An unconditional quantile analysis of employee depression

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Abstract

This paper investigates the relationship between the distribution of workplace depression and the effects of job demands, control, manager support and job security. Using unconditional quantile analysis, we show that a demanding job is associated with a greater increase in depression for those suffering from worse depression than for workers with low/average depression. In contrast, autonomy or manager support is associated with a larger reduction in workplace-related depression for employees with higher levels of depression than for those with low/average work-related depression. These effects (both negative and positive) are approximately 60-90% larger for those with high depression than estimates at the mean. The effects at the 90th percentile of depression are three-to-eight times larger than at the 10th percentile. This heterogeneity in impacts of job characteristics on worker depression suggests significant benefits from targeted workplace mental-health policies.

JEL classifications: D23, L22, L23.
Keywords: Job demands and control, autonomy, depression, unconditional quantile regression, job characteristics, mental health.

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1 Introduction

Motivation. The influential job-demand-control-support (JDCS) theory posits that more demanding jobs induce poor health outcomes, including an employee's psychological well-being (Karasek, 1979; Karasek et al., 1998; Johnson and Hall, 1988; Karasek, 1990; Warr, 1990b; Leka and Houdmont, 2010).[1] The JDCS theory also argues that an employee's health outcomes will be better if they have more control over their work – that is, autonomy – and if they enjoy support from their manager and colleagues. However, the impact of workplace conditions, such as autonomy and work demands, on an employee's depression could depend on their existing mental health. In this paper we explore whether a change in the workplace environment impacts employees with low and high depression differently; specifically, using distributional analysis we investigate the difference responses employees have to work conditions depending on their current levels of depression.

Research question and results. We propose a theoretical framework in which the state of an employee's mental health, measured by their work-related depression, affects how their mental health is impacted by work demands and other job characteristics; the crux of the argument is that a worker's state of depression will partly determine how they are affected by work demands, autonomy and other aspects of organizational design. We hypothesize that high work demands have a larger negative impact on a person who is already depressed. Furthermore, we posit that there will be a greater positive impact from manager support, autonomy and job security when an employee is in a worse psychological state.

To examine this theory, we use the British Workplace Industrial Relations Survey 2011 (WERS) (Department for Business, Innovation and Skills, 2015). This survey has information on self-reported employee depression (Warr, 1990a), which is our dependent variable. To examine our psychological-state theory, we estimate a series of unconditional-quantile regressions. This allows us to explore how the marginal effect on the population quantiles for depression of four job characteristics – job demands, worker autonomy, job security and managerial support – potentially vary given an employee's current psychological state (depression). This paper, to the best of our knowledge, is the first to relate how changes in working conditions impact distributional outcomes of depression, using the re-centered influence function regression method developed in Firpo et al. (2018).

Consistent with the JDCS literature, we find that work-related depression outcomes are worse if an employee has greater work demands. Similarly, better employee work-related depression is associated with greater manager support, job security and autonomy. The previous JDCS literature, however, focuses on changes at the mean. In our unconditional quantile regression estimates the relationship between depression and these job characteristics differs markedly, depending employee's depression state. Specifically, the marginal effect of an increase in job demands is three-to-four times larger at the 80th or 90th quantile of depression than at the 10th quantile. Similarly, while job security, managerial support and autonomy are all associated with lower levels of depression, the marginal reduction in the depression quantiles is increasing (overall) in the depression quantiles. For instance, the marginal effect is approximately eight-times larger (in absolute terms) at the 80th quantile than at the 10th. The marginal reduction is two-times larger for employee autonomy than at the 80th than at the 10th quantile. These estimates control for other employee characteristics,

[1] See Van der doef and Maes (1999) for a survey of the empirical literature on the JDC theory and psychological outcomes of employees.

such as occupation, education, age and tenure. Moreover, unlike much of the JDCS literature, we are able to control for unobserved managerial heterogeneity and establishment-level work practices by using establishment-level fixed effects, something that is not necessarily controlled for even in longitudinal studies.

Contribution and policy implications. Our results show that previous analysis on work-related mental health outcomes, by focusing on changes in the mean, fails to capture the heterogeneous impact of job characteristics for employees with different psychological states. This is true for both the negative impacts from high work demands, but also the positive impacts of more control, managerial support of employees and job security.

The nuance of our findings are important because the JDCS literature has become the basis for recommendations as to how businesses can improve the welfare of their workforce from bodies such as the World Health Organization (Leka et al., 2003) and the European Union (Cox et al., 2000, p. 67). It provides a critical foundation for the analysis of health and jobs (Leka et al., 2003, 2010; Kelly and Moen, 2020) and has helped developed macro frameworks linking social conditions, empowerment, inequality, discrimination and health (Thoits, 2010). Our results suggest that reducing job demands has more impact for those already suffering from significant depression. Similarly, an increase in manager support, job security or autonomy are associated with a larger decrease in depression for those with higher depression. Taken together, this implies that targeted adjustment of job characteristics for those that already suffer from depression will potentially lead to a greater improvement in work-related mental-health outcomes than a one-size-fits-all workplace policy.

2 Related literature and theoretical framework

Studies in the 1940s began to explore the connection between socio-psychological factors and mental and physical health. An important element of this research was to establish a focus on individual experiences of stress; that is, individuals vary in their responses to various situations given their interpretation of it and their coping skills (Lazarus, 1966; Lazarus and Folkman, 1984; Robinson, 2018).[2]

The jobs-demand-control (JDC) model (Karasek, 1979; Karasek et al., 1981) links an individual's health with their work environment, particularly their psychological job demands and their decision latitude (control over work and skill discretion).[3] The idea is that high (or excessive) work-related demands are wearing on an individual, manifesting in poor health outcomes. The framework also contends that an individual's wellbeing is enhanced if they have some decision autonomy (often termed control/latitude); autonomy can create a sense of buy-in and encourage engagement, as well as allowing workers to mitigate some of the impact of a demanding work environment.[4]

An additional factor – lack of support at work (isolation) – was added to this model to create the jobs-demand-control-support (JDCS) framework (Johnson and Hall, 1988; Johnson et al., 1989).[5]

[2]One of the major conclusions of the landmark Whitehall I studies is that individual responses to stressors beyond notions of class or status are important (Marmot et al., 1978).

[3]For a review see Cooper (1998) and Dunham (2001).

[4]See the related concept of self determination and its application to the workplace, for example in Deci et al. (2017).

[5]Models that emphasize support are often referred to as iso-strain models.

Support, particularly from a manager, can provide a coping mechanism for the worker, potentially improving their mental-health outcomes. Similarly, the security of their employment can be a major stressor for workers, given th1qe financial predicament losing their job could cause. Job security was introduced by Siegrist (1996) as part of the *effort-rewards imbalance* model.

Motivated by the JDC, and the extended JDCS frameworks, empirical studies have linked high job demands and/or low decision-making autonomy to cardiovascular disease (Karasek et al., 1981; Marmot et al., 1997; Kuper and Marmot, 2003), mortality (Marmot et al., 1991) and poor psychological wellbeing (Van der doef and Maes, 1999; Stansfeld and Candy, 2006; Melchior et al., 2007; Cottini and Lucifora, 2013). Oshio et al. (2015) find a strong association between stress at work and mental health of employees, controlling for time-invariant factors using longitudinal data. Accounting for individual-level fixed effects, Sato et al. (2020) find mental health deteriorates for both blue- and white-collar workers from working long hours, working weekends and late at night. Our study adds to this empirical literature by considering how the impacts of job characteristics and the design of an organization impact mental health depending on the existing mental health of an employee. Importantly, we also control for unobserved establishment/firm characteristics, which could affect the observed relationships, by including establishment fixed effects in our estimates.

2.1 Theoretical framework

To structure our empirical analysis, we augment the JDCS model to propose a psychological-state-contingent framework of how organizational design and practice affects workplace-related depression.

