnover rates among long-term caregivers, their tenure with the current organization is 7 years ($p < .001$ vs. 13 years for IT workers). The socioeconomic status of these care providers is considerably lower than that of IT participants: Only 15% have a college degree ($p < .001$), and average earnings were less than half of what IT workers made, $37,800 a year ($p < .001$).

4.3. Measures

Before describing individual measures used in this study, we note that surveys were conducted during the work day and averaged 45 minutes. Given the large amount of information on work, family, and health outcomes to be collected, for some measures it was not feasible to use full scales as originally developed. To decide what items to delete in order to reserve time for other measures to be collected, pilot studies using the full scales were used to determine 1) what the alpha was with particular items deleted, and 2) whether the shortened scale predicted key outcomes in the pilot study sample. Items were also shortened based on ease of interpretation in the long CAPI interview; cognitive testing suggested that some items were confusing or hard to follow when stated verbally.

Well-being Outcomes: *Job satisfaction* was assessed by a three-item scale developed by Cammann et al. (1983). Respondents were asked to evaluate their agreement to statements such as “In general, you are satisfied with your job.” (1 = strongly disagree to 5 = strongly agree). Alphas across the four waves ranged from 0.81 to 0.90. *Emotional exhaustion* consists of three items from the original subscale of emotional exhaustion in the Maslach Burnout Inventory (Maslach & Jackson, 1986). A sample question is “You feel emotionally drained from your work: How often do you feel this way?” (1 = never to 7 = every day). Alphas across the four survey waves ranged from 0.87 to 0.92. *Work-to-family conflict* and *family-to-work conflict* reflect the degree to which role responsibilities from work are incompatible with family or personal life, or vice versa. They were each assessed by a five-item subscale developed by Netemeyer, Boles and McMurrian (1996). Respondents were asked how much they agree with statements such as “Due to your work-related duties, you have to make changes to your plans for family or personal activities.” (1 = strongly disagree to 5 = strongly agree). Alphas across the four waves ranged from 0.88 to 0.91 for work-to-family conflict and from 0.82 to 0.87 for family-to-work conflict. *Psychological distress* was measured by the K6, a six-item scale widely used to assess non-specific psychological distress (Kessler et al., 2003). Sample questions include “During the past 30 days, how much of the time did you feel so sad nothing could cheer you up?" We summed up responses (1 = none of the time to 5 = all of the time) to obtain a score ranging from 6 to 30, with higher scores indicating more distress. Alphas across the four waves ranged from 0.77 to 0.86.

Key Predictors: To identify patterned clusters representing workers with distinct demands and resources, we draw on six variables. *Psychological job demands* and *decision authority* were measured based on the Job Content Questionnaire (Karasek et al., 1998). Psychological job demands includes three questions: "You do not have enough time to get your job done," "Your job requires very fast work," and "Your job requires very hard work." (1 = strongly disagree to 5 = strongly agree), with alphas ranging from 0.56 to 0.60. Decision authority includes three questions: "Your job allows you to make a lot of decisions on your own," "On your job, you have very little freedom to decide how you do your work," and "You have a lot of say about what happens on your job," with alphas ranging from 0.60 to 0.76 across the four waves.[[1]] *Weekly hours worked* was constructed by summing up responses to two questions: "About how many hours do you work in a typical week in this job?" and, if respondents had more than one job, "On average, how many hours per week do you work at this other job(s)?" *Shift work* is a dichotomous variable that takes the values of 1 if respondents' work schedules were regular evening shift, regular night shift, rotating shift, or split shift, and 0 if they worked a regular daytime schedule. *Schedule control* reflects the degree to which respondents feel they have control over their work time (Thomas & Ganster, 1995). A sample question of this eight-item scale is "How much choice do you have over when you take vacations or days off?" (1 = very little to 5 = very much). Alphas across the four waves ranged from 0.68 to 0.82. *Family supportive supervisor behaviors (FSSB)* measures employee perceptions of supervisors' behavioral support for family and personal life (Hammer et al., 2013). It is different from general supervisor support, as some supervisors are supportive of employees' job but not family concerns. A sample question of this four-item scale is "Your supervisor makes you feel comfortable talking to him/her about your conflicts between work and non-work." (1 = strongly disagree to 5 = strongly agree). Alphas ranged from 0.87 to 0.90.

Covariates: In all models we control for sociodemographic variables found to be correlated with job conditions and well-being, including *gender* (women = 1), *age*, *race/ethnicity* (non-Hispanic White, non-Hispanic Black, Hispanic, and Asian), and *nativity*. To capture socioeconomic status, we control for *educational attainment* (high school or less, some college, or college), *tenure* (the length of time the worker had been employed at their organization), and *manager status*. Given that workers may adjust their working conditions based on home demands (Schneider et al., 2013), which may also affect their well-being (Voydanoff, 2002), we control for three measures of family roles and relationships assessed at waves 1 and 4. *Marital status change* indicates whether respondents remained married, remained single, got married, or divorced between Wave 1 and Wave 4. Based on reports of

[1]In view of the low alpha values of psychological job demands and decision authority (which is also the case in previous studies such as Keller et al., 2017), we experimented with alternative versions. Specifically, based on itemrest correlations, we removed the items "You do not have enough time to get your job done" and "On your job, you have very little freedom to decide how you do your work" from relevant scales. Alphas changed to 0.60–0.73 for psychological job demands and 0.63–0.73 for decision authority. But our main findings (i.e., job constellations identified and their associations with well-being) are robust to inclusion/exclusion of these items (results not shown; available upon request). Thus, we use all items to construct psychological job demands and decision authority.

parental status (whether respondent had a child younger than 18 living at home) in waves 1 and 4, we categorized respondents into four groups: no children in the home in both waves, none in Wave 1 but children in the home by Wave 4, children in the home in Wave 1 but not in Wave 4, and children in the home both waves. Similarly, we constructed a four-category measure for continuity and change in *adult care responsibilities* (providing care for an adult relative for at least three hours per week in the past six months). A workplace intervention designed to promote workers' control over schedule and supervisory support for family life was implemented between waves 1 and 2. The intervention effect is not the focus of this research, but we adjusted for it by adding a dichotomous variable to distinguish those who were assigned to the intervention group (= 1) and those who were not (= 0).

