Labour Economics 76 (2022) 102176

Contents lists available at ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

The impact of working conditions on mental health: Novel evidence from the UK

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ARTICLE INFO

JEL codes:
I1
J24
J28
J81

Keywords:
Mental health
Working conditions
Job demand
Job control

ABSTRACT

This paper investigates the causal impact of working conditions on mental health in the UK, combining new longitudinal data on working conditions from the European Working Conditions Survey with microdata from the UK Household Longitudinal Survey (Understanding Society). Our empirical strategy accounts for the endogenous sorting of individuals into occupations by including individual fixed effects. We address the potential endogeneity of occupational change over time by focusing only on individuals who remain in the same occupation (ISCO 3-digit), exploiting the variation in working conditions within each occupation over time. This variation, determined primarily by general macroeconomic conditions, is likely to be exogenous from the individual point of view.

Our results indicate that, for female workers, improvements in working conditions such as skills and discretion, working time quality, and work intensity improve mental health outcomes such as loss of confidence, anxiety, social dysfunction, and risk of clinical depression. These effects are clinically relevant and substantial for younger and older female workers and larger for workers in occupations characterised by an inherently higher level of job strain. We detail how different dimensions of job quality impact different mental health outcomes for different age groups. Our results have important implications for public policies and firms which aim to improve workers' wellbeing and productivity through workplace interventions focused on mental health.

1. Introduction

Employment is widely recognized as a crucial social determinant of workers' health (Marmot et al., 2008). Against this background, increasing attention has been devoted by scholars and policymakers to the link between employment and working conditions (job quality) and common psychiatric problems, such as depression and anxiety (Barnay, 2016; Harvey et al., 2017). For example, the Mental Health Foundation (2021) has recently recognized that working conditions and the environment can significantly affect mental health. Moreover, job quality has become a central policy goal at the EU level and beyond, stemming from initiatives targeting 'more and better jobs', such as the European Employment Strategy (1997), the Lisbon Strategy (2000) and the European Mental Health Action Plan 2013–2020. Such strategies highlight the importance of promotions, prevention, and interventions in the workplace, as well as their role in improving mental wellbeing throughout the lifespan (WHO, 2015).

The association between working conditions and mental health has been long conceptualized, discussed, and documented in the epidemiological, medical, and sociological literature (see, e.g., Karasek (1979), Harvey et al. (2017), Leijten et al. (2015), Huisman et al. (2008), Bentley et al. (2015), Plaisier et al. (2007), Tyssen et al., (2000)). Such studies find an association between worse working conditions (e.g., higher physical or psychological work demands and lower control in meeting these demands) and higher stress levels and worse mental health. Moreover, studies have provided evidence of mental health benefits (especially concerning anxiety and depression) following improvements in employees' degree of job control and reductions

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https://doi.org/10.1016/j.labeco.2022.102176
Received 15 August 2021; Received in revised form 19 April 2022; Accepted 4 May 2022
Available online 8 May 2022
0927-5371/

in job demands (see, e.g., the extensive review by Egan et al. 2007 and Bambra et al. 2007). However, the evidence of a *causal* link between job quality and workers' mental health is scarce, and the identification of such a causal link is problematic due to reverse causality concerns and unobserved confounding factors. This paper provides novel evidence on the causal impact of working conditions on mental health in the UK, combining new comprehensive longitudinal data on working conditions from the European Working Conditions Survey with microdata from the UK Household Longitudinal Survey (Understanding Society).

Understanding the link between employment conditions and mental health has major economic and social relevance. Nowadays, almost 1 billion people worldwide have a mental disorder (The Lancet Global Health, 2020). The two most common disorders, depression and anxiety, are among the primary drivers of disability worldwide, with an increasing impact on the number of years lived with disability, and on people's lives, from personal wellbeing to work and relationships (James et al., 2018; Purebl et al., 2015). Furthermore, lost productivity as a result of anxiety and depression costs the global economy US$ 1 trillion each year, a cost projected to rise to $6 trillion by 2030. WHO (2015, 2017) projected that, by 2030, mental health problems (particularly depression) will be the leading cause of mortality and morbidity globally.

In the last decade, the economic literature has investigated the links between working conditions and workers' health. As summarized in an extensive review by Barnay (2016), the general finding in this literature is that detrimental working conditions, such as irregular working hours, temporary contracts, and physically/psychosocially demanding tasks are associated with worse mental health. Focusing on the papers that more closely related to our analysis, Cottini and Lucifora (2013) use three waves of the European Working Conditions Survey to show that adverse working conditions (defined in terms of job demands and job hazard) are strongly associated with a higher probability of reporting mental health problems at the workplace in 15 European countries. Cottini and Ghinetti (2017, 2018) use Danis, data to document that physical hazards and psychosocial working conditions (no support from colleagues, job worries and repetitive work), as well as employment insecurity (fear of job loss, involuntary transfers, reemployment difficulties), are important determinants of both mental and physical health.

Identifying the causal impact of job quality on mental health is empirically challenging. Because health may limit the freedom of individuals to choose specific jobs, and individuals can change (or lose) their job as a consequence of health changes, reverse causality is a major concern in this context (Ravesteijn et al., 2018). Moreover, several confounding factors are likely to be correlated with both occupation and health, e.g. time-invariant factors such as education and genetic predisposition for certain jobs, as well as preference for health and mortality (Barnay, 2016). Furthermore, occupational health theories and evidence highlight that health status might influence job choice through the avoidance of potentially hazardous occupational exposure through an initial selection process ('hire effect'), or through a 'healthy worker survivor effect' which induces workers to reduce their workplace exposures for health-related reasons, whether or not exposure affects their health (Arrighi and Hertz-Picciotto, 1994; Dumas et al., 2013; Picciotto et al., 2013). All this induces a selection effect of individuals into a certain occupation (*sorting*). The direction of the induced bias is hard to predict: while some selection mechanisms (e.g., better health and socioeconomic endowments allow for selection in better jobs) point to an overestimation of the true adverse effect of hazardous conditions on health (Ravesteijn et al., 2018), other mechanisms (e.g., the healthy worker effect) lead to an attenuation of the true causal link (Picciotto et al., 2013).

Different strategies have been adopted to limit the impact of the threats mentioned above and to identify a causal effect. Some papers address this issue by estimating dynamic models that account for the selection due to unobserved time-invariant characteristics. For instance, Robone et al. (2011) employ a dynamic panel model on BHPS data, showing that contractual and working conditions have some influence on the health and psychological wellbeing of workers, heterogeneous between men and women. Fletcher et al. (2011) estimate the health impact of 5-year exposure to physical and environmental conditions in the US. Controlling for first-observed health and five-period lagged health in their empirical model, they show that physical requirements and environmental conditions harm self-reported health status, especially for women. However, their models still suffer from the potential endogeneity of occupational change. Finally, Ravesteijn et al. (2018) study the impact of occupational characteristics on health, employing a dynamic model on German longitudinal data, and find that high physical occupational demands and low job control have adverse effects on health, which increase with age. Their identification strategy assumes that occupational stressors are constant over time for a given occupational title, which implies that the variation in working conditions derives solely from individuals changing occupations, which may be endogenous. Moreover, this approach ignores the changes in working conditions and job quality that occur within the same occupation over time, which is a restrictive assumption.

The profound transformation of the labor market experienced by most OECD countries, including the UK, due to increasing competition from low-wage countries and the rise of technology and automation (see e.g. Gardiner et al., 2020 and OECD, 2019) has led to major modifications in working conditions, together with significant changes in the characteristics and job content of different occupations. For example, recent studies from the US, the UK and Europe showed that, in the last 20 years, the degree of routinisation (repetitiveness and standardization) has increased while physical demand and social interactions have decreased for most occupations. Other components of job quality have instead evolved differently according to occupational type (Akçomak et al., 2016; Bisello et al., 2019; Freeman et al., 2020; Menon et al., 2020). With respect to the latest financial crisis, Kronenberg and Boehnke (2019) provide evidence suggesting that in England the Great Recession induced changes in the nature of work (workload, working hours, overtime, training) which can affect work-related common mental distress.

This paper aims to identify the causal impact of working conditions on mental health in the UK. We use data from seven waves (2009–2016) of Understanding Society (US), a panel representative survey of adults resident in households in the United Kingdom. We measure depressive symptoms using the General Health Questionnaire index (GHQ), which screens for general mental health problems and psychological morbidity and has been validated for the UK and worldwide (Goldberg et al., 1997). Respondents' occupation is reported at a highly detailed level using the International Standard Classification of Occupations classification (ISCO-88, 4 digits). We link to each ISCO reported in the US survey, several indicators of working conditions measured at the ISCO level from the 5th (2010) and 6th (2015) waves of the European Working Conditions Survey (EWCS). The use of external data on working conditions allows us to avoid possible endogeneity issues related to justification bias arising when health and working conditions come from the same source (Barnay, 2016). Moreover, the EWCS allows us to characterize occupations according to several independent dimensions and compute synthetic indices comparable over waves, such as physical environment, work intensity, working time quality, skills and discretion, and job prospects.

Our empirical strategy accounts for the endogenous sorting of individuals into occupations through the inclusion of individual fixed effects that remove time-invariant unobserved heterogeneity. By doing this, we identify the effect of working conditions, relying on their *variation over time*. Clearly, this variation may derive from individuals *switching between* occupations or from working conditions changing *within* occupations. To avoid the potential endogeneity of occupational change, we focus only on individuals who remain in the same occupation (who do not change ISCO), thus exploiting solely the variation in the average level of job quality indicators for each given ISCO over time. This variation, determined mainly by the 2009 economic crisis and broader macroeconomic conditions (Kronenberg and Boehnke, 2019), is likely to be exogenous from the individual point of view. Changes in some dimensions of work related to technological change – such as in the physical environment (exposure to pollutants, noise, contact with chemical or biological material) – may be more likely detected in the longer run. However, other dimensions – such as increased demands (tight deadlines or work at high speed, for instance) or prospects (career advancements within the firm, the possibility of losing one's job, becoming unemployed) – may rapidly change due to adjustments in workplace and safety regulations or because of altered macroeconomic conditions. Our analysis shows that several working conditions actually changed significantly between 2010 and 2015 in the UK, and we exploit these short-run changes for identification. Our results are particularly relevant in the context of the UK, where the wider costs of mental health problems have been estimated to cost the UK economy £70–100 billion per year – or 4.5% of gross domestic product (Chief Medical Officer's report, 2013). In the UK, 1 in 6.8 people experience mental health problems in the workplace (Lelliott et al., 2008), mental health disorders are responsible for 13% of all sickness absence days (Office for National Statistics, 2014) and absenteeism costs employers £8.4 billion annually (£335 per employee) (Sainsbury Centre for Mental Health, 2009).

We contribute to the existing literature in several ways. First, our methodological approach, which exploits within-occupation change in working conditions, is novel and, in our view, able to quantify a causal link between working conditions and mental health. Second, while most papers focus on a specific dimension of work, we define job quality as a multidimensional concept. In particular, we distinguish several aspects of working conditions captured by newly available indices provided by the EWCS, which allow us to investigate the links between work and health in greater depth and provide more accurate policy implications. Third, we exploit a validated measure of depression such as the GHQ and disentangle the overall impact on mental distress into three clinically meaningful dimensions: anxiety/depression, social dysfunction, and loss of confidence. This disaggregation enables us to identify which specific dimensions of respondents' mental health are affected by changes in working conditions. Finally, we focus on the UK, an interesting case in this context, as it is ranked 5th among EU countries in terms of the number of current depressive symptoms (3.8 against an EU average of 2.7) (Eurostat, 2021). With regards to working quality, meanwhile, the UK is among the top countries in EU28 in terms of skill use and discretion (decision latitude, cognitive dimension, organisational participation and training), but also in terms of work intensity (quantitative demands, pace determinants and emotional demands) (see Eurofund, 2017), and therefore represents an ideal setting to investigate the impact of job strain on mental distress.

Our results indicate that improvements in working conditions have a beneficial, statistically significant, and clinically relevant impact on depressive symptoms, mostly for female workers. Remarkably, work's skill and discretion dimensions matter the most: a one standard deviation increase in the skills and discretion index leads to a lower depression score by 2.84 points. This effect roughly corresponds to the improvement in mental health associated with an increase in household income by 1.8%. The risk of clinical depression is reduced by 7.8 percentage points if skill and discretion at work improve in the same way: this is a significant effect considering that the depression prevalence among females is equal to 26%. The results differ by age: improvements in skills and discretion benefit younger workers (through increases in decision latitude and training) and older workers (through higher cognitive roles), as do improvements in working time quality; however, changes in work intensity and physical environment matter only for younger and older workers, respectively. Moreover, each aspect of job quality impacts different dimensions of mental health. Specifically, skills and discretion primarily affect the loss of confidence and anxiety; working time quality impacts anxiety and social dysfunction; and work intensity affects the feeling of social dysfunction among young female workers. Finally, we show that improvements in levels of job control (higher skills and discretion) and job demand (lower intensity) lead to greater health benefits, especially for occupations that are inherently characterised by higher job strain.

The paper proceeds as follows. Section 2 describes the data and presents some descriptive statistics. Section 3 illustrates the empirical approach and discusses our identification strategy. Section 4 presents and comments on the results. Finally, Section 5 discusses policy implications and concludes.

2. Data

2.1. Understanding society

We use data from seven waves (2009–2016) of Understanding Society (US), a panel survey representative of adults resident in households in the United Kingdom. The survey collects yearly data on health, work, education, income, family, and social life from members aged 16+ living in approximately 40,000 households in Britain (Lynn, 2009).

The longitudinal dimension of the survey enables us to follow individuals over time, which is a feature that we exploit in our identification strategy, as we will explain below. The survey provides rich and detailed information on respondents' employment, health and sociodemographic status. Respondents' occupation is reported in great depth using the International Standard Classification of Occupations classification (ISCO-88) at 4-digit level. We will use this variable to link our individual data in the US to job quality measures computed at the occupation level from an external database, as described in Section 2.2.