Following the JDCS literature, demanding work creates stress, potentially manifesting as poor mental health; that is, job demands are associated with higher rates of depression, all else constant. On the other hand, workplace stress – and its manifestation as depression – can be alleviated by both greater worker autonomy and support from their manager. Consequently, we predict lower levels of work-related depression when an employee has both greater autonomy and more manager support, assuming other things equal.

We posit, however, that the impact on an individual's mental health of a given situation or event will depend on their current mental health; in other words, the impact of job characteristics are state contingent, where the state is the current mental-health of each employee. We capture an employee's current mental state by the level of their self-reported work-related depression. More explicitly, we surmise that an employee suffering from higher levels of depression is less resilient to a negative event than an otherwise similar colleague with lower leves of work-related depression. Extending the JDCS framework, we hypothesize that there will be a larger negative impact on an employee's workplace depression from a demanding job if they already have high levels of depression related to their work. Conversely, while job demands still have a negative mental health impact, this impact will be smaller if an employee has lower levels of workplace depression, as they have (on average) more resilience and hence are better able to cope.

As noted above, consistent with the JDCS framework, autonomy, managerial support and job security will all reduce work-related depression. In addition, however, we posit that the benefit that each of these practices provides to an employee will be greater for an employee who already suffers from depression than for someone similar with lower levels of depression. That is, we predict there will be a greater reduction in depression from autonomy, manager support and job security for employees with higher levels of depression.

The predictions of our state-contingent JDCS model are summarized in the two empirical hypotheses below.

Hypothesis 1. [JDCS] *Higher work demands are associated with higher levels of work-related depression in employees. Conversely, greater worker autonomy/control, manager support and job security are associated with lower work-related depression.*

Hypothesis 2. [State-contingent impacts] *More onerous work demands are associated with a greater increase in work-related depression for workers who already have higher levels of work-related depression. Further, more autonomy/control, manager support and job security for employees is associated with a greater decrease in workplace depression for employees who have higher levels of work-related depression.*

The first hypothesis is a restatement of the key prediction of the JDCS framework, focusing on the relationship between characteristics of one's job and outcomes in terms of work-related mental health (depression). The second (state-contingent) hypothesis is novel in this context; the impact of job characteristics depends on the existing mental-health condition of an employee.

While we would expect the state of mental health for an employee to change over time, unfortunately we do not have this information in our data. Rather, we explore this hypothesis using a cross-section of employees, where the employees have a range of existing mental-health outcomes or levels. One distinct advantage our data does have is that we are able to control for establishment-level factors that could potentially impact on an employee's mental-health outcomes. Before we turn to the specifics of our data and empirical approach, we illustrate our key predictions in a simulation.

2.2 An empirical framework of workplace depression with state-dependent sensitivity

As outlined above, Hypothesis 1 states that the level of workplace depression will be higher when work demands are greater and lower with more worker autonomy. Hypothesis 2 suggests that the rate of increase in workplace depression will be higher with higher levels of depression; similarly the workplace depression will decrease at an increasing rate at higher levels of depression. Here we show how an underlying individual unobserved psychological characteristic could be produce these relationships relating to levels of workplace depression (Hypothesis 1) and their rates of change (Hypothesis 2). As part of this we show that increasing job demands (autonomy) have an positive (negative) and increasing on the quantiles of the depression distribution, which is the focus of the empirical analysis below in Sections 4 and 5. In this way, this model also links the individual-level JDCS model to changes in the distribution of mental-health outcomes.

To do this, we model individual depression levels as a function of work-related factors, where the marginal effects of these factors depend on a latent unobservable job-strain variable. Specifically, for individual i, let:

$$y_i = \alpha + \beta_1 s_i \cdot x_{1i} + \beta_2 s_i \cdot x_{2i} + \varepsilon_i \tag{1}$$

where:

- y_i denotes the level of depression for individual i,
- x_{1i} is work demands,
- x_{2i} is worker autonomy,
- $s_i \in \mathbb{R}_+$ is an unobserved individual characteristic representing job strain or baseline psychological vulnerability,
- $\beta_i \in \mathbb{R}$ for $i = 1, 2$, capture how to work demands and autonomy interacts with individual job strain vulnerability,
- ε_i is a mean-zero idiosyncratic error term, independent of (x_{1i}, x_{2i}, s_i).

We impose the following conditions:

1. **JDCS predictions hold** The marginal effect of work pressure increases with job strain and the marginal effect of autonomy decreases with job strain, so that $\beta_1 \geq 0$ and $\beta_2 \leq 0$.
2. **Distribution of strain:** The variable s_i is continuously distributed in the population with full support on $\mathbb{R}_+$.
3. **Positive dependence:** There is a positive stochastic relationship between job strain vulnerability and depression: individuals with higher s_i tend to have higher values of y_i.

This allows for the following proposition.

2.2.1 Model Setup.

One of the key points to the theoretical analysis is to establish that for a large class of distributions increasing job demands (or equivalently decreasing job resources or support) has a positive and increasing affect on the quantiles of the depression distribution.[6] For simplicity we focus on a single job demand, such as work pressure, labelled x. For convenience we drop the subscript i relying on context.

Let x and s be two independent random variables representing a latent input and a scaling shock, respectively. We assume:

- $x \sim f$ with support on $[0, \infty)$
- $s \sim g$ with support on $[0, \infty)$
- x and s are independent

We consider a transformation of the form:

$$y = s(bx + 1)$$

where $b > 0$ is a fixed scaling parameter. This structure arises naturally in settings where an underlying input x is first linearly transformed and then multiplicatively scaled by a random factor

[6] Note that equivalent analysis can establish that autonomy has an increasing negative impact on workplace depression.

s. We are interested in how the distribution, and in particular the quantiles, of y respond to a shift in the distribution of x.

We define a shifted version of y:

$$y' = s(b(x+\delta)+1) = s(bx+b\delta+1)$$

for some fixed $\delta > 0$, and study the relationship between the quantiles of y and y'.

2.2.2 Simulation Study (Exponential Case).

To illustrate the quantile-shifting effect under simple positive-support distributions, we simulate the variables x and s independently from exponential distributions with rate parameter $\lambda = 1$, corresponding to mean 1. Similarly, we set $b = 1$ and $\delta = 1$ so that

$$y = s(bx+1)$$

and its shifted counterpart

$$y' = s(b(x+1)+1) = s(bx+b+1).$$

We simulate 10^6 replications of the pair (x, s) and compute the deciles of y and y'. The figure below plots the difference between corresponding deciles of y' and y, showing that the effect of shifting x by 1 leads to a strictly positive and increasing gap across quantiles.

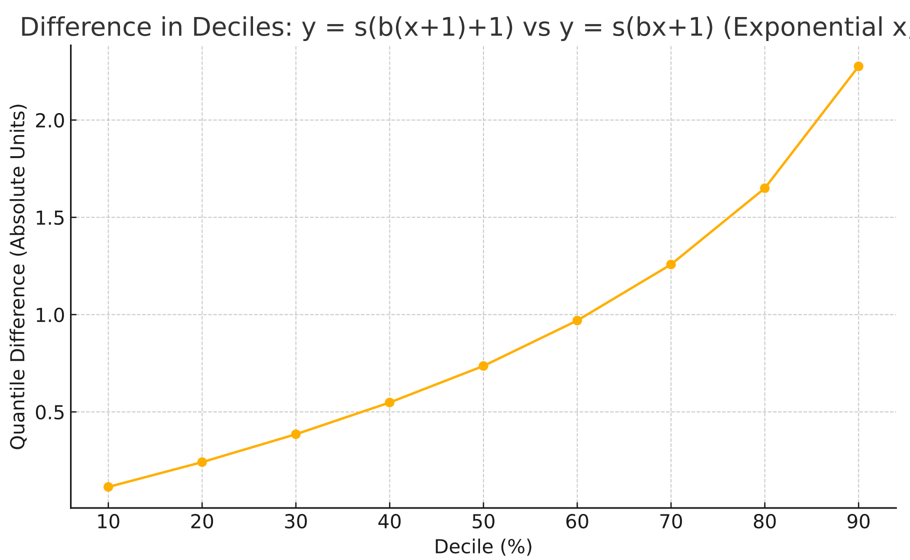

Figure 1: Difference in deciles between $y' = s(b(x+1)+1)$ and $y = s(bx+1)$, where $x, s \sim$ Exponential(1).