4.4. Statistical analysis

Measurement invariance tests and confirmatory factor analyses.—As a first step, we tested measurement invariance over time. We compared the model fit of measurement models with freely estimated factor loadings (configurational invariance) and that of measurement models with factor loadings constrained to be equal across wave (metric invariance). Given recent criticisms about using chi-square difference tests to determine measurement invariance (e.g., high susceptibility to sample size; see Schmitt & Kuljanin, 2008), we focused on the difference in CFI, following prior studies such as Mauno et al. (2016). The differences in CFI were tiny (Appendix Table A), all smaller than the 0.01 cutoff point established by Cheung and Rensvold (2002: 251), indicating that the assumption of measurement invariance holds. To determine whether the scales used in our analyses were distinct, we evaluated factor structures of psychological job demands, decision authority, schedule control, and FSSB through a series of confirmatory factor analyses (CFAs). Four substantive models were estimated: (A) a single-factor model, where all items were treated as unidimensional; (B) a two-factor model which examined psychological job demands and decision authority (job strain) as one dimension, and schedule control and FSSB (time strain) as a second dimension; (C) a three-factor model which examined psychological job demands and FSSB as two separate dimensions, and decision authority and schedule control as a single dimension given the concern that these two scales may have measured the same underlying concept; (D) a four-factor model which treated each of the four measures as separate constructs. As shown in Appendix Table B, for all four waves, only Model D (four-factor model) produced acceptable fit statistics and was a significant improvement over models A, B, and C based on chi-square difference tests, indicating independence of these measures.

Group-based multi-trajectory modeling.—To determine whether there are identifiable patterns of job demands and resources and whether these patterns are stable over time (Hypothesis 1a), we used group-based multi-trajectory modeling (Nagin et al., 2016). This recently developed method is ideal for identifying latent clusters of individuals following similar trajectories across multiple indicators (in our case, six job demands and resources, each measured at four points in time). Following the recommendation of Nagin et al. (2016), we first estimated a trajectory model for each of the six task- and time-based demands (psychological job demands, work hours, shift work) and resources (decision authority, schedule control, and FSSB) with varying numbers of groups (up to ten). Appropriate distribution models were used: Poisson for work hours, binary logit for shift work, and censored normal models for others. To determine the number of latent trajectories for each of the six indicators, we evaluated various fit criteria (Klijn et al., 2015): BIC, average posterior probability of assignment, odds of correct classification, and mismatch between estimated and assigned group probabilities. The objective here was to clarify the types of distinctive trajectories that were important to be represented in the multi-trajectory model. We then estimated a set of multi-trajectory models with different number of groups to determine the best-fitting model.

OLS regression models with lagged dependent variables.—Lastly, we used the identified job constellations to predict well-being outcomes at Wave 4. Using the lagged dependent variable approach to model change, we controlled for Wave 1 well-being as well as a rich set of demographical, socioeconomic, and home-related variables to examine how *changes* in well-being varied by job constellation (Hypothesis 2a). We used OLS models for simplicity, but censored normal models yielded substantively similar results (available upon request). To test Hypothesis 2b, we used interaction models to examine whether industry (IT vs. LTC) moderated the relationship between job constellations and changes in well-being.

5. Results

5.1. Descriptive statistics

In Table 1 we present descriptive statistics for IT and LTC workers separately; means, standard deviations, Cronbach's alphas, and bivariate correlations for the overall sample are shown in Table 2. In terms of demands, LTC workers reported higher psychological job demands than IT workers (e.g., 3.83 vs. 3.68 at Wave 1, $p < .001$). Work hours, however, follow a reverse pattern: IT workers put in on average 6 more hours per week on their job compared with LTC workers (47 vs. 41, $p < .001$). A decline in job demands occurred for workers in both industries over the 18-month study period, although the magnitude was more noticeable among IT workers (−0.25 vs. −0.09, $p < .001$). Compared with IT workers, LTC workers were far more likely to work in jobs that require shifts (39% vs. 1% at Wave 1, $p < .001$). As for resources, IT workers reported considerably greater decision authority ($p < .001$) and schedule control ($p < .001$), and were more likely to have family-supportive supervisors ($p < .01$) than LTC workers. There is also evidence showing that IT workers gained more schedule control by Wave 4 than did LTC workers (0.12 vs. 0, $p < .001$).

For well-being outcomes, the presumably advantaged high-tech IT workers reported significantly lower levels of job satisfaction ($p < .001$) and higher levels of work-to-family conflict ($p < .001$) than LTC workers. In terms of emotional exhaustion and psychological distress, however, the LTC workers fared worse ($p < .001$). Family-to-work conflict was similar between IT and LTC workers.

5.2. Identifying job demands/resources constellations

Using group-based multi-trajectory modeling to test Hypothesis 1a, we found that at minimum a five-group multi-trajectory model was required. We then fitted a five-, six-, and seven-group multi-trajectory model, finding that the five-group model contained distinctive groups—the additional group in the six-group model did not represent a distinctive one compared with the five-group model—and yielded groups of reasonable sizes (the smallest group represented 5% of our sample). In Figure 2 we depict the means of the five constellations from Wave 1 to Wave 4 for each of the six demands/resources variables. The five lines in Figure 2 represent the five job constellations, with their names listed at the bottom. Overall, it is the *level* rather than *change* in demands/resources measures that distinguishes one job constellation from another. With the exception of psychological job demands, most lines are flat, suggesting these constellations capture exposure to largely consistent work environments, providing support for the stability portion of Hypothesis 1a.

