WORK & STRESS, APRIL–JUNE 2004, VOL. 18, NO. 2, 149–166

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The relationships between work characteristics and mental health: Examining normal, reversed and reciprocal relationships in a 4-wave study

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Keywords: Longitudinal research; Demand-Control-Support model; Well-being; Causation; Reciprocal relationships; Structural equation modelling.

This longitudinal study examined the causal relationships between job demands, job control and supervisor support on the one hand and mental health on the other. Whereas we assumed that work characteristics affect mental health, we also examined reversed causal relationships (mental health influences work characteristics). Further, the topic of the appropriate time lag for testing causal relationships was addressed. Our hypotheses were tested in a 4-wave study among a heterogeneous sample of 668 Dutch employees using structural equation modelling. The results provide evidence for reciprocal causal relationships between the work characteristics and mental health, although the effects of work characteristics on well-being were causally predominant. The best model fit was found for a 1-year time lag. Compared to earlier—predominantly cross-sectional—results, the present study presents a stronger case for the effects of work characteristics on the development of strain. The results also emphasize the need for a dynamic view of the relationship between work and health; the one-directional viewpoint in many work stress models does not seem to fully capture the relations between work characteristics and well-being.

1. Introduction

For several decades the Demand-Control-Support model (DCS model; Johnson & Hall, 1988; Karasek & Theorell, 1990) has been one of the dominant work stress models in the field of occupational health psychology. According to the model, employees working in high strain jobs (i.e. jobs characterized by high job demands, low job control and low social support) will experience a higher than average number of health problems over time (e.g. high blood pressure, low mental health) than workers in other jobs. This strain or 'iso-strain' hypothesis has been tested extensively, revealing mixed support for this hypothesis

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Work & Stress ISSN 0267-8373 print/ISSN 1464-5335 online © 2004 Taylor & Francis Ltd
http://www.tandf.co.uk/journals/
DOI: 10.1080/02678370412331270860

(Belkić, Schnall, Landsbergis, & Baker, 2004; de Lange, Taris, Kompier, Houtman, & Bongers, 2003; Van der Doef & Maes, 1999 for reviews).

Structural models such as the DCS model focus on specific aspects in the complex psychosocial work environment to explain how individuals perceive and react to their job. One basic assumption of the DCS model (and most other work stress models) is that the relationship between work and health is *one-directional*, such that work characteristics as measured at one point in time influence health at a later point in time. Such effects of work characteristics on health will be denoted as *normal* causal relationships in the remainder of this study. The DCS model does not take into account that the associations between work characteristics and health may also be explained by *reversed* causal relationships (in which Time 1 health influences Time 2 job demands) or *reciprocal* (bi-directional) relationships in which the DCS dimensions and health mutually influence each other (Williams & Podsakoff, 1989; Zapf, Dormann, & Frese, 1996). We believe that in order to obtain a better understanding of the relationship between work characteristics and health, one should also investigate these other possible relationships between work and health (Bollen, 1989; Hurrell, Nelson, & Simmons, 1998).

The present paper focuses on the question of whether the associations between work characteristics and health are due to normal causal relationships (i.e. work characteristics influence health) or reversed/reciprocal relationships. The answer to this question has practical as well as theoretical implications, as evidence for reversed or reciprocal causal relationships implies that adjustments to the interpretation and presentation of the Demand-Control-Support model are needed. Evidence for reversed causal effects would necessitate further theorizing as to the specific underlying mechanisms that might explain such reversed effects, as currently little theorizing is available (cf. Spector, Zapf, Chen, & Frese, 2000; Zapf *et al*., 1996). Following these researchers, our point of departure is that reversed effects of mental health status may be due to either *real* positive or negative changes of the work environment (environmental changes) or to changes in the *evaluation* of the *same* work environment (perceptual changes). For example, a negative reversed lagged effect of depression on the DCS dimensions might be explained by two different processes, namely the depressed worker (a) perceives his or her work environment more negatively (perceptual change), or the depressed worker 'drifts off' to a more negative work environment as a result of (b) a job transfer, or (c) changes within the same job (environmental change; Zapf *et al*., 1996). Before trying to disentangle such reverse causation mechanisms, the primary question is whether we can indeed find evidence for reversed effects of mental health on work across time.

We first present a brief review of the evidence for reversed and reciprocal causal relationships between work characteristics and health. Then we examine the (normal and reversed) relationships between work characteristics and health in a 4-wave study using data from a heterogeneous sample of 688 Dutch employees.

1.1. *Evidence for reversed and reciprocal causal relationships*

Few longitudinal studies in occupational health psychology have explored reversed and reciprocal causal relationships. In a recent review, de Lange *et al*. (2003) found that only 2 of 19 (11%) of high-quality longitudinal studies examining the effects of demands, control and support on worker health explicitly tested reversed or reciprocal causal relationships. These two studies provided no support for reversed or reciprocal causal relationships. Zapf *et al*. (1996) found that only 15 of the 39 longitudinal organizational stress studies in their review explored reversed causal relationships. Seven of these 15 studies (47%) supported these relationships. For example, Kohn and Schooler (1982) found evidence for an effect of anxiety on time pressure, whereas Marcelissen, Winnubst, Buunck, and Wolff (1988) found an effect of health complaints (e.g. strain, worry, and diastolic blood pressure) on co-worker support.

Recent longitudinal studies on work stress have also presented evidence for reversed or reciprocal causal relationships. For example, Bakker, Schaufeli, Sixma, Bosveld, & van Dierendonck (2000) found that high levels of Time 1 depersonalization were associated with higher Time 2 frequency and intensity of patient demands, whereas de Jonge *et al*. (2001) reported a positive longitudinal effect of emotional exhaustion on job demands. Similarly, Leiter and Durup (1996) found a reversed relationship between emotional exhaustion on the one hand and work overload and supervisor support on the other. Taris, Bok, & Caljé (1998) found evidence for reciprocal effects between job characteristics and depression. Depressive workers who experienced a job change reported less positive outcomes compared to non-depressive workers who changed jobs. Finally, Taris (1999) reported that job characteristics (e.g. variety, autonomy and job security) and mental health (depression, self-esteem and general health) mutually influenced each other.

