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Interaction of working conditions, job satisfaction, and sickness absences: Evidence from a representative sample of employees ☆

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ABSTRACT

We study the predictors of sickness absences among 2800 Finnish workers responding to the cross-sectional Quality of Work Life Survey in 1997. The data contain detailed information on the prevalence of adverse working conditions at the workplace from a representative sample of wage and salary earners. We show by using recursive multivariate models that the prevalence of harms at the workplace is associated with job dissatisfaction and dissatisfaction with sickness absences. The policy lesson is that the improvement of working conditions should be an integral part of any scheme aimed at decreasing sickness absence.

Introduction

The European Survey on Working Conditions reveals a large cross-country variation in absenteeism. The share of the EU workforce that has been absent at least 1 day during a year owing to illness or injury varies from a low of 6.7% in Greece to a high of 24% in Finland (Gimeno, Benavides, Benach, & Amick, 2004).[1] Given that Finland has the highest share of sickness absenteeism, it is of interest to analyse the determinants of absenteeism there. Norway and Sweden have experienced substantial changes in the number of sickness absences over the past 15 years (Holmlund, 2004). Absences have been more stable in Finland. Consequently, structural factors (including adverse working conditions) are likely to account for much of the total number of sickness absences and the Finnish evidence is therefore useful for other countries.

This paper examines how the working environment as measured along several different dimensions may affect sickness absences. The contribution of this paper is that we analyse the interaction between adverse working conditions, job satisfaction and sickness absences. This is particularly relevant from the policy perspective, because management always has some control over the working environment and therefore an influence on job satisfaction. A reduction in absences would partly compensate for the shrinking of the labour force owing to the rapid ageing of the population in the industrialised countries.

Our paper fills important gaps in current knowledge. First, there is evidence that job dissatisfaction increases sickness absences (e.g. Brown & Sessions, 1996; Clegg, 1983; Dionne & Dostie, 2007; Farrell & Stamm, 1988). The existing evidence stems from single equation models, however. In this paper, we use a data set, the Finnish Quality of Work Life Survey, that enables us to model the relationship between adverse working conditions, job satisfaction, and sickness absences. The interaction of these variables has not been previously analysed by means of recursive multivariate models. Second, Dionne and Dostie (2007) point out that most of the literature uses data from one company or

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[1] See Barmby, Ercolani, and Treble (2002), for another international comparison of sickness absences.

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a very small sample of firms.[2] This makes it hard to generalise the results obtained. In particular, the focus on small samples means that employer characteristics are not usually included among explanatory variables. We use data that constitute a representative sample of employees. Lastly, we evaluate a wider range of detailed risk factors at workplaces than has been typical in previous research.

Finland has a relatively centralized wage bargaining system, which sets a floor to firm-level pay determination. The system leads to wage compression. This may prevent the creation of wage differentials that would compensate for adverse working conditions. The evidence shows that perceived working conditions have a minor role in the determination of individual wages (Böckerman & Ilmakunnas, 2006). In contrast, adverse working conditions stimulate job dissatisfaction. It is interesting to study whether this dissatisfaction increases sickness absences.

Modelling approaches

Theoretical underpinnings

Allen (1981) develops an economic model for the determination of the equilibrium number of absences. Absences are understood as the outcome of the worker's labour-leisure choice, subject to constraints imposed by the employer. The idea of Allen's model is that if the contracted working time is greater than the number of the desired working hours, employees have an incentive to miss work. Because information in the labour market is not perfect and searching is always costly, some employees may accept a job offer even though at the contracted number of work hours their marginal rate of substitution between leisure and income does not equal the wage rate. Absenteeism is, therefore, viewed as a way to adjust the personal labour supply. A worker is absent whenever the benefits of not working are greater than the costs. These costs include the potential wage penalties for being absent.

Allen's (1981) model produces the following empirical prediction: The prevalence of adverse working conditions (with the increased likelihood of work-related injuries and diseases) decreases employees' total utility from work, making absence more likely, other things being equal. This happens especially when the wage does not compensate for adverse working conditions (as suggested by the findings in Böckerman and Ilmakunnas, 2006).[3] Taken together, we expect that absences decline as there is an increase in the wage level, and their number increases while work is being done in adverse working conditions.

Thinking beyond Allen's (1981) model, it is possible that higher-paying jobs tend to be more pleasant, which would predict that a higher wage is associated with fewer absences.[4] The positive correlation between pay and pleasant jobs may arise from unobservable differences in productivity (e.g. Hwang, Reed, & Hubbard, 1992) or search frictions in the labour market (e.g. Lang & Majumdar, 2004).