Three clusters shown in Figure 2 conform to “high strain”—high demands and low resources—job types, as evidenced by high psychological job demands (3.5–4), low to moderate decision authority (3–3.5), low schedule control (around 2.5), and moderate FSSB (around 3.5). But they differ in work hours and work schedules. Members of one cluster, represented by the black solid lines, put in on average 37 hours per week with no shift work, whereas members of another cluster, represented by the black dotted lines, work similar hours but consist almost exclusively of employees doing shift work; we therefore name the first cluster the *high-strain/low hours* constellation (23.1% of the sample) while the second one the *high-strain/low hours/shift work* constellation (17.9% of the sample). In contrast to these two constellations, workers in another high-strain job type—represented by the dark gray solid lines with squares—have long work hours (63 hours) and mixed work schedules (about 50% reported shift work). We name this constellation *high-strain/long hours* (5.3% of the sample).

Members in the fourth cluster—gray dotted lines with dots—have high and declining psychological job demands (from 4.1 to 3.8 across waves), long work hours (50), and moderate to high decision authority (4), schedule control (3.5), and FSSB (3.7); hence the “*active*” constellation name, consisting of 25.2% of the sample. The last constellation—gray solid lines with triangles—with lower and declining job demands (from 3.4 to 3.2 across waves), moderately long work hours (43), as well as the highest decision authority (> 4), schedule control (4), and FSSB (> 4), represents the *lower-strain* constellation, making up 28.5% of the sample. Note that, although comparatively lower, the psychological job demands of this lower-strain constellation are still considerable (around 3.3 on a scale of 1 to 5). Taken as a whole, Hypothesis 1a is supported: the identified job constellations are stable; we do not find the passive job type in the IT and LTC work settings, and three forms of high-strain jobs emerge that differ in working hours and shift schedules.

5.3. Distributions of demands/resources constellations across industries

Respondents in these five job constellations differ greatly from each other. As expected in Hypothesis 1b, a chi-square test shows that industry matters significantly (chi2(4) = 649.64, $p < .001$). LTC workers are overrepresented in the three high-strain constellations: 34% (n = 313), 31% (n = 287), and 8% (n = 74) of them are in the “high strain/low hours,” “high strain/low hours/shift work,” and “high strain/long hours” constellations, respectively. Conversely, IT employees are much more likely to be in the “active” (42%, n = 289 vs. 13%, n = 117 for LTC workers) or “lower strain” job constellation (48%, n = 332 vs. 14%, n = 127 for LTC workers). Note that while the employees in IT and LTC tend to work in distinctive job environments, a range of patterned working conditions can be found in both industrial contexts.

Despite distinctive organizational environments, Appendix Table C shows that similar processes around demographic and socioeconomic characteristics seem to be operating predicting who is in each constellation regardless of industry. For example, older workers are more likely to be in the lower-strain cluster whether in IT or LTC ($p < .001$), partly reflecting their longer tenure. Non-Hispanic whites are more likely to be in the active or lower-strain cluster ($p < .001$), as are those born in the United States ($p < .001$). In both settings, those with an active job earn more and are more likely to be managers ($p < .001$), although the highest-earning ones are IT workers with high-strain jobs and working long hours. In terms of home contexts, no difference is found across job constellations for IT workers. But among LTC workers, being continuously married is associated with having a lower-strain job ($p < .001$), while continuous singlehood is associated with having a high-strain job requiring long hours ($p < .001$).

5.4. Demands/resources constellations and changes in well-being

To test Hypothesis 2a, models in Table 3 show to what extent demands/resources constellations relate to changes in well-being over 18 months while adjusting for covariates. For *job satisfaction*, holders of the three high-strain job types report the largest decreases in job satisfaction, followed by workers with active jobs, whereas working in a lower-strain constellation—the reference group—fares best. Wald tests further indicate that the three high-strain job constellations do not differ from each other in terms of changes in job satisfaction. A different pattern emerges for *emotional exhaustion*, however. Employees in the lower-strain constellation fare best, and compared with this group, those in the other four constellations do not differ from each other, all of whom saw significantly larger increases in emotional exhaustion over the 18-month study period.

Those in the “high-strain/long hours” constellation report the highest increase in *work-to-family conflict*, whereas those in the lower-strain job constellation experience the least permeation of work stress into the home domain. The other three constellations are in the middle, and Wald tests show that these three groups do not differ significantly from each other in terms of change in work-to-family conflict. *Family-to-work conflict* and *psychological distress* show similar patterns as emotional exhaustion. Wald tests reveal that, compared with those in the lower-strain constellation, members in the other four constellations do not differ from each other, with all members of all four reporting significantly larger increases in family-to-work conflict and psychological distress over the 18 months.

Taken as a whole, and consistent with Hypothesis 2a, those with the most positive improvements in well-being work in the lower-strain constellation of job conditions. Employees in this lower demands and high control and support environments report large increases in job satisfaction and considerable declines in emotional exhaustion, work-family conflict, and psychological distress. Workers in high-strain job constellations, by contrast, fare worst on these well-being outcomes. This is regardless of whether their high-strain constellations differ by work schedules or work hours, with one exception; increases in work-to-family conflict is largest for employees in the high strain/long hours constellation. Employees in the active job constellation are by and large more similar to those in high-strain than in lower-strain constellations in terms of changes in well-being.

In a post hoc analysis, we investigated whether the person-centered approach offers a better understanding of changes in well-being than the variable-centered approach. Specifically, we fit two models using the variable-centered approach: (1) one model in which each of the three job demands (psychological job demands, work hours, and shift work) is interacted with each of the three job resources (decision authority, schedule control, and FSSB) at each of the first three waves to predict well-being (also controlling for covariates), and (2) one model where each of the six job characteristics is interacted with one another at each of the first three waves to predict well-being (also controlling for covariates). We compared these two models with models in Table 3, representing the person-centered approach. As shown in Appendix Table D, across all outcomes, the person-centered approach yielded much smaller BIC values, indicating better explanatory power compared with the variable-centered approach.