Thus, it seems that there is some reason to assume that work characteristics and mental health mutually influence each other. However, many of the studies discussed above suffer from methodological shortcomings. First, not all studies employed a design in which the same variables were measured at all occasions for the same panel of respondents. Such a design is needed to adequately test reversed or reciprocal causal relationships, as it allows for examining changes in variables and in associations between variables over time (Kessler & Greenberg, 1981).

Second, not all studies used structural equation modelling (SEM) for testing these effects. Several researchers (Williams & Podsakoff, 1989) advise the use of SEM instead of simpler techniques because SEM can: (1) account for correlated measurement errors over time; (2) estimate different types of causation simultaneously in a multi-variable/multi-wave model; and (3) control for various method and third variable problems (Zapf *et al*., 1996). Further, SEM can be used for determining causal priority or causal predominance when finding reciprocal relationships. That is, if lagged effects of both work characteristics on health and health on work are found, SEM can be used to test whether the normal or the reversed causal relationship is causally predominant (Byrne, 2002; Rogosa, 1980).

Third, the majority of these longitudinal studies neglected the issue of the appropriateness of the time lag used in these studies for examining the relationship between work and health. One basic assumption in longitudinal research is that the time lag between the waves of a study corresponds with the underlying, 'true' time lag. If the time lag in the study does not correspond with the true time lag, the effects of the causal variables on the outcomes will be biased. If a particular time lag is shorter than the underlying causal process, it is likely that effects of the causal variable on the effect variable are underestimated (the causal variable will not have fully consummated its impact on the effect variable). If the time lag is too long, it is possible that other processes have influenced the effect variable, implying that the causal effects are biased as well (Taris, 2000). Generally speaking, we have little information about the 'right' length of time lags in occupational health research (Dormann & Zapf, 2002; Frese & Zapf, 1988; Taris & Kompier, 2003; Zapf *et al*., 1996). This was clearly demonstrated in the review by de Lange *et al*. (2003) in which only 7 of 45 longitudinal studies (16%) presented a clear rationale for the time lag that was employed. In addition, there is some diversity in the recommendations made for the appropriate time lag in examining longitudinal relationships between work and health. While Zapf *et al*. (1996) recommend that the same time lag be used if a study includes more than two measurements, Frese (1984) argues that in such cases processes may be captured better using different time lags. In practice, the length of time lags is often based on the practical facilities of the research project or the time available to the researchers and the participants. Research that compares the results across different time lags is thus clearly needed. Relevant to this issue, Dormann and Zapf (1999) compared findings on the effects of work characteristics on worker well-being for several time lags (4 months, 8 months and 1 year intervals, respectively). When examining the moderating effects of social support by supervisors and colleagues relative to social stressors at work and depressive symptoms, they only found effects for an 8-month time lag. Recently, Dormann and Zapf (2002) examined this question more thoroughly in a 4-wave study and found that a time lag of at least 2 years (compared to 4-year time lags) was adequate for examining the relationship between social stressors at work, irritation, and depressive symptoms.

1.2. *The present study*

The present study deals with the issues outlined above in the context of a 4-wave full panel design (1994, 1995, 1996, 1997), providing evidence regarding (1) the nature of the relationships between work characteristics and health, and (2) the length of the time interval during which the effects of work characteristics on health — or vice versa — occur. As regards the first issue, we examine the following research questions and hypotheses

Question 1: Which causal relationship(s) exist(s) between the DCS measures and mental health?

Considering the significant correlations between the DCS dimensions and various outcomes presented in earlier reviews on the Demand-Control-(Support) model (de Lange *et al*., 2003; Schnall *et al*., 1994; Van der Doef & Maes, 1999), we expect that there will be a significant lagged relationship between the DCS measures and mental health (*Hypothesis 1*). If Hypothesis 1 is retained, the question concerning the nature of the causal process that is responsible for this association becomes salient. We examine three types of causal relationships. First, whether job demands, job control and social support influence mental health over time (normal causal relationships). Second, whether mental health influences job demands, job control and social support (reversed causal relationships). Third, whether job demands, job control, social support and mental health reciprocally influence each other.

De Lange *et al*. (2003) reviewed 19 high quality longitudinal studies examining the DCS model and found evidence for normal causal relationships between the dimensions of the DCS model and different health outcomes over time. Consequently, we expect that there will be normal causal relationships between the DCS measures and indicators of mental health across time. Additionally, the research reviewed above also revealed evidence for reversed or reciprocal relationships between work and health. Considering the evidence for both normal and reversed effects found in the aforementioned longitudinal studies, we expect to find reciprocal causal relationships rather than normal or reversed causal relationships only (*Hypothesis 2*).

This study also examines which time lag between the waves yields the strongest lagged effects of the independent on the outcome variables.

Question 2. Which time lag shows the strongest results for demonstrating the relationship between the DCS dimensions and mental health across time?

As Dormann and Zapf (1999, 2002) found the strongest effects for time lags of 8 months and 2 years, it is expected that a 1-year time lag (i.e. the smallest possible time lag in the present study (versus 2 or 3 years)), would be most appropriate for demonstrating the relationship between the DCS dimensions and mental health (*Hypothesis 3*).

2. Method

2.1. *Sample*

The current study was conducted within the framework of the 4-wave prospective Dutch cohort Study on Musculoskeletal disorders, Absenteeism, Stress and Health (SMASH). At baseline (i.e. 1994), 1789 employees working in 34 different companies, located throughout the Netherlands, participated in this study. These 34 companies were recruited in co-operation with Occupational Health Services and included various industrial and service branches. In order to be included, companies should not have been involved in major reorganizations during the 3 years of the study, and the pre-study annual turn-over rate of their workforce had to be lower than 15%. Further, only respondents were selected who had been working for at least 1 year and more than 20 h per week in their current job. Blue-collar jobs as well as white-collar jobs and different occupations were selected.

At each wave (i.e. 1994, 1995, 1996 and 1997) the respondents completed a self-administered questionnaire, tapping concepts such as general working conditions, changes in the workplace, psychosocial work characteristics, work satisfaction, physical work load, psychosocial and physical health, and background factors (Ariëns *et al*., 2001; Hoogendoorn *et al*., 2000). The data in this study are based on the annual questionnaires measuring psychosocial variables. To ensure valid and reliable results, employees who held a temporary contract and employees receiving a benefit because of (partial) disability were excluded, meaning that 47 of the 1789 respondents were excluded. Further, employees who experienced job changes during the study were excluded, as these transitions may distort the nature of the (normal) causal relationships ($N = 1074$ at baseline; cf. de Lange, Taris, Kompier, Houtman, & Bongers, 2002). The selected stayers reported no job changes (during the past 12 months), or any changes regarding their colleagues or supervisor(s).