Explaining workers' sickness absences by means of adverse working conditions

Reduced-form models are used to establish the direct connection between working conditions and sickness absences. Our measure of absences is the number of absences during the last 6 months, which is a discrete variable and has a skewed distribution. We therefore estimate a Poisson regression as our baseline specification (e.g. Cameron & Trivedi, 1998). As explanatory variables we have indicator variables that describe adverse working conditions and various individual and workplace characteristics. To relax the assumption of equal mean and variance required in the use of the Poisson model, we estimate negative binomial models. Further, we take advantage of probit models to analyse the probability of having a positive number of absences.

Interaction of adverse working conditions, dissatisfaction and sickness absences

In the second, extended model, we use working conditions, job dissatisfaction, and absenteeism as binary indicators. The model is formed to test the existence of a specific channel according to which adverse working conditions are related to job dissatisfaction, which in turn has an impact on sickness absences. The model is formed in three steps. In the first step we explain the binary indicators of adverse working conditions z_j, $j = 1, \ldots K$, by variables X_1 in a probit model. X_1 includes various industry, occupation, and firm variables. This follows the view, familiar from the compensating wage differentials literature, that working conditions may be endogenous (e.g. Daniel & Sofer, 1998). In the second stage, a binary indicator of job dissatisfaction d is explained in another probit model by the disamenities z_j and variables X_2, which include job characteristics and employees' personal characteristics. In the final stage, a binary indicator of sickness absenteeism q is explained by job dissatisfaction d and some personal characteristics X_3.

The model forms a system of $K+2$ probit models that have endogenous dummy explanatory variables. It is assumed that in all three stages there are unobserved individual characteristics and, therefore, the error terms of the probit models are correlated. The unobserved individual characteristics can, for example, be attitudinal factors that affect absences or unobservable health characteristics that are not captured in our data. The system is recursive in the sense that sickness absences do not explain

[2] Reflecting the overall literature, the Finnish research (e.g. Kivimäki et al., 2000; Väänänen et al., 2003; Vahtera et al., 2004; Virtanen et al., 2001) uses data from very specific sectors of the labour market, like the municipal sector.

[3] Compensating wage differentials could work mainly on the extensive margin, i.e. regarding the decisions whether to accept a particular job or not. Working conditions have arguably a lesser role in the intensive margin, i.e. whether to work on a specific day, conditional on having a particular type of job, because most of the employed persons not on a performance contract will get paid anyway.

[4] To test this hypothesis, we have analysed the correlation between working conditions and income by estimating probit models for the indicators of adverse working conditions. Overall, there is some evidence that higher-paying jobs are more pleasant, but the connection of the variables is far from perfect and the relationship varies between different indicators of working conditions.

satisfaction and disamenities, and satisfaction does not explain disamenities. Hence, it is possible to estimate the model as a multivariate probit model (see Greene, 2008). We use the Geweke-Hajivassiliou-Keane simulated maximum likelihood estimator implemented to Stata by Cappellari and Jenkins (2003). No exclusion restrictions are needed for the identification of the model (Wilde, 2000), but it may still be a good practice to include them. We therefore assume that the variables X_1, X_2, and X_3 are not exactly the same, as will be explained below.

Data

We use the Quality of Work Life Survey (QWLS) of Statistics Finland (SF) from 1997. QWLS provides a representative sample of Finnish wage and salary earners, because the initial sample for QWLS is derived from a monthly Labour Force Survey (LFS) of SF, where a random sample of the working age population is selected for a telephone interview. The 1997 QWLS was based on LFS respondents in September and October who were 15–64 years old with a normal weekly working time of at least 5 h; 3795 individuals were selected for the QWLS sample and invited to participate in a personal face-to-face interview. Out of this sample 2978 persons, or around 78%, participated (see Lehto & Sutela, 1999). Owing to missing information on some variables for some workers, our sample size is about 2800 observations. QWLS is supplemented with information from the LFS and registers maintained by SF. It contains an identifier for the geographical location of the employer, which is used to include regional unemployment in the models. The variables are described in the Appendix (Table A1).

Sickness absences are documented as the self-reported number of absences because of illness during the past 6 months. A major advantage of the QWLS data is that it also contains short sickness absences that are not recorded by the Social Insurance Institution (KELA), which pays out sickness benefits to the affected employees. The reason for this is that short sickness absences do not entitle employees to payment of sickness benefits, but they obtain normal pay from the employers. This is important, because most of the absences are presumably short. However, the 1997 QWLS data do not contain information about the duration of individual sickness spells.