Figure 1 captures the key intuition of Hypotheses 1 and 2 and relates it to changes in quantiles. A similar result could be illustrated for the increasing benefit of autonomy across the deciles for job-strain. This provides a direct link to the unconditional quantile regression estimation conducted below, which examines impact of changing the explanatory variables, being job demands, autonomy, managerial support and job security in particular, on the marginal quantiles of our outcome variable of workplace depression. We turn to this empirical analysis now, first describing the data.

3 Data Set and Variables

The differing impact of work conditions and organizational design across the distribution of employee depression is a key focus of this study, possible given recent advances in empirical distributional analysis. To study this, we use the UK Workplace Employment Relations Survey (WERS) 2011, a cross-industry random sample of 2680 British establishments.[7] We utilize the Survey of Employees component, a random sample of over 20,000 employees, with up to 25 employees drawn from each of these establishments.[8] One advantage of this survey is that it has novel information on depression and work conditions (autonomy, job demands and supervisor support) as well as other individual characteristics (education, age, gender, tenure, ethnic background and so on). Another strength, given it has an employee-establishment link, is that we can control for unobserved establishment-level effects. For consistency, our analysis focuses on working age ($18-65$ year-old) employees.

The employee questionnaire was self completed and was given to all employees in workplaces with 25 or fewer employees. In larger workplaces, 25 employees were randomly selected to participate. There were 21981 responses giving a response rate was 54.3%. In order to be able to run quantiles with workplace dummy varaibles we restricted the same to at least 10 responses per workplace. Casewise deletion was applied for incomplete responses. Applying these 2 restrictions gave a sample of 16070.

3.1 Dependent Variable: Depression

The measure of *Depression* in the WERS 2011 survey utilizes one dimension (the first factor) of the depression-enthusiasm index of Warr (1990a), and is based on responses to the question '[t]hinking of the past few weeks, how much of the time has your job made you feel: Tense; Depressed; Worried; Gloomy; Uneasy; Miserable?'. For each question the possible responses were on a 5-point Likert scale, of 'Never', 'Occasionally', 'Some of the time', 'Most of the time' and 'All of the time'.[9] For each of the six questions we code responses 1 to 5 in order of increasing negative emotion, with 5 being 'All of the time'. To generate the *Depression* variable, we take the first factor of these six questions, then standardized to produce a z-score (Cronbach's $\alpha = 0.9129$).

The JDCS literature uses a variety of both self-assessed and clinical measures of mental health/well-being. Encouragingly, Bonde (2008, p. 441) notes that empirical investigations of the JDCS model and the risk of depression are 'surprisingly uniform' using different measures of mental health.

[7]The survey population is all workplaces in Britain that have 5 or more employees and are operating in Sections C-S of the Standard Industrial Classification (2007). This population accounts for 35% of all workplaces and 90% of all employees in Britain. A workplace is defined as comprising 'the activities of a single employer at a single set of premises'.

[8]See Van Wanrooy et al. (2013) for more details.

[9]For example, for 'Depressed', the answers in our sample were: Never (51.50%), Occasionally (23.97%), Some of the time (17.40%), Most of the time (4.97%), All of the time (2.16%).

3.2 Explanatory variables

Job-Demands-Control-Support (JDCS) variables. Based on the job demands questions from Karasek (1979), every employee was asked '[d]o you agree or disagree with the following statements about your job? My job requires that I work very hard' and 'I never seem to have enough time to get my work done'. Possible answers to both questions were on a 5-point Likert scale from Strongly Disagree (1) to Strongly Agree (5). The variable *Job Demands* is constructed by summing and then standardizing these questions into a single measure. We also include occupation dummies to control for differences arising from the demands that might occur due to the technological nature of some jobs.

Each surveyed employee was asked: '[i]n general, how much influence do you have over the following? The tasks you do in your job; The pace at which you work, How you do your work, The order in which you carry out tasks, The time you start or finish your working day'. The possible answers to these five questions were captured in the four-point Likert scale: A lot (4), Some (3), A little (2), None (1). These questions have their origin in Hackman and Oldham (1975) and have been extensively used over the last four decades. The statistical validation of these questions as a single measure (of autonomy), and their distinctness from empowerment, is covered in Spreitzer (1995). The numerical answers for these five questions are averaged and standardized, to produce the z-score *Autonomy.*[10]

The inclusion of employee isolation was one of the first major extensions to the JDC theory. It posits that appropriate support helps individuals cope with their jobs, reducing stress and hence stress-related illness. Early applications focused on isolation/support with regard to peers, however as the literature highlights, providing subordinates support to aid them in doing their job better is an important role of a supervisor/manager (Kristensen et al., 2005). Our measure, *Manager support*, is based the question '[n]ow thinking about the managers at this workplace, to what extent do you agree or disagree with the following? Encourage people to develop their skills'. Responses to this question were scaled on a 5-point Likert scale from Strongly Disagree (0) to Strongly Agree (4). *Manager support* is a z-score produced by standarizing this variable.

Insecurity of employment can be a major stressor for workers. We derive the variable *Job Secure* from the question '[d]o you agree or disagree with the following statements about your job? I feel my job is secure in this workplace'. Reponses on a Likert scale are again standarized to give a z-score for *Job Secure* which we use in analysis; see OECD (2017) for a survey of best practice is working condition survey questions, including support and job security.

Other individual controls. From WERS, we generate controls for educational attainment, with dummies for *Incomplete High School*, having completed *High School* and for workers with a *Degree* or equivalent (less than high school is the omitted category). We also include controls for *Age*, *Tenure* (total years working at the workplace), being married or in a de facto relationship, having a preschool aged child, usual hours of work per week, 1-digit occupation codes and a dummy variable for *Male.*[11]. Ethnicity is split into 5 categories *White* (the omitted category), *Asian*, *Black*, *Mixed*

[10] While the concept of autonomy is well defined it is debatable as to whether it should be considered a reflexive or formative index. Statistically this makes little difference, if one instead performs factor analysis the variables load on to a single factor which has a Cronbach α of 0.8409. Most importantly simple averaging and factor analysis make no practical difference: the single factor has a correlation with the simple average of 98% so the regression results are essentially identical.

[11] For the age and tenure variables, years are taken as the midpoints of the categories in the survey, with more than

(ancestry from 2 or more of the preceding ethnic groups) and *Other Background*.[12] See Table B.4 for the summary statistics and Table 2 for correlations between the key JDCS variables (Table A.1 in the Appendix shows the correlations between the control variables, depression and the JDCS varaibles).

Table 1: Summary statistics for quantile regressions ($N = 16,070$)[a]

	Mean (S.D)
Depression	0.004 (0.981)
Job demands	0.018 (0.999)
Autonomy	0.004 (0.987)
Job security	-0.018 (1.002)
Manager support	-0.003 (0.993)
Male	0.447 (0.497)
Age	42.366 (11.661)
Tenure	6.712 (4.437)
Incomplete High School	0.350 (0.477)
High School	0.136 (0.342)
Degree	0.350 (0.477)
Vocational qual.	0.591 (0.492)
Usual hours	35.530 (12.700)
Married/partner	0.705 (0.456)
Child, preschool	0.080 (0.271)
White	0.936 (0.245)
Mixed	0.010 (0.101)
Asian	0.037 (0.188)
Black	0.014 (0.117)
Other	0.003 (0.057)
Managers	0.073 (0.260)
Professional	0.208 (0.406)
Assoc. Prof.	0.177 (0.381)
Admin	0.185 (0.388)
Trades	0.054 (0.227)
Other Service	0.109 (0.312)
Sales	0.046 (0.209)
Plant Operators	0.050 (0.217)
Elementary	0.099 (0.299)

[a] Source: WERS2011.

10 years of tenure coded as 12.5 years.