2.1.1. *Attrition rate:* The response rates were relatively high and varied between 84% ($N = 1742$) at baseline to 85% ($N = 1473$) at the third follow-up measurement. Non-response analysis revealed that drop-outs tended to report more strain and less job control across time, a quite common phenomenon (Taris, 2000, for a review). After listwise deletion of missing values, the sample included 668 employees (69% male; average age at baseline was 35.4 years, $SD = 8.7$; average number of years of employment was 9.8 years, $SD = 7.8$).

2.2. *Measures*

2.2.1. *Job demands:* Job demands were measured using a 5-item Dutch translation of Karasek's (1985) Job Content Questionnaire (e.g. 'My job requires working very fast', 1 = strongly disagree', 4 = 'strongly agree'). The reliability (Cronbach's α) of this scale varied from .65 to .72 across occasions (median = .71).

2.2.2. *Job control:* Consistent with Karasek's (1985) conceptualization, job control was measured as the mean of two scales. *Skill discretion* was measured using a 5-item scale (e.g. 'My job requires that I learn new things'), and *decision authority* was measured using a 3-item scale (e.g. 'My job allows me to take many decisions on my own', 1 = 'strongly disagree', 4 = 'strongly agree'). The reliabilities of this scale ranged from .81 to .83 (median $\alpha = .83$).

2.2.3. *Social support from supervisors:* Social support from supervisors was measured using a 4-item Dutch version of Karasek's (1985) Job Content Questionnaire (e.g. 'My supervisor pays attention to what I say', 1 = 'strongly disagree', 4 = 'strongly agree'). The reliability (Cronbach's α) of this scale varied from .82 to .88 across occasions (median = .86).

2.2.4. *Mental health:* The current study included three indicators of mental health.

1. *Depression* was measured with an 11-item Dutch version of the CES-D scale (Kohout, Berkman, Evans, & Cornoni-Huntley, 1993; Radloff, 1977). This scale taps symptoms of depressive mood (e.g. 'The past two weeks I felt lonely', 1 = 'hardly ever or never', 2 = 'sometimes', 3 = 'much or most of the time'). The reliability varied from .81 to .87 (median $\alpha = .85$).
2. *Job satisfaction* was measured by a single item ('Do you enjoy your work?', 1 = '(almost) never', 4 = '(almost) always'). A meta-analysis of Wanous, Reichers, & Hudy (1997) demonstrated that single-item measures of job satisfaction are usually highly correlated with multi-item scales.
3. *Emotional exhaustion* was measured by a 7-item dichotomous subscale of the Maslach Burnout inventory (Schaufeli & Van Dierendonck (1993) e.g. 'I feel emotionally drained from my work', 0 = 'no', 1 = 'yes'). The reliability varied from .72 to .78 (median $\alpha = .77$).

2.2.5. *Covariates:* Age and gender were used as covariates in the analysis. These variables are often related to the outcome variables employed in this study. Failing to control for these variables may result in bias in the effects of other variables (de Jonge & Kompier, 1997; Karasek & Theorell, 1990; Schnall *et al*., 1994). In preliminary analyses we also controlled for level of education and years of experience in the present job. These variables were not included further as preliminary analyses revealed that these were not substantially related ($p > .05$) to the outcome variables.

2.3. *Statistical analysis*

Correlational analyses were conducted to obtain more basic insight into the data. Structural equation modelling (SEM; Jöreskog & Sörbom, 1993) was used to test and compare various competing models for the relationships among demands, control and social support of supervisors and indicators of mental health across time. SEM has the advantage of providing global measures of fit for latent variable models (Brannick, 1995). In the present research we performed a comparative analysis in which the fit of several competing models was assessed to determine which model fitted the data best (Kelloway, 1998). All model tests were based on the covariance matrix and maximum likelihood estimation. A non-significant or small chi-square value indicates that the model fits the data well. However, in large samples even small and substantively unimportant differences between the estimated model and the 'true' underlying model will result in rejection of the model that is tested (Bentler & Chou, 1987). Therefore, we also considered other indices in judging the fit of our models, including the goodness-of–fit index (GFI: based on a ratio of the squared discrepancies to the observed variances; Jöreskog & Sorbom, 1993), the non-normed fit index (NNFI: represents the increase in fit when comparing any hierarchical step-up comparison of two models; Bentler & Bonett, 1980) and the root-mean square error of approximation (RMSEA: based on the analysis of the residuals; Jöreskog & Sorbom, 1993). Levels of .90 or better for GFI and NNFI and levels of 1.05 or lower for RMSEA indicate that models fit the data reasonably well (Byrne, 2002).

Considering the problems caused by estimating all observed items and latent variables (insufficient power and under-identification, Bentler & Chou, 1987; Schumacker & Lomax, 1996), we assumed the scale and latent variables to be identical. However, following the two-step approach proposed by James, Mulaik and Brett (1982) we first tested the measurement models for each of the variables before fitting the structural models. These analyses showed that the factor structures of the research variables were consistent across time. Finally, all results presented below are based on the standardized results from the covariance matrices of the variables.