The distribution of sickness absences is shown in Fig. 1. Roughly 40% of all workers report a positive number of absences for the period of the past 6 months. A majority of those who have been absent owing to illness have been absent only once. After that there is a steep decline, as expected. The Poisson distribution seems to approximate the distribution of our dependent variable quite closely. We also form an indicator for those that have been absent at least once, which is used with probit models.

Job dissatisfaction is measured by the four-point Likert scale. We form a dissatisfaction dummy (*Unsatisfied*) that indicates the two highest dissatisfaction categories 3 and 4 (6.3% of respondents). The most important variables for self-reported working conditions describe harms and hazards at the workplace. There are questions on different types of perceived harms with a five-point Likert scale, in which the highest category corresponds to the perception

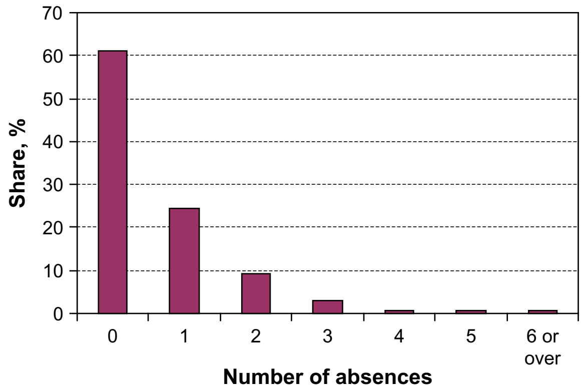

Fig. 1. Distribution of the number of sickness absences during the past 6 months.

that the feature of working conditions is ‘very much’ an adverse factor. Also for perceived hazards there are questions where the highest category among the three possibilities is the one in which the respondent considers the feature as ‘a distinct hazard’. Responses to the questions about different kinds of adverse working conditions are aggregated by forming a dummy variable that equals one if there is at least one clearly adverse factor (*Harm*) and a dummy that equals one if there is at least one distinct hazard (*Hazard*). The other dummy variables for working conditions, described in the Appendix (Table A1), are constructed similarly. We include control variables that can be regarded as ‘the usual suspects’ based on the absenteeism literature (e.g. Brown & Sessions, 1996; Holmlund, 2004). Among the control variables, the *Regional unemployment* rate captures the regional variation.

Results

Reduced-form models

The Poisson regression results reveal that adverse working conditions are important determinants of sickness absences. Experiencing at least one notable harm or hazard or experiencing uncertainty clearly increases absences (Table 2, Columns 1–2). The finding for uncertainty is in accordance with the earlier Finnish studies (Kivimäki, Vahtera, Pentti, & Ferrie, 2000). One apparent explanation is that experiencing uncertainty at the workplace reduces employees' overall commitment to work, which is reflected as an increase of absences, among other things. This line of thinking is consistent with the observation that experiencing uncertainty has a clear positive impact on on-the-job search (see the results on the QWLS data in Böckerman & Ilmakunnas, 2008). Furthermore, experiencing conflicts at the workplace positively contributes to sickness absences, but the indicator for physically strenuous work (our *Heavy physically* variable) is not significant.

We summarise the most interesting results regarding the control variables (Table 1, Columns 1–2). There is almost no effect of education on absenteeism. Permanent workers do not have sickness absences more often. Virtanen, Kivimäki, Elovainio, Vahtera, and Cooper (2001) note that contingent employees have lower levels of absences compared with permanent employees, by using data from 10 Finnish hospitals. Their result seems to be specific to that labour market. On the other hand, workers with over 10 years' tenure in the same firm (for a given age) are more often absent. Absences should be lower in team work, because they cause more problems for co-workers (Heywood & Jirjahn, 2004), but this does not hold in our data.