5.5. Industry Differences in the relationship between job constellations and well-being

Lastly, to test Hypothesis 2b, we examine whether being in the same constellation of job conditions has different well-being implications depending on the specific industrial context. Being in a “high strain/long hours” constellation stands out as having different effects by industry. The negative well-being consequences of working in this constellation (relative to in the lower-strain constellation) is significantly larger for IT than LTC workers. Specifically, we see for IT workers greater declines in job satisfaction (the interaction term between industry and the “high strain/long hours” job constellation $p < .05$) and larger increases in emotional exhaustion (interaction term $p < .1$), work-to-family conflict (interaction term $p < .1$), family-to-work conflict (interaction term $p < .05$), and psychological distress (interaction term $p < .001$) (results from interaction models not shown but available upon request). Thus, compared with long-term care workers, IT workers seem to be more vulnerable in terms of well-being outcomes when working in jobs characterized by high strain and long hours. Our Hypothesis 2b is therefore not supported.

6. Discussion

Working conditions as they occur together to shape particular contexts have long been theorized to matter for health and well-being. And yet, despite argument from preeminent occupational health theories that the well-being effects of job attributes do not operate independently of one another and can best be understood as patterned constellations, little empirical research to date examines whether such patterned constellations of job conditions are stable, how they coalesce to change health over time, or how these patterns, or their effects, may differ by industry. In making the case for the value of a person-centered longitudinal approach, we drew on data from two diverse industries: a high-tech workforce and a long-term care workforce. We identified five patterned, stable constellations of job demands and resources across these two industries: *high strain/low hours*, *high strain/low* *hours/shift work*, *high strain/long hours*, *active*, and *lower strain*. IT workers were overrepresented in the lower-strain or active constellations of working conditions, whereas long-term care providers were more often in high-strain constellations. We found workers in the lower-strain constellation experienced increased job satisfaction and decreased emotional exhaustion, lower work-family conflict, and less psychological distress over an 18-month period. Workers in high-strain job constellations fared worse on these outcomes, as did active-job holders. Additionally, the negative well-being implications for performing high-strain/long hours jobs were more strongly experienced by IT workers than long-term care workers. These findings have theoretical, methodological, and practical implications.

6.1. Theoretical and methodological contributions

Our findings contribute to the occupational strain and well-being literature in several ways. First, despite the long-held realization that job demands and resources tend to come together in patterned ways, little empirical research examines the intra-individual organization of work conditions. To the best of our knowledge, we are the first to identify patterned longitudinal clusters of both task-based and time-based job demands and resources. The incorporation of time-based job conditions is critical given the large number of workers who are stressed because of time pressures (Jacobs & Gerson, 2004; Moen et al., 2016) and reinforces the broad reach of the job demands-resources theoretical paradigm (Bakker & Demerouti, 2007, 2017; Demerouti et al., 2001). In support of this, we find time-based job demands/resources to be distinct from task-based ones, identifying three high-strain job constellations that differ by work time and our CFA analysis suggests that decision authority and schedule control are distinct concepts.

As expected in Hypothesis 1a, we did not find a "passive" job type in the two types of industries we studied. This finding highlights the need to identify *naturally-occurring* job constellations rather than simply dichotomizing variables and relying on cutoff values to create groups. The set of constellations we found extends prior research (Igic et al., 2017; Mauno et al., 2016) by providing a more nuanced understanding of the ways in which time- and task-based demands and resources co-occur. For example, we found three types of high-strain job constellations that differ in work hours and schedules but only one type of lower-strain job constellation, suggesting that high-strain jobs are more diverse in work time than lower-strain jobs, and that time and task demands are distinct attributes that may not always be coterminous. Workers can put in fewer hours yet still report high levels of psychological job demands, as evidenced by the high strain/low hours cluster, which calls into question the conventional treatment of psychological job demands and long hours as equivalent. More studies are needed to disentangle these two aspects of work-related demands.

Our second contribution to the work and well-being literature is to show that job demands/resources constellations are associated with *changes* in a set of well-being outcomes. We document a well-being hierarchy of constellations as expected in Hypothesis 2a. Located at the top is the constellation of job conditions promoting well-being, characterized by lower psychological job demands, moderately long work hours (43), a regular daytime working schedule, high decision authority, high schedule control, and high supervisor support for family and personal life. Note that, in terms of socioeconomic status, being in this lower-strain constellation is not associated with the highest level of educational attainment or income, or with managerial status (Appendix Table C). The subjective well-being implications of work environments, therefore, do not seem to derive from socioeconomic status alone. Future qualitative studies would be useful to shed light on the interrelationships between and processes linking working conditions, economic resources, and well-being.

On the other end, located at the bottom of the well-being hierarchy are people working in high-strain constellations. Recall we detected three such job constellations that differ widely in work hours and work schedules, but importantly, these different constellations do not translate into differences in changes in well-being. This seems to suggest that, relative to more objective work conditions (work hours, work schedules), what may be more important for well-being is psychological job demands, as well as a sense of control over how and when work is done. Since work hours and schedules are typically rigid and difficult if not impossible to alter, this finding offers a more practical suggestion to improve worker well-being: by offering workers more control and lowering their psychological demands (Kelly et al., 2014; Moen et al., 2016). In particular, given that schedule control tends to be much lower than decision authority (Figure 2), employee control over the time and timing of their jobs is a potentially fruitful way to promote well-being. We also note that, in terms of changes in work-to-family conflict, employees in the high strain/long hours constellation experience greater increases compared with their peers in the two other high-strain constellations, suggesting that long hours may particularly impinge on workers' ability to navigate the work to family interface. Employees in the active job constellation are more similar to those in high-strain than in low-strain constellations in terms of changes in well-being. As both high-strain and active job constellations have high job demands in common, this suggests that high job demands may be harmful for well-being regardless of the job resources available.