[12]These are UK Office of National Statistics Standard Classification of Ethnic Groups used in UK government data collection. *White* is the omitted category because it is the largest group.

Table 2: JDCS variable correlations[a]

	Depression	Job demands	Autonomy	Job security
Job demands	0.3086**	-		
Autonomy	-0.2058**	0.0354**	-	
Job security	-0.3201**	-0.0112	0.1902**	-
Manager support	-0.3636**	-0.0186*	0.2935**	0.3089**

[a] Notes: ** p<.01, * p<.05.

3.3 Transparency and Openness

We describe all manipulations and all measures in the study, and we adhered to the Journal of Applied Psychology methodological checklist. All data and research materials are available from the WERS 2011 website `https://doi.org/10.5255/UKDA-SN-7226-7`. The analysis code is available at this OSF repository link.[13] Data were analyzed using STATA 18 and we utilize the RIF-regression STATA commands developed by Rios-Avila (2020) and Stackreg developed by Tauchmann and Oberfichtner (2021). This study's design and its analysis were not preregistered.

4 Method: Unconditional quantile regression

As detailed in our theoretical framework, an employee's response to their work environment is hypothesized to depend on their current mental state. Consequently, usual regression analysis, which examines changes around the mean, could obfuscate these important nuances. Consequently, to capture different impacts of changes in the work environment across the distribution of depression, we estimate unconditional quantile regressions developed by Firpo et al. (2009). This technique transform our dependent variable *Depression* using a recentred influence function. It does this transformation without reference to any of the explanatory variables (Porter, 2014; Baltagi and Ghosh, 2017). As a result, the estimated coefficients can be interpreted directly as marginal effects, but marginal effects on the corresponding quantile of *Depression*, as opposed to the mean of *Depression* as would be the case with a standard linear regression.[14]

Explicitly, the unconditional quantile regression utilizes the following transformation of the dependent variable y

$$RIF(y; q_\tau) = q_\tau + \frac{\tau - \mathbf{1}\{y \leq q_\tau\}}{f_y(q_\tau)}, \tag{2}$$

where τ is the particular quantile of the variable y, q_τ is the value of the variable y at that specific quantile, $\mathbf{1}\{y \leq q_\tau\}$ is an indicator function that takes the value of 1 if $y \leq q_\tau$ and 0 otherwise and, finally, $f_y(q_\tau)$ is the density of y evaluated at the quantile τ (Porter, 2014).

For convenience let z_i denote $RIF(y_i, q_\tau)$, the RIF of y for a quantile τ evaluated at y_i. Then z_i can loosely be interpreted as the relative contribution of y_i to the τ^{th} quantile. Thus in the regression $z = \beta_0 + \beta_1 x$ for some variable x, β_1 is an estimate of the marginal effect of a change in the average value of x on the τ^{th} quantile of y.[15]

There are two significant innovations in this paper: the use of recentered influence functions (RIF's) to estimate unconditional quantiles and the inclusion of establishment-level fixed effects. The theory behind the former is presented above. We now turn to the estimation method for RIF's and the inclusion of establishment fixed effects.

One of the advantages of the use of RIF's to analyse unconditional quantiles is that the statistical innovation is all in the construction of the dependent variable, which is done independently of

[13] If the OSF link does not work copy and paste the following url into your browser: `https://osf.io/bej75/?view_only=a23329c2805d4c039a0ecd2f7f513eab`.

[14] In fact, the RIF-regression coefficients in the case of the mean are identical to a standard regression.

[15] The RIF is based on the Gateaux directional derivative of a functional (Firpo et al., 2009).

'right-hand side' regressors and hence standard methods can be used for regression estimation. In particular, we will use a system of linear equations for our analysis estimated by the method of Seemingly Unrelated Regression (SUR).

The dependent variable in regression k is $D_{i,k}$, which will be either *Depression* or a RIF transformation of *Depression* corresponding to a particular quantile. The subscript i denotes the individual and the subscript k indexes the regression by the corresponding dependent variable. The ten regressions we are interested in have different dependent variables: $D_{i,\text{mean}}$ and the RIF for the 10^{th} to the 90^{th} quantiles (deciles) denoted $D_{i,10}$ to $D_{i,90}$. Thus $k \in \{\text{mean}, 10, \ldots, 90\}$. $D_{i,\text{mean}}$ is the untransformed *Depression* measure for individual i, which is used in standard OLS analysis of the mean.

A significant issue for much of the JDCS literature is the possible presence of relevant but unobserved establishment/firm factors. There are many such potential factors including, but not limited to, firm technology, unmeasured management practices, the personality of the CEO, the dynamics of the senior management team, or government regulations that apply differentially across industry/firm size. The issue of management practices has been addressed directly by establishing an extended list of job demands and resources (Demerouti et al., 2001; Bakker and Demerouti, 2017). The other issues exceed what is possible with extant datasets, either cross-sectional or longitudinal. As a result there is the potential that the results in most of the existing literature are biased.[16]

Unlike most papers in the literature we are using a large matched employer-employee data set, allowing us to estimate establishment-level fixed effects.[17] To do so, we specify for each k a standard linear model:

$$D_{i,k} = \beta_k^J J_i + \beta_k^A A_i + \beta_k^S S_i + \beta_k^M M_i + \mathbf{B}_k X_i + u_{j[i],k} + e_{i,k}, \quad k \in \{\text{mean}, 10, \ldots, 90\} \tag{3}$$

where D_i is *Depression* for individual i, J_i represents *Job Demands*, A_i the employee's *Autonomy*, S_i is individual job security, M is individual management support and X_i exogenous employee characteristics, $u_{j[i]}$ is the establishment-level fixed effect/constant. The system of equations is estimated jointly as a SUR[18] by specifying a joint, but 'unrestricted', multivariate Normal distribution $N(\mu, \mathbf{\Sigma})$ for the individual level errors $e_{i,k}$. The e's are mean zero ($\mu = 0$) and unrestricted variance-covariance is

$$\mathbf{\Sigma} = \begin{pmatrix} \sigma_1^2 & \cdots & \sigma_{1,10} \\ \vdots & \ddots & \vdots \\ \sigma_{10,1} & \cdots & \sigma_{10}^2 \end{pmatrix}. \tag{4}$$

Since the fixed-effects models in equation (3) are linear we will follow the standard *within* approach of de-meaning the data rather than estimating establishment level constants directly. This equivalence is particularly important because the estimated coefficients are consistently estimated despite the presence of unobserved establishment/firm characteristics that could influence work-related depression.

[16]The small number of papers in the literature that do have match employee-employer dataset have estimated multilevel (mixed) models. There is a significant trade-off between the two approaches with the best method being determined by the nature of the research question. Multilevel models give estimates of the effects of included establishment-level variables, such as organization size. However, to the degree that the establishment-level random effects (establishment-level errors) are correlated with employee-level variables the coefficient estimates for the individual-level variables will not be consistent. From a causal perspective the alternative use of establishment-level dummy variables (fixed effects) avoids the issue of inconsistency or bias as just described. Moreover, it captures all relevant establishment level of facts through a dummy variable and hence this aggregated or combined measure fails to give us disaggregated measures of individual establishment effects that may be of interest.

[17]A dummy variable for each establishment.

[18]Note, since the right-hand side variables and sample are identical across equations the pooling is only important for estimating the covariances needed for cross-equation testing. Coefficient estimates and their standard errors are the same as if the equations were estimated separately.

5 Results: Unconditional quantiles of depression with establishment fixed effects

Table 3 reports the estimation results from the system described by equation 3. Column (1) shows the benchmark results for the conditional mean, that is the standard regression with *Depression* as the dependent variable. Each of the columns (2)-(10) in the table corresponds to distributional estimates at a given quantile (using the corresponding RIF as the dependent variable). Table 3 just gives the results for the key JDCS variables: *Job demands*, *Autonomy*, *Job security* and *Manager support*. All regressions contain establishment fixed effects and a full set of individual level controls, as described in Section 3.2. Coefficient estimates for the controls are given in Table A.3 in the Appendix.