The advantage of using an external dataset (European Working Conditions Survey) to compute occupation-specific indicators of working conditions is that these measures are assessed and computed independently of US respondents' personal experiences and unobservable personal traits. This helps us overcome the endogeneity that would arise if health outcomes and working conditions were subjective evaluations by the same person, simultaneously influenced by individual unobservable attitudes and personalities. In addition, this strategy ensures that our estimates are not affected by 'justification bias' (see, e.g., Kapteyn et al. 2011, Blundell et al. 2021) whereby more depressed individuals may tend to report worse working conditions partly to justify their mental health status.

We include in our analysis several additional variables provided by the survey. First, we use socio-demographic characteristics, such as age, living arrangements and marital status, and the number of children and grandchildren. We also exploit additional information about the current main job, such as the number of hours typically worked per week, and the job sector, classified according to the Standard Industrial Classification of economic activities (SIC). We further include data on respondents' monthly income (at the household level), net of tax, national insurance contributions and council tax liability.

2.1.1. Indicator of mental health

We measure depressive symptoms through the General Health Questionnaire index (GHQ). The GHQ is a tool for the detection and measurement of psychopathology. The overall GHQ index is widely considered to be a measure of psychological (dys)function. It has been repeatedly validated as a screening instrument for general mental health problems and psychological morbidity in the community and among primary care patients in several studies in the UK and worldwide (Goldberg et al., 1997; Goldberg and Williams, 1988; Schmitz et al., 1999). The reliability and validity of the instrument have promoted a wide utilization of the GHQ index in the economics literature as a generic measure of mental health (Carrino et al., 2020; Clark, 2003; Cornaglia et al., 2015; Davillas and Jones, 2021; Dustmann and Fasani, 2016; García-Gómez et al., 2010). The GHQ collects self-reported information on respondents' loss of concentration, loss of sleep, feeling of playing useful roles, incapability of making decisions, feeling of being under strain, ability to overcome difficulties, enjoyment of day-to-day activities, inability to face up to problems, feeling of unhappiness/depression, loss of

Table 1
Items in the General Health Questionnaire, Understanding Society Survey.

Components and questions	Answer
Anxiety and depression	
"Have you recently…"	
lost much sleep over worry?	0 Not at all; 1 No more than usual; 2 Rather more than usual; 3 Much more than usual
felt constantly under strain?	
felt you couldn't overcome your difficulties?	
been feeling unhappy or depressed?	
Social dysfunction	
been able to concentrate on whatever you're doing?	0 Better than usual; 1 Same as usual; 2 Less than usual; 3 Much less than usual
felt that you were playing a useful part in things?	
felt capable of making decisions about things?	
been able to enjoy your normal day-to-day activities?	
been able to face up to problems?	
been feeling reasonably happy, all things considered?	
Loss of confidence	
been losing confidence in yourself?	0 Not at all; 1 No more than usual; 2 Rather more than usual; 3 Much more than usual
been thinking of yourself as a worthless person?	

confidence, feeling of worthlessness, and general happiness. It consists of 12 items, each evaluating how often respondents experienced a given positive or negative condition (the complete list of items is included in Table 1). Each symptom is evaluated using a zero-to-three Likert scale and then summed into an overall index that ranges between 0 and 36, with higher values signaling worse health. A score of 12+ has been identified as a threshold signaling the presence of common mental disorders (Goldberg et al., 1997; Goldberg and Williams, 1988). Therefore, we generated a binary GHQ caseness index to identify respondents lying above and below the cut-off. We further disaggregate the GHQ score in three separate and clinically meaningful factors (anxiety/depression, social dysfunction, loss of confidence), identified by Graetz (1991). This three-factor structure of the GHQ index has been replicated in several confirmatory analyses (Gao et al., 2004; Shevlin and Adamson, 2005) where Graetz's components have been shown to be highly informative. Graetz's components are widely used in academic research on mental health across different disciplines, including economics (see, e.g., Dustmann and Fasani 2016, Colantone et al. 2019, Carrino et al. 2020). Therefore, in our empirical analysis, we adopt this disaggregation of the GHQ index to identify which dimensions of respondents' psychology are affected by changes in working conditions. We construct three sub-measures of mental wellbeing (GHQ – Anxiety and depression; GHQ – Social dysfunction; GHQ – Confidence loss).

We rescale the GHQ scores to range between 0 and 100 so that each regression coefficient can be interpreted as the percentage point effect of the corresponding variable on mental distress.

2.2. European Working Conditions Survey indicators

We use two waves of the European Working Conditions Survey (EWCS), 2010 and 2015, to compute time-varying indicators of working conditions at the occupation level. EWCS data, based on face-to-face interviews, contain rich information on the working conditions of more than 43,000 individuals in several European countries. The survey asks questions on topics such as employment status, working conditions, work-life balance, working time duration and organization. Information on workers' occupation is consistently available from 2010 to 2015 at the 4-digit level (ISCO-88), which allows us to compute measures of working conditions at a very detailed occupation level. Repeated waves of the EWCS enable us to analyze how working conditions and job quality change over time for each occupation category. We restrict the sample to Great Britain and Ireland, which leaves us with approximately 2,600 observations per wave.

For each occupation and wave, we compute the average value of the different indicators of working conditions (described below) and then link the information to the same occupational titles in Understanding Society. Given the rather limited sample size in the EWCS when restricted to the UK and Ireland, we decided to compute the job quality measures at the ISCO88 3-digit level (rather than 4) in order to increase the sample size in each cell. We drop the occupations with fewer than 10 individuals per wave, leaving us with 47 codes.

To measure working conditions, we use five indices of job quality developed by Eurofound in its report on job quality (Eurofound, 2017). The development of the indices reflects the multidimensional nature of the concept of job quality and the fact that each dimension – as captured in the respective index – has an independent influence on the health and wellbeing of workers. These indicators reflect *job resources* (physical, psychological, social or organisational aspects) and *job demands*. More specifically, the job quality indices are as follows: physical environment; work intensity; working time quality; skills and discretion; prospects.

The ***physical environment*** index captures the physical hazards and physical conditions under which work is performed. It includes measures of ambient risks (such as vibrations from machinery, loud noise, and high temperatures), posture-related risks (ergonomic), and biochemical risks.

The ***work intensity*** index covers quantitative demands, pace determinants (such as working at high speed and working to tight deadlines) and interdependency.

Skills and discretion are the dimensions of job quality dealing with whether or not work allows workers to use their skills and develop and grow through their work experience. It includes the skills content of the job (the cognitive dimension of work), workers' development through training, the latitude of workers to make decisions and worker participation in organisational decision-making.

The ***working time quality*** index includes duration (long working hours), atypical working time, working time arrangements, and flexibility.

The ***prospects*** index consists of measurements of perceived job security and career prospects.

The correlation between these indices is weak, as documented by Eurofound (2017). All indices are measured on a scale from 0 to 100. Except for work intensity, the higher the index score, the better the job quality. Table 2 summarizes the dimensions captured by the five indices and lists the specific items included in the construction of each index.

Table 3 reports the initial and the final levels of the five indices in our sample period (2010–2015). While all dimensions of job quality have changed between 2010 and 2015, the most pronounced increase is observed in skills and discretion (+9.4%) and prospects (+8.9%), which suggest that jobs in 2015 required more skills, offered more autonomy and provided better prospects than in 2010. Physical environment and work intensity have remained relatively stable over this period, while the index of working time quality slightly decreased (-2%), implying that workers have, on average, experienced worse working time arrangements.

Table 2
Job quality indices in the EWCS.

Index	Dimensions	Components
Physical environment *(higher values, better quality)*	Ambient	Exposure to vibrations from hand tools, machinery Exposure to noise so loud that you would have to raise your voice to talk to people Exposure to high temperatures that make you perspire even when not working Exposure to low temperatures whether indoors or outdoors Exposure to breathing in smoke, fumes, powder or dust
	Posture related	Posture-related painful or tiring positions Carrying or moving heavy loads Repetitive hand or arm movements
	Biological, chemical conditions	Handling or being in direct contact with dangerous substances such as chemicals or infectious materials
Working time quality *(higher values, better quality)*	Duration	Long working hours (48 h or more a week); Long working days (10h or more a day)
	Non-atypical working time	Night work, Saturday work, Sunday work, Shift work
	Control over working time arrangements	Set by the company; Can choose between different schedules; Can adapt working hours; Entirely determined by self. Change in working time arrangements: No regular change; Change the same day; Change the day before; Change several days in advance; Change several weeks in advance
Work intensity *(higher values, worse quality)*	Quantitative demands	Working at very high speed (three-quarters of the time or more). Working to tight deadlines (three-quarters of the time or more). Enough time to get the job done (never or rarely). Frequent disruptive interruptions
	Pace determinants and interdependency	Interdependency: three or more pace determinants. Work pace dependent on: the work done by colleagues. Work pace dependent on: direct demands from people such as customers, passengers, pupils, patients, etc. Work pace dependent on: numerical production targets or performance targets. Work pace dependent on: automatic speed of a machine or movement of a product. Work pace dependent on: the direct control of your boss
Skills and discretion *(higher values, better quality)*	Cognitive dimension	Solving unforeseen problems. Carrying out complex tasks. Learning new things. Working with computers, smartphones and laptops, etc. (at least a quarter of the time). Ability to apply your own ideas in work
	Decision latitude	Ability to choose or change order of tasks. Ability to choose or change speed or rate of work. Ability to choose or change methods of work. Having a say in choice of work colleagues
	Training	Training paid for or provided by employer over the past 12 months (or paid by oneself if self-employed). On-the-job training over the past 12 months
Prospects *(higher values, better quality)*	Employment status	Kind of employment contract in main job
	Career prospects	Job offers good prospects for career advancement
	Job security	Might lose job in the next six months

Source: Eurofound (2017).

Table 3
Indices of job quality: mean values in 2010 and 2015 and changes over time.

	2010	2015	change	% change
Skills and discretion	64.22	70.28	6.06	9.43
Physical environment	85.61	85.35	-0.25	-0.29
Work intensity	43.66	43.83	0.17	0.40
Working time quality	83.26	81.34	-1.92	-2.30
Prospect	65.40	71.25	5.84	8.93

Source: EWCS 2010 and EWCS 2015.

These overall trends can result from changes in the distribution of occupations (for instance, if high-quality occupations have declined in relative terms in recent years) and/or changes in each occupation's quality. Therefore, in Fig. 1, we report the average scores observed in each job quality index in 2010 and 2015, for each ISCO 1-digit category, while Fig. 2 shows the percentage changes of the five job quality indices within each ISCO 1-digit category. Fig. 1 allows us to grasp the observed differences in job quality across occupations: for example, there is a 10-point divide in skills and discretion between professionals and technicians, clerks, service workers, and plant operators. Physical environment and work intensity are less differentiated across occupations, although there is approximately a 10-point difference in intensity between craft workers or plant operators and most of the professionals, service workers and elementary occupations. Finally, working time quality is relatively higher (by over 10 points) for associate professionals and clerks with respect to both managers, craft workers and plant operators. Against this background, Fig. 2 shows that the positive variation in skill and discretion and prospects indices is primarily driven by a large increase in the indices for low-skilled occupations, particularly for elementary occupations. At the same time, for these groups of occupations, there has been a worsening of working time quality. Interestingly, the limited variation in work intensity observed in Table 3 masks significant heterogeneity across ISCO categories. For example, work intensity increased for professionals, technicians and service workers, while it decreased for managers, clerks and elementary occupations. The physical environment index remained stable in almost all occupations. This last finding is not surprising, given the short period under analysis.

Changes in working conditions within occupations may result from changes in each occupation's sectoral composition rather than a conse-

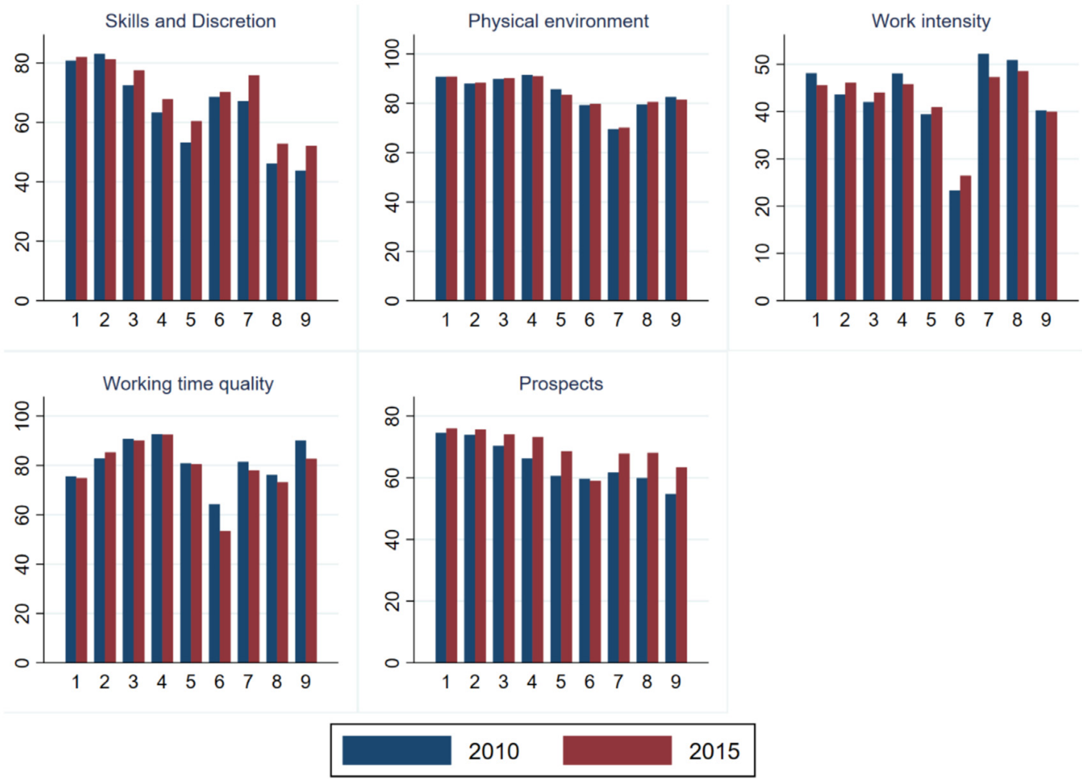

Fig. 1. Job quality indices scores in 2010 and 2015, by ISCO 1-digit codes.
Note: ISCO 1-digit codes on the horizontal axis: 1 = Legislators, senior officials and managers; 2 = Professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. Source: EWCS data.

quence of genuine changes in working quality in the same occupation-industry cell. We, therefore, used the 2010 and 2015 waves of the UK Labor Force Survey (UK-LFS) to determine whether the distribution of employment across sectors evolved differently in the nine ISCO 1-digit categories. The data, reported in Fig. A1 in Appendix 1, suggest that the sectoral composition of each ISCO group has remained almost stable over the period under analysis, suggesting that the trends in working conditions reflect changes in working quality in the same occupation-industry cell.