The employer characteristics are largely statistically insignificant. Interestingly, the *Public sector* variable is not significant, but the variable for education in the field of health care obtains a significantly positive coefficient. Since most health care workers are in the public sector, this supports the view that absenteeism is high at least in some public sector activities. Absenteeism is not concentrated

Table 1
Results from reduced-form models for sickness absences

Dependent variable	Number of absences	Number of absences	Dummy for a positive number of absences
Estimation method	Poisson regression	Negative binomial	Probit
Adverse working conditions			
Harm	0.151 (2.04)**	0.145 (2.04)**	0.023 (1.00)
Hazard	0.267 (3.45)***	0.275 (3.79)***	0.068 (3.07)***
Uncertainty	0.166 (2.32)**	0.174 (2.47)**	0.081 (3.94)***
No voice	0.101 (1.31)	0.097 (1.28)	0.016 (0.71)
Neglect	0.057 (0.73)	0.029 (0.38)	−0.004 (0.16)
Atmosphere	0.092 (0.85)	0.040 (0.39)	−0.023 (0.72)
Conflicts	0.228 (2.07)**	0.225 (2.05)**	0.057 (1.41)
Heavy physically	0.053 (0.45)	0.044 (0.39)	0.071 (1.48)
Heavy mental	0.022 (0.18)	0.028 (0.23)	0.028 (0.69)
Controls			
Wage (second quantile)	0.141 (1.17)	0.143 (1.31)	0.088 (2.84)***
Wage (third quantile)	0.122 (0.93)	0.127 (1.08)	0.108 (3.32)***
Wage (fourth quantile)	−0.109 (0.70)	−0.120 (0.88)	0.028 (0.79)
Night work	0.209 (1.03)	0.227 (1.12)	0.172 (1.76)*
Shift work	−0.030 (0.24)	−0.040 (0.32)	0.042 (0.84)
Temporary	−0.105 (1.05)	−0.097 (1.00)	−0.004 (0.11)
Part-timer	−0.129 (0.98)	−0.131 (1.01)	−0.064 (1.92)*
Team work	0.041 (0.54)	0.043 (0.60)	−0.018 (0.83)
Female	0.057 (0.59)	0.091 (0.98)	0.068 (2.47)**
Age ≤24 years	0.403 (3.05)***	0.419 (3.24)***	0.146 (3.27)***
Age 25–34 years	0.209 (2.46)**	0.222 (2.69)***	0.059 (2.14)**
Age 45–54 years	−0.202 (2.23)**	−0.197 (2.22)**	−0.093 (3.68)***
Age 55–64 years	−0.303 (2.23)**	−0.299 (2.27)**	−0.098 (2.47)**
Single	−0.225 (2.23)**	−0.204 (2.10)**	−0.068 (2.23)**
Spouse working	−0.125 (1.54)	−0.098 (1.29)	−0.022 (0.95)
Secondary education	−0.143 (1.35)	−0.140 (1.37)	−0.015 (0.46)
Polytechnic education	−0.258 (1.74)*	−0.276 (1.90)*	−0.061 (1.34)
University education	0.045 (0.21)	0.003 (0.02)	−0.021 (0.39)
Humanities	0.160 (0.85)	0.144 (0.81)	0.012 (0.22)
Business	0.117 (1.01)	0.124 (1.09)	−0.014 (0.41)
Technical	0.142 (1.39)	0.159 (1.55)	0.031 (0.92)
Health care	0.276 (2.17)**	0.296 (2.32)**	0.119 (2.57)**
Union member	−0.154 (1.75)*	−0.159 (1.88)*	−0.058 (2.17)**
Manager	−0.144 (1.90)*	−0.135 (1.83)*	−0.032 (1.38)
Tenure ≤5	0.162 (1.69)*	0.158 (1.70)*	0.038 (1.34)
Tenure >10	0.271 (2.64)***	0.251 (2.63)***	0.052 (1.84)*
Working capacity	−0.154 (8.92)***	−0.163 (8.46)***	−0.063 (8.57)***
Public sector	−0.052 (0.43)	−0.048 (0.43)	−0.030 (0.84)
Foreign firm	−0.065 (0.54)	−0.085 (0.75)	0.009 (0.23)
Plant size 10–49	0.002 (0.02)	0.002 (0.03)	0.018 (0.73)
Plant size 50–499	0.220 (2.15)**	0.214 (2.26)**	0.065 (2.25)**
Plant size >499	0.126 (0.94)	0.129 (0.96)	0.044 (1.03)
Growing employment	0.045 (0.41)	0.054 (0.50)	−0.013 (0.41)
Unstable firm	−0.016 (0.19)	−0.020 (0.24)	0.005 (0.17)
Female share	0.011 (0.13)	−0.021 (0.24)	−0.011 (0.40)
Regional unemployment	−0.032 (4.03)***	−0.034 (4.12)***	−0.009 (3.64)***
Industry indicators	Yes	Yes	Yes
Number of observations	2815	2815	2815

Notes: Robust z statistics in parentheses (clustering by region). The reported probit results are marginal effects.
*Significant at 10%; **significant at 5%; ***significant at 1%.