We turn now to the key results of the paper – a comparison of the JDCS coefficients (marginal effects) across the quantiles. The results are quite striking; for all four JDCS variables there is a very strong trend across the quantiles and this trend is both statistically significant and statistically significantly different from the benchmark estimates for the mean (column 1). This pattern is easiest to see in Figure 2. The subtle details of establishing the correct level of statistical significance are given in Section 5.1, with the corresponding tests in Table 4.

Table 3: Employee *Depression* at work: JDCS unconditional quantile estimates by RIF with fixed effects (establishment-level clustered standard errors in parentheses)[a]

	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
Job demands	0.274***	0.089***	0.144***	0.198***	0.244***	0.295***	0.313***	0.381***	0.440***	0.332***
	(0.008)	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)	(0.012)	(0.014)	(0.019)	(0.019)
Autonomy	-0.115***	-0.020***	-0.045***	-0.063***	-0.085***	-0.108***	-0.131***	-0.169***	-0.208***	-0.163***
	(0.009)	(0.005)	(0.006)	(0.008)	(0.009)	(0.011)	(0.012)	(0.015)	(0.020)	(0.020)
Job security	-0.217***	-0.042***	-0.086***	-0.120***	-0.168***	-0.210***	-0.243***	-0.314***	-0.405***	-0.327***
	(0.009)	(0.005)	(0.006)	(0.008)	(0.009)	(0.011)	(0.012)	(0.016)	(0.022)	(0.021)
Manager support	-0.252***	-0.049***	-0.099***	-0.156***	-0.199***	-0.259***	-0.275***	-0.327***	-0.431***	-0.389***
	(0.009)	(0.005)	(0.006)	(0.007)	(0.009)	(0.011)	(0.012)	(0.015)	(0.021)	(0.021)
Observations	16070	16070	16070	16070	16070	16070	16070	16070	16070	16070
No. establishments	1463	1463	1463	1463	1463	1463	1463	1463	1463	1463
R^2	0.262	0.070	0.109	0.146	0.162	0.167	0.170	0.169	0.153	0.125
o^2	0.294	0.086	0.131	0.168	0.188	0.196	0.198	0.197	0.178	0.138
ρ	0.126	0.118	0.113	0.114	0.114	0.116	0.120	0.115	0.106	0.114

[a] Notes: *** p < .001, ** p<.01, * p<.05.

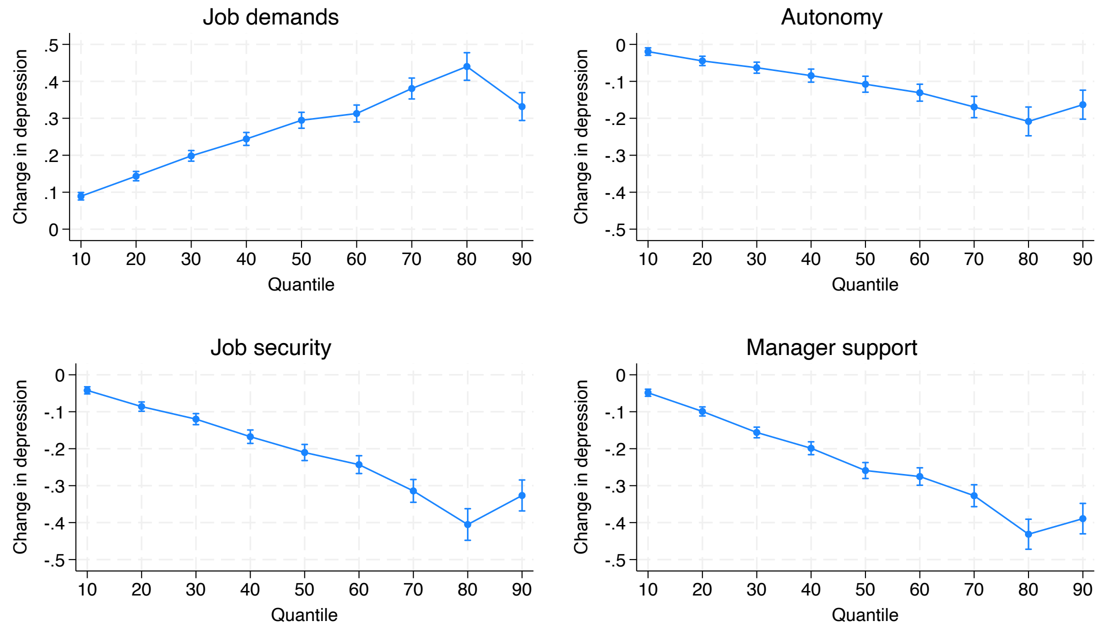

Figure 2: Marginal effects on depression by quantile for job demands, autonomy, job security and manager support (estimates based on establishment fixed effects with clustered standard errors)

Job demands, in the form of time pressure, are a major source of workplace stress and in turn, depression. Consistent with the large existing body of research Column 1 shows that a one standard deviation increase in job demands is associated with a 0.274 standard deviation increase in *Depression*. However, at the 10th percentile, that is for very low levels of *Depression*, the marginal effect of policies that increase work demands is only 32% of the size (0.089) as the effect at the mean. At the other end of the distribution the largest calculated marginal effects are at the 80th percentile. The marginal effect of an increase in job demands at the 80th percentile is 0.440. That is, for people suffering from significant depression the negative impact of additional stress is up to 60.5% larger than the average effect. Thus focusing on average affects across the whole distribution conceals an important and intuitive fact that the impact of stressors at work are relative small (negligible) for people in good mental health, but much worse than previously thought for people in poor mental health.[19]

Furthermore the pattern is monotonic across most of the percentiles, consistent with the idea of *Depression* as a state variable that influences the marginal effects of a policy changes, so that those with the worst depression tend to experience the largest impact from the increase in a stressor.

Autonomy, *Job security* and *Manager support* are mitigating factors identified by the literature as helping alleviate stress and associated depression. The benchmark model of Column 1 indicates that three factors have large and statistically significant negative marginal effects. For low levels of depression, for example the 10th percentile, people are in good mental health and hence there is little for these factors to alleviate. Consequently, the marginal effect are less than a fifth of those for the mean (respectively $17.4\%, 19.4\%$ and 19.4%). Conversely, at the 80th percentile the marginal effects for these factors are over 60% bigger than for the mean (respectively $80.8\%, 86.6\%$ and 71.0%). Again we observe a pattern in which *Depression* appears to act as a state variable changing the marginal effects.

It is curious to observe that the effects in all four panels of Figure 2 are not quite monotonic,

[19]This, of course, does not account for the possible dynamic build-up of depression; see Section 6 for a further discussion of this issue.

there is a kink around the 80-90th percentile. It is unclear what is causing this kink. One possible explanation is that people with the worst mental states may become 'unresponsive' to treatment by the JDCS factors, pushing their marginal effects back towards zero.[20] In a clinical setting treatment resistant depression, especially for those suffering from Major Depressive Disorder, is a well documented issue, Sackeim (2001), Gaynes et al. (2020). Investigating these top-tail kinks and the possibility of 'treatment resistance', with regard to workplace policies and conditions, is an interesting and important avenue for future research.

Comparing the ratio of the marginal effects at 90th and 10th percentiles – from the top to the bottom – yields even starker results. The ratios are: 3.73 for *Job demands*; 8.15 for *Autonomy*; 7.79 for *Job security*; and 7.93 for *Manager support*. The effects for the JDCS factors are much larger for those with high depression than for those with low depression, and this is consistent across all these factors. This has important practical implications, namely the benefits of improving workplace psychosocial conditions for those already suffering from depression are much larger than previously thought. The converse holds at the other end of the distribution; the gains for those not suffering from significant depression of policy changes are negligible. In summary, there is very strong evidence to support both Hypothesis 1 and 2.

From a research perspective, these results also indicate the importance of accounting for heterogeneity in terms of mental health; *Depression* here acts as a state variable, moderating the effect size of factors affecting mental health. Our large sample size provides sufficient power to precisely identify even quite small effect sizes. Furthermore, these results indicate that previous findings of insignificance at the mean for some factors might be obscuring potentially large and significant effects in the tails of the distribution.