2.3. Sample selection and descriptive statistics

We start with an overall sample of approximately 300,000 observations from 72,216 individuals interviewed between 2009 and 2017. We then restrict it to focus on respondents of working age, i.e., those below the State Pension age at the time of interview (227,140 obs.). This corresponds to selecting males younger than 65 years old and women younger than 60 to 65 years old (depending on their birth date) (see Thurley and Keen 2017). We further exclude 44,758 observations of respondents who report being out of paid work (working zero hours per week) at the time of the interview.

Moreover, in order to perform a data linkage with the information from the EWCS survey, we exclude observations for respondents who work in occupations (ISCO 3 digit) for which there is no valid information in the EWCS: specifically, we drop 5625 observations because the respondents' occupation codes are missing from the EWCS, and 21,253 observations for which the corresponding occupation information in the EWCS (waves 5 and 6) is based on fewer than 10 interviews (in either wave).

Furthermore, as the EWCS information refers to the years 2010 and 2015, we restrict our sample to respondents who were both interviewed in 2010 and 2015. To increase our sample size, we also include respondents who, although not interviewed in either 2010 or 2015, were interviewed in 2011 (or otherwise in 2009) and in 2016 (or otherwise in 2014). This selection leaves us with 15,930 individuals and 31,860 observations. Hence, we keep two cases per individual relative to two periods: period 1 (year 2010, or otherwise 2011 or 2009), and period 2 (year 2015, or otherwise 2016 or 2014). After dropping individuals with missing relevant information on our main dependent and independent variables in either period, we are left with 26,010 observations (13,005 individuals).

As detailed in the next section, our empirical strategy will focus on respondents who do not change occupation type, as measured by the ISCO 3-digit code, between periods 1 and 2. This produces a final working sample of 8661 individuals (17,322 observations). A discussion on the implications of this selection is included in Section 3.

Since our final sample is selected according to a number of variables as explained above, we checked whether the distribution of occupations in our sample is representative and comparable to the national data for the same period. Therefore, we draw on the 2010 and 2015 waves of the UK Labour Force Survey (LFS) and compare the distribution of employment across 2-digit occupations[1] in the LFS and in our Understanding Society sample. Fig. 3 shows this comparison and reveals that they are very similar.

Table 4 reports summary descriptive statistics by gender of all the variables included in the analysis. Descriptive statistics computed by age and gender are reported in Appendix 1, Table A1.

[1] Occupations in the LFS are classified according to the Standard Occupational Classification (SOC) 2000. We used the crosswalk available at http://www.camsis.stir.ac.uk/occunits/distribution.html#ISCO to convert SOC2000 4-digit codes into ISCO88 4-digit codes.

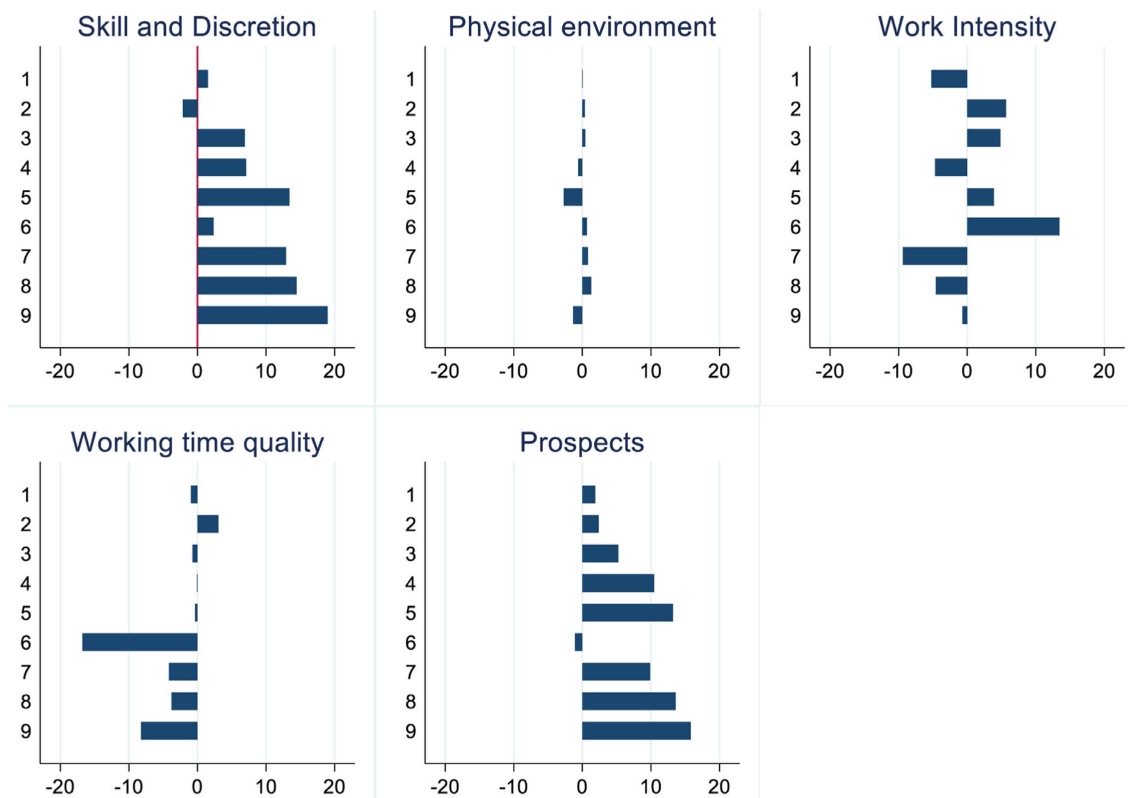

Fig. 2. Changes (%) in job quality indices between 2010 and 2015 in different ISCO 1-digit codes.
Note: ISCO 1 digit codes on the vertical axis: 1 = Legislators, senior officials and managers; 2 = Professionals; 3 = Technicians and associate professionals; 4 = Clerks; 5 = Service workers and shop and market sales workers; 6 = Skilled agricultural and fishery workers; 7 = Craft and related trades workers; 8 = Plant and machine operators and assemblers; 9 = Elementary occupations. Source: EWCS data.

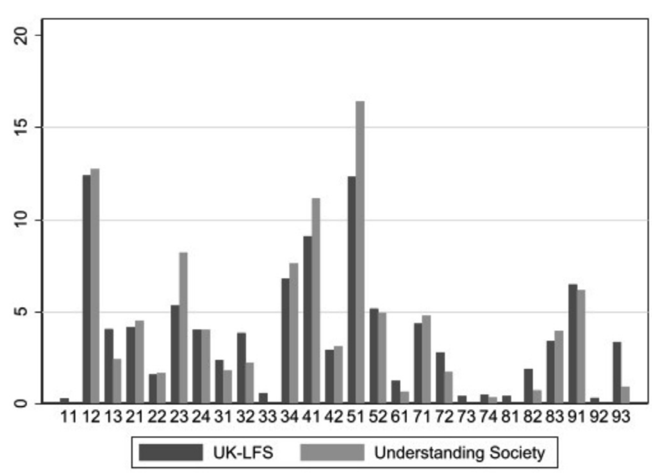

Fig. 3. Distribution (%) of 2-digit occupations in our final sample of Understanding Society and in the LFS.
Note: Authors' calculations based on Understanding Society and UK-LFS, 2010 and 2015 data.

Table 4
Summary descriptive statistics, Understanding Society sample.

	Males		Females	
	mean	sd	mean	sd
GHQ score	28.14	12.45	30.81	14.03
GHQ caseness	0.20	0.40	0.26	0.44
GHQ component: Anxiety and depression	26.21	18.83	29.89	20.41
GHQ component: Social dysfunction	34.05	10.25	35.43	11.22
GHQ component: Loss of confidence	14.26	19.46	18.78	21.77
Skills and discretion	71.21	13.94	69.41	12.72
Physical environment	85.26	8.60	88.52	4.59
Work intensity	45.58	6.86	41.67	8.48
Working time quality	81.83	8.71	86.11	6.86
Prospect	69.04	7.55	69.85	6.52
Weekly working hours	38.59	9.06	29.62	10.56
Age	43.73	10.71	42.76	10.41
Number of children	1.06	1.26	1.15	1.26
Number of grandchildren	0.12	0.32	0.14	0.35
In couple	0.80	0.40	0.73	0.44
Log (net family income)	8.79	0.50	8.76	0.50
Changed firm (yes/no)	0.14	0.34	0.12	0.33
Changed job within same firm (yes/no)	0.07	0.26	0.08	0.27
N obs	8,048		9,274	

Note: The sample includes 4,637 women and 4,024 men interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015.

Focusing on our main variables of interest, the table shows that mental distress is more common among female workers, who have a higher average level of the GHQ index (30.81 against 28.14 for males). Women also have a higher probability of being at risk of depression than men, as captured by the GHQ caseness indicator, in line with previous evidence that, among full-time employed workers, women are more likely to have a common mental health problem than men (McManus et al., 2016).

When focusing on the GHQ components, we see that gender differences in mental distress are primarily a result of females having on average higher levels of confidence loss and anxiety and depression compared to males, while the measure of social dysfunction is similar across the genders.

In terms of working conditions, males tend to work in jobs characterised by poorer physical environment, higher intensity, and worse working time quality. On the other hand, they tend to score higher on the skill and discretion index.

Finally, we note that, although the respondents in the sample remain engaged in the same type of occupation as measured by the ISCO 3-digit classification between the two selected periods, they still report having changed the firm where they are employed or having changed job within the same firm. For example, 8% of women in our sample changed job within the same firm between the two time periods while remaining in the same ISCO 3-digit group.

3. . Empirical framework

The identification of the causal effect of occupation on health is threatened by several issues, well described in Ravesteijn et al. (2018). As discussed in the introduction, the first and most relevant is reverse causality, as health may limit the freedom of individuals to choose certain jobs, and individuals can change job in response to health changes. The second is the existence of confounding factors correlated with occupation and affecting health. Time-invariant factors include, for example, education and genetic predisposition for specific works, as well as preference for health and mortality. All these factors induce a selection effect of individuals into a certain occupation (sorting).

Let us consider the following model specification for individual mental health:

$$H_{i,t} = \boldsymbol{\beta}' WC_{i,t} + \boldsymbol{\theta}' X_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{1}$$

where i denotes the individual and t the time; H is the mental health outcome variable (either the GHQ score or the GHQ caseness), WC a vector of working condition indicators, X a vector of time-varying covariates, α_i is an individual fixed effect, while $\varepsilon_{i,t}$ is an i.i.d. error term. Because working conditions do not vary at the individual level, we adjust the standard errors for clustering at the ISCO-3-digit level. X includes information on respondents' age, age squared, weekly working hours, number of children, household income (in logs), and binary indicators for living as a couple and having any grandchildren, as well as fixed effects for job sector. Our results are robust to the inclusion of additional controls, such as physical health status and sectoral- and region-specific macroeconomic conditions. The $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are the vectors of unknown parameters to be estimated. Our primary interest lies in $\boldsymbol{\beta}$, which measures the causal effect of working conditions on mental health. We consider the case $T = 2$, i.e., a balanced panel, and consider its mean-differentiated, or, equivalently, its first-differences form as follows:

$$\Delta H_{i,t} = \boldsymbol{\beta}' \Delta WC_{i,t} + \boldsymbol{\theta}' \Delta X_{i,t} + \epsilon_{i,t} \tag{2}$$

where $\epsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$. This equation allows us to eliminate the time-invariant unobserved determinants of health. It also controls for time-varying determinants of mental health correlated with working conditions. The previous theoretical and empirical literature has argued that the impact of working conditions on mental health may differ by gender and workers' age (Bildt and Michélsen, 2002; Fila et al., 2017; Fletcher et al., 2011; La Torre et al., 2018; Leijten et al., 2015; Nieuwenhuijsen et al., 2010; Roberts et al., 2011; Robone et al., 2011; Shields et al., 2021; Shultz et al., 2010). Besides the observational fact that women in a full-time job are more likely to have a common mental disorder than men (McManus et al., 2016), men's and women's mental health has been shown to be differently affected by different working conditions; for example, women are more reactive than men to working schedules, physical demands, and environmental conditions. Furthermore, several sociological theories suggest that older and younger workers would benefit differently from improvements in different job aspects, and also as a result of their experience, cognitive development and different exposure to work-family conflicts (Baltes and Baltes, 1993; Carmichael et al., 2010; Carstensen, 1991; Shultz et al., 2010; Zaniboni et al., 2013). Thus, we run our models separately for men and women and three age groups: young (aged 16–35), middle (aged 36–49), and old (aged > 50) workers. Splitting the sample in this way allows us to flexibly incorporate the health effects of occupational characteristics, which are non-linear in age and differ by gender (as shown, for instance, by the empirical analyses of Fletcher et al. (2011) and Ravesteijn et al. (2018)). Moreover, by letting the coefficients of job characteristics vary along these dimensions, we can identify demographic subgroups more at risk of mental health deterioration due to adverse working conditions.

In the mainstream of the literature, $\Delta WC_{i,t}$ is typically measured by exploiting individuals' *occupation changes, while working conditions for the same job are assumed to be constant over time*. This identification approach based on job changes may fail to eliminate endogeneity due to reverse causation since individuals can change job in response to health changes (Ravesteijn et al., 2018).