Table 2
Results from recursive models

	Sickness absences	Unsatisfied	Disamenities (Harm, Hazard, Uncertainty)
Harm		0.437 (2.28)**	
Hazard		0.330 (1.58)	
Uncertainty		0.327 (1.51)	
Unsatisfied	0.301 (1.95)*		
Controls			
Wage	No	Yes	No
Temporary	Yes	Yes	No
Part-timer	Yes	Yes	No
Female	Yes	Yes	No
Age	Yes	Yes	No
The level of education	Yes	Yes	No
The field of education	Yes	Yes	No
Manager	No	Yes	No
Tenure	Yes	Yes	No
Working capacity	Yes	No	No
Public sector	No	No	Yes
Foreign firm	No	No	Yes
Plant size	No	No	Yes
Unstable firm	No	No	Yes
Regional unemployment	Yes	No	No
Industry indicators	No	No	Yes
Occupation indicators	No	No	Yes

Notes: Robust *z* statistics in parentheses.
*Significant at 10%; **significant at 5%; ***significant at 1%.

in the smallest plants, where it is more difficult to replace the labour input of the absent persons.

Sickness absences are less common in the regions with high unemployment. Virtanen, Kivimäki, Elovainio, Virtanen, and Vahtera (2005) have also reported that high local unemployment decreases short-term absences among Finnish public sector workers. There are two explanations for this (e.g. Askildsen, Bratberg, & Nilsen, 2005). High unemployment may discipline workers and there may be compositional effects over the business cycle. The latter refers to a situation in which marginal workers (for instance, workers with poor health) that are more prone to be absent from work are hired during economic upswings. Because labour market regulations that have an effect on absences are similar in all regions, the regional variation in absences most likely reflects the discipline effect of unemployment.[5] Since the QWLS data are cross-sectional, our unemployment variable may also capture other regional effects. The unreported industry indicators reveal that absences are more frequent in manufacturing than in other sectors, which is in accordance with the findings by the Confederation of Finnish Industries (2006).

The results from the negative binomial model (Table 1, Column 2) are very similar to those from the Poisson regression. We also estimated the zero-inflated (or zero-altered) Poisson regression model to account for the prevalence of zero counts in the dependent variable (Cameron & Trivedi, 1998). The results regarding the effects of harms and hazards remain the same. (The results are not reported in the tables.)

To make it easier to read the results from the probit models (Table 1, Column 3), they are reported as marginal effects on the probability of being absent. For binary variables, these are calculated as differences in probabilities. Experiencing at least one notable hazard or experiencing uncertainty clearly increases the likelihood of reporting a positive number of sickness absences. However, *Harm* is no longer significant. The estimated marginal effects are quite large. To illustrate this, according to the point estimates, those who have at least one clear hazard at the workplace have a 7% higher probability of reporting a positive number of absences.

The control variables show that employees who are located in the second or the third highest wage category are more likely to have sickness absences than employees located in the lowest wage category, other things being equal. This is in conflict with the theory that predicts that absences should decline as there is an increase in the wage level (e.g. Allen, 1981; Brown & Sessions, 1996). The non-monotonic effect of wage on the existence of absences implies that it is more difficult for firms to decrease absences by increasing the employees' wage level than by reducing their exposure to adverse working conditions.

Females are roughly 7% more likely to report a positive number of sickness absences compared with males. The age effect appears to be large. Employees that are under 24 years are 15% more likely to report a positive number of absences compared with employees aged 35–44 years. Older employees have presumably longer sickness absence spells in contrast to the more frequent absences among younger workers. This is supported by the results of a study on the 2003 QWLS (Ilmakunnas, Skirbekk, van Ours, & Weiss, 2007), where the emphasis is on age effects in the incidence and duration of absences.

Among the other variables, the impact of marital status, health care education, tenure, working capacity, plant size and regional unemployment have significant effects with the same signs as in the Poisson model. The results regarding the control variables vary somewhat across the models. However, the influence of working conditions and regional unemployment on absences is more consistent across the models than the impact of specific worker or firm characteristics.

Recursive models

The estimation of reduced-form models with job satisfaction as one of the explanatory variables for sickness absences reveals that job (dis)satisfaction (*Unsatisfied*), contrary to expectation, does not directly contribute to the number of absences. (The results are not reported in tables.) For example, the *z* value of *Unsatisfied* is 0.45 when it is included as one of the explanatory variables for the Poisson regression model. This provides the motivation to use multivariate models to examine the robustness of this result.