Our third contribution: We provide new knowledge regarding both similarities and variations across two very dissimilar industries in terms of job constellations and well-being. As expected in Hypothesis 1b, IT workers tend to be working in either active or lower-strain jobs. By contrast, long-term care workers generally work in high-strain jobs. Nevertheless, IT professionals report on average greater work-to-family conflict and lower job satisfaction than those in long-term care. In terms of the well-being implications of job constellations, however, the well-being benefits of being in a lower-strain job constellation hold in both organizations. In other words, being in a "good" cluster of job conditions appears to promote well-being, regardless of the particular industry the worker is in. By contrast, being in the "high strain/long hours" cluster seems to be more detrimental for IT than health-care workers. This goes against our expectation (Hypothesis 2b) that work demands and long hours would be more likely to be considered "normal" among professional workers and therefore less consequential for their well-being. A possible explanation is that work processes in health care are often guided by protocols, so having a say in how the work is done might be less relevant to long-term care workers once protocols have been established. Further, many of these care workers may be struggling with insufficient rather than long hours. Combined, being in the constellation characterized by high demands, low control, and long hours may impose less well-being threats for long-term care than IT workers. Given the relatively small size of this cluster, however, there is real need for additional research shedding light on how job constellations are experienced differently by workers in different industrial settings.

Fourth, previous research tends to focus on job conditions as distributed at one point in time; it is therefore unclear whether and how patterns of job demands and resources may shift over time. Ours is among the first to follow workers over a relatively long period (18 months) to demonstrate that demands and resources—whether task-based or time-based—remain stable from one wave to another. This provides additional support for a previous study based on ten years of data finding that 73% of participants fell into stable categories (Igic et al., 2017). Cross-sectional studies, therefore, can perhaps have greater confidence that the snapshots they capture are fairly accurate descriptions of workers' job conditions more generally.

6.2. Practical implications

Responding to the call by Bakker and Demerouti (2017), our person-centered approach contributes to the knowledge base by identifying constellations of demands and resources that are relevant to the experiences of many contemporary workers. One benefit of the person-centered longitudinal analysis is that it identifies both typical (theoretically predicted) and atypical (not predicted by theory) groups of workers according to the ways job conditions are experienced in the real world. For example, we identified a constellation of those who have high psychological job demands but work few hours. This risky group, in terms of well-being, would otherwise remain hidden if using predefined cut-off criteria. If similar patterns emerge across different samples, this may yield new insights for job redesign. One case in point: along with other person-centered research (e.g., Igic et al., 2017; Mauno et al., 2016), we show that most job constellations are stable, and the "passive" job type seems to be very rare, suggesting a need to revisit or update existing workplace interventions to better reflect and inform this reality.

Our person-centered approach also assists in identifying individuals most at risk for experiencing declines in well-being or most likely to thrive at work. This begins to build a solid foundation for developing distinct intervention strategies tailored to workers in different job environments. Rather than examining variables in a piecemeal fashion and designing separate interventions accordingly, a person-centered, holistic approach could be more cost-effective in the development of work redesigns that optimize well-being. For example, our results suggest the well-being risks of working in high-strain job constellations. Additionally, given our findings on differences across two industries, practitioners need to contextualize the job constellations/well-being interface to better serve workers located in distinct settings.

Our finding on the stability of patterned job constellations is important for practical purposes as well. A natural prediction from the job demands-resources model is that, if workers were relocated from a high-strain to a low-strain job, their well-being would improve accordingly. But we contribute to the evidence that many workers face persistent exposure to certain job constellations that can be positive in some cases and negative in others. This persistence may be particularly harmful for employees in high-strain constellations because duration of exposure to an unfavorable work situation is related nonlinearly to health, such that long-term exposure has comparatively stronger detrimental effects than short-term exposure

(Tsutsumi et al., 2009). What's more, even a positive change in work environment—such as from a high-strain to a less distressing job—may not result in corresponding improvements in worker health (de Lange et al., 2002), unless it is systematically introduced in the norms and organization of work (Kelly et al., 2014; Moen et al., 2016), highlighting the need to revamp the ecological contexts of work, especially for workers who are chronically exposed to poor psychosocial work environments.

6.3. Limitations and conclusions

This study has several limitations. First, despite its longitudinal design, the time window is limited to only 18 months; a longer time frame may be needed to understand continuity and change in constellations of job conditions. Second, focusing on two organizations in two different industries limits the generalizability of the findings, even though it permits key job characteristics to be held constant within each site (such as industry, employer, organizational culture, etc.) and enables comparisons across these two growing industries. Other patterns of demands and resources may well be detected in other industries. Third, data limitations preclude us from examining more job characteristics. Investigating whether additional measures cluster with the job resources and demands we examine here, and how the resulting constellations predict changes in well-being are important arenas for future theorizing and research. Fourth, we cannot speak to causal direction; there may well be factors influencing both employees' constellations of demands and resources and changes in subjective well-being we could not capture in our study.

Despite these considerations, our study is one of the first to examine work environments as they are actually experienced by workers in two different industries, as patterned clusters of working conditions that remain stable over as long as 18 months. As the labor market continues to experience structural and technological changes, scholars and policy makers should attend to redesigning the ecological contexts of work, fashioning working conditions in ways that can best promote worker well-being, attending as well to the well-being costs of working in particular job constellations in particular industrial contexts.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

This research was conducted as part of the Work, Family and Health Network (http://www.WorkFamilyHealthNetwork.org), which is funded by a cooperative agreement through the National Institutes of Health and the Centers for Disease Control and Prevention: Eunice Kennedy Shriver National Institute of Child Health and Human Development (Grant # U01HD051217, U01HD051218, U01HD051256, U01HD051276), National Institute on Aging (Grant # U01AG027669), Office of Behavioral and Social Sciences Research, and National Institute for Occupational Safety and Health (Grant # U01OH008788, U01HD059773). Grants from the University of Minnesota's College of Liberal Arts, McKnight Foundation, William T. Grant Foundation, Alfred P. Sloan Foundation, and the Administration for Children and Families provided additional funding. The contents of this publication are solely the responsibility of the authors and do not necessarily represent the official views of these institutes and offices.