In this paper, we propose a novel approach, in which $\Delta WC_{i,t} = \overline{WC}_{i,t} - \overline{WC}_{i,t-1}$ where $\overline{WC}_{i,t}$ is a vector including the average level of the working condition indicators for the ISCO 3-digit in which the individual works at time t. We estimate Eq. (1) selecting *the subset of workers who do not change* ISCO 3-digit between time t and t-1. Therefore, $\Delta WC_{i,t} = \Delta \overline{WC}_{i,t}$ isolates the change in working conditions for individual i due to the change in the (average level of) the working conditions from the individuals' ISCO 3-digits changes. The variation in the average level of the working condition indicators for a given ISCO is exogenous from the individual point of view.

A possible threat to our estimates may derive from the non-random nature of our estimation sample, which excludes workers who changed occupation. However, it should be noted that remaining in the same ISCO 3-digit group allows sampled workers to change job, so we are *not* excluding all job switchers (see also Table 4). In other words, we keep in our sample workers who changed job (for example, because they changed firms) within the same ISCO 3-digit group (and therefore maintaining the same working conditions). Moreover, we tested the consistency of our estimates through the estimation of a Heckman selection model (Heckman, 1976), where we explicitly model the probability to remain in the same ISCO 3-digit between the two time points. We find that the coefficient for the inverse Mills ratio is never statistically significant in any of the proposed specifications. Details of this procedure and results are reported in Appendix 2.

4. Results

4.1. Main results

Our main results, based on models (1–2), are shown in Table 5. We report the coefficients of the five indices of working conditions on the continuous GHQ score (Panel A) and on the caseness GHQ index (Panel B). All working conditions indices are standardised to have mean zero and standard deviation one in our sample, so that each coefficient can be interpreted as the impact of one standard deviation increase in the various indices on GHQ score. The models are estimated separately on a sample of men and women who did not change occupation(ISCO 3-digit) in the selected time interval, controlling for a set of time-varying confounders and including individual fixed effects. Columns 1 and 2 refer to the whole female and male sample, respectively, while columns 3–5 and 6–8 report results stratified by gender and age (three groups: 16–35, 36–50, 50 years old or older).

Our results show that, on average, improvements in ISCO-specific working conditions have a beneficial, statistically significant, and clinically relevant impact on depressive symptoms for women. A one standard deviation increase in jobs' skills and discretion, which roughly parallels the difference between the average index values for clerks and sales workers, leads to a lower depression score by 2.84 points (Panel A, (1)), which corresponds to approximately 20% of the GHQ score standard deviation (14) – a meaningful effect by the *Cohen-d* standards

Table 5
Main results: effect of changes in working conditions on GHQ depression score and caseness index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Women	Men	Women			Men		
VARIABLES			Age 16–35	Age 36–50	Age > 50	Age 16–35	Age 36–50	Age > 50
				Panel A: GHQ score				
skills and discretion	-2.845***	0.546	-4.238**	-1.419	-5.580***	0.195	0.862	0.039
	(0.983)	(0.571)	(1.631)	(1.278)	(2.038)	(0.948)	(1.034)	(0.728)
physical environment	-0.909	0.556	-0.316	-0.667	-4.371***	1.644	0.279	0.163
	(0.569)	(0.745)	(0.747)	(1.068)	(1.230)	(1.096)	(1.083)	(0.702)
intensity	0.534	0.184	1.406***	0.168	-0.499	0.197	0.202	-0.164
	(0.447)	(0.282)	(0.484)	(0.517)	(0.794)	(0.508)	(0.411)	(0.550)
working time quality	-0.974*	0.125	-1.767**	0.198	-3.179**	0.279	-0.225	0.474
	(0.579)	(0.283)	(0.716)	(0.774)	(1.280)	(0.411)	(0.616)	(0.410)
prospects	0.736	-0.564*	1.240	0.429	1.019	-0.438	-0.408	-0.839**
	(0.461)	(0.288)	(0.827)	(0.651)	(1.050)	(0.339)	(0.491)	(0.413)
Average outcome	30.81	28.14	29.91	31.21	31.28	27.26	28.86	27.67
				Panel B: GHQ caseness				
skills and discretion	-0.078*	0.015	-0.120**	-0.031	-0.156**	-0.001	0.039	-0.032
	(0.042)	(0.019)	(0.047)	(0.051)	(0.070)	(0.033)	(0.030)	(0.035)
physical environment	-0.032	0.007	-0.051*	-0.011	-0.114**	-0.028	0.011	0.035
	(0.020)	(0.023)	(0.026)	(0.035)	(0.050)	(0.038)	(0.037)	(0.032)
intensity	0.009	0.000	0.029**	-0.007	0.004	0.018	-0.015	0.001
	(0.011)	(0.009)	(0.014)	(0.016)	(0.027)	(0.017)	(0.015)	(0.018)
working time quality	-0.016	-0.002	-0.036	0.012	-0.071	0.001	-0.008	0.003
	(0.024)	(0.011)	(0.031)	(0.027)	(0.046)	(0.017)	(0.017)	(0.014)
prospects	0.003	-0.017*	-0.006	-0.009	0.047	0.006	-0.025*	-0.023
	(0.019)	(0.010)	(0.024)	(0.023)	(0.038)	(0.016)	(0.014)	(0.019)
Average outcome	0.265	0.198	0.253	0.271	0.270	0.184	0.211	0.187
Observations	9,274	8,048	2,946	4,642	1,686	2,338	3,966	1,744
# of individuals	4637	4024	1473	2321	843	1169	1983	872
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The sample includes 4,637 women and 4,024 men interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects, controls for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1 in our sample. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

(Cohen, 2013). Looking at the binary GHQ index, we find that a standard deviation increase in skills and discretion reduces the risk of clinical depression by 7.8 percentage points (Panel B, (1)). This is a large effect compared to an average depression prevalence of 26% (among women). The impact of working time quality is also statistically significant, although smaller in magnitude: a one standard deviation increase in jobs' working time quality reduces depression score by 0.97 points.

For the male sample, we find a limited reaction of depressive symptoms to changes in working conditions. In particular, we estimate a statistically significant but small reduction in the GHQ score (by 0.57 units) and risk of depression (1.7 probability points) to a one standard deviation improvement in the job prospects index. Although this reinforces existing evidence suggesting that providing incentives to workers for career advancements or reducing temporary contracts can improve workers' mental wellbeing (Moscone et al., 2016), we note that the prospect index (although computed externally from the European Working Conditions Survey) is the one most characterised by inherently subjective evaluations. Therefore, we prudently refrain from placing emphasis on the results from this index and rely on future research instead to focus on this topic. In the remainder of this paper, we will not comment on its coefficients[2]; nevertheless, we will still include the prospect index among the controls to avoid omitted variable bias (as stated in Section 2.2, the five indices of job quality provided by the EWCS are independent, weakly but still somewhat correlated measures of working conditions). Moreover, we will show that our findings are relatively robust to the exclusion of the prospect index from the group of control variables (see Table 8 in Section 5).

To appreciate the size of these effects, we can compare them with the estimated correlations between mental health and income. According to our estimates (see Table A2 in Appendix 1), a one percent increase in household income is associated to a reduction of the GHQ score by 1.6 points for women (and 1.76 for men). This means that household income should increase by approximately 1.8 percent (=2.84/1.6) to lead to a reduction in GHQ score similar to that produced by a standard deviation increase in the skill and discretion index.

When disaggregating by age, we find that the effects of working conditions on psychological wellbeing are concentrated among younger and older female workers (columns 3 and 5). In both the younger and the older group, for an improvement in skills and discretion by one standard deviation, the depression score would drop by 4.2 points (younger workers) and 5.6 points (older workers); similarly, the risk of clinical depression would drop by 12 and 15.6 probability points, for younger and older workers respectively. Furthermore, improvements in working time quality reduce the GHQ depression score for both groups, with a larger effect among older workers (-3.18 points versus -1.77 for younger workers). Still, we do not find a corresponding statistically significant impact on the risk of depression.

Our results also highlight age-specific effects of physical environment and intensity. In particular, our estimates show that improvements in physical environment are beneficial, especially for older workers: for a standard deviation increase in the index, the GHQ score of older workers would drop by 4.37 points, and the depression risk would be reduced by 11.4 probability points. As expected, the effect on younger workers is weaker and not statistically significant. On the other hand, job intensity changes mainly affect younger workers: a change in the intensity index by one standard deviation would lead to a lower GHQ score by 1.4 points and a lower risk of depression by 2.9 probability points. No similar effect is found for older workers.

[2] Results for the prospect index are available upon request from the authors.

Table 6
Effect of changes in working conditions on GHQ components.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Women	Men	Women			Men		
VARIABLES			Age 16–35	Age 36–50	Age > 50	Age 16–35	Age 36–50	Age > 50
			Panel A: GHQ anxiety					
skills and discretion	-3.687**	1.163*	-5.597**	-1.813	-6.583**	1.032	1.446	0.724
	(1.510)	(0.644)	(2.467)	(1.971)	(2.770)	(1.054)	(1.222)	(1.300)
physical environment	-1.127	0.864	-0.602	-0.134	-6.408***	1.726	0.377	1.155
	(0.863)	(0.766)	(1.327)	(1.287)	(1.737)	(1.296)	(1.119)	(1.257)
intensity	0.597	0.488	1.926***	0.130	-0.939	0.329	0.453	0.102
	(0.679)	(0.429)	(0.696)	(0.724)	(1.347)	(0.705)	(0.594)	(0.865)
working time quality	-1.148	0.119	-1.906*	0.043	-3.358**	0.267	-0.309	0.690
	(0.876)	(0.493)	(1.053)	(1.099)	(1.580)	(0.469)	(1.034)	(0.738)
Average outcome	29.89	26.21	28.87	30.50	29.97	25.98	27.18	24.33
			Panel B: GHQ social dysfunction					
skills and discretion	-1.747**	0.260	-2.997***	-0.457	-4.127**	-0.035	0.682	-0.739
	(0.743)	(0.598)	(1.058)	(1.149)	(1.569)	(1.110)	(0.932)	(0.780)
physical environment	-0.855*	0.249	-0.316	-1.088	-2.644**	1.207	0.277	-0.831
	(0.443)	(0.778)	(0.581)	(0.946)	(1.195)	(1.265)	(0.994)	(0.716)
intensity	0.653**	-0.107	1.642***	0.056	0.054	0.146	-0.027	-0.738
	(0.313)	(0.282)	(0.421)	(0.437)	(0.602)	(0.602)	(0.360)	(0.558)
working time quality	-0.777*	-0.046	-1.777***	0.438	-2.637**	0.269	-0.304	0.013
	(0.440)	(0.298)	(0.577)	(0.754)	(1.130)	(0.466)	(0.486)	(0.437)
Average outcome	35.43	34.05	34.41	35.76	36.30	32.50	34.67	34.70
			Panel C: GHQ loss of confidence					
skills and discretion	-4.455***	0.170	-5.238**	-2.973*	-8.112*	-0.793	0.199	1.167
	(1.239)	(0.862)	(2.402)	(1.559)	(4.033)	(1.550)	(1.377)	(1.165)
physical environment	-0.633	0.864	0.332	-0.074	-5.583**	2.774*	-0.044	1.161
	(0.949)	(0.960)	(1.064)	(1.610)	(2.326)	(1.563)	(1.623)	(1.298)
intensity	0.049	0.448	-0.378	0.559	-1.192	0.086	0.273	1.180
	(0.545)	(0.365)	(0.634)	(0.686)	(1.143)	(0.770)	(0.600)	(0.921)
working time quality	-1.217	0.653**	-1.364	-0.129	-4.656*	0.327	0.227	1.590*
	(0.860)	(0.247)	(1.079)	(1.249)	(2.382)	(0.792)	(0.432)	(0.941)
Average outcome	18.78	14.26	18.45	18.95	18.86	14.09	14.79	13.26
Observations	9274	8048	2946	4642	1686	2338	3966	1744
# of individuals	4,637	4,024	1,473	2,321	843	1,169	1,983	872
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The sample includes 4,637 women and 4,024 men, interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects, controls for prospect index and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1 in our sample. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Age-stratified analyses do not reveal any further underlying pattern for men. Our findings are consistent with previous literature that provided some evidence that job characteristics are more detrimental to the health of females and older workers (see, e.g., Fletcher et al., 2011; Ravesteijn et al., 2018).

4.2. Mental health factors

Table 6 reports the results for models that employ as outcomes the three main components of the GHQ depression score, namely anxiety (Panel A), social dysfunction (Panel B) and loss of confidence (Panel C). This disaggregation has been proposed by Graetz (1991), who identified these three different and clinically meaningful factors as composing the overall GHQ score. The three-factor structure of the GHQ index has been replicated in several confirmatory analyses (Gao et al., 2004; Shevlin and Adamson, 2005) and is now widely used in academic research on mental health across different disciplines, including economics (see e.g. Dustmann and Fasani 2016, Carrino et al. 2020, Colantone et al. 2019). In our context, such disaggregation allows us to better disentangle the mechanisms through which changes in working conditions affect the psychological wellbeing of workers.

For the whole sample of women (column 1), we find that improvements in skills and discretion have a statistically significant and beneficial effect on workers' anxiety, social dysfunction and loss of confidence. Moreover, we find that improvements in jobs' physical environment, work intensity and working time quality improve female workers' wellbeing by reducing their feelings of social dysfunction. For male workers (column 2), improvements in the index of job prospects lead to reductions in anxiety and increases in confidence.

When looking at age-stratified models, the results in Table 6 (Columns 3–5) provide valuable insights that expand upon the findings in Table 5. Improvements in skills and discretion have a strong positive effect on the anxiety and social dysfunction levels of younger and older workers while also increasing feelings of confidence for all age groups. Improvements in the physical environment increase the wellbeing of older workers, with large effects on anxiety and confidence and somewhat smaller effects on social dysfunction. At the same time, other age groups do not show any effect. Changes in job intensity increase younger workers' feelings of anxiety and social dysfunction, with no effects found for other age groups. Improvements in working time quality have a large beneficial effect on older workers' feelings of anxiety, social dysfunction and confidence while also reducing (to a lesser extent) younger workers' levels of anxiety and social dysfunction.