[5] This conclusion is in accordance with the finding that in regions with low unemployment the variables that capture the number of temporary workers and growing employment are not higher.

The idea in the recursive structure is that firm characteristics and occupation determine the working conditions, that adverse working conditions together with personal characteristics and wage determine job dissatisfaction, and that dissatisfaction together with personal characteristics, health, and regional unemployment determine absenteeism. As disamenities, we focus on the *Harm*, *Hazard*, and *Uncertainty* variables, because they had the most significant effect on sickness absences based on reduced-form models (Table 1, Columns 1–3). When choosing the explanatory variables we use exclusion restrictions by choosing different sets of explanatory variables in the equations. The explanatory variables for each type of adverse working condition (*Harm*, *Hazard*, or *Uncertainty*) are employer-related variables (*Public sector*, *Foreign firm*, *Plant size*, *Unstable firm*) as well as indicators for industry and occupation. The variables in the equation for job dissatisfaction are the three disamenities, *Wage* categories, *Manager* indicator, employment relationship variables (*Temporary*, *Part-timer*), and personal characteristics (*Female*, *Age* categories, the indicators for the level and field of education, and *Tenure* categories). Finally, having a positive number of sickness absences is explained by *Unsatisfied*, the employment relationship variables, personal characteristics, *Working capacity* and *Regional unemployment*. We include *Working capacity* in the equation for sickness absences, because we focus on the existence of absenteeism that has nothing to do directly with reduced working capacity. Regional unemployment is likely to be relevant for absences, but there is no particular reason to assume that it matters for job satisfaction or working conditions.

The findings are summarised in Table 2. We estimate the multivariate probit model by including equations for all three job disamenity variables at the same time. Hence, the model contains five equations (i.e. $K = 3$ above). The first column of the table reports the coefficient of *Unsatisfied* from the equation for sickness absences and the second column reports the coefficients of adverse working conditions from the equation for job dissatisfaction. We report only the main coefficients of interest. (The coefficients of other explanatory variables included are not reported in order to save space.) Note that the figures in the table are the estimated coefficients, not the marginal effects, which would vary between different combinations of outcomes. For the binary dependent variables, the recursive models reveal that the prevalence of harms at the workplace is associated with job dissatisfaction (Table 2, Column 2) and dissatisfaction, in turn, is associated with having sickness absences (Table 2, Column 1). There are statistically significant correlations between the error terms of the equations. The correlations arise from the unobserved individual characteristics that are not included among the explanatory variables. Hence, the analysis of interaction between working conditions, job satisfaction and absences requires the use of multivariate models that are able to take into account these correlations.

Discussion and conclusions

We have examined the predictors of sickness absence and especially the effect of adverse working conditions. Our paper contributes to the literature, because we use a data set that makes it possible to model the relationship between adverse working conditions, job satisfaction, and sickness absences. Furthermore, most of the existing literature uses data from one company or a very small sample of firms. The QWLS data constitute a representative sample of wage and salary earners, instead.

This paper shows by using recursive multivariate models that the prevalence of harms at the workplace is associated with job dissatisfaction and dissatisfaction with sickness absences. The policy lesson is that the improvement of working conditions must be an integral part of any scheme that is aimed at decreasing sickness absences. Firm-level investments in a better working environment and job satisfaction become increasingly important in the coming era of labour shortage in the industrialised countries, because a reduction in sickness absences would provide a considerable increase in the effective labour supply. However, when considering the government policies to improve working conditions, it is important to stress that management has strong incentives to keep absenteeism down itself, because it involves a loss of labour. One obvious problem with the improvements of working conditions is that it is not always possible, because some jobs and tasks are simply unpleasant, no matter what management does.