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Highlights

- Job conditions are not independent but patterned; we identify five patterned, stable clusters of job demands and resources.
- Workers in the lower-strain (both task- and time-based) constellation experience improved well-being over 18 months.
- Workers in high-strain job constellations show declines in a variety of well-being outcomes over 18 months.
- Industrial contexts affect distributions of job constellations and their well-being consequences.

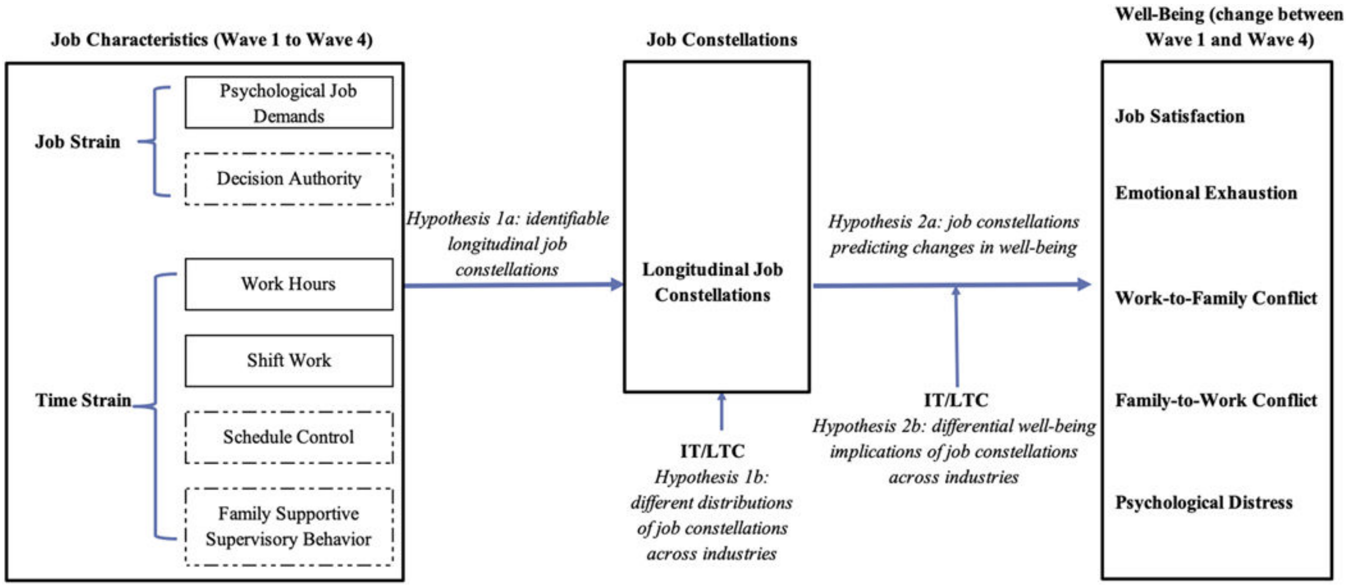

Fig. 1.

Conceptual model. Notes: 1. For job characteristics shown on the far left, boxes with solid lines indicate job demands and boxes with dash lines indicate job resources. 2. IT: information technology; LTC: long-term care facilities. These are two organizations from which our data were collected. Comparing these two growing industries is one focus of this research.