4.3. In-depth analysis of working quality components

Until now, we have employed as explanatory variables of interest the five indices of working quality developed by Eurofound (2017), aggregates of several sub-factors, as described in Table 2. In order to expand the main results presented above, we re-estimated our model (1–2) by

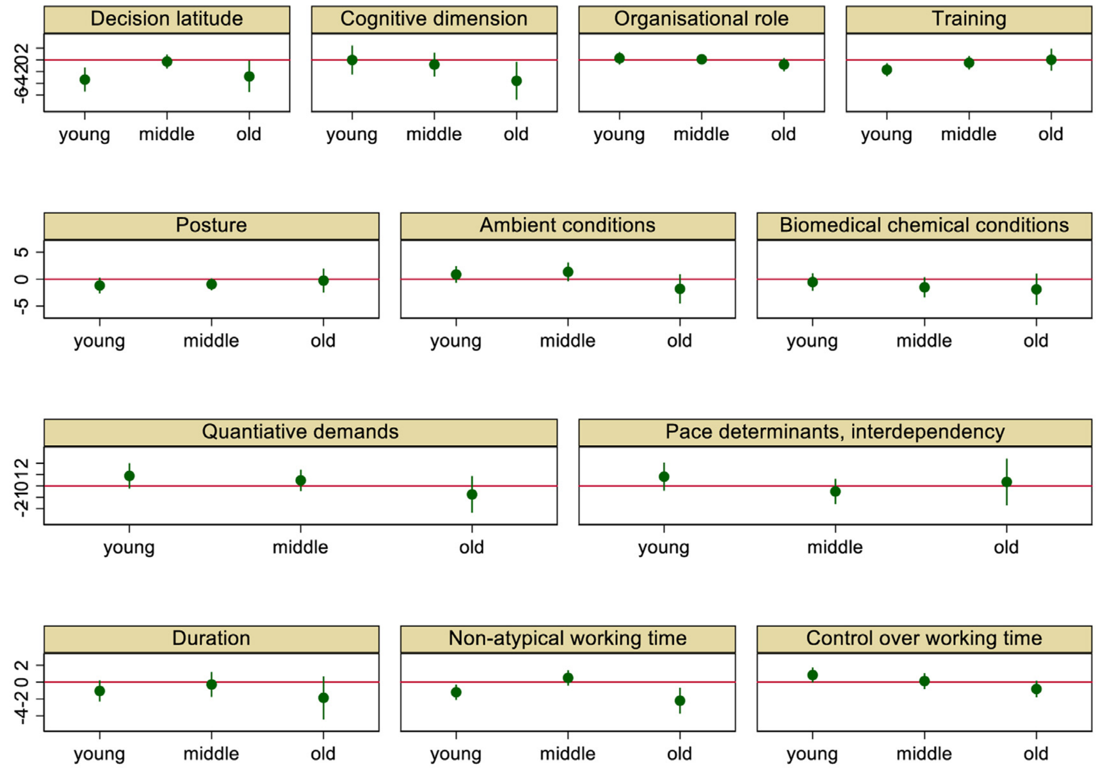

Fig. 4. Effect of sub-factors of working quality on the GHQ mental health score for female workers
Notes: Each row in the figure reports estimated coefficients from a separate regression model, estimated for female workers by age group (young: aged 16–35; middle: aged 36–49; old: aged > 50). In row 1 we disentangled the components of skills and discretion; row 2 refers to the components of physical environment; row 3 refers to work intensity; row 4 refers to working time quality; row 5 refers to Job prospects. In each regression, the sample included 4637 women, interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects, controls for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren.

substituting each of the four aggregate indices of working conditions with their sub-indices. We perform this substitution for one index at a time, e.g. we replace the aggregate index of skills and discretion with the 4 sub-indices (decision latitude, cognitive dimension, organisational role, training), and we leave the remaining four aggregate indices as regressors (working time quality, intensity, physical environment, and prospect). The rest of the econometric model remains as described in Section 3. Fig. 4 shows the estimated coefficients we obtained for each group of sub-indices, on the female sample, by age group (results for men are shown in Appendix 1, Fig. A2).

Skills and discretion emerged as a crucial determinant of mental health in our main analysis. By looking at its components, we find that (i) improvements in decision latitude lead to significant reductions in depression scores for both younger and older workers; moreover, (ii) older workers' mental health benefits greatly from improvements in the job's cognitive dimension, while (iii) younger workers benefit from increased training components.

In the main results, we found that the aggregate index of physical environment was linked to better mental health for older workers. Here, we find no evidence that this effect is driven by a specific channel, as we find no statistically significant effect for single sub-components for any age group. Although a possible reason for the lack of statistical significance of the single components lies in their correlation, we found that the highest correlation score is 0.6 (between ambient and biochemical conditions). Moreover, the joint effect of the three sub-indices of physical environment is statistically significant (at the 10% level) for the older age group.

Similarly, while we previously found that the mental health of younger female workers suffers from higher work intensity, we do not find a statistically significant effect for the single sub-components. However, we found that their effect on mental health is jointly statistically significant, highlighting the importance of using multidimensional job quality indices.

Working time quality emerged as an important driver of younger and older female workers' mental health in our main model. This result is most likely driven by improvements in working time arrangements, e.g. a reduction in the number of night or weekend shifts, which are beneficial for younger, but especially older, workers. This is consistent with the existing literature, which showed that long hours are connected to mental health concerns, particularly in women (see, e.g., Weston et al. (2019), who used Understanding Society data to find that working extra-long hours and weekends is associated with higher depressive symptoms among females).

4.5. Heterogeneity by pre-existing job-strain levels

We now test whether the observed beneficial effects of working conditions are stronger for jobs that were characterised by pre-existing higher exposure to psychosocial stressors. In particular, we borrow the conceptual framework from the demand-control model developed by Karasek (1979) and Karasek and Theorell (1990), which classifies occupations in terms of the combination of two characteristics: psychological work demands and the amount of control workers have to meet these demands. The model predicts that workers will face increased strain when demands are increased, and control and/or support are decreased. Moreover, the combined worsening of demands and control leads to greater strain than would be caused by these factors separately. Therefore, jobs with higher demands lead to high levels of workers' stress. However, higher levels of job control can buffer the detrimental effects of high work demands and lower the levels of work stress experienced by workers (Fila et al., 2017; Shultz et al., 2010). Based on this framework, we hypothesize that improvements in work characteristics strictly related to job demand and job control would lead to higher health improvements for jobs characterised by higher levels of job strain (i.e. higher demand and low control) than for non-strain jobs.

We follow Carrino et al. (2020) and match each respondent's occupation with information from a validated gender-specific job exposure matrix (FINJEM) built by Solovieva et al. (2014), which assesses psychosocial factors at work within Karasek's job-strain model. They built job control and job demand indices at ISCO-88 level (4-digit), from the Health 2000 Study, a large survey of adult Finnish workers. The survey consisted of several questionnaires, a home interview, and a health examination. The psychological job demands scale is based on items such as 'work fast', 'work hard', 'excessive work', 'not enough time', and 'hectic job'. The job-control scale is the sum of two subscales: decision authority (measured with the following items: 'allows own decisions', 'decision freedom', and 'a lot of say on the job') and skill discretion (measured with 'learn new things', 'requires creativity', 'high skill level', 'variety', and 'develop own abilities'). The exposure estimates for job demands and job control were dichotomised using a gender-specific median as a cut-off point. Job strain was operationalised using the quadrant matrix by Karasek: jobs with above-the-median levels of job demands and below-the-median levels of job control were classified as high-strain. Other categories are as follows: low strain (low demands and high control), passive (low demands and low control) and active (high demands and high control). Fig. A3 in Appendix 1 shows the average values of our five standardized working conditions indicators for each job category.

A notable advantage of the FINJEM measures of job strain is that they were validated using data from the national Finnish Work and Health Surveys (1997–2009), and showed good accuracy in identifying individuals exposed to low job control and high job strain with impact on mental health (Solovieva et al., 2014). Moreover, based on their definition, the FINJEM measures of job demand and job control are closely linked to the variables on skills and discretion, and work intensity, in the EWCS survey. Finally, the FINJEM refers to the decade of the 2000s and the years immediately preceding the beginning of our study period.

We link each respondent in the Understanding Society survey to the FINJEM categorization of job strain based on respondents' ISCO-4 digit current occupation. We only focus on female respondents, as the main analysis showed that changes in working conditions are particularly relevant for women. Out of the sample of 4637 women, 9.1% are employed in high-strain, 42% in passive, 16% in active, and 32% in no-strain occupations. We then estimate models (1–2) for each sub-group.

The results for the GHQ continuous depression score are visualised in Fig. 5, and the results for the GHQ caseness index are shown in Fig. 6 (full results are shown in Table A3 in Appendix 1). Overall, our findings show that improvements in levels of job control (higher skills and discretion) and job demand (lower intensity) lead to greater health benefits for occupations which are inherently characterised by higher job strain. As shown in Figs. 5 and 6, a unitary increase in skills and discretion leads to statistically significant reductions in depression scores and in the risk of clinical depression for high-strain and passive occupations, but not for active and no-strain jobs. Similar findings are obtained for changes in work intensity, which affect the mental health of workers in high-strain, passive, and active jobs, but not the mental health of workers in no-strain occupations.

5. Robustness checks

We test the robustness of our results by performing several sensitivity checks. All tests use the baseline specification on GHQ depression score, as reported in Table 5, Panel A.

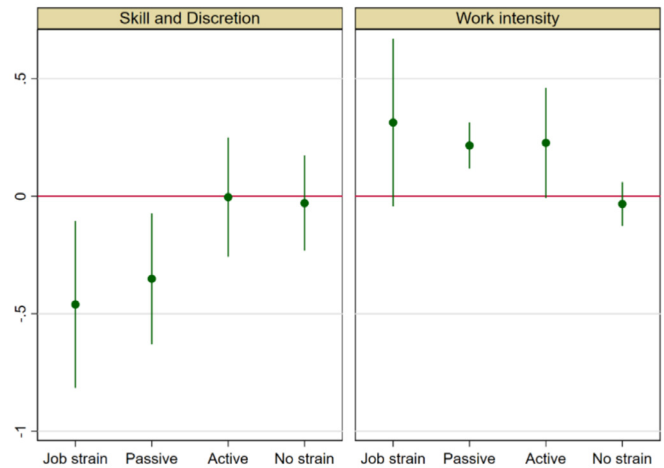

Fig. 5. Effect of job quality on GHQ score by levels of job strain (FINJEM).

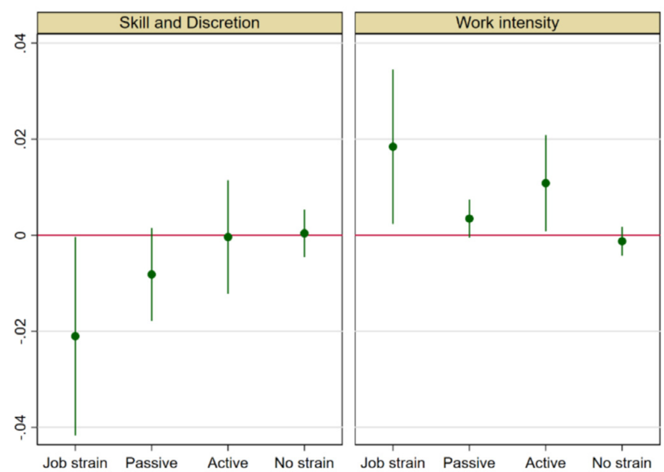

Fig. 6. Effect of job quality on GHQ caseness (at risk of clinical depression) by levels of job strain (FINJEM)

Note: Figs. 5 and 6 report coefficients from two regression models estimated for female workers and separately by the job-strain categorization of their job, according to the FINJEM job exposure matrix (matched through the ISCO 4-digit code). In Fig. 5, the dependent variable is the GHQ depression score. In Fig. 6, the dependent variable is the GHQ caseness indicator of risk of clinical depression. In each regression, the sample included 4,637 women, interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects, controls for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren.

As explained in Section 3, our analysis is based solely on workers who do not switch occupations over time: in this way, the variation in working conditions is derived exclusively from changes within occupations and not from individuals switching between occupations, which may be endogenous.

However, we keep in our sample workers who change job *within the same occupation* (defined at 3 digit ISCO), for example, because they change firm (see Table 4). These switches do not entail any variation in occupation-specific working conditions, and our estimates should thus not suffer from reverse causality. Nevertheless, to test whether the inclusion of job switchers within occupation affects our results, we replicate our main estimates, excluding them from the original sample. The estimates' results are reported in Table 7 and reveal that our findings are robust to excluding job switchers. Notably, the coefficients of the indica-

Table 7
Robustness checks: baseline estimates (dependent variable: GHQ depression scores) excluding job switchers within ISCO.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Women	Men	Women			Men		
			Age 16–35	Age 36–50	Age > 50	Age 16–35	Age 36–50	Age > 50
skills and discretion	-3.156***	0.215	-3.833**	-2.351	-5.750***	-1.063	0.842	0.712
	(1.025)	(0.681)	(1.591)	(1.400)	(2.094)	(1.148)	(1.148)	(0.634)
physical environment	-0.890	0.184	-0.297	-0.821	-3.827***	0.222	0.276	0.076
	(0.540)	(0.901)	(0.804)	(1.105)	(1.191)	(1.547)	(1.177)	(0.636)
intensity	0.582	-0.000	1.338***	0.355	-0.363	-0.289	0.195	-0.147
	(0.416)	(0.337)	(0.372)	(0.537)	(0.788)	(0.672)	(0.477)	(0.575)
working time quality	-1.096*	0.179	-1.837**	-0.040	-3.382**	0.174	-0.172	0.696
	(0.617)	(0.319)	(0.790)	(0.785)	(1.371)	(0.438)	(0.706)	(0.421)
Average outcome	30.99	28.22	30.14	31.36	31.25	27.27	28.90	27.75
Observations	7,446	6,414	2,118	3,818	1,510	1,596	3,260	1,558

Notes: All regressions include individual and sector fixed effects, controls for prospect index and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 8
Robustness checks: baseline estimates (dependent variable: GHQ depression scores) with the inclusion of different sets of controls.