Finally, as argued above, the inclusion of establishment-level fixed effects is important to control for unobserved factors, such as management style in a particular firm and hence for establishing causal estimates of the variables of interest.[21] Across the quantiles, the explanatory power of the fixed effects is of a similar magnitude to the explanatory power of the observed variables.[22] The lower R^2 for the quantile models than the benchmark (column 1) is an artifact of the RIF transformation that reduces the variation compared with untransformed *Depression*.[23]

5.1 Testing heterogeneity in effects across quantiles

The regression results in Table 3 and Figure 2 show three general patterns: the strongest marginal effects are at the highest quantiles, the weakest marginal effects are at the lowest quantiles and both of these endpoints are well away from the traditional analysis at the mean provided by the linear regression results with *Depression* as the dependent variable. However, since the coefficient on a given variable, for the mean or one of the quantiles, is estimated in a separate equation it is not appropriate to base hypothesis tests solely on the equation-level coefficients and standard errors. The extra complication arises because the coefficients for a given variable across equation will be correlated because they come from the same sample.

Formally, we are interested in the following two-sided hypothesis tests on the equality of the key coefficients: (1) left-tail versus right-tail ($H_0 : \beta^j_{10} = \beta^j_{90}$); (2) left-tail versus mean ($H_0 : \beta^j_{10} = \beta^j_{\text{mean}}$); and (3) mean versus right-tail ($H_0 : \beta^j_{90} = \beta^j_{\text{mean}}$), where $j \in \{J, A, S, M\}$. That is for each

[20] Measurement issue with the standard Likert scales not being able to detect differences between the most severe forms of depression should also be investigated.

[21] The JDCS coefficients in the fixed-effects models of Table A.3 are almost identical to the estimates with the same specification without fixed effects (Table A.2, indicating that the fixed effects are substantially orthogonal to the impact of the JDCS variables.

[22] For example, in the first column the establishment fixed effects are of practical importance, explaining $\rho = 12.6\%$ of the residual variation of *Depression* not explained by the observed variables. Since the R^2_o is approximately 30%, it follows that approximately $(100 - 30) = 70\%$ of the overall variation is due to the 'error' terms $u_{j[i]} + e_i$, and hence $0.126 \times 70\% \approx 9\%$ of the variation in *Depression*, is due to unobserved establishment-level invariant factors.

[23] R^2 is the within R^2, indicating the fraction of the variance in *Depression* about the establishment means explained by the estimated model, which is approximately 27% for the mean and $7 - 17\%$ for the quantiles. Similarly, R^2_o is the overall R^2, which is the fraction of the variance in *Depression* (unadjusted) explained by the estimated model. In this case, R^2_o is approximately 30% for the mean and approximately 11% for the quantiles.

of the coefficients corresponding to the four key variables *Job demands* (D), *Autonomy* (A), *Job security* (S) and *Managerial support* (M).

Due to the cross-equation correlations the standard error of the difference in the corresponding coefficients from two different equations includes three terms. For example,

$$se(\beta^j_{10} - \beta^j_{90}) = \sqrt{se(\beta^j_{10})^2 + se(\beta^j_{90})^2 - 2\text{cov}(\beta^j_{10}, \beta^j_{90})}, \tag{5}$$

and similarly for the other hypotheses (where *se* means standard error and cov is covariance).

Since the cross-equation correlations were estimated by the SUR, we use equation 5 to estimate F-tests of our three hypotheses for each of the four key regressors. The F-tests and corresponding *p-values* are reported in Table 4.[24]

Table 4: Across equation tests of variable coefficients from *Depression* regressions (mean/OLS and unconditional quantile estimates by RIF) with fixed effects and workplace level clustered standard errors [a]

β for variable	Hypothesis 1 $H_0 : \beta_{10} = \beta_{90}$	Hypothesis 2 $H_0 : \beta_{10} = \beta_{\text{ols}}$	Hypothesis 3 $H_0 : \beta_{90} = \beta_{\text{ols}}$
Job demands	F(1,1462) = 151.1	F(1,1462) = 453.4	F(1,1462) = 16.3
	p = 0.000	p = 0.000	p = 0.000
Autonomy	F(1,1462) = 49.4	F(1,1462) = 122.3	F(1,1462) = 10.2
	p = 0.000	p = 0.000	p = 0.001
Job security	F(1,1462) = 168.9	F(1,1462) = 354.8	F(1,1462) = 47.2
	p = 0.000	p = 0.000	p = 0.000
Manager support	F(1,1462) = 259.5	F(1,1462) = 523.6	F(1,1462) = 75.8
	p = 0.000	p = 0.000	p = 0.000

[a] Source WERS2011. *p*-values rounded to 3 decimal places ($p = 0.000$ means $p < 0.0005$.

The results of all of the across equation coefficient Hypothesis tests 1–3 are strongly significant for all four variables after controlling for a standard set of individual controls (demographics, education etc) and establishment-level fixed effects. This indicates the natural interpretations of Table 3 and Figure2 are correct. There are strongly heterogeneous differences in the marginal effects of job demands, control and support across the percentiles of the depression distribution.

6 General Discussion

Drawing on recent developments in econometric theory, we account for the heterogeneous effects of work conditions on depression. Our results show that an increase in job demands is associated with an increase in average work-related depression, but this increase is greater for those with higher levels of depression. An increase in worker autonomy, manager support and job security are all associated with a decrease in average depression, but these decreases are larger for workers who have higher levels of depression. Consistent with our theory of psychological state-contingency, we find that accounting for heterogeneity is critical. Specifically, we show that previous estimates understate the potential benefits of improving management practices on reducing depression for those with the highest levels of depression. Moreover, given its skewed impacts, improving mental-health outcomes in those worst affected has the potential to significantly improve the lives of the worst-affected individuals, as well as dramatically reducing the costs of mental illness to society overall.

[24]The test are calculated using *sutest* in Stata 18.

6.1 Theoretical implications

As noted previously, the JDCS framework provides a theoretical foundation linking workplace stress and autonomy to health outcomes, such as work-related depression. Its impact on academic research and policy formulation cannot be overstated. The empirical evidence in this paper suggests a refinement to the JDCS framework.

In Section 2.1 we advance a psychological state-contingent version of the JDCS framework, arguing that the impacts of work demands, autonomy, support and other relevant work conditions will depend on the current mental health of the worker. Overall, the findings that there is a larger impact of these conditions, both negative and positive on individuals with more depression opens a new avenue for research. Given our data, we examine individuals with different levels of depression using a cross-section of workers.

These results are revealing, however, they raise another important potential avenue for future research: a structural approach to depression dynamics. The dependence of the marginal effects of work conditions on the depressive state suggest an equation of motion for the depressive state. Furthermore, the depressive state for an individual may, over certain ranges, exhibit 'depreciation', that is, over certain ranges people may, given time and a suitable environment, recover. The joint recovery-illness process has not to the best of our knowledge been considered in the longitudinal studies and probably requires a structural approach to estimation, beyond the scope of this study.

6.2 Practical implications

The scale of mental-health problems, and depression in particular, are enormous. Globally, depression is the third largest source of lived disability (James et al., 2018).[25] The OECD found that mental-health issues such as depression affect more than one in six people in the European Union costing 600 billion Euro — or 4% of GDP – every year (OECD/EU, 2018). Similarly, Greenberg et al. (2015) found that in 2010 the economic cost of major depressive disorder in the US to be USD$210.5 billion.[26] Job stress is a major contributing factor; estimates of the annual cost of work stress in the EU are as high as US$187 billion (Hassard et al., 2014, 2018). Nekoei et al. (2024) find in Sweden that the negative impacts of burnout from high-stress jobs are long lasting for not only the employee but for their spouse and children too.

In this paper we advance novel distributional predictions and empirical evidence for the preeminent JDCS framework of psychological health risks at work. This is important given both the costs of mental health (4% of GDP in the EU) and the influence the JDCS framework has had on policy prescriptions by the WHO, the EU and others. All this makes depression – and, in particular, workplace mental health – is an important policy and workplace safety issue.