2.3.1. *Competing structural models:* To examine the causal relationships between the DCS dimensions and indicators of mental health we tested a baseline model versus several competing nested models. These models were:

1. *Baseline model* (M_0): Includes temporal stabilities and synchronous (i.e. within-wave) effects of variables over time and controls for the influence of covariates (age and gender). This model is used as the reference model.
2. *Normal causation model* (M_1): This model resembles M_0, but includes additional cross-lagged structural paths from the Time 1, Time 2 and Time 3 DCS dimensions to Time 2, Time 3 and Time 4 mental health (depression, job satisfaction and emotional exhaustion; Figure 1).
3. *Reversed causation model* (M_2): This models resembles M_0, but is extended with cross-lagged structural paths from Time 1, Time 2 and Time 3 mental health

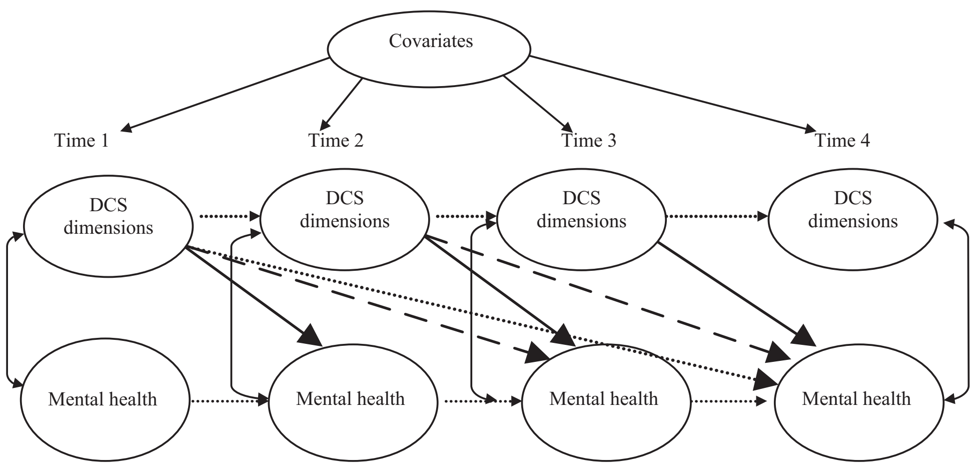

Figure 1. Normal causal relationship model (M_1) with different time lag effects.
Note. ——▶: 1-year effects; – –▶: 2-year effects; ·······▶: 3-year effects; DCS dimensions: job demands, control and social support of supervisor; indicators of mental health are: depression, job satisfaction and emotional exhaustion.

(depression, job satisfaction and emotional exhaustion) to Time 2, Time 3 and Time 4 DCS dimensions.

4. *Reciprocal causation model* (M_3): This model resembles M_0, but includes additional reciprocal cross-lagged structural paths from the DCS dimensions on well-being and vice versa (i.e. the normal paths included in model M_1 as well as the reversed paths included in model M_2).

Three additional models (M_4-M_6) tested whether the structural cross-lagged paths presented in models M_1-M_3 were the same for corresponding time intervals. That is, the effects for all 1-year intervals (Time 1 to Time 2, Time 2 to Time 3, and Time 3 to Time 4) were assumed to be the same; and the same was assumed for the two-year intervals (Time 1 to Time 3 and Time 2 to Time 3). Model M_4 is identical to M_1, save that the same-length lagged effects are constrained to be equal; model M_5 corresponds with M_2; and M_6 corresponds with M_3. This strategy allows us to test whether the results presented across the same time lags are consistent or that the strength of effects varies across time.

3. Results

3.1. *Correlational analyses*

Table 1 presents the means, standard deviations, and correlations between the different measures. Correlations between the measures were in the expected direction. As regards the across-time stability of these variables, the Time 1-Time 2 test-retest correlations ranged from .49 (for Depression) to .67 (for Control: median correlation was .55, all $ps < .001$); the Time 2-Time 3 test-retest correlations ranged from .56 (for Social support supervisor) to .68 (for Control: median correlation was .61; all $ps < .001$); the Time 3−Time 4 test-retest correlations ranged from .49 (Social Support) to .71 (Control; median correlation was .60; all $ps < .001$). Although these correlations are substantial, there is quite some across-time variation in the variables included in this study. For example, even a Time 3−Time 4 correlation as high as .71 for Control implies that both measures share no more than 50% of their variance.

Question 1: Which causal relationship(s) exist(s) between the DCS measures and mental health?

In order to answer question 1, the results of the six competing structural models described in the Method (M_0-M_6) were compared. Table 2 presents the fit indices for these models. The fit of all models was satisfactory (NNFI, GFI $\geq .90$ and RMSEA $\leq .05$). Further, we tested whether models M_1-M_6 fitted the data significantly better than the baseline model (Table 3). Relevant to question 1, this analysis shows whether a model including relationships between work and health shows a better fit than a model without these relationships.

The chi-squared difference tests in Table 3 show that M_1-M_6 all fit the data significantly better than the baseline model. Thus, there are longitudinal relationships between the DCS dimensions and mental health (Hypothesis 1 confirmed). To determine whether these relationships were consistent across time, we computed three additional chi-square difference tests that compared models M_1-M_3 to the corresponding models M_4-M_6 (Table 3). These tests revealed that the differences between the constrained models M_4-M_6 and their unconstrained counterparts M_1-M_3 were non-significant. Considering these non-significant results and the relatively better incremental fit indices for M_4-M_6 (cf. Table

Table 1. Correlations, means and standard variables for the study variables ($N = 668$).