	(1) Original	(2) Physical health v1	(3) Physical health v2	(4) Macro controls v1	(5) Macro controls v2	(6) Excl. prospects index	(7) Excl. controls
skills and discretion	-2.845***	-2.903***	-2.653***	-2.873***	-2.966***	-1.936***	-2.703***
	(0.983)	(0.957)	(0.933)	(0.978)	(0.998)	(0.685)	(0.977)
physical environment	-0.909	-0.842	-0.752	-0.898	-0.905	-0.610	-0.738
	(0.569)	(0.543)	(0.540)	(0.569)	(0.556)	(0.511)	(0.574)
intensity	0.534	0.509	0.528	0.558	0.591	0.514	0.615
	(0.447)	(0.444)	(0.451)	(0.456)	(0.467)	(0.463)	(0.451)
working time quality	-0.974*	-0.977*	-0.977*	-0.998*	-1.020*	-0.530	-1.016*
	(0.579)	(0.566)	(0.576)	(0.571)	(0.584)	(0.554)	(0.581)
Disability index 0–100			0.030***				
			(0.008)				
# functional limitations		1.695***					
		(0.574)					
# diagnosed conditions		0.853					
		(0.628)					
Sectoral GVA				-0.160*			
				(0.088)			
GVA – cycle comp.					-1.425***		
					(0.526)		
GVA – trend comp.					-0.071		
					(0.102)		
Average outcome	30.81	30.83	30.81	30.81	30.81	30.81	30.81
Observations	9,274	9,087	9,274	9,274	9,274	9,274	9,274

Notes:All regressions include individual and sector fixed effects, controls for prospect index (except in col. 6) and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1. In column 2 we add self reported number of functional limitations (mobility and walking; lifting, carrying or moving objects; manual dexterity; continence in bladder or bowel; hearing; sight; difficulties with own personal care) and the number of health conditions diagnosed by a doctor (asthma, arthritis, congestive heart failure, coronary heart disease, angina, heart attack, stroke, emphysema, hyperthyroidism, hypothyroidism, chronic bronchitis, liver condition, cancer, diabetes, epilepsy, high blood pressure). In column 3 we include a disability index built following Poterba et al. (2011), based on the information on the presence of each disability and health conditions mentioned above. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

tors of working conditions remain remarkably stable in this alternative specification.

In Table 8, we run an additional set of sensitivity checks to test whether our estimates are robust to alternative specifications where we add and remove some regressors. We focus on the female sample only, and we report the results for all age groups together. Results disaggregated by age are reported in Tables A4a-A4c in Appendix 1.

In column (1) we report our baseline specification as a reference. In columns (2) and (3) we add two alternative measures of individual physical health, based on self-reported information, that might affect mental health and mediate the effect of working conditions, especially when evaluating the impacts of the job's physical environment. As the link between mental health and physical health has been shown to be bi-directional, e.g. worse mental health can affect physical health (Johnson-Lawrence et al., 2013; Kolappa et al., 2013; Schuch et al., 2017), we aim to check the robustness of the coefficients for our main variables of interest, rather than to comment on the association between physical and mental health. Respondents are asked whether they experience functional limitations (7 questions) and are currently suffering from a condition diagnosed by a doctor (16 conditions). We first estimated a model (column 2) where we control for the number of reported functional limitations (e.g. mobility, activities of daily living), and the number of diagnosed health conditions (e.g. heart diseases, cancer, bronchitis). We then followed Poterba et al. (2011) and built a disability index (range 0–100; higher score signals worse health), through the Principal Component Analysis, based on information on the presence of each specific functional limitation and each particular health condition diagnosed by a doctor (as in Belloni et al., 2016). The full list of limitations and conditions used is available in the footnote to Table 8. Results in columns (2) and (3) in Table 8 align with our main findings - including those for the physical environment index - suggesting that physical health is not a significant confounder. Tables A4a, A4b and A4c in Appendix 1 report results for the same robustness tests stratified by age and gender, which again are very close to our main findings.

In columns (4) and (5) we include alternative measures of macroeconomic conditions. Earlier in the text, we stated that the time variation in working conditions observed in the EWCS could be induced by varying macroeconomic conditions, i.e. the 2009 crisis and the partial recovery afterwards. The change in the macroeconomic environment may well directly affect workers' (perceived) mental health, not just indirectly through its impact on working conditions. To disentangle the two effects, we add some meaningful indicators of macroeconomic conditions to the set of regressors based on the gross value added (ONS, 2021). We use data disaggregated by interview year, industry, and region, thus providing a great deal of variation in macroeconomic conditions.[3] The first specification (column 4) includes the gross value added in levels. In an additional specification (column 5), we decompose the gross value added into a cycle and trend component using the Hodrick-Prescott filter (Hodrick and Prescott, 1997) based on the yearly time series 1998–2018. Column 4 confirms that better macroeconomic conditions, as captured by higher gross value added, have a direct, positive, and significant effect on workers' mental health. Column 5 reveals that it is the cycle component rather than the trend that impacts health: mental health improves during booms and worsens in recessions. The analysis by age (see Tables A4 in Appendix 1) suggests that both females in their middle age and especially older females are sensitive to macroeconomic conditions: the point estimate of the cycle component for the latter age group is approximately twice that of the former. Most importantly, the effect of working conditions on mental health – both point estimates and significance – remains almost unchanged once the macroeconomic conditions variables are added to the model (columns 4 and 5).

In column 6, we exclude the prospect index. Earlier (see Section 4.1), we pointed out that inherently subjective preferences characterize this index. Qualitatively, our main findings remain confirmed, even if the magnitude of the skill and discretion and working time quality indices is reduced. Finally, column 7 shows that our results are fully confirmed even if we exclude all the control variables from the model. This result might indicate that controls included in the baseline are poorly correlated with working conditions variables.

6. Discussion and conclusions

In this paper, we have combined information on working conditions from the EWCS survey in 2010 and 2015 with longitudinal microdata from Understanding Society to estimate the impact of job quality on workers' mental health. Overall, our approach builds and improves upon previous studies that sought to identify a causal relationship between working conditions and mental health (Bentley et al., 2015; Fletcher et al., 2011; Ravesteijn et al., 2018; Robone et al., 2011) by implementing a novel empirical strategy which focuses on workers who remain in the same type of job throughout the study period. This approach, in turn, allows us to identify the effect of working conditions on health by exploiting changes in job quality over time (controlling for individual fixed effects) rather than relying on the (most likely endogenous) decision of workers to change occupation. We exploit new detailed indicators of working conditions, which better represent the multidimensionality of job quality and allow us to study changes in working conditions over time, together with rich and validated tools measuring mental health and its components.

Our main findings are threefold. First, we find that, on average, among female workers in the UK, better job characteristics such as skills and discretion and, to a less extent, working time arrangements lead to significant and sizable improvements in mental health. Quantitatively, an increase by one standard deviation in the skills and discretion index, which roughly corresponds to the difference between clerks and sales workers, reduces the risk of clinical depression by seven probability points from an average of 26% and constitutes a clinically meaningful effect. We estimate that this improvement is comparable to the one associated with a 2 percent increase in household income. Skills and discretion primarily affect workers' anxiety and self-confidence. At the same time, their social functioning (e.g., concentration and decision making) is found sensitive to other dimensions of work such as working time arrangements, intensity, and the physical environment. These findings provide causal evidence to support conceptual frameworks in occupational medicine like Karasek (1979) and Harvey et al., (2017), which highlight the detrimental effect on mental health outcomes of workplace risk factors such as imbalanced job design and occupational uncertainty.[4]

Second, we find evidence of heterogeneous effects of job characteristics by age among women. Improvements in skills and discretion have a beneficial impact on both younger and older workers' mental health. The former group is sensitive to job latitude (e.g., choosing the order of tasks, speed, and work methods) and training. Older workers, conversely, benefit from a higher cognitive dimension of work (choosing the complexity of tasks and applying their ideas at work). Older workers' mental health – especially anxiety and confidence – is also affected by changes in the physical environment (e.g., posture requirements, ambient conditions) and working time arrangements, especially atypical work schedules. Finally, changes in work intensity affect younger workers' depressive symptoms, although the effect is not large.

These age-specific findings support the predictions of lifespan aging theories (Baltes and Baltes, 1993; Carstensen, 1991), suggesting that older workers would benefit most from increased skill variety, whereas younger workers would benefit most from increased task variety (Zaniboni et al., 2013). Our results are also in line with the conceptual framework of Shultz et al. (2010): they hypothesize that older workers, who may be experiencing more age-related reductions in both cognitive and physical resources, are more exposed to worse physical environments and benefit largely from higher job controls to buffer the stress resulting from the physical requirements. Furthermore, older workers' higher sensitivity to working time arrangements is likely to depend on their more prominent involvement in informal social support activities (grandchild care, long-term care) than younger workers, which translates into a higher likelihood of work-family conflict (Carmichael et al., 2010). We also provide new insights on the mixed evidence on the link between on-the-job training and mental health (Junge et al., 2015; van Berkel et al., 2014), supporting the hypothesis (Gazioglu and Tansel, 2006) that training might improve mental health through its positive impact on job satisfaction.

Third, we show that improvements in job control (corresponding to our skills and discretion index) and job demand (work intensity) are

[3] Regional gross value added (balanced) by industry: all International Territorial Level (ITL) regions: ITL1 and UK chained volume measures in 2018 money value. Data are rescaled in 1,000 units.

[4] Similarly to us, these studies highlight the role of work intensity, physical environment, job control, atypical working time and temporary employment status. Note that our study lacks information on other stressors such as procedural justice, organisational change, lack of value and respect within the workplace which are covered in the paper by (Harvey et al., 2017).

especially beneficial for workers employed in jobs inherently characterised by a combination of high psychological demands and/or low job control. This result confirms the theoretical predictions of the demand-control model proposed by Karasek (1979) and suggests that policy and workplace interventions should target high-strain jobs as a priority.

Our result that working conditions are less impactful on men than they are on women is in line with evidence from Robone et al. (2011) and Roberts et al. (2011) for the UK and Fletcher et al. (2011) for the US. These studies found that the psychological wellbeing of women is more greatly affected than that of men by working schedules and commuting time, physical demands, and environmental conditions. Our findings also partially support Bildt and Michélsen (2002) reporting that men's and women's mental health is associated with very different job characteristics. Conversely, our results challenge findings from Bardasi and Francesconi (2004), who found that temporary work arrangements and part-time employment were not associated with long-lasting negative health among male and female workers in Britain in the 1990s. While our result can be partially explained by women's greater responsibility for day-to-day household tasks (including childcare and housework) that makes them more sensitive to the work-family conflicts induced by employment characteristics (Burr and Colley, 2017; Roberts et al., 2011; Van Houtven et al., 2013), we hope that our findings, which employ an alternative empirical strategy aimed at causal identification and a more detailed dashboard of working condition indices, will stimulate new research on the gender heterogeneity of the link between work and health.

Our findings are robust to a large number of sensitivity tests, which include accounting for sample selection bias, alternative choices of the sample, as well as including alternative measures of physical health and macroeconomic indicators as independent variables. Nevertheless, our analysis is not free from limitations, which could be addressed by future work. First, our analysis of changes in working conditions only relies on two points in time, allowing us to study the short-term effect of job quality, which we show is substantial. However, we cannot assess the health outcomes of longer-term dynamics in working conditions, such as the cumulative effect of being subject to repeated changes in job quality. Second, we conducted our analysis at the ISCO-3 digits, a very detailed classification level. ISCO-4 digits could capture the remaining within-group heterogeneity in job features. However, the within-cell number of observations in the UK EWCS is too low, at least in the analysed waves.

We believe our results have important implications for policymakers. We provide new evidence that improving the quality of specific aspects of work could be a valuable mechanism for addressing and preventing the mental health difficulties of workers, especially for older and younger groups. These groups have been recently affected by significant transformations in the labor market. For example, older workers in the UK and worldwide face a longer working horizon due to policies aimed at prolonging working lives (e.g. through the postponement of the State Pension age) (see OECD, 2017). Crucially, recent evidence has shown that workers in high-strain occupations, and especially women in the UK, suffer from worse mental health and higher depression as a consequence of having to work longer before reaching the pension age (Carrino et al., 2020), which reduces the welfare gains from increasing employment in older age. Our results suggest that workplace interventions that help improve workers' control over their tasks and working time and the physical job environment can significantly reduce the risk of depression and might increase the societal benefits of policies promoting longer working. Younger workers, on the other hand, are at risk of facing poorer working conditions and precarious unemployment, especially in the transition from education to work, due to their fewer political, economic, social, and cultural resources (Ryan, 2001; Schoon, 2015; Shields et al., 2021). Moreover, younger workers have been particularly hit by shutdowns and job losses during the COVID-19 pandemic (Bell and Blanchflower, 2020; OECD, 2020).

While policymakers are designing and implementing policies to restore economic activities and well-being and 'level up' inequalities (OECD, 2021) after the crisis caused by the pandemic, our findings provide support for calls on targeted interventions on job quality. Workplace interventions aiming at improving decision latitude, training, work schedules, and career prospects can improve the mental health of younger and older workers, leading to better wellbeing throughout and after the recovery (Bambra et al., 2007; Egan et al., 2007). Moreover, mental health support interventions are highly cost-effective and productivity-enhancing for firms (Knapp et al., 2011). Finally, while depressive symptoms are now a leading cause of disability worldwide, with significant repercussions on social wellbeing and public finances, critical gaps exist in the treatment procedures, as fewer than half of those affected in the world receive effective treatments (Purebl et al., 2015). We, therefore, hope our study will prompt further research on understanding how to integrate better job quality with existing mental health treatments.