Our research highlights the need for effective managers – and managerial training – so supervisors are aware of the deleterious effects of excessive work demands and a lack of decision autonomy can have on their subordinates. Furthermore, our results make clear that a focus on the average effects of the JDCS variables masks the large range of effect magnitudes. From a contemporaneous perspective, the impact of mitigation policies on those with lows levels of depression are quite low, while for those with high levels of depression are quite large. This suggests potential gains from targeting mitigation interventions. Research to date, however, has not considered the potential additional cost or feasibility of tailoring work conditions to the depressive state of employees. Furthermore, failing to make mitigation strategies available to employees with relatively low depressive states may expose a firm to potential legal liability for employees who subsequently develop depression.

More broadly, from a public-policy perspective, the treatment of depression typically involves at least some portion of the cost falling to the national health system (either insurance or treatment).

[25] From a study based on 354 causes in 195 countries, James et al. (2018) finds that "[i]n terms of YLDs,[years lived with disability] low back pain, headache disorders, and dietary iron deficiency were the leading Level 3 causes of YLD counts in 1990, whereas low back pain, headache disorders, and depressive disorders were the leading causes in 2017 for both sexes combined."

[26] In a similar vein, the Productivity Commission (2020) estimates that mental-health issues cost Australia around AUD$200-220 billion per year, approximately one tenth of the annual economic output.

Indeed, depression is a major component of the total cost of mental health treatment in many countries.[27] Correctly identifying the size of the marginal effects in the target sub population is critical in optimally designing any future policy interventions. Moreover, given the physiological-stress mechanism causes not only depression but a number of other serious health problems like heart disease, the benefits of reducing workplace stress are likely substantial.

6.3 Limitations and future directions

While we would argue the results of this paper are both revealing and important, this study has its limitations. As mentioned previously, we use cross-sectional data. While this allows us to examine the distribution of depression and control for unobserved establishment/firm-level factors, a longitudinal study would be required to track changes in depression and their work conditions over time. Marrying longitudinal data to our state-contingent psychological model would be a very worthwhile future research project.

We have taken a novel approach in this paper, using a unconditional quantile regression to examine how the impact of JDCS factors differs across the distribution of depression. Given, as far as we know, this is the first study of its kind, more research is needed to ascertain the generality of our results. Our focus has been on job demands, autonomy, support and security in the workplace. It might also be worthwhile examining the impact on mental health from other types of job characteristics.

Moreover, our focus has been on depression. It would be worthwhile evaluating the distributional effects of the JDCS factors for other health outcomes.

Similarly, the psychological state-contingent model developed here could be applied to other related mental-health conditions, such as burnout. Moreover, this framework could equally apply for more positive mental-health outcomes, such as satisfaction and subjective wellbeing.

7 Conclusion

In this paper we analyze how the relationship between workplace depression and the key variables in the Job-demands-control-support (JDCS) framework – job demands, worker control, manager support and a worker's job security – changes as a worker's state of mental health (depression) changes. To do this we estimate an unconditional quantile regression, which allows for different impacts of the explanatory variables across the distribution of depression. In our estimates, we are also able to control for unobserved establishment/firm factors using a fixed-effects specification. As it turns out, there are markedly different impacts across the distribution. Our results suggest that, overall, job demands increase depression more for those who are already suffering from depression that for those with lower levels of depression. Conversely, autonomy, manager support and job security are all associated with a larger reduction in workplace-related depression for employees with higher levels of depression than for those with low/average work-related depression. These significant heterogeneous impacts of work demands, autonomy and support have implications for the JDCS theory itself, as well as for the implementation of mental-wellbeing programs in workplaces.

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[27] Dieleman et al. (2016) estimated spending on depressive disorder was $71b in the US in 2013. See Sobocki et al. (2006) for an estimate of the costs of depression in the EU.

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A Appendix

Table A.1: Correlations for Key Variables[a]

	Depression	Autonomy	Job Demands	Job Security	Skills encouraged
JDCS					
Depression	1.00	0.31	-0.21	-0.32	-0.36
Job demands	0.31	1.00	0.04	-0.01	-0.02
Autonomy	-0.21	0.04	1.00	0.19	0.29
Job security	-0.32	-0.01	0.19	1.00	0.31
Manager suppourt	-0.36	-0.02	0.29	0.31	1.00
Employee controls					
Male	0.03	-0.09	0.00	-0.03	-0.09
Age	-0.03	0.05	0.05	-0.06	-0.02
Tenure	0.06	0.08	0.04	-0.04	-0.08
Usual hours	0.14	0.18	0.10	0.01	-0.03
Married/partner	-0.00	0.08	0.07	-0.02	0.01
Child, preschool	0.01	0.02	0.02	-0.02	-0.03
Education					
Incomplete High School	-0.01	-0.06	-0.06	-0.01	-0.05
High School	-0.00	-0.02	-0.04	-0.01	-0.02
Degree	0.04	0.13	0.11	-0.02	0.06
Vocational qual.	0.01	0.06	-0.01	-0.03	0.02
Ethnicity					
White	-0.02	0.02	-0.02	-0.00	-0.01
Mixed	-0.01	-0.02	0.00	-0.01	0.00
Asian	0.02	-0.02	0.03	0.01	0.01
Black	0.01	-0.01	-0.01	-0.01	-0.00
Other	0.02	-0.00	0.00	-0.00	-0.00
Occupation					
Managers	0.00	0.07	0.17	0.03	0.08
Professional	0.05	0.21	0.09	0.02	0.09
Assoc. Prof.	0.02	0.01	0.08	-0.05	-0.01
Admin	-0.02	-0.07	-0.01	-0.07	-0.03
Trades	-0.01	-0.06	-0.01	0.00	-0.04
Other Service	-0.04	-0.01	-0.10	0.05	0.06
Sales	-0.01	-0.06	-0.09	0.04	-0.01
Plant Operators	0.01	-0.09	-0.10	0.00	-0.11
Elementary	-0.02	-0.11	-0.12	0.02	-0.09

[a] Source: WERS2011.

Table A.2: *Depression* at work: JDCS unconditional quantile estimates by RIF (establishment-level clustered standard errors in parentheses)[a]

	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
Job demands	0.281***	0.089***	0.144***	0.199***	0.250***	0.306***	0.327***	0.397***	0.450***	0.337***
	(0.008)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.011)	(0.013)	(0.018)	(0.018)
Autonomy	-0.113***	-0.020***	-0.045***	-0.064***	-0.085***	-0.108***	-0.128***	-0.163***	-0.203***	-0.164***
	(0.008)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.011)	(0.014)	(0.019)	(0.019)
Job security	-0.216***	-0.038***	-0.088***	-0.120***	-0.170***	-0.218***	-0.248***	-0.315***	-0.401***	-0.301***
	(0.008)	(0.004)	(0.005)	(0.007)	(0.008)	(0.010)	(0.011)	(0.014)	(0.019)	(0.019)
Manager support	-0.256***	-0.054***	-0.102***	-0.157***	-0.202***	-0.263***	-0.278***	-0.337***	-0.439***	-0.389***
	(0.009)	(0.005)	(0.006)	(0.007)	(0.008)	(0.010)	(0.011)	(0.014)	(0.019)	(0.020)
Observations	16070	16070	16070	16070	16070	16070	16070	16070	16070	16070
R^2	0.295	0.087	0.132	0.169	0.189	0.197	0.199	0.198	0.179	0.139

[a] Notes: *** $p < .001$, ** $p < .01$, * $p < .05$.