Variables	*M*	*SD*	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
1 Age	35.93	8.71	1.00																									
2 Gender*	1.31	0.46	−.14	1.00																								
3 Dem T1	2.60	0.46	.03	.01	1.00																							
4 Dem T2	2.52	0.49	.02	.01	.56	1.00																						
5 Dem T3	2.64	0.49	.03	.00	.53	.62	1.00																					
6 Dem T4	2.58	0.47	.04	.01	.51	.58	.64	1.00																				
7 Cont T1	2.81	0.50	.11	−.21	−.04	−.02	−.06	.02	1.00																			
8 Cont T2	2.86	0.48	.11	−.16	.00	−.04	−.06	.03	.67	1.00																		
9 Cont T3	2.86	0.46	.11	−.18	−.08	−.06	−.09	−.02	.63	.68	1.00																	
10 Cont T4	2.84	0.48	.08	−.20	−.05	−.06	−.08	.01	.64	.67	.71	1.00																
11 Sup T1	2.73	0.55	.06	.03	−.18	−.10	−.13	−.13	.25	.18	.18	.18	1.00															
12 Sup T2	2.66	0.58	.04	.05	−.11	−.21	−.16	−.16	.13	.30	.21	.21	.51	1.00														
13 Sup T3	2.64	0.58	.07	.04	−.14	−.18	−.24	−.21	.13	.18	.23	.18	.47	.56	1.00													
14 Sup T4	2.62	0.59	.01	.04	−.16	−.20	−.20	−.25	.21	.24	.24	.34	.41	.52	.49	1.00												
15 Dep T1	1.26	0.27	−.04	.13	.12	.13	.09	.14	−.17	−.16	−.13	−.16	−.08	−.11	−.14	−.16	1.00											
16 Dep T2	1.29	0.29	−.02	.11	.12	.18	.18	.17	−.13	−.19	−.14	−.14	−.11	−.16	−.16	−.12	.49	1.00										
17 Dep T3	1.32	0.32	−.04	.21	.11	.17	.12	.17	−.14	−.15	−.17	−.17	−.06	−.12	−.15	−.12	.41	.59	1.00									
18 Dep T4	1.32	0.33	−.02	.15	.08	.15	.10	.17	−.10	−.15	−.18	−.21	−.04	−.13	−.13	−.10	.41	.50	.57	1.00								
19 Sat T1	3.37	0.70	.04	.10	−.08	−.06	−.09	−.08	.26	.26	.22	.20	.23	.16	.15	.13	−.18	−.21	−.17	−.20	1.00							
20 Sat T2	3.33	0.72	.04	.10	−.04	−.14	−.11	−.04	.25	.37	.27	.25	.21	.31	.23	.16	−.24	−.32	−.23	−.21	.53	1.00						
21 Sat T3	3.31	0.73	.07	.07	−.09	−.13	−.13	−.11	.26	.31	.35	.31	.22	.23	.33	.16	−.17	−.26	−.26	−.27	.52	.58	1.00					
22 Sat T4	3.30	0.74	.09	.05	−.07	−.12	−.12	−.16	.27	.30	.30	.35	.18	.26	.21	.22	−.23	−.30	−.29	−.34	.49	.56	.62	1.00				
23 Emo T1	0.15	0.17	−.01	.03	.40	.31	.32	.31	−.14	−.12	−.14	−.11	−.16	−.15	−.15	−.09	.32	.34	.27	.27	−.27	−.24	−.21	−.24	1.00			
24 Emo T2	0.14	0.18	−.02	.01	.29	.41	.33	.32	−.09	−.18	−.14	−.14	−.12	−.23	−.18	−.09	.33	.50	.35	.30	−.23	−.37	−.23	−.28	.58	1.00		
25 Emo T3	0.14	0.18	.00	.03	.30	.36	.46	.34	−.11	−.13	−.16	−.13	−.16	−.22	−.24	−.11	.29	.37	.39	.33	−.22	−.30	−.32	−.31	.53	.62	1.00	
26 Emo T4	0.13	0.18	.02	.03	.29	.36	.37	.46	.01	−.05	−.11	−.11	−.12	−.21	−.25	−.07	.28	.36	.32	.46	−.16	−.17	−.21	−.32	.49	.56	.58	1.00

* 0 = female and 1 = male. NB. Correlations of .05 and over are significant at $p < .05$; Dem = Job demands; Cont = Control; Sup = Social Support; Dep = Depression; Sat = Job satisfaction; Emo = Emotional Exhaustion. T1/T2/T3/T4 refer to Time 1, Time 2, Time 3 and Time 4, respectively.

Table 2. Fit indices for the stability model versus the nested (competing) causal structural models.

Model	χ^2	df	NNFI	GFI	RMSEA
M_0 Baseline model	393.44	180	.95	.95	.043
M_1 Normal causality	253.88	126	.95	.97	.040
M_2 Reversed causality	316.29	126	.93	.96	.048
M_3 Reciprocal causality	180.56	72	.93	.98	.048
M_4 Normal + equal relationships over time	288.29	153	.96	.97	.037
M_5 Reversed + equal relationships over time	340.75	153	.94	.96	.043
M_6 Reciprocal + equal relationships over time	240.54	126	.96	.97	.037
M_7 M_6+ equal normal and reversed relationships	290.44	153	.96	.97	.037

All chi-square values significant at $p < .001$; coefficients and numbers refer to model fit indices: χ^2, NNFI = Non-normed fit index, GFI = Goodness-of-fit index, RMSEA = Root-mean square error of approximation.

2), we concluded that the cross-lagged structural patterns did not vary across time. Further analyses were therefore based on M_4–M_6.

As regards the type of relationships between work and health (i.e. only normal effects, only reversed effects, or reciprocal causal relationships), we compared the fit of different models corresponding with these notions (Models M_4, M_5 and M_6, respectively). The results confirmed Hypothesis 2: the reciprocal model (M_6) accounted best for the data, relative to the normal causation model (M_4 versus M_6: $\Delta\chi^2$ (27, $N = 668$) = 47.75, $p < .05$) and the reversed causation model (M_5 versus M_6: $\Delta\chi^2$ (27, $N = 668$) = 100.21, $p < .05$).

As to this bi-directional relationship, the question remains as to which relation is causally dominant: the normal or the reversed pattern? To this aim, we tested the equality of the normal and reversed cross-lagged patterns (Model M_7). The chi-squared difference between the models with and without equality constraints was significant (M_6 versus M_7: $\Delta\chi^2$ (27, $N = 668$) = 49.90, $p < .05$). Consequently, the normal and the reversed cross-lagged patterns are unequal; one is causally predominant. The fit indices of the normal (M_4) and reversed (M_5) causation model (cf. Table 2) show that the normal causation model fits the data better than the reversed causation model. This suggests that the normal cross-lagged effects are dominant compared to the reversed effects, an impression that was confirmed by inspection of the parameter estimates in these models.

Question 2. Which time lag shows the strongest results for demonstrating the relationship between the DCS dimensions and mental health across time? A 'Knight's move'.

Table 3. Chi-square difference tests of different structural models.

Model		$\Delta\chi^2$	Δdf
Comparison with M_0			
M_0 versus M_1	Baseline model versus Normal causality model	139.56**	54
M_0 versus M_2	Baseline model versus Reversed causality model	77.15*	54
M_0 versus M_3	Baseline model versus Reciprocal causality model	212.88**	108
M_0 versus M_4	Baseline model versus Normal + equal relationships model	105.15**	27
M_0 versus M_5	Baseline model versus Reversed + equal relationships model	52.69*	27
M_0 versus M_6	Baseline model versus Reciprocal + equal relationships model	152.90**	54
Equal time lag effects?			
M_1 versus M_4	Normal causality model versus Normal + equal relationships model	34.41	27
M_2 versus M_5	Reversed causality model versus Reversed + equal relationships model	24.46	27
M_3 versus M_6	Reciprocal causality model versus Reciprocal + equal relationships model	59.98	54

*$p < .05$, **$p < .001$; $\Delta\chi^2$ = difference in chi-square values; Δdf = difference in degrees of freedom.