Funding

Ludovico Carrino is supported by the Economic and Social Research Council (WORKLONG project, ES/P000487/1; IN–CARE project, ES/S01523X/1) and the Joint Programme Initiative 'More Years, Better Lives'. It also represents independent research partly supported by the ESRC center for Society and Mental Health at King's College London (ESRC Reference: ES/S012567/1).

The paper uses data from Understanding Society, an initiative funded by the Economic and Social Research Council and various government departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by the National center for Social Research and TNS BMRB. The research data are distributed by the UK Data Service. The University of Essex. Institute for Social and Economic Research, NatCen Social Research, Kantar Public. (2018). *Understanding Society: Waves 1–8, 2009–2017 and Harmonised BHPS: Waves 1–18, 1991–2009. 9th Edition.* UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA–SN–6614–10.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Acknowledgments

The authors thank Rob Alessie, Mauricio Avendano, Lex Burdorf, Karen Glaser and Solveig Cunningham, as well as participants at the Population Association of America Conference 2022 for their valuable insights on previous versions of this paper.

Appendix 1. additional tables and figures

Figs. A1–A3, Tables A1–A3, Tables A4A, A4B, A4C and A5.

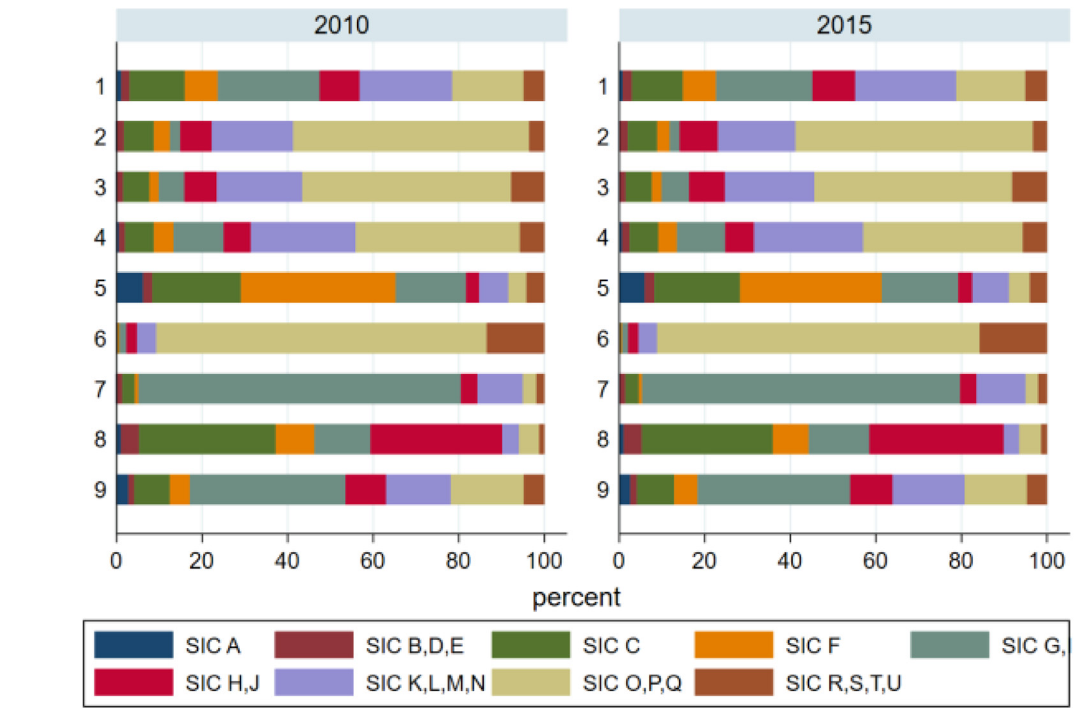

Fig. A1. Sectoral composition of ISCO groups
Notes: Each bar shows the sectoral distribution (over SIC07 1-digit codes) for each occupation group (ISCO88 1-digit group). A – Agriculture, forestry and fishing; B,D,E – Energy and water; C – Manufacturing; F – Construction; G,I – Distribution, hotels and restaurant; H,J – Transport and communication; K,L,M,N – Banking and finance; O,P,Q – Public admin, education and health; R,S,T,U – Other services. **Source**: Labour Force Survey 2010 and 2015 (pooled across 4 quarters).

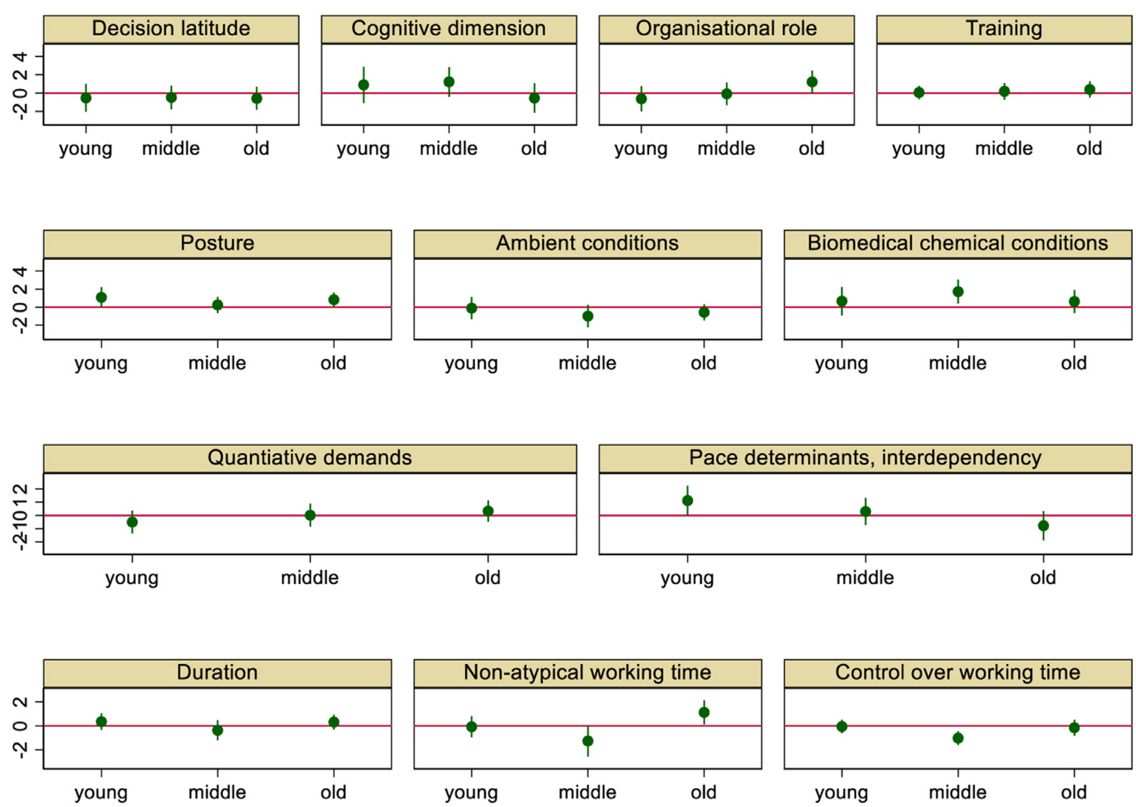

Fig. A2. Effect of sub-factors of working quality on GHQ mental health score for male workers
Note: Each row in the figure reports estimated coefficients from a separate regression model, estimated for male workers by age group (young: aged 16–35; middle: aged 36–49; old: aged > 50). In row 1 we disentangled the components of skills and discretion; row 2 refers to the components of physical environment; row 3 refers to work intensity; row 4 refers to working time quality. In each regression, the sample included 4,024 men, interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects, controls for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren.

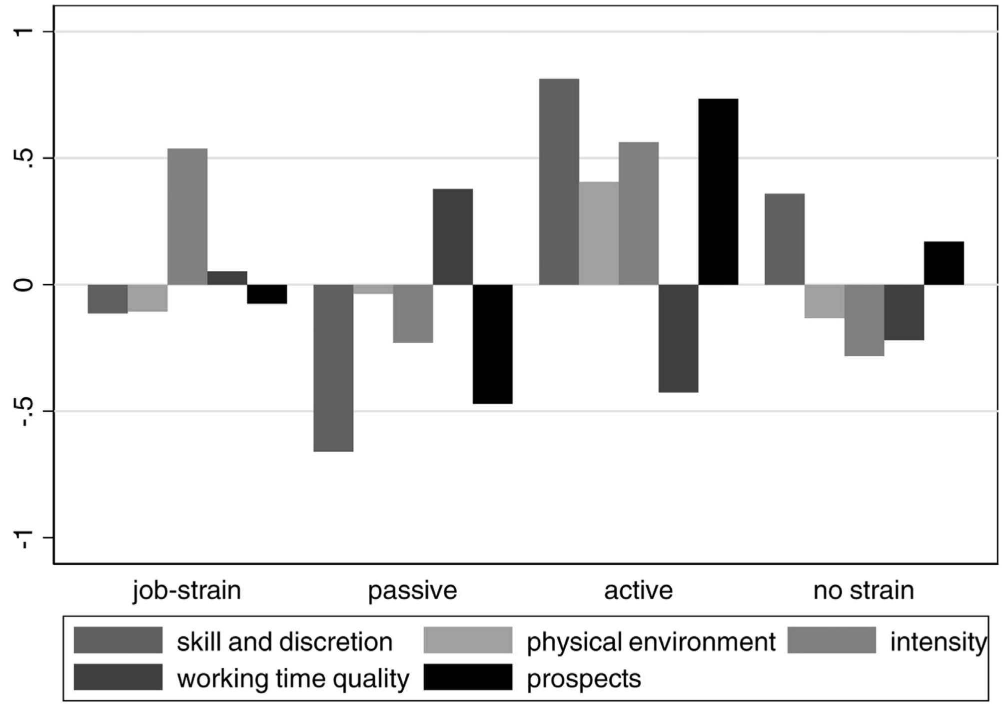

Fig. A3. Average values of standardized indicators of working conditions and FINJEM job categorization.

Table A1
Descriptive statistics by gender and age group.

	Females						Males					
	YOUNG		MIDDLE		OLD		YOUNG		MIDDLE		OLD	
	Mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	Mean	s.d.
GHQ score	29.91	14.18	31.21	13.94	31.28	13.96	27.26	12.12	28.86	12.72	27.67	12.15
GHQ caseness	0.25	0.43	0.27	0.44	0.27	0.44	0.18	0.39	0.21	0.41	0.19	0.39
GHQ component: Anxiety and depression	28.87	20.63	30.50	20.33	29.97	20.21	25.98	18.27	27.18	19.15	24.33	18.66
GHQ component: Social dysfunction	34.41	11.39	35.76	11.16	36.30	10.95	32.50	10.55	34.67	10.25	34.70	9.60
GHQ component: Loss of confidence	18.45	22.17	18.95	21.58	18.86	21.56	14.09	19.05	14.79	19.83	13.26	19.09
Skills and discretion	69.35	12.81	69.84	12.60	68.32	12.80	70.94	13.90	71.83	13.69	70.17	14.48
Physical environment	88.24	4.61	88.70	4.55	88.50	4.67	85.13	8.77	85.57	8.49	84.74	8.60
Work intensity	41.58	8.19	41.86	8.57	41.31	8.72	45.72	6.49	45.72	6.75	45.06	7.52
Working time quality	85.90	6.54	86.11	7.03	86.47	6.92	82.69	8.17	81.44	8.90	81.57	8.88
Prospect	69.95	6.57	69.96	6.48	69.35	6.54	68.90	7.55	69.37	7.51	68.48	7.59
Weekly working hours	29.66	10.81	29.73	10.39	29.22	10.57	37.90	9.08	39.47	8.23	37.54	10.53
Age	30.54	5.68	45.65	4.88	56.17	3.13	30.74	5.68	45.40	4.90	57.34	3.63
Number of children	0.54	0.90	1.36	1.26	1.64	1.41	0.46	0.84	1.24	1.29	1.45	1.36
Number of grandchildren	0.00	0.06	0.13	0.33	0.42	0.49	0.00	0.07	0.07	0.26	0.37	0.48
In couple	0.66	0.47	0.76	0.43	0.76	0.43	0.67	0.47	0.85	0.35	0.84	0.37
Log (net family income)	8.74	0.47	8.78	0.51	8.72	0.54	8.76	0.47	8.81	0.49	8.77	0.53
Number of observations	2,946		4,642		1,686		2,338		3,966		1,774	

Notes: The sample includes 4,637 women and 4,024 men interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015.