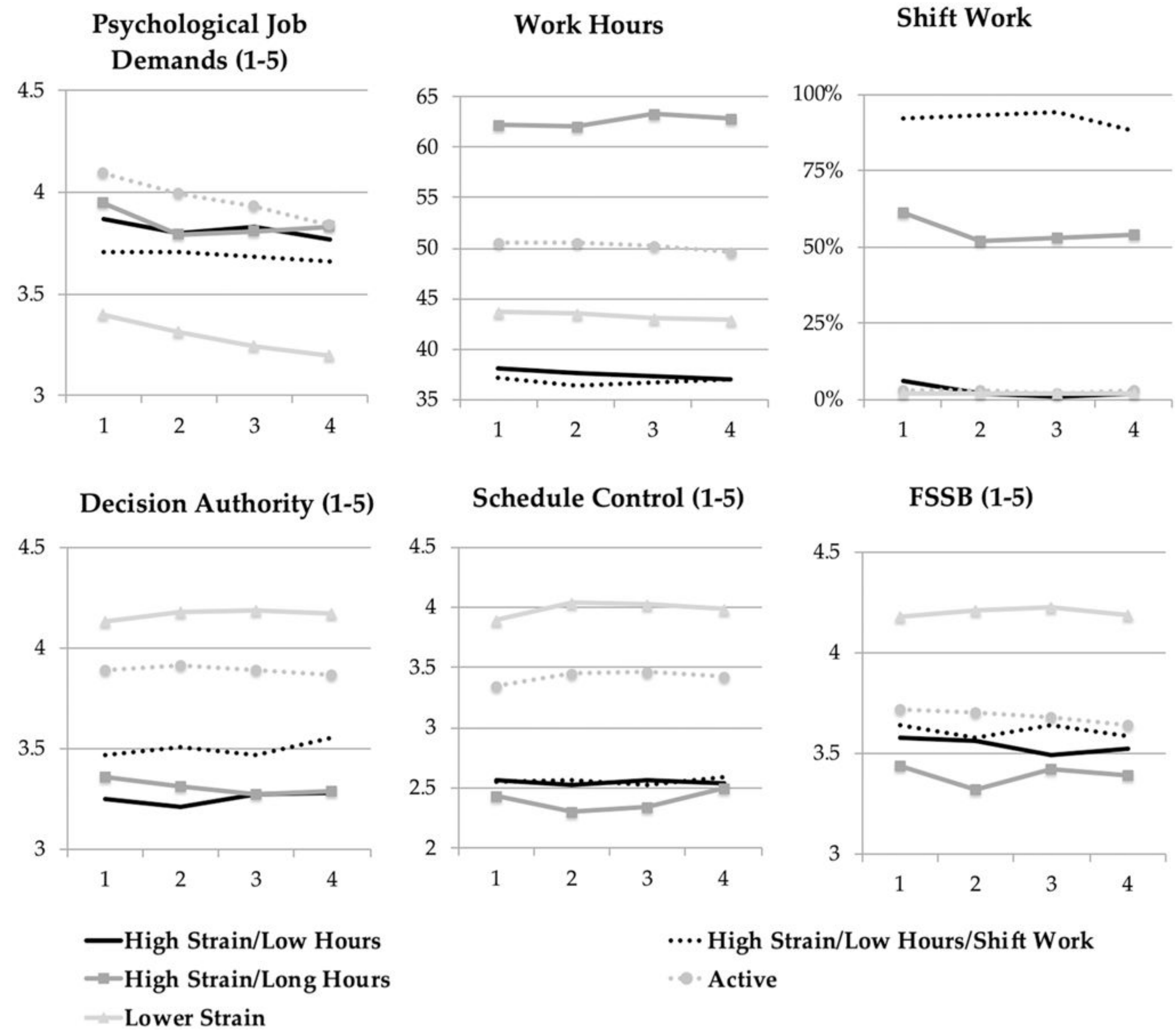

Fig. 2.
Means of job demands/resources variables at four waves six months apart, by job constellation membership.

Table 1:

Descriptive Statistics, by Industry (IT/LTC)

	IT		LTC (Long-TermCare)		
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	
Well-being Outcomes					
Job Satisfaction (W1)	4.02	0.76	4.25	0.61	***
Job Satisfaction (W4)	3.98	0.78	4.17	0.65	***
Emotional Exhaustion (W1)	4.29	1.54	4.44	1.62	
Emotional Exhaustion (W4)	3.97	1.52	4.23	1.68	**
Work-to-Family Conflict (W1)	3.12	0.94	2.79	0.90	***
Work-to-Family Conflict (W4)	2.86	0.88	2.68	0.87	***
Family-to-Work Conflict (W1)	2.12	0.67	2.07	0.58	
Family-to-Work Conflict (W4)	2.09	0.63	2.05	0.54	
Psychological Distress (W1)	10.63	3.15	11.76	4.31	***
Psychological Distress (W4)	10.18	3.31	11.00	4.04	***
Task- and Time-based Demands and Resources					
Psychological Job Demands (W1)	3.68	0.71	3.83	0.72	***
Psychological Job Demands (W4)	3.44	0.69	3.74	0.71	***
Psychological Job Demands (W4-W1)	−0.25	0.67	−0.09	0.73	***
Work Hours (W1)	47.10	7.34	41.49	11.22	***
Work Hours (W4)	46.29	8.62	40.87	11.00	***
Work Hours (W4-W1)	−0.81	8.79	−0.62	9.23	
Shift work (W1)	1%		39%		***
Shift work (W4)	1%		35%		***
Shift work (W4-W1)	0%		−4%		**
Decision Authority (W1)	3.89	0.68	3.57	0.78	***
Decision Authority (W4)	3.92	0.64	3.59	0.74	***
Decision Authority (W4-W1)	0.03	0.66	0.02	0.72	
Schedule Control (W1)	3.62	0.68	2.76	0.78	***
Schedule Control (W4)	3.74	0.63	2.76	0.80	***
Schedule Control (W4-W1)	0.12	0.55	0.00	0.75	***
Family Supportive Supervisor Behaviors (W1)	3.86	0.81	3.74	0.85	**
Family Supportive Supervisor Behaviors (W4)	3.86	0.80	3.66	0.85	***
Family Supportive Supervisor Behaviors (W4-W1)	0.00	0.87	−0.08	0.94	
Covariates (Wave 1)					
Female	38%		93%		***
Age	46.01	8.36	39.66	12.13	***
Race					
Non-Hispanic white	70%		68%		
Non-Hispanic Black	4%		16%		***
Hispanic	6%		12%		***
Asian	20%		4%		***

	IT		LTC (Long-TermCare)		
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	
Native-born	74%		75%		
Educational Attainment					
High School or Lower	2%		35%		***
Some College	18%		50%		***
College or Higher	80%		15%		***
Tenure (in years)	13.00	8.90	7.24	6.90	***
Personal income	96574	21947	37800	18726	***
Manager	24%		13%		***
Changes in Marital Status					
Continuously married	82%		59%		***
Continuously single	15%		29%		***
Got married	2%		6%		***
Divorced	1%		6%		***
Changes in Parental Status					
No child living at home both waves	36%		39%		
No (W1) --> Yes (W4)	4%		5%		
Yes (W1) --> No (W4)	3%		2%		
Child living at home both waves	57%		53%		
Changes in Adult Care					
No both waves	67%		61%		*
No (W1) --> Yes (W4)	9%		10%		
Yes (W1) --> No (W4)	13%		15%		
Yes both waves	11%		15%		
Randomized to STAR	51%		46%		*

Note: The last column reports *t*-test results examining whether IT and LTC workers are significantly different in respective variables.

*** $p<0.001$

** $p<0.01$

* $p<0.05$

Table 2:

Means, Standard Deviations, Bivariate Correlations, and Cronbach's Alphas for Key Predictors and Outcomes at Wave 1 and Wave 4