Our analyses suggest that work and mental health mutually influence each other. However, before the final model is obtained we must take an additional step. Just as the Knight's move in chess consists of two steps, a follow-up analysis to those presented above may yield more insight into the question as to which time lag or combination of time lags shows the best fit, i.e. across which time span the processes studied here operate. Our 4-wave panel study allows for examining the effects of three time lags (1, 2 and 3 years, and combinations of these three).

For this follow-up analysis six additional models were tested. The reciprocal causal model that was evaluated as the best model in step 1 was used as the baseline model (M_6 in Table 4). The other models specified reciprocal relationships across a time lag of 1 year only (M_8), across 2 years only (M_9) or across 3 years only (M_{10}). Further, combinations of these time lags were examined (M_{11}: a combination of 1- and 2-year intervals, M_{12}: a combination of 1- and 3-year intervals; and M_{13}: a combination of 2- and 3-year intervals). The fit indices of these models in Table 4 revealed that all models fitted the data reasonably well (GFI, NNFI $>.90$ and RMSEA $<.05$).

Table 5 shows that only the models with 1-year cross-lagged paths (M_8), the combination of 1- and 2-year intervals (M_{11}) and the combination of 1- and 3-year intervals (M_{12}) fit the data about equally well as the reference model M_6, as evidenced by non-significant increases in χ^2 values. Thus, models M_8, M_{11} and M_{12} present the same fit to the data compared to the baseline model, whereas the other models fit the data significantly worse. As parsimonious models (i.e. models with relatively few parameters) should be preferred to more complex models with the same fit (Kelloway, 1998), the model that only specified the relationships across a 1-year time lag (M_8) was chosen as the best-fitting model. Figure 2 presents the final model with the significant standardized cross-lagged structural paths. Note that these effects were constrained to be equal across all 1-year time intervals (i.e. the effects presented in Figure 2 apply to the Time 2−Time 3 and Time 3−Time 4 intervals as well).

Figure 2 presents evidence for normal as well as reversed relationships. Time 1 job demands influence Time 2 depression ($\beta = .04$, $p < .05$) and emotional exhaustion ($\beta = .11$, $p < 05$). These effects show that an increase in job demands is related to an increase in depression and emotional exhaustion across time. In addition, Time 1 social support of supervisors influences Time 2 emotional exhaustion ($\beta = -.06$, $p < .05$). An increase in social support of supervisors is related to a decrease in levels of emotional exhaustion across time. Furthermore, Time 1 job control influences Time 2 job satisfaction ($\beta = .10$, $p < .05$); an increase in job control is related to an increase in job satisfaction across time.

Table 4. Fit indices for different structural nested models (based on different time lags).

Model	χ^2	df	NNFI	GFI	RMSEA
M_6 Baseline model, reciprocal relationships that are constrained across time	240.54	126	.96	.97	.037
M_8 Reciprocal model/1-year time lag	283.75	162	.97	.97	.034
M_9 Reciprocal model/2-year time lag	334.51	162	.95	.96	.040
M_{10} Reciprocal model/3-year time lag	359.79	162	.94	.96	.044
M_{11} Reciprocal model/1 + 2-year time lags	262.13	144	.96	.97	.035
M_{12} Reciprocal model/1 + 3-year time lags	262.75	144	.96	.97	.035
M_{13} Reciprocal model/2 + 3-year time lags	312.59	144	.95	.96	.042

All chi-square values are significant at $p < .001$; NNFI = Non-normed fit index, GFI = Goodness of fit index, RMSEA = Root-mean square error of approximation.

Table 5. Chi-square difference tests of different structural models (based on different time lags).

Model		$\Delta\chi^2$	Δdf
Comparison with M_6			
M_6 versus M_8	Baseline Reciprocal causal model versus Reciprocal model/1-year time lag	43.12	36
M_6 versus M_9	Baseline Reciprocal causal model versus Reciprocal model/2-year time lag	93.97*	36
M_6 versus M_{10}	Baseline Reciprocal causal model versus Reciprocal model/3-year time lag	119.25*	36
M_6 versus M_{11}	Baseline Reciprocal causal model versus Reciprocal model/1 + 2-year time lag	21.59	18
M_6 versus M_{12}	Baseline Reciprocal causal model versus Reciprocal model/1 + 3-year time lag	22.21	18
M_6 versus M_{13}	Baseline Reciprocal causal model versus Reciprocal model/2 + 3-year time lag	72.05*	18
Comparison with M_8, M_{11}, M_{12}			
M_8 versus M_{11}	Reciprocal model/1-year time lag versus Reciprocal model/1 + 2-year time lag	21.62	18
M_8 versus M_{12}	Reciprocal model/1-year time lag versus Reciprocal model/1 + 3-year time lag	21	18

*$p < .001$; $\Delta\chi^2$ = difference in chi-square values (of for instance M_0 versus M_1); Δdf = difference in degrees of freedom (of for instance M_0 versus M_1).

The reversed relationships were somewhat weaker than the normal relationships. Reversed effects were found from Time 1 Job satisfaction to Time 2 job control ($\beta = .05$, $p < .05$) and Time 2 social support of supervisors ($\beta = .04$, $p < .05$), and from Time 1 emotional exhaustion to Time 2 job demands ($\beta = .04$, $p < .05$) and Time 2 social support of supervisors ($\beta = -.05$, $p < .05$). Thus, an increase in Time 1 job satisfaction is related to an increase in Time 2 job control and Time 2 social support of supervisors across time, whereas an increase in Time 1 emotional exhaustion results in an increase of Time 2 job demands and decrease of Time 2 social support of supervisors.

4. Discussion

Considering the paucity of longitudinal studies that explicitly examine different types of causal relationships and the potential impact of different time lags on the results, we addressed these issues in a 4-wave panel study. We explored different causal relationships between the DCS dimensions and indicators of mental health with 1-year, 2-year and 3-year (combinations of) time lags. The results revealed that there were cross-lagged relationships between the DCS dimensions and mental health (Hypothesis 1 confirmed). Furthermore, evidence was found for reciprocal causal relationships between the DCS dimensions and indicators of mental health (Hypothesis 2 confirmed). The strongest effects were found for a 1-year time lag (Hypothesis 3 confirmed), whereas the effects of job characteristics on health were stronger than the reverse effects. This pattern of results underscores the importance of job demands, job control and the social support of supervisors in the development of mental health across time. Consequently, these results also support the causal ordering of these work characteristics in well-known work stress models such as the Demand-Control-Support model (Karasek & Theorell, 1990).

In line with earlier longitudinal research (de Jonge *et al*., 2001; Leiter & Durup, 1996), reciprocal relationships were found for the relationship between job demands, social support of supervisors and emotional exhaustion. Furthermore, we found reciprocal relationships between job control and job satisfaction. In other words, consistently normal as well as reversed cross-lagged effects were found across the waves of our study.

How can the reversed effects found in this study be explained? As mentioned in the introduction, the available literature (Spector *et al*., 2000; Zapf *et al*., 1996) provides only a few clues with respect to the mechanisms that may account for reversed causation. Following Zapf *et al*. (1996) and Spector *et al*. (2000), we believe that reversed effects of

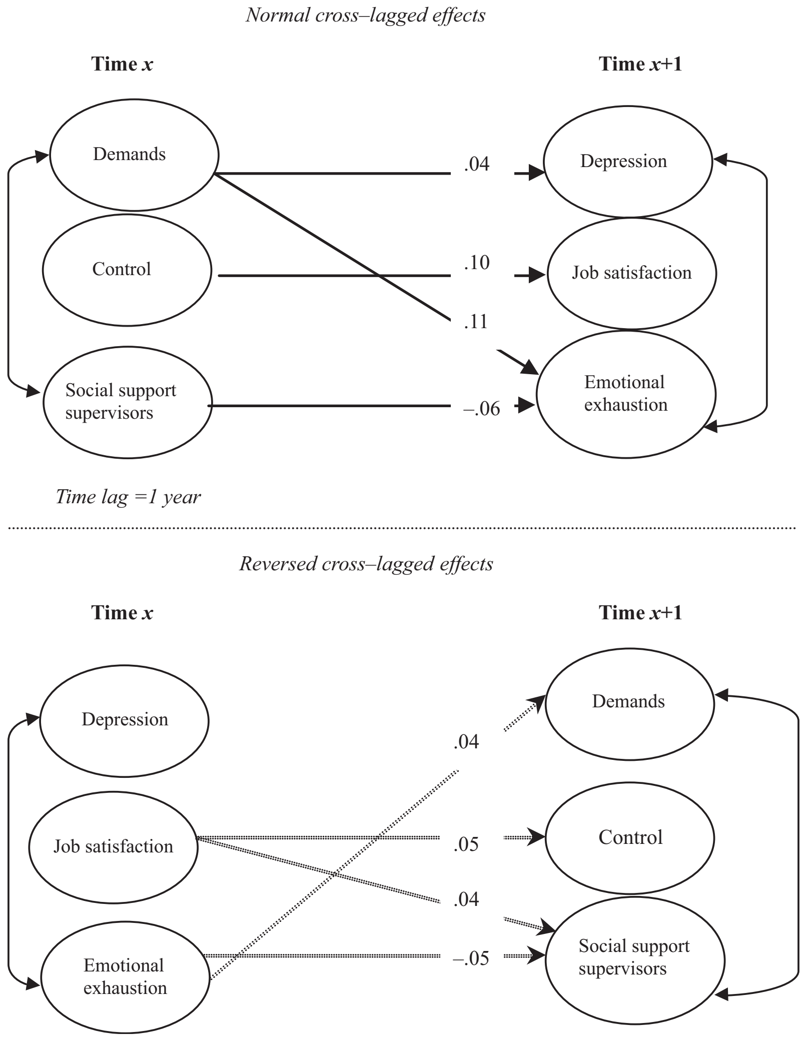

Figure 2. Reciprocal causal relationships between work and health based on a time lag of 1 year. Note. Standardized effects are presented (after controlling for covariates); stability effects not shown; R^2 = total amount of variance of specific variable explained by the model. R^2 for demands: 32% at T2, 43% at T3, 47% at T4; R^2 for control: 46% at T2, 52% at T3, 58% at T4; R^2 for social support: 26% at T2, 35% at T3, 33% at T4: R^2 for depression: 19% at T2, 36% at T3, 34% at T4; R^2 for job satisfaction: 27% at T2, 39% at T3, 45% at T4; R^2 for emotional exhaustion: 28% at T2, 41% at T3, 39% at T4.

mental health can be due to two basic mechanisms. First, *real* changes in one's work environment may occur due to one's mental health status. For example, it seems plausible that healthy workers have a better chance of getting promoted or finding a better job than other workers; all other factors being equal, few employers will consider a depressed job applicant more fit for the job than his or her non-depressed competitors (cf. Taris, 1999; Zapf *et al*., 1996). Reported changes in job characteristics across time may thus relate to the change from the current to a new job, but may also occur within the current job. Examples of such within-job changes are more support or more interesting tasks for healthier employees (those with a higher coping capacity). As this study only included employees who did not experience job changes (or changes in their colleagues or supervisors) across time, this type of explanation seems to be less plausible here.

The last mechanism focuses on changes in the employee's *evaluation* of the *same* work environment (i.e. the person's perception of the same working conditions changes as a result of their mental health status). For instance, the reversed effect of emotional exhaustion on demands and social support may be explained by assuming that the more fatigued employees perceive their work environment more *negatively* over time. As a consequence, the relatively unhealthy workers report higher job demands and lower levels of supervisor social support across time. Zapf *et al*. (1996) termed this negative re-interpretation effect the 'true strain-stressor process', whereas Spector *et al*. (2000) introduced the 'stressor creation hypothesis' (in the context of negative affectivity). One might say that these explanations all draw on the assumption that relatively unhealthy workers are apt to perceive their work environment in an increasingly *gloomy* fashion. Alternatively, the reversed effect of job satisfaction on job control might be explained by positive re-evaluation effects. One may assume that the satisfied workers colour their perceptions of the work characteristics more rosy ('rosy' perception mechanism), meaning that they will perceive more job control across time (Fletcher, 2003). Either, both or none of these two mechanisms may apply and we believe that occupational health psychology would benefit from clever thinking (theory) and from innovative empirical studies towards these mechanisms (Taris & Kompier, 2003).

4.1. *Study limitations*

At least two limitations of our study need to be discussed. First, the best fitting structural model (Figure 2) showed relatively low standardized regression coefficients. Hence, relatively little variance in the outcomes is accounted for in this study. However, according to Semmer, Zapf, and Greif (1996), small standardized effects are to be expected as they argue that there is an upper limit of 15 to 20% variance in strain that can be explained by job stressors. Moreover, it is important to note that the cross-lagged effects of, for instance, job demands on emotional exhaustion refer to predicting *change*s in emotional exhaustion from time 1 to time 2 (i.e. after controlling for Time 1−Time 2 stability effects). By definition these effects will be small, as many phenomena will be relatively stable across the 1-year time interval employed in this study. Thus, the small effects found in this study are common in longitudinal research. Further, we should not underestimate the cumulative effects of these relationships across time. Just like drops of water may dent a stone in time, the small effects found in our research may accumulate, possibly resulting in severe health complaints over time.

Second, this study is based on survey data. One problem of using survey data only is the risk of self-report bias, e.g. due to personality traits such as negative affectivity (Schnall *et al*., 1994). By combining self-report measures with 'objective' measures researchers can mitigate the effects of methodological and/or conceptual overlap between the measured variables, thus reducing the risk of falling in the 'triviality trap' (Kasl, 1978; Kristensen, 1996). On the other hand Spector (1992), in a meta-analysis, has shown that the variance in self-report measures of job conditions can largely be attributed to variations in the objective work environment. Based on the work of Spector (1992) and Semmer *et al*. (1996, p. 304) we argue that results from self-report data 'may be better than is often assumed' and that the discussion about self-report data versus 'objective' measures is not very constructive. Nevertheless, the impact of common method variance should be further examined in future research. For example, Lindell and Whitney (2001) describe a potentially interesting method that can be used for testing these effects.

4.2. *Study implications*

In spite of these limitations, we feel that the present study has important practical implications, both practical and scientific. The most important practical lesson that follows from the more dominant normal causal relationship between the DCS characteristics and mental health is that interventions directed at decreasing job demands, and increasing job control or social support of supervisors may improve the mental health of employees (see also Kompier & Taris, 2004; Semmer, 2003). However, the reciprocal relationships found between work and mental health indicate that, in general, professionals in the field of work and organizational psychology should bear in mind that well-being may affect work characteristics as well.

Scientifically, our results revealed that the associations between work characteristics and health should not be construed as the result of a one-directional process in which work characteristics influence health. Although for those employees who stay in the same type of work ('stayers') this normal causal process seems to be the most prominent, our results appear to confirm earlier findings that health also influences workers' job conditions. The results of this study thus indicate that the one-directional view in the original DCS model and similar models may be too narrow. Karasek and Theorell (1990, p. 99) also underscored the importance of using a broader perspective for the relationship between work and health, and proposed a dynamic version of the Demand-Control model, which integrates environmental effects with person-based information (such as self-esteem). Our results seem to be consistent with this dynamic view in which work has effects on strain levels of the employee, but in which it is also possible that health indicators influence work characteristics.

From this study we may derive four recommendations for future (longitudinal) research:

1. *Investigate different causal relationships*. Our study provided evidence for reciprocal causal relationships. We recommend that future research not only examines normal, but also reversed and reciprocal causal relationships between (the same and other) job characteristics and indicators of well-being. Such research may reveal to what degree the present results generalize to other settings (Rothman & Greenland, 1998).
2. *Explore multiple outcomes*. In our study we utilized job satisfaction, depression and emotional exhaustion as indicators of mental health. More research that focuses on different, preferably objective outcome variables is needed. Such research may also enhance our understanding of the degree to which common method variance has affected our (and previous) results. In addition, future research might explore in more detail the strength of across-time relations as a function of the type of outcome variable.
3. *Employ similar and different time lags*. The results from this study indicated that a 1-year time lag is appropriate for demonstrating the causal relationships between the DCS dimensions and the indicators of mental health employed in this study. On the other hand, in the studies of Dormann & Zapf (1999, 2002) evidence was found for a time lag of 8 months and of 2 years when examining the moderating effects of social support by supervisors and colleagues in the context of the effects of social

stressors at work on depressive symptoms. More longitudinal research is needed to replicate these results and to test other (especially shorter) time lags (cf. Hoogendoorn *et al*., 2002). We believe that the preferable length of time lag(s) will depend on the type of outcome being measured, the amount of exposure to the stressors of interest, and whether or not changes in work characteristics or job changes have taken place. It is important that the time lag suits the process and aetiology of the relationships between the research variables over time.

4. *Formulate and test different theoretical explanations for reciprocal relationships between work and health*. More and better explanations are needed for reversed or reciprocal causal relationships. The aforementioned explanations provided by Zapf *et al*. (1996) and the dynamic version of Karasek and Theorell's (1990) Demand-Control model only provide first steps towards a fuller understanding of reverse causation processes. One important factor in such additional theorizing will be the nature of across-time changes in work characteristics. Such changes may be based on either *real* or *perceived* changes. In this paper we tried to control for the effects of major job changes by restricting our data to participants who did not change jobs (or experience any changes in their colleagues or supervisors) during the study interval, suggesting that most of the changes in the work characteristics that occurred in this study refer to changes in the perceptions of these characteristics. However, in order to test reversed effects resulting in *real* changes of the environment it is important to examine a response group with job changes across time as well (de Lange, Taris, Kompier, Houtman, & Bongers, in press). Further theorizing on the possible effects of health on work characteristics will definitely enhance our understanding of the reversed or reciprocal effects between work and health.

Acknowledgements

This study was partly supported by the Dutch Ministry of Social Affairs and Employment; The Dutch Ministry of Public Health, Welfare, and Sports; and the Dutch National Institute for Social Security. The first author thanks Professor Peter Molenaar (University of Amsterdam) for checking some of our SEMs, and Femke de Lange for valuable discussions on earlier drafts of this paper.

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