Table A2
Main results: reporting the full list of controls (dependent variable: GHQ score).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Women	Men	Women			Men		
			Age 16–35	Age 36–50	Age > 50	Age 16–35	Age 36–50	Age > 50
skills and discretion	-2.845***	0.546	-4.238**	-1.419	-5.580***	0.195	0.862	0.039
	(0.983)	(0.571)	(1.631)	(1.278)	(2.038)	(0.948)	(1.034)	(0.728)
physical environment	-0.909	0.556	-0.316	-0.667	-4.371***	1.644	0.279	0.163
	(0.569)	(0.745)	(0.747)	(1.068)	(1.230)	(1.096)	(1.083)	(0.702)
intensity	0.534	0.184	1.406***	0.168	-0.499	0.197	0.202	-0.164
	(0.447)	(0.282)	(0.484)	(0.517)	(0.794)	(0.508)	(0.411)	(0.550)
working time quality	-0.974*	0.125	-1.767**	0.198	-3.179**	0.279	-0.225	0.474
	(0.579)	(0.283)	(0.716)	(0.774)	(1.280)	(0.411)	(0.616)	(0.410)
prospects	0.736	-0.564*	1.240	0.429	1.019	-0.438	-0.408	-0.839**
	(0.461)	(0.288)	(0.827)	(0.651)	(1.050)	(0.339)	(0.491)	(0.413)
Working hours	0.026	0.028	-0.017	0.086**	0.027	0.002	0.063	-0.032
	(0.024)	(0.024)	(0.059)	(0.034)	(0.063)	(0.045)	(0.044)	(0.064)
Age	0.337	0.234	0.512	1.126	-4.950	0.585	-0.059	1.733
	(0.346)	(0.334)	(0.706)	(0.870)	(3.572)	(0.682)	(0.949)	(2.113)
Age squared	-0.007***	-0.007***	-0.011	-0.013*	0.038	-0.010	-0.005	-0.018
	(0.002)	(0.002)	(0.008)	(0.007)	(0.028)	(0.008)	(0.008)	(0.017)
N of children	-3.556*	0.317	-0.313	-6.873***	4.878***	5.856*	-1.759	1.052
	(1.932)	(1.591)	(2.321)	(0.932)	(1.283)	(3.260)	(1.600)	(2.391)
N of grandchildren	-1.059	0.753	-1.859	-2.169	0.867	0.453	1.273	-0.077
	(1.052)	(0.730)	(1.971)	(1.640)	(1.008)	(3.185)	(1.052)	(0.965)
In couple	-1.237*	-0.382	-1.098	-1.139	-3.475	-0.966	0.557	-1.298
	(0.719)	(0.979)	(0.931)	(1.497)	(2.338)	(1.062)	(1.991)	(1.775)
Log (household income)	-1.615**	-1.763***	-0.992	-2.142***	-1.287	-0.970	-2.334**	-1.755
	(0.618)	(0.443)	(0.843)	(0.786)	(1.471)	(0.639)	(0.927)	(1.054)
Wave=2	1.339	2.201	1.751	0.172	3.035	1.797	1.914	1.725
	(1.461)	(1.469)	(2.179)	(2.346)	(5.219)	(2.070)	(2.175)	(2.624)
Average outcome	30.81	28.14	29.91	31.21	31.28	27.26	28.86	27.67
Observations	9,274	8,048	2,946	4,642	1,686	2,338	3,966	1,744
Number of pidp	4,637	4,024	1,473	2,321	843	1,169	1,983	872
Sector FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: The sample includes 4,637 women and 4,024 men interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions include individual and sector fixed effects. Working conditions indices are standardised to have mean 0 and standard deviation 1 in our sample. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3
Heterogeneous effects of job demand (intensity) and job control (skills and discretion) by levels of job strain (female sample).

VARIABLES	(1) Women Job strain	(2) Passive job	(3) Active job	(4) No strain job
		Panel A: GHQ score		
skills and discretion	-6.261**	-4.778**	-0.055	-0.399
	(2.214)	(1.822)	(1.566)	(1.316)
intensity	2.476*	1.703***	1.791*	-0.261
	(1.293)	(0.372)	(0.841)	(0.351)
Average outcome	31.78	30.83	30.41	30.71
		Panel B: GHQ caseness		
skills and discretion	-0.286**	-0.111*	-0.005	0.005
	(0.129)	(0.063)	(0.073)	(0.032)
intensity	0.146**	0.027*	0.086**	-0.010
	(0.058)	(0.015)	(0.036)	(0.011)
Average outcome	0.299	0.264	0.252	0.263
Observations	846	3,916	1,486	3,026
Number of pidp	423	1,958	743	1,513
Sector FE	YES	YES	YES	YES

Note: We report the estimated effect of a unitary change in 'skills and discretion' and 'intensity' indices on mental health GHQ score (Panel A) and GHQ caseness (Panel B), estimated separately by the job-strain categorization of respondents' job. Job strain is measured with the FINJEM job exposure matrix (matched through the ISCO 4-digit code). In each regression, the sample included 4637 women, interviewed in Understanding Society, aged between 16 and 65 years old, who continued to work in the same ISCO 3-digit occupation between 2010 and 2015. All regressions controlled for the other working conditions indices (physical environment, working time quality, prospects), as well as individual and sector fixed effects, respondents' age, age squared, weekly working hours, number of children, household income (in log), and it included binary indicators for living as a couple and having any grandchildren.

Table A4A
Robustness checks reported in Table 8, disaggregated by age. Dependent variable: GHQ depression scores with the inclusion of different sets of controls. Age 16–35.

	(1) original	(2) physical health v1	(3) physical health v2	(4) macro level v1	(5) macro level v2	(6) no prospect	(7) no controls
skills and discretion	-4.238**	-4.310***	-4.032**	-4.181**	-4.169**	-2.829**	-3.836**
	(1.631)	(1.581)	(1.638)	(1.591)	(1.606)	(1.111)	(1.533)
physical environment	-0.316	-0.348	-0.615	-0.214	-0.214	-0.044	-0.221
	(0.747)	(0.764)	(0.821)	(0.771)	(0.773)	(0.895)	(0.723)
intensity	1.406***	1.405***	1.504***	1.418***	1.414***	1.345**	1.484***
	(0.484)	(0.488)	(0.511)	(0.478)	(0.484)	(0.526)	(0.470)
working time quality	-1.767**	-1.808**	-1.666**	-1.819**	-1.812**	-1.159	-1.753**
	(0.716)	(0.708)	(0.750)	(0.685)	(0.686)	(0.698)	(0.694)
# functional limitations		1.421					
		(1.023)					
# diagnosed conditions		-0.585					
		(2.396)					
Disability index 0–100			0.031				
			(0.028)				
Sectoral GVA				-0.021			
				(0.192)			
GVA – cycle comp.					0.129		
					(1.220)		
GVA – trend comp.					-0.030		
					(0.165)		
Observations	2,946	2,946	2,842	2,946	2,946	2,946	2,946
Average outcome	29.91	29.91	29.90	29.91	29.91	29.91	29.91

Notes: All regressions include individual and sector fixed effects, controls for prospect index and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4B
Robustness checks reported in Table 8, disaggregated by age. Dependent variable: GHQ depression scores with the inclusion of different sets of controls. Age 36–50.

	(1) Original	(2) physical health v1	(3) physical health v2	(4) macro level v1	(5) macro level v2	(6) no prospect	(7) no controls
skills and discretion	-1.419	-1.386	-1.238	-1.459	-1.553	-0.867	-1.374
	(1.278)	(1.238)	(1.311)	(1.296)	(1.297)	(0.721)	(1.304)
physical environment	-0.667	-0.482	-0.265	-0.699	-0.719	-0.453	-0.305
	(1.068)	(0.968)	(1.034)	(1.079)	(1.065)	(0.940)	(1.064)
intensity	0.168	0.126	0.192	0.208	0.249	0.165	0.180
	(0.517)	(0.501)	(0.536)	(0.523)	(0.531)	(0.524)	(0.518)
working time quality	0.198	0.221	0.092	0.197	0.197	0.472	0.255
	(0.774)	(0.735)	(0.767)	(0.772)	(0.777)	(0.692)	(0.759)
# functional limitations		2.163***					
		(0.593)					
# diagnosed conditions		1.380*					
		(0.722)					
Disability index 0–100			0.035***				
			(0.009)				
Sectoral GVA				-0.275*			
				(0.152)			
GVA – cycle comp.					-1.733**		
					(0.743)		
GVA – trend comp.					-0.176		
					(0.174)		
Observations	4,642	4,642	4,584	4,642	4,642	4,642	4,642
Average outcome	31.21	31.21	31.23	31.21	31.21	31.21	31.21

Notes: All regressions include individual and sector fixed effects, controls for prospect index and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A4C
Robustness checks reported in Table 8, disaggregated by age. Dependent variable: GHQ depression scores with the inclusion of different sets of controls. Age ≥ 50.

	(1) Original	(2) physical health v1	(3) physical health v2	(4) macro level v1	(5) macro level v2	(6) no prospect	(7) no controls
skills and discretion	-5.580***	-5.675***	-5.114**	-5.387**	-5.655**	-4.349***	-5.571***
	(2.038)	(2.066)	(2.199)	(2.059)	(2.135)	(1.427)	(2.020)
physical environment	-4.371***	-4.425***	-4.073***	-4.193***	-4.240***	-3.901***	-4.315***
	(1.230)	(1.213)	(1.196)	(1.231)	(1.207)	(1.268)	(1.164)
intensity	-0.499	-0.542	-0.485	-0.499	-0.468	-0.526	-0.482
	(0.794)	(0.807)	(0.781)	(0.785)	(0.787)	(0.795)	(0.788)
working time quality	-3.179**	-3.196**	-3.279**	-2.904**	-2.945**	-2.489**	-3.235**
	(1.280)	(1.273)	(1.287)	(1.265)	(1.281)	(1.050)	(1.287)
# functional limitations		0.734					
		(1.248)					
# diagnosed conditions		0.857					
		(0.769)					
Disability index 0–100			0.024*				
			(0.014)				
Sectoral GVA				-0.178			
				(0.469)			
GVA – cycle comp.					-3.058**		
					(1.487)		
GVA – trend comp.					0.313		
					(0.627)		
Observations	1,686	1,686	1,661	1,686	1,686	1,686	1,686
Average outcome	31.28	31.28	31.30	31.28	31.28	31.28	31.28

Notes: All regressions include individual and sector fixed effects, controls for prospect index and for respondents' age, age squared, weekly working hours, number of children, household income (in log), as well as binary indicators for living as a couple and having any grandchildren. Working conditions indices are standardised to have mean 0 and standard deviation 1. Robust standard errors (adjusted for clustering at the ISCO 3-digit level) in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A5
Results from Heckman selection model robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Women	Men	Women			Men		
VARIABLES			Age 16–35	Age 36–50	Age > 50	Age 16–35	Age 36–50	Age > 50
					GHQ score			
Inverse Mills ratio ($\sigma_{\epsilon,\omega}$)	.0748	.0671	.0104	-0.0105	.1213	-0.0078	.1323	.0035
	(0.1432)	(0.0911)	(0.1725)	(0.5254)	(0.2619)	(0.0808)	(0.2303)	(0.2354)
F-test for exclusion restrictions (P>χ^2) first stage regression	0	0	0	0	0	0	0	0
Nobs	7,135	5,870	2,745	3,292	1,098	2,102	2,641	1,127
Nobs selected	4,637	4,024	1,473	2,321	843	1,169	1,983	872
Nobs not selected	2,498	1,846	1,272	971	255	933	658	255

Appendix 2. Heckman selection model

As noted by Wooldridge (2001, p. 582), including the inverse Mills ratio in the main estimation equation does not lead to consistent estimates in the case of a fixed-effects panel data models.

We can, however, exploit the specific nature of our data, i.e., $T = 2$, and consider the model in its first-differentiated version (Eq. (2), Section 3):

$$\Delta H_i = \boldsymbol{\beta}' \Delta WC_i + \boldsymbol{\theta}' \Delta X_i + \epsilon_i \tag{A1}$$

where $\Delta H_i = H_{i,2} - H_{i,1}$ and similarly for the r.h.s. variables. This allows us to apply the standard Heckman selection approach (Heckman, 1976) for cross-sectional data.

We then add to the above equation the following selection equation:

$$s_2 = 1\left[\boldsymbol{\gamma}' Z_{i,2} + \omega_{i,2}\right] \tag{A.2}$$

where $s_2 = 1$ for workers that in period 2 are in the same ISCO group as in period 1, and 0 otherwise.

We further assume, as standard, that Z is exogenous in (A.1), and that ω is independent of Z (and therefore of ΔWC and ΔX). The model is completed by a distributional assumption on the unobserved errors $(\epsilon_i,\ \omega_{i,2})$, for which we assume a bivariate normal distribution with zero expectations, variances σ^2_ϵ, $\sigma^2_\omega = 1$ and covariance $\sigma_{\epsilon,\omega}$. The non-zero covariance allows for the possibility that (non) changing ISCO might be correlated with unobservables that affect mental health changes.

The expected variation in mental health (ΔH_i), given that the worker remained in the same ISCO group between period 1 and 2, is given by:

$$E(\Delta H_i | s_2 = 1) = \ \boldsymbol{\beta}' \Delta WC_i + \boldsymbol{\theta}' \Delta X_i + \sigma_{\epsilon,\omega} \frac{\phi\left(\boldsymbol{\gamma}' Z_{i,2}\right)}{\Phi\left(\boldsymbol{\gamma}' Z_{i,2}\right)} \tag{A.3}$$

where $\frac{\phi(\boldsymbol{\gamma}' Z_{i,2})}{\Phi(\boldsymbol{\gamma}' Z_{i,2})}$ is the inverse Mills ratio evaluated in $\boldsymbol{\gamma}' Z_{i,2}$. A.3 highlights that an estimation of $\boldsymbol{\beta}$ can be obtained using only the sample of workers who do not change ISCO provided we include the inverse Mills ratio as an additional regressor.

The mental health equation (A.1) can therefore be consistently estimated by OLS – or, equivalently, the model described in Section 3 by FE regression – provided that $\sigma_{\epsilon,\omega}$ is equal to zero, i.e. the two error terms in equations A.1 and A.2 are uncorrelated. A sample selection bias arises if instead $\sigma_{\epsilon,\omega}$ is different from zero.

$\boldsymbol{\gamma}$ is unknown in A.3, but we can replace it with its estimate obtained from the standard probit model derived from (A.2):

$$P(s_2 = 1 | Z_{i,2}) = \Phi\left(\boldsymbol{\gamma}' Z_{i,2}\right)$$

where $Z_{i,2} \equiv \{\Delta WC_i,\ \Delta X_i, WC_{i,2}, X_{i,2}\}$. The exclusion restrictions are, therefore $(WC_{i,2}, X_{i,2})$, i.e., the five working conditions indicators – plus the standard set of control variables included in the original model (sector fixed effects, respondents' age, age squared, weekly working hours, number of children, log of household income, binary indicators for living as a couple and having any grandchildren) – included *in levels as in period 2* (wave 2015). We assume that these variables do not affect the degree of *variation* in mental health but rather the probability of remaining in the same ISCO. Obviously, the probit model is estimated based on the whole sample of workers, including those who changed ISCO.

We estimate the Heckman model when the outcome variable is the GHQ score; standard errors are clustered at ISCO level. The F-tests presented in Table A5 clearly show that the exclusion restrictions are strongly predictive of ISCO switches in the probit equations. Most importantly, in any of the proposed specifications from (1) to (8), we cannot reject the null that $\sigma_{\epsilon,\omega} = 0$. This result indicates that the estimates presented in the main text are consistent and not affected by issues of sample selection.

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