The potential limitations of the QWLS data are important to take into account when one interprets the results. First, there could be some tendency for employees to overstate adverse working conditions to justify their absence, because both working conditions and sickness absences are self-reported. However, employees' identities are not revealed to their employers after the survey, which should reduce this particular source of bias in the answers. Second, the number of days absent or the duration of sickness spells could sometimes be more relevant than the number of spells of absence. Our data do not contain information about the duration of sickness spells. Since the measure of sickness absences captures the number of spells of absence during the past 6 months, a substantial part of them are likely to be short-term absences that are not directly related to long-lasting health-related absences. The focus on this type of absenteeism is justified, because we model the effects of job satisfaction. However, there is another strand of literature that stresses the differences between short-duration and long-duration absence (e.g. Kivimäki et al., 1997, 2003; Marmot, Feeney, Shipley, North, & Syme, 1995). Third, workers are not "densely" sampled from workplaces in the QWLS data. Therefore, it is possible to argue that our findings could be attributable to individual workers who are dissatisfied with their employment, rather than adverse working conditions in some workplaces that affect all workers equivalently. The literature has stressed the impact of stable personality dispositions and transient mood states on a variety of job-related outcomes (e.g. Thoresen, Kaplan, Barsky, de Chermont, & Warren, 2003). That being said, a major strength of our data set is that it is a representative random sample of employees.

Appendix

Table A1. Definitions and descriptive statistics of variables

Variable	Average (standard deviation)	Definition/measurement
Sickness absences		
Number of absences	0.65 (1.17)	The number of times person has been absent from work due to illness during the past 6 months (Fig. 1)
Positive number of absences	0.39 (0.49)	Positive number of absences = 1, otherwise = 0
Job satisfaction		
Unsatisfied	0.06 (0.24)	Job dissatisfaction is measured by means of alternatives 1 (very satisfied: 30.6% of respondents), 2 (quite satisfied: 63.1%), 3 (rather dissatisfied: 5.3%), and 4 (very dissatisfied: 1%). The Unsatisfied variable gets value one for the two highest dissatisfaction categories 3 and 4, otherwise = 0
Adverse working conditions		
Harm	0.29 (0.45)	At least one adverse factor that affects work 'very much' (includes heat, cold, vibration, draught, noise, smoke, gas and fumes, humidity, dry indoor air, dust, dirtiness of work environment, poor or glaring lighting, irritating or corrosive substances, restless work environment, repetitive, monotonous movements, difficult or uncomfortable working positions, time pressure and tight time schedules, heavy lifting, lack of space, mildew in buildings) = 1, otherwise = 0
Hazard	0.34 (0.47)	At least one factor is experienced as 'a distinct hazard' (includes accident risk, becoming subject to physical violence, hazards caused by chemical substances, radiation hazard, major catastrophe hazard, hazard of infectious diseases, hazard of skin diseases, cancer risk, risk of strain injuries, risk of succumbing to mental disturbance, risk of grave work exhaustion, risk of causing serious injury to others, risk of causing serious damage to valuable equipment or product) = 1, otherwise = 0
Uncertainty	0.58 (0.49)	Work carries at least one insecurity factor (includes transfer to other duties, threat of temporary dismissal, threat of permanent dismissal, threat of unemployment, threat of becoming incapable of work, unforeseen changes) = 1, otherwise = 0
No voice	0.67 (0.47)	'Not at all' able to influence at least one factor in work (includes contents of tasks, order in which tasks are done, pace of work, working methods, division of tasks between employees, choice of working partners, equipment purchases) = 1, otherwise = 0
Neglect	0.23 (0.42)	At least one supportive factor 'never' experienced in work (includes advice or help, support and encouragement from superiors, support and encouragement from co-workers, feeling of being a valued member of work community, opportunity to plan work, opportunity to apply own ideas in work, feeling of own work as productive and useful) = 1, otherwise = 0
Atmosphere	0.11 (0.31)	Experiences at least one negative aspect of work atmosphere 'daily or almost daily' or positive aspect 'never' (includes negative aspects conflicts or argument with someone else in work community or with a customer, being subject or threatened by physical violence, use of unfriendly words or gestures by co-workers or superiors, and positive aspects praise for work from co-workers or customers, opportunities for learning new things and developing in one's occupation) = 1, otherwise = 0
Conflicts	0.06 (0.24)	At least one type of conflict appears in work unit 'a lot' (includes competitive spirit, conflicts between superiors and subordinates, conflicts between employees, conflicts between employee groups) = 1, otherwise = 0
Heavy physically	0.05 (0.22)	Current tasks physically 'very demanding' = 1, otherwise = 0
Heavy mentally	0.06 (0.24)	Current tasks mentally 'very demanding' = 1, otherwise = 0
Wage		
Wage (first quantile)	0.25 (0.43)	The logarithm of hourly earnings that is calculated based on the annual earnings (FIM) obtained from tax registers and by using regular weekly hours from LFS. Weekly hours are converted to the annual figures by multiplying them by 48. (We assume that annual leave is 4 weeks, which is the Finnish standard.) First quantile = 1, otherwise = 0 (reference)
Wage (second quantile)	0.25 (0.43)	Logarithm of hourly annual earnings, second quantile = 1, otherwise = 0
Wage (third quantile)	0.25 (0.43)	Logarithm of hourly annual earnings, third quantile = 1, otherwise = 0
Wage (fourth quantile)	0.25 (0.43)	Logarithm of hourly annual earnings, fourth quantile = 1, otherwise = 0
Working time		
Night work	0.01 (0.10)	Night work = 1, otherwise = 0
Shift work	0.04 (0.20)	Uninterrupted three-shift work = 1, otherwise = 0
Temporary	0.18 (0.38)	Fixed-term employment relationship = 1, otherwise = 0
Part-timer	0.10 (0.30)	Part-time work = 1, otherwise = 0
Team work		
Team work	0.32 (0.46)	Works in teams 'almost all the time' or 'about three quarters of the time' = 1, otherwise = 0
Human capital variables		
Female	0.53 (0.50)	1 = female, 0 = male
Age ≤24 years	0.08 (0.28)	Age ≤24 = 1, otherwise = 0
Age 25–34 years	0.25 (0.43)	Age 25–34 = 1, otherwise = 0
Age 35–44 years	0.30 (0.46)	Age 35–44 = 1, otherwise = 0 (reference)