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
1. Psychological Job Demands (W1)	3.77	0.72	*0.57*																					
2. Psychological Job Demands (W4)	3.61	0.71	0.52	*0.59*																				
3. Work Hours (W1)	43.9	10.13	0.14	0.05	--																			
4. Work Hours (W4)	43.19	10.4	0.06	0.07	0.61	--																		
5. Shift work (W1)	22%	--	−0.01	0.06	−0.12	−0.08	--																	
6. Shift work (W4)	20%	--	0.00	0.04	−0.10	−0.08	0.77	--																
7. Decision Authority (W1)	3.71	0.75	−0.12	−0.10	0.13	0.17	−0.16	−0.17	*0.67*															
8. Decision Authority (W4)	3.73	0.72	−0.06	−0.14	0.10	0.10	−0.14	−0.14	0.55	*0.70*														
9. Schedule Control (W1)	3.13	0.85	−0.14	−0.16	0.18	0.17	−0.34	−0.32	0.46	0.39	*0.79*													
10. Schedule Control (W4)	3.18	0.88	−0.13	−0.23	0.18	0.15	−0.35	−0.31	0.37	0.48	0.69	*0.81*												
11. FSSB (W1)	3.79	0.84	−0.15	−0.08	−0.02	0.05	−0.09	−0.09	0.33	0.22	0.29	0.24	*0.88*											
12. FSSB (W4)	3.75	0.84	−0.09	−0.12	−0.01	0.02	−0.11	−0.10	0.21	0.37	0.26	0.34	0.41	*0.90*										
13. Job Satisfaction (W1)	4.15	0.69	−0.10	−0.05	−0.03	0.00	0.04	0.05	0.33	0.22	0.18	0.10	0.30	0.16	*0.84*									
14. Job Satisfaction (W4)	4.09	0.71	−0.07	−0.08	−0.02	0.00	0.01	0.03	0.23	0.34	0.12	0.19	0.23	0.33	0.55	*0.87*								
15. Emotional Exhaustion (W1)	4.38	1.59	0.44	0.30	0.09	0.02	0.01	0.00	−0.27	−0.19	−0.26	−0.22	−0.29	−0.20	−0.37	−0.30	*0.88*							
16. Emotional Exhaustion (W4)	4.12	1.62	0.33	0.42	0.06	0.09	0.04	0.02	−0.16	−0.26	−0.22	−0.27	−0.15	−0.26	−0.23	−0.33	0.59	*0.90*						
17. Work-to-Family Conflict (W1)	2.94	0.93	0.38	0.23	0.26	0.18	−0.04	−0.06	−0.18	−0.14	−0.15	−0.09	−0.28	−0.15	−0.34	−0.27	0.54	0.37	*0.90*					
18. Work-to-Family Conflict (W4)	2.76	0.88	0.27	0.38	0.17	0.24	0.01	0.01	−0.12	−0.21	−0.13	−0.22	−0.15	−0.22	−0.23	−0.32	0.38	0.52	0.57	*0.91*				
19. Family-to-Work Conflict (W1)	2.09	0.62	0.08	0.06	0.00	0.01	0.02	0.02	−0.15	−0.17	−0.10	−0.10	−0.13	−0.09	−0.23	−0.18	0.24	0.15	0.37	0.28	*0.83*			
20. Family-to-Work Conflict (W4)	2.07	0.58	0.07	0.09	−0.02	0.01	0.02	0.02	−0.15	−0.20	−0.11	−0.14	−0.08	−0.12	−0.18	−0.24	0.20	0.23	0.24	0.43	0.48	*0.86*		
21. Psychological Distress (W1)	11.28	3.89	0.17	0.18	−0.03	−0.05	0.08	0.10	−0.28	−0.29	−0.30	−0.25	−0.19	−0.18	−0.21	−0.16	0.43	0.37	0.31	0.25	0.24	0.21	*0.83*	
22. Psychological Distress (W4)	10.65	3.77	0.12	0.20	−0.04	−0.02	0.05	0.07	−0.19	−0.29	−0.22	−0.24	−0.08	−0.19	−0.15	−0.22	0.32	0.42	0.18	0.32	0.18	0.28	0.58	*0.84*

Note: Cronbach's alpha is reported on diagonal line in italics.

Table 3:

OLS Models Predicting Changes in Well-being over 18 Months

VARIABLES	Job Satisfaction	Emotional Exhaustion	Work-to-Family Conflict	Family-to-Work Conflict	Psychological Distress
Cluster (Ref. = Lower strain)					
High strain/low hours	−0.361***d (0.050)	0.614*** (0.110)	0.314***c (0.060)	0.206*** (0.042)	0.756** (0.255)
High strain/low hours/ shift work	−0.313***d (0.055)	0.535*** (0.120)	0.373***c (0.067)	0.199*** (0.047)	0.733** (0.283)
High strain/long hours	−0.297*** (0.076)	0.707*** (0.168)	0.558***a, b (0.094)	0.197** (0.065)	0.785* (0.395)
Active	−0.173***a, b (0.041)	0.557*** (0.093)	0.424*** (0.052)	0.137*** (0.035)	0.647** (0.213)
IT (Ref. = LTC [Long-Term Care])	−0.211*** (0.053)	0.157 (0.113)	0.141* (0.064)	0.091* (0.045)	0.414 (0.270)
Lagged Dependent Variable (W1)	0.490*** (0.023)	0.535*** (0.022)	0.452*** (0.021)	0.414*** (0.021)	0.517*** (0.021)
Control Variables (see Note 1)	Yes	Yes	Yes	Yes	Yes
Constant	2.244*** (0.151)	0.975*** (0.252)	1.043*** (0.139)	1.020*** (0.102)	4.705*** (0.608)
Observations	1,610	1,607	1,610	1,610	1,610
R-squared	0.343	0.388	0.370	0.267	0.361

Notes: 1. All models control for gender, age, race/ethnicity, nativity, educational attainment, tenure, manager status, marital status, parental status, adult care responsibility, and being assigned to an intervention that aims to improve schedule control and supervisory support. These estimates are omitted for the sake of space, but are available upon request.

2. We performed pairwise Wald tests for differences in well-being between different clusters. Results are shown in superscripts:

[a] (p < .05 compared with “high strain/low hours”)

[b] (p < .05 compared with “high strain/low hours/shift work”)

[c] (p < .05 compared with “high strain/long hours”)

[d] (p < .05 compared with “active”). Comparisons with the “lower strain” cluster are denoted by stars (as the lower-strain cluster is the reference group).

3. Standard errors in parentheses.

*** p<0.001

** p<0.01

* p<0.05