Table A.3: *Depression* at work: JDCS unconditional quantile estimates by RIF with fixed effects (establishment-level clustered standard errors in parentheses, *** $p <.001$, ** $p <.01$, * $p <.05$)

	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
Male	0.003	0.004	-0.003	0.005	-0.009	-0.025	0.008	0.001	0.023	0.035
	(0.017)	(0.010)	(0.013)	(0.016)	(0.020)	(0.024)	(0.026)	(0.031)	(0.043)	(0.038)
Age	-0.006***	-0.002***	-0.004***	-0.005***	-0.006***	-0.007***	-0.007***	-0.007***	-0.008***	-0.008***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Tenure	0.013***	0.007***	0.010***	0.013***	0.015***	0.018***	0.018***	0.018***	0.016***	0.009*
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Incomplete High School	-0.022	0.007	0.003	-0.009	-0.031	-0.030	-0.027	-0.037	-0.016	0.012
	(0.023)	(0.016)	(0.020)	(0.022)	(0.026)	(0.031)	(0.032)	(0.040)	(0.052)	(0.049)
High School	-0.040	0.029	0.026	0.012	-0.049	-0.046	-0.049	-0.049	-0.081	-0.040
	(0.027)	(0.018)	(0.024)	(0.026)	(0.031)	(0.038)	(0.039)	(0.050)	(0.066)	(0.058)
Degree	-0.013	0.038*	0.066**	0.046	0.008	-0.017	-0.041	-0.076	-0.029	-0.026
	(0.026)	(0.016)	(0.022)	(0.025)	(0.030)	(0.036)	(0.037)	(0.046)	(0.059)	(0.054)
Vocational qual.	-0.022	0.016	0.013	-0.004	-0.011	-0.038	-0.047*	-0.007	-0.039	-0.027
	(0.015)	(0.010)	(0.012)	(0.014)	(0.017)	(0.021)	(0.022)	(0.027)	(0.034)	(0.033)
Usual hours	0.006***	0.003***	0.004***	0.005***	0.007***	0.009***	0.008***	0.009***	0.008***	0.006***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married/partner	-0.013	0.008	0.011	0.013	-0.014	-0.014	-0.014	-0.052	-0.053	0.020
	(0.015)	(0.010)	(0.013)	(0.015)	(0.017)	(0.021)	(0.023)	(0.029)	(0.038)	(0.035)
Child, preschool	-0.052*	-0.020	-0.017	-0.019	-0.006	-0.044	-0.081*	-0.066	-0.069	-0.110
	(0.026)	(0.016)	(0.020)	(0.024)	(0.029)	(0.037)	(0.038)	(0.048)	(0.064)	(0.058)
Mixed	-0.107	-0.088	0.027	0.019	-0.026	-0.131	-0.181	-0.270*	-0.344*	-0.141
	(0.059)	(0.047)	(0.052)	(0.060)	(0.074)	(0.087)	(0.095)	(0.114)	(0.144)	(0.131)
Asian	0.158***	0.034	0.042	0.018	0.059	0.146*	0.154*	0.088	0.245*	0.373***
	(0.046)	(0.023)	(0.030)	(0.038)	(0.046)	(0.059)	(0.062)	(0.075)	(0.103)	(0.100)

Continued on next page

Table A.3 – continued from previous page

	(1) Mean	(2) Q10	(3) Q20	(4) Q30	(5) Q40	(6) Q50	(7) Q60	(8) Q70	(9) Q80	(10) Q90
Black	0.057	0.011	-0.048	-0.058	-0.061	-0.048	-0.019	0.001	0.010	0.125
	(0.073)	(0.039)	(0.055)	(0.064)	(0.072)	(0.083)	(0.092)	(0.122)	(0.158)	(0.146)
Other	0.245	-0.012	-0.071	0.080	0.049	0.083	0.279	0.396	0.515	0.406
	(0.140)	(0.073)	(0.098)	(0.096)	(0.125)	(0.157)	(0.170)	(0.252)	(0.360)	(0.354)
Managers	0.112**	0.177***	0.209***	0.114**	0.108*	0.077	0.074	0.037	0.042	0.046
	(0.042)	(0.027)	(0.034)	(0.038)	(0.047)	(0.057)	(0.061)	(0.075)	(0.100)	(0.091)
Professional	0.100**	0.157***	0.163***	0.129***	0.113**	0.099	0.160**	0.078	0.037	-0.008
	(0.038)	(0.026)	(0.033)	(0.036)	(0.043)	(0.053)	(0.056)	(0.067)	(0.088)	(0.080)
Assoc. Prof.	0.058	0.136***	0.122***	0.061	0.047	0.045	0.078	0.041	0.003	0.004
	(0.038)	(0.026)	(0.032)	(0.036)	(0.042)	(0.051)	(0.054)	(0.066)	(0.086)	(0.080)
Admin	0.023	0.097***	0.069*	0.011	-0.005	-0.036	-0.004	0.014	0.003	0.034
	(0.038)	(0.026)	(0.032)	(0.034)	(0.041)	(0.049)	(0.052)	(0.064)	(0.084)	(0.079)
Trades	-0.013	0.058	0.022	-0.013	0.001	0.058	0.060	-0.049	-0.139	-0.139
	(0.045)	(0.031)	(0.041)	(0.044)	(0.052)	(0.061)	(0.065)	(0.079)	(0.103)	(0.095)
Other Service	-0.013	0.102***	0.085*	0.015	0.012	-0.068	-0.056	-0.095	-0.104	-0.079
	(0.040)	(0.029)	(0.036)	(0.038)	(0.046)	(0.055)	(0.057)	(0.069)	(0.089)	(0.081)
Sales	0.028	0.101**	0.016	-0.019	-0.014	0.052	0.046	-0.041	0.044	-0.041
	(0.050)	(0.036)	(0.044)	(0.048)	(0.055)	(0.068)	(0.074)	(0.090)	(0.121)	(0.111)
Plant Operators	-0.028	-0.016	0.005	-0.022	-0.057	-0.040	-0.007	-0.047	-0.015	-0.128
	(0.050)	(0.035)	(0.043)	(0.049)	(0.055)	(0.065)	(0.069)	(0.084)	(0.111)	(0.111)
Constant	-0.058	-1.191***	-0.986***	-0.835***	-0.568***	-0.346***	-0.053	0.277**	0.793***	1.357***
	(0.051)	(0.037)	(0.045)	(0.050)	(0.057)	(0.069)	(0.074)	(0.090)	(0.117)	(0.109)
Observations	16070	16070	16070	16070	16070	16070	16070	16070	16070	16070
No. establishments	1463	1463	1463	1463	1463	1463	1463	1463	1463	1463

B Data Transparency Appendix

The data reported in this manuscript were obtained from publicly available data, the Workplace Employment Relations Survey 2011 `https://doi.org/10.5255/UKDA-SN-7226-7`. A bibliography of publications and reports using the WERS2011 is available at: WERS 2011 Publications/reports. The variables and relationships examined in the present article have not been examined in any previous or current articles, or to the best of our knowledge in any papers that will be under review soon.

The following table details our previous and current studies using WERS2011.

Table B.4: Papers using WERS2011

Variable in database	MS1 (Status = under review)	MS2 (Status = under review)	MS3 (Status = this manuscript)
Depression		X	X
Depression 10% quantile			X
Depression 20% quantile			X
Depression 30% quantile			X
Depression 40% quantile			X
Depression 50% quantile			X
Depression 60% quantile			X
Depression 70% quantile			X
Depression 80% quantile			X
Depression 90% quantile			X
Job demands		X	X
Job security		X	X
Manager support		X	X
Autonomy	X	X	X
Pay	X	X	
Satisafction with power	X		
Job satisafction	X		
Male	X	X	X
Age	X	X	X
Tenure	X	X	X
Incomplete High School	X	X	X
High School	X	X	X
Degree	X	X	X
Vocational qual.			X
Usual hours		X	X
Married/partner		X	X
Child, preschool		X	X
White	X	X	X
Mixed	X	X	X
Asian	X	X	X
Black	X	X	X
Other	X	X	X
Managers	X	X	X
Professional	X	X	X
Assoc. Prof.	X	X	X
Admin	X	X	X
Trades	X	X	X
Other Service	X	X	X
Sales	X	X	X
Plant Operators	X	X	X
Elementary (occupations)	X	X	X
Industry dummy variables	X	X	