Appendix (*continued*)

Variable	Average (standard deviation)	Definition/measurement
Age 45–54 years	0.28 (0.45)	Age 45–54 = 1, otherwise = 0
Age 55–64 years	0.08 (0.26)	Age 55–64 = 1, otherwise = 0
Single	0.18 (0.38)	Not married = 1, otherwise = 0
Spouse working	0.56 (0.50)	Spouse is working = 1, otherwise = 0
Comprehensive	0.24 (0.43)	Comprehensive education = 1, otherwise = 0 (reference)
Secondary education	0.56 (0.50)	Upper secondary or vocational education = 1, otherwise = 0
Polytechnic education	0.12 (0.32)	Polytechnic or lower university degree = 1, otherwise = 0
University education	0.09 (0.28)	Higher university degree = 1, otherwise = 0
Humanities	0.06 (0.24)	Field of education is humanities or teachers' education = 1, otherwise = 0
Business	0.16 (0.37)	Field of education is business, law or social science = 1, otherwise = 0
Technical	0.27 (0.44)	Field of education is technical, natural science or computer science = 1, otherwise = 0
Health care	0.10 (0.30)	Field of education is health care, social work, etc. = 1, otherwise = 0
Union member	0.79 (0.41)	Member of trade union = 1, otherwise = 0
Manager	0.32 (0.47)	Tasks involve supervision of work of others or delegation of tasks = 1, otherwise = 0
Work history		
Tenure $\leq$5	0.43 (0.50)	Tenure $\leq$5 years, otherwise 0
Tenure 6–10	0.17 (0.38)	Tenure 6–10 years, otherwise 0 (reference)
Tenure >10	0.36 (0.48)	Tenure >10 years, otherwise 0
Self-assessed health		
Working capacity	8.62 (1.38)	Self-assessment of working capacity. The variable is scaled from 0 (total inability to work) to 10 (top condition)
Employer characteristics		
Public sector	0.34 (0.48)	Employer is state or municipality = 1, otherwise = 0
Foreign firm	0.07 (0.26)	Employer is private, mainly foreign-owned enterprise = 1, otherwise = 0
Plant size <10	0.28 (0.45)	Size of plant under 10 employees = 1, otherwise = 0 (reference)
Plant size 10–49	0.36 (0.48)	Size of plant 10–49 employees = 1, otherwise = 0
Plant size 50–499	0.28 (0.45)	Size of plant 50–499 employees = 1, otherwise = 0
Plant size >499	0.08 (0.27)	Size of plant over 499 employees = 1, otherwise = 0
Growing employment	0.11 (0.31)	The number of employees has increased in the plant during the past 3 years = 1, otherwise = 0
Unstable firm	0.16 (0.37)	Financial situation is 'unstable' = 1, otherwise = 0
Female share	0.41 (0.49)	Share of females in the company is 'high' = 1, otherwise = 0
Regional variable		
Regional unemployment	17.08 (4.74)	The regional unemployment rate based on 12 NUTS3-regions (Source: LFS by Statistics Finland)
Indicators for industries and occupations		
Industries		14 dummies based on Standard Industry Classification
Occupations		10 dummies based on the classification of occupations by